

Reliability-Based System Modelling for Renewable Energy Mini-grids Development

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Abbreviations

AC	Alternating Current
BESS	Battery Energy Storage System
BOS	Balance of System
CHP	Combined Heat and Power
COPT	Capacity Outage Probability Table
CRF	Capital Recovery Factor
DC	Direct Current
DER-CAM	Distributed Energy Resources Customer Adoption Model
EENS	Expected Energy Not Supplied
ESMAP	Energy Sector Management Assistance Program
EVA	Ethylene-Vinyl Acetate
FMMEA	Failure Modes, Mechanisms, Effects Analysis
FOR	Forced Outage Rate
HOMER	Hybrid Optimization of Multiple Energy Resources
IGBT	Insulated Gate Bipolar Transistor
KiBaM	Kinetic Battery Model
kW	Kilowatt
kWh	Kilowatt-hour
LCOE	Levelised Cost of Energy
LeTID	Light and Elevated-Temperature-Induced Degradation
LID	Light-Induced Degradation
LOLE	Loss of Load Expectation
LOLP	Loss Of Load Probability
LPSP	Loss of Power Supply Probability
MCB	Miniature Circuit Breaker

MILP	Mixed Integer Linear Programming
MOSFET	Metal-Oxide-Semiconductor Field-Effect Transistor
MTTF	Mean Time to Failure
NLR	National Laboratory of the Rockies
NPC	Net Present Cost
NPV	Net Present Value
OLS	Ordinary Least Square
OSeMOSYS	Open Source Energy Modelling System
PCB	Printed Circuit Board
PERC	Passivated Emitter and Rear Cell
PID	Potential-Induced Degradation
PoF	Physics of Failure
PV	Photovoltaic
RAM	Reliability-Availability-Maintainability
RBD	Reliability Block Diagram
REA	Rural Electrification Agency
REopt	Renewable Energy Optimisation
RETScreen	Renewable-Energy and Energy-efficiency Technology Screening
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SEI	Solid Electrolyte Interphase
SEM	Solar Energy Mini-grid
SEM-RBRM	Solar Energy Mini-grid Reliability-Based Regression Model
SOC	State of Charge
TELS	Total Electrical Load Served
TMY	Typical Meteorological Year
UV	Ultraviolet

VIF

Variance Inflation Factors

Abstract

Solar Energy Mini-Grids (SEMs) are increasingly deployed as decentralised electrification solutions in regions where conventional grid expansion remains technically, economically, or institutionally constrained. Although existing SEM design and optimisation frameworks have advanced system planning significantly, most remain fundamentally deterministic, assuming continuous subsystem availability and thereby neglecting the stochastic failure behaviour of critical components. This assumption leads to systematically optimistic estimates of system performance, particularly with respect to the Total Electrical Load Served (TELS), which is a key indicator of service reliability, operational effectiveness, and financial viability.

This thesis addresses the absence of a practical reliability-integrated modelling framework capable of linking subsystem failure behaviour directly to system-level energy delivery. The research develops a SEM Reliability-Based Regression Model (SEM-RBRM) to predict actual, time-varying TELS over the operational lifetime of an SEM by explicitly incorporating subsystem reliability into performance modelling. The proposed framework combines deterministic SEM simulation, multivariate regression modelling, and reliability engineering analysis within a unified analytical structure.

A baseline deterministic SEM model was first developed using Hybrid Optimization of Multiple Energy Resources (HOMER) to simulate the performance of a hybrid photovoltaic–battery–diesel–converter configuration under varying environmental and load conditions. Time-series simulation outputs were then used to formulate a regression-based performance model relating TELS to key operational variables. The resulting model demonstrated predictive accuracy of $R^2 \approx 0.99$, confirming that inverter output, generator contribution, and battery power explain most of the variability in deterministic SEM performance. However, this model represents an upper-bound performance estimate because it does not account for subsystem failure, degradation, or downtime.

To address this limitation, subsystem reliability was modelled using exponential reliability functions and integrated via a Reliability Block Diagram (RBD) representation of SEM architecture. This enabled the formulation of a reliability-adjusted performance function in which effective load served is expressed as the product of deterministic TELS and system availability over time. The results show that subsystem reliability exerts a

measurable and progressive constraining effect on energy delivery, and that deterministic models consistently overestimate long-term SEM performance. Sensitivity analysis further identified the power converter as the dominant critical-path component due to its series position within the system topology.

By integrating reliability engineering directly into SEM performance prediction, this thesis contributes a computationally efficient, scalable, and decision-relevant framework for reliability-aware mini-grid design, evaluation, and long-term planning.

Declaration

I certify that this work has not been accepted in substance for any degree and is not concurrently submitted for any degree other than that of Doctor of Philosophy (PhD) of the Liverpool John Moores University. I also declare that this work is the result of my own investigations except where otherwise stated.

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Chapter 1: Introduction

1.1. Context and Motivation

Access to reliable electricity remains one of the most critical development challenges worldwide, with a disproportionate impact on sub-Saharan Africa and other underserved regions. Despite decades of grid expansion efforts, national electricity systems in many low- and middle-income countries continue to exhibit limited coverage, poor reliability, and insufficient capacity to meet growing demand. In this context, renewable energy mini-grids, particularly SEMs, have emerged as a practical and scalable solution for accelerating electricity access while simultaneously supporting decarbonisation objectives.

SEMs offer advantages over conventional grid extension, including rapid deployment, modular scalability, and the ability to exploit abundant solar resources. Hirsch, Parag and Guerrero (2018) posited that mini-grids are being used to improve reliability and resilience of electrical grids as well as manage the addition of distributed clean energy resources like wind and solar photovoltaic (PV) generation to reduce fossil fuel emissions. Consequently, substantial public and private investment have been directed toward their deployment, and thousands of SEM systems have been installed globally. Even mobile SEM systems as presented by Majd *et al.* (2023) are equally emerging as pivotal solutions. ESMAP (2019) documented that global and regional market assessments report estimate at least ~19,000 mini-grids installed across 134 countries, representing a major expansion of decentralized electrification systems.

However, field studies, meta-analyses, and systematic reviews show that a substantial share of renewable mini-grid projects struggle to remain viable and reliable beyond their pilot or early operational years. Duran and Sahinyazan (2020), Duran and Sahinyazan (2021) compiled data on 104 renewable mini-grid projects worldwide and noted that 13% of the projects were unsuccessful. They hypothesised that “The presence of energy storage or demand management technologies is a significant driver of mini-grid project success”. Their additional hypothesis was that “Community-based ownership is a significant driver of mini-grid project success”. They used an econometric model having Project Success as the dependent variable to test these hypotheses through a probit regression with independent variables of mini-grid Ownership Category, Storage,

Demand Management System, Region of Installation, Renewable Proportion, and Total Project Cost per Capita. They found that their first hypothesis was partially supported with energy storage having a significant positive effect on project success while demand management technologies had insignificant effect. However, their second hypothesis was validated with significant positive relationship observed between the community-based ownership model and project success. Mwale *et al.* (2024) found, in the Malawi context, that 7 out of 19 renewable energy mini-grids studied failed to survive beyond their pilot phases, putting the failure scenarios at 37%. Users and operators also report service-quality problems such as supply interruptions, restricted hours of service, demand–capacity mismatch, and load shedding. In particular, Effiong, Anandarajah and Dessens (2026) found that empirical studies report wide variation in service availability and hours of supply, with several studies documenting demand–capacity mismatch and load shedding in operational mini-grids. These recurrent interruptions, unmet peak demand, and deteriorating service quality can reduce user confidence and weaken the credibility of mini-grid-based electrification strategies.

A dominant contributor to this underperformance is inadequate system design at the planning stage. Research by Zhang and Wei (2022b) and Gupta and Bhargava (2024) indicated that most existing renewable mini-grid design and optimisation practices focus primarily on techno-economic objectives such as cost minimisation, energy efficiency, environmental performance, or renewable energy penetration/fraction. These practices do not explicitly model component unavailability and failure behaviour. Consequently, a large share of renewable mini-grid sizing and optimisation studies effectively assume continuous component availability unless reliability constraints, outage scenarios, or explicit failure models are incorporated separately.

In reality, SEM systems comprise multiple interdependent subsystems: photovoltaic modules, inverters, battery banks, and auxiliary generators, each subject to stochastic failure, degradation, environmental stress, and maintenance-related downtime. Ignoring these reliability effects leads to systematically optimistic projections of system performance, particularly with respect to the TELS, a key determinant of service quality, revenue generation, and financial viability.

In this research, a SEM is treated as a stochastic engineered system whose performance is governed by the joint probabilistic availability of its constituent subsystems over time. System performance is therefore not solely a function of installed

capacity or solar resource availability, but of the reliability behaviour of interconnected components throughout the system lifecycle.

This PhD is motivated by the need for modelling approaches that move beyond idealised assumption of continuous SEM subsystem availability and provide actual, reliability-aware and time-varying predictions of sustainable mini-grid performance. By explicitly integrating subsystem failure behaviour into system-level performance modelling, this research seeks to support more robust design decisions, reduce operational risk, and improve the long-term sustainability of SEM deployments.

1.2. Problem Statement

Current SEM modelling approaches exhibit a fundamental limitation: system reliability is either neglected or treated as a post-design assessment metric rather than as an intrinsic determinant of system performance. In practical operation, subsystem failures, degradation, and maintenance downtime directly constrain the amount of electrical energy that can be delivered to end users. However, existing modelling approaches do not provide a direct quantitative mechanism for translating subsystem failure rates into actual estimates of system-level energy delivery. As a result, there is no explicit linkage between subsystem reliability informed by their failure rates and the TELS, which is the primary metric of interest for system sizing, financial appraisal, and service quality assessment.

This disconnect leads to systematic overestimation of TELS during system planning. Such overestimation results in inappropriate system sizing, underestimated operational risk, flawed revenue projections, and reduced resilience to demand growth and component failure. Over the system lifetime, these deficiencies manifest as frequent outages, unmet peak demand, accelerated component degradation, and declining end-user satisfaction.

While reliability indices such as Expected Energy Not Supplied (EENS), System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are widely used to characterise outage risk, they are not integrated into the core performance models used to predict energy delivery at the design stage. SAIDI and SAIFI are often treated as single metric values rather than functions of time, hence they are unable to reflect the risk of a reduction in electricity supply

throughout the simulated time period. Loss of Load Probability (LOLP) being a function of time solely measures how frequently energy supply is inadequate. Although EENS is most directly related to TELS, it is still not a substitute for the reliability-adjusted $TELS_r(t)$ as EENS, LOLP, SAIDI and SAIFI do not account for SEM subsystem failure rates.

The central problem addressed in this PhD is therefore the absence of a practical, transparent, and reliability-integrated modelling framework that can predict TELS by explicitly accounting for the probabilistic availability of mini-grid subsystems over the operating lifetime.

1.3. Research Gap

Despite extensive research on SEMs and their increasing deployment, a fundamental gap persists between performance modelling and reliability analysis. As Lambert, Gilman and Lilienthal (2006) and Zhang and Wei (2022b) show, most SEM optimisation frameworks estimate energy delivery under deterministic assumptions based mainly on renewable resource availability, load demand, and dispatch logic. Consequently, subsystem failure behaviour is not explicitly linked to system-level performance prediction. Reliability, where considered, is typically introduced separately through adequacy indices that do not consider SEM subsystem failure rates, operating-strategy studies, or post-design constraints, as in Billinton (2005) and Wang *et al.* (2014a), rather than being integrated directly into system-level energy-output modelling.

This separation means that TELS being a key decision-relevant metric cannot be properly estimated at the design stage when reliability-informed decisions are most critical. Incidentally, HOMER defines TELS as the actual amount of electrical energy supplied to load. However, studies such as Wassie and Ahlgren (2023b) show that delivered energy can differ substantially from expected generation once operational constraints emerge. As Sayegh *et al.* (2023) further indicate, uncertainty modelling in microgrids still focuses largely on resource and demand variability rather than subsystem failure behaviour.

As a result, system designers and investors still lack a practical reliability-informed modelling framework capable of linking subsystem failure behaviour directly to actual lifetime TELS outcomes for robust sizing, risk-aware planning, and long-term

sustainability assessment. This gap directly motivates the aim and objectives of this research.

1.4. Aim and Objectives of the Research

The overarching aim of this PhD is to develop a SEM reliability-based regression model (SEM-RBRM) that enables prediction of the TELS over the operational lifetime of a mini-grid by explicitly integrating subsystem reliability into performance modelling.

To achieve this aim, the research pursues the following specific objectives:

- (1) To critically evaluate existing SEM modelling approaches in order to identify limitations in how reliability is treated within performance prediction. [Chapter 2].
- (2) To develop a baseline multivariate regression model that estimates TELS for a SEM under idealised component availability assumptions. [Chapters 3, 4, 5].
- (3) To formulate and integrate a subsystem reliability model that quantifies the impact of component failure rates on system-level energy delivery. [Chapters 4, 5, 6].
- (4) To demonstrate the proposed SEM-RBRM through application to actual model scenarios operating under contrasting climatic and operational conditions. [Chapter 7].

This research is based on the proposition that SEM performance models which neglect subsystem reliability systematically overestimate the electrical load that can be delivered in practice. By integrating subsystem failure behaviour into performance prediction, the proposed SEM-RBRM provides an actual and decision-relevant estimate of TELS.

1.5. Novelty and Contribution

This PhD makes the following original contributions. First, it introduces a unified reliability-based regression modelling framework that links subsystem failure rates to system-level energy delivery performance. Second, it integrates time-varying reliability engineering concepts into performance prediction rather than treating reliability as a separate post-design assessment. Third, it provides a continuous predictive

forecast of reliability-adjusted TELS throughout the simulated period that can influence decision-making or indicate when action needs to be taken. Fourth, it informs decision makers on installed SEM capacity upgrade requirements and the associated timing stemming from the model predictions. This it does by quantifying the delta between TELS and the reliability-adjusted $TELS_r$, which LOLP, EENS, SAIDI and SAIFI cannot quantify. Finally, by framing system performance prediction as a reliability-constrained regression problem, the research introduces a scalable surrogate modelling approach that bridges detailed reliability analysis and early-stage design decision making.

1.6. Structure of the Thesis

This thesis is structured to reflect the logical development of a reliability-informed modelling framework for predicting actual performance of SEMs. The overall research workflow and the relationship between methodological stages and thesis chapters are illustrated in Figure 1.1. The figure shows the progression from baseline SEM performance modelling under ideal component availability to the development of a reliability-informed regression framework (SEM-RBRM). Renewable resource uncertainty and subsystem availability uncertainty are treated explicitly, leading to regression-based prediction of actual TELS, followed by validation and application to two model scenarios.

Chapter 2 presents a critical review of the literature on SEMs, focusing on system performance modelling, component failure modes, and existing reliability assessment approaches. This chapter establishes the theoretical and methodological foundations for the research and highlights the limitations of current modelling practices.

Chapter 3 examines commonly used SEM modelling tools and workflows, with particular attention to how system performance is typically evaluated under idealised component availability assumptions. This chapter motivates the need for alternative modelling approaches that integrate reliability into performance prediction.

Chapter 4 addresses uncertainty associated with renewable energy resources, specifically solar intermittency, and develops the baseline system modelling framework used in this research. This chapter provides the basis for subsequent regression-based performance modelling under ideal availability conditions.

Chapter 5 develops a baseline regression model for predicting the TELS without reliability considerations. This chapter corresponds to the initial regression-based performance modelling stage shown in Figure 1.1 and serves as a reference point for evaluating the impact of reliability integration. The chapter further validates the baseline regression model using appropriate validation techniques to assess predictive accuracy and robustness.

Chapter 6 introduces subsystem availability uncertainty through reliability engineering concepts, including failure rate modelling and reliability block diagrams. This chapter integrates subsystem reliability into the regression framework, resulting in the proposed SEM-RBRM.

Chapter 7 demonstrates the applicability of the proposed SEM-RBRM through two model scenarios of SEMs operating under contrasting climatic and operational conditions.

Finally, **Chapter 8** summarises the key findings of the research, discusses limitations of the proposed approach, and outlines recommendations for future work.

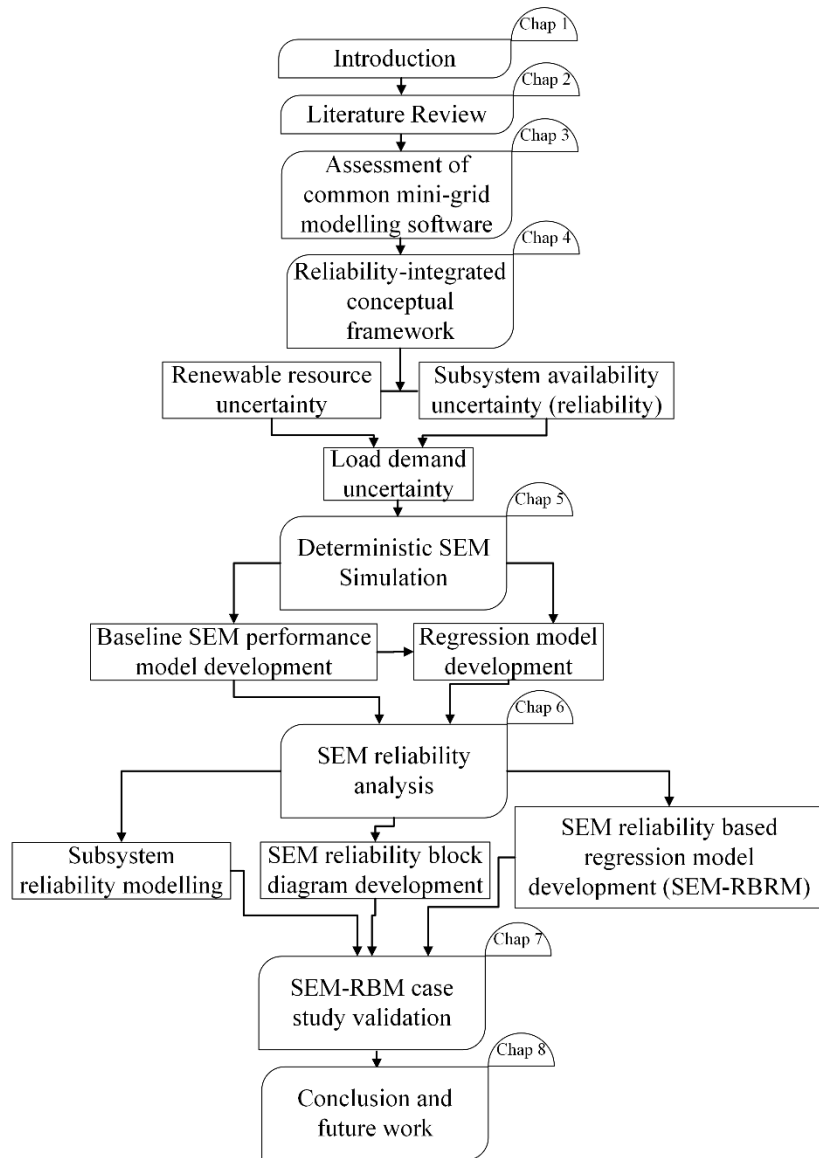


Figure 1.1: Research Workflow Illustrating the Methodological Structure of the PhD.

Chapter 2: Reliability-Aware Performance Modelling of SEMs

2.1. Introduction

SEMs have emerged as a critical technological solution for providing electricity access in regions where conventional grid expansion is economically or geographically infeasible. Over the past two decades, decentralised renewable energy systems have been deployed widely across Sub-Saharan Africa, South Asia, and remote island communities as part of global electrification initiatives. These systems typically integrate photovoltaic generation, battery energy storage, power electronic converters, and balance of system (BOS) infrastructure to deliver electricity to local distribution networks. As SEM deployments have expanded from pilot installations to long-term infrastructure assets, the need for a more representative modelling frameworks capable of predicting system performance over extended operational lifetimes has become increasingly important.

To support planning and investment decisions, a variety of modelling frameworks have been developed for analysing the techno-economic performance of hybrid renewable energy systems. Simulation–optimisation tools such as HOMER by UL Solutions (originally developed at the National Laboratory of the Rockies -NLR), have become widely used in both academic research and practical project design. These platforms allow system designers to evaluate candidate configurations of photovoltaic arrays, battery storage systems, and auxiliary generators under varying environmental and economic conditions. Through chronological simulation of hourly system operation and economic ranking of alternative system configurations, such tools provide estimates of system cost, energy production, and load coverage.

These modelling approaches have significantly advanced the analytical capabilities available to designers of decentralised energy systems. They enable evaluation of renewable resource variability, load growth scenarios, and economic trade-offs associated with different system configurations. Environmental uncertainty, particularly variability in solar irradiance, is commonly incorporated through time-series simulation using typical meteorological year (TMY) datasets. As a result, optimisation models can capture the intermittent nature of solar energy generation and its implications for storage dispatch and system sizing.

Despite these advances, several studies and field observations have reported discrepancies between predicted and realised performance of deployed mini-grid systems. Operational mini-grids frequently experience lower-than-expected energy delivery, increased maintenance requirements, and extended downtime resulting from subsystem failures. Hacke *et al.* (2018) stated that the inverters constitute between 43% and 70% of the PV power plant service requests observed from the operation and maintenance records. Nagarajan *et al.* (2019) further reported that inverter failures accounted for 36% of lost energy during a 27-month reliability study period for PV fielded systems. Hacke *et al.* (2018) and Nagarajan *et al.* (2019) works on quantifying inverter failures as well as the FMMEA performed on batteries by Hendricks *et al.* (2015) have been identified as significant contributors to reduced system availability and increased operational costs. These observations suggest that while environmental variability is routinely incorporated into SEM modelling frameworks, subsystem reliability behaviour may not be adequately represented in current performance prediction models.

This issue arises from a fundamental modelling assumption embedded within most SEM optimisation frameworks: installed subsystem capacity is typically assumed to be continuously available throughout the simulation horizon. As Zhang and Wei (2022a) noted in their review of hybrid renewable-energy system configuration optimisation, most existing studies prioritise economic, energy-efficiency, and environmental objectives, Gilman, Lambert and Lilienthal (2006) also described HOMER as a tool that models system physical behaviour and life-cycle cost primarily on the basis of technology selection, dispatch, and resource conditions rather than stochastic component-failure processes. In other words, once a photovoltaic array, inverter, or battery bank is installed within the model, it is assumed to operate within its rated capacity limits whenever environmental conditions permit generation or discharge. Under this assumption, system performance is determined primarily by renewable resource availability, storage state-of-charge constraints, and load demand profiles.

However, SEM systems are complex engineered infrastructures composed of multiple interacting subsystems, each subject to degradation, failure, and repair processes over time. Photovoltaic modules experience gradual efficiency degradation due to environmental exposure and material ageing. Power electronic converters exhibit failure mechanisms associated with thermal cycling, semiconductor fatigue, and capacitor degradation. Battery energy storage systems undergo electrochemical ageing processes

that reduce capacity and increase internal resistance. BOS components including connectors, cables, protection devices, and racking structures, may also fail due to mechanical stress, environmental exposure, or electrical faults.

These subsystem behaviours introduce stochastic variations in system availability that are not captured by deterministic modelling approaches. Reliability engineering literature has long recognised that the operational capacity of complex engineered systems is governed not only by design specifications but also by the probabilistic availability of individual components. In systems where subsystems operate in functional series configuration, the failure of a single critical component may temporarily reduce or eliminate the ability of the system to deliver its intended function.

Consequently, the quantity of electricity delivered by a SEM over its operational lifetime depends not only on environmental resource availability but also on the stochastic reliability behaviour of its constituent subsystems. As Bagen and Billinton (2005) demonstrated in their sequential simulation of stand-alone renewable power systems, and as Wang *et al.* (2014b) later showed in reliability-constrained stand-alone microgrid planning, energy delivery is shaped jointly by resource variability and subsystem reliability or availability constraints. TELS, a key performance metric for decentralised energy systems, is therefore influenced by both environmental variability and subsystem availability dynamics. Wassie and Ahlgren (2023a) showed empirically that the amount of electricity actually delivered to load in an off-grid PV mini-grid can diverge markedly from expected generation when real operational constraints and reliability shortfalls emerge in practice.

The body of literature relevant to this issue spans several overlapping research domains. First, deterministic optimisation frameworks dominate SEM design practice and focus primarily on techno-economic system sizing under environmental uncertainty. Second, subsystem-level reliability research provides detailed analyses of failure modes and degradation mechanisms in photovoltaic modules, power electronic converters, and battery storage systems. Third, reliability engineering offers probabilistic methodologies for modelling failure and repair processes in complex engineered systems. Finally, uncertainty modelling in renewable energy systems has advanced considerably in relation to resource and demand variability.

Although these strands of scholarship have each contributed valuable insights, they have largely evolved in parallel rather than in integration. Deterministic SEM optimisation models estimate energy delivery under idealised electromechanical conditions, whereas reliability studies analyse subsystem failure behaviour without directly constraining predicted energy output. The absence of a unified modelling framework linking subsystem reliability behaviour to actual lifetime energy delivery therefore represents a significant methodological limitation in existing SEM modelling literature.

This chapter critically reviews the literature relevant to reliability-aware performance modelling of SEMs. It first examines deterministic SEM optimisation frameworks and the modelling assumptions that underpin them. The chapter then reviews subsystem reliability behaviour across photovoltaic modules, power electronic converters, battery storage systems, and BOS components. Reliability engineering methodologies applicable to complex energy systems are subsequently evaluated, followed by a review of state-of-the-art SEM modelling tools and their treatment of reliability and uncertainty. The chapter concludes by synthesising these literature streams to identify the structural research gap that motivates the development of the reliability-integrated modelling framework proposed in this thesis.

2.2. Deterministic Performance Modelling of SEMs

The performance modelling of SEMs has evolved primarily within the field of hybrid renewable energy system optimisation. Over the past three decades, numerous simulation–optimisation frameworks have been developed to support the planning and techno-economic evaluation of decentralised energy systems. These modelling tools simulate the interaction between renewable energy resources, electrical loads, and energy storage technologies to determine optimal system configurations capable of delivering electricity reliably at minimum cost.

Most of these modelling frameworks are built upon deterministic simulation structures in which system behaviour is calculated using predefined component performance characteristics and environmental input data. Under this paradigm, subsystem components—such as photovoltaic arrays, battery storage units, and power electronic converters—are assumed to operate according to their nominal technical

specifications whenever environmental conditions permit. While environmental variability is typically incorporated through time-series data for solar irradiance, temperature, and load demand, the operational availability of system components is generally treated deterministically.

This modelling philosophy has enabled significant progress in the analysis and design of hybrid renewable energy systems. However, it also introduces important limitations when evaluating the long-term performance of mini-grid systems where subsystem reliability behaviour may significantly influence operational outcomes. Understanding how deterministic modelling frameworks represent system performance is therefore essential for identifying the modelling limitations addressed in this research.

2.2.1. Historical Development of SEM Optimisation Models

The development of hybrid renewable energy system modelling tools began in the early 1990s, when researchers sought to evaluate the feasibility of combining renewable generation technologies with conventional diesel generators for electrification in remote locations. Early studies by Baring-Gould *et al.* (1996) at the U.S. NLR laid the foundation for computational tools capable of simulating hybrid system performance under varying resource conditions.

One of the earliest and most widely adopted modelling tools in this domain is HOMER. HOMER introduced a simulation-optimisation methodology that combines chronological system simulation with economic optimisation. The software evaluates thousands of candidate system configurations by simulating their operation over an annual time horizon and ranking them according to techno-economic metrics such as Net Present Cost (NPC) and Levelised Cost of Energy (LCOE).

In HOMER-type frameworks, system operation is simulated at discrete time intervals (typically hourly) across a representative year. For each time step, the model calculates power flows among generation sources, storage systems, and loads using deterministic component performance models. The general energy balance governing system operation can be expressed as:

$$P_{PV}(t) + P_{BESS}(t) + P_{DG}(t) = P_{Load}(t) + P_{loss}(t) \quad (2.1)$$

where $P_{PV}(t)$ = photovoltaic generation power, $P_{BESS}(t)$ = battery charge/discharge power, $P_{DG}(t)$ = auxiliary generator power, $P_{Load}(t)$ = electrical load demand, and $P_{loss}(t)$ = system losses.

Within this modelling framework, renewable energy production is determined primarily by environmental conditions and installed generation capacity. Photovoltaic power output is typically calculated using irradiance-based performance models derived from semiconductor device physics. A simplified representation of PV power generation can be expressed as:

$$P_{PV}(t) = \eta_{PV}AG(t) \quad (2.2)$$

where η_{PV} represents module conversion efficiency, A is the effective module area, and $G(t)$ is incident solar irradiance at time t .

Although more advanced PV models incorporate temperature effects, angle-of-incidence corrections, and module degradation factors, these parameters are generally treated as deterministic inputs within optimisation frameworks.

Battery storage behaviour is similarly represented through deterministic state-of-charge (SOC) equations that govern the charging and discharging behaviour of energy storage systems. The SOC dynamics of a battery system can be expressed as:

$$SOC(t) = SOC(t-1) + \frac{\eta_c P_{charge}(t)\Delta t}{E_{rated}} - \frac{P_{discharge}(t)\Delta t}{\eta_d E_{rated}} \quad (2.3)$$

where $SOC(t)$ is the state of charge at time t , E_{rated} is the rated battery capacity, $P_{charge}(t)$ and $P_{discharge}(t)$ are the charging and discharging powers at time t , η_c and η_d represent charge and discharge efficiencies, and Δt is the simulation time step.

Such formulations enable deterministic simulation of storage dispatch and allow optimisation algorithms to determine optimal battery capacity for meeting load demand under renewable resource variability.

Beyond HOMER, several additional modelling platforms have been developed for evaluating hybrid renewable systems. For example, Leng (1998) introduced RETScreen as a project assessment tool for renewable energy technologies. Mishra *et al.* (2022) described REopt Lite as a techno-economic optimisation framework for behind-the-meter distributed energy resources. Lund (2007) presented EnergyPLAN as an advanced energy-system analysis model for renewable-energy strategy development. Lastly, Howells *et al.* (2011) introduced OSeMOSYS as an open-source energy modelling system.

Tools such as RETScreen, REopt, EnergyPLAN, and OSeMOSYS have therefore been widely applied in energy system planning, techno-economic assessment, and renewable integration studies across a broad range of scales and applications. While these platforms differ in their optimisation techniques and application domains, they share a common modelling philosophy: system performance is evaluated under deterministic assumptions regarding component availability. The deterministic simulation–optimisation architecture typical of these modelling frameworks is illustrated in Figure 2.1. The figure shows the sequential modelling loop used in conventional SEM simulation tools. Environmental inputs, such as solar irradiance time-series, are first used to estimate photovoltaic power generation through PV performance models. Battery dispatch

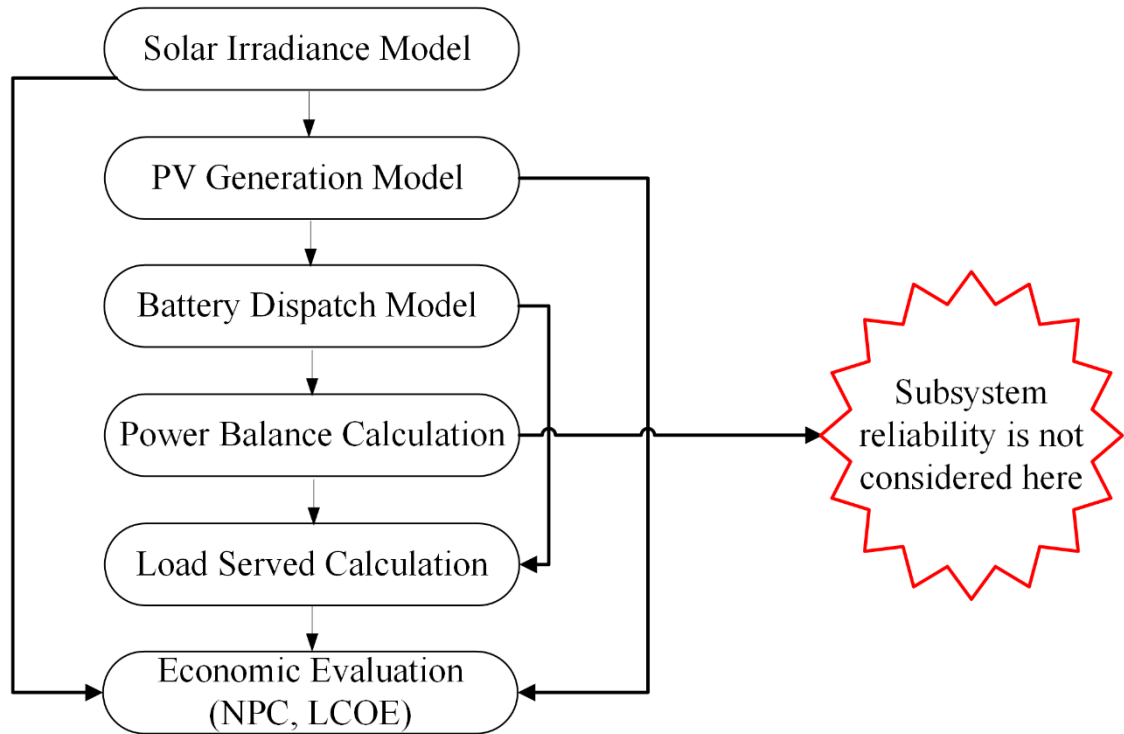


Figure 2.1: Deterministic Simulation–Optimisation Structure of Conventional SEM Modelling Frameworks.

algorithms subsequently determine charging and discharging behaviour based on system state-of-charge constraints. These energy flows are combined within a system power balance calculation to determine whether available generation capacity is sufficient to meet electrical demand during each simulation time step. Finally, economic performance indicators such as Net Present Cost and Levelised Cost of Energy are calculated to evaluate candidate system configurations.

While this modelling architecture provides a powerful framework for evaluating techno-economic system performance under renewable resource variability, it implicitly assumes that subsystem components operate continuously within their rated performance specifications. Photovoltaic arrays, inverters, and battery storage systems are therefore treated as fully available assets whose operational behaviour depends only on environmental conditions and dispatch constraints.

Consequently, stochastic subsystem failure behaviour and maintenance processes are not explicitly represented within the simulation loop illustrated in Figure 2.1. This deterministic assumption simplifies the optimisation process and reduces computational complexity, but it may introduce discrepancies when predicting the long-term operational performance of actual SEMs where subsystem failures and repairs occur over time.

The implications of this deterministic capacity assumption for predicting system performance metrics like TELS are examined in greater detail in the following section.

2.2.2. Deterministic Capacity Realisation Assumption

A fundamental assumption embedded within most SEM optimisation frameworks is that installed subsystem capacity is continuously available throughout the simulation horizon. This assumption can be described as the deterministic capacity realisation assumption, whereby system components are assumed to operate according to their rated specifications whenever required.

Under this assumption, the effective generation capacity of a photovoltaic system is determined solely by environmental resource availability and installed capacity. The operational state of the generation subsystem is therefore represented as:

$$C_{PV}^{effective}(t) = C_{PV}^{installed} \quad (2.4)$$

whenever irradiance conditions permit power generation.

Similarly, battery systems are assumed to maintain their rated capacity and power capabilities throughout the simulation period, subject only to state-of-charge constraints. Converter systems, including inverters and charge controllers, are typically represented through fixed efficiency parameters and power limits.

This deterministic representation simplifies optimisation by eliminating the need to model subsystem failure behaviour or maintenance processes. However, it implicitly assumes that subsystem components do not experience operational downtime due to mechanical failure or degradation beyond predefined lifetime replacement events.

The deterministic capacity realisation assumption also influences the estimation of key performance metrics used in SEM modelling. One such metric is the TELS, which represents the cumulative quantity of electrical energy delivered to consumers over a specified simulation horizon:

$$TELS = \int_0^T P_{Load}^{served}(t) dt \quad (2.5)$$

Under deterministic modelling assumptions, the value of $P_{Load}^{served}(t)$ depends primarily on the availability of renewable resources and the installed capacity of system components.

While this modelling approach provides valuable insights into the economic feasibility of candidate system designs, it does not explicitly account for subsystem failure processes that may interrupt system operation.

2.2.3. Limitations of Deterministic SEM Modelling

Although deterministic optimisation frameworks have proven valuable for system design and planning, several limitations have been identified in the literature when applying these models to field-deployed mini-grid systems.

First, empirical studies of operational photovoltaic systems have demonstrated that subsystem failures occur with non-negligible frequency during system lifetimes (Jordan and Kurtz, 2014; Jordan *et al.*, 2020). Field reliability studies conducted by Tina, Gagliano and Raiti (2006), Jordan and Kurtz (2014) and Jordan *et al.* (2020) have reported significant failure rates in inverter systems, power electronics, and BOS components. Inverter failures in particular have been identified as a major contributor to downtime in photovoltaic plants due to the thermal and electrical stresses experienced by semiconductor switching devices (Nagarajan *et al.*, 2019).

Second, battery energy storage systems exhibit complex degradation behaviour influenced by cycling patterns, temperature conditions, and state-of-charge operating ranges. As Shamarova *et al.* (2022) emphasise in their review of battery energy storage system modelling in renewable microgrids, battery lifetime in stationary applications varies substantially with operating conditions, while Luo, Zhang and Tang (2023) likewise show that temperature and state-of-charge swing ranges materially affect ageing trajectories in lithium-ion cells. Electrochemical ageing processes—including solid electrolyte interphase (SEI) growth, lithium plating, and cathode degradation—can reduce battery capacity and increase internal resistance over time. Edge *et al.* (2021) identified these mechanisms as central causes of lithium-ion battery degradation during normal operation, and O'Kane *et al.* (2022) further showed that interacting degradation pathways such as SEI growth and lithium plating can produce multiple routes to end-of-life depending on how the battery is used. These processes may affect both the energy storage capability and the operational availability of battery systems in SEM installations.

Third, photovoltaic modules themselves experience gradual performance degradation due to environmental exposure and material ageing. Long-term studies of PV module fleets by Jordan *et al.* (2022), Theristis *et al.* (2023) and other researchers have reported annual degradation rates typically ranging between 0.5% and 1% per year under standard operating conditions. While such degradation is sometimes incorporated into optimisation models as a deterministic annual efficiency decline, sudden failure events associated with module damage, connector faults, or bypass diode failures are rarely represented explicitly.

The deterministic modelling assumption therefore neglects the stochastic nature of subsystem reliability behaviour. In real engineering systems, component failures occur

randomly over time and may temporarily reduce the operational capacity of the system. When multiple subsystems are connected in functional series configuration, the availability of the overall system depends on the reliability of each individual component.

In reliability engineering, the availability of a repairable subsystem at time t $A(t)$ is typically expressed as:

$$A(t) = R(t) + \int_0^t R(t-x)n(x) dx \quad (2.6)$$

where $R(t)$ represents the reliability function at time t , x is the possible renewal time, $R(t-x)$ is the reliability over the interval from renewal time x to the observation time t , and $n(x)$ is the renewal density function. For systems comprising multiple subsystems operating in series configuration, overall system availability can be approximated as the product of individual subsystem availabilities:

$$A_{SEM} = \prod_{i=1}^n A_i \quad (2.7)$$

This relationship implies that failures of critical subsystems—such as inverters or battery management systems—can significantly influence the ability of the system to deliver electricity to consumers.

Despite these well-established reliability concepts, most SEM optimisation frameworks do not incorporate subsystem availability into their chronological simulation algorithms. Instead, reliability considerations are typically addressed indirectly through simplified assumptions such as deterministic component lifetimes or periodic replacement schedules.

Consequently, deterministic modelling frameworks may overestimate the quantity of electricity that can be delivered by mini-grid systems over their operational lifetimes. This limitation becomes particularly significant in decentralised energy systems where redundancy is limited, and subsystem failures may directly interrupt electricity supply.

These observations highlight the need for modelling approach capable of integrating subsystem reliability behaviour into SEM performance evaluation. Such a reliability-informed model should have the ability to inform decision makers on the anticipated shortfall between deterministic and reliability-informed energy supply predictions with field-deployed SEMs. The results of the model will also provide insight on the optimal time to order additional or replacement units for operational SEM subsystems upgrade. Additionally, such model will enable efficient allocation of often scarce resources in enhancing the reliability of redundant energy supply subsystems while prioritising the reliability enhancement of series-connected subsystems. The following sections therefore examine the reliability characteristics of SEM subsystems in greater detail, beginning with a review of electrical failure behaviour across photovoltaic modules, power electronic converters, battery storage systems, and BOS components.

2.3. Reliability Behaviour of SEM Subsystems

SEMs consist of multiple interconnected electrical subsystems whose coordinated operation determines the ability of the system to deliver electricity to end users. Figure 2.2 is a hierarchical arrangement of key components that make up SEM subsystems. Typical SEM subsystems shown in the figure are integrated and include photovoltaic generation units, battery energy storage systems, power electronic converters, and BOS infrastructure including electrical distribution networks, protection devices, and monitoring equipment. These subsystems devolve into their key components which further drive the respective subsystem reliabilities at that level. Subsystem

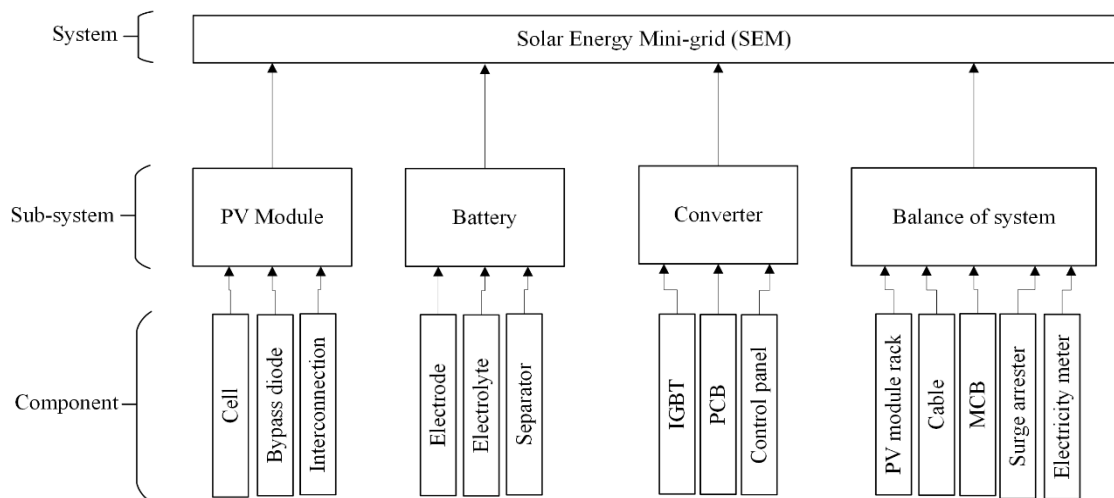


Figure 2.2: Typical Hierarchy of SEM System, its Sub-systems and Components.

reliabilities aggregate to determine the overall SEM reliability – depending on their series, parallel or mixed configurations.

While deterministic optimisation models of mini-grids primarily evaluate energy balance and techno-economic performance, the long-term operational capability of the system is fundamentally governed by the reliability behaviour of these subsystems.

As discussed in Section 2.2, the operational availability of repairable components depends on the balance between failure and repair processes, and the availability of a system composed of multiple components is determined by the combined availability of its constituent elements. In SEM systems, the delivery of electricity

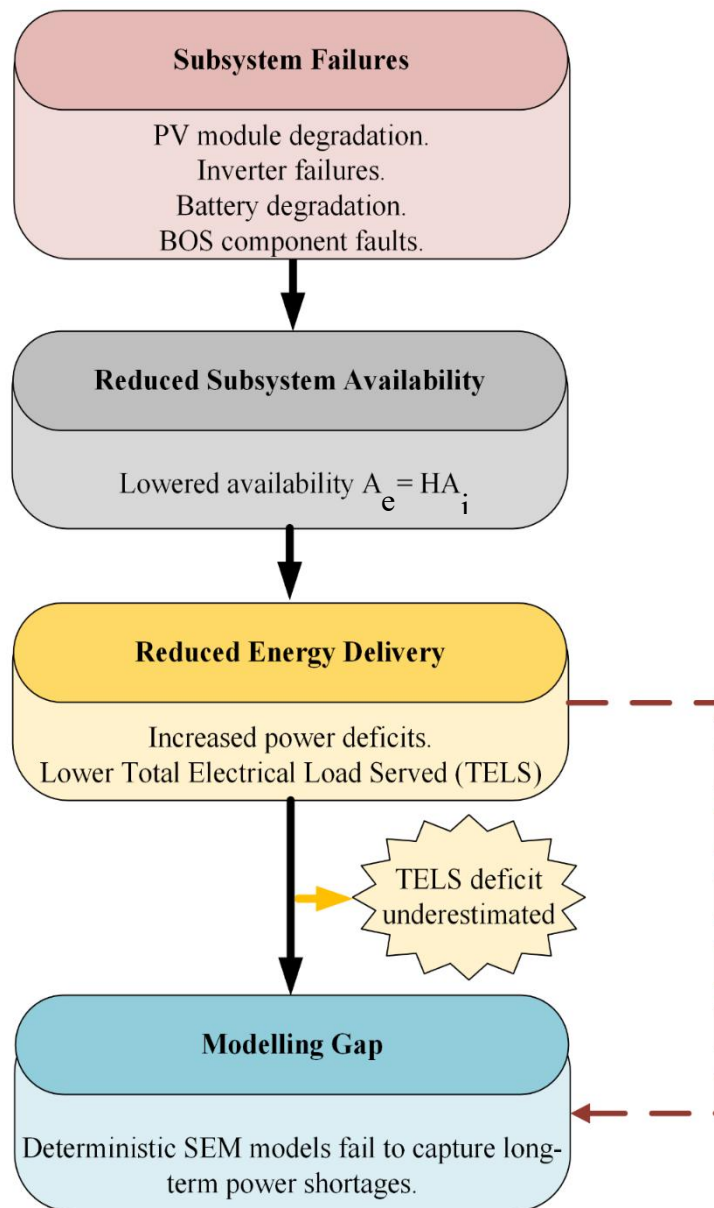


Figure 2.3: Reliability Structure of a SEM.

requires the simultaneous operation of generation, conversion, storage, and distribution subsystems. Consequently, failures occurring in any of these subsystems may reduce the system's capacity to deliver electricity to consumers.

The functional reliability structure of a simplified SEM is illustrated in Figure 2.3. The figure demonstrates that the ability of a mini-grid to deliver electricity depends on the operational status of several interacting subsystems. Subsystem failures adversely affect subsystem availability, resulting in a lower TELS than that predicted by deterministic SEM models. Therefore, deterministic SEM models may overestimate the electrical load served. In practical systems, the reliability behaviour of these subsystems is governed by degradation processes, environmental stresses, and operational conditions that influence both failure probability and maintenance requirements. The following subsections review the principal reliability characteristics of photovoltaic modules, power electronic converters, battery energy storage systems, and BOS components based on empirical studies reported in the literature.

2.3.1. Photovoltaic Module Degradation and Failure Mechanisms

PV modules represent the primary energy generation component of SEMs. Modern crystalline silicon photovoltaic modules are designed for operational lifetimes exceeding twenty-five years; however, long-term field studies have demonstrated that PV modules experience multiple degradation processes that gradually reduce electrical output over time.

A comprehensive review conducted by Jordan and Kurtz (2013) analysed nearly 2000 published degradation-rate data points for photovoltaic modules and systems worldwide, reporting an overall median degradation rate of approximately 0.5% per year (with an overall mean of approximately 0.8% per year) and crystalline-silicon module medians generally around 0.5–0.6% per year. Although this degradation rate appears relatively modest, cumulative losses over multi-decade operational lifetimes can significantly reduce total energy production (see Table 6.2 for PV modules failure rate data).

PV module degradation can be represented using a simple linear degradation model:

$$P_{PV}(t) = P_0(1 - \delta t) \quad (2.8)$$

where $P_{PV}(t)$ represents the module power output at time t , P_0 represents the initial rated power, and δ represents the annual degradation rate.

More complex degradation processes may follow nonlinear behaviour due to interacting environmental stresses such as temperature cycling, humidity exposure, and ultraviolet radiation.

One of the most widely reported failure mechanisms in PV modules is microcracking of silicon cells. Mechanical stresses introduced during manufacturing, transportation, or installation may create microscopic cracks within the crystalline structure of solar cells. Experimental investigations by Kajari-Schröder *et al.* (2011) demonstrated that microcracks can propagate during thermal cycling, eventually interrupting current pathways and reducing module power output.

Another important degradation phenomenon is light-induced degradation (LID), which occurs during the initial exposure of boron-doped crystalline silicon cells to sunlight. LID arises from the formation of boron–oxygen defect complexes within the silicon lattice, leading to temporary reductions in module efficiency. Niewelt *et al.* (2016) observed light and elevated-temperature-induced degradation (LeTID) in passivated emitter and rear contact (PERC) photovoltaic technologies.

Potential-induced degradation (PID) represents another reliability concern in photovoltaic systems operating at high system voltages. PID occurs when leakage currents flow through module encapsulation layers under strong electric fields, producing charge accumulation and electrical shunting within solar cells. Studies by Pingel *et al.* (2010) demonstrated that severe PID effects can reduce module power output by more than 30%.

Electrical interconnection components also contribute to module degradation. Interconnect ribbons and solder joints connecting solar cells may experience fatigue due to repeated thermal cycling. Investigations by Bosco, Silverman and Kurtz (2016), Jordan *et al.* (2017), Lippiatt, Westerberg and Rose (2018), and Meier *et al.* (2018) identified solder joint fatigue as a major contributor to long-term module reliability issues.

These studies demonstrate that although photovoltaic modules exhibit relatively high reliability compared with other system components, degradation processes may still influence the long-term generation capacity of SEM systems.

2.3.2. Reliability of Power Electronic Converters

Power electronic converters—including inverters, charge controllers, and DC–DC converters—represent one of the most critical subsystems within SEM architectures. These devices are responsible for conditioning and converting electrical power between different voltage levels and current types, enabling the integration of photovoltaic generation, battery storage systems, and electrical loads within a common energy management framework. Unlike photovoltaic modules, which operate through relatively passive semiconductor processes, power electronic converters contain numerous active components operating under dynamic electrical and thermal stress conditions. As a result, converter reliability often represents a major limiting factor in the operational availability of photovoltaic energy systems as documented by Golnas (2013b) and Deline *et al.* (2024).

Several field reliability studies have identified inverter systems as the most failure-prone components within photovoltaic installations (Golnas, 2013a; Nagarajan *et al.*, 2019). Analysis of operational data from large European PV plants by Moser (2017) reported that inverter failures accounted for a substantial proportion of system downtime events, with mean time to failure significantly lower than that observed for photovoltaic modules (also see Table 6.2 for inverter failure rate data). Similarly, reliability investigations conducted by Tina, Grasso and Gagliano (2015) indicated that inverter malfunction represents one of the primary causes of operational interruptions in grid-connected photovoltaic systems. These findings are supported by maintenance records from utility-scale PV installations, which consistently identify power electronic components as a dominant contributor to system failure events.

The works of Nguyen and Kwak (2020) and Khatir *et al.* (2023) reaffirmed that the reliability behaviour of power electronic converters is strongly influenced by the thermal stresses experienced by semiconductor switching devices such as insulated-gate bipolar transistors (IGBTs) and metal–oxide semiconductor field-effect transistors (MOSFETs). These devices operate under high switching frequencies and variable

electrical loads, producing significant heat generation within semiconductor junctions. Repeated thermal cycling during system operation leads to mechanical stresses within device packaging materials, gradually degrading solder joints, bond wires, and substrate interfaces.

Research by Ciappa (2002) demonstrated that bond-wire fatigue represents one of the dominant ageing mechanisms in power electronic modules. As devices repeatedly heat and cool during operation, thermal expansion mismatches between different packaging materials produce cyclic mechanical stresses that eventually lead to bond-wire lift-off or solder joint cracking. These degradation processes ultimately result in electrical discontinuities that cause device failure.

In addition to semiconductor degradation, passive components within converter systems may also influence reliability. Wang and Blaabjerg (2014) and Baumann *et al.* (2024) documented that electrolytic capacitors used in DC-link circuits represent reliability concern due to their susceptibility to electrolyte evaporation and dielectric degradation. Capacitor lifetime is strongly dependent on operating temperature and electrical ripple current. Empirical reliability models suggest that capacitor lifetime approximately halves for every 10°C increase in operating temperature, illustrating the importance of thermal management in inverter design.

The temperature dependence of electronic component failure rates is commonly described using an Arrhenius-type relationship:

$$\lambda(T) = \lambda_0 \exp\left(\frac{-E_a}{kT}\right) \quad (2.9)$$

where $\lambda(T)$ represents the temperature-dependent failure rate, E_a represents the activation energy associated with the degradation process, k is Boltzmann's constant, and T represents the operating temperature.

This relationship indicates that elevated operating temperatures accelerate chemical and material degradation processes within electronic components. Consequently, thermal management strategies—including heat sink design, forced air cooling, and temperature-aware control algorithms—play a critical role in improving converter reliability.

Environmental conditions may further influence inverter performance and longevity. Dust accumulation, moisture ingress, and voltage surges caused by lightning strikes or switching transients may all contribute to converter failure. These factors are particularly relevant in remote mini-grid installations where environmental conditions may be harsh and maintenance resources limited. As a result, converter reliability remains a key factor influencing the long-term operational availability of SEMs.

2.3.3. Battery Energy Storage System Degradation

Battery energy storage systems (BESS) play a fundamental role in SEMs by buffering fluctuations in renewable generation and maintaining electricity supply during periods of low solar irradiance. However, battery systems are subject to complex electrochemical ageing processes that influence both performance and operational reliability. These degradation processes are influenced by multiple factors including temperature, depth-of-discharge cycling, charge rate, and state-of-charge operating conditions (see Table 6.2 for battery failure rate data).

Historically, many mini-grid installations have relied on lead–acid battery technologies, particularly in early rural electrification projects. Lead–acid batteries are relatively inexpensive and widely available, but they are susceptible to several degradation mechanisms that limit operational lifetime. One of the most common degradation mechanisms is sulfation, which occurs when lead sulphate crystals accumulate on battery electrodes during repeated charge–discharge cycles. Under conditions of prolonged partial state-of-charge operation, these crystals may become irreversible, reducing active electrode surface area and decreasing battery capacity.

Another degradation phenomenon affecting lead–acid batteries is electrolyte stratification, which occurs when acid concentration becomes unevenly distributed within the battery electrolyte. Stratification may accelerate corrosion of positive grid plates and reduce battery efficiency during charge and discharge cycles. Boovaragavan *et al.* (2009) and Juanico (2024) identified positive grid corrosion as a major ageing mechanism limiting the lifetime of lead–acid batteries in renewable energy systems.

In recent years, lithium-ion battery technologies have become increasingly prevalent in mini-grid applications due to their higher energy density, improved cycling

performance, and reduced maintenance requirements. However, lithium-ion batteries exhibit their own degradation processes, including growth of the solid electrolyte interphase (SEI) layer on electrode surfaces, lithium plating during high-rate charging, and structural degradation of cathode materials.

The growth of the SEI layer represents one of the primary ageing mechanisms in lithium-ion batteries. During battery operation, electrolyte decomposition products accumulate on the anode surface, forming a passivation layer that consumes active lithium ions and reduces battery capacity. Although the SEI layer stabilises electrode reactions, its continued growth during cycling gradually decreases battery performance.

Another degradation mechanism associated with lithium-ion batteries is lithium plating, which occurs when lithium ions deposit as metallic lithium on the anode surface during rapid charging or low-temperature operation. Lithium plating can reduce battery capacity and may lead to internal short circuits under severe conditions.

Battery capacity degradation can be represented using an exponential capacity fade model:

$$C(t) = C_0 e^{-ft} \quad (2.10)$$

where C_0 represents the initial battery capacity, f represents the degradation rate constant, and t represents operational time.

As battery capacity decreases, the ability of the storage system to supply electricity during periods of low renewable generation may be reduced. Consequently, battery degradation directly influences the reliability of SEM systems by limiting the duration over which energy can be supplied when photovoltaic generation is insufficient.

Temperature also plays a critical role in battery ageing behaviour. Elevated operating temperatures accelerate electrochemical reaction rates and increase degradation rates, while low temperatures may reduce battery efficiency and increase internal resistance. Effective battery management systems are therefore required to monitor temperature, control charging behaviour, and prevent unsafe operating conditions such as overcharging or deep discharge.

2.3.4. BOS Reliability

Beyond primary subsystems such as photovoltaic modules, converters, and battery storage systems, SEMs include numerous BOS components that contribute to overall system reliability. These components include mounting structures, electrical cables, connectors, circuit breakers, surge protection devices, monitoring equipment, and power distribution infrastructure.

Although BOS components are often considered relatively simple compared with primary subsystems, failures within these components may still significantly affect system performance (see Table 6.2 for BOS failure rate data). In particular, electrical connection failures represent a common source of operational problems in photovoltaic installations. Loose or degraded connectors may increase contact resistance, produce localised heating and potentially lead to arc faults.

Field maintenance studies conducted by Klise, Lavrova and Gooding (2018), Burnham *et al.* (2024), Walker *et al.* (2025) on operational photovoltaic plants have shown that wiring faults and connector degradation represent a significant proportion of service interventions. Environmental exposure plays a significant role in these failures. Ultraviolet radiation may degrade polymer insulation materials used in electrical cables, while humidity and temperature cycling can accelerate corrosion of metallic connectors.

Surge protection devices represent another important BOS component influencing system reliability. Photovoltaic systems installed in regions with high lightning activity may experience transient voltage surges that damage electrical equipment. Surge protection devices are designed to divert these transient currents away from sensitive electronic components, but repeated exposure to lightning-induced surges may degrade protective devices over time.

Mechanical structures supporting photovoltaic arrays also influence system reliability. Mounting structures must withstand environmental loads such as wind, snow, and thermal expansion. Structural degradation or improper installation may lead to misalignment of photovoltaic modules or mechanical damage to module frames.

Monitoring and control systems represent an additional component of modern mini-grid installations. Failure of monitoring equipment may not directly interrupt power

generation but can reduce the ability of system operators to detect and diagnose faults, potentially prolonging system downtime.

Overall, these BOS components collectively influence the reliability and maintainability of SEMs. Although individual BOS components may have relatively low failure probabilities, their combined effect may still influence overall system availability, particularly in remote installations where maintenance interventions may be delayed.

Table 2.1: Major Failure Mechanisms in SEM Subsystems*.

Subsystem	Failure Mechanism	Physical / Operational Cause	Impact on System Performance	Key References
Photovoltaic Modules	Microcracks in silicon cells	Mechanical stress during transport, installation, or thermal cycling	Reduced current flow, localised power loss, accelerated degradation	Kajari-Schröder <i>et al.</i> (2011); Köntges <i>et al.</i> (2017)
	Light-Induced Degradation (LID)	Formation of boron–oxygen complexes under initial illumination	Temporary reduction in module efficiency	Jordan and Kurtz (2013)
	Potential-Induced Degradation (PID)	Leakage currents caused by high system voltage and humidity	Significant power loss (up to 30%) in severe scenarios	Pingel <i>et al.</i> (2010)
	Solder bond fatigue	Thermal expansion mismatch in interconnect ribbons	Electrical disconnection between cells	Meier <i>et al.</i> (2018)
	Encapsulant browning and delamination	UV exposure and chemical ageing of EVA encapsulation	Optical losses and corrosion of internal contacts	Jordan and Kurtz (2013)
Power Electronic Converters	Semiconductor device fatigue (IGBT/MOSFET)	Thermal cycling and electrical stress during switching operations	Converter shutdown or reduced power output	Ciappa (2002); Blaabjerg, Liserre and Ma (2011)
	Bond-wire lift-off	Repeated temperature cycling in semiconductor packaging	Electrical discontinuity and device failure	Ciappa (2002)
	DC-link capacitor ageing	Electrolyte evaporation and dielectric degradation	Voltage instability and inverter failure	(Wang, Yang and Blaabjerg, 2013)
	Overvoltage / surge damage	Lightning strikes or switching transients	Catastrophic inverter failure	Martzloff (1989); Hernández, Vidal and Jurado (2008);

				Nasir <i>et al.</i> (2019)
	Cooling system failure	Fan malfunction or blocked heat sinks	Thermal overload and component degradation	Blaabjerg, Liserre and Ma (2011)
Battery Energy Storage Systems	Sulfation (lead-acid batteries)	Repeated partial state-of-charge operation	Reduced capacity and increased internal resistance	Pavlov (2011)
	Electrolyte stratification	Uneven acid concentration due to insufficient mixing	Reduced charge acceptance and plate corrosion	Pavlov (2011)
	SEI layer growth (Li-ion batteries)	Electrolyte decomposition at anode surface	Gradual capacity loss	Vetter <i>et al.</i> (2005)
	Lithium plating	High charging rates or low temperatures	Capacity loss and safety risk	Yang <i>et al.</i> (2017)
	Thermal runaway	Exothermic reaction triggered by overheating	Catastrophic battery failure	Spotnitz and Franklin (2003)
BOS Components	Cable insulation degradation	UV exposure, temperature cycling, humidity	Short circuits or electrical leakage	(Melios <i>et al.</i> , 2022); (Anghelescu, Handra and Diaconu, 2025)
	Connector corrosion	Environmental exposure and poor sealing	Increased contact resistance and power losses	Köntges <i>et al.</i> (2017)
	Surge protection failure	Repeated lightning-induced voltage transients	Reduced protection against electrical surges	(Hernandez, Vidal and Jurado, 2008); (Commission, 2017); (Martzloff, 1983)
	Mounting structure fatigue	Mechanical stress from wind and thermal expansion	Structural misalignment of PV modules	(Lou, Zhang and Pan, 2024); (Beinert <i>et al.</i> , 2016)

	Monitoring system malfunction	Sensor failure or communication errors	Reduced ability to detect system faults	(Alam <i>et al.</i> , 2023); (Ferlito <i>et al.</i> , 2024); (Lazzaretti <i>et al.</i> , 2020)
*See Table 6.2 for subsystem failure rate data				

2.4. Reliability Engineering Methodologies

Reliability engineering provides analytical tools for evaluating the ability of engineered systems to perform their intended functions under specified conditions for a given period of time. The discipline originated in the aerospace and defence industries during the mid-twentieth century, where system failures could have catastrophic consequences. Since then, reliability engineering has been widely applied to numerous engineering sectors including nuclear power generation, telecommunications networks, manufacturing systems, and electrical power systems.

Traditional reliability analysis focuses on quantifying the probability that system components will operate without failure over a specified time horizon. In complex engineered systems, failures arise from multiple interacting factors including material degradation, environmental stresses, operational loads, and manufacturing variability. Reliability engineering methodologies therefore employ probabilistic models, stochastic processes, and statistical analysis to describe the behaviour of such systems.

In the context of renewable energy systems, reliability modelling has gained increasing importance as PV installations and hybrid energy systems have expanded in scale and complexity. Early investigations into photovoltaic system reliability conducted by Stember, Huss and Bridgman (2009) developed a reliability–availability–maintainability (RAM) framework integrated with life-cycle energy-cost analysis for photovoltaic power systems. Reliability analyses of large European renewable-energy fleets by Spinato *et al.* (2009) further demonstrated that power-electronic subassemblies (e.g., converters) can be disproportionately failure-prone and therefore major contributors to downtime in field operation. Subsequent studies by Blaabjerg, Liserre and Ma (2011) highlighted the reliability challenges associated with power electronic converters in renewable energy systems and the need for reliability-oriented design approaches.

Despite these advances, reliability modelling methodologies have not been fully integrated into the techno-economic modelling frameworks used for SEM design and optimisation. Most existing SEM modelling tools focus primarily on energy balance and economic optimisation while assuming deterministic component availability. Understanding the strengths and limitations of different reliability modelling techniques is therefore essential for identifying appropriate approaches for incorporating subsystem reliability behaviour into SEM performance models.

Reliability modelling methodologies can broadly be grouped into four principal categories: structural reliability modelling, stochastic state-transition modelling, probabilistic simulation methods, and physics-of-failure modelling. Each approach offers distinct analytical capabilities and exhibits different advantages and limitations when applied to renewable energy systems.

2.4.1. Reliability Block Diagrams

RBDs represent one of the most widely used structural modelling techniques in reliability engineering. The RBD approach represents a system as a network of functional blocks connected according to their operational dependencies. Each block corresponds to a system component whose reliability characteristics are known or estimated.

The method was originally developed in early reliability analyses of aerospace systems during the 1950s and has since become a standard technique in reliability engineering. In this approach, system reliability is determined from the reliability of individual components and the configuration of the system architecture.

For a system composed of components operating in series configuration, system reliability can be expressed as

$$R_{SEM}(t) = \prod_{i=1}^n R_i(t) \quad (2.11)$$

where $R_i(t)$ represents the reliability of component i and n is the number of components.

For parallel configurations where redundant components exist, system reliability becomes

$$R_{SEM}(t) = 1 - \prod_{i=1}^n [1 - R_i(t)] \quad (2.12)$$

Parallel configurations increase system reliability by allowing the system to continue operating even if one component fails.

Reliability block diagrams have been widely applied in electrical power system reliability analysis. Billinton and Allan (1985) used RBD techniques to analyse generation and transmission system reliability in electrical networks. Similarly, Endrenyi (1980) demonstrated how structural reliability models can be used to evaluate power system component reliability.

In renewable energy systems, RBD models have been applied to analyse the reliability of photovoltaic systems composed of PV modules, inverters, and battery systems. Yang *et al.* (2011) used RBD modelling to evaluate inverter reliability in wind and photovoltaic power systems and to demonstrate that power electronic converters often represent the dominant reliability constraint.

The principal advantage of RBD modelling lies in its intuitive representation of system structure and its ability to identify critical components. However, the method assumes statistical independence of component failures and does not explicitly represent dynamic system behaviour or repair processes.

2.4.2. Markov Reliability Models

Markov reliability models provide a stochastic modelling framework capable of representing systems that transition among multiple operational states over time. Unlike RBD models, which provide static representations of system structure, Markov models explicitly represent the dynamic evolution of system states.

In a Markov model, a system is represented as a set of discrete states corresponding to different combinations of component operational conditions. For example, a simple inverter subsystem might be represented by two states: operational and failed. More complex models may include additional states representing degraded operation or partial functionality.

Transitions between states occur according to probabilistic failure and repair rates. The probability of the system occupying a given state evolves according to differential equations known as Kolmogorov forward equations.

For a simple two-state component, the probability of being operational evolves as

$$\frac{dP_0(t)}{dt} = -\lambda P_0(t) + \mu P_1(t) \quad (2.13)$$

where $P_0(t)$ represents the probability of the operational state, $P_1(t)$ represents the probability of failure, λ represents failure rate, and μ represents repair rate.

Markov reliability models have been widely applied in power system reliability analysis. Billinton and Allan (1985) used Markov modelling to analyse generation system reliability in electric power systems. Similarly, Trivedi (2001) applied Markov models to evaluate reliability and availability in communication networks.

In renewable energy systems, Markov modelling has been used to represent wind turbine reliability and hybrid system reliability. Li *et al.* (2019) developed Markov reliability models for wind turbine systems incorporating component failure and repair processes.

However, Markov models suffer from a major limitation known as the state-space explosion problem. As the number of components increases, the number of possible system states grows exponentially, making the model computationally difficult to solve.

2.4.3. Monte Carlo Simulation Technique in Reliability Modelling

Monte Carlo simulation technique has been employed in some probabilistic modelling approaches that evaluate system reliability by simulating random failure events across many system operation scenarios. With this technique, component failure times are generated according to statistical probability distributions, and system behaviour is evaluated repeatedly across many simulation iterations. Monte Carlo simulation may require large numbers of simulation iterations to obtain statistically stable results.

Failure times are commonly generated using exponential distributions:

$$f(t) = \lambda e^{-\lambda t} \quad (2.14)$$

Monte Carlo simulation has been applied in power system reliability analysis. Billinton and Li (1994) demonstrated how Monte Carlo techniques can evaluate reliability of complex generation and transmission systems under stochastic operating conditions.

Monte Carlo methods are particularly useful when analytical reliability solutions become difficult to obtain. Zio (2009) emphasised that Monte Carlo simulation provides a powerful tool for analysing complex engineering systems involving multiple interacting components and uncertain operating conditions.

In renewable energy systems, Monte Carlo methods have been applied to analyse hybrid renewable energy systems. Billinton (2005) used Monte Carlo simulation to evaluate LOEE, Loss of Load Expectation (LOLE) and their probability distributions as the reliability indices of isolated power systems incorporating renewable generation. He assumed a starting failure of 4% for the back-up diesel generator without explicitly considering the failure rates of other subsystems in his simulation.

2.4.4. Physics-of-Failure Modelling

Physics-of-Failure (PoF) modelling represents a fundamentally different approach to reliability analysis. Instead of modelling failures as random events, PoF models attempt to predict component lifetime based on the underlying physical mechanisms responsible for degradation.

Failure mechanisms in electronic systems often arise from thermal fatigue, corrosion, electromigration, or electrochemical degradation processes. These mechanisms can be analysed using material science principles to estimate component lifetime.

For example, fatigue failure in electronic solder joints subjected to thermal cycling can be described using the Coffin-Manson relationship:

$$N_f = C(\Delta T)^{-m} \quad (2.15)$$

where N_f is the number of cycles to failure, C is material/empirical fatigue constant, ΔT is temperature excursion per cycle and m is the fatigue exponent.

Physics-of-failure modelling has been widely applied in microelectronics reliability analysis. Pecht (2009) demonstrated that PoF methods provide improved prediction of electronic component lifetime compared with purely statistical reliability models. Gaonkar *et al.* (2023) presented the methodology involved in employing PoF approach for reliability prediction in Figure 2.4. The methodology begins by identifying component geometry and material type with associated variabilities. It is then followed by system life-cycle profiling and a FMMEA process based on expected conditions. The methodology concludes with the determination of the relevant reliability metric using the site-based time to failure information of each critical failure mechanism.

In renewable energy systems, PoF models have been applied to analyse degradation of photovoltaic modules and power electronic converters. Blaabjerg, Liserre and Ma (2011) applied PoF methods to evaluate reliability of power electronic converters used in wind and photovoltaic systems.

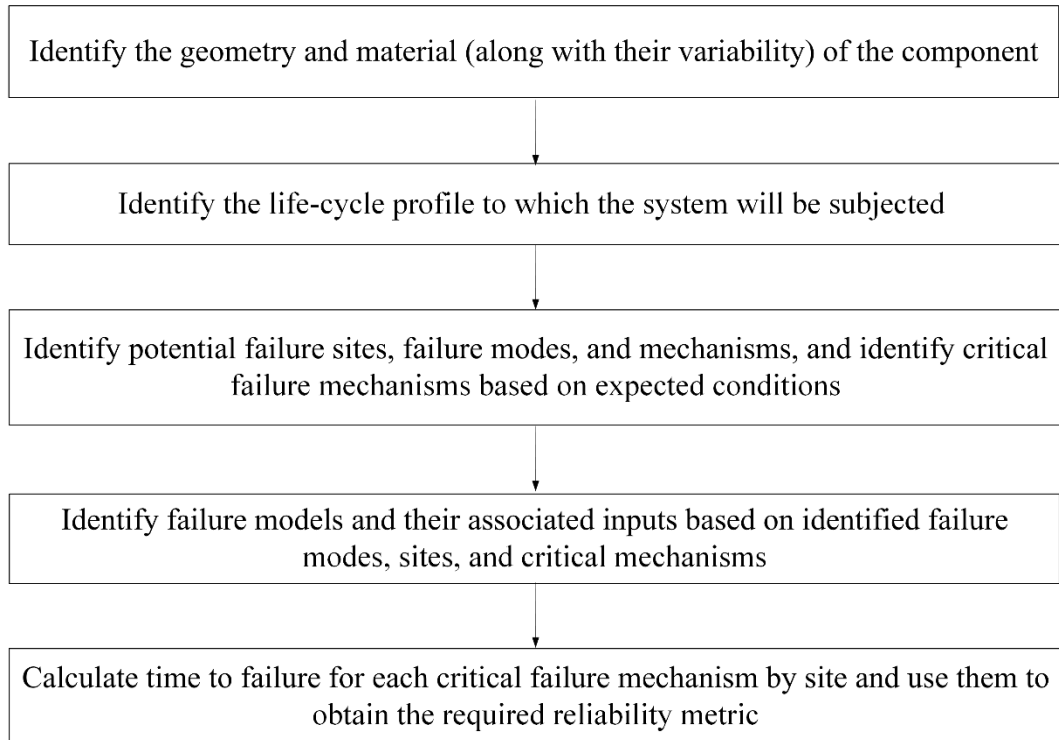


Figure 2.4: Steps of a Physics of Failure-based Reliability Prediction Methodology

However, PoF modelling typically requires detailed knowledge of material properties, environmental stresses, and device design parameters. As a result, these models are often applied at the component level rather than the system level.

2.4.5. Comparative Evaluation of Reliability Modelling Approaches

The reliability modelling methodologies reviewed in the preceding subsections represent complementary analytical approaches developed within the broader field of reliability engineering. While each method provides useful tools for analysing failure behaviour in engineering systems, their suitability for modelling SEMs depends on several factors including the representation of system structure, the ability to capture stochastic failure processes, the treatment of degradation mechanisms, and the computational requirements associated with system-level analysis.

Structural modelling techniques, stochastic state-transition models, probabilistic simulation approaches, and physics-of-failure frameworks differ fundamentally in the level of abstraction at which reliability behaviour is represented. Structural approaches such as reliability block diagrams primarily describe the functional interconnections among system components and allow the overall system reliability to be derived from the reliability characteristics of individual subsystems. These models are particularly effective for identifying critical system components and evaluating the influence of component reliability on overall system availability. However, because structural models typically assume independent failure processes and do not explicitly represent temporal degradation dynamics, their ability to capture the complex operational behaviour of renewable energy systems may be limited.

In contrast, stochastic modelling approaches based on Markov processes provide a more rigorous representation of system reliability by explicitly modelling transitions between operational and failure states. By incorporating failure and repair rates into a dynamic state-transition framework, Markov models enable analysts to evaluate system availability under varying operational conditions and maintenance strategies. Such models have been widely used in the reliability analysis of electric power systems and communication networks. Nevertheless, as system complexity increases, the number of possible states grows rapidly, leading to significant computational challenges. This

state-space expansion often limits the practical applicability of Markov models when analysing systems composed of many interacting components.

Probabilistic simulation techniques such as Monte Carlo methods provide a flexible alternative for analysing reliability behaviour in complex systems. Rather than deriving analytical reliability expressions, these methods evaluate system performance through repeated simulation of stochastic failure events. Monte Carlo approaches are particularly useful when system interactions, environmental variability, and operational uncertainties cannot be represented easily using analytical reliability models. Consequently, these techniques have been widely applied in power system reliability studies and in the analysis of hybrid renewable energy systems. However, the computational requirements associated with large numbers of simulation iterations may become significant when modelling long-term system behaviour.

Physics-of-failure approaches represent yet another perspective on reliability modelling by focusing on the physical mechanisms responsible for component degradation. By analysing failure mechanisms such as thermal fatigue, corrosion, or electrochemical ageing, physics-based models attempt to predict component lifetime based on material properties and environmental stress conditions. These models provide valuable insights into the degradation behaviour of individual components such as photovoltaic modules, power electronic devices, and battery systems. However, because physics-of-failure models typically operate at the component level, integrating them into system-level performance models can be challenging without substantial simplification.

Taken together, these observations indicate that no single reliability modelling methodology provides a complete solution for analysing the reliability behaviour of SEMs. Structural reliability models offer simplicity and clear representation of system architecture, stochastic models capture dynamic failure and repair processes, simulation methods enable modelling of complex system interactions, and physics-based approaches provide insight into component degradation mechanisms. Each methodology therefore contributes valuable analytical capabilities but also exhibits limitations when applied individually.

These methodological differences are summarised in Table 2.2, which compares the principal characteristics of the major reliability modelling approaches identified in literature.

Table 2.2: Comparative Characteristics of Reliability Modelling Methodologies

Methodological Approach	Analytical Capability	Primary Limitation	Typical Application Areas
Structural reliability modelling	Representation of system architecture and component interdependence	Limited representation of dynamic failure behaviour	Industrial systems, power system reliability analysis
Stochastic state-transition modelling	Dynamic representation of failure and repair processes	Rapid growth of state-space for large systems	Power generation systems, telecommunications networks
Probabilistic simulation modelling	Flexible modelling of stochastic interactions and uncertainties	High computational requirements	Hybrid energy systems, reliability risk analysis
Physics-of-failure modelling	Mechanism-based prediction of component degradation	Limited scalability to system-level modelling	Electronics reliability, material degradation studies

The literature reviewed in this section demonstrates that a wide range of reliability modelling techniques has been developed for analysing failure behaviour in complex engineering systems. However, despite the maturity of these methodologies within reliability engineering, their integration into the modelling of SEMs remains limited. Existing SEM optimisation tools typically focus on techno-economic performance evaluation and assume deterministic subsystem availability, without explicitly representing stochastic failure processes or component degradation.

Consequently, the reliability characteristics of key subsystems such as power electronic converters, battery storage systems, and BOS infrastructure are rarely incorporated into system performance simulations. This modelling simplification may lead to overly optimistic estimates of system availability and long-term energy delivery performance.

The limited integration of reliability engineering methodologies into SEM modelling frameworks therefore represents an important gap in the current literature. Addressing this gap requires the development of modelling approaches capable of

incorporating subsystem reliability behaviour within the optimisation and performance evaluation of SEMs.

2.5. State-of-the-Art SEM Modelling Tools

The planning and design of SEMs require modelling tools capable of evaluating system performance under variable renewable resource conditions, fluctuating electricity demand, and long-term financial constraints. Over the past two decades, numerous modelling frameworks have been developed to support decision-making in hybrid renewable energy systems and distributed energy networks. These tools typically integrate simulation, optimisation, and techno-economic evaluation to determine optimal system configurations and operational strategies.

Most SEM modelling tools adopt an energy balance simulation framework, in which electricity generation, storage, and load demand are simulated over a discrete time horizon using meteorological resource data and projected electricity demand profiles. The modelling process evaluates the ability of different system configurations to meet electricity demand while minimising economic costs or maximising system efficiency. In practice, the modelling approaches used in these tools can be broadly categorised into three methodological classes: simulation-based optimisation platforms, mathematical optimisation models based on mixed-integer programming, and project-level financial evaluation tools.

Although these modelling platforms provide valuable capabilities for techno-economic analysis of renewable energy systems, they often rely on deterministic representations of system components and operational behaviour. In many modelling frameworks, subsystem availability is implicitly assumed to remain constant throughout the simulation period, and stochastic failure behaviour is not explicitly represented. Consequently, the reliability characteristics of system components may not be fully captured in system performance simulations.

The following subsections review several widely used modelling tools and approaches applied in SEM design and evaluation, with particular emphasis on how system operation and subsystem performance are represented in existing modelling frameworks.

2.5.1. HOMER (Hybrid Optimization of Multiple Energy Resources)

HOMER is among the most widely used tools for modelling hybrid renewable energy systems and decentralised power systems. Originally developed by the U.S. NLR, the HOMER platform evaluates alternative system configurations by simulating system operation over a defined time horizon, typically using hourly time-series data for renewable resources and electricity demand.

The modelling approach implemented in HOMER combines time-series simulation with optimisation of component sizing. For each candidate system configuration, the model performs chronological simulation of energy flows among system components such as photovoltaic arrays, battery storage systems, diesel generators, and electrical loads. The software then evaluates economic performance metrics to determine the most cost-effective system configuration.

The primary economic metric used in HOMER is the NPC of the system, which represents the total lifecycle cost of the system over its operational lifetime. NPC is calculated as

$$NPC = \frac{C_{ann}}{CRF(i, n)} \quad (2.16)$$

where C_{ann} represents the total annualised cost of the system and $CRF(i, n)$ represents the capital recovery factor given by

$$CRF(i, n) = \frac{i(1 + i)^n}{(1 + i)^n - 1} \quad (2.17)$$

where i is the discount rate and n is the project lifetime.

Several studies have applied HOMER to the design and optimisation of SEM systems. For example, Lambert, Gilman and Lilienthal (2006) demonstrated the application of HOMER in the design of hybrid renewable systems combining photovoltaic, wind, and diesel generation. Similarly, Sen and Bhattacharyya (2014) employed HOMER in the techno-economic evaluation of off-grid electrification strategies for developing regions. Maleki and Askarzadeh (2014) used hybrid-system

sizing/optimisation approaches for off-grid rural electrification model scenarios involving PV, diesel generation, and battery storage.

Despite its widespread use, HOMER typically represents component behaviour deterministically. Component lifetimes are defined as fixed parameters, and system operation is simulated under the assumption that components remain operational until scheduled replacement occurs. Consequently, stochastic failure events are not explicitly modelled, and system availability is effectively assumed to be constant throughout the simulation period.

2.5.2. REopt Energy System Optimisation Model

REopt is an energy system optimisation platform developed by the U.S. National Renewable Energy Laboratory to support decision-making for distributed energy resources. Unlike HOMER, which relies primarily on simulation-based optimisation, REopt formulates the system design problem as a mathematical optimisation model solved using mixed-integer linear programming (MILP).

In the REopt framework, the objective function typically minimises the lifecycle cost of the energy system:

$$\min \sum_{t=1}^T (C_{\text{energy},t} + C_{\text{operation},t} + C_{\text{investment}}) \quad (2.18)$$

subject to operational constraints representing energy balance, component capacities, and storage dynamics. For example, the energy balance constraint may be expressed as

$$P_{PV}(t) + P_{\text{battery}}(t) + P_{\text{grid}}(t) = P_{\text{load}}(t) \quad (2.19)$$

where $P_{PV}(t)$ represents photovoltaic generation, $P_{\text{battery}}(t)$ represents battery discharge, and $P_{\text{grid}}(t)$ represents grid supply.

REopt enables detailed modelling of system operation, including battery dispatch strategies, demand response measures, and integration with utility grid infrastructure. The optimisation framework allows simultaneous evaluation of component sizing decisions and operational scheduling.

Several studies have used REopt for analysing distributed energy systems and microgrids. Anderson *et al.* (2017) demonstrated the application of REopt in the optimisation of microgrid design for resilience and cost reduction. Other studies have applied REopt to evaluate renewable energy integration strategies in commercial and institutional facilities.

However, like HOMER, REopt generally assumes deterministic component availability. Component failures are not explicitly represented within the optimisation framework, and system operation is evaluated under the assumption that all components remain available throughout the modelling period.

2.5.3. RETScreen Clean Energy Project Analysis Tool

RETScreen is a clean energy project analysis platform developed by Natural Resources Canada for evaluating the technical and financial feasibility of renewable energy and energy efficiency projects. Unlike system simulation tools such as HOMER or optimisation frameworks such as REopt, RETScreen focuses primarily on project-level performance assessment rather than detailed operational modelling of hybrid energy systems.

The RETScreen modelling framework integrates simplified energy production models with financial analysis tools to estimate the economic viability of renewable energy installations. Energy production estimates are derived using performance models that combine equipment specifications with historical meteorological data obtained from global climate databases. These models are typically based on steady-state energy conversion relationships rather than detailed time-series simulations of system operation.

Financial evaluation within RETScreen is conducted using widely used economic performance indicators including net present value (NPV), internal rate of return (IRR), and simple payback period. The net present value of a project is calculated as

$$NPV = \sum_{t=0}^n \frac{C_t}{(1+i)^t} \quad (2.20)$$

where C_t represents the net cash flow in year t , i represents the discount rate, and n represents the project lifetime.

Because RETScreen focuses primarily on feasibility analysis, the tool does not simulate detailed operational interactions between system components such as photovoltaic arrays, battery storage systems, and power electronic converters. Instead, energy production is estimated using aggregate performance models that approximate system behaviour at the project level.

Several studies have used RETScreen to evaluate renewable energy deployment strategies in developing regions. For example, Ukoima *et al.* (2023) used RETScreen to assess the economic feasibility of hybrid renewable energy systems for rural electrification in Nigeria. Similarly, Psomopoulos *et al.* (2015) applied RETScreen in the evaluation of photovoltaic installations for distributed power generation in rural communities.

Despite its usefulness for project feasibility analysis, RETScreen does not incorporate reliability modelling capabilities. Component failures, degradation processes, and maintenance events are not explicitly represented within the modelling framework. Consequently, while RETScreen can provide useful insights into the economic feasibility of renewable energy projects, it cannot capture the operational reliability behaviour of SEM systems.

2.5.4. MILP-Based Microgrid Optimisation Models

In addition to commercial modelling platforms, a substantial body of academic research has developed optimisation frameworks for microgrid design and operation based on MILP. These models formulate the microgrid planning problem as a mathematical optimisation problem in which decision variables represent component capacities, energy dispatch schedules, and operational strategies.

MILP models have become widely used in microgrid planning because they allow simultaneous optimisation of multiple design variables while satisfying operational constraints. Typical decision variables include photovoltaic capacity, battery storage size, dispatch schedules, and grid import/export decisions. The optimisation objective often

involves minimising the total lifecycle cost of the system while satisfying technical constraints related to energy balance, component capacities, and operational limits.

The general form of a microgrid optimisation problem can be expressed as

$$\min \sum_{t=1}^T C_{\text{gen}}(t) + C_{\text{storage}}(t) + C_{\text{grid}}(t) \quad (2.21)$$

where $C_{\text{gen}}(t)$ is generation cost at time t , $C_{\text{storage}}(t)$ is storage cost at time t , $C_{\text{grid}}(t)$ is grid interaction cost at time t .

Equation (2.21) is subject to energy balance constraints such as

$$P_{\text{PV}}(t) + P_{\text{battery}}(t) + P_{\text{grid}}(t) = P_{\text{load}}(t) \quad (2.22)$$

where

$P_{\text{PV}}(t)$ represents photovoltaic power generation, $P_{\text{battery}}(t)$ represents battery charging or discharging power, $P_{\text{grid}}(t)$ represents power exchanged with the grid and $P_{\text{load}}(t)$ signifies load.

MILP optimisation models have been applied extensively in microgrid research. Morais *et al.* (2010) developed one of the earliest MILP frameworks for optimising isolated microgrid systems incorporating renewable generation and storage technologies. More recently, Mashayekh *et al.* (2017) proposed multi-energy microgrid optimisation models capable of integrating electricity and thermal energy systems within a unified optimisation framework.

Other studies have extended MILP models to incorporate demand response strategies, distributed generation technologies, and energy storage systems. For example, Parisio, Rikos and Glielmo (2014) formulated microgrid operation as a MILP and explicitly models distributed generators (DGs), storage devices, and controllable loads (demand-side management / demand response) within the optimisation problem. Steen *et al.* (2015) extended an established MILP platform (DER-CAM) used for buildings/microgrids to represent distributed generation technologies (e.g., CHP, PV), storage (electric + thermal), and demand response measures in the same optimisation framework. Liu, Ferrari and Chen (2023) proposed a MILP-based distributed energy

management approach for networked microgrids, explicitly considering distributed energy resources and responsive loads coordinated via price signals (i.e., demand response behaviour) within a solvable MILP framework.

Lasseter (2011) and Mathiesen *et al.* (2015) examined the role of optimisation-based microgrid planning in improving energy efficiency and renewable energy integration.

Despite their flexibility, most MILP-based microgrid optimisation models assume deterministic system behaviour. Component failures and stochastic degradation processes are rarely represented explicitly within optimisation formulations. Instead, reliability considerations are often incorporated indirectly through reserve capacity requirements or redundancy constraints.

Consequently, while MILP models provide powerful tools for system optimisation, they may not fully capture the reliability behaviour of field-deployed SEM installations.

2.5.5. Reliability-Aware Microgrid Modelling Studies

Although most SEM modelling tools assume deterministic component behaviour, several studies have attempted to incorporate reliability considerations into microgrid modelling frameworks. These studies often combine reliability engineering techniques with energy system modelling to evaluate the impact of component failures on system performance.

One common approach involves integrating probabilistic reliability assessment with microgrid simulation models. For example, Bagen and Billinton (2005) used Monte Carlo simulation to evaluate the reliability of isolated power systems incorporating renewable generation. Their work demonstrated that stochastic failure modelling can significantly influence estimates of system reliability and expected energy supply.

Similarly, Atwa *et al.* (2010) investigated the reliability impacts of distributed generation in electrical distribution systems using probabilistic reliability evaluation techniques. Their study showed that distributed generation can improve system reliability

under certain operating conditions but may also introduce new reliability challenges related to intermittent generation.

Reliability metrics commonly used in these studies include LOLP and EENS. The EENS can be expressed as

$$\text{EENS} = \sum_{t=1}^T (P_{\text{demand}}(t) - P_{\text{supply}}(t))^+ \quad (2.23)$$

where t represents the time index, T is the total number of time steps, $P_{\text{demand}}(t)$ is power demand at time t , $P_{\text{supply}}(t)$ is available supplied power at time t , $(P_{\text{demand}}(t) - P_{\text{supply}}(t))^+$ is the power deficit at time t and the positive operator indicates periods in which electricity demand exceeds available generation capacity.

More recent research has explored the integration of reliability analysis with microgrid planning models. For example, Wang *et al.* (2014a) investigated reliability-constrained microgrid planning strategies incorporating probabilistic component failure models. Similarly, Abul'Wafa and Taha (2014) and Weng, Zhou and Zhan (2022) analysed the reliability performance of microgrids using probabilistic simulation techniques.

Despite these developments, reliability-aware modelling remains relatively rare in SEM optimisation frameworks. Many reliability studies focus on evaluating system reliability metrics rather than integrating reliability considerations directly into system design optimisation.

2.6. Structural Modelling Gap

SEMs represent complex engineered systems composed of multiple interconnected subsystems including photovoltaic generation units, power electronic converters, battery energy storage systems, and electrical distribution infrastructure. The operational performance of these systems depends not only on the individual behaviour of each component but also on the structural relationships between components within the system architecture. In reliability engineering, the structural configuration of system elements is recognised as a fundamental factor influencing overall system reliability,

since failures within one subsystem may propagate through the system and affect the ability of other subsystems to operate effectively.

The importance of system structure in reliability analysis has been extensively studied within the broader field of reliability engineering. Early theoretical work by Enderlein (1966) introduced mathematical models for analysing the reliability of systems composed of multiple interacting components arranged in series and parallel configurations. Later developments in reliability engineering led to the widespread adoption of techniques such as RBDs and fault tree analysis for representing structural relationships among system components. These techniques have been applied extensively in industries such as aerospace engineering, nuclear power generation, and telecommunications systems where system reliability is critical.

Within the electrical power systems domain, structural reliability modelling has also played a significant role in evaluating the reliability of generation and transmission systems. Studies by Billinton and Allan (1996) demonstrated how the reliability of large-scale electric power systems depends strongly on the configuration of generation units, transmission lines, and distribution networks. Similarly, Endrenyi (1980) emphasised that system reliability cannot be evaluated solely based on individual component reliability; instead, it must consider the interconnection structure that determines how component failures influence overall system functionality.

Despite these well-established principles in reliability engineering, the structural representation of SEM systems within many existing modelling frameworks remains relatively simplified. In most SEM modelling tools, the system is represented primarily through energy flow relationships rather than explicit structural dependencies between components. For example, photovoltaic generation, battery storage, and electrical loads are often represented as independent elements linked through energy balance equations describing the flow of electricity between components. While this modelling approach is effective for evaluating system energy balance and economic performance, it may not adequately capture the structural dependencies that influence reliability behaviour.

In practical SEM installations, subsystem interactions are strongly governed by the physical architecture of the system. Photovoltaic modules generate direct current

electricity that must pass through power electronic converters before it can be delivered to electrical loads. Battery storage systems depend on charge controllers and battery management systems to regulate charging and discharging processes. Distribution infrastructure such as wiring, protection devices, and switchgear connects generation sources to end users. Because many of these components operate in a functional series configuration, failure of a critical subsystem may interrupt the entire energy delivery chain even when other subsystems remain operational.

Empirical reliability studies of photovoltaic power systems provide evidence of the importance of such structural dependencies. For example, Moser (2017) and Moser *et al.* (2017) analysed operational data from photovoltaic installations in Europe and found that inverter failures accounted for a substantial proportion of system downtime events. Similarly, Golnas (2013a) observed that inverter reliability significantly influences the overall operational availability of photovoltaic power systems. These findings highlight the fact that subsystem failures can propagate through the system architecture and influence overall energy delivery capability.

In the context of microgrid research, several studies have begun to explore the influence of system architecture on reliability behaviour. Bagen and Billinton (2005) investigated the reliability of small, isolated power systems incorporating renewable generation and demonstrated that system architecture plays a key role in determining reliability performance. More recent work by Wang *et al.* (2014a) examined reliability evaluation of microgrids with distributed energy resources and showed that system configuration strongly influences reliability metrics such as EENS.

However, many of these reliability analyses are conducted independently from the modelling frameworks used for SEM design and optimisation. As discussed in Section 2.5, widely used modelling tools such as HOMER, REopt, and many academic optimisation models primarily represent system operation through energy balance relationships and economic performance metrics. In these models, subsystem reliability is typically represented indirectly through simplified lifetime assumptions or replacement schedules rather than through explicit structural reliability models.

This modelling abstraction introduces a significant limitation in the representation of SEM system behaviour. When subsystem failures are not explicitly

linked to the structural architecture of the system, optimisation models may overestimate system performance and availability. For example, a system configuration identified as optimal based on energy balance and cost considerations may still experience significant reliability limitations if critical subsystems such as inverters or battery management systems exhibit high failure rates.

The structural modelling gap identified here therefore reflects an important methodological limitation in existing SEM modelling frameworks. While current models provide valuable capabilities for analysing energy flows and economic performance, they often lack the ability to represent the structural relationships between subsystems that govern system reliability behaviour. Addressing this limitation requires modelling approaches capable of integrating system architecture representation with subsystem reliability analysis.

Developing such modelling frameworks is particularly important for SEM systems deployed in remote or off-grid environments, where maintenance resources may be limited and system failures can significantly affect energy access. Improved structural modelling approaches could enable actual evaluation of system reliability and support the design of SEM systems that are both economically efficient and operationally robust.

2.7. Conceptual Positioning of Reliability-Integrated SEM Modelling

The preceding sections of this chapter have reviewed the modelling approaches used for analysing SEM systems, the reliability characteristics of major SEM subsystems, and the reliability engineering methodologies available for analysing failure behaviour in complex engineered systems. This review has highlighted that although extensive research exists in both renewable energy system modelling and reliability engineering, these two research domains remain only partially integrated within existing SEM modelling frameworks.

Most modelling approaches developed for SEM design and optimisation have been derived from broader research in hybrid renewable energy system analysis and distributed energy resource planning. Simulation-based optimisation platforms such as HOMER and mathematical optimisation frameworks such as REopt and mixed-integer linear programming microgrid models have been widely applied to evaluate system

configurations under varying resource conditions and load demand profiles. These modelling tools simulate energy flows between photovoltaic generation units, battery storage systems, and electrical loads while evaluating economic performance metrics such as lifecycle cost, net present cost, and levelised cost of electricity.

While these modelling tools provide valuable insights into system design and techno-economic performance, their analytical frameworks typically focus on energy balance and cost optimisation rather than reliability-aware system evaluation. As discussed in earlier sections, subsystem reliability behaviour is often represented using simplified lifetime assumptions or replacement schedules, rather than through explicit modelling of stochastic failure processes. Consequently, the operational availability of key SEM subsystems may not be fully represented in system performance simulations.

At the same time, reliability engineering research has produced a wide range of analytical methods capable of evaluating failure behaviour in complex systems. Techniques such as reliability block diagrams, Markov reliability models, probabilistic simulation methods, and physics-of-failure modelling have been widely applied in industries including aerospace engineering, nuclear power systems, telecommunications networks, and electronic device reliability analysis. These methodologies provide powerful tools for analysing how component degradation and failure processes influence system-level reliability.

However, these reliability engineering approaches are rarely incorporated directly into SEM modelling frameworks used for system design and optimisation. Instead, reliability evaluation is often conducted as a separate analysis after system configurations have already been determined using deterministic optimisation models. This separation between system optimisation and reliability evaluation represents a key methodological limitation within the current SEM modelling literature.

The conceptual positioning of reliability-integrated SEM modelling therefore lies at the intersection of two research domains: renewable energy system modelling and reliability engineering. Within this conceptual framework, SEM systems are not viewed solely as energy production and distribution systems, but also as reliability-critical engineered systems whose performance depends on the behaviour of interconnected subsystems subject to degradation and failure processes.

A reliability-integrated SEM modelling framework therefore seeks to combine three key analytical elements. The first element involves explicit representation of SEM system architecture, allowing the structural relationships between photovoltaic generation units, power electronic converters, battery storage systems, and distribution infrastructure to be captured within the modelling framework. Structural representation enables the analysis of how failures in critical subsystems propagate through the system and influence overall energy delivery capability.

The second element involves modelling of subsystem reliability behaviour and failure processes associated with major SEM components. Photovoltaic modules experience degradation mechanisms such as microcracking and potential-induced degradation, power electronic converters are subject to thermal stress and semiconductor fatigue, and battery energy storage systems exhibit complex electrochemical ageing processes influenced by operational conditions. Incorporating these reliability characteristics into system models enables the evaluation of a time-varying subsystem availability.

The third element involves integration of reliability modelling with system performance evaluation, enabling the impact of subsystem failures on energy delivery capability to be analysed within the broader context of SEM system operation. This integration allows system designers to evaluate alternative system configurations not only in terms of economic efficiency but also in terms of their ability to deliver reliable electricity under actual operating conditions.

By integrating these analytical elements, reliability-integrated SEM modelling frameworks can provide a more comprehensive representation of system behaviour compared with conventional deterministic modelling approaches. Such frameworks enable the evaluation of system performance metrics that reflect both economic efficiency and operational reliability, providing improved insights for the design and planning of decentralised renewable energy systems.

This conceptual positioning highlights the contribution of the research presented in this thesis. By integrating subsystem reliability modelling with SEM system performance evaluation, the research aims to address the methodological limitations identified in existing SEM modelling frameworks. The modelling approach developed in

this research therefore seeks to provide an actual representation of SEM system behaviour, supporting improved evaluation of long-term system performance and reliability.

Table 2.3: Mapping of Research Gaps, Research Questions, Objectives, and Methodological Approach

Identified Research Gap	Research Question	Research Objective	Methodological Approach
Existing SEM modelling tools primarily assume deterministic subsystem behaviour and do not explicitly represent stochastic failure processes affecting photovoltaic modules, power electronic converters, battery storage systems, and BOS components.	How can subsystem reliability behaviour be incorporated into modelling frameworks for SEMs?	To develop a modelling approach that incorporates subsystem failure characteristics into SEM performance evaluation.	Reliability modelling of SEM subsystems based on literature-derived failure mechanisms; integration of subsystem reliability parameters within system modelling framework.
Current SEM optimisation models focus on techno-economic performance metrics such as lifecycle cost and energy balance, with limited consideration of system reliability and operational availability.	How does subsystem reliability behaviour influence the long-term operational performance of SEMs?	To evaluate the impact of subsystem reliability characteristics on SEM system availability and energy delivery performance.	System performance simulation incorporating subsystem reliability parameters; evaluation of system-level reliability metrics such as availability and expected energy supply performance.
Reliability analysis and system optimisation are often treated as separate processes in existing SEM research, reducing the ability of reliability considerations to influence system design decisions.	How can reliability considerations be integrated into SEM system design and evaluation processes?	To integrate subsystem reliability modelling with SEM system performance evaluation for improved system design analysis.	Integration of reliability modelling techniques with system-level SEM simulation to evaluate reliability-aware system performance.

2.8. Chapter Summary

This chapter reviewed the literature relevant to SEM modelling, subsystem reliability behaviour, and reliability engineering methodologies applicable to SEM systems. The review established the analytical context for developing reliability-

integrated SEM modelling approaches. The key findings from the literature can be summarised as follows:

(1) Existing SEM modelling frameworks are primarily designed for techno-economic optimisation. Simulation and optimisation tools such as HOMER, REopt, RETScreen, and mixed-integer linear programming microgrid models are widely used for evaluating hybrid renewable energy systems. These tools simulate energy flows between photovoltaic generation, battery storage, and electrical loads using time-series resource and demand data, while optimisation algorithms determine system configurations that minimise lifecycle cost or maximise economic performance.

(2) Major SEM subsystems exhibit distinct reliability and degradation characteristics. Photovoltaic modules are subject to degradation mechanisms including microcracking, potential-induced degradation, and solder fatigue caused by environmental stresses such as temperature cycling and ultraviolet radiation. Power electronic converters represent one of the most failure-prone components in photovoltaic systems due to thermal stresses affecting semiconductor switching devices and electrolytic capacitors. Battery energy storage systems experience electrochemical degradation processes such as solid electrolyte interphase growth, lithium plating, and capacity fade resulting from repeated charge–discharge cycling.

(3) Reliability engineering provides established analytical methods for evaluating system failure behaviour. Structural reliability models such as reliability block diagrams, stochastic models including Markov processes, probabilistic simulation techniques such as Monte Carlo analysis, and physics-of-failure approaches have been widely applied in industries including aerospace systems, power system reliability assessment, and electronic device reliability analysis.

(4) Despite these analytical advances, subsystem reliability behaviour is rarely incorporated into SEM modelling frameworks. Most existing modelling tools assume deterministic subsystem performance and represent component degradation using simplified lifetime parameters or replacement schedules. Consequently, system performance simulations often neglect stochastic subsystem failure behaviour that may influence long-term system availability.

(5) Structural relationships between SEM subsystems are often simplified in existing modelling approaches. Many optimisation models represent SEM systems primarily in terms of energy balance relationships between generation, storage, and load components. This modelling abstraction does not fully capture the structural dependencies between subsystems such as photovoltaic arrays, inverters, battery management systems, and distribution infrastructure, through which failures may propagate across the system.

(6) These limitations highlight a structural modelling gap in current SEM modelling approaches. Integrating subsystem reliability behaviour with system architecture representation and energy system performance modelling represents an important research direction for improving the evaluation of SEM systems operating in decentralised and off-grid environments.

Chapter 3: HOMER Modelling Framework for SEM Analysis

3.1. Introduction

Chapter 2 established that the performance of SEM systems is governed not only by energy balance and economic optimisation but also by component-level degradation and stochastic failure mechanisms. It was further identified that most existing SEM modelling tools focus primarily on deterministic techno-economic analysis, with limited representation of reliability behaviour.

Building upon these findings, this chapter presents the implementation of a system-level modelling framework using HOMER for the simulation of a 100kW PV modules capacity SEM system. The purpose of this chapter is twofold. First, to establish a baseline model capable of representing the operational behaviour of SEM systems under actual environmental and load conditions. Second, to critically evaluate the assumptions embedded within this modelling framework and assess their implications for system performance and reliability. HOMER is widely used for hybrid renewable energy system design due to its ability to integrate renewable resource variability, storage dynamics, and economic optimisation. However, as discussed in Chapter 2, such tools rely on simplified and deterministic component models, particularly for battery storage systems.

Accordingly, this chapter presents the modelling framework and component-level formulations, while identifying key limitations. This provides the foundation for the reliability-integrated modelling approach developed in Chapter 4. Furthermore, Figure 3.1 provides a methodology look-ahead that cuts across Chapters 3 to 6. The figure presents the key roles of PV generation and battery energy storage models in the HOMER SEM system modelling framework as detailed in Chapter 3. In chapter 4, there is the sequencing of time-series simulation of TELS, R_{SEM} determination from RBD, regression modelling of TELS from the simulation data and its integration with the R_{SEM} . Chapter 5 quantifies the relationship between SEM system operational variables and TELS followed by the establishment of a validated regression-based representation of the SEM system performance. The methodology workflow concludes with chapter 6 presenting the SEM subsystem reliability characterisation, RBD design, formulation of SEM-RBRM and deterministic versus reliability-adjusted SEM performances comparison.

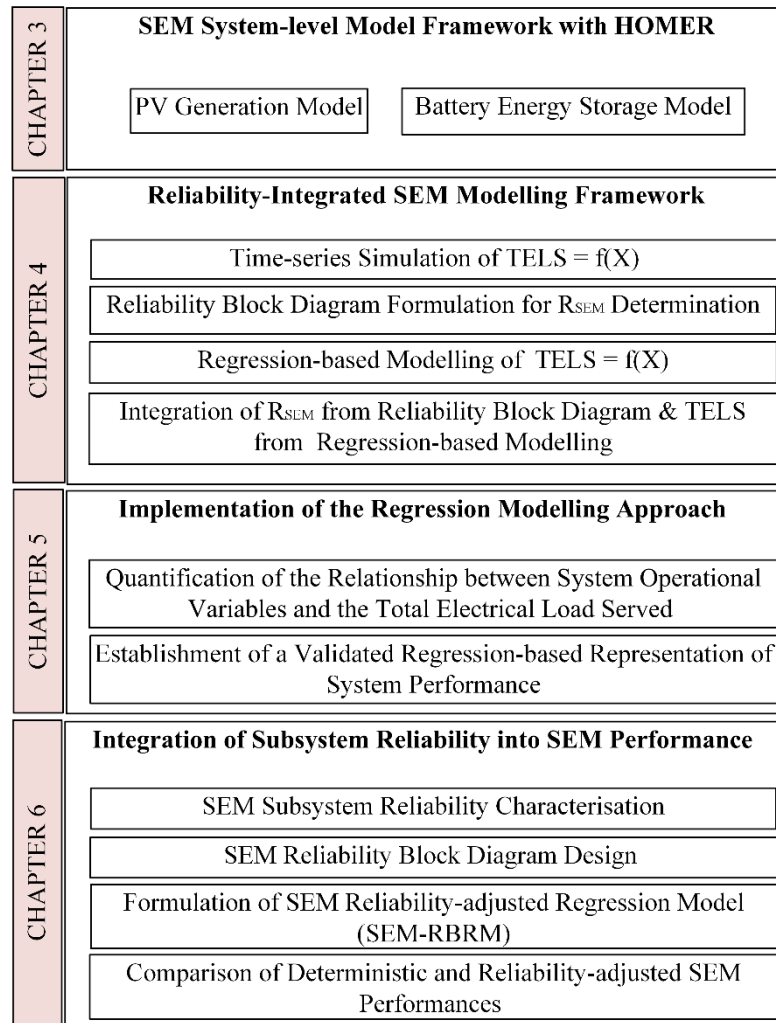


Figure 3.1: Overall Methodology Workflow for the Development of the Reliability-adjusted Regression Model of SEM.

3.2. SEM Simulation Framework in HOMER

The SEM system considered in this study is modelled using HOMER, a widely used optimisation and simulation platform for hybrid renewable energy systems. A SEM comprising 99.8kW PV modules, 50kW converter, 100kWh lithium-ion battery, and 58kW diesel generator capacity is selected to represent a typical SEM configuration applicable to rural electrification and distributed energy systems, while maintaining scalability for larger deployments. The selected SEM capacity is consistent with the classification of mini-grid systems defined by the Rural Electrification Agencies (REA). Systems within this capacity range are commonly deployed for electrification of small

communities and commercial clusters in off-grid regions. The selected SEM capacity ensures that the modelling framework reflects actual deployment scenarios while maintaining sufficient system complexity to capture interactions between generation, storage, and backup subsystems.

HOMER performs time-series simulations using hourly (or sub-hourly) input data, including solar irradiance, ambient temperature, and electrical load demand. Figure 3.2 shows the 35 variables considered in the HOMER simulation of the SEM (the complete dataset of the 35 variables can be found in the attached excel datafile named *2026 Dave Chibuike Nwosu PhD Thesis Data*). TELS was used as the dependent variable for the purpose of the regression modelling as defined by Eq.(4.1).

Time	Global Solar (kW/m ²)	PV Solar Altitude (°)	PV Solar Azimuth (°)	PV Angle of Incidence (°)
PV Incident Solar (kW/m ²)	PV Power Output (kW)	AC Primary Load (kW)	AC Primary Load Served (kW)	Deferrable Load Served (kW)
Deferrable Load Storage Level (kWh)	Genset Power Output (kW)	Genset Operating Status	Genset Fuel (L)	Total Electrical Load Served (kW)
Renewable Penetration (%)	Excess Electrical Production (kW)	Unmet Electrical Load (kW)	Total Renewable Power Output (kW)	Inverter Power Input (kW)
Inverter Power Output (kW)	Rectifier Power Input (kW)	Rectifier Power Output (kW)	100kWh Li- Ion Maximum Charge Power (kW)	100kWh Li-Ion Maximum Discharge Power (kW)
100kWh Li- Ion Charge Power (kW)	100kWh Li- Ion Discharge Power (kW)	100kWh Li-Ion Input Power (kW)	100kWh Li- Ion Energy Content (kWh)	100kWh Li-Ion State of Charge (%)
100kWh Li- Ion Energy Cost (\$/kWh)	AC Required Operating Capacity (kW)	DC Required Operating Capacity (kW)	AC Operating Capacity (kW)	DC Operating Capacity (kW)

Figure 3.2: Variables used in the HOMER Simulation of the SEM.

For each time step, the software determines system operation based on component models, resource availability, and dispatch strategies. The optimisation process evaluates multiple system configurations and identifies the optimal design based on minimisation of NPC, subject to operational constraints. The overall simulation workflow is illustrated in Figure 3.3. The simulation steps highlighted in the figure starts by naming and describing the project including its geographical location. This is followed by stating the project's economic, financial and technical assumptions. A HOMER simulation is performed with diverse SEM input parameters with the objective of using the net present cost metric to determine the winning SEM system architecture meeting the desired TELS requirements. The simulation steps advances with the recording of the economic metrics and summary of cost types while concluding with a calculation report output.

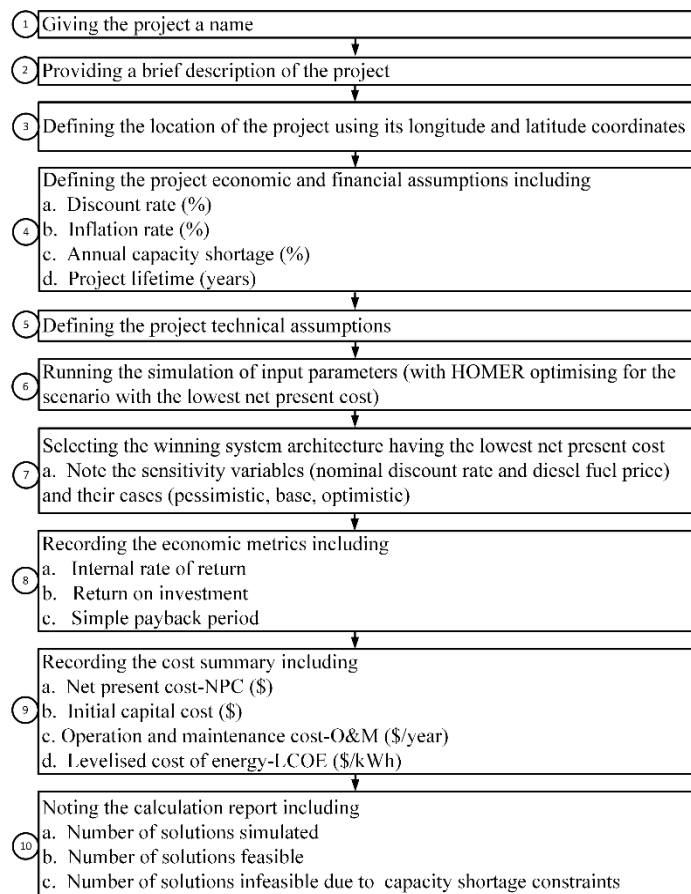


Figure 3.3: HOMER Model Simulation Steps

While this framework enables comprehensive techno-economic evaluation, it is important to recognise that HOMER assumes deterministic system behaviour.

Component failures, stochastic degradation, and uncertainty in operating conditions are not explicitly represented. As discussed in Chapter 2, these factors are critical in determining the reliability and long-term performance of SEM systems.

3.2.1. Photovoltaic (PV) Module Output Model

The electrical output of the photovoltaic array is calculated using the standard HOMER formulation:

$$P_{PV}(t) = Y_{PV} \cdot f_{PV} \cdot \frac{G(t)}{G_{STC}} \cdot [1 + \alpha_P(T_c(t) - T_{STC})] \quad (3.1)$$

where:

$P_{PV}(t)$: PV output power [kW]

Y_{PV} : rated PV capacity [kW]

f_{PV} : derating factor [-]

$G(t)$: solar irradiance [kW/m²]

G_{STC} : standard irradiance (1 kW/m²)

α_P : temperature coefficient [%/°C]

$T_c(t)$: cell temperature [°C]

T_{STC} : reference temperature (25°C)

This model accounts for variations in solar irradiance and cell temperature, incorporating a derating factor to represent system-level losses. The formulation provides a first-order approximation of PV performance and is widely used in system-level simulations.

However, the model assumes spatially uniform irradiance and does not explicitly incorporate degradation mechanisms such as module ageing, soiling, or electrical mismatch. Over extended simulation periods, these effects can significantly reduce PV output, particularly in harsh environmental conditions.

As highlighted in Chapter 2, overestimation of generation capacity directly affects system reliability metrics, as it may lead to underestimation of unmet load and

overestimation of system availability. Therefore, while the PV model is suitable for baseline analysis, its limitations must be considered when interpreting simulation results.

3.2.2. Maximum Battery Charge Power

The maximum battery charge power at each time step is determined by multiple constraints, including kinetic limitations, maximum charge rate, and maximum allowable current.

The kinetic limitation is derived from the Kinetic Battery Model (KiBaM), which governs the rate at which energy can be absorbed based on internal charge dynamics:

Kinetic constraint:

$$P_{\text{charge,kinetic}} = \frac{k \cdot Q_{\text{max}} \cdot c - k \cdot Q_1(t)}{1 - e^{-k\Delta t}} \quad (3.2)$$

Charge rate constraint:

$$P_{\text{charge,rate}} = r_c \cdot Q_{\text{max}} \quad (3.3)$$

Current constraint:

$$P_{\text{charge,current}} = N_b \cdot I_{\text{max}} \cdot V_{\text{nom}} \quad (3.4)$$

The maximum allowable charge power is:

$$P_{\text{charge,max}} = \eta_c \cdot \min (P_{\text{kinetic}}^m, P_{\text{rate}}^m, P_{\text{current}}) \quad (3.5)$$

where:

$P_{\text{charge,kinetic}}$: kinetic charging power limit [kW]

$Q_1(t)$: available energy [kWh]

Q_{max} : maximum battery charge capacity [kWh]

k : rate constant [h^{-1}]

c : fraction of total charge in the available-charge well [–]

η_c : charge efficiency

Δt is time-step duration

$P_{charge,rate}$: charge-rate-limited charging power [kW]

r_c : charging rate coefficient [h^{-1}]

$P_{charge,current}$: maximum charging power based on current limit

N_b : number of battery cells/modules/batteries

I_{max} : maximum allowable charging current

V_{nom} : nominal voltage

$P_{charge,max}$:

$P_{kinetic}^m$: maximum charging power allowed by the kinetic battery model

P_{rate}^m : maximum charging power allowed by the charge-rate limit

$P_{current}$: charging power allowed by the current limit

This formulation ensures that the battery operates within safe operational limits. However, the model assumes fixed parameters and does not account for temperature-dependent charge acceptance or electrochemical limitations.

In practical systems, battery charging behaviour is strongly influenced by temperature, state of charge, and ageing. As discussed in Chapter 2, failure to capture these dependencies can lead to overestimation of energy absorption capability, particularly under high state-of-charge conditions. This has implications for system optimisation, as excess renewable energy may not be effectively stored in real systems.

3.2.3. Maximum Battery Discharge Power

The maximum discharge power is similarly determined using the KiBaM framework:

The maximum discharge power is given by:

$$P_{discharge} = \frac{k \cdot Q_1(t)}{1 - e^{-k\Delta t}} \quad (3.6)$$

$$P_{discharge,max} = \eta_d \cdot P_{discharge} \quad (3.7)$$

where $P_{discharge}$ is maximum allowable discharge power, $P_{discharge,max}$ is maximum effective discharge power, and η_d is discharge efficiency.

This formulation defines the ability of the battery to supply load demand at each time step. However, it does not explicitly incorporate voltage constraints or dynamic electrochemical effects. In real battery systems, high discharge currents can result in voltage drop and reduced usable power, particularly under transient loading conditions. As identified in Chapter 2, such limitations are critical in determining system reliability, especially during peak demand periods. Consequently, the HOMER formulation may overestimate the ability of the battery system to meet load demand under dynamic conditions.

3.2.4. Kinetic Battery Model (KiBaM)

Manwell and McGowan (1993) proposed the Kinetic Battery Model which represents the battery as a two-reservoir system consisting of available and bound energy as shown in Figure 3.4. From the figure, the available energy tank holds the energy that is readily available for conversion to DC electricity. The bound energy tank contains the energy that is chemically bound which is not immediately available for withdrawal. The rate at which bound charge becomes available is proportional to the difference in ‘head’ of the two tanks. The exchange of energy between these reservoirs is governed by a rate constant of a chemical reaction/diffusion process, enabling the model to capture recovery effects and rate-dependent capacity.

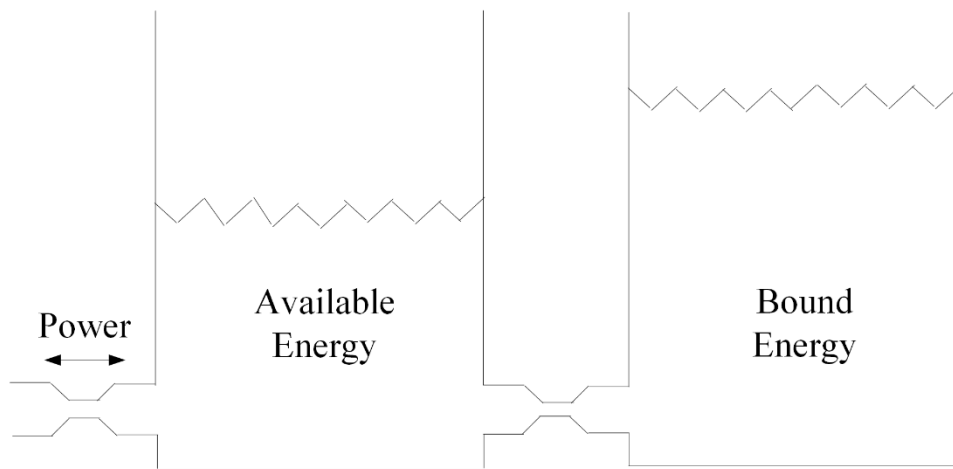


Figure 3.4: The Two-tank Kinetic Battery Model.

The KiBaM represents the battery as two energy reservoirs:

$$Q(t) = Q_1(t) + Q_2(t) \quad (3.8)$$

with dynamic behaviour:

$$\begin{aligned} \frac{dQ_1}{dt} &= -P(t) + k \left(Q_2 - \frac{Q_1}{c} \right) \\ \frac{dQ_2}{dt} &= -k \left(Q_2 - \frac{Q_1}{c} \right) \end{aligned}$$

where

$Q(t)$: total battery charge at time t

$Q_1(t)$: available energy at time t

$Q_2(t)$: bound energy at time t

$\frac{dQ_1}{dt}$: rate of change of available energy with respect to time

$-P(t)$: effect of battery power use on available energy

$\frac{dQ_2}{dt}$: rate of change of bound energy with respect to time

This model captures recovery effects and rate-dependent capacity behaviour. However, the parameters k , c , and $Q(t)$ are assumed constant and do not account for temperature or ageing effects. This approach provides a computationally efficient representation of battery behaviour and has been widely adopted in hybrid energy system modelling. However, it assumes constant parameters and does not account for dependencies on temperature, state-of-charge, or ageing.

As a result, the model may not accurately represent battery performance under actual operating conditions, particularly in systems with variable renewable generation. This limitation is particularly relevant for SEM systems, where battery storage plays a critical role in maintaining system reliability.

3.2.5. Functional and Thermal Models

The electrical behaviour of the battery is given by:

$$P_{\text{out}} = V_0 I - I^2 R_0 \quad (3.9)$$

Thermal behaviour is described by:

$$mC_p \frac{dT}{dt} = I^2 R_0 - h(T - T_{amb}) \quad (3.10)$$

where:

P_{out} : output power of the battery

V_0 : ideal battery voltage or open-circuit voltage

I : battery current

R_0 : internal resistance of the battery

m : mass of the battery

C_p : specific heat capacity of the battery material

$\frac{dT}{dt}$: rate of change of battery temperature with time

h : heat transfer coefficient

T : battery temperature

T_{amb} : ambient temperature

These models account for energy losses and temperature rise. However, they assume uniform temperature distribution and do not capture spatial variations within the battery pack or stochastic failure behaviour, which may be significant in large-scale energy storage systems.

3.2.6. Degradation and End-of-Life Modelling

Battery degradation is modelled using:

Calendar degradation:

$$k_t = B \cdot e^{-E_a/(k_B T)} \quad (3.11)$$

Cycle degradation:

$$N = A \cdot D^{-\beta} \quad (3.12)$$

where:

k_t : temperature-dependent degradation rate constant

B : pre-exponential factor (also called the Arrhenius constant or frequency factor)

k_B : Boltzmann constant

E_a : activation energy

T : absolute temperature

N : number of cycles to failure or cycle life

A : empirical cycle-life constant

D : depth of discharge

β : cycle-life exponent

Battery end-of-life is defined based on a predefined capacity loss threshold. This determines replacement intervals within the simulation. However, degradation is represented as a deterministic process. As identified in Chapter 2, real battery systems exhibit stochastic degradation and failure behaviour, which is not captured in this formula.

3.2.7. Critical Modelling Assumptions and Implications

The battery modelling approach implemented in HOMER is based on the Kinetic Battery Model, which introduces several simplifying assumptions. As discussed in Chapter 2, these assumptions have significant implications for both optimisation and reliability assessment.

Key assumptions include:

- (1) Constant model parameters independent of temperature and ageing
- (2) Absence of stochastic failure mechanisms
- (3) Simplified efficiency representation
- (4) Lack of voltage-based operational constraints

These assumptions enable computational efficiency but may introduce systematic bias in simulation results. In particular:

- (1) System availability may be overestimated.
- (2) LOLP may be underestimated.

(3) Battery lifetime predictions may be overly optimistic.

These limitations highlight the gap between conventional SEM modelling approaches and the requirements for reliability-aware system design, as identified in Chapter 2.

3.2.8. Model scenario Description

To ensure that the modelling framework reflects representative operating conditions, a model scenario is considered based on a semi-urban location in Awka, Anambra State, Nigeria. The selected site corresponds to a commercial cluster (Top Mark Plaza) comprising approximately 50–60 small businesses, including retail shops, service providers, and small-scale enterprises.

The load profile for the system reflects a mixed commercial demand pattern, characterised by peak consumption during daytime operating hours and reduced demand during night-time periods. This type of load behaviour is typical of mini-grid applications in developing regions, where energy demand is driven by business activities rather than residential usage alone.

The selection of this model scenario is motivated by the increasing deployment of SEMs across Sub-Saharan Africa to address energy access challenges. In particular, the Rural Electrification Agency (REA) in Nigeria has identified mini-grids as a key solution for electrifying underserved communities, with system capacities typically ranging up to 100kW PV modules capacity. The chosen model scenario therefore represents an actual and relevant application of SEM systems in practice.

Environmental input data, including solar irradiance and temperature profiles, are derived from standard meteorological datasets representative of the region. These inputs are used within the HOMER simulation environment to generate time-series system performance data. By grounding the modelling framework in a representative model scenario, the analysis ensures that the simulation results and subsequent modelling developments are both practically relevant and representative of typical SEM deployment scenarios.

3.3. Summary

This chapter has presented the deterministic modelling framework used to simulate the performance of SEM systems. A hybrid SEM configuration consisting of photovoltaic generation, battery storage, diesel backup, and power conversion has been defined and implemented using the HOMER simulation environment. The modelling approach captures system behaviour under varying environmental and load conditions, providing time-series data for system performance.

Key modelling assumptions and limitations have been identified, particularly the reliance on deterministic simulation and the assumption of continuous component operation. While this approach provides valuable insight into energy flows and system performance, it does not account for subsystem failures or reliability-related effects.

These limitations highlight the need for an extended modelling framework that incorporates subsystem reliability into system performance evaluation. This motivates the development of the reliability-integrated modelling framework presented in Chapter 4, where system availability and failure behaviour are explicitly incorporated into SEM performance modelling.

Chapter 4: Reliability-Integrated Modelling Framework for SEMs

4.1. Introduction

SEM systems are increasingly deployed as a viable solution for decentralised power generation, particularly in off-grid and remote regions. Their performance is typically evaluated using deterministic modelling approaches, as demonstrated in Chapter 3, where simulation tools such as HOMER are used to analyse system behaviour under varying environmental and load conditions. While such approaches provide valuable insight into energy flows, system sizing, and techno-economic performance, they inherently assume continuous and uninterrupted operation of all system components.

As discussed in Chapter 2, this assumption represents a key limitation of conventional SEM modelling frameworks. In practice, subsystem failures, and stochastic operating conditions can significantly affect system availability and energy delivery. The absence of reliability considerations in deterministic models can therefore lead to overestimation of system performance and insufficient understanding of long-term operational behaviour.

To address this limitation, this chapter develops a time-varying reliability-integrated modelling framework for SEM systems. The proposed approach extends the deterministic modelling framework presented in Chapter 3 by incorporating subsystem reliability into system-level performance prediction. This is achieved by combining three key elements: time-series simulation data representing system operation, reliability modelling based on RBD, and regression-based statistical modelling to establish relationships between system variables and energy delivery.

The central concept of this chapter is the integration of system performance and reliability into a unified time-varying modelling framework, in which the TELS is expressed as a function of both operational variables and subsystem availability. This enables the evaluation of SEM systems under more actual conditions, where energy delivery is constrained not only by resource availability and system configuration but also by the probability of component failure.

4.2. Conceptual Framework for Reliability Integration

The deterministic SEM modelling approach presented in Chapter 3 evaluates system performance based on operational variables such as solar irradiance, load demand, and component capacities. While this approach captures system behaviour under varying operating conditions, it assumes continuous and uninterrupted component operation. As highlighted in Chapter 2, this assumption limits the ability of the model to represent field-deployed system performance, where subsystem failures and degradation influence energy delivery. To address this limitation, a conceptual framework is developed in which SEM performance is expressed as a function of both operational behaviour and subsystem reliability. This framework forms the basis for integrating deterministic simulation outputs with reliability modelling.

4.2.1. Reliability–Performance Coupling

In deterministic form, SEM performance is expressed as:

$$TELS(t) = f(X(t)) \quad (4.1)$$

where $TELS(t)$ is the Total Electrical Load Served and $X(t)$ represents the system operational variables.

However, in practical operation, energy delivery depends not only on system capability but also on whether the system is operational. To incorporate this effect, system performance is reformulated as:

$$TELS_r(t) = f(X(t), R_{SEM}(t)) \quad (4.2)$$

where $TELS_r(t)$ is the reliability-adjusted load served and $R_{SEM}(t)$ is the system reliability.

For implementation, this relationship is expressed using a multiplicative coupling:

$$TELS_r(t) = R_{SEM}(t) \cdot TELS(t) \quad (4.3)$$

This formulation reflects the principle that energy delivery is conditional on system availability, with $R_{SEM}(t)$ acting as an availability factor that scales the deterministic output.

4.2.2. Physical Interpretation

The reliability–performance coupling has a clear physical meaning in the context of SEM systems. The deterministic term $TELS(t)$ represents the maximum achievable energy delivery under ideal conditions, while $R_{SEM}(t)$ represents the probability that the system is operational.

When $R_{SEM}(t) = 1$, the system is fully available and delivers the full predicted load. When $R_{SEM}(t) < 1$, system downtime due to subsystem failures reduces the effective energy delivered.

For example, if:

$$R_{SEM}(t) = 0.85$$

then the system is operational 85% of the time, and the effective load served is reduced accordingly. This interpretation ensures that the model reflects real operating conditions, where failures limit system performance.

4.2.3. Representation of Operational Variables

The operational state of the SEM system is represented by the variable vector:

$$X(t) = [G(t), P_{PV}(t), P_{bat}(t), P_{gen}(t), P_{inv}(t), L(t)] \quad (4.4)$$

where $G(t)$: solar irradiance, $P_{PV}(t)$: PV power output, $P_{bat}(t)$: battery charge/discharge power, $P_{gen}(t)$: diesel generator output, $P_{inv}(t)$: inverter output, $L(t)$: load demand.

These variables are obtained from HOMER simulations (Chapter 3) and describe the deterministic operating condition of the system at each time step. Thus, $X(t)$ captures system behaviour under varying environmental and load conditions, while $R_{SEM}(t)$ introduces the effect of subsystem availability.

4.2.4. Time-Varying Reliability Behaviour

System reliability is derived from the reliability of individual subsystems. Assuming statistically independent failures, the reliability of subsystem i is expressed as:

$$R_i(t) = e^{-\lambda_i t} \quad (4.5)$$

where λ_i is the failure rate and t is the operating time.

The overall system reliability is given by:

$$R_{SEM}(t) = \prod_{i=1}^n R_i(t) \quad (4.6)$$

Substituting Eq.(4.6) and Eq.(4.5) into Eq.(4.3) yields:

$$TELS_r(t) = \left(\prod_{i=1}^n e^{-\lambda_i t} \right) \cdot TELS(t) \quad (4.7)$$

This formulation introduces a time-varying reliability component into the SEM performance model, enabling representation of SEM performance as the probability of subsystem failure increases over time.

It is important to note that this approach assumes that SEM performance is proportional to availability, such that subsystem failures reduce effective operating time rather than partially degrading output. This assumption is appropriate for system-level modelling and ensures compatibility with the reliability modelling approach developed in Section 4.5.

4.3. Categorisation of SEM Uncertainties

SEM systems operate under multiple sources of uncertainty arising from environmental variability, component reliability, and load demand fluctuations. These uncertainties influence system performance, energy delivery, and long-term operational behaviour. As discussed in Chapter 2, conventional SEM models often simplify or neglect these uncertainties, particularly in relation to subsystem failure behaviour, which limits their ability to represent field-deployed system performance.

To provide a structured basis for modelling, uncertainties in SEM systems are categorised into three primary domains: renewable resource uncertainty, subsystem reliability uncertainty, and load demand uncertainty. This categorisation enables the identification of the dominant factors affecting system performance and supports the development of the reliability-integrated modelling framework introduced in Section 4.2.

4.3.1. Renewable Resource Uncertainty

Renewable resource uncertainty arises from the stochastic nature of solar irradiance, which varies due to atmospheric conditions, seasonal changes, and geographical location. Solar irradiance can be expressed as:

$$G(t) = \bar{G}(t) + \delta G(t) \quad (4.8)$$

where $\bar{G}(t)$ is the mean or expected irradiance profile, $\delta G(t)$ represents stochastic fluctuations around the mean.

This variability directly affects PV power generation and introduces fluctuations in system energy input. As a result, it influences battery charging behaviour, generator dispatch, and overall system operation. In this study, renewable resource uncertainty is implicitly captured through the time-series input data used in HOMER simulations (Chapter 3), which are based on historical or TMY datasets. These datasets provide a representative approximation of solar variability over time. However, high-frequency stochastic variations and extreme events are not explicitly modelled, as the primary focus of this research is on subsystem reliability rather than short-term resource fluctuations.

4.3.2. Subsystem Reliability Uncertainty

Subsystem reliability uncertainty arises from the stochastic nature of component failures and degradation processes. Unlike renewable variability, which affects energy availability, reliability uncertainty determines whether system components are operational.

The reliability of SEM subsystem is expressed in Eq.(4.5). Subsystem failures can occur in key components such as PV modules, battery systems, converters, and diesel generators. These failures may lead to partial or complete system outages, particularly when critical components (e.g., converters) are involved. As identified in Chapter 2, conventional SEM models do not explicitly incorporate subsystem reliability, instead assuming ideal component operation or simplified lifetime behaviour. This omission represents a major limitation in predicting system performance. In the present study, subsystem reliability uncertainty is explicitly modelled and forms the central focus of the proposed framework. Reliability modelling is integrated with system performance to quantify the impact of component failures on energy delivery.

4.3.3. Load Demand Uncertainty

Load demand uncertainty arises from variability in user consumption patterns, operational conditions, and behavioural factors. The load profile can be expressed as:

$$L(t) = \bar{L}(t) + \delta L(t) \quad (4.9)$$

where $\bar{L}(t)$ is the expected load demand, and $\delta L(t)$ represents stochastic variations.

Load variability affects system operation by influencing generator dispatch, battery cycling, and the balance between supply and demand. Mismatches between generation and load can result in unmet demand or excess energy. In this study, load uncertainty is implicitly captured through the simulation dataset, where the $TELS(t)$ reflects the interaction between generation capacity and load demand. As a result, load variability is incorporated into the regression model without requiring explicit stochastic modelling.

4.3.4. Rationale for Focus on Subsystem Reliability

While all three categories of uncertainty influence SEM performance, this research focuses primarily on subsystem reliability uncertainty. This focus is justified for several reasons. First, as identified in Chapter 2, existing SEM models already account for renewable variability and load demand through time-series simulation inputs. In contrast, subsystem failure behaviour is not explicitly represented, creating a significant modelling gap. Second, subsystem failures have a more direct and critical impact on system performance. Unlike resource variability, which affects energy availability, component failures can lead to complete system outages, making their influence more severe in reliability analysis. Third, subsystem reliability can be integrated into system-level models using analytical approaches such as Reliability Block Diagrams, without requiring computationally intensive stochastic simulations. This enables efficient modelling while capturing essential failure behaviour. Finally, incorporating subsystem reliability provides a novel contribution to SEM modelling by linking component-level failure mechanisms with system-level energy delivery, thereby improving the realism and applicability of the model.

4.3.5. Role of Uncertainty Categorisation in the Proposed Framework

The categorisation of uncertainties provides a structured foundation for the modelling framework developed in this chapter. Each category is treated differently within the proposed approach: Renewable resource uncertainty is captured through simulation inputs, load demand uncertainty is reflected in the system response variable $TELS(t)$, and subsystem reliability uncertainty is explicitly modelled and integrated into system performance. This selective treatment ensures that the framework remains computationally efficient while addressing the most critical limitation identified in previous chapters, namely the absence of reliability-aware modelling. By clearly distinguishing between diverse sources of uncertainty, the framework enables a targeted integration of reliability into SEM performance modelling. This provides a coherent basis for the development of the reliability model (Section 4.5), regression model (Section 4.6), and their integration in Section 4.7.

4.4. SEM System Definition and Dataset

The development of the reliability-integrated modelling framework requires a representative SEM system and a structured dataset that captures system behaviour under actual operating conditions. In this study, a hybrid SEM system is defined and simulated using the deterministic modelling approach described in Chapter 3. The resulting dataset provides the basis for regression model development and subsequent integration with reliability modelling.

4.4.1. System Configuration and Rationale

The SEM system considered in this study is based on a hybrid configuration consisting of (1) a PV generation system, (2) a battery energy storage system, (3) a power electronic converter, and (4) a diesel generator for backup generation. This configuration reflects a typical off-grid SEM architecture, where renewable generation is complemented by storage and backup systems to ensure reliable energy supply. The selection of this system configuration is motivated by several considerations. First, the PV system serves as the primary renewable energy source, capturing the variability of solar irradiance discussed in Section 4.3. Second, the battery system enables energy storage and load balancing, allowing excess generation to be stored and used during periods of low irradiance. Third, the converter is required for power conditioning and energy transfer between system components, making it a critical subsystem in terms of reliability. Finally, the diesel generator provides redundancy, ensuring that load demand can be met when renewable generation and storage are insufficient. This hybrid configuration is particularly suitable for the present study, as it exhibits both operational variability and reliability dependency, enabling the investigation of interactions between system performance and subsystem availability.

4.4.2. Simulation Environment and Operating Conditions

The SEM system is simulated using HOMER, as described in Chapter 3. The simulation is conducted over a full-year period with time-resolved data, enabling the capture of dynamic system behaviour under varying environmental and load conditions. The simulation incorporates time-series solar irradiance data $G(t)$, ambient temperature

profiles, a predefined load demand profile $L(t)$, and system component specifications (PV, battery, generator, converter). The use of time-series simulation allows the model to capture key operational dynamics, including variability in PV generation, battery charge–discharge cycles, generator dispatch behaviour, and system response to changing load demand. The simulation outputs represent deterministic system behaviour, where all components are assumed to operate without failure. These outputs form the baseline performance $TELS(t)$, which is later adjusted through the reliability framework developed in Sections 4.5 and 4.7.

4.4.3. Dataset Structure and Variables

The simulation generates a time-series dataset that describes the operational state of the SEM system at each time step. The dataset includes both input variables and system response variables, which are used for regression model development. The operational variable vector is defined as Eq.(4.4).

The corresponding system response variable is:

$$Y(t) = TELS(t) \quad (4.10)$$

For regression modelling, the dataset can be expressed in matrix form as:

$$\mathbf{X} = \begin{bmatrix} X(t_1) \\ X(t_2) \\ \vdots \\ X(t_n) \end{bmatrix} = \begin{bmatrix} G(t_1) & P_{PV}(t_1) & P_{bat}(t_1) & P_{gen}(t_1) & P_{inv}(t_1) & L(t_1) \\ G(t_2) & P_{PV}(t_2) & P_{bat}(t_2) & P_{gen}(t_2) & P_{inv}(t_2) & L(t_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ G(t_n) & P_{PV}(t_n) & P_{bat}(t_n) & P_{gen}(t_n) & P_{inv}(t_n) & L(t_n) \end{bmatrix} \quad (4.11)$$

and the response vector as:

$$\mathbf{Y} = \begin{bmatrix} TELS(t_1) \\ TELS(t_2) \\ \vdots \\ TELS(t_n) \end{bmatrix} \quad (4.12)$$

This dataset structure forms the basis for regression modelling in Section 4.6, where the relationship between system variables and energy delivery is quantified. It is

important to note that the dataset reflects deterministic system behaviour and does not explicitly include subsystem failure events. This limitation is addressed in the proposed framework by integrating reliability modelling (Section 4.5) with the regression model, enabling the development of a reliability-adjusted performance model.

4.5. Reliability Modelling Using Reliability Block Diagrams (RBD)

To quantify subsystem reliability and its impact on system performance, RBDs are employed in this study. RBDs provide a structured and physically intuitive representation of how individual component reliabilities combine to determine overall system reliability. The use of RBDs is particularly suitable for SEM systems, as it allows the functional relationships between generation, storage, and conversion subsystems to be explicitly represented. In addition, RBDs offer analytical tractability, enabling closed-form expressions for system reliability that can be directly integrated into the performance model developed in Section 4.2.

4.5.1. Basic RBD Configurations

The reliability of a system depends on how its components are functionally arranged. Two fundamental configurations are considered: series systems and parallel systems.

Series Systems. The system reliability for a series configuration is expressed in Eq.(2.11). This configuration represents systems with strong dependency between components. In the context of SEM systems, components such as power converters exhibit series behaviour, as their failure interrupts power delivery regardless of energy availability.

Parallel Systems. In a parallel configuration, the system operates as long as at least one component is functional. This represents redundancy, where multiple components can perform the same function. The system reliability is expressed in Eq.(2.12). This formulation represents the complement of the probability that all components fail simultaneously. In SEM systems, energy sources such as PV, battery, and diesel generator can operate in parallel, providing multiple pathways for energy supply. This redundancy enhances system reliability.

4.5.2. SEM System Reliability Structure

The SEM system considered in this study exhibits a hybrid reliability structure combining both series and parallel configurations. Specifically:

- the generation subsystems (PV, battery, and diesel generator) operate in parallel,
- the power converter operates in series with the generation subsystem.

This structure reflects the physical operation of the SEM system, where energy can be supplied by multiple sources, but must pass through the converter to reach the load.

Based on this configuration, the overall system reliability is expressed as:

$$R_{SEM}(t) = R_{converter}(t) \cdot \left[1 - \frac{(1 - R_{PV}(t))(1 - R_{battery}(t))}{(1 - R_{generator}(t))} \right] \quad (4.13)$$

This expression can be interpreted as follows:

the term

$$(1 - R_{PV})(1 - R_{battery})(1 - R_{generator})$$

represents the probability that all energy sources fail simultaneously;

the term,

$$1 - (1 - R_{PV})(1 - R_{battery})(1 - R_{generator})$$

represents the probability that at least one energy source is available. Multiplication by $R_{converter}(t)$ accounts for the fact that energy cannot be delivered without a functioning converter. $R_{converter}(t)$, $R_{PV}(t)$, $R_{battery}(t)$, and $R_{generator}(t)$ represent the time-varying reliability of the converter, photovoltaic system, battery, generator and BOS respectively.

Thus, the model captures both redundancy in generation and critical dependency in power conversion, which are key characteristics of SEM systems. The value of

$R_{SEM}(t)$ in Eq.(4.13) is primarily driven by the subsystems failure rates and is not explained by the diurnal variations of solar irradiance.

4.5.3. Time-Varying Reliability Representation

The reliability of each subsystem is defined using the exponential failure model of Eq.(4.5) in Section 4.2.4. Substituting Eq.(4.5) into Eq.(4.13) allows system reliability to be evaluated as a function of time, capturing the effect of increasing failure probability on system availability.

This time-varying formulation enables the integration of reliability into the SEM performance model, as presented in Section 4.7.

4.5.4. Assumptions

The RBD-based reliability model is developed under the following assumptions:

- subsystem failures are statistically independent,
- failure rates are constant over time (exponential distribution), given that circa 95% subsystem failures occur within the useful life (constant failure rate) segment of the reliability bathtub curve.
- components are considered to have binary states (operational or failed),
- partial degradation effects are represented indirectly through availability.

These assumptions are appropriate for system-level modelling and allow analytical integration with the regression-based performance model.

4.6. Regression Model Development

The deterministic SEM simulation described in Section 4.4 produces a comprehensive time-series dataset that captures system behaviour under varying environmental and load conditions. While this dataset provides detailed numerical insight, it does not directly yield a generalised analytical relationship between system inputs and energy delivery. To enable efficient prediction and integration with reliability

modelling, a regression-based approach is adopted to establish an explicit functional relationship between system operational variables and the TELS. This regression model serves as a surrogate representation of the SEM system, allowing system performance to be evaluated without repeated simulation.

4.6.1. Regression Model Formulation

The deterministic relationship between system inputs and output is expressed by Eq.(4.1). To obtain an explicit analytical form, a multiple linear regression model is adopted:

$$TELS(t) = \beta_0 + \sum_{i=1}^n \beta_i X_i(t) + \epsilon(t) \quad (4.14)$$

where β_0 is the intercept representing baseline system output, β_i are regression coefficients associated with each predictor variable, $X_i(t)$ are the input variables, n is the number of input variables, and $\epsilon(t)$ is the residual error term.

The predictor variables include solar irradiance, PV output, battery power, generator output, inverter output, and load demand, as defined in Eq.(4.11). The use of regression modelling allows the complex relationships embedded within the simulation data to be approximated in a computationally efficient form.

4.6.2. Physical Interpretation of the Model

The regression model provides a quantitative representation of how different system components contribute to energy delivery. Each coefficient β_i reflects the sensitivity of $TELS(t)$ to the corresponding variable. For example, a positive coefficient associated with $P_{PV}(t)$ indicates that increased PV generation contributes positively to load served, while the coefficient associated with $P_{bat}(t)$ reflects the role of storage in balancing supply and demand. Similarly, the coefficient for $P_{gen}(t)$ represents the contribution of backup generation during periods of energy deficit. Thus, the regression model not only enables prediction of system performance but also provides insight into the relative importance of different subsystems in meeting load demand.

4.6.3. Limitations of the Regression Model

Despite its advantages, the regression model has several limitations that must be acknowledged. First, the model is derived from deterministic simulation data and therefore assumes ideal component operation. Subsystem failures and degradation effects are not explicitly represented in the dataset, which may lead to overestimation of system performance under real operating conditions. Second, the linear formulation may not fully capture complex nonlinear relationships present in the system, although this can be partially addressed through the inclusion of interaction terms. Third, the accuracy of the regression model depends on the quality and representativeness of the simulation data, including the selection of input variables and operating conditions. These limitations highlight the need for integrating reliability modelling with the regression framework. This integration, presented in Section 4.7, enables the development of a reliability-adjusted performance model that accounts for both operational variability and subsystem availability.

4.7. Reliability-Integrated Model

The regression model developed in Section 4.6 provides a deterministic relationship between system operational variables and energy delivery, while the reliability model presented in Section 4.5 quantifies subsystem availability. However, when considered independently, these models do not fully represent SEM system behaviour under actual operating conditions, where both operational variability and subsystem failures influence performance. To address this limitation, the present study integrates the regression-based performance model with the reliability model to develop a unified reliability-integrated SEM performance model.

4.7.1. Model Formulation

The reliability-integrated model is constructed by combining the deterministic regression model with the system reliability function. The resulting formulation is expressed by substituting the regression model from Eq.(4.14) into Eq.(4.3) which yields:

$$TELS_{,r}(t) = R_{SEM}(t) \cdot \left(\beta_0 + \sum_{i=1}^n \beta_i X_i(t) + \epsilon(t) \right) \quad (4.15)$$

where $TELS_{,r}(t)$: reliability-adjusted energy delivery [kW], $R_{SEM}(t)$: system reliability obtained from RBD modelling (Section 4.5), $\beta_0 + \sum \beta_i X_i(t)$: deterministic system performance from regression, and $\epsilon(t)$: residual error term.

This formulation provides a direct coupling between system performance and subsystem availability.

4.7.2. Justification of the Integration Approach

The multiplicative integration approach adopted in Eq.(4.3) is justified on physical, analytical, and methodological grounds. From a physical perspective, energy delivery in SEM systems is conditional on system availability. Even if sufficient energy is generated, it cannot be delivered to the load if critical components are non-operational. The reliability term therefore acts as an availability factor that scales the deterministic output. From an analytical perspective, the multiplicative formulation provides a computationally efficient means of incorporating reliability into the performance model. Unlike stochastic simulation methods, which require repeated evaluation under different failure scenarios, this approach allows reliability effects to be incorporated directly through a closed-form expression. From a methodological perspective, the proposed model bridges the gap between deterministic SEM modelling (Chapter 3) and reliability engineering (Section 4.5). It enables both operational variability and subsystem failures to be represented within a single modelling framework, addressing the key limitation identified in Chapter 2.

4.7.3. Behaviour Under Different Operating Conditions

The reliability-integrated model exhibits physically consistent behaviour under different system conditions. When system reliability is high:

$$R_{SEM}(t) \approx 1$$

the model reduces to:

$$TELS_{,r}(t) \approx TELS(t)$$

indicating that system performance is dominated by operational variables and closely matches the deterministic model. When system reliability decreases:

$$0 < R_{SEM}(t) < 1$$

the effective energy delivery is reduced proportionally, reflecting the impact of subsystem failures on system availability. In the limiting scenario where:

$$R_{SEM}(t) \rightarrow 0$$

the system becomes largely unavailable, and energy delivery approaches zero:

$$TELS_{,r}(t) \rightarrow 0$$

These behaviours confirm that the model captures the expected physical response of SEM systems under varying reliability conditions.

4.7.4. Contribution and Novelty

The time-varying reliability-integrated model developed in this section represents a key contribution of this research. Unlike conventional SEM modelling approaches, which evaluate system performance under deterministic assumptions, the proposed model explicitly incorporates time-varying subsystem reliability into performance prediction.

The main contributions of the model are as follows:

- (1) it provides a unified representation of SEM performance that combines operational behaviour and time-varying subsystem availability,

- (2) it enables quantification of the impact of subsystem failures on energy delivery,
- (3) it offers a simpler alternative to stochastic reliability modelling approaches,
- (4) it supports time-varying reliability-aware system design and evaluation.

By integrating regression-based modelling with reliability analysis, the proposed framework bridges the gap between energy system modelling and reliability engineering. This directly addresses the research gap identified in Chapter 2 and establishes the foundation for the validation and analysis presented in Chapter 5.

4.8. Model Implementation Strategy

The implementation of the proposed reliability-integrated modelling framework follows a structured workflow that combines deterministic simulation, statistical modelling, and reliability analysis. This approach ensures consistency between system behaviour captured in the dataset and the reliability-adjusted performance model.

The process begins with deterministic SEM simulation using HOMER, as described in Chapter 3, to generate time-series data representing system operation under varying environmental and load conditions. These outputs are then extracted and organised into a structured dataset, as defined in Section 4.4, with operational variables $X(t)$ and response variable $TELS(t)$. Subsequently, a regression model is developed using the dataset to establish an analytical relationship between system inputs and energy delivery, as presented in Section 4.6. This model provides a computationally efficient representation of deterministic system performance. In parallel, subsystem reliability is modelled using Reliability Block Diagrams (Section 4.5), where failure rates are used to determine the time-varying system reliability $R_{SEM}(t)$. The last step involves integrating the regression model with the reliability model using the formulation developed in Section 4.7:

$$TELS_{\cdot r}(t) = R_{SEM}(t) \cdot TELS(t)$$

This integration enables the evaluation of system performance under both operational variability and subsystem failure conditions. Overall, the implementation strategy provides a systematic pathway from simulation data to a reliability-aware time-

varying performance model, ensuring that the framework remains both computationally efficient and physically representative.

4.9. Significance of the Proposed Framework

The reliability-integrated modelling framework developed in this chapter represents a significant advancement over conventional SEM modelling approaches. Traditional models evaluate system performance under deterministic assumptions, focusing primarily on energy balance and system optimisation, while neglecting the impact of subsystem failures on energy delivery. By explicitly incorporating subsystem reliability into system performance modelling, the proposed framework provides a more actual representation of SEM behaviour. The integration of regression modelling with reliability analysis enables efficient prediction of system performance while accounting for failure-induced downtime, thereby improving predictive accuracy under practical operating conditions. In addition to enhancing model realism, the framework supports reliability-aware system design by enabling the evaluation of system configurations based on both performance and availability. This allows for improved decision-making in terms of component selection, redundancy, and system configuration. Furthermore, the proposed approach bridges the gap between deterministic energy system modelling and reliability engineering. By combining simulation outputs, statistical modelling, and reliability analysis within a unified framework, the model addresses the key limitation identified in Chapter 2 and contributes to advancing the state of knowledge in SEM modelling.

4.10. Summary

This chapter has developed a reliability-integrated modelling framework for SEMs. Building on the deterministic modelling approach presented in Chapter 3, the framework incorporates subsystem reliability and regression-based modelling to provide a more comprehensive representation of system performance. A structured methodology was established in which simulation data were used to develop a regression model, while system reliability was quantified using Reliability Block Diagrams. These components were subsequently integrated to express system performance as a function of both operational variables and subsystem availability. The proposed framework addresses the

limitations of conventional SEM models by explicitly accounting for subsystem failures and their impact on energy delivery. As a result, it enables a more actual assessment of system performance under practical operating conditions and provides a foundation for reliability-aware system design and analysis. The application and validation of the proposed model are presented in the following chapter.

Chapter 5: Results and Model Development

5.1. Introduction

This chapter presents the results and development of the baseline SEM performance model derived from the deterministic simulation framework established in Chapter 3 and the modelling methodology introduced in Chapter 4. The primary objective is to quantify the relationship between system operational variables and the $TELS(t)$, and to establish a validated regression-based representation of system performance.

Building on the conceptual and analytical framework developed in Chapter 4, this chapter focuses on the implementation of the regression modelling approach using the time-series dataset generated from HOMER simulations. The regression model provides an explicit functional relationship between system inputs and energy delivery, forming the deterministic component of the reliability-integrated model introduced in Section 4.7.

The chapter first presents the key outputs of the SEM simulation and examines the behaviour of system variables under varying operating conditions. This is followed by the development, calibration, and validation of the regression model, including assessment of multicollinearity, goodness-of-fit, and model assumptions. The results are then interpreted from an engineering perspective to identify the dominant factors influencing system performance.

Finally, a baseline SEM performance model is established, and its limitations are discussed, particularly in relation to the absence of subsystem reliability effects. This provides a clear transition to Chapter 6, where reliability modelling is applied to extend the deterministic framework into a reliability-integrated performance model.

5.2. Deterministic SEM Simulation Results

The deterministic simulation of the SEM system, described in Chapter 3, provides time-series data capturing system behaviour under varying environmental and load conditions. These results form the foundation for regression model development and

subsequent reliability integration. This section presents the key simulation outputs, examines the behaviour of system variables, and establishes the relationships between operational inputs and the $TELS(t)$. Table 5.1 shows the summary of the results dataset utilised in this PhD (For the complete dataset, please refer to the attached excel datafile named *2026 Dave Chibuike Nwosu PhD Thesis Data*). The table contains the simulation baseline, the Awka, the Liverpool, as well as the SEM RAM data.

Table 5.1: Summary of Modelling Results Dataset of the PhD

Time	Time (hr)	1	2	10	11	8759	8760
	Time	1/1/2026 12:00:00 AM	1/1/2026 1:00:00 AM	1/1/2026 9:00:00 AM	1/1/2026 10:00:00 AM	12/31/2026 10:00:00 PM	12/31/2026 11:00:00 PM
Baseline Data (Drawn from Awka Data)	Global Solar (kW/m2)	0	0	0.476	0.552	0	0
	PV Power Output (kW)	0	0	49.83	56.91	0	0
	Inverter Power Input (kW)	0.2227	0.2571	17.06	25.43	0.1999	0.2521
	Battery Input Power (kW)	-0.2227	-0.2571	0	0	-0.1999	-0.2521
	Diesel Gen Power Output (kW)	0	0	0	0	0	0
	TELS (kW)	0.2116	0.2442	16.21	24.15	0.1899	0.2395
	TELS.r (kW)	0.2116	0.2442	16.21	24.15	0.1680	0.2119
	TELS.r & TELS Delta ΔTELS (kW)	0.0000	-0.00001	-0.00215	-0.00352	-0.02190	-0.02763
	TELS.r & TELS Delta (ΔTELS%)	0.00%	0.00%	-0.01%	-0.01%	-11.53%	-11.53%
	TELS-fitted (kW)	0.2112	0.2440	16.26	24.17	0.1922	0.2420
	TELS-fitted.r (kW)	0.2112	0.2440	16.26	24.17	0.1700	0.2141
	TELS-fitted.r & TELS-fitted Delta ΔTELS (kW)	0.00000	-0.00001	-0.00216	-0.00353	-0.0222	-0.0279
	TELS-fitted.r & TELS-fitted Delta (ΔTELS%)	-0.001%	-0.003%	-0.013%	-0.015%	-11.533%	-11.535%
	RESIDUALS	0.0004	0.0002	-0.0566	-0.0185	-0.0023	-0.0026
Awka Data	Global Solar (kW/m2)	0	0	0.476	0.5522	0	0
	PV Power Output_Awka (kW)	0	0	49.8305	56.9103	0	0
	Inverter Power Input_Awka (kW)	0.2227	0.2571	17.0611	25.4258	0.1999	0.2521
	Battery Input Power_Awka (kW)	-0.2227	-0.2571	0	0	-0.1999	-0.2521
	DGen Power Output_Awka (kW)	0	0	0	0	0	0
	TELS_Awka (kW)	0.2116	0.2442	16.2081	24.1545	0.1899	0.2395
	TELS.r_Awka (kW)	0.2116	0.2442	16.21	24.15	0.16800	0.21187
	ΔTELS_Awka (kW)	0.0000	0.0000	-0.00215	-0.00352	-0.02190	-0.02763
	ΔTELS%_Awka	0.00%	0.00%	-0.01%	-0.01%	-11.53%	-11.53%
	TELS-fitted_Awka (kW)	0.2112	0.2440	16.26	24.17	0.1922	0.2420
	TELS-fitted.r_Awka (kW)	0.2112	0.2440	16.26	24.17	0.1700	0.2141
	ΔTELS-fitted_Awka (kW)	0.00000	-0.00001	-0.00216	-0.00353	-0.02217	-0.02791
	ΔTELS%-fitted_Awka (%)	-0.001%	-0.003%	-0.013%	-0.015%	-11.53%	-11.53%
	RESIDUALS_Awka	0.00043	0.00019	-0.05659	-0.01852	-0.00234	-0.00257
Liverpool Data	Global Solar_Liverpool (kW/m2)	0	0	0.1404	0.2533	0	0
	PV Power Output_Liverpool (kW)	0	0	48.89	82.38	0	0
	Inverter Power Input_Liverpool (kW)	5.79	6.68	14.36	20.34	0	6.55
	Battery Input Power_Liverpool (kW)	-5.79	-6.68	34.53	31.32	0	-6.55
	DGen Power Output_Liverpool (kW)	0	0	0	0	14.43	0.00
	TELS_Liverpool (kW)	5.50	6.35	13.64	19.32	14.43	6.23
	TELS.r_Liverpool (kW)	5.50	6.35	13.64	19.32	12.94	5.58
	ΔTELS (kW)_Liverpool	-0.00008	-0.00016	-0.00164	-0.00255	-1.49	-0.64
	ΔTELS (Δ%)_Liverpool	0%	0%	0%	0%	-10%	-10%
	TELS-fitted_Liverpool (kW)	6.27	7.10	10.74	16.21	8.41	7.12
	TELS-fitted.r_Liverpool (kW)	6.27	7.10	10.74	16.21	7.54	6.38
	ΔTELS-fitted_Liverpool (kW)	-0.00009	-0.00018	-0.0013	-0.0021	-0.87	-0.74
	ΔTELS%-fitted_Liverpool	0%	0%	0%	0%	-10%	-10%
	Residuals_Liverpool	-0.7718	-0.7518	2.9006	3.1092	6.02	-0.90
SEM Reliability Data-Awka	Rpv	1.0000	1.0000	1.0000	1.0000	0.9897	0.9897
	Rinv	1.0000	1.0000	0.9999	0.9999	0.8847	0.8847
	Rbos	0.9991	0.9991	0.9990	0.9990	0.8976	0.8976
	Rbat	1.0000	1.0000	1.0000	1.0000	0.9973	0.9973
	Rgen	0.9991	0.9991	0.9990	0.9990	0.8976	0.8976
	Rsem	1.0000	1.0000	0.9999	0.9999	0.8847	0.8847
SEM Reliability Data-Liverpool	Rpv	1.0000	1.0000	1.0000	1.0000	0.9899	0.9899
	Rinv	1.0000	1.0000	0.9999	0.9999	0.8966	0.8966
	Rbos	1.0000	1.0000	1.0000	1.0000	0.9901	0.9901
	Rbat	1.0000	1.0000	1.0000	1.0000	0.9962	0.9962
	Rgen	1.0000	1.0000	1.0000	1.0000	0.9901	0.9901
	Rsem	1.0000	1.0000	0.9999	0.9999	0.8966	0.8966

5.2.1. Overview of Simulation Outputs (HOMER)

The HOMER simulation generates time-resolved outputs representing the operation of the SEM system over a full annual cycle. Key outputs include PV power output, battery charge–discharge behaviour, diesel generator output, inverter power flow, load demand, and the resulting $TELS(t)$. Figure 5.1 to Figure 5.4 show the output time series for the Awka location. The scatter plots illustrate daily and seasonal solar-resource variations and the corresponding performances of the SEM subsystems in determining the TELS outputs.

Figure 5.1 plots the SEM PV power output determined by diurnal and seasonal solar irradiance variations. Input simulation parameters that drive its value include the rated capacity of the array, the PV derating factor, the solar radiation incident on the PV

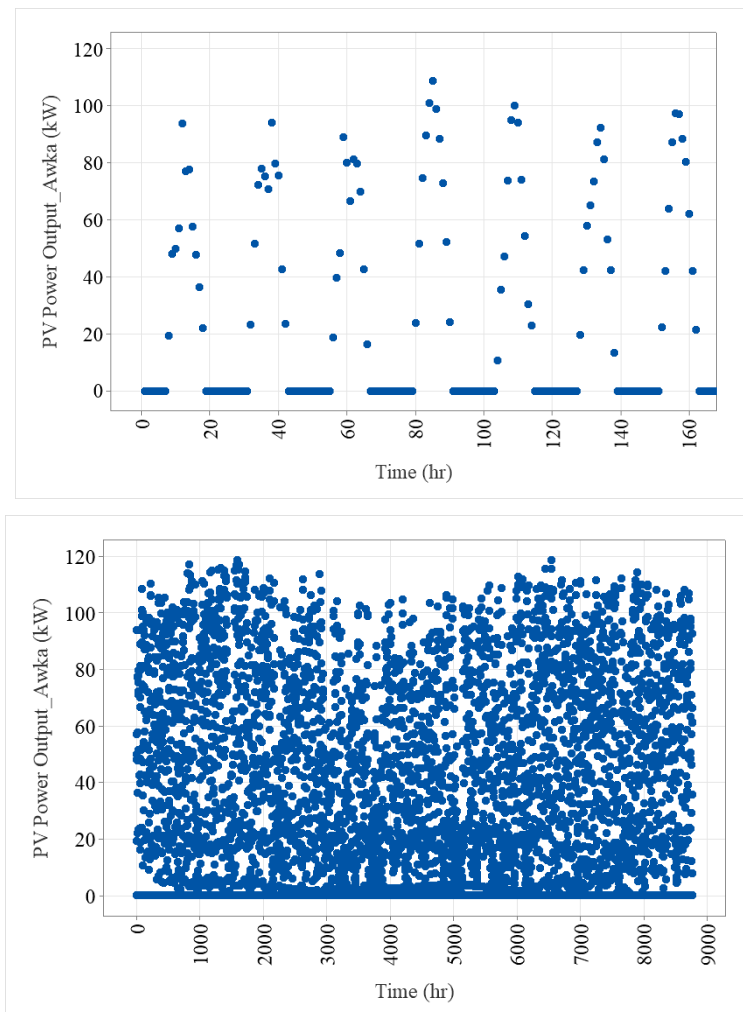


Figure 5.1: Weekly and Yearly Time Series Plot of PV Power Output_Awka.

array, the temperature coefficient of power, the PV cell temperature difference under current time step and standard test conditions.

Figure 5.2 illustrates the SEM Battery Input Power. It is determined by the difference between the battery charge and discharge power.

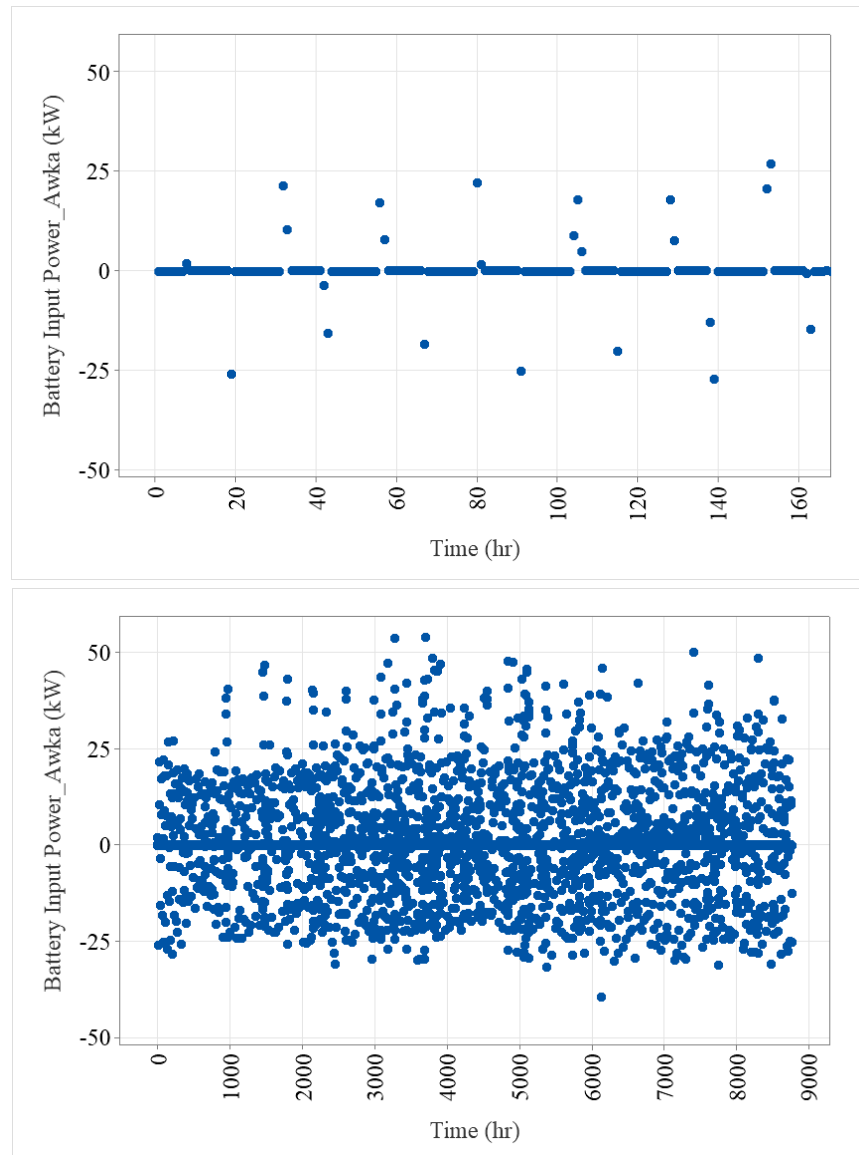


Figure 5.2: Weekly and Yearly Time Series Plot of Battery Input Power_Awka.

Figure 5.3 shows the Diesel Generator Power Output. The figure highlights the limited running time of the diesel generator as a backup power source over the considered timeframe. The diesel generator power output has an inverse relationship with the PV power output for the SEM. This means that with more power being supplied by the PV as the preferred primary source to support the TELS, lesser power is needed from the diesel generator for the same purpose.

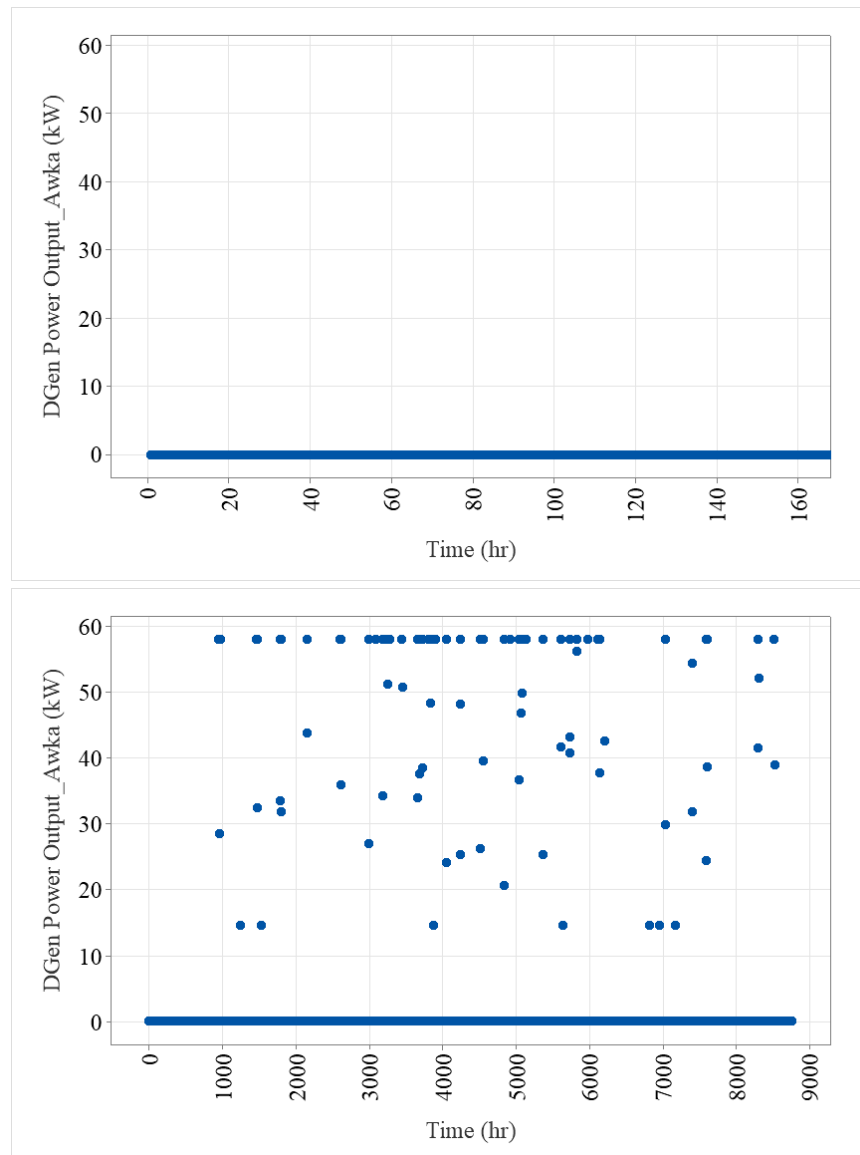


Figure 5.3: Weekly and Yearly Time Series Plot of Diesel Generator Power Output_Awka.

Figure 5.4 highlights the TELS. The figure shows that the TELS exhibits a non-monotonic behaviour with respect to time. TELS is primarily sustained by the PV power output and battery input power with occasional support from the diesel generator.

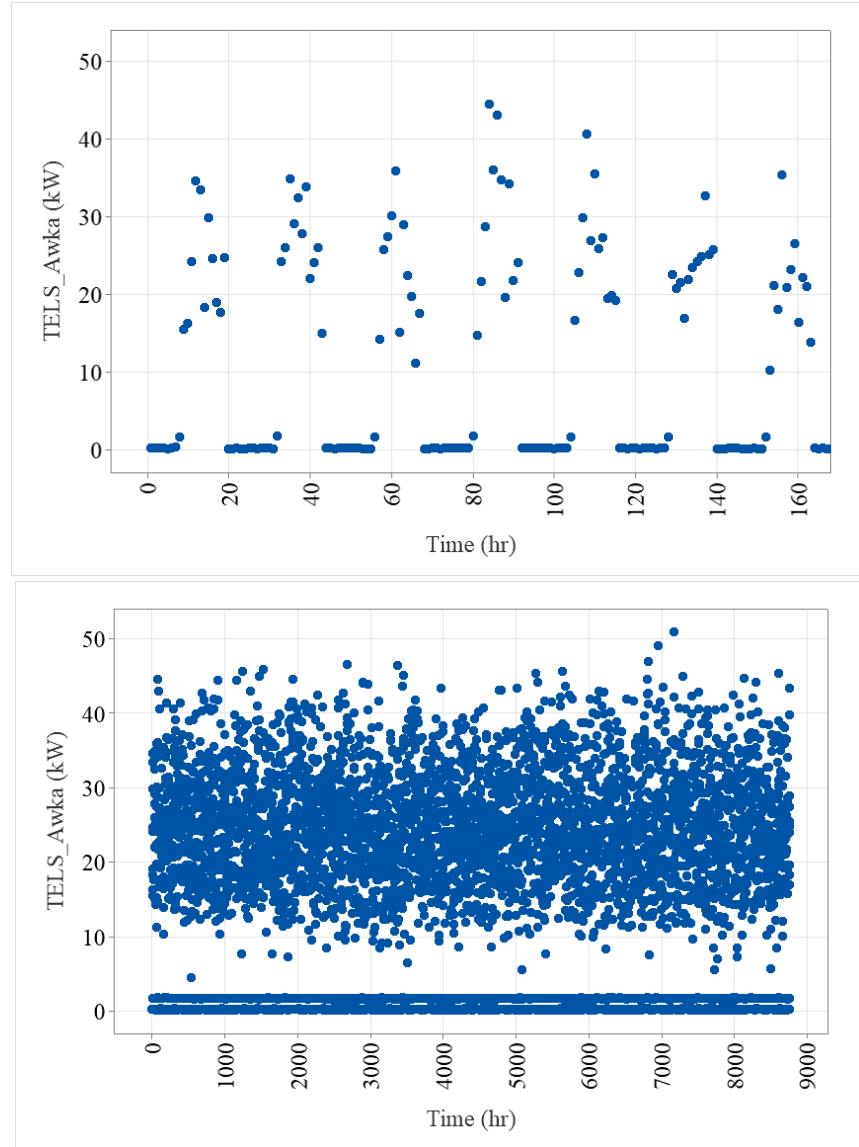


Figure 5.4: Weekly and Yearly Time Series Plot of TELS_Awka.

The simulation reflects a hybrid system in which PV generation serves as the primary energy source, supported by battery storage for load balancing and a diesel generator for backup supply. The inverter facilitates power conversion and acts as a critical interface between generation and load.

These outputs confirm that system performance is governed by the interaction between renewable generation, storage dynamics, and load demand. The resulting $TELS(t)$ represents the effective energy delivered to the load under deterministic conditions, assuming continuous system operation.

5.2.2. Behaviour of Key System Variables

The simulation results reveal distinct operational patterns for each subsystem.

Photovoltaic output $P_{PV}(t)$ exhibits strong diurnal variation, with peak generation during daytime periods and negligible output at night. This behaviour directly reflects solar irradiance patterns and introduces variability into the system energy supply.

Load demand $L(t)$ follows a commercial consumption profile, with increased demand during daytime operating hours and reduced demand during off-peak periods. The mismatch between generation and demand necessitates the use of storage and backup generation.

Battery power $P_{bat}(t)$ plays a critical role in balancing supply and demand. During periods of excess PV generation, the battery is charged, while during low generation periods, it discharges to support the load. This dynamic behaviour stabilises system performance and reduces reliance on the diesel generator.

The diesel generator $P_{gen}(t)$ operates primarily during periods of insufficient renewable generation and storage depletion. Its contribution ensures that load demand is met when other energy sources are unavailable, highlighting its role in system reliability under deterministic assumptions.

Figure 5.5 is an overlay of TELS and the 3 power sources of the SEM namely PV power output, battery input power and diesel generator power output. During the day, there is usually enough solar irradiance to sustain the TELS. Excess energy generated by the PV module is used to charge the battery while the generator stays offline. At times of low solar irradiance (such as cloudy or rainy periods) or at night, the battery discharges to sustain the TELS. Where there is insufficient energy from the PV modules and battery to support the TELS, the diesel generator comes online to sustain the TELS.

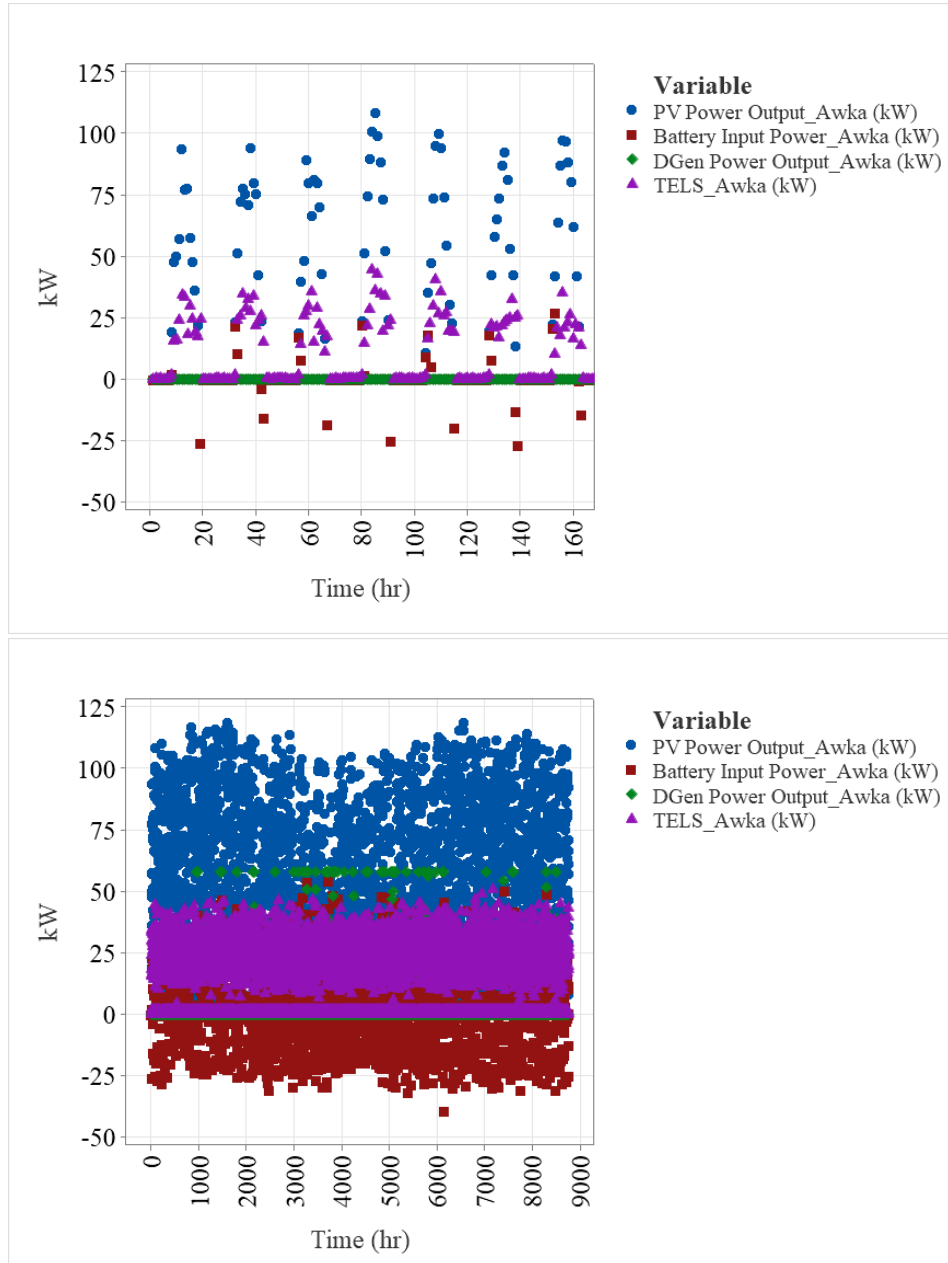


Figure 5.5: Weekly and Yearly Interaction Between Generation, Storage, and TELS.

Overall, the system demonstrates coordinated operation between subsystems, with energy flows dynamically adjusted to maintain load supply. However, these results assume ideal component performance and do not account for subsystem failures.

5.2.3. Relationship Between Input Variables and TELS

The $TELS(t)$ is determined by the combined effect of generation, storage, and load demand. Analysis of the simulation data indicates that $TELS(t)$ is strongly influenced by variables directly associated with energy delivery, particularly inverter power, generator output, and battery contribution.

Figure 5.6 shows that Global Solar, PV Incident Solar and PV Power Output share the same data pattern. The TELS is limited by the Inverter Power Input. The diesel generator is seldom used to support the TELS given its sparse data series and driven by PV power output adequacy level. The battery input power shows that the battery took in more charges than it discharged to the TELS – depicting a higher PV power output adequacy over the considered timeframe.

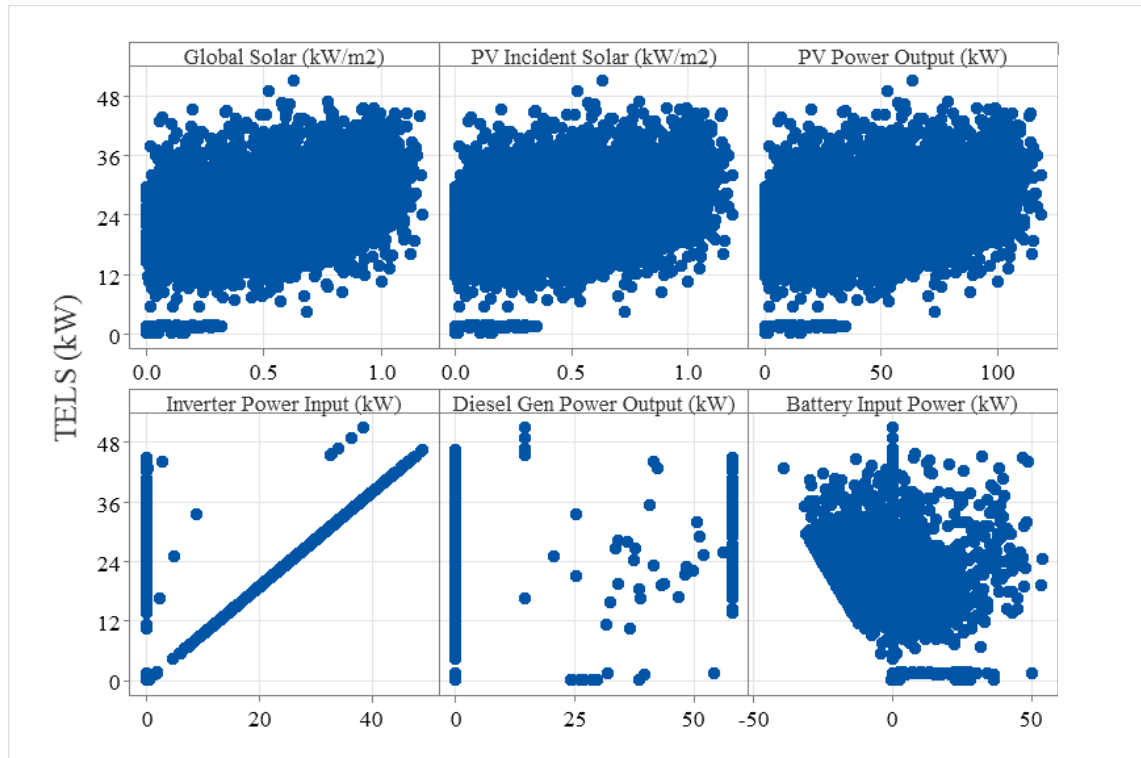


Figure 5.6: Relationship Between Key Variables and TELS.

The results show that inverter power exhibits the strongest correlation with $TELS(t)$, reflecting its role as the final delivery point of energy to the load. Generator output and battery power also show considerable influence, indicating their importance in maintaining system performance during supply-demand imbalance.

In contrast, variables such as global solar, PV incident solar and PV power output exhibit weaker direct relationships with $TELS(t)$, as their effects are mediated through system components such as storage and conversion systems.

These observations provide the basis for regression model development in Section 5.3, where the quantitative relationships between input variables and system performance are formally established.

5.3. Regression Model Development and Validation

The deterministic simulation results presented in Section 5.2 provide the basis for developing a regression-based surrogate model of SEM system performance. The objective of this section is to establish a statistically robust and physically meaningful relationship between system operational variables and the $TELS(t)$, while ensuring that the model satisfies key statistical assumptions and is suitable for integration with the reliability framework introduced in Chapter 4. See Eq.(4.1) and (4.14) for the regression model formulation.

5.3.1. Variable Selection and Pre-processing

Initial exploratory analysis of the dataset presented in Table 5.1 revealed redundancy among several predictor variables, particularly those associated with solar input and derived power outputs. For example, global solar irradiance and PV output exhibit strong correlation, as PV generation is directly dependent on irradiance conditions. Including both variables in the regression model therefore introduces unnecessary duplication and weakens model interpretability.

To address this issue, variable selection was performed based on a combination of statistical relevance and physical significance. Variables were retained if they directly contributed to energy delivery and showed meaningful association with $TELS(t)$. For example, selected variables including Global solar, Diesel Generator Power Output, Inverter Power Input, Battery Input Power and Time together explained 99.49% of the variation in TELS. The rest of the variables did not significantly contribute to the variation and hence were excluded. As a result, the final predictor set was reduced to the above

stated significant predictor variables, which collectively represent the primary pathways through which energy is delivered to the load.

Prior to model fitting, the dataset was also examined for consistency, ensuring that variables were expressed in compatible units, free from missing values, and suitable for regression analysis.

5.3.2. Model Fitting and Coefficient Estimation

The regression model was fitted using ordinary least squares (OLS) estimation. The resulting model obtained from the baseline system simulated data presented in Table 5.1 can be expressed as:

$$TELS = -0.0046 + 0.3940G_{sol} + 0.48526P_{gen} + 0.94206P_{inv} - 0.01455P_{bat} + 0.00000088T \quad (5.1)$$

where

G_{sol} is Global Solar (kW/m²)

P_{gen} is Diesel Gen Power Output (kW)

P_{inv} is Inverter Power Input (kW)

P_{bat} is Battery Input Power (kW)

T is Time in hours.

-0.0046, 0.3940, 0.48526, 0.94206, -0.01455, 0.00000088 are regression coefficients obtained from the regression analysis and quantify the contribution of each input variables to the TELS.

The estimated coefficients provide quantitative insight into the contribution of each subsystem to the TELS. In particular, inverter power is expected to have the strongest influence, as it represents the final stage of energy delivery to the load, while generator and battery contributions reflect backup supply and load balancing respectively.

Figure 5.7 compares the regression model predictions of *TELS* with the corresponding values obtained from HOMER simulation. The 45-degree reference line indicates perfect agreement between predicted and simulated values. The close alignment of data points along this line demonstrates the ability of the regression model to closely capture deterministic system behaviour. Data points falling outside the reference line represent the error associated with regression model prediction.

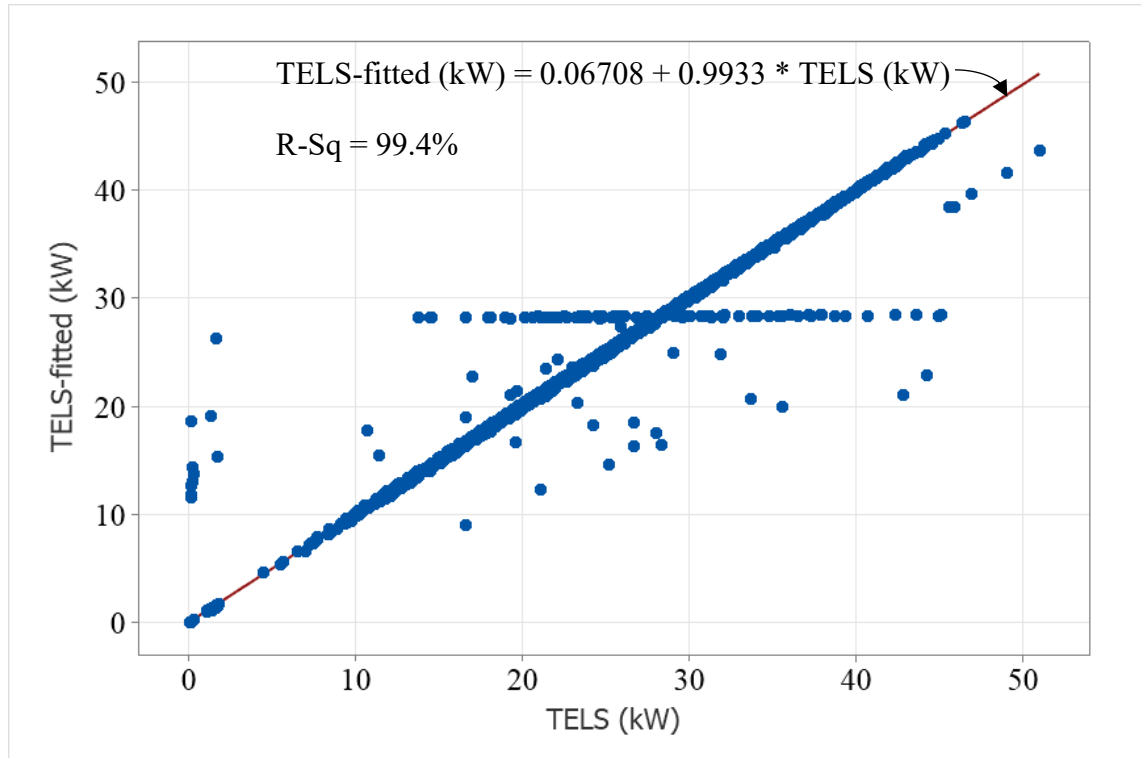


Figure 5.7: Predicted (TELS-fitted) vs Simulated *TELS*.

5.3.3. Model Validation and Goodness-of-Fit.

The performance of the regression model was evaluated using standard goodness-of-fit metrics, including the coefficient of determination (R^2), adjusted R^2 , and predicted R^2 . The model achieved a high R^2 value (approximately 0.99), indicating that the selected predictors explain the majority of the variation in *TELS*.

However, this result must be interpreted with caution. The high R^2 value is partly a consequence of the deterministic nature of the simulation data and the strong physical relationships between variables. Therefore, model validation is not based solely on goodness-of-fit metrics but also considers predictive accuracy and residual behaviour.

5.3.4. Residual Analysis and Model Assumptions

Residual analysis was conducted to assess whether the regression model satisfies the underlying assumptions of linear regression. This includes evaluating normality, independence, and homoscedasticity of residuals. The regression model residuals are calculated using Eq. (5.2).

$$e_i = y_i - \hat{y}_i \quad (5.2)$$

where

e_i = i-th residual in kW, y_i = i-th TELS value and $\hat{y}_i$ = i-th TELS-fitted value.

Figure 5.8, Figure 5.9, and Figure 5.10 show the residual diagnostics for the TELS regression model. In Figure 5.8, the residuals are shown to be partially distributed randomly. A cluster of data points with a cross pattern was recognized which strongly suggests that the points could represent separate groups in the data. The pattern is also a possible indication of non-constant variance of the residuals.

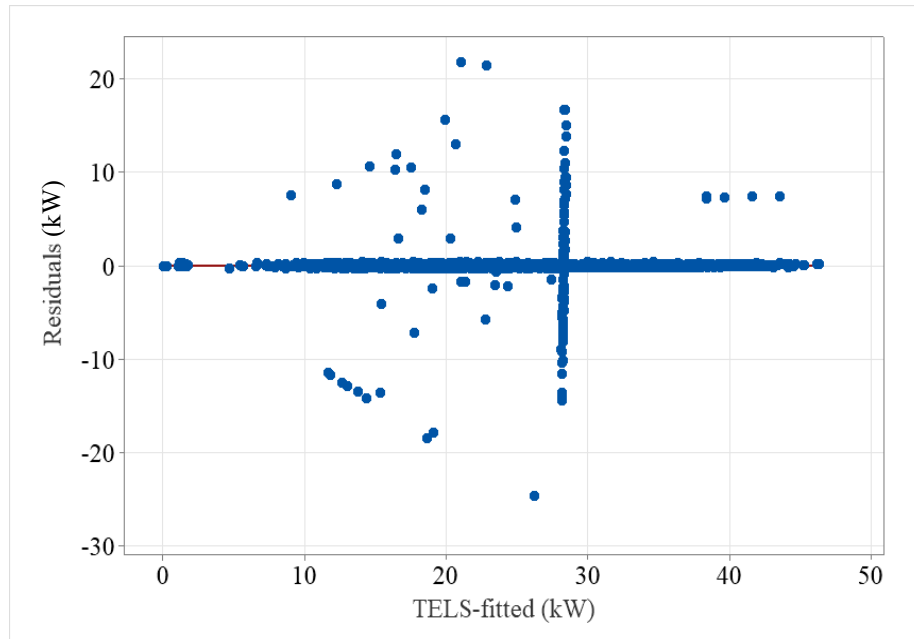


Figure 5.8: Residuals vs TELS-fitted (kW) Showing the Distribution of Residuals across Predicted Values of TELS.

As highlighted in Figure 5.9, the residuals versus time plot does not show any trend in the data. It however shows a pattern along the x-axis. Hence, the assumption that the residuals are independent from one another can be fairly upheld.

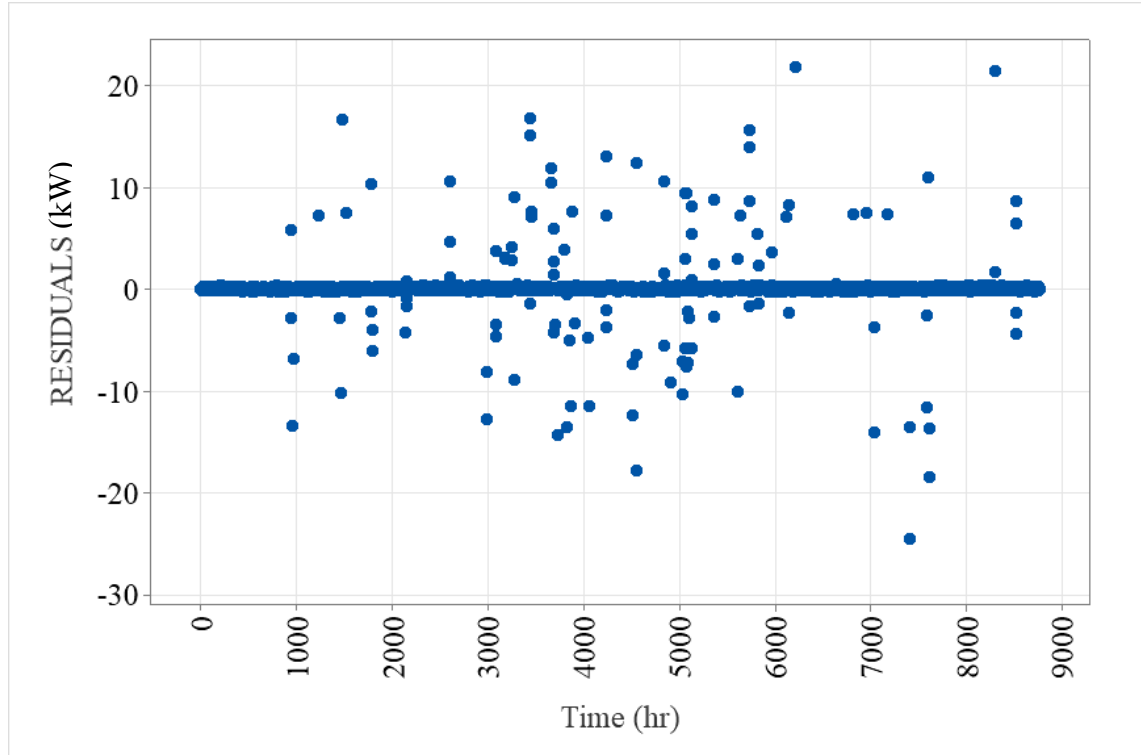


Figure 5.9: Residuals vs Time Illustrating Temporal Patterns in the Data.

From Figure 5.10, the normal probability plot of the residuals shows three groups of data that fairly follow three different straight lines individually. While the first and third data groups quantify the error associated with the regression model prediction, the second group of data that almost follow an imaginary vertical line corresponds to the data cluster around the 45° red line in Figure 5.7 within which the $R^2 = 99.4\%$.

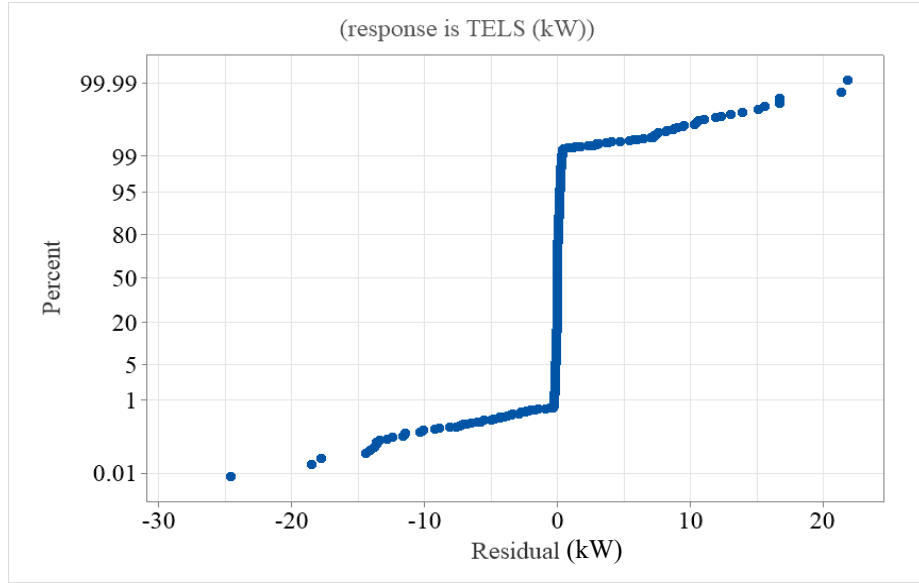


Figure 5.10: Normal Probability Plot of Residuals (with 95% CI)
Indicating Approximate Normality of Residuals.

The residual analysis confirms that the regression model provides a statistically acceptable representation of the deterministic SEM system behaviour and is suitable for use in subsequent modelling stages.

5.4. Physical Interpretation of Regression Results

The regression model developed in Section 5.3 provides a quantitative relationship between system operational variables and the *TELS*. While statistical validation confirms goodness-of-fit of the model, it is essential to interpret these results in terms of the physical behaviour of the SEM system. This section examines the contribution of individual subsystems and identifies the dominant factors influencing system performance.

5.4.1. Influence of Generation Subsystems

The regression results indicate that inverter power P_{inv} has the strongest influence on *TELS*. This observation is physically consistent, as the inverter represents the final stage of energy delivery to the load. Regardless of the source of generation, all usable energy must pass through the inverter before reaching the demand side. Consequently, variations in inverter output directly translate to changes in the *TELS*.

Diesel generator output P_{gen} also exhibits a significant positive relationship with *TELS*. This reflects the role of the generator as a backup energy source, particularly during periods of insufficient solar generation or low battery charge. The generator ensures continuity of supply and contributes directly to maintaining system performance under energy-deficit conditions.

In contrast, solar irradiance and PV output do not appear as dominant predictors in the final regression model. This does not imply that renewable generation is unimportant; rather, it reflects the fact that the effect of solar input is mediated through system components such as the battery and inverter. Therefore, the regression model captures the effective contribution of energy delivery pathways, rather than raw energy availability.

Figure 5.11 illustrates A Pareto chart showing the relative influence of inverter output, generator output, and battery power on *TELS*. The figure highlights the dominant role of inverter power in determining system performance, followed by generator and battery contributions.

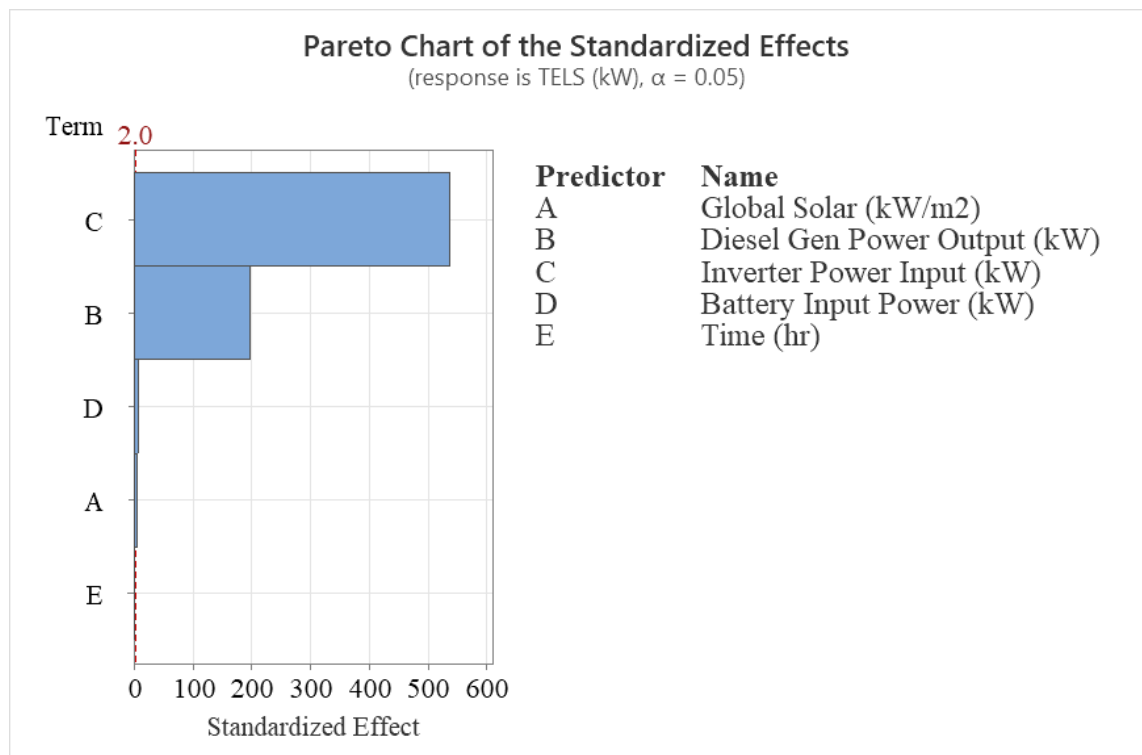


Figure 5.11: Contribution of Generation Subsystems to *TELS*.

5.4.2. Role of Energy Storage and Load Balancing

Battery power P_{bat} plays a critical role in balancing the mismatch between generation and load demand. The regression results show that battery contribution has a measurable influence on *TELS*, reflecting its function as an intermediary between intermittent renewable generation and variable load demand.

During periods of excess PV generation, the battery stores energy that would otherwise be unused. This stored energy is later discharged when generation is insufficient, thereby sustaining load supply without immediate reliance on the diesel generator. This behaviour enhances system efficiency and reduces dependence on backup generation.

The influence of battery power in the regression model demonstrates that energy storage is not merely a supporting component but an active contributor to system performance. Its ability to smooth fluctuations in generation and demand is essential for maintaining stable operation in hybrid SEM systems.

Figure 5.12 is an overlay time-series plot showing PV output, battery charge/discharge behaviour, and load demand over a representative period. The figure illustrates how the battery compensates for fluctuations in renewable generation and supports load supply during periods of low solar input. The PV capacity of 100kW is sized as twice the capacity of the 50kW converter to compensate for periods of low solar irradiance during cloudy, rainy, morning or evening times. This ensures that significant energy output is achieved during these times to support the required load. When none of these solar irradiance-limiting conditions exist, the excess PV energy generation not consumed by the load is used to charge the batteries or clipped by the converter.

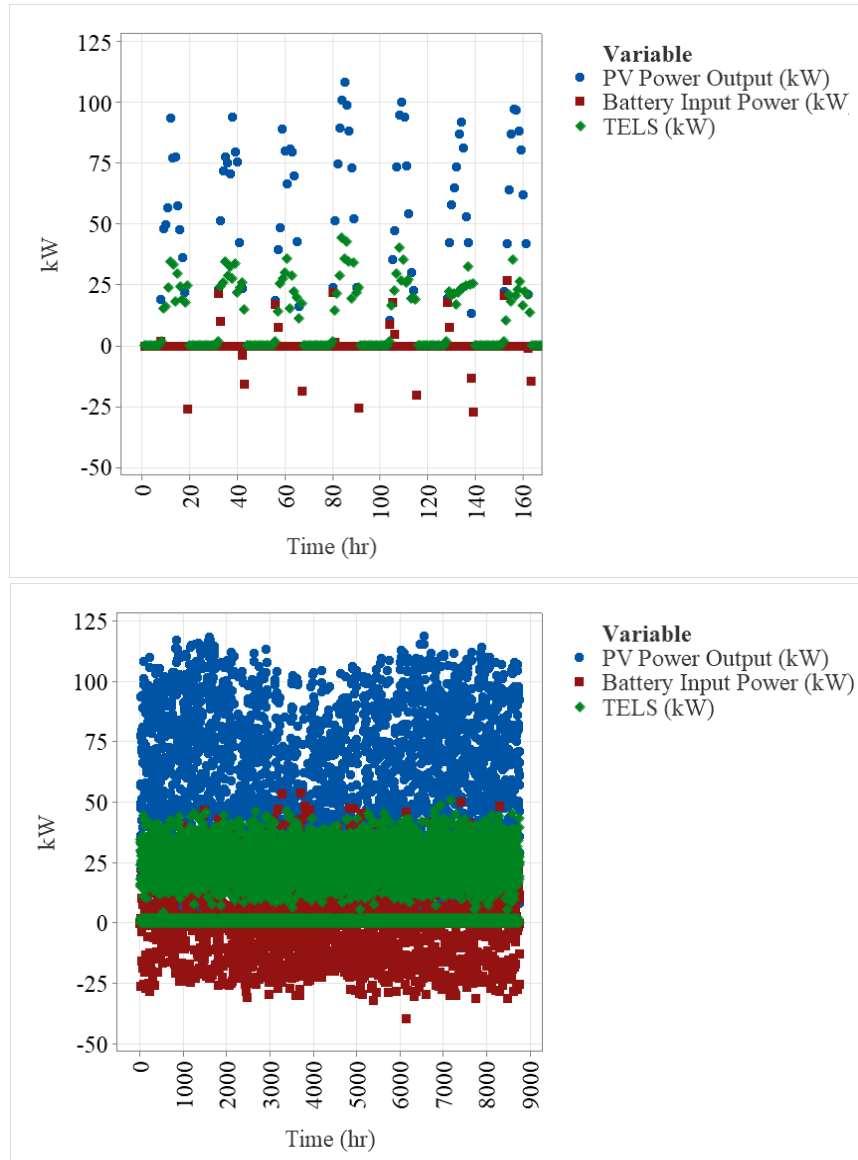


Figure 5.12: Weekly and Yearly Interaction between PV Generation, Battery Operation and Load.

5.4.3. Dominant Factors Affecting TELS

The combined interpretation of regression coefficients indicates that system performance is primarily governed by variables directly associated with energy delivery, rather than energy availability. In particular, inverter output emerges as the dominant factor, as it represents the actual transfer of usable power to the load.

Generator output serves as a secondary but critical contributor, particularly in ensuring reliability during periods of energy deficit. Battery power provides a balancing mechanism that enhances system flexibility and reduces reliance on backup generation.

The absence of solar irradiance as a dominant predictor highlights an important insight: while renewable resources define the potential energy input to the system, the realised performance depends on system configuration and component interaction. This reinforces the importance of considering system-level behaviour rather than isolated component performance.

Overall, the regression results demonstrate that SEM system performance is governed by the interplay between generation, storage, and conversion processes. This understanding is essential for interpreting the limitations of deterministic modelling and motivates the integration of reliability considerations in subsequent chapters.

5.5. Development of the Baseline SEM Performance Model

The regression analysis presented in Section 5.3, together with the physical interpretation in Section 5.4, enables the formulation of a baseline SEM performance model. This model provides an explicit analytical relationship between key system variables and the *TELS*, representing the deterministic behaviour of the SEM system under ideal operating conditions. The baseline model forms the foundation for subsequent reliability integration in Chapter 6.

5.5.1. Final Regression Model Expression

Based on the variable selection and regression fitting process, the deterministic SEM performance model is expressed in Eq.(5.1). This formulation reflects the dominant energy delivery pathways identified in Section 5.4. Inverter output acts as the primary determinant of load served, while generator and battery contributions capture the effects of backup generation and load balancing. The model therefore provides a physically consistent representation of SEM system performance under deterministic conditions.

5.5.2. Model Simplification and Practical Form

For practical implementation, the regression model of Eq.(5.1) can be expressed in a simplified form that emphasises its physical interpretation:

$$TELS = 0.950048P_{inv} + 0.48188P_{gen} - 0.00846P_{bat} \quad (5.3)$$

where 0.950048, 0.48188, and - 0.00846 are adjusted regression coefficients incorporating the intercept term and reflecting the relative contribution of each subsystem.

This simplified formulation highlights that the TELS is effectively governed by the combined contribution of energy delivered through the inverter, supplemented by generator output and supported by battery operation. The model can therefore be interpreted as an energy flow-based representation of system performance.

The simplified model is particularly useful for rapid estimation and system-level analysis, as it avoids unnecessary complexity while retaining the key relationships governing SEM operation.

Figure 5.13 compares the time-series values of TELS(t) obtained from HOMER simulation and the corresponding values predicted by the simplified regression model. The close agreement between the two curves demonstrates the validity of the simplified model for representing deterministic system behaviour.

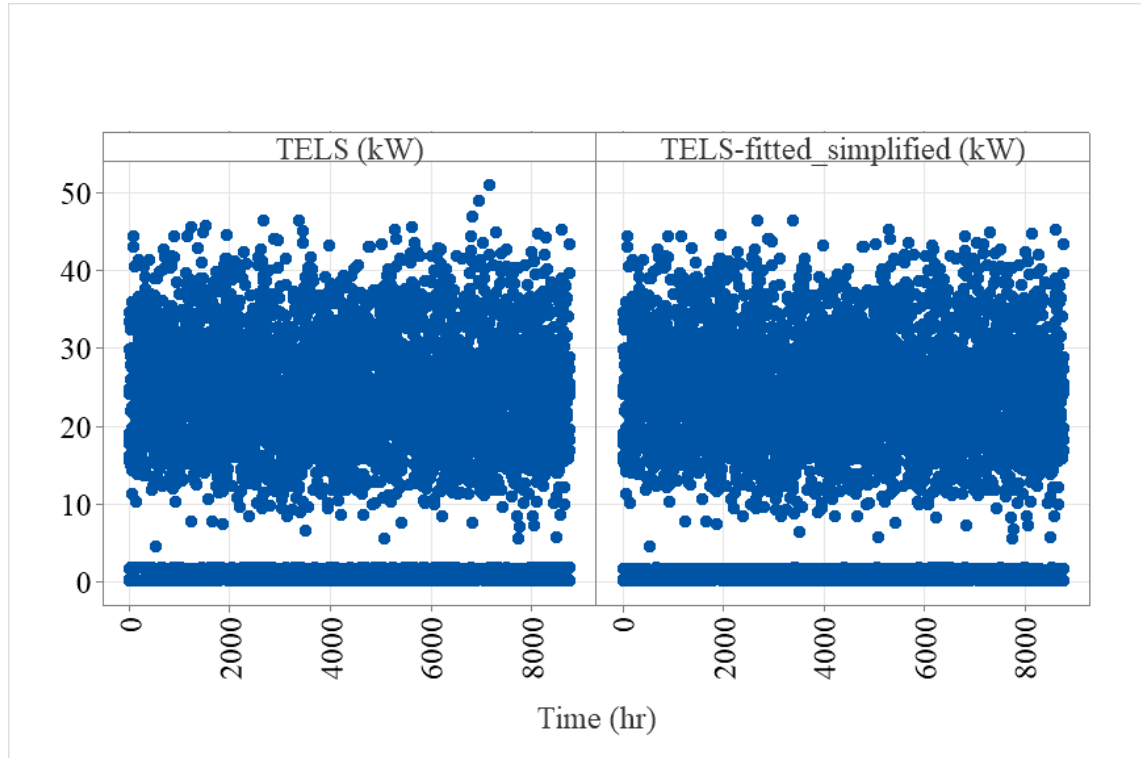


Figure 5.13: A Comparison of Simulated and Modelled TELS.

5.5.3. Limitations of the Deterministic Model

Despite its effectiveness in capturing system behaviour, the baseline SEM performance model is subject to several limitations inherent to deterministic modelling approaches. The model assumes continuous and uninterrupted operation of all system components, thereby neglecting the effects of subsystem failures and degradation. As a result, it represents an idealised upper bound of system performance.

Furthermore, the regression model is derived from simulated data, which reflects predefined operating conditions and may not fully capture field-deployed variability. The model also assumes linear relationships between variables, which may not account for complex nonlinear interactions under extreme operating conditions.

Most importantly, the model does not explicitly incorporate system reliability, meaning that it cannot account for performance reductions due to component failures or

downtime. This limitation is particularly significant in the context of long-term system operation, where reliability plays a critical role in determining actual energy delivery.

These limitations highlight the need for extending the deterministic framework to include reliability considerations. This extension is addressed in Chapter 6, where subsystem reliability is integrated with the baseline performance model to develop a reliability-aware SEM modelling approach.

5.6. Summary

This chapter has presented the results of deterministic SEM system simulation and the development of a regression-based performance model. Time-series outputs obtained from HOMER were analysed to characterise system behaviour under varying operating conditions, highlighting the interaction between generation, storage, and load demand.

A regression model was developed to establish a quantitative relationship between key operational variables and the *TELS*. Following variable selection and multicollinearity mitigation, the model was formulated using inverter output, generator output, and battery power as the primary predictors. The model demonstrated strong predictive capability, with high goodness-of-fit and acceptable residual behaviour, confirming its suitability as a deterministic representation of SEM system performance.

Physical interpretation of the regression results showed that system performance is primarily governed by energy delivery pathways, with inverter output emerging as the dominant factor, supported by generator and battery contributions. This highlights the importance of system-level interactions in determining effective energy delivery, rather than reliance on individual component performance.

However, the baseline regression model is inherently limited by its deterministic nature. The assumption of continuous and uninterrupted component operation results in an idealised representation of system performance and does not account for subsystem failures, degradation, or downtime. As a result, the model represents an upper bound of achievable system performance under real operating conditions.

These limitations motivate the need for incorporating reliability considerations into SEM modelling. Accordingly, the following chapter extends the deterministic framework by integrating subsystem reliability with the regression-based performance model, enabling a more actual assessment of system behaviour under practical operating conditions.

Chapter 6: Reliability Analysis and Integration

6.1. Introduction

The deterministic SEM performance model developed in Chapter 5 provides an analytical representation of system behaviour based on operational variables, assuming continuous and uninterrupted component operation. While this model closely captures energy flow and system interactions under ideal conditions, it does not account for subsystem failures and their impact on system availability. As highlighted in Chapter 4, this limitation results in an overestimation of system performance and restricts the applicability of the model to field-deployed SEM operating conditions.

The purpose of this chapter is to extend the deterministic framework by incorporating subsystem reliability into SEM performance modelling. Building on the reliability formulation developed in Chapter 4, subsystem failure behaviour is quantified and integrated with the baseline regression model to evaluate system performance under actual conditions. This enables the assessment of how component reliability influences overall energy delivery and system operation over time.

The chapter begins by defining the reliability characteristics of individual SEM subsystems and evaluating system reliability using Reliability Block Diagrams. The time-varying behaviour of system reliability is then analysed to understand the impact of component failures on system availability. Subsequently, the reliability model is integrated with the regression-based performance model to develop a reliability-adjusted representation of system output.

Finally, the chapter evaluates the impact of reliability on system performance by comparing deterministic and reliability-integrated results. This analysis provides insight into performance degradation due to subsystem failures and highlights the importance of incorporating reliability considerations in SEM system design and evaluation.

6.2. Subsystem Reliability Modelling

The reliability framework introduced in Chapter 4 provides the theoretical basis for representing subsystem failure behaviour. In this chapter, that framework is applied to the SEM system defined in Chapter 3, using representative failure characteristics for each subsystem to evaluate their impact on overall system reliability.

6.2.1. Failure Rate Modelling and Assumptions

Subsystem reliability is characterised using constant failure rates, assuming an exponential failure distribution. This assumption is appropriate for system-level modelling and enables analytical tractability when integrating reliability with performance models.

The reliability of each subsystem i is expressed by Eq.(4.5). The subsystems considered include PV system, charge controllers, inverters, battery storage system, diesel generator, and BOS.

Each subsystem is assigned a representative failure rate based on typical values reported in the literature for similar energy systems as compiled by Sarita, Saket and Khan (2023), Marqusee and Stringer (2023) and highlighted in Table 6.2. The failure rates of the subsystems and their individual corresponding annual operating hours were normalised over the same 8760-hour period. The key steps to this involved the initial determination of the subsystem reliabilities, $R_{i,t}$ at $t = 1$ and $t = T$ for $0 < t \leq T$ and $0 < T \leq 8760$ hours where T is the total number of operating hours of each subsystem in a year as shown in Table 6.1. $R_{i,T}$ is then set to equal $R_{i,8760}$. The generation of the subsystems' reliability profiles, $R_{i,x}$ for year 1 at any hour 'x' is then performed by interpolating between $R_{i,1}$ and $R_{i,T}$ within the time range of $t = 1$ and $t = 8760$ using the following formula:

$$R_{i,x} = R_{i,1} + ((R_{i,8760} - R_{i,1}) * \left(\frac{t_x - t_1}{t_{8760} - t_1}\right)) \quad (6.1)$$

The results of the subsystem reliability profiles' normalisation for PV, inverter, battery and generator are shown in Figure 6.1 to Figure 6.8.

Table 6.1: Typical Operating Hours of SEM Subsystems for Awka and Liverpool Locations in a Year

Location	PV	Inverter	Battery	Diesel Generator
Awka	4469	8651	1182	120
Liverpool	4386	7706	1682	1127

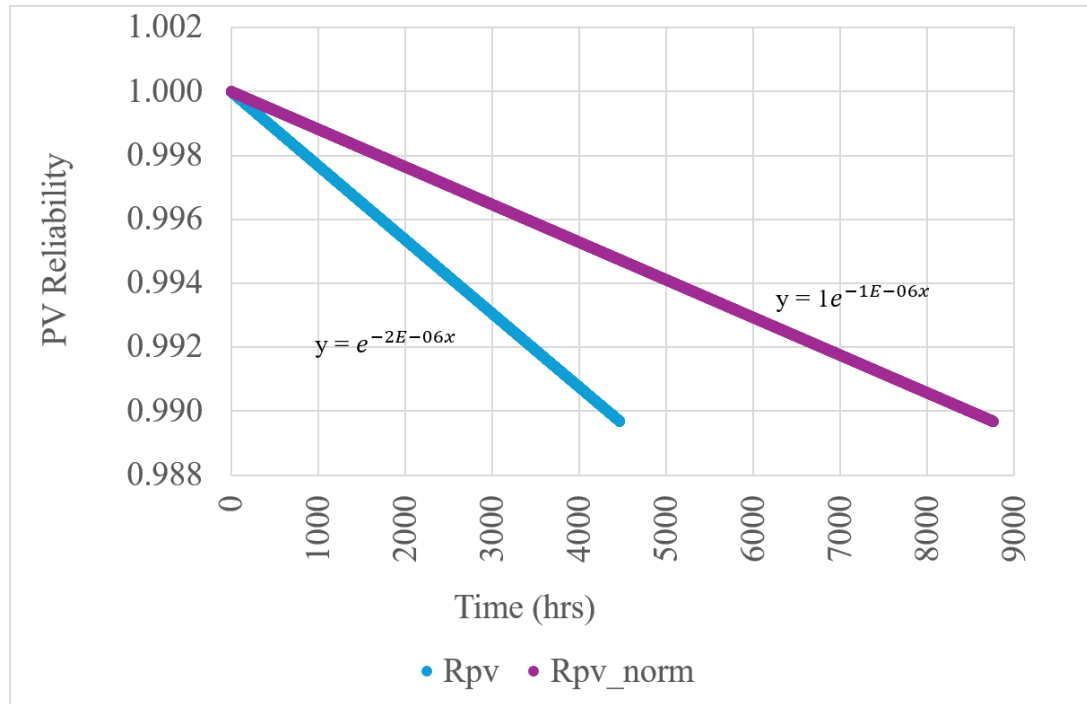


Figure 6.1: PV Reliability Normalisation Over an 8760 Period – Awka Scenario

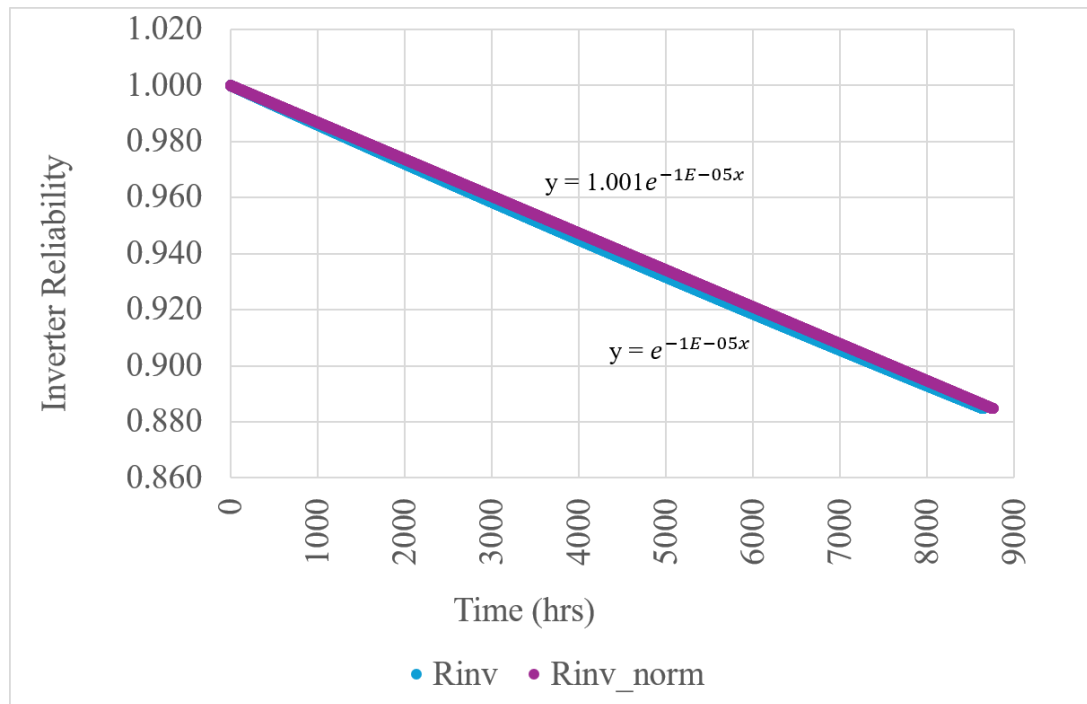


Figure 6.2: Inverter Reliability Normalisation Over an 8760 Period – Awka Scenario

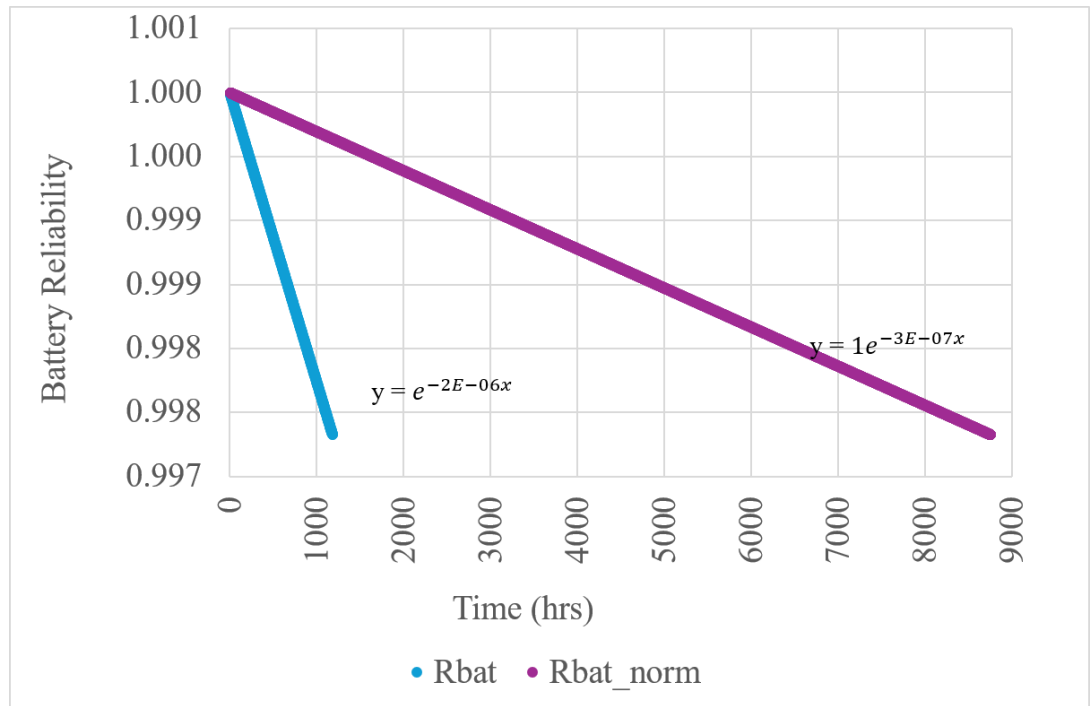


Figure 6.3: Battery Reliability Normalisation Over an 8760 Period – Awka Scenario

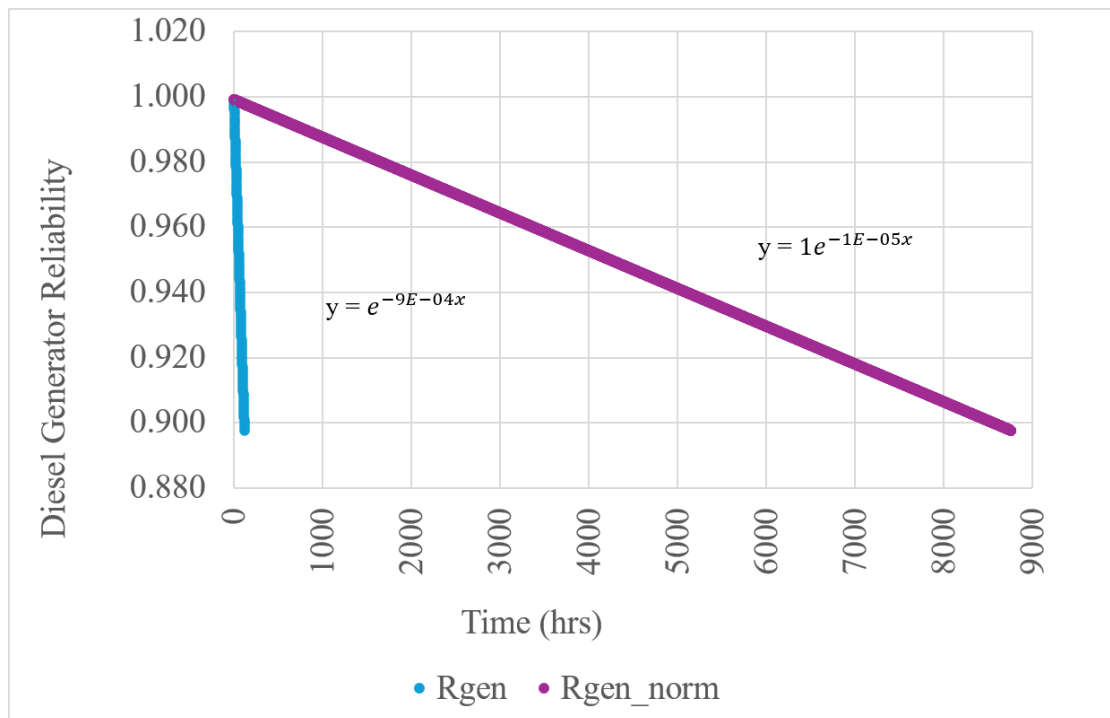


Figure 6.4: Diesel Generator Reliability Normalisation Over an 8760 Period – Awka Scenario

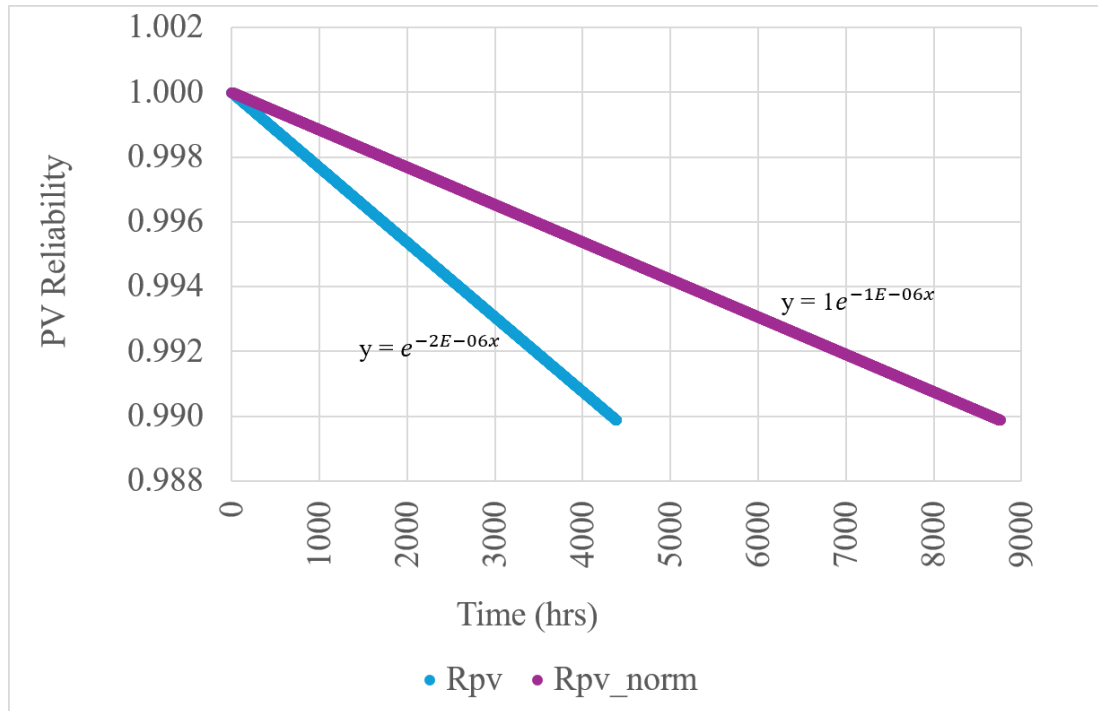


Figure 6.5: PV Reliability Normalisation Over an 8760 Period – Liverpool Scenario

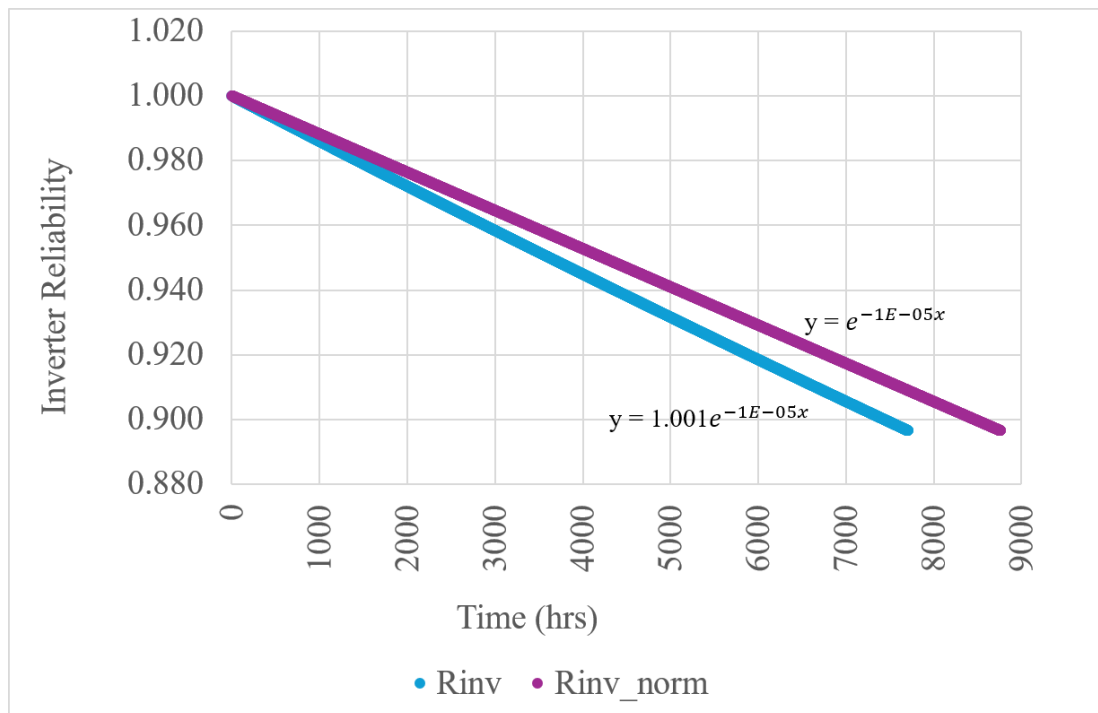


Figure 6.6: Inverter Reliability Normalisation Over an 8760 Period– Liverpool Scenario

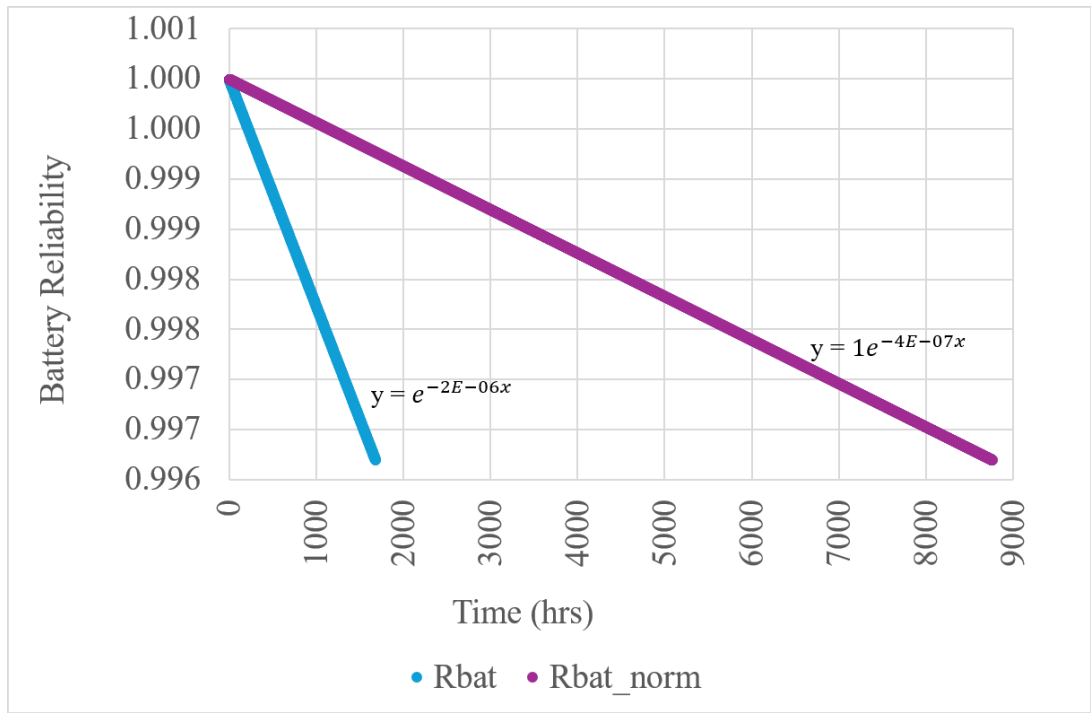


Figure 6.7: Battery Reliability Normalisation Over an 8760 Period– Liverpool Scenario

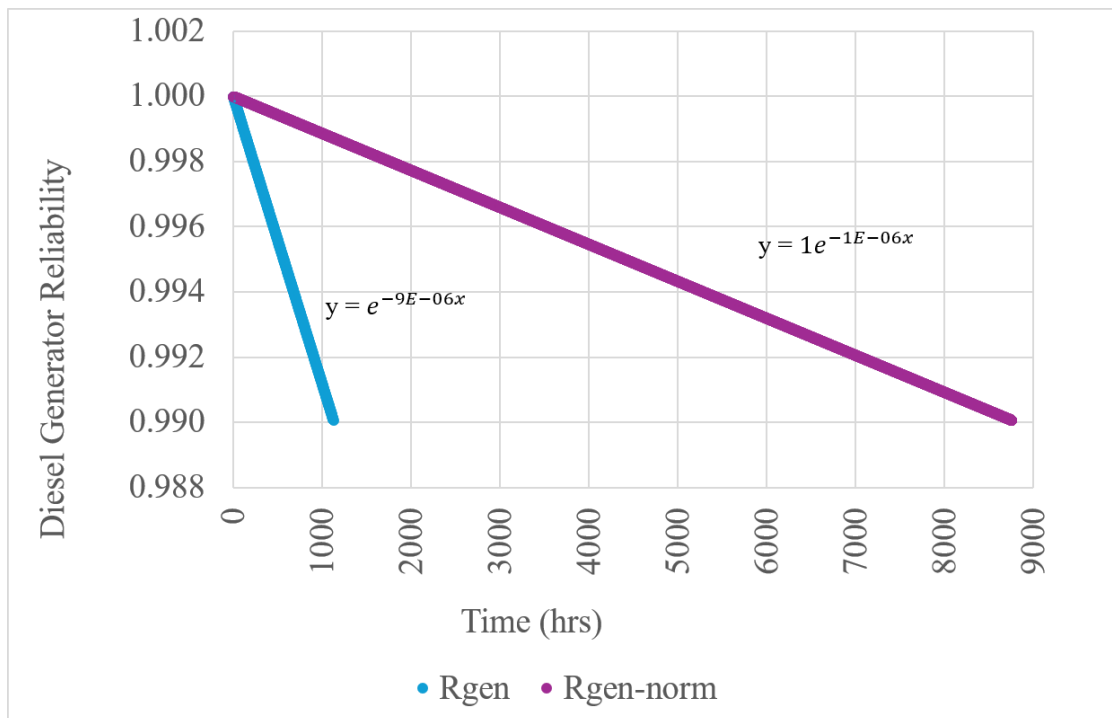


Figure 6.8: Diesel Generator Reliability Normalisation Over an 8760 Period– Liverpool Scenario

It is worth noting that the failure rate for diesel generators can be reported in three different ways namely: failure to start per demand, failure while running often expressed as MTTF, and mission failure expressed as the probability of not surviving a given outage duration. In this research, the BOS failure rate value of 0.077680/yr as reported by Sarita, Saket and Khan (2023) is used for the diesel generator for demonstration purposes given the multiple ways diesel generator failure rates are reported in literature.

Table 6.2: SEM Subsystems Representative Failure Rates

Subsystem	Failure Rate (1/yr)	Failure Rate (1/hr)	Source
PV Modules	0.020337	2.32158E-06	(Sarita, Saket and Khan, 2023)
Charge controllers	0.065153	7.43756E-06	
Inverters	0.124100	1.41667E-05	
Batteries	0.019856	2.26667E-06	
BOS	0.077680	8.86758E-06 ^a	
Diesel generator (MTTF = 1,100 run-hours)	7.884	0.0009 ^b	(Marqusee and Stringer, 2023)
	^a the modelling used this value equivalent to 0.077680/yr as the failure rate per hour for the diesel generator. ^b Unusually high failure rate of the diesel generator observed in literature		

6.2.2. Time-Varying Reliability Functions

The exponential formulation in Eq.(4.5) enables the evaluation of subsystem reliability as a function of time. As operating time increases, the probability of subsystem survival decreases, reflecting the increasing likelihood of failure. This time-varying behaviour is critical for assessing system performance over extended operation, as it directly influences system availability and energy delivery.

Figure 6.9 shows the reliability functions $R_i(t)$ for the PV system, inverter, battery, and generator over time. The figure illustrates the rate at which reliability decreases for each subsystem, highlighting differences in failure behaviour based on component characteristics. It is noteworthy that despite the relatively high failure rate of the diesel generator as highlighted in Table 6.2, its reliability decline rate is moderated by low usage frequency as shown in Figure 5.3.

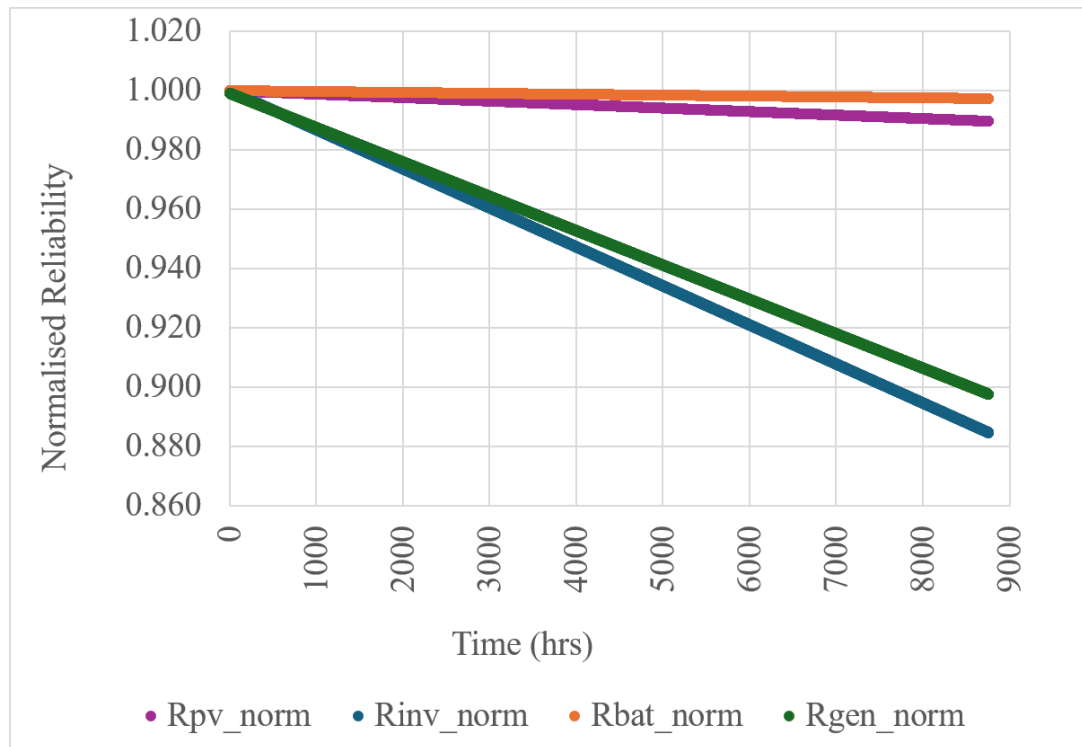


Figure 6.9: Time-varying Normalised Reliability of SEM Subsystems.

6.2.3. Reliability Characteristics of SEM Subsystems

The reliability behaviour of individual subsystems varies depending on their functional role and operating conditions within the SEM system. The PV system typically exhibits relatively high reliability due to its passive operation and limited mechanical components. In contrast, the diesel generator is subject to mechanical wear and operational stress, leading to comparatively higher failure rates.

The battery system exhibits intermediate reliability, with performance influenced by charge–discharge cycling and degradation mechanisms. The power converter, as a critical interface component, plays a key role in system operation, as its failure can interrupt power delivery regardless of energy availability.

These differences in subsystem reliability highlight the importance of considering component-specific behaviour when evaluating overall system performance.

Subsystems that act as single points of failure, such as converters, can have a disproportionate impact on system availability.

6.3. System Reliability Evaluation Using Reliability Block Diagrams

The subsystem reliability characteristics defined in Section 6.2 provide the basis for evaluating the overall reliability of the SEM system. To translate individual component behaviour into system-level performance, RBDs are employed. As established in Chapter 4, RBDs provide a structured representation of how subsystem reliability contributes to overall system availability. In this chapter, the approach is applied specifically to the SEM configuration considered, with emphasis on physical system behaviour rather than theoretical formulation.

6.3.1. SEM Reliability Block Diagram Representation

The SEM system is represented as a combination of generation, storage, and conversion subsystems arranged according to their functional relationships. In practical operation, energy can be supplied through multiple generation pathways, including photovoltaic output, battery discharge, and diesel generator operation. However, all energy delivered to the load must pass through the power converter.

This functional structure leads to a hybrid reliability configuration in which generation subsystems operate in parallel, while the converter operates in series with the combined generation system. The resulting RBD representation therefore captures both redundancy and critical dependency within the SEM system. This representation provides a physically meaningful basis for evaluating system reliability, as it reflects the actual pathways through which energy flows in the system.

Figure 6.10 is a schematic diagram illustrating a typical SEM reliability structure, where PV, battery, and diesel generator subsystems are arranged in parallel, and the converter (inverter + charge controller) is connected in series with the combined generation system. The diagram highlights the redundancy of energy sources and the critical role of the converter in enabling energy delivery.

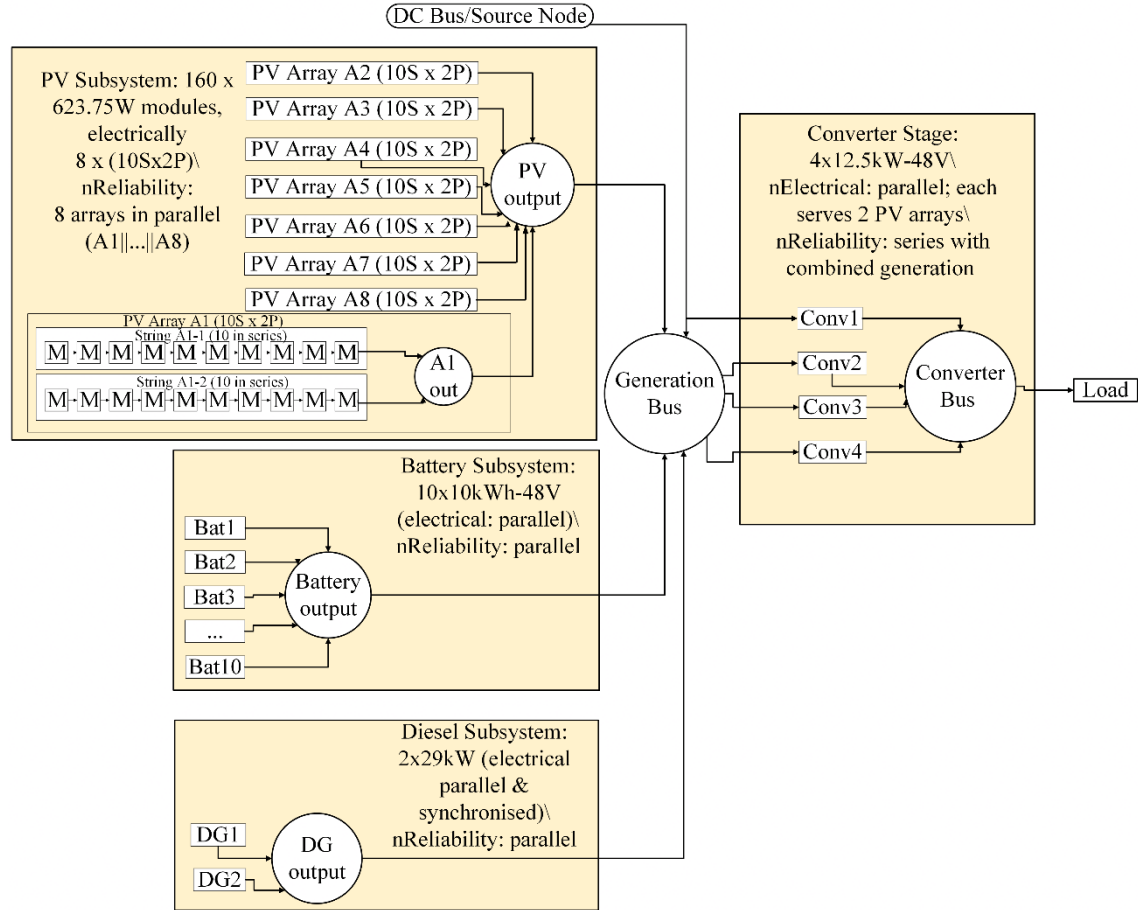


Figure 6.10: Reliability Block Diagram of a Typical SEM System.

6.3.2. Series and Parallel Configurations in SEM Systems

The hybrid structure of the SEM system combines both parallel and series reliability behaviour. The generation subsystem exhibits parallel characteristics, as the system can continue to operate if at least one energy source (PV, battery, or generator) is available. This redundancy enhances system reliability by providing multiple pathways for energy supply. If the reliability of any of the energy sources approaches 100%, the probability that at least one energy source is available tends to 1 as seen in Eq.(4.13). This translates to $R_{SEM}(t)$ being entirely dependent on the converter reliability. However, the ability of the SEM to satisfy the required load under this condition will not only

depend on $R_{\text{converter}}(t)$ but also on the available energy output from one or a combination of the energy sources as dictated by the converter control system at any point in time.

In contrast, the converter introduces a series dependency, as its failure prevents energy from being delivered to the load regardless of the availability of generation sources. This makes the converter a critical component in determining overall system reliability.

This combination of redundancy and dependency is a defining feature of SEM systems and must be explicitly accounted for in reliability modelling. Failure to represent this structure accurately would lead to either overestimation or underestimation of system availability.

6.3.3. Overall System Reliability Formulation

Based on the RBD structure, the overall system reliability can be expressed by Eq.(4.13). This formulation captures two key aspects of SEM reliability. First, the term inside the brackets represents the probability that at least one generation source is available, reflecting the parallel configuration of energy sources. Second, multiplication by $R_{\text{conv}}(t)$ accounts for the series dependency introduced by the converter, which acts as a necessary pathway for energy delivery.

The resulting system reliability function provides a time-varying measure of system availability, which can be directly integrated with the regression-based performance model developed in Chapter 5. This integration forms the basis for evaluating the impact of subsystem failures on energy delivery, as presented in Section 6.5.

6.4. Reliability Behaviour of the SEM System

The system reliability formulation developed in Section 6.3 provides a quantitative basis for evaluating how subsystem failure behaviour influences overall SEM availability. This section analyses the time-varying reliability of the system and examines the contribution of individual subsystems to system performance. The objective is to

understand how reliability evolves over time and to identify the components that have the greatest impact on system availability.

6.4.1. Time Evolution of System Reliability

The overall system reliability $R_{SEM}(t)$, defined in Eq.(4.13), decreases over time as the probability of subsystem failure increases. This behaviour reflects the cumulative effect of component degradation and failure, even under the assumption of constant failure rates.

Figure 6.11 shows the variation of $R_{SEM}(t)$ and $UA_{SEM}(t)$ over time. The R_{SEM} curve illustrates a monotonic decrease in system reliability, reflecting the increasing probability of failure as operating time increases. The rate of decline is influenced by the combined effect of subsystem failure rates and system configuration. The UA_{SEM} curve shows the corresponding increase of SEM unavailability as the reliability decreases over time.

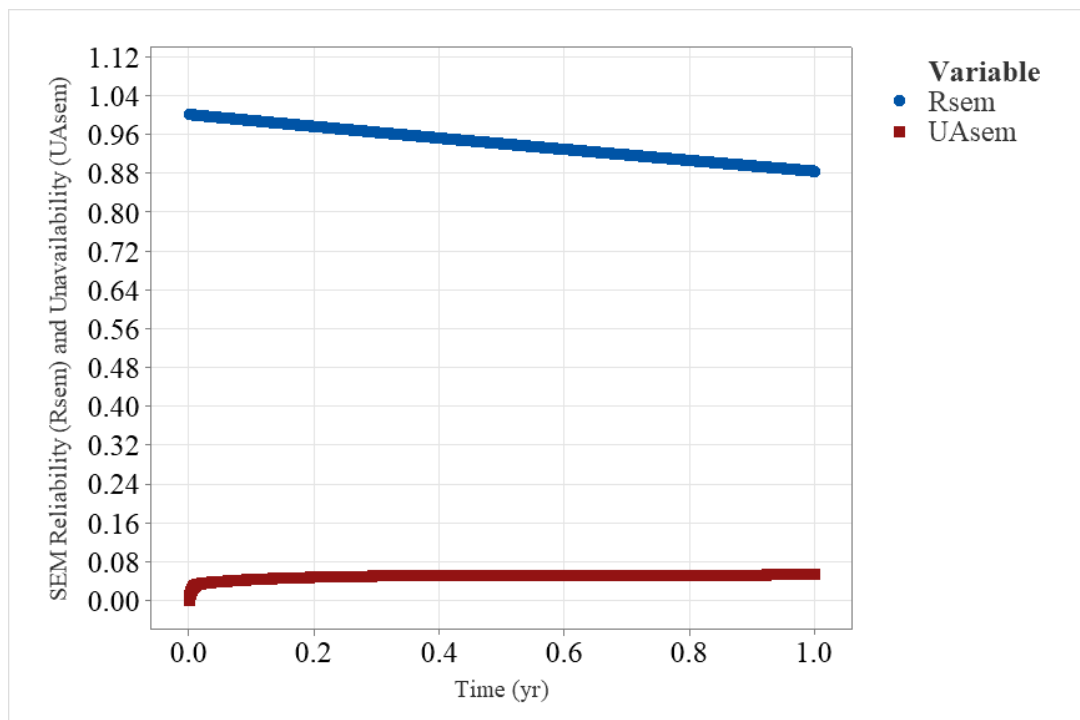


Figure 6.11: Time Evolution of SEM System Reliability and Corresponding Unavailability.

The reliability curve demonstrates that system availability remains relatively high during early operating periods but decreases progressively over time. This behaviour

is consistent with exponential reliability models and highlights the importance of considering time-varying effects in system evaluation. Importantly, the rate at which reliability decreases is not uniform and depends on the relative contribution of individual subsystems.

6.4.2. Influence of Individual Subsystems on Reliability

The contribution of each subsystem to overall system reliability is governed by both its failure rate and its role within the system configuration. As discussed in Section 6.3, the SEM system combines parallel redundancy in generation subsystems with a series dependency on the converter.

Among the subsystems, the converter has a particularly strong influence on system reliability due to its series configuration. Even if all generation sources are available, failure of the converter results in complete system unavailability. This makes the converter a critical component whose reliability directly limits overall system performance.

In contrast, the photovoltaic system, battery, and generator contribute to system reliability through a parallel configuration. The presence of multiple energy sources provides redundancy, reducing the likelihood of complete system failure. However, simultaneous failure of all generation subsystems results in loss of energy supply, even if the converter remains operational.

Figure 6.9 presents a comparative plot showing the reliability functions of individual subsystems. The figure illustrates how the converter imposes a limiting effect on system reliability, while the parallel configuration of generation subsystems provides partial redundancy.

This analysis highlights that system reliability is not solely determined by individual component reliability, but by the interaction between subsystem characteristics and system configuration. Components that act as single points of failure have a disproportionate impact on overall system availability.

6.4.3. Availability and Unavailability Analysis

System availability, $A_{SEM}(t)$ can be directly interpreted from the reliability function as the probability that the system is operational at a given time. Conversely, system unavailability is defined as:

$$UA_{SEM}(t) = 1 - A_{SEM}(t) \quad (6.2)$$

where $UA_{SEM}(t)$ represents the probability that the system is unable to deliver energy due to subsystem failure.

Figure 6.12 illustrates $A_{SEM}(t)$, $UA_{SEM}(t)$ and $R_{SEM}(t)$ over time. The figure highlights the decreasing availability and corresponding increase in unavailability as operating time progresses, highlighting the growing impact of subsystem failures.

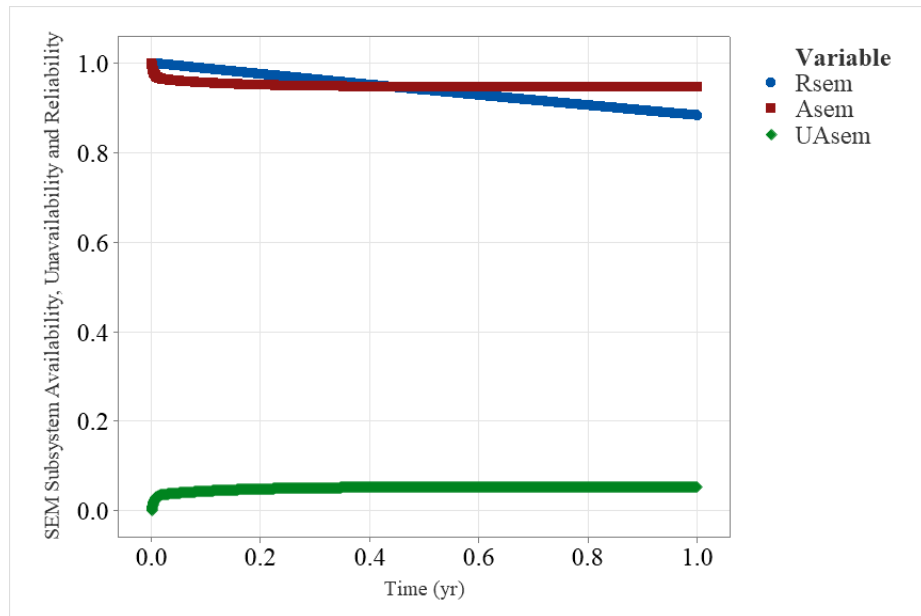


Figure 6.12: System Availability and Unavailability over Time.

The analysis shows that, although system availability remains high during initial operation, the probability of system downtime increases with time. This has direct implications for energy delivery, as reduced availability leads to a corresponding reduction in the effective load served.

The concept of availability provides a critical link between reliability modelling and system performance. While reliability quantifies the likelihood of subsystem survival,

availability determines the fraction of time during which the system can deliver energy. This distinction is particularly important for integrating reliability with the performance model developed in Chapter 5.

6.5. Impact of Reliability on System Performance

The integration of subsystem reliability with the deterministic SEM performance model introduces a time-varying reduction in effective energy delivery. This section quantifies the impact of reliability on system performance by comparing deterministic and reliability-adjusted outputs, evaluating performance degradation, and analysing the sensitivity of system performance to reliability variations.

6.5.1. Comparison of $TELS$ and $TELS_r$

The deterministic model predicts continuous energy delivery based solely on operational variables, whereas the reliability-integrated model accounts for system availability. The difference between $TELS$ and $TELS_r$ therefore represents the impact of subsystem failures on effective load served.

Figure 6.13 is a time-series comparison of $TELS$ and $TELS_r$. The deterministic plots represent ideal system performance, while the reliability-adjusted plots reflect reduced energy delivery due to subsystem failures. The increasing divergence between the two plots over time highlights the growing influence of reliability effects.

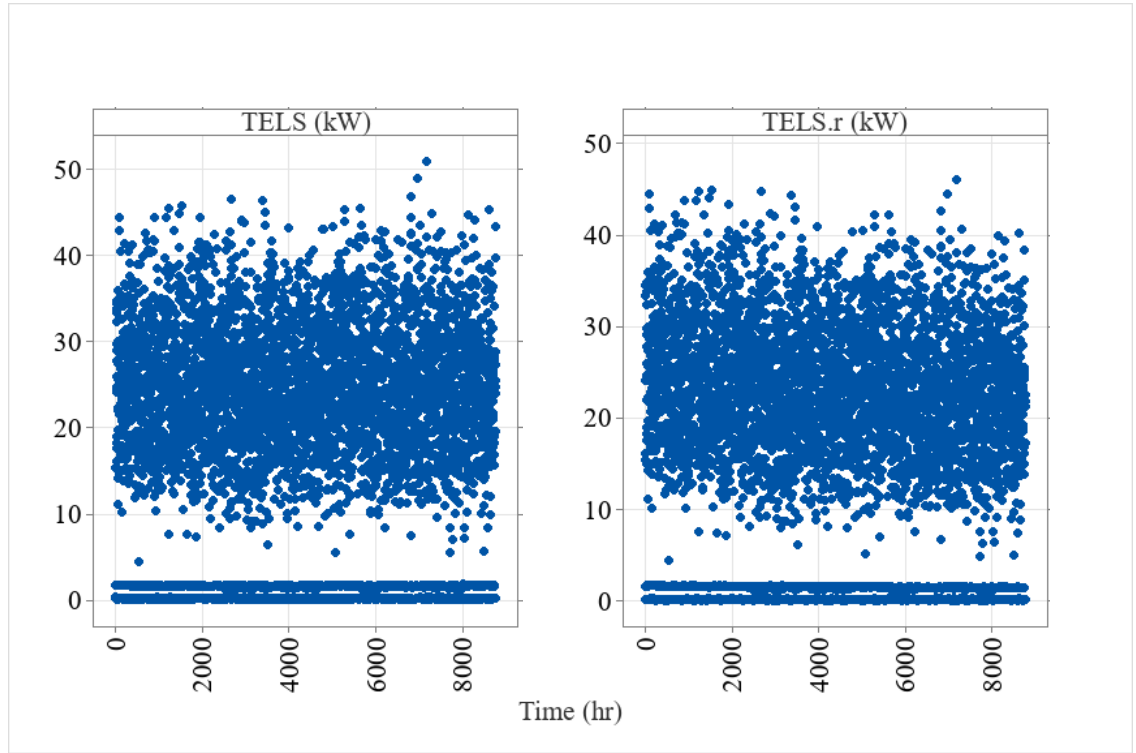


Figure 6.13: Deterministic vs Reliability-Adjusted SEM Performance.

The results show that, during early operation, both models exhibit similar behaviour due to high system reliability. However, as operating time increases and reliability decreases, the reliability-adjusted performance deviates progressively from the deterministic prediction. This divergence demonstrates that ignoring reliability leads to overestimation of long-term system performance.

6.5.2. Performance Degradation Due to Failures

The reduction in system performance due to reliability effects can be quantified using the relative performance loss:

$$\Delta\text{TELS}(t) = \text{TELS}(t) - \text{TELS}_r(t) \quad (6.3)$$

and the corresponding percentage reduction:

$$\% \text{ Loss}(t) = \frac{-(\text{TELS}_r(t) - \text{TELS}(t))}{\text{TELS}(t)} \times 100 \quad (6.4)$$

Figure 6.14 is a plot showing the percentage reduction in TELS(t) over time due to subsystem failures. The figure illustrates that performance loss increases with time, reflecting the cumulative effect of decreasing system reliability.

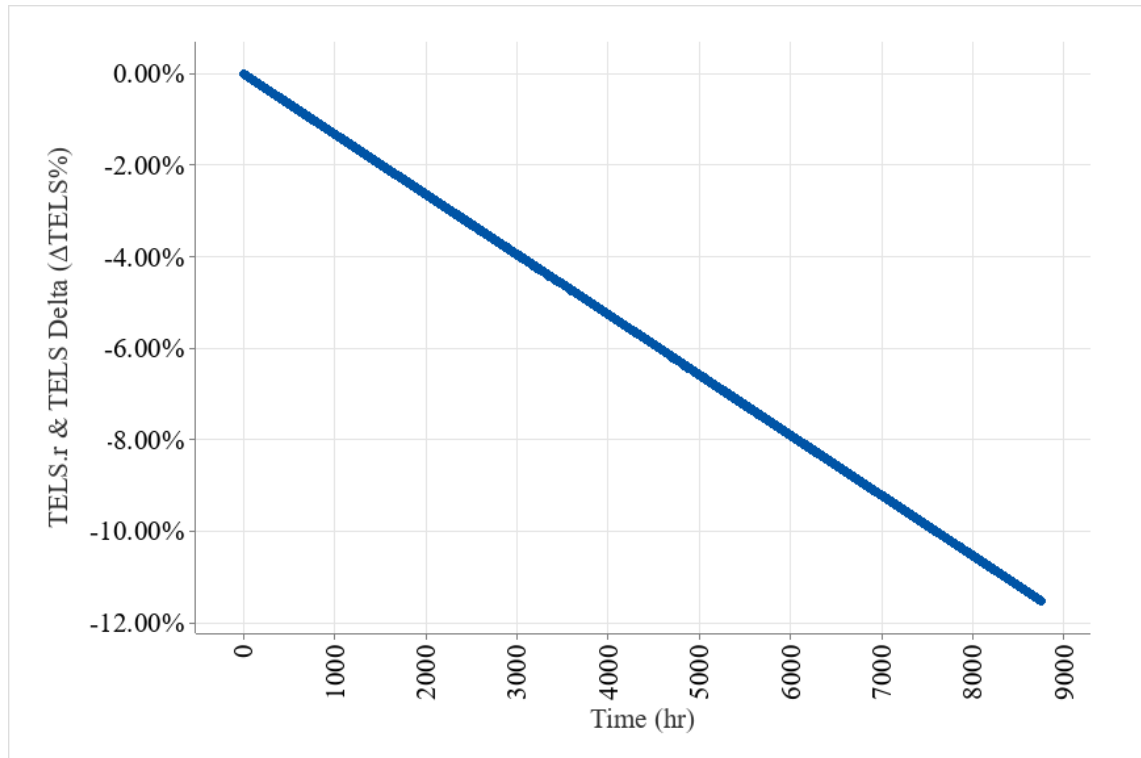


Figure 6.14: Performance Degradation Due to Reliability Effects.

The analysis indicates that performance degradation is initially minimal but becomes more significant over extended operation. This behaviour reflects the exponential decrease in subsystem reliability and highlights the importance of considering failure effects in long-term system planning.

From a system design perspective, these results demonstrate that deterministic models may significantly overestimate energy delivery, particularly when evaluating system performance over extended time horizons.

6.5.3. Sensitivity of System Performance to Reliability

The impact of reliability on system performance is not uniform across all subsystems. Sensitivity analysis shows that system performance is particularly affected by components that act as single points of failure, such as the power converter.

A reprocessing of Eq.(5.1) to express the R_{SEM} in terms of subsystem reliabilities yielded the following regression model derivative:

$$R_{SEM} = -0.003234 + 0.9993 * R_{inv} + 0.003885 * R_{pv} + 0.0000007064 * R_{gen} \quad (6.5)$$

where R_{pv} is solar PV reliability, R_{gen} represents diesel generator reliability and R_{inv} is inverter reliability.

Using the illustrative baseline values of $R_{pv} = 0.9802$, $R_{gen} = 0.0004$, and $R_{inv} = 0.8834$, the model yielded a baseline R_{SEM} value of 0.8833. The one-way sensitivity analysis, conducted by varying each explanatory variable independently by $\pm 5\%$ while holding the remaining variables constant, demonstrated substantial heterogeneity in the influence of the three predictors. Among these, R_{inv} exerted the greatest effect on model output: a $\pm 5\%$ change in R_{inv} changed R_{SEM} by $\pm 5\%$. By comparison, R_{pv} produced a smaller but still material response, with the same $\pm 5\%$ perturbation shifting R_{SEM} by $\pm 0.02\%$. In contrast, a $\pm 5\%$ change in R_{gen} had $\pm 0\%$ effect on R_{SEM} . The resulting sensitivity ranking was therefore $R_{inv} > R_{pv} > R_{gen}$, indicating that the model output is overwhelmingly dominated by variation in R_{inv} across the tested range.

A sensitivity plot of R_{SEM} to subsystem reliability changes in Figure 6.15 shows the effects of independently varying R_{inv} , R_{pv} , R_{gen} on R_{SEM} .

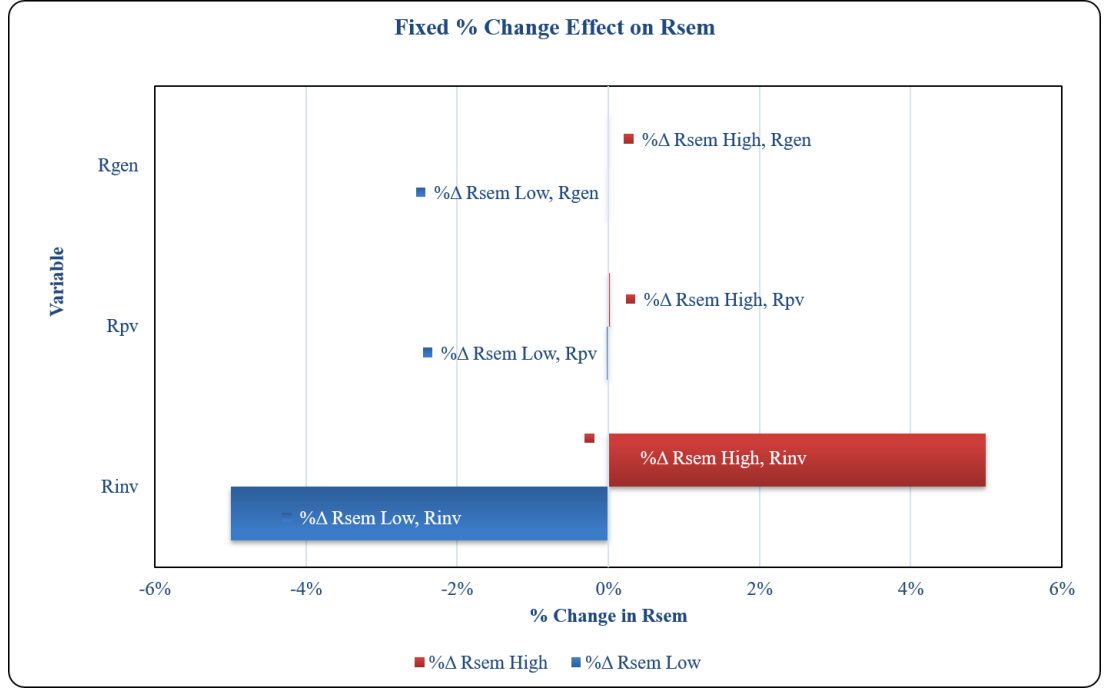


Figure 6.15: SEM Subsystem Reliability Change Influence on R_{SEM} with R_{inv} , R_{pv} , and R_{gen} Independently Changed by $\pm 5\%$.

From an interpretative perspective, these findings indicate that the predictive behaviour of the model is highly dependent on the specification of R_{inv} , with R_{pv} serving as a secondary but meaningful contributor and R_{gen} exerting negligible practical influence. This pattern is consistent with the relative magnitudes of the model coefficients, particularly the large positive coefficient associated with R_{inv} and the moderate positive coefficient associated with R_{pv} . The sensitivity profile also suggests that uncertainty in R_{inv} is likely to have the greatest implications for the robustness and reliability of the model output, and therefore this parameter should be prioritised in both data validation and future model refinement. Conversely, the limited responsiveness of R_{SEM} to changes in R_{gen} suggests that, within the bounds considered here, this variable is unlikely to be a critical driver of outcome variability. Taken together, the results imply that any substantive attempt to improve predictive confidence, scenario interpretation, or operational decision-making should focus primarily on constraining uncertainty around R_{inv} , while also accounting for the non-negligible contribution of R_{pv} .

The results confirm that improvements in inverter reliability yield the greatest enhancement in overall system performance, due to its series configuration within the

system. In contrast, improvements in generation subsystem reliability provide diminishing returns due to their parallel arrangement.

This finding has important implications for SEM system design, indicating that reliability improvements should prioritise critical components rather than uniformly targeting all subsystems.

6.6. Discussion of Results

The results presented in Sections 6.4–6.5 provide a comprehensive evaluation of how subsystem reliability influences SEM system performance. The integration of reliability into the deterministic framework reveals both expected and non-trivial system behaviours, with important implications for modelling accuracy and system design. This section critically interprets these findings in relation to the modelling assumptions, system configuration, and the research gap identified in Chapter 2. The assumptions of the SEM regression model were validated by checking normality of residuals which shows approximate satisfaction as shown in 5.3.4. The regression model results were statistically validated with the consideration of standard goodness-of-fit metrics, including the coefficient of determination (R^2), as discussed in Section 5.3.3. The reliability model robustness was checked by performing sensitivity analysis of the SEM reliability performance over changes in subsystem reliabilities as detailed in Section 6.5.3.

6.6.1. Interpretation of Reliability Behaviour

The time-varying reliability trends observed in Figure 6.11 demonstrate a progressive reduction in system availability, which is consistent with the exponential failure model defined in Eq.(4.5). Under the assumption of constant failure rates, this behaviour reflects the classical reliability theory framework, where component lifetimes follow a memoryless exponential distribution. In such systems, the probability of survival decreases monotonically with time, independent of prior operating history. This formulation is widely adopted in system-level reliability analysis due to its analytical simplicity and suitability for early-stage design evaluation, particularly in energy systems where detailed degradation data may be unavailable.

However, while the exponential model explains the general trend of decreasing reliability, the rate and shape of the decline observed for the SEM system are not governed solely by individual component failure rates. Instead, they are strongly influenced by the system configuration and interaction between subsystems, as captured by the Reliability Block Diagram formulation in Eq.(4.13). This highlights an important distinction in reliability engineering: system-level reliability is an emergent property that depends not only on component characteristics but also on how those components are functionally interconnected.

As illustrated in Figure 6.9, the power converter imposes a limiting effect on overall system reliability due to its series configuration within the SEM architecture. In reliability theory, components arranged in series act as critical path elements, where failure of any single component results in total system failure. The converter therefore represents a classic *single point of failure*, and its reliability directly constrains the upper bound of system availability. This observation is consistent with findings in the literature on power electronic systems and hybrid energy systems, where converters and inverters are frequently identified as dominant contributors to system failure due to thermal stress, switching losses, and operational loading conditions.

The significance of this result lies in demonstrating that improvements in non-critical components cannot compensate for weaknesses in critical-path elements. Even if the reliability of generation subsystems is high, the overall system reliability remains bounded by the weakest series component. This reinforces a key principle in reliability engineering: system reliability is often dominated by the least reliable component in the critical path, rather than by the average reliability of all components.

In contrast, the parallel configuration of generation subsystems (PV, battery, and diesel generator) introduces redundancy, which mitigates the impact of individual component failures. In reliability theory, parallel systems are characterised by their ability to maintain functionality as long as at least one component remains operational. The probability of system failure therefore becomes the joint probability of all parallel components failing simultaneously, which is significantly lower than individual failure probabilities.

This behaviour is reflected in the relatively slower decline of the combined generation reliability term in Eq.(4.13), where the expression

$$1 - (1 - R_{PV})(1 - R_{bat})(1 - R_{gen})$$

captures the probability that at least one energy source remains available. The presence of multiple generation pathways effectively enhances system resilience by distributing risk across subsystems.

From a broader perspective, this finding aligns with established principles in hybrid energy system design, where redundancy is intentionally introduced to address the inherent intermittency of renewable energy sources. In SEM systems, the integration of storage and backup generation serves not only an energy-balancing function but also a reliability-enhancing role. This dual functionality is particularly important in off-grid and remote applications, where system downtime has direct socio-economic consequences.

Furthermore, the interaction between series and parallel configurations in the SEM system creates a hybrid reliability structure, in which the benefits of redundancy are constrained by critical dependencies. This interplay is a defining characteristic of field-deployed energy systems and underscores the importance of modelling system topology explicitly. Simplified approaches that treat components independently or ignore system structure may significantly misrepresent reliability behaviour.

6.6.2. Impact of Reliability on System Performance

The comparison between deterministic and reliability-integrated performance, as illustrated in Figure 6.13, provides a direct quantification of how subsystem reliability influences effective energy delivery in SEM systems. In the deterministic model, system performance is evaluated under the assumption of continuous availability, such that the $TELS(t)$ reflects only the interaction between operational variables. However, the reliability-integrated model $TELS_r(t)$, defined in Eq.(4.3), introduces a probabilistic scaling factor that accounts for system availability, thereby transforming performance evaluation from a purely deterministic to a stochastic-informed representation.

The divergence between $TELS(t)$ and $TELS_r(t)$ observed over time highlights a fundamental limitation of deterministic energy system modelling. While deterministic

approaches are effective for short-term operational analysis and system sizing, they inherently assume idealised conditions and therefore represent an upper bound of system performance. The results demonstrate that this assumption leads to systematic overestimation of energy delivery, particularly when evaluating system behaviour over extended operational periods.

From a theoretical perspective, this behaviour can be interpreted through the concept of availability-weighted performance, where the effective output of a system is the product of its nominal performance and its probability of being operational. This formulation is widely used in reliability engineering and power system adequacy studies, where metrics such as LOLP and EENS are used to quantify reliability-related performance degradation. The reliability-integrated model developed in this work can be viewed as an analytical analogue to such metrics, providing a continuous and time-varying measure of performance reduction.

The increasing gap between deterministic and reliability-adjusted performance reflects the cumulative nature of failure processes. As shown in Figure 6.14, the percentage reduction in $TELS(t)$ grows over time, indicating that reliability effects become more significant as system operation progresses. This behaviour is consistent with long-term reliability theory, where even systems with relatively low failure rates experience noticeable degradation in effective performance due to the accumulation of failure probabilities.

Importantly, the results demonstrate that the impact of reliability is not uniform across all operating conditions. During periods of high system reliability (i.e., early operation), the deterministic and reliability-adjusted models produce nearly identical outputs, suggesting that deterministic modelling may be sufficient for short-term analysis. However, as reliability decreases, the discrepancy becomes increasingly pronounced, indicating that reliability considerations are essential for long-term performance evaluation, lifecycle analysis, and investment planning.

From an engineering perspective, these findings have significant implications. The observed performance degradation implies that system design decisions based solely on deterministic models may lead to underestimation of required capacity or overestimation of system reliability. For example, systems designed without accounting

for reliability may fail to meet load demand under actual operating conditions, particularly in critical applications such as off-grid electrification.

Furthermore, the results highlight the importance of integrating reliability into energy system modelling frameworks, rather than treating it as a separate or secondary consideration. In many existing studies, reliability is assessed independently using probabilistic methods, while performance modelling remains deterministic. The approach adopted in this work bridges this gap by embedding reliability directly into the performance model, enabling a unified evaluation of system behaviour.

This integration also provides a computational advantage. While stochastic simulation methods such as Monte Carlo analysis can capture reliability effects in detail, they are often complicated and require extensive data. The analytical formulation presented here achieves similar insight with significantly lower complexity, making it suitable for system-level analysis and optimisation.

6.6.3. Sensitivity to Subsystem Reliability

The sensitivity analysis presented in Section 6.5.3 provides critical insight into how variations in subsystem reliability influence overall SEM system performance. By evaluating the response of the reliability-adjusted output $TELS_r(t)$ to changes in individual subsystem reliability, it is possible to identify the components that exert the greatest control over system behaviour and, consequently, those that should be prioritised in design and reliability improvement strategies.

From a theoretical standpoint, system sensitivity to component reliability is governed by both the failure rate of the component and its structural position within the system, as defined by the Reliability Block Diagram in Eq.(4.13). In reliability engineering, this concept is closely related to importance measures, such as Birnbaum importance, which quantify the contribution of individual components to overall system reliability. Components that lie on critical paths or in series configurations typically exhibit higher importance, as their failure directly affects system functionality.

The results clearly indicate that system performance is most sensitive to the reliability of the power converter. This is consistent with its role as a series component in

the SEM architecture. As shown in Eq.(4.13), the overall system reliability is directly proportional to $R_{conv}(t)$, meaning that any reduction in converter reliability leads to a proportional reduction in system availability and, consequently, in $TELS_r(t)$. This behaviour is reflected in Figure 6.15, where variations in converter reliability produce the largest change in system performance.

This finding aligns with existing studies in power systems and microgrid reliability, where power electronic interfaces, including converters and inverters, are frequently identified as dominant contributors to system failure. Their exposure to thermal cycling, switching stresses, and environmental conditions makes them particularly susceptible to failure, and their central role in energy conversion places them on the critical path of system operation.

In contrast, the sensitivity of system performance to the reliability of individual generation subsystems (PV, battery, and diesel generator) is comparatively lower. This is a direct consequence of their parallel configuration within the system. In such configurations, the system can tolerate the failure of one or more components as long as at least one energy source remains operational. As a result, the marginal benefit of improving the reliability of any single generation subsystem is reduced.

This phenomenon reflects the principle of diminishing returns in redundant systems, where incremental improvements in already redundant components yield progressively smaller gains in overall system reliability. The reliability expression in Eq.(4.13) demonstrates that the combined generation reliability is dominated by the probability of simultaneous failure, rather than individual failure events. Consequently, improving one subsystem in isolation does not significantly reduce the probability of total generation failure unless all subsystems are improved simultaneously. From a performance perspective, this behaviour is propagated through the reliability-integrated model in Eq.(4.3), where the impact of subsystem reliability on $TELS_r(t)$ is mediated by the system reliability function. The sensitivity results therefore confirm that system performance is primarily influenced by components that constrain overall availability, rather than those that contribute to energy supply under normal conditions.

The implications of these findings for SEM system design are substantial. First, they suggest that reliability improvement efforts should be prioritised based on

component importance rather than uniform enhancement across all subsystems. Specifically, improving the reliability of the converter is likely to yield the greatest increase in overall system performance. This could involve the use of higher-quality components, improved thermal management, redundancy in power electronics, or preventive maintenance strategies.

Second, the results highlight the importance of considering system topology in reliability analysis. Simplified approaches that treat components independently or assume equal importance may fail to capture the true drivers of system performance. The integration of reliability modelling with system configuration, as demonstrated in this work, provides a significant basis for identifying critical components and optimising system design.

Finally, the sensitivity analysis reinforces the value of the reliability-integrated modelling framework proposed in this thesis. By linking subsystem reliability to system performance through an analytical formulation, the framework enables direct evaluation of how design decisions and component characteristics influence overall system behaviour. This capability is particularly important for applications in off-grid and hybrid energy systems, where reliability is a key determinant of system effectiveness and user satisfaction.

6.6.4. Implications for SEM System Design and Modelling

The results obtained in this chapter have significant implications for both the design of SEM systems and the methodologies used to model their performance. By explicitly integrating subsystem reliability into the performance framework, the analysis demonstrates that system behaviour cannot be fully understood through deterministic modelling alone. Instead, performance must be evaluated as a function of both operational capability and system availability.

From a system design perspective, one of the most important findings is the disproportionate influence of critical-path components on overall performance. As demonstrated in Sections 6.4 and 6.5, the power converter acts as a single point of failure due to its series configuration within the system. This implies that improving the reliability of such components can yield significantly greater performance gains than

equivalent improvements in non-critical subsystems. Consequently, design strategies should prioritise enhancing the robustness of converters and other critical interfaces, for example through improved thermal management, redundancy in power electronics, or the selection of higher-reliability components.

In contrast, the presence of parallel redundancy among generation subsystems (PV, battery, and diesel generator) reduces the sensitivity of system performance to individual component failures. While redundancy enhances resilience, the results indicate diminishing returns when improving the reliability of already redundant components. This suggests that system optimisation should not focus solely on increasing component reliability uniformly, but rather on achieving an optimal balance between redundancy and critical component robustness. Such insights are particularly relevant in cost-constrained SEM deployments, where resource allocation must be carefully prioritised.

From a modelling perspective, the findings highlight the limitations of conventional deterministic approaches commonly used in SEM design tools, including HOMER-based analyses. While these methods are effective for system sizing and energy flow analysis, they inherently assume continuous system availability and therefore tend to overestimate long-term performance. The results in Section 6.5 show that this assumption leads to measurable discrepancies between predicted and actual system behaviour when reliability effects are considered.

The reliability-integrated modelling framework developed in this work addresses this limitation by embedding system availability directly into the performance model. This approach provides a unified representation of system behaviour that captures both operational dynamics and failure effects, without the need for complicated stochastic simulation methods. As a result, the framework offers a practical and scalable tool for evaluating SEM systems at the design stage, particularly in applications where reliability is a critical requirement.

Furthermore, the integration of regression-based modelling with reliability analysis enables efficient sensitivity evaluation and performance prediction. Unlike traditional reliability studies that focus solely on failure probabilities, the proposed approach links reliability directly to energy delivery metrics, allowing designers to assess the real impact of failures on system output. This capability is particularly valuable for

decision-making in off-grid and hybrid energy systems, where reliability directly affects service quality and user satisfaction.

The findings also suggest that future SEM modelling approaches should adopt a more holistic perspective, incorporating both system configuration and reliability characteristics. Simplified models that treat components independently or ignore system topology may fail to capture critical interactions, leading to suboptimal design decisions. By contrast, the framework presented in this thesis demonstrates how system structure, component reliability, and operational behaviour can be integrated into a coherent modelling approach.

6.6.5. Contribution to Knowledge and Research Gap

The results presented in this chapter directly address the research gap identified in Chapter 2, where it was established that existing SEM modelling approaches predominantly rely on deterministic formulations and do not explicitly account for subsystem reliability. While conventional tools and methodologies, such as HOMER-based analyses, provide detailed insights into system operation and energy flows, they assume continuous system availability and therefore do not capture the impact of component failures on long-term system performance.

In the existing literature, reliability is often treated as a separate analytical domain, typically addressed using probabilistic methods such as Monte Carlo simulation, Markov modelling, or standalone reliability block diagram analysis. Although these approaches provide valuable insights into failure behaviour, they are rarely integrated directly with system performance models. As a result, there remains a disconnect between reliability analysis and energy system modelling, limiting the ability to evaluate how subsystem failures influence actual energy delivery.

The primary contribution of this work is the development of a reliability-integrated SEM performance model that bridges this gap. By combining the regression-based deterministic model derived in Chapter 5 with the system reliability formulation defined in Section 6.3, the study introduces a unified framework in which system performance is explicitly modulated by system availability. The resulting formulation,

expressed in Eq.(4.3), provides a direct analytical link between subsystem failure behaviour and effective energy delivery.

This integration represents a significant advancement over conventional approaches in several ways. First, it moves beyond purely deterministic modelling by incorporating time-varying reliability effects, thereby providing a more actual representation of system behaviour under practical operating conditions. Second, it avoids the computational complexity associated with stochastic simulation methods, offering a tractable and efficient alternative for system-level analysis. Third, it enables direct quantification of performance degradation due to failures, as demonstrated in Section 6.5, where the divergence between $TELS(t)$ and $TELS_r(t)$ is explicitly evaluated.

In addition to methodological integration, the work contributes new insights into the relationship between system configuration and reliability. The analysis demonstrates that system performance is governed not only by component reliability but also by the structural arrangement of subsystems, with critical-path components such as converters exerting a dominant influence. This finding reinforces the importance of topology-aware modelling, which is often overlooked in simplified SEM analyses.

Furthermore, the sensitivity analysis presented in Section 6.5.3 provides a practical framework for prioritising reliability improvements based on their impact on system performance. This represents an important contribution to system design methodology, as it enables targeted optimisation of critical components rather than uniform enhancement across all subsystems.

6.7. Summary

This chapter has extended the deterministic SEM performance framework developed in Chapter 5 by incorporating subsystem reliability into system-level modelling. Building on the theoretical foundation established in Chapter 4, subsystem failure behaviour was quantified using exponential reliability functions and integrated through a Reliability Block Diagram representation of the SEM system.

The analysis demonstrated that system reliability is governed not only by individual component failure rates but also by system configuration. In particular, the

converter was identified as a critical-path component whose reliability imposes a limiting effect on overall system availability, while the parallel configuration of generation subsystems provides redundancy that enhances system resilience.

The integration of reliability with the regression-based performance model resulted in a unified formulation in which system output is directly modulated by system availability. Comparison between deterministic and reliability-adjusted performance showed that conventional models systematically overestimate energy delivery, particularly over extended operating periods. The results further quantified the impact of subsystem failures, with performance degradation increasing as system reliability decreases over time.

Sensitivity analysis highlighted the dominant influence of critical components on system performance, demonstrating that improvements in converter reliability yield significantly greater benefits than equivalent improvements in redundant subsystems. These findings provide important insights for SEM system design, emphasising the need to prioritise reliability enhancements based on system topology and component importance.

Overall, the chapter has demonstrated that incorporating reliability into SEM modelling is essential for actual performance evaluation. The proposed reliability-integrated framework provides a computationally efficient and analytically tractable approach for linking subsystem failure behaviour with system-level energy delivery. This represents a key contribution of the research and addresses the limitations of existing deterministic modelling approaches identified in Chapter 2.

The validated reliability-integrated model developed in this chapter forms the basis for the application and model scenario analysis presented in Chapter 7, where the framework is evaluated under different operating scenarios and representative conditions.

Chapter 7: Application of the Reliability-Integrated SEM Model Scenarios

7.1. Introduction

The reliability-integrated SEM performance model developed in Chapters 5 and 6 provides a unified framework for evaluating system behaviour by combining deterministic performance with subsystem reliability. While the preceding chapters established the theoretical formulation and demonstrated its impact under controlled conditions, it is necessary to assess the scenarios' applicability of the model. The purpose of this chapter is therefore to apply the proposed framework using representative model scenarios, thereby evaluating its robustness, and practical relevance. This chapter extends the analysis by implementing both the deterministic and reliability-integrated models under different operating conditions, including variations in environmental inputs, load profiles, and system configurations. By comparing results across two scenarios, the study aims to demonstrate how system performance is influenced by contextual factors and to evaluate whether the key findings identified in Chapter 6 remain consistent under actual conditions. The chapter begins by describing the selected model scenarios and the associated data inputs, including location-specific environmental conditions and load characteristics. The deterministic SEM model is first applied to establish baseline system performance, followed by the implementation of the reliability-integrated model to evaluate the effect of subsystem failures. Comparative analysis is then conducted to quantify differences in performance and to assess the sensitivity of the model to varying conditions. Finally, the chapter provides practical insights into SEM system design and operation, based on the results obtained from the model scenarios. This includes identifying key factors influencing system performance, evaluating the importance of reliability in field-deployed applications, and highlighting considerations for system planning and deployment.

7.2. Model Scenarios Description and Data Sources

This section describes the model scenarios used to evaluate the applicability and robustness of the reliability-integrated SEM performance model. The selected model

scenarios are designed to represent field operating conditions under different environmental and demand scenarios, enabling assessment of model behaviour beyond the baseline system defined in Chapter 3.

7.2.1. Description of Study Locations

Two representative model scenarios are considered to capture variation in environmental conditions and system operation. The first model scenario corresponds to a semi-urban commercial location in Awka, Anambra State, Nigeria, previously introduced in Chapter 3. This site represents a typical off-grid deployment scenario in a developing region, characterised by high solar irradiance, variable load demand, and reliance on hybrid energy systems for reliable electricity supply. The load profile is dominated by daytime commercial activity, with moderate variability reflecting business operations. The second model scenario represents a temperate-climate location, such as a site in the United Kingdom, where solar irradiance is lower and more variable due to seasonal and weather-related effects. This scenario provides a contrasting operating environment, allowing evaluation of how reduced renewable resource availability influences system performance and reliability impact.

7.2.2. System Configuration for Model Scenarios

For consistency, the SEM configuration used in both model scenarios is based on the 100kW PV modules capacity system defined in Chapter 3. The system consists of:

- a PV array as the primary generation source
- battery energy storage for load balancing
- a diesel generator for backup supply
- a power converter for energy conversion and delivery

While the overall configuration remains unchanged, the operating behaviour of the system varies depending on local environmental conditions and load demand. This approach ensures that differences in system performance are attributable to external factors rather than changes in system design, enabling a controlled comparison between model scenarios.

7.2.3. Data Inputs and Assumptions

The analysis uses time-series data for solar irradiance, temperature, and load demand as inputs to the SEM simulation and modelling framework. For the Awka model scenario, environmental data is derived from representative meteorological datasets for the region, reflecting high solar availability and relatively stable seasonal variation. For the temperate-climate model scenario, data reflects lower average irradiance and greater variability, particularly during winter periods.

Load profiles for both model scenarios are defined based on typical demand patterns for commercial and mixed-use applications. The Nigerian model scenario exhibits a predominantly daytime load profile, while the temperate-climate model scenario includes more distributed demand across the day.

The deterministic simulation outputs, generated using HOMER as described in Chapter 3, provide the input data for regression modelling (Chapter 5) and reliability integration (Chapter 6). Subsystem reliability parameters, including failure rates, are assumed to be consistent across both model scenarios to isolate the effect of environmental and operational differences on system performance.

Key modelling assumptions include:

- constant subsystem failure rates (as defined in Chapter 6)
- independent failure behaviour between subsystems
- consistent system configuration across model scenarios

These assumptions ensure that the analysis focuses on evaluating the impact of operating conditions and reliability integration, rather than introducing additional complexity from system redesign or parameter variation.

7.3. Application of Deterministic SEM Model

The deterministic SEM performance model developed in Chapter 5 is applied in this section to evaluate baseline system behaviour for the selected model scenarios. The objective is to establish reference performance under the assumption of continuous

system availability, providing a benchmark against which reliability-integrated results can be compared in subsequent sections.

7.3.1. Simulation of Baseline Performance

The deterministic model, defined in Eq.(5.1), is applied to the time-series datasets described in Section 7.2. For each model scenario, the $TELS(t)$ is computed based on system operational variables, including inverter output, generator contribution, and battery behaviour.

Figure 7.1 is a time-series plot showing TELS for both the Awka (Nigeria) and Liverpool (UK - temperate climate) model scenarios. The figure illustrates differences in energy delivery patterns driven by variations in solar resource availability and load demand.

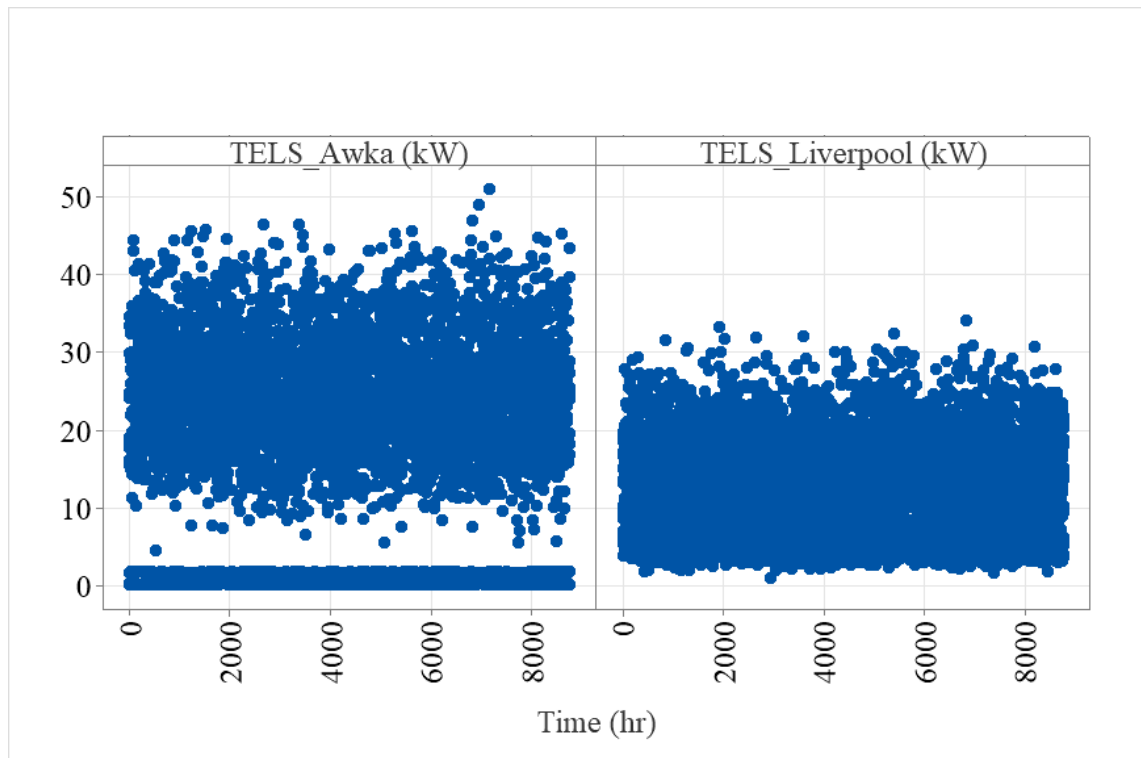


Figure 7.1: Deterministic SEM Performance for Model scenario Locations.

The results indicate that the Awka model scenario exhibits higher and more stable energy delivery due to consistently strong solar irradiance and a well-matched daytime load profile. In contrast, the temperate-climate model scenario shows greater

variability in *TELS*, with lower overall energy delivery, particularly during periods of reduced solar input.

These differences reflect the influence of environmental conditions on system operation, even when system configuration remains unchanged. In particular, reduced solar availability in the temperate scenario leads to increased reliance on battery storage and diesel generation to meet demand.

7.3.2. Behaviour of System Components

The deterministic simulation results also provide insight into the behaviour of individual system components and their contribution to overall performance.

Figure 7.2 shows an overlay plot of PV output, battery power (charge/discharge), diesel generator output, and load demand for the Awka scenario representative period.

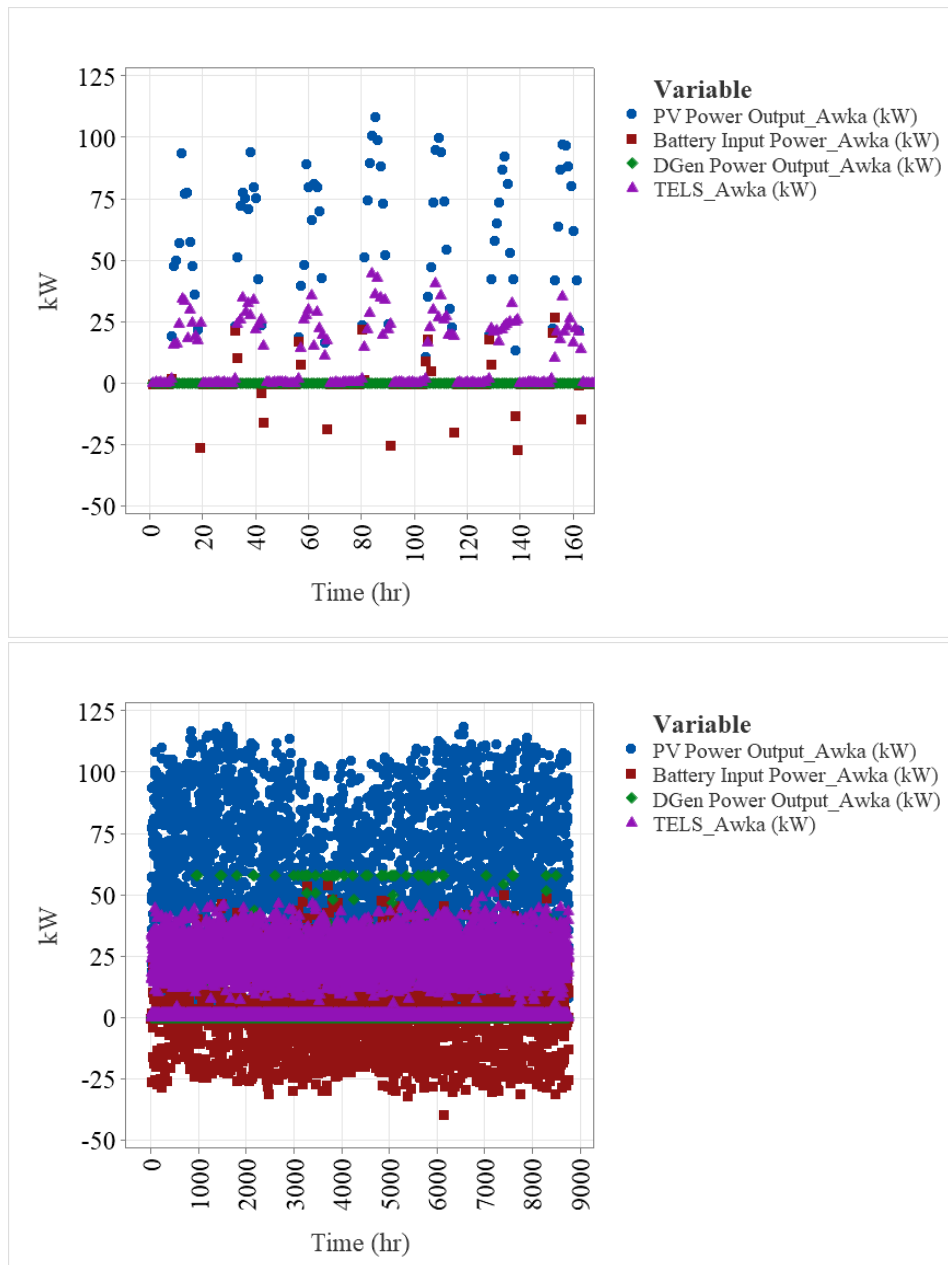


Figure 7.2: Weekly and Yearly Component-Level Operation in Deterministic SEM Model for Awka.

The figure highlights how different subsystems interact to maintain energy supply under varying operating conditions.

Figure 7.3 presents an overlay plot showing PV output, battery power (charge/discharge), diesel generator output, and load demand for the Liverpool scenario representative period. The figure highlights how different subsystems interact to maintain energy supply under varying operating conditions.

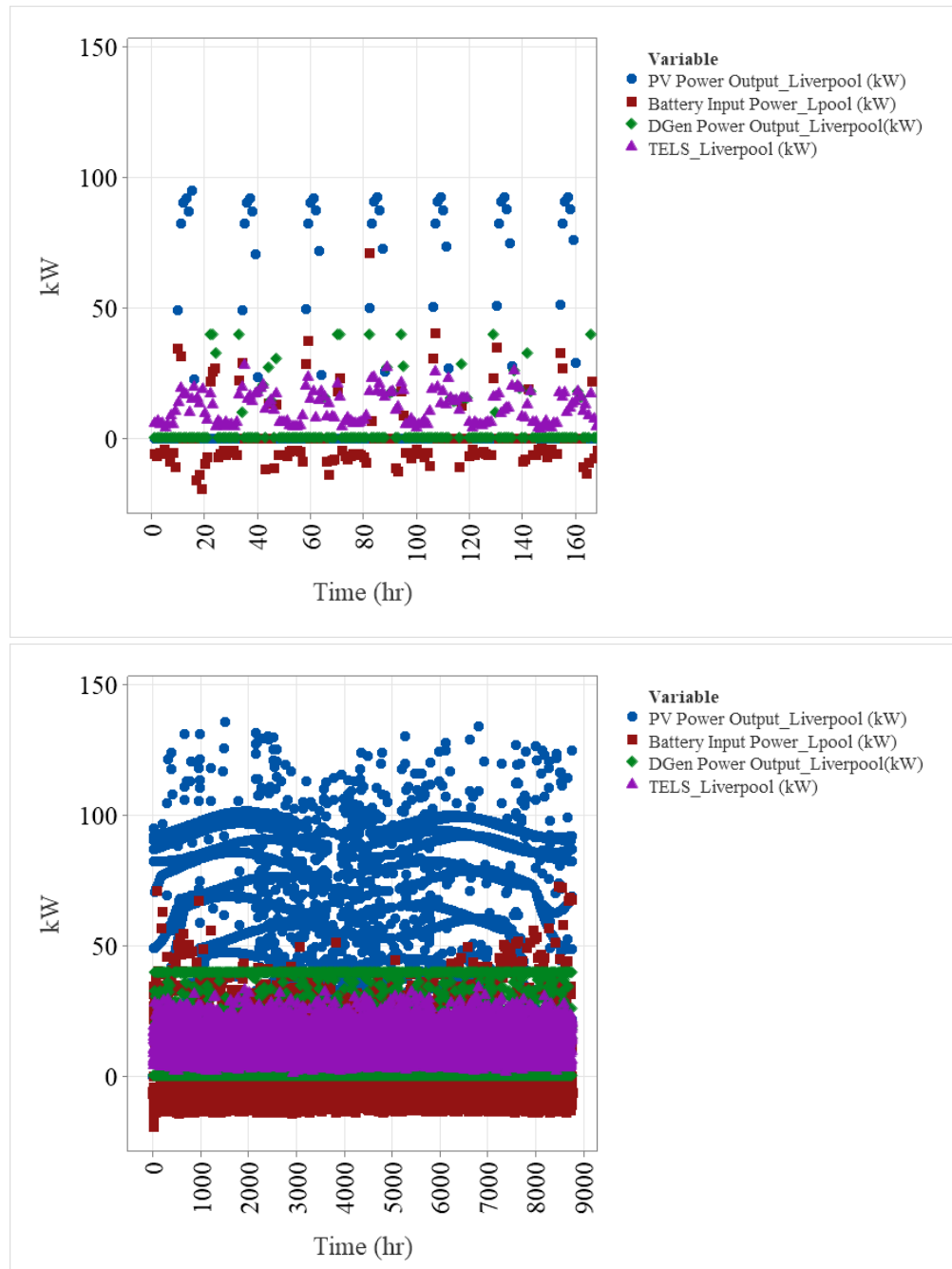


Figure 7.3: Weekly and Yearly Component-Level Operation in Deterministic SEM Model for Liverpool.

In the Awka model scenario, PV generation plays a dominant role in meeting load demand, with battery storage used primarily for short-term balancing. The diesel generator is activated intermittently during periods of peak demand or reduced solar output. This indicates a system operating close to renewable-dominated conditions.

In contrast, the temperate-climate model scenario exhibits frequent use of the diesel generator, reflecting reduced solar contribution and increased dependence on

backup generation. The battery system plays a more active role in balancing supply and demand, particularly during periods of fluctuating solar input.

7.3.3. Interpretation of Deterministic Model Results

The deterministic results highlight that system performance is strongly influenced by environmental conditions and load characteristics. The higher performance observed in the Awka model scenario demonstrates the advantage of high solar resource availability, while the variability in the temperate-climate scenario reflects the challenges associated with intermittent renewable generation.

From a modelling perspective, these results confirm that the regression-based model developed in Chapter 5 remains applicable across different operating conditions, capturing variations in system behaviour through changes in input variables. However, it is important to note that these results represent idealised performance, as the model assumes continuous system availability.

This assumption becomes particularly significant when comparing the two model scenarios. In the temperate-climate scenario, where the system relies more heavily on backup generation and storage, the potential impact of subsystem failures is likely to be greater. This suggests that the limitations of deterministic modelling are more pronounced under conditions of increased system stress or reduced redundancy.

7.4. Application of Reliability-Integrated Model

The reliability-integrated SEM performance model developed in Chapter 6 is applied in this section to the model scenarios described in Section 7.2. The objective is to evaluate how subsystem reliability influences system performance under different environmental and operational conditions, and to assess whether the trends observed in Chapter 6 remain consistent in actual deployment scenarios.

7.4.1. Implementation of Reliability Model

The reliability-integrated model is implemented using Eq.(4.3). The same subsystem failure rates and reliability assumptions used in Chapter 6 are applied to both model scenarios to ensure consistency.

For each time step, the deterministic output is scaled by the corresponding system reliability, resulting in a time-varying representation of effective energy delivery that accounts for subsystem availability. This approach ensures that differences between model scenarios arise from environmental and operational conditions, rather than changes in reliability parameters.

Figure 7.5 is a time-series plot showing the reliability-adjusted performance $TELS_r$ for both the Awka and temperate-climate model scenarios. The figure illustrates how system performance is reduced compared to deterministic predictions due to the influence of subsystem reliability.

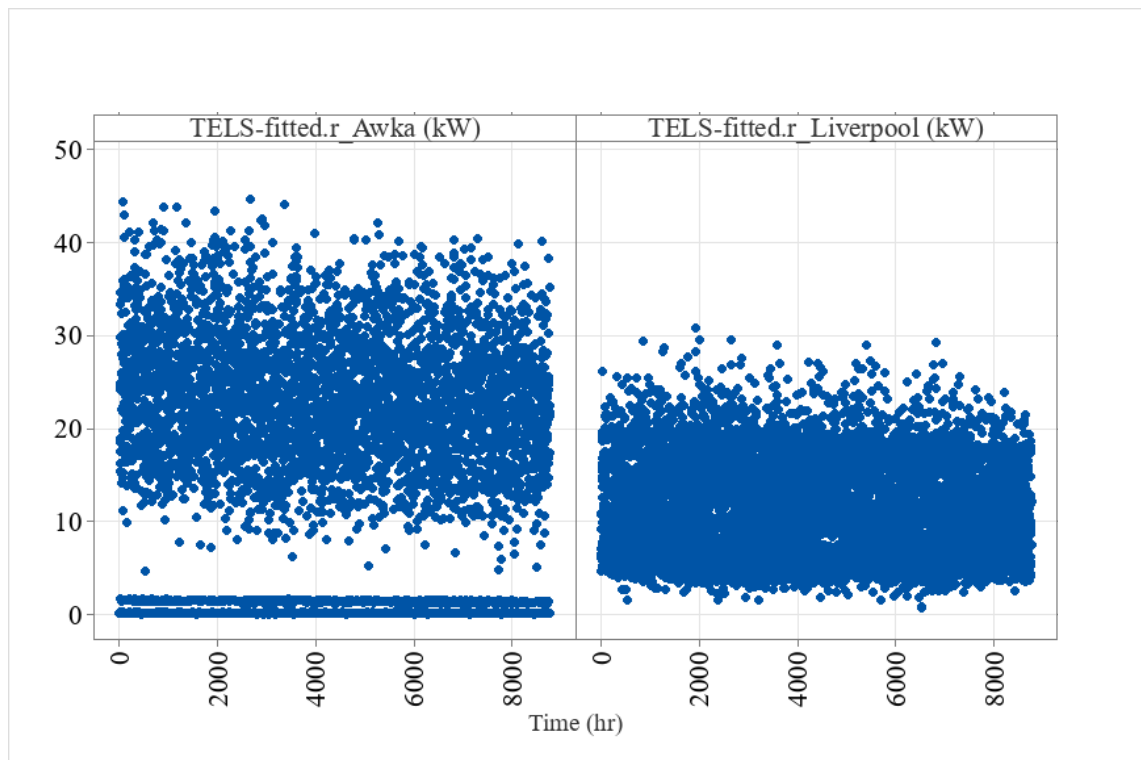


Figure 7.4: Reliability-Integrated SEM Performance.

7.4.2. Reliability-Adjusted Performance Evaluation

The reliability-integrated results reveal a consistent reduction in system performance across both model scenarios when compared to deterministic predictions. This reduction reflects the probabilistic nature of system availability and the cumulative effect of subsystem failures over time.

Figure 7.5 is a comparative plot showing $TELS(t)$ and $TELS_r(t)$ for both model scenarios. The divergence between the plots illustrates the impact of reliability on effective energy delivery, with increasing deviation over time.

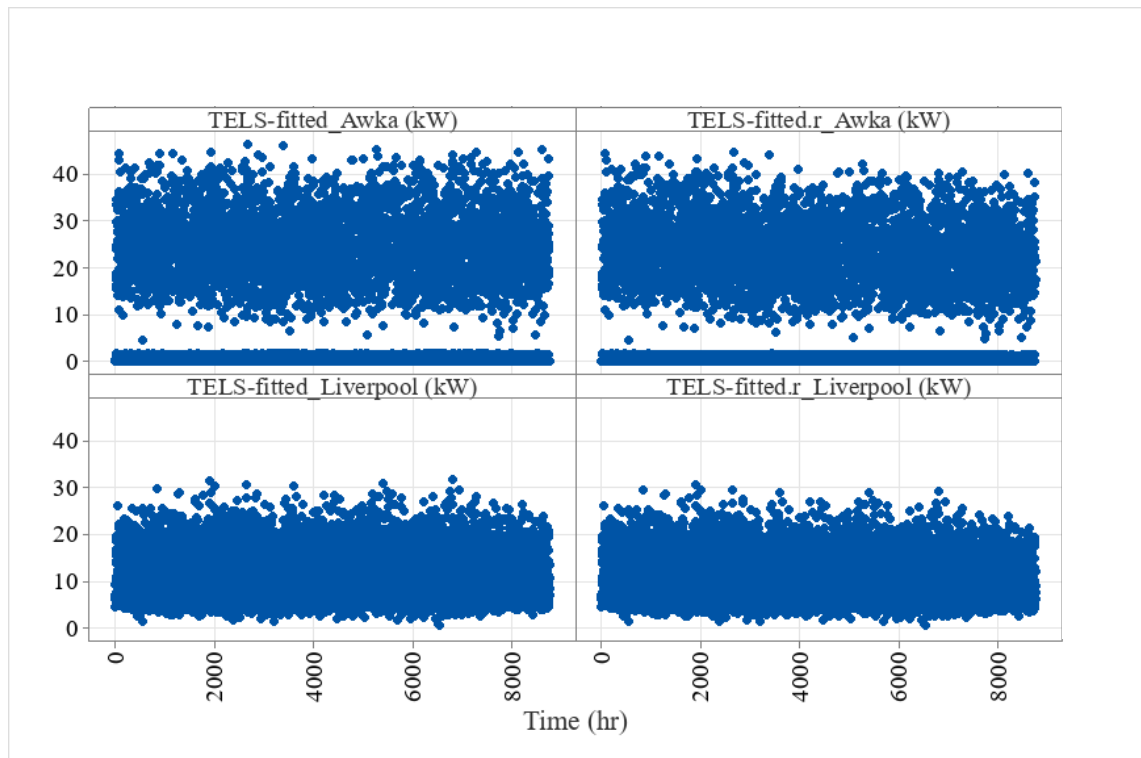


Figure 7.5: Deterministic vs Reliability-Integrated Performance

In the Awka model scenario, the reduction in performance is relatively moderate, particularly during periods of high solar availability. The strong contribution of PV generation and the presence of redundancy in energy sources help maintain system performance despite reliability effects. As a result, the deterministic and reliability-adjusted outputs remain closely aligned during early operation, with divergence becoming more noticeable over longer time periods.

In contrast, the temperate-climate model scenario exhibits a more pronounced reduction in performance. The lower and more variable solar input increases reliance on battery storage and diesel generation, which introduces additional stress on system components. Under these conditions, subsystem failures have a greater impact on system availability, leading to a larger gap between deterministic and reliability-integrated performance.

7.4.3. Interpretation Across Model scenarios

The results demonstrate that the impact of reliability on system performance is strongly dependent on operating conditions. In environments with high renewable resource availability and balanced load profiles, such as the Awka model scenario, the system exhibits greater resilience to subsystem failures due to higher level of redundancy provided by battery storage and diesel generator.

In contrast, in environments with lower renewable resource availability as in the Liverpool scenario, the system becomes more sensitive to reliability effects. Increased reliance on backup generation and storage introduces additional failure pathways and reduces system redundancy, amplifying the impact of subsystem failures on overall performance. These are illustrated in Figure 7.6, and Figure 7.7.

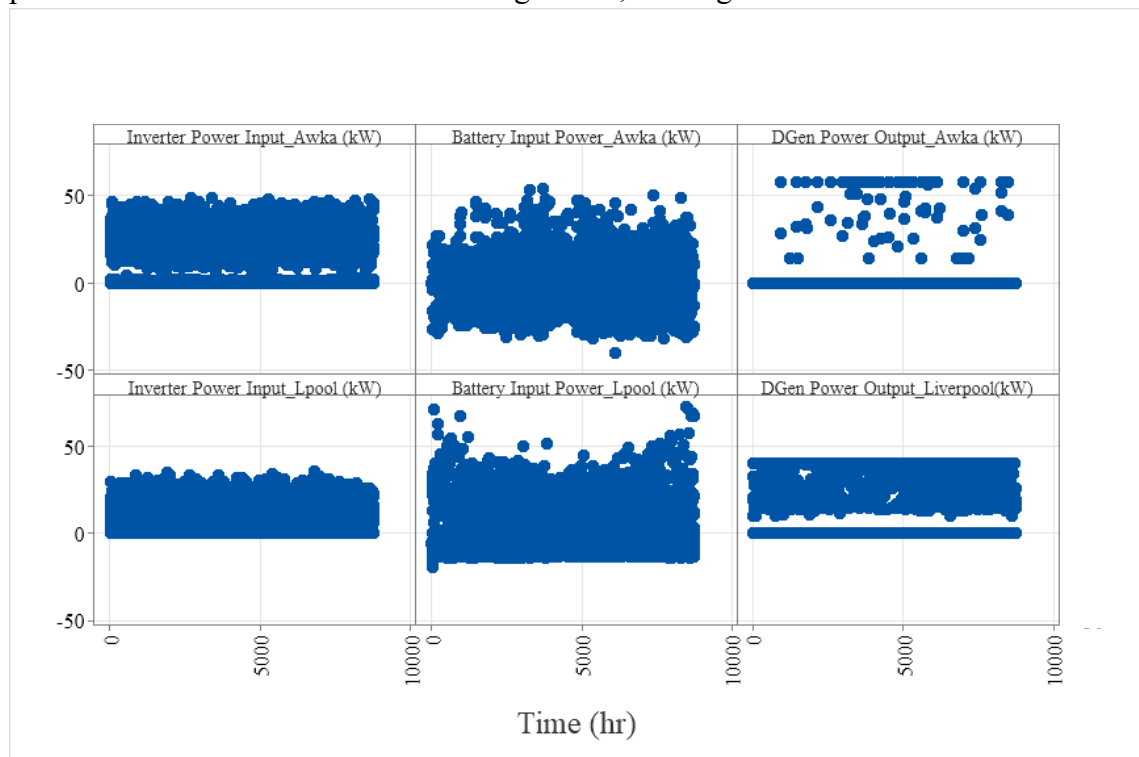


Figure 7.6: SEM Performance Across Model scenarios.

Figure 7.7 shows a plot comparing SEM percentage reduction in TELS(t) due to reliability effects for both model scenarios. The figure highlights that performance degradation is more significant in the Awka climate scenario, particularly over extended operating periods.

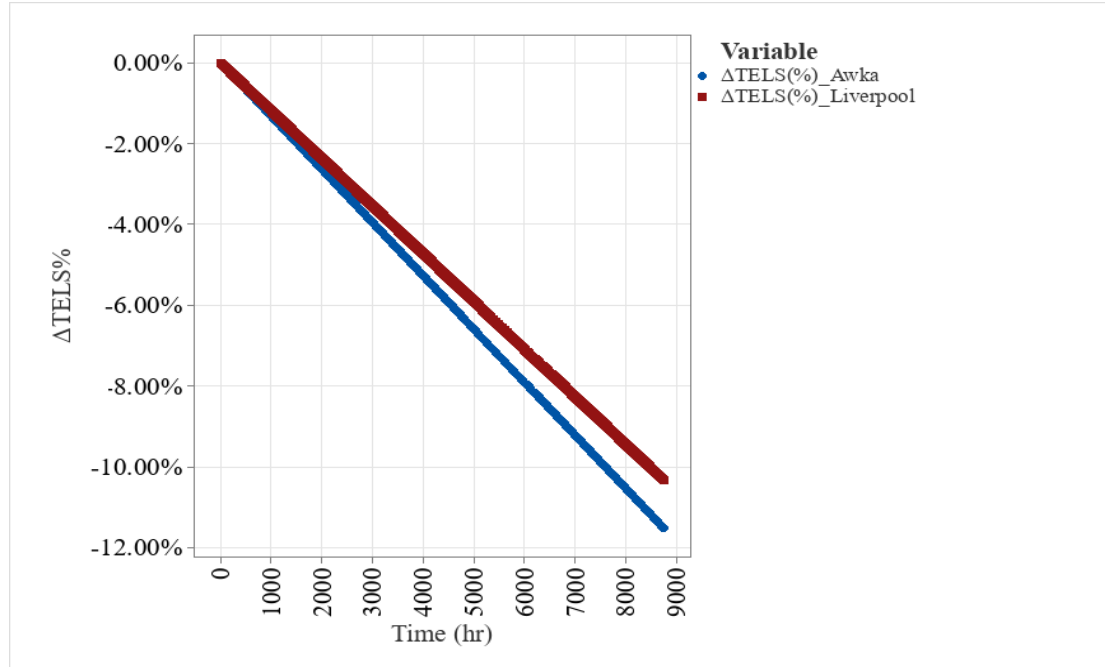


Figure 7.7: SEM Percentage Performance Reduction Across Model scenarios.

These findings reinforce the conclusion from Chapter 6 that deterministic models are insufficient for evaluating SEM performance under field actual conditions. They also demonstrate that the reliability-integrated model captures important variations in system behaviour that depend on environmental and operational context.

7.5. Comparative Analysis Across Model scenarios

The application of deterministic and reliability-integrated models to multiple model scenarios enables a detailed comparative evaluation of SEM system behaviour under varying environmental and operational conditions. This section synthesises the results from Sections 7.3 and 7.4 to quantify differences in system performance, examine the influence of external factors, and assess the consistency of reliability effects across scenarios.

7.5.1. Deterministic vs Reliability-Integrated Performance

A direct comparison of deterministic $TELS(t)$ and reliability-adjusted $TELS_{,r}(t)$ across the two model scenarios highlights the extent to which subsystem reliability influences system performance. Figure 7.5 is a combined plot showing $TELS(t)$ and $TELS_{,r}(t)$ for both Awka and Liverpool (temperate climate) model scenarios. The figure illustrates differences in baseline performance as well as the magnitude of reliability-induced performance reduction.

The results confirm that deterministic performance consistently exceeds reliability-adjusted performance in both scenarios, reinforcing the conclusions drawn in Chapter 6. However, the magnitude of this difference varies significantly between model scenarios. The Awka scenario exhibits 11.53% reduction in TELS for the first year, while the temperate-climate scenario shows 10.34% decline in TELS for the same period, particularly during periods of low renewable generation.

This variation demonstrates that the impact of reliability is not uniform but instead depends on the interaction between system configuration and operating conditions.

7.5.2. Influence of Environmental and Load Conditions

The differences observed between model scenarios can be directly attributed to variations in solar resource availability and load characteristics. In the Awka model scenario, high and relatively stable solar irradiance results in consistent PV generation, reducing dependence on auxiliary subsystems and maintaining system redundancy. This leads to a lower sensitivity to subsystem failures, as reflected in the smaller gap between $TELS(t)$ and $TELS_{,r}(t)$.

In contrast, the temperate-climate model scenario is characterised by lower and more variable solar input, leading to increased reliance on battery storage and diesel generation. This shift in system operation introduces additional stress on critical components and reduces effective redundancy hitherto provided by the battery and diesel generator as they become mainstream subsystems, thereby amplifying the impact of subsystem failures.

Figure 7.8 is a comparative plot illustrating PV generation, load demand, and reliability-adjusted performance for both model scenarios. The figure highlights how differences in solar availability and load patterns influence overall system behaviour and reliability impact.

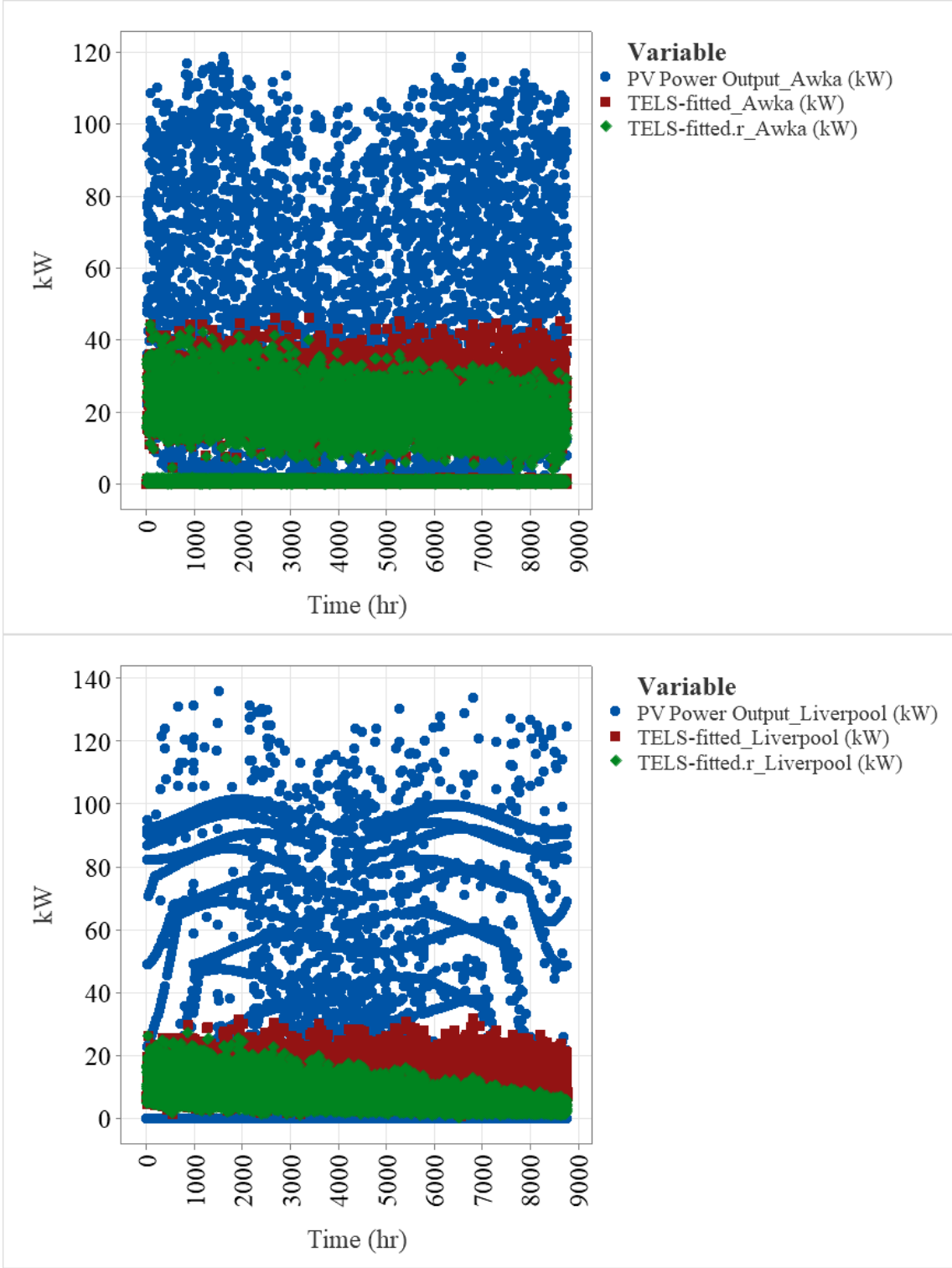


Figure 7.8: Influence of Environmental Conditions on System Performance.

These results emphasise that environmental conditions play a central role in determining not only system performance but also the extent to which reliability affects that performance.

7.5.3. Cross-Scenario Performance Comparison

To quantify the differences in system behaviour, performance metrics such as average load served and percentage performance reduction are evaluated for each model scenario.

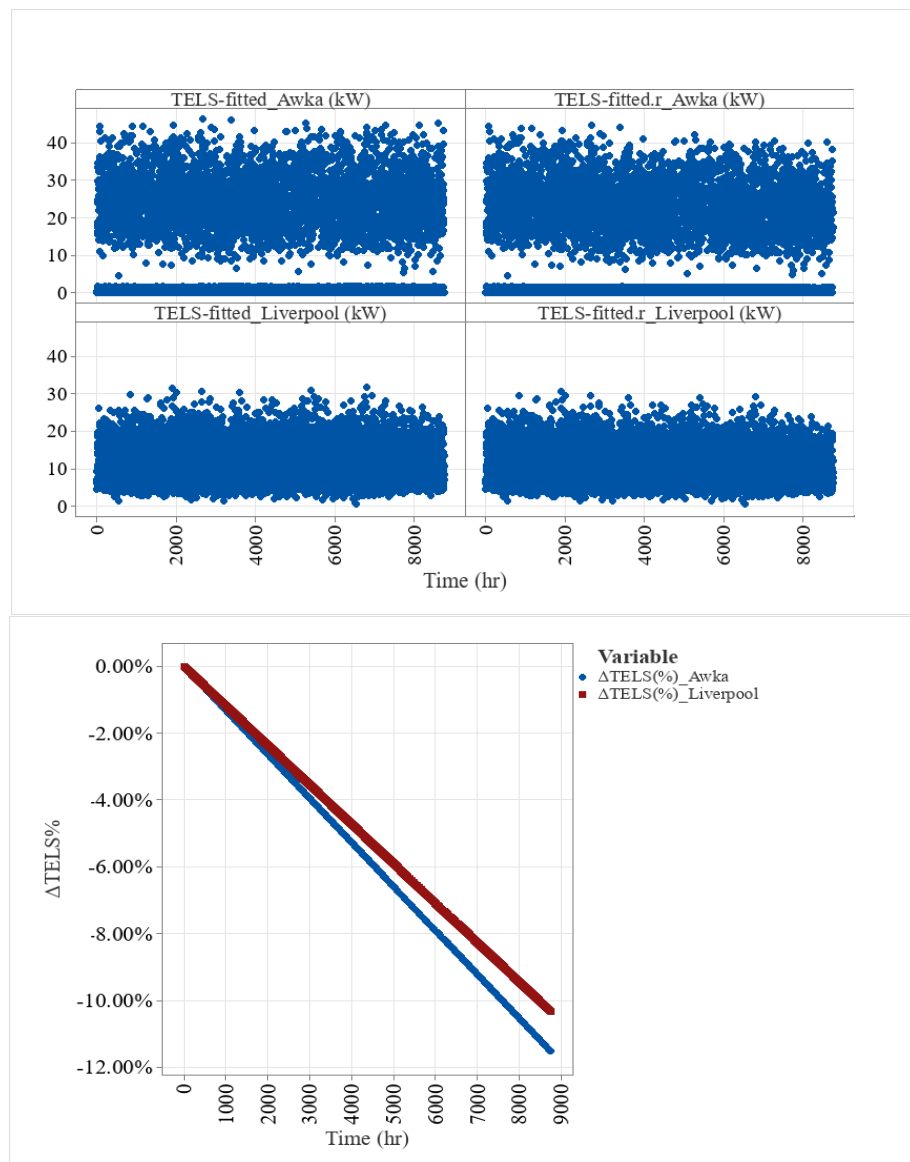


Figure 7.9: Comparative Performance Metrics Across Model scenarios

Figure 7.9 shows that while the Awka system achieves higher overall performance, it also experiences higher relative performance degradation due to reliability effects. In contrast, the temperate-climate system in Liverpool exhibits both lower baseline performance and lower sensitivity to reliability due to its normalised R_{SEM} .

The model successfully captures variations in system behaviour arising from different operating conditions, while maintaining the fundamental relationship between reliability and performance identified in Chapter 6.

7.6. Practical Implications and Design Insights

The application of the reliability-integrated SEM modelling framework provide several important insights for the design, operation, and evaluation of SEMs. By linking subsystem reliability with system-level energy delivery, the analysis moves beyond theoretical modelling and offers practical guidance for improving system performance under field-deployed conditions.

7.6.1. Reliability-Aware System Design

One of the most significant implications of this work is the need to incorporate reliability considerations explicitly into SEM system design. The results presented in Sections 7.4–7.7 demonstrate that deterministic models systematically overestimate system performance, particularly under long-term operation. As a result, design decisions based solely on deterministic simulations may lead to underestimation of system capacity requirements or overestimation of system reliability.

The reliability-integrated model provides a more actual basis for design by accounting for subsystem availability. This enables designers to evaluate not only how much energy a system can deliver under ideal conditions, but also how much energy is likely to be delivered in practice. Such an approach is particularly important for off-grid and rural electrification applications, where system failure directly impacts service reliability and user satisfaction.

7.6.2. Prioritisation of Critical Components

The sensitivity analysis presented in Chapter 6 and confirmed in the model scenario results highlights the dominant influence of critical-path components, particularly the power converter. As a series component, the converter directly constrains system availability, and its failure leads to complete interruption of energy delivery regardless of the status of other subsystems.

This finding has clear design implications. Rather than uniformly improving the reliability of all system components, design strategies should prioritise enhancing the reliability of critical components. This may involve:

- selection of higher-quality converter technologies
- implementation of redundancy in power electronics
- improved thermal management and protection systems.
- adoption of preventive maintenance strategies

Such targeted improvements are likely to yield greater performance benefits than equivalent investments in non-critical subsystems, making them more cost-effective in practical applications.

7.6.3. Optimisation of Redundancy and System Configuration

The results also demonstrate the importance of redundancy in enhancing system resilience. The parallel configuration of generation subsystems (PV, battery, and diesel generator) reduces the likelihood of total system failure by providing multiple pathways for energy supply. However, the analysis shows that the benefits of redundancy are subject to diminishing returns, particularly when system performance is constrained by critical series components.

This suggests that optimal SEM system design requires a balance between redundancy and critical component reliability. Excessive redundancy in generation subsystems may not significantly improve overall performance if system availability is limited by a single critical component. Conversely, insufficient redundancy may increase vulnerability to resource variability and subsystem failures.

The proposed modelling framework provides a useful tool for evaluating this trade-off, enabling designers to explore different system configurations and identify optimal design strategies based on both performance and reliability considerations.

7.6.4. Implications for System Planning and Operation

Beyond system design, the findings of this study have important implications for system planning and operational management. The time-varying nature of reliability effects, as demonstrated in Figure 6.11 and Figure 6.12, indicates that system performance degrades over time due to cumulative failure probability. This highlights the need for incorporating reliability considerations into long-term planning and lifecycle analysis.

For example, system planners can use the reliability-integrated model to estimate expected performance over the system lifetime, allowing for better assessment of energy supply reliability and service quality. Similarly, operators can use the model to identify periods of increased vulnerability and implement maintenance or operational strategies to mitigate the impact of subsystem failures.

In addition, the framework can support decision-making related to component replacement, maintenance scheduling, and system upgrades, by quantifying the impact of reliability improvements on overall system performance.

7.6.5. Broader Implications for SEM Deployment

The insights derived from this study are particularly relevant for SEM deployment in developing regions, where reliability is a critical factor in ensuring sustainable energy access. In such contexts, system downtime can have significant economic and social consequences, affecting businesses, healthcare, and daily activities.

The ability to model and predict reliability-adjusted performance provides a valuable tool for policymakers and project developers, enabling more informed decisions regarding system design, investment, and risk management. By incorporating reliability into performance evaluation, it is possible to design systems that not only meet energy demand but also deliver consistent and dependable service.

More broadly, the approach developed in this thesis contributes to the advancement of reliability-aware energy system modelling, with potential applications beyond SEM systems. The principles of integrating performance and reliability can be extended to other hybrid energy systems, microgrids, and renewable energy applications, supporting the development of more robust and resilient energy infrastructures.

7.7. Discussion on Model Theoretical Consistency and Robustness

The application of the proposed reliability-integrated SEM performance models across two simulated scenarios provides a basis for evaluating its theoretical consistency and robustness. This section discusses the extent to which the SEM-RBRM models capture system behaviour under varying operating conditions and examines its applicability beyond the specific scenarios considered in this study.

The hybrid energy systems literature as documented by Diaf *et al.* (2007), Esan *et al.* (2019), Memon and Akbari (2023), Fendzi Mbasso *et al.* (2024) commonly benchmark served-load performance using chronological simulation outputs and benchmarks reliability using probabilistic adequacy and component/system reliability methods such as loss of power supply probability (LPSP), LOLP, LOLE, expected energy not served, capacity outage probability tables, and reliability block or series-system formulations.

Accordingly, the present section establishes theoretical consistency of the three connected models of Eq.(4.3), Eq.(5.1), and Eq.(6.5) from four complementary perspectives: first, statistical adequacy of the fitted relationships; second, engineering plausibility of the signs and magnitudes of the coefficients; third, consistency with accepted served-load and adequacy benchmarks in the mini-grid literature; and fourth, consistency with canonical reliability theory and published subsystem reliability evidence.

7.7.1. Served-Load Benchmark for the TELS Model

The conceptual basis for benchmarking the TELS model is the established notion of TELS in hybrid-system analysis. Lambert, Gilman and Lilienthal (2006) described HOMER as a chronological micropower-system model for simulating the

physical behaviour and life-cycle cost of hybrid systems, while HOMER Energy defines TELS as the electrical energy that goes toward serving primary and deferrable loads. Accordingly, the TELS of Eq.(5.1) is interpreted as an empirical reduced-form representation of an already accepted served-load construct in hybrid mini-grid modelling.

7.7.2. Adequacy Benchmark for Load Service

In the autonomous and islanded hybrid-systems literature, load-service models are typically benchmarked against adequacy indices. Diaf *et al.* (2007) explicitly used LPSP as a core design and benchmark criterion in autonomous hybrid-system sizing, while Esan *et al.* (2019) assessed a PV–diesel–battery mini-grid using a capacity outage probability table and report benchmark values for LOLP, LOLE, and expected load loss. These studies establish loss of power supply probability (LPSP), LOLP, LOLE, and EENS or expected load loss as the most appropriate adequacy benchmarks for the present $TELS_r$ model of Eq.(4.15).

7.7.3. Reliability Benchmark for the R_{SEM} Model

The canonical engineering benchmark for system reliability is the series-system model. Heckert *et al.* (2002) states that when all required subsystems must operate and failures are independent, overall system reliability is obtained by multiplying the reliabilities of the required components. This implies that the present R_{SEM} model should be interpreted as an empirical reliability approximation and checked against a multiplicative benchmark such as $R_{series} = R_{inv} \times R_{pv}$ whenever the inverter and PV subsystem form a required service path.

7.7.4. Engineering Interpretation of the TELS Model Coefficients

The positive coefficient on global solar irradiance is consistent with the expectation that greater solar resource availability should increase renewable generation potential and therefore increase the ability of the mini-grid to serve load. Likewise, the positive coefficient on diesel generator output is physically plausible because the generator directly contributes dispatchable power when renewable production is

inadequate. The positive coefficient on inverter input is also plausible because inverter throughput reflects the conversion pathway by which useful electrical energy is delivered to the load.

The negative coefficient on battery input power is defensible when battery input is interpreted as charging power rather than discharge power. HOMER control guidance distinguishes load-following from cycle-charging operation, and under cycle charging the system may divert surplus generation into the battery rather than directly into the load. Keskinis *et al.* (2025) similarly showed that battery charging can increase after generator-on events under cycle charging. Accordingly, a negative short-run relationship between charging input power and immediate load served is physically reasonable.

The coefficient on time is extremely small and therefore suggests that time is acting only as a weak chronological control. This is consistent with the broader hybrid-systems literature, where time is usually represented through chronological simulation rather than through a dominant direct coefficient. The time variable should therefore be interpreted cautiously and accepted only if residual analysis shows that it is not masking autocorrelation, seasonality, or other omitted temporal structures.

7.7.5. Statistical Validation of the TELS Model

The TELS equation is validated statistically using the coefficient of determination, adjusted coefficient of determination, overall F-statistic, and associated significance level to determine whether the included predictors jointly explain observed variation in served load.

Each coefficient was assessed using its standard error, t-statistic, p-value, and confidence interval, while residual analysis examined linearity, homoscedasticity, residual normality, influential observations, and possible serial dependence.

7.7.6. Predictive and Benchmark Validation of the TELS Model

The regression model is statistically acceptable as it demonstrated predictive value on unseen observations with a test R^2 of 99.16% while using a chronological 70% train–30% test split.

In addition, the TELS equation benchmarks against chronological hybrid-system outputs such as HOMER's served-load results and against adequacy indices such as LPSP, LOLP, LOLE, and EENS.

7.7.7. Reliability Interpretation of the R_{SEM} Model Coefficients

The near-unit coefficient on inverter reliability is strongly supported by the PV reliability literature. Torres Navarro *et al.* (2025) report that the inverter is consistently the least reliable subsystem in PV RAM studies. Baschel *et al.* (2018) showed that inverter and transformer faults account for a major share of photovoltaic-system energy loss, and Li *et al.* (2021) demonstrated that inverter thermal stress significantly degrades system reliability. These findings provide a clear literature basis for treating the inverter as the dominant reliability driver in the present R_{SEM} equation.

The positive but much smaller coefficient on PV reliability is also consistent with the literature, because PV modules are generally more reliable than inverters but are still subject to degradation, fault mechanisms, and environmental stress. The extremely small coefficient on diesel generator reliability, however, should be interpreted cautiously. Marqusee and Don II (2020) showed that even well-maintained single-generator systems have finite outage-survival reliability. Cho, Chun and Hong (2016) and Memon and Akbari (2023) treated the diesel generator as an important adequacy support component in renewable-dominant systems. Therefore, the present R_{gen} coefficient should be tested under low-solar and prolonged-deficit conditions rather than generalized without sensitivity assessment.

7.7.8. Benchmarking the R_{SEM} Model Against Canonical Reliability Theory

A central requirement for the R_{SEM} model is benchmarking against the canonical reliability benchmark for required components. Under the series-system assumption, system reliability is obtained by multiplying the reliabilities of the individual required components. Therefore, the present empirical R_{SEM} equation should be compared with a benchmark form such as $R_{series} = R_{inv} \times R_{pv}$ over the observed operating range.

7.7.9. Benchmarking of the Reliability-Adjusted Served-Load Model

The final connected equation, $TELS_{.r} = TELS * R_{SEM}$, combines gross served-load capability with system dependability. This is conceptually consistent with the adequacy literature because the practical value of a mini-grid depends not only on its nominal generation and conversion capacity, but also on the likelihood that this service pathway remains available during operation. Hybrid-system adequacy studies typically represent this distinction using COPT, LOLP, LOLE, LPSP, FOR rather than nominal power alone.

On this basis, $TELS_{.r}$ can be defended as a reliability-adjusted dependable-load indicator, provided that two conditions are satisfied. First, the $TELS$ model must already be credible as an estimate of gross load served. Second, R_{SEM} must remain a valid bounded reliability measure. If both conditions hold, $TELS_{.r}$ provides a more decision-relevant output than gross served load alone because it reflects service quantity and service dependability together.

7.7.10. Model Robustness Across Scenarios

The results presented in Sections 7.3–7.5 demonstrate that the model consistently captures the relationship between system operation and reliability across distinct environmental contexts. In both the Awka and temperate-climate modelled scenarios, the deterministic model provides a stable baseline representation of system performance, while the reliability-integrated model introduces a consistent and physically meaningful reduction in effective energy delivery.

The key behavioural trends identified in Chapter 6, including the divergence between $TELS(t)$ and $TELS_{.r}(t)$ and the increasing impact of reliability over time, are preserved across both modelled scenarios. This consistency indicates that the model structure is robust to variations in environmental inputs and load profiles. In particular, the ability of the model to reproduce the same qualitative trends under different conditions suggests that the underlying formulation, as defined in Eq.(6.4), is not dependent on a specific dataset but reflects fundamental system behaviour.

Furthermore, the regression-based component of the model, developed in Chapter 5, maintains predictive capability across modelled scenarios without requiring

recalibration. This demonstrates that the selected predictor variables—namely inverter output, generator contribution, and battery power—capture essential system dynamics that remain valid across different operating environments. This finding supports the general applicability of the regression formulation as a surrogate model for SEM performance.

From a methodological perspective, robustness is also reflected in the stability of model outputs under varying input conditions. The absence of erratic or non-physical behaviour in the reliability-adjusted results confirms that the integration of reliability does not introduce instability into the model. Instead, it systematically modifies system performance in accordance with reliability theory, reinforcing the validity of the approach.

7.7.11. Benchmark Against Established Modelling Approaches

Although direct validation against field data is beyond the scope of this study, the model can be evaluated against established theoretical expectations and modelling approaches reported in the literature. In particular, the observed reduction in system performance due to reliability effects is consistent with reliability metrics used in power system adequacy studies, such as EENS and LOLE, where system availability directly influences effective energy delivery.

The reliability-integrated formulation used in this work can be interpreted as a continuous-time analogue of these metrics, providing a time-resolved representation of performance degradation. This alignment with established reliability concepts provides indirect validation of the model, as it demonstrates consistency with well-established theoretical frameworks.

In addition, previous studies on hybrid energy systems have highlighted the importance of incorporating reliability into system evaluation, particularly for off-grid and microgrid applications. However, these studies often rely on stochastic simulation techniques, such as Monte Carlo methods, which, while robust, are complicated. The analytical approach adopted in this work achieves comparable insight into reliability effects while maintaining computational efficiency, representing a practical alternative for system-level analysis.

7.7.12. Extension of the SEM-RBRM with Monte Carlo Simulation

Monte Carlo simulation technique may be employed to extend the capabilities of Eq.(4.15) as expanded in Table 7.1. This can be achieved by defining the operationally possible value boundaries and the probability distributions of Eq.(4.15) predictors as shown in Table 7.2 and Table 7.3 respectively. This will be followed by the pre-determination of the confidence level of the $TELS_r$ mean and the number of simulation scenarios highlighted in Table 7.4. The Monte Carlo simulation yields the descriptive statistics of the model predictors and $TELS_r$ including the mean, standard deviation, median, minimum and maximum values as well as the 95% confidence interval for $TELS_r$ mean (see Table 7.5 and Table 7.6). The simulation can also provide information on the correlation between any of the 2 predictors and that between $TELS_r$ and any of the predictors as shown in Table 7.7 and Figure 7.12. The probability density function as well as the cumulative distribution of $TELS_r$ are highlighted in Figure 7.10 and Figure 7.11. Additionally, contribution to variance of each of predictor variables to $TELS_r$ shown in Figure 7.14 can be established from the simulation while sensitivity analysis of the predictors change influence on $TELS_r$ with predictors independently changed by $\pm$ standard deviation is obtainable as presented in Figure 7.13.

Table 7.1: Model Expression for $TELS_r$

Target	Numeric Expression
$TELS_r$	$(-0.0046 + (0.3940 * \text{Global_Solar}) + (0.48526 * \text{Diesel_Gen_Power_Output}) + (0.94206 * \text{Inverter_Power_Input}) - (0.01455 * \text{Battery_Input_Power}) + (0.00000088 * \text{Time}) * (\text{Rinv} * (1 - (1 - \text{Rpv}) * (1 - \text{Rbat}) * (1 - \text{Rgen})))$

Table 7.2: Monte Carlo Simulation Plan for $TELS_r$

Predictor	Simulation Role	Filters	
		Min	Max
Battery Input Power	Input	.	.
Diesel Gen Power Output	Input	$\geq .00$	.
Global Solar	Input	$\geq .00$	≤ 1.36
Inverter Power Input	Input	$\geq .00$	.
Rbat	Input	$\geq .00$	≤ 1.00
Rgen	Input	$\geq .00$	≤ 1.00
Rinv	Input	$\geq .00$	≤ 1.00
Rpv	Input	$\geq .00$	≤ 1.00
Time	Input	$\geq .00$	.
$TELS_r$	Target	.	.

Table 7.3: Probability Distributions for TELS.r Predictors

Probability Distributions			
Predictor	Distribution Identification		Parameter Value
Battery Input Power	Normal	mean	.170
		stddev	7.991
Diesel Gen Power Output	Normal	mean	.673
		stddev	5.928
Global Solar	Normal	mean	.233
		stddev	.323
Inverter Power Input	Normal	mean	11.803
		stddev	13.735
Rbat	Normal	mean	.999
		stddev	.001
Rgen	Normal	mean	.948
		stddev	.029
Rinv	Normal	mean	.942
		stddev	.033
Rpv	Normal	mean	.995
		stddev	.003
Time	Normal	mean	4380.500
		stddev	2528.939

Table 7.4: Monte Carlo Simulation Stopping Criteria

Stopping Criteria			
Maximum scenarios			100000
Mean within specified precision	Target		TELS.r
	Threshold		1.0%
	Confidence level		95.0%

Table 7.5: Descriptive Statistics of TELS.r Predictors

Predictor	Mean	Std. Deviation	Minimum	Maximum
Battery Input Power	3.099	7.221	-24.36	33.35
Diesel Gen Power Output	4.915	3.649	.00	27.07
Global Solar	.374	.232	.00	1.35
Inverter Power Input	17.164	10.144	.01	60.60
Rbat	.999	.001	1.00	1.00
Rgen	.945	.027	.83	1.00
Rinv	.939	.031	.81	1.00
Rpv	.995	.003	.98	1.00
Time	4632.612	2323.043	1.36	14209.76

Table 7.6: Descriptive Statistics of TELS.r

	Mean	Std. Deviation	Median	Minimum	Maximum	95% Confidence Interval for Mean		Percentiles				
						Lower	Upper	5.0%	25.0%	50.0%	75.0%	95.0%
TELS.r	17.522	9.136	16.514	.11	55.04	17.346	17.697	4.509	10.558	16.514	23.174	34.173

Table 7.7: Correlations between TELS.r Predictors

Correlations									
	Battery Input Power	Diesel Gen Power Output	Global Solar	Inverter Power Input	Rbat	Rgen	Rinv	Rpv	Time
Battery Input Power	1.000	.500	.121	-.215	-.002	-.002	-.002	-.002	.002
Diesel Gen Power Output	.500	1.000	-.044	-.093	-.005	-.005	-.005	-.005	.005
Diesel Gen Power Output	.121	-.044	1.000	.799	.008	.008	.008	.008	-.008
Inverter Power Input	-.215	-.093	.799	1.000	.004	.004	.004	.004	-.004
Global Solar	-.002	-.005	.008	.004	1.000	1.000	1.000	1.000	-1.000
Rgen	-.002	-.005	.008	.004	1.000	1.000	1.000	1.000	-1.000
Inverter Power Input	-.002	-.005	.008	.004	1.000	1.000	1.000	1.000	-1.000
Rpv	-.002	-.005	.008	.004	1.000	1.000	1.000	1.000	-1.000
Rbat	.002	.005	-.008	-.004	-1.000	-1.000	-1.000	-1.000	1.000

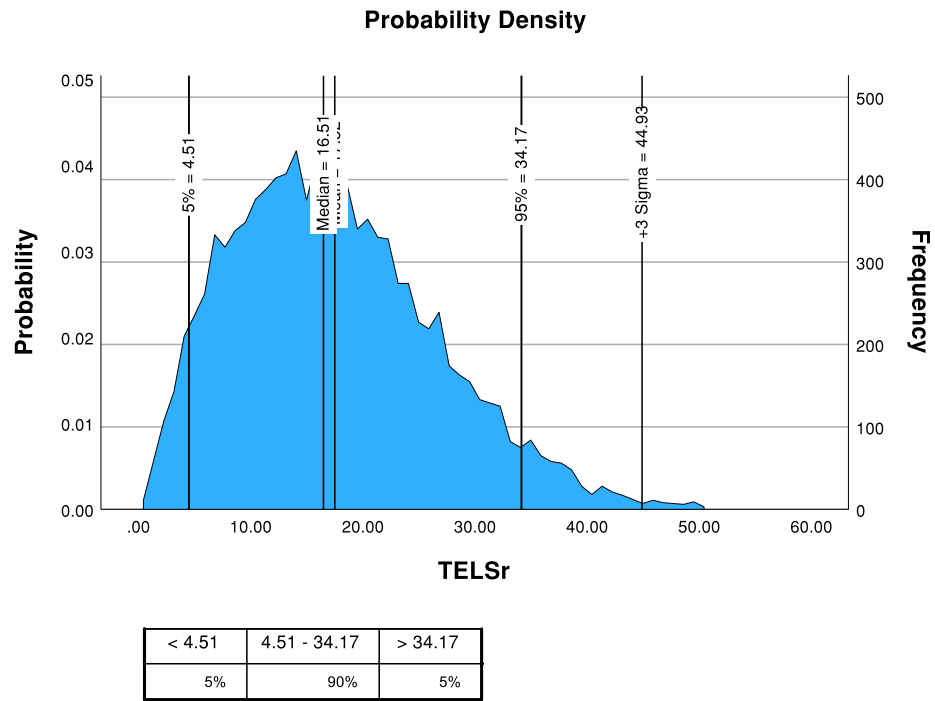


Figure 7.10: Probability Density Function of TELS.r

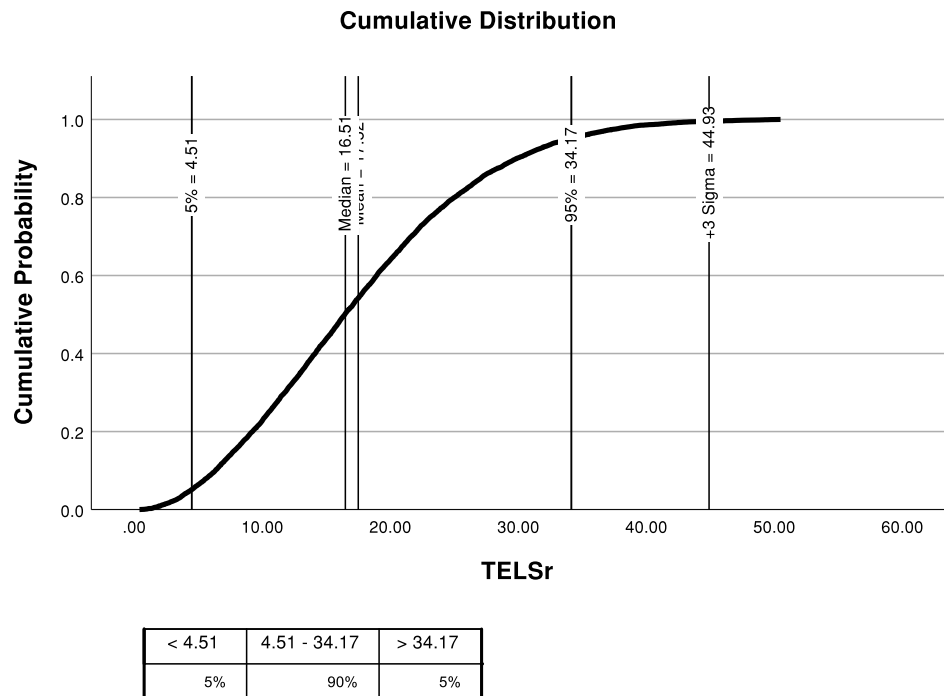


Figure 7.11: Cumulative Distribution of TELS.r

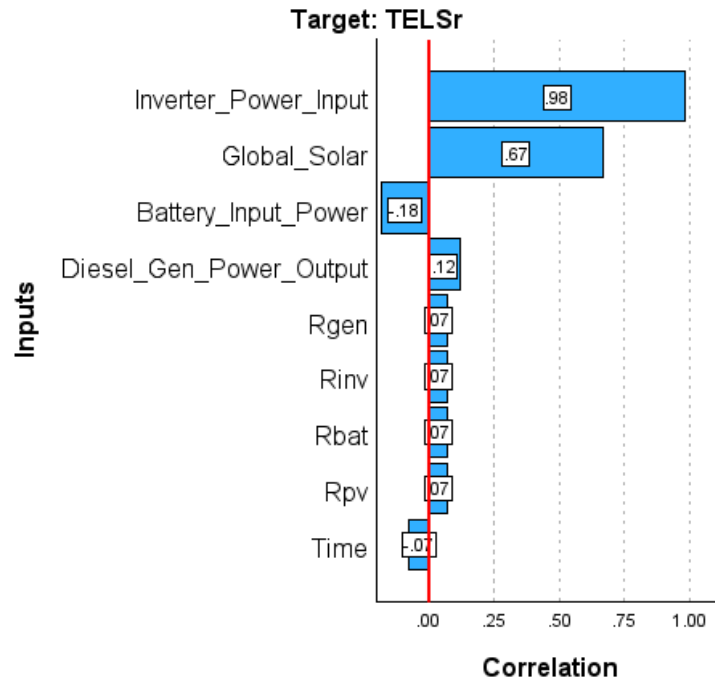


Figure 7.12: Tornado Chart Showing the Correlation between TELSr and SEM-RBRM Predictor Variables

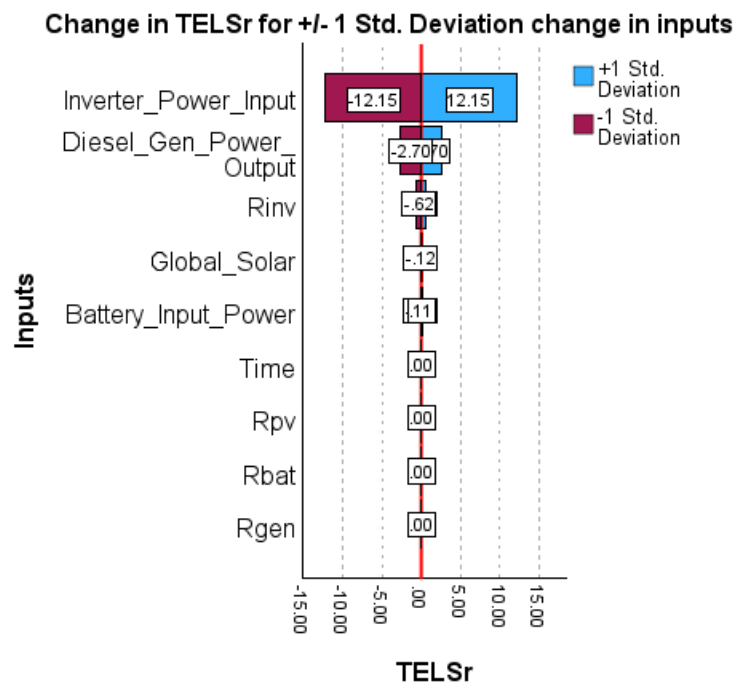


Figure 7.13: SEM Performance Predictors Change Influence on TELS.r with Predictors Independently Changed by $\pm$ Standard Deviation.

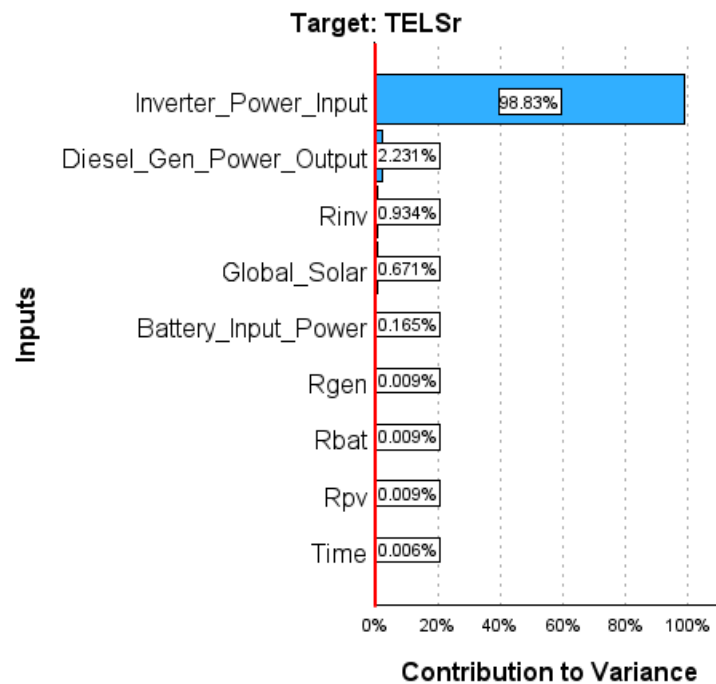


Figure 7.14: Tornado Chart Showing the Contribution to Variance of Each SEM-RBRM Predictor Variables to TELS.r.

7.7.13. Generalisability of the Proposed Framework

The generalisability of the proposed model is partially supported by its modular structure, which separates deterministic performance modelling from reliability evaluation. This separation allows the framework to be adapted to different system configurations and operating conditions without requiring fundamental changes to the model formulation.

The regression-based performance model can be recalibrated using data from different SEM systems, while the reliability component can incorporate alternative failure rate data or more advanced reliability models. As a result, the framework is not likely to be limited to the specific system configuration considered in this study but has the potential of being extended to a wide range of hybrid energy systems, including microgrids with different generation mixes or storage technologies.

The modelled scenarios analyses further demonstrate that the model captures key variations in system behaviour arising from environmental and operational

differences. The consistent identification of critical components, such as the converter, and the observed relationship between resource availability and reliability impact indicate that the model reflects fundamental system characteristics rather than scenario-specific behaviour.

7.7.14. Limitations in Validation and Scope

While the results demonstrate significant model consistency and theoretical validity, certain limitations must be acknowledged. The use of simulated data for model development and validation introduces uncertainty regarding field-deployed applicability. Although HOMER provides a widely accepted platform for energy system simulation, field-deployed system performance may be influenced by factors not captured in the model, such as maintenance practices, operational constraints, and environmental degradation.

Additionally, the assumption of constant failure rates simplifies the reliability analysis but does not account for infant mortality, wear-out processes or failure dependencies. Incorporating Weibull distributions or condition-based failure modelling, could further enhance the robustness of the framework.

Despite these limitations, the consistency of results across model scenarios and alignment with established reliability theory provide strong evidence of model validity at the system level.

7.8. Summary

This chapter has applied the reliability-integrated SEM performance model, developed in Chapters 5 and 6, to representative model scenarios in order to evaluate its practical applicability, robustness, and generalisability. By considering contrasting operating environments, the analysis has demonstrated how system performance varies under different environmental and load conditions, and how these variations influence the impact of subsystem reliability on effective energy delivery.

The deterministic SEM model was first applied to establish baseline system performance, showing clear differences between model scenarios driven by variations in solar resource availability and load characteristics. The reliability-integrated model was

then implemented to account for subsystem availability, resulting in a consistent reduction in effective load served across all scenarios. The comparison between deterministic and reliability-adjusted performance confirmed that conventional modelling approaches systematically overestimate system output, particularly over extended operating periods.

Comparative analysis across model scenarios showed that the magnitude of reliability impact is strongly dependent on operating conditions. Systems operating in high-resource environments exhibited greater resilience to subsystem failures, while systems in more constrained environments demonstrated increased sensitivity to reliability effects. These findings confirm that reliability must be evaluated in the context of both system configuration and environmental conditions.

The validation results demonstrated that the proposed modelling framework maintains consistent behaviour across different scenarios, capturing key relationships between system operation and reliability without requiring structural modification. This confirms the robustness and general applicability of the approach, supporting its use as a practical tool for SEM system evaluation and design.

In addition, the chapter has provided important design and operational insights, highlighting the need for reliability-aware system design, prioritisation of critical components, and consideration of long-term system performance. The findings emphasise that integrating reliability into SEM modelling is essential for actual performance assessment and informed decision-making in field-deployed applications.

Overall, the chapter has validated the reliability-integrated modelling framework and demonstrated its capability to provide scalable, and practically relevant insights into SEM system behaviour. This establishes a strong foundation for the final chapter, which summarises the key contributions of the research and outlines directions for future work.

Chapter 8: Conclusions and Future Work

8.1. Conclusions

This research has developed and partially validated a reliability-integrated modelling framework for SEM systems, addressing a key limitation in conventional deterministic approaches. The results demonstrate that subsystem reliability has a measurable and time-varying impact on system performance, and that neglecting reliability leads to systematic overestimation of energy delivery.

Quantitative analysis indicates that the inclusion of reliability reduces the effective $TELS(t)$ compared to deterministic predictions, with performance reductions increasing over time. Across the model scenarios considered, the reliability-integrated model showed that performance degradation was initially negligible (typically less than 2–5% during early operation), but increased progressively with operating time, reaching significant levels under extended operation. In the temperate-climate model scenario, where renewable resource availability is lower, the percentage reduction in energy delivery was observed to exceed that of the high-resource Awka scenario by a noticeable margin, indicating greater sensitivity to subsystem failures.

The regression-based performance model developed in Chapter 5 achieved a high coefficient of determination ($R^2 \approx 0.99$), confirming that key operational variables—namely inverter output, generator contribution, and battery power—capture over 99% of the variability in deterministic SEM performance. However, the results clearly show that this deterministic model represents an upper performance bound, as it assumes continuous system availability and does not account for failure behaviour.

The reliability analysis identified the power converter as the most critical component influencing system performance. Due to its series configuration within the SEM architecture, system reliability is directly proportional to converter reliability, as defined in Eq.(4.13). Sensitivity analysis demonstrated that a marginal improvement in converter reliability produces a disproportionately large increase in system performance compared to equivalent improvements in generation subsystems. In contrast, improvements in PV, battery, or generator reliability resulted in diminishing returns due

to their parallel configuration, confirming the theoretical expectations of redundancy in reliability systems.

The integration of reliability with the deterministic model provides a unified analytical framework that links system performance directly to subsystem availability. This formulation enables continuous, time-varying quantification of performance degradation and avoids the complexity associated with stochastic simulation methods such as Monte Carlo analysis, while still capturing key reliability effects.

Application of the model across two model scenarios demonstrated consistent behaviour and confirmed the generalisability of the framework. The results showed that systems operating under high solar resource conditions exhibited greater resilience, with smaller performance deviations between $TELS(t)$ and $TELS_{,r}(t)$, whereas systems in lower-resource environments exhibited higher performance degradation and increased dependence on backup generation. This confirms that the impact of reliability is strongly dependent on environmental conditions and system operating regime.

From a broader perspective, this research makes several key contributions. First, it introduces a coupled performance–reliability modelling framework that integrates subsystem failure behaviour directly into SEM performance evaluation. Second, it demonstrates that system configuration—particularly the interaction between series and parallel subsystems—plays a significant role in determining reliability outcomes. Third, it provides a simple and scalable modelling approach that can be applied to SEM systems without requiring extensive stochastic simulation.

In conclusion, the findings confirm that incorporating reliability into SEM modelling is essential for a more representative system evaluation. The proposed framework provides an enhanced tool for quantifying the impact of subsystem failures on energy delivery, enabling more informed system design, planning, and operation. By bridging the gap between deterministic modelling and reliability engineering, this research contributes to the development of more resilient and reliable hybrid energy systems. The objectives of this PhD have been achieved in the corresponding chapters as follows: objective 1 → chapter 2; objective 2 → chapter 3,4,5 presented by Eq.(5.1) and Eq.(5.3); objective 3 → chapter 4,5,6 shown by Eq. (4.2), (4.3), (4.5) to (4.7); objective 4 → chapter 7.

8.2. Contributions to Knowledge

The following original contributions to knowledge were made by this PhD:

1. it was established from literature a fundamental modelling assumption embedded within most SEM optimisation frameworks where installed subsystem capacity is typically assumed to be continuously available throughout the simulation horizon. It further determined that SEM subsystem behaviours introduce stochastic variations in system availability that are not captured by deterministic modelling approaches. Consequently, this work reinforced the notion that quantity of electricity delivered by a SEM over its operational lifetime depends not only on environmental resource availability but also on the stochastic reliability behaviour of its constituent subsystems.
2. it introduces a unified reliability-based regression modelling framework for SEMs that directly links subsystem failure rates to system-level energy delivery. This was achieved by combining three key elements: time-series simulation data representing system operation, reliability modelling based on RBD, and regression-based statistical modelling to establish relationships between system variables and energy delivery.
3. it integrates reliability engineering concepts into performance prediction rather than treating reliability as a separate post-design assessment. This enables the evaluation of SEM systems under more actual conditions, where energy delivery is constrained not only by resource availability and system configuration but also by the probability of component failure.
4. Finally, by framing system performance prediction as a reliability-constrained regression problem, the research introduces a scalable surrogate modelling approach that bridges detailed reliability analysis and early-stage design decision making.

8.3. Limitations

While the proposed framework provides significant improvements over conventional approaches, certain limitations must be acknowledged.

The assumption of subsystem non-repairability and constant failure rates simplifies the analysis but does not capture complex degradation and ageing mechanisms or maintenance effects. In practice, component failure rates may vary over time, particularly for systems subject to environmental stress and operational cycling. Incorporating more advanced reliability models predicated on Weibull distributions or condition-based failure modelling, could further enhance the efficiency of the framework.

Furthermore, the RBD-based reliability model assumptions highlighted in Section 4.5.4 may not capture detailed component-level degradation behaviour.

Additionally, the model assumes independent subsystem failures, which may not fully represent field conditions where failure events can be correlated. Incorporating dependency effects would further enhance the robustness of the model with its attendant complex modelling approaches.

Moreso, the model assumes simplified operating and environmental conditions with limited generalisability to real-world SEM systems.

Finally, the regression model is based on HOMER simulated data and may not fully capture field-deployed SEM variability. Validation using field or experimental data would provide additional confidence in the model's applicability.

These limitations provide opportunities for future research, particularly in extending the framework to include maintenance strategies, and stochastic modelling approaches.

8.4. Future Work

While the proposed reliability-integrated SEM modelling framework provides a robust and analytically efficient approach for evaluating system performance, several areas remain for further investigation and development. These opportunities for future work aim to enhance the accuracy, applicability, and practical relevance of the model.

One key area for future research is the incorporation of condition-dependent failure models. In this study, subsystem reliability was represented using constant failure rates and exponential distributions, which provide a simplified but tractable

approximation of failure behaviour. However, field-deployed components often exhibit non-constant failure rates due to ageing, wear, and environmental stress. Future work could extend the model to include Weibull or other non-exponential reliability distributions, enabling more robust representation of component degradation over time.

Another important extension involves the inclusion of maintenance and repair strategies. The current model assumes non-repairable systems, focusing on failure probability rather than system recovery. In practice, SEM systems are subject to maintenance interventions, component replacement, and repair cycles. Incorporating repairable system models, such as availability-based formulations or Markov processes, would allow evaluation of maintenance policies and their impact on long-term system performance.

The integration of stochastic modelling approaches represents a further area for development. While the analytical formulation proposed in this thesis provides computational efficiency, it does not explicitly capture random variability in failure events. Future work could further extend the proposed framework with Monte Carlo simulation techniques to assess results under probabilistic scenarios and assess uncertainty in system performance.

In addition, the regression-based performance model developed in this study could be enhanced through the use of advanced data-driven techniques, such as machine learning or nonlinear modelling approaches. While the linear regression model achieved significant predictive accuracy, more complex models may capture nonlinear interactions between system variables, particularly under extreme operating conditions or in larger, more complex systems.

Another area for future research is the application of the framework to diverse SEM configurations and larger scale microgrid systems. The current study focuses on a specific hybrid configuration consisting of PV, battery, generator, and converter subsystems. Extending the model to include additional technologies, such as wind generation, hybrid storage systems, or grid-connected configurations, would further demonstrate its general applicability.

Furthermore, validation using field-deployed operational data represents a crucial step for future work. While the current study relies on simulation data from

HOMER, field data from operational SEM systems would provide valuable insight into actual system behaviour and enable calibration and validation of both the regression and reliability components of the model.

Finally, the framework could be extended to support optimisation and decision-making applications, such as system sizing, component selection, and cost–reliability trade-off analysis. Integrating economic considerations with reliability-aware performance modelling would enable a more comprehensive evaluation of SEM systems, supporting both technical and financial decision-making.

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Appendix A: Regression Model Results – Awka Scenario

Method

Test set fraction 30.0%

Regression Equation

TELS = -0.0046
 (kW) + 0.3940*Global Solar (kW/m²)
 + 0.48526*DGen Power Output (kW)
 + 0.94206*Inverter Power Input (kW)
 - 0.01455*Battery Input Power (kW)
 + 0.00000088*Time (hr)

Coefficients

Term	Coef	SE Coef	95% CI	T-Value	P-Value
Constant	-0.0046	0.0261	(-0.0558, 0.0467)	-0.17	0.861
Global Solar (kW/ m ²)	0.3940	0.0737	(0.2495, 0.5385)	5.34	0.000
Diesel Gen Power Output (kW)	0.48526	0.00246	(0.48044, 0.49008)	197.30	0.000
Inverter Power Input (kW)	0.94206	0.00176	(0.93862, 0.94550)	536.34	0.000
Battery Input Power (kW)	-0.01455	0.00208	(-0.01863, -0.01046)	-6.99	0.000
Time (hr)	0.000001	0.000005	(-0.000008, 0.000010)	0.19	0.851
Term	VIF				
Constant					
Global Solar (kW/m ²)	4.02				
Diesel Gen Power Output (kW)	1.38				
Inverter Power Input (kW)	4.09				
Battery Input Power (kW)	1.92				
Time (hr)	1.00				

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC	Test S	Test R-sq
0.936604	99.49%	99.49%	5496.25	99.48%	16606.65	16653.68	1.20503	99.16%

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value
Regression	5	1058090	99.49%	1058090	211618	241235.10
Global Solar (kW/m2)	1	661005	62.16%	25	25	28.57

Diesel Gen Power Output (kW)	1	25339	2.38%	34149	34149	38928.60
Inverter Power Input (kW)	1	371703	34.95%	252343	252343	287659.85
Battery Input Power (kW)	1	43	0.00%	43	43	48.80
Time (hr)	1	0	0.00%	0	0	0.04
Error	6126	5374	0.51%	5374	1	
Total	6131	1063464	100.00%			
Source	P-Value					
Regression	0.000					
Global Solar (kW/m ²)	0.000					
Diesel Gen Power Output (kW)	0.000					
Inverter Power Input (kW)	0.000					
Battery Input Power (kW)	0.000					
Time (hr)	0.851					
Error						
Total						

Fits and Diagnostics for Unusual Observations

Training Set

Obs	TELS (kW)	Fit	SE Fit	95% CI	Resid	Std Resid	Del Resid
139	25.7837	25.9640	0.0522	(25.8616, 26.0664)	-0.1803	-0.19	-0.19
153	10.2610	9.9328	0.0553	(9.8244, 10.0411)	0.3282	0.35	0.35
202	36.6741	36.3680	0.0563	(36.2576, 36.4784)	0.3061	0.33	0.33
211	26.9764	27.1640	0.0542	(27.0579, 27.2702)	-0.1876	-0.20	-0.20
225	15.0924	14.7230	0.0593	(14.6068, 14.8392)	0.3694	0.40	0.40
803	21.6173	21.2690	0.0564	(21.1584, 21.3796)	0.3483	0.37	0.37
949	38.5590	38.6486	0.0529	(38.5449, 38.7522)	-0.0896	-0.10	-0.10
952	34.0695	27.6472	0.1219	(27.4081, 27.8862)	6.4223	6.92	6.94
955	25.4962	27.6586	0.1220	(27.4194, 27.8979)	-2.1624	-2.33	-2.33
956	0.3547	13.4323	0.0645	(13.3059, 13.5587)	-13.0776	-14.00	-14.22
979	21.3771	27.5707	0.1221	(27.3314, 27.8100)	-6.1936	-6.67	-6.69
1381	16.2233	16.5278	0.0606	(16.4091, 16.6466)	-0.3045	-0.33	-0.33
1473	18.0735	27.5844	0.1218	(27.3457, 27.8231)	-9.5109	-10.24	-10.33
1474	15.9347	15.3998	0.0696	(15.2633, 15.5362)	0.5349	0.57	0.57
1526	45.8271	38.2082	0.0407	(38.1284, 38.2880)	7.6189	8.14	8.19
1546	19.3239	19.0330	0.0525	(18.9301, 19.1359)	0.2909	0.31	0.31
1793	22.1665	27.5516	0.1219	(27.3127, 27.7905)	-5.3851	-5.80	-5.81
1794	11.4136	15.0717	0.0677	(14.9390, 15.2043)	-3.6581	-3.92	-3.92
2146	23.9480	27.5899	0.1214	(27.3520, 27.8278)	-3.6419	-3.92	-3.93
2151	29.0762	27.6174	0.1213	(27.3796, 27.8551)	1.4588	1.57	1.57
2154	27.4252	27.6588	0.1214	(27.4209, 27.8967)	-0.2336	-0.25	-0.25
2197	26.1070	25.7829	0.0521	(25.6808, 25.8849)	0.3241	0.35	0.35
2316	38.1377	37.7981	0.0585	(37.6834, 37.9129)	0.3396	0.36	0.36
2338	25.3576	24.8872	0.0740	(24.7422, 25.0322)	0.4704	0.50	0.50

2443	29.0894	29.2734	0.0514	(29.1726, 29.3742)	-0.1840	-0.20	-0.20
2461	27.9440	27.5797	0.0598	(27.4625, 27.6969)	0.3643	0.39	0.39
2603	29.4913	27.6354	0.1211	(27.3980, 27.8728)	1.8559	2.00	2.00
2607	32.9489	27.6260	0.1212	(27.3884, 27.8635)	5.3229	5.73	5.75
2608	28.0112	17.0875	0.0763	(16.9380, 17.2370)	10.9237	11.70	11.83
2865	14.6407	14.3159	0.0514	(14.2151, 14.4167)	0.3248	0.35	0.35
2918	13.6958	13.9698	0.0535	(13.8649, 14.0747)	-0.2740	-0.29	-0.29
2964	40.3511	40.4937	0.0583	(40.3794, 40.6080)	-0.1426	-0.15	-0.15
2987	23.7945	23.4325	0.0568	(23.3211, 23.5439)	0.3620	0.39	0.39
2988	31.9926	31.5868	0.0648	(31.4597, 31.7139)	0.4058	0.43	0.43
2995	20.1617	27.6079	0.1211	(27.3706, 27.8452)	-7.4462	-8.02	-8.06
2996	0.2144	12.7199	0.0597	(12.6029, 12.8369)	-12.5055	-13.38	-13.58
3084	32.0562	27.7597	0.1227	(27.5193, 28.0002)	4.2965	4.63	4.63
3085	24.8111	27.6581	0.1211	(27.4206, 27.8956)	-2.8470	-3.07	-3.07
3185	31.3048	27.5449	0.1220	(27.3058, 27.7840)	3.7599	4.05	4.05
3186	19.6102	16.2772	0.0716	(16.1368, 16.4176)	3.3330	3.57	3.57
3254	31.1583	27.6774	0.1211	(27.4399, 27.9148)	3.4809	3.75	3.75
3255	29.0387	24.3966	0.1070	(24.1869, 24.6062)	4.6421	4.99	5.00
3275	19.2389	27.4309	0.1245	(27.1868, 27.6750)	-8.1920	-8.82	-8.88
3302	35.1012	34.5752	0.0835	(34.4115, 34.7389)	0.5260	0.56	0.56
3419	20.0159	19.6223	0.0615	(19.5017, 19.7429)	0.3936	0.42	0.42
3442	26.7913	27.5816	0.1211	(27.3441, 27.8190)	-0.7903	-0.85	-0.85
3445	43.5563	27.8723	0.1260	(27.6254, 28.1193)	15.6840	16.90	17.31
3446	45.0966	27.7570	0.1222	(27.5174, 27.9966)	17.3396	18.67	19.23
3449	36.0360	27.7967	0.1235	(27.5546, 28.0387)	8.2393	8.87	8.93
3595	30.4283	30.6194	0.0540	(30.5134, 30.7253)	-0.1911	-0.20	-0.20
3619	28.6086	28.8239	0.0528	(28.7205, 28.9274)	-0.2153	-0.23	-0.23
3661	38.7352	27.6815	0.1212	(27.4440, 27.9190)	11.0537	11.90	12.04
3683	29.5949	27.5848	0.1211	(27.3473, 27.8222)	2.0101	2.16	2.17
3684	24.2310	17.8529	0.0785	(17.6989, 18.0068)	6.3781	6.83	6.86
3687	31.3658	31.5243	0.0510	(31.4244, 31.6242)	-0.1585	-0.17	-0.17
3729	13.7989	27.5222	0.1217	(27.2835, 27.7608)	-13.7233	-14.78	-15.05
3730	18.5824	18.2477	0.0814	(18.0882, 18.4072)	0.3347	0.36	0.36
3826	22.9493	22.9922	0.1008	(22.7946, 23.1899)	-0.0429	-0.05	-0.05
3850	23.2149	27.5350	0.1216	(27.2966, 27.7735)	-4.3201	-4.65	-4.66
3873	16.6129	27.5120	0.1219	(27.2730, 27.7510)	-10.8991	-11.74	-11.87
3874	16.6026	8.8427	0.0442	(8.7561, 8.9292)	7.7599	8.29	8.34
3921	14.5710	14.1630	0.0656	(14.0344, 14.2916)	0.4080	0.44	0.44
4051	23.4658	27.6420	0.1209	(27.4049, 27.8790)	-4.1762	-4.50	-4.50
4052	0.1811	11.3671	0.0532	(11.2627, 11.4715)	-11.1860	-11.96	-12.10
4236	35.5215	27.7280	0.1216	(27.4895, 27.9665)	7.7935	8.39	8.44
4237	33.6421	20.3471	0.0541	(20.2410, 20.4532)	13.2950	14.22	14.46
4243	21.4263	22.9416	0.1004	(22.7449, 23.1384)	-1.5153	-1.63	-1.63
4262	27.5971	27.2330	0.0576	(27.1201, 27.3459)	0.3641	0.39	0.39
4284	21.1144	20.7332	0.0595	(20.6165, 20.8498)	0.3812	0.41	0.41
4305	11.8381	11.4500	0.0629	(11.3267, 11.5733)	0.3881	0.42	0.42
4507	20.9238	27.6172	0.1208	(27.3804, 27.8541)	-6.6934	-7.21	-7.24

4508	0.1986	12.3426	0.0576	(12.2296, 12.4556)	-12.1440	-12.99	-13.17
4525	11.8571	12.1235	0.0514	(12.0227, 12.2244)	-0.2664	-0.28	-0.28
4556	1.3127	18.6359	0.0858	(18.4676, 18.8041)	-17.3232	-18.57	-19.12
4835	22.6712	27.5083	0.1222	(27.2687, 27.7479)	-4.8371	-5.21	-5.22
4836	25.2073	14.3432	0.0459	(14.2532, 14.4331)	10.8641	11.61	11.74
4840	29.7767	27.6087	0.1209	(27.3717, 27.8458)	2.1680	2.33	2.34
4841	31.2874	31.4472	0.0509	(31.3474, 31.5469)	-0.1598	-0.17	-0.17
4914	18.9783	27.4969	0.1224	(27.2571, 27.7368)	-8.5186	-9.17	-9.24
4934	15.7723	16.0538	0.0542	(15.9475, 16.1601)	-0.2815	-0.30	-0.30
4963	30.1625	30.3402	0.0508	(30.2407, 30.4398)	-0.1777	-0.19	-0.19
4977	15.0561	14.6574	0.0639	(14.5321, 14.7827)	0.3987	0.43	0.43
5034	17.9030	27.5379	0.1215	(27.2997, 27.7762)	-9.6349	-10.37	-10.47
5035	10.6775	17.3563	0.0770	(17.2054, 17.5072)	-6.6788	-7.16	-7.18
5052	31.3154	30.9760	0.0553	(30.8677, 31.0843)	0.3394	0.36	0.36
5054	33.1157	33.2867	0.0541	(33.1806, 33.3928)	-0.1710	-0.18	-0.18
5056	36.1530	36.2978	0.0538	(36.1924, 36.4033)	-0.1448	-0.15	-0.15
5058	31.2290	27.6919	0.1212	(27.4543, 27.9295)	3.5371	3.81	3.81
5059	16.9580	22.2126	0.0974	(22.0217, 22.4035)	-5.2546	-5.64	-5.66
5078	37.9320	27.8524	0.1254	(27.6065, 28.0983)	10.0796	10.86	10.96
5081	21.0463	27.5940	0.1210	(27.3569, 27.8312)	-6.5477	-7.05	-7.08
5082	22.1261	23.7558	0.1039	(23.5520, 23.9595)	-1.6297	-1.75	-1.75
5102	25.3452	27.5402	0.1217	(27.3016, 27.7787)	-2.1950	-2.36	-2.36
5130	22.4972	27.6194	0.1209	(27.3823, 27.8564)	-5.1222	-5.52	-5.53
5362	25.5891	27.6522	0.1210	(27.4150, 27.8895)	-2.0631	-2.22	-2.22
5365	30.6578	27.6081	0.1210	(27.3708, 27.8454)	3.0497	3.28	3.29
5366	21.0462	11.9671	0.0574	(11.8545, 12.0796)	9.0791	9.71	9.79
5385	12.1132	11.7215	0.0631	(11.5978, 11.8452)	0.3917	0.42	0.42
5443	30.4977	30.6808	0.0522	(30.5784, 30.7831)	-0.1831	-0.20	-0.20
5605	42.1661	41.8746	0.0550	(41.7667, 41.9824)	0.2915	0.31	0.31
5628	45.5365	38.1776	0.0489	(38.0817, 38.2734)	7.3589	7.87	7.91
5650	22.6825	22.2333	0.0709	(22.0944, 22.3722)	0.4492	0.48	0.48
5724	42.3287	27.8146	0.1238	(27.5719, 28.0573)	14.5141	15.63	15.95
5725	35.5312	19.4853	0.0862	(19.3163, 19.6543)	16.0459	17.21	17.64
5729	37.1014	27.8156	0.1241	(27.5723, 28.0589)	9.2858	10.00	10.08
5774	25.2044	24.7949	0.0650	(24.6674, 24.9224)	0.4095	0.44	0.44
5824	30.6434	27.7000	0.1215	(27.4619, 27.9382)	2.9434	3.17	3.17
5825	25.9036	26.7794	0.1175	(26.5490, 27.0098)	-0.8758	-0.94	-0.94
5843	15.8412	15.4200	0.0672	(15.2884, 15.5517)	0.4212	0.45	0.45
5899	28.6252	28.8053	0.0511	(28.7050, 28.9056)	-0.1801	-0.19	-0.19
5985	13.2701	12.9171	0.0582	(12.8030, 13.0312)	0.3530	0.38	0.38
6080	1.6730	1.3742	0.0514	(1.2735, 1.4750)	0.2988	0.32	0.32
6109	41.7481	41.8408	0.0545	(41.7340, 41.9476)	-0.0927	-0.10	-0.10
6111	35.3187	27.6474	0.1212	(27.4098, 27.8851)	7.6713	8.26	8.31
6134	42.9255	43.1644	0.0728	(43.0218, 43.3071)	-0.2389	-0.26	-0.26
6137	25.8752	27.5414	0.1219	(27.3024, 27.7805)	-1.6662	-1.79	-1.79
6138	26.6670	18.0496	0.0797	(17.8933, 18.2060)	8.6174	9.23	9.30
6181	19.7758	20.0433	0.0524	(19.9405, 20.1461)	-0.2675	-0.29	-0.29

6307	28.6748	28.8789	0.0545	(28.7720, 28.9857)	-0.2041	-0.22	-0.22
6355	26.7491	26.9395	0.0511	(26.8394, 27.0396)	-0.1904	-0.20	-0.20
6369	15.9284	15.6081	0.0560	(15.4983, 15.7179)	0.3203	0.34	0.34
6396	16.2136	16.4808	0.0522	(16.3784, 16.5831)	-0.2672	-0.29	-0.29
6540	18.7231	19.0185	0.0575	(18.9057, 19.1313)	-0.2954	-0.32	-0.32
6541	24.1972	24.4591	0.0524	(24.3564, 24.5619)	-0.2619	-0.28	-0.28
6635	24.2643	23.7180	0.0864	(23.5487, 23.8873)	0.5463	0.59	0.59
6708	19.0210	19.2960	0.0541	(19.1900, 19.4020)	-0.2750	-0.29	-0.29
6805	44.4848	44.2339	0.0532	(44.1296, 44.3381)	0.2509	0.27	0.27
6807	46.8790	39.4499	0.0443	(39.3630, 39.5367)	7.4291	7.94	7.98
6896	1.6527	1.3531	0.0514	(1.2524, 1.4538)	0.2996	0.32	0.32
6970	23.2940	22.9431	0.0564	(22.8326, 23.0536)	0.3509	0.38	0.38
7016	1.7439	1.4409	0.0519	(1.3392, 1.5426)	0.3030	0.32	0.32
7027	24.5710	27.6856	0.1220	(27.4465, 27.9247)	-3.1146	-3.35	-3.36
7028	0.2637	14.0464	0.0665	(13.9160, 14.1768)	-13.7827	-14.75	-15.02
7166	50.9380	43.4177	0.0443	(43.3309, 43.5044)	7.5203	8.04	8.08
7171	26.6669	26.8551	0.0518	(26.7534, 26.9567)	-0.1882	-0.20	-0.20
7267	27.7536	27.9494	0.0539	(27.8437, 28.0550)	-0.1958	-0.21	-0.21
7291	28.2787	28.4781	0.0549	(28.3705, 28.5856)	-0.1994	-0.21	-0.21
7305	13.1399	12.8411	0.0526	(12.7380, 12.9442)	0.2988	0.32	0.32
7328	1.4543	1.1428	0.0534	(1.0380, 1.2476)	0.3115	0.33	0.33
7399	1.7306	14.9571	0.0735	(14.8130, 15.1012)	-13.2265	-14.17	-14.40
7580	0.1574	11.5232	0.0560	(11.4134, 11.6329)	-11.3658	-12.16	-12.31
7603	14.4453	27.5459	0.1224	(27.3059, 27.7858)	-13.1006	-14.11	-14.34
7691	24.8250	24.4508	0.0608	(24.3316, 24.5701)	0.3742	0.40	0.40
7747	29.7016	29.9112	0.0580	(29.7975, 30.0248)	-0.2096	-0.22	-0.22
7761	7.0124	6.6394	0.0619	(6.5180, 6.7608)	0.3730	0.40	0.40
7762	12.0875	11.7524	0.0575	(11.6397, 11.8650)	0.3351	0.36	0.36
8003	30.3711	29.9391	0.0704	(29.8012, 30.0770)	0.4320	0.46	0.46
8026	17.2313	16.8881	0.0603	(16.7700, 17.0063)	0.3432	0.37	0.37
8083	25.7428	25.9257	0.0515	(25.8248, 26.0267)	-0.1829	-0.20	-0.20
8127	44.6921	44.6496	0.0512	(44.5492, 44.7501)	0.0425	0.05	0.05
8145	15.8395	15.4113	0.0687	(15.2767, 15.5458)	0.4282	0.46	0.46
8203	26.5624	26.7513	0.0531	(26.6473, 26.8554)	-0.1889	-0.20	-0.20
8216	1.7647	1.4543	0.0537	(1.3491, 1.5596)	0.3104	0.33	0.33
8251	26.5847	26.7736	0.0532	(26.6692, 26.8779)	-0.1889	-0.20	-0.20
8295	35.3122	35.4658	0.0567	(35.3546, 35.5769)	-0.1536	-0.16	-0.16
8296	30.0714	27.7343	0.1233	(27.4926, 27.9761)	2.3371	2.52	2.52
8297	25.4553	24.7661	0.1099	(24.5507, 24.9815)	0.6892	0.74	0.74
8408	1.6908	1.4027	0.0507	(1.3032, 1.5022)	0.2881	0.31	0.31
8456	1.6826	1.3753	0.0535	(1.2703, 1.4803)	0.3073	0.33	0.33
8467	29.5254	29.7365	0.0586	(29.6216, 29.8514)	-0.2111	-0.23	-0.23
8510	37.1022	27.8106	0.1252	(27.5651, 28.0561)	9.2916	10.01	10.09
8515	16.6047	18.5637	0.0838	(18.3994, 18.7280)	-1.9590	-2.10	-2.10
8611	27.0062	27.1995	0.0545	(27.0927, 27.3064)	-0.1933	-0.21	-0.21
8625	21.3639	20.9102	0.0727	(20.7676, 21.0527)	0.4537	0.49	0.49
8683	25.1327	25.3141	0.0514	(25.2133, 25.4150)	-0.1814	-0.19	-0.19

8707	26.1930	26.3825	0.0532	(26.2781, 26.4868)		-0.1895	-0.20	-0.20
Obs	HI	Cook's D	DFITS					
139	0.0031104	0.00	-0.01077		X			
153	0.0034839	0.00	0.02076		X			
202	0.0036157	0.00	0.01972		X			
211	0.0033443	0.00	-0.01162		X			
225	0.0040035	0.00	0.02505		X			
803	0.0036259	0.00	0.02247		X			
949	0.0031864	0.00	-0.00541		X			
952	0.0169455	0.14	0.91149	R	X			
955	0.0169787	0.02	-0.30615	R	X			
956	0.0047416	0.16	-0.98179	R	X			
979	0.0169873	0.13	-0.87991	R	X			
1381	0.0041844	0.00	-0.02112		X			
1473	0.0168987	0.30	-1.35429	R	X			
1474	0.0055209	0.00	0.04267		X			
1526	0.0018888	0.02	0.35610	R				
1546	0.0031427	0.00	0.01747		X			
1793	0.0169291	0.10	-0.76302	R	X			
1794	0.0052195	0.01	-0.28398	R	X			
2146	0.0167875	0.04	-0.51301	R	X			
2151	0.0167638	0.01	0.20513		X			
2154	0.0167919	0.00	-0.03287		X			
2197	0.0030907	0.00	0.01930		X			
2316	0.0039048	0.00	0.02274		X			
2338	0.0062352	0.00	0.03990		X			
2443	0.0030153	0.00	-0.01082		X			
2461	0.0040746	0.00	0.02493		X			
2603	0.0167153	0.01	0.26060		X			
2607	0.0167359	0.09	0.74969	R	X			
2608	0.0066328	0.15	0.96700	R	X			
2865	0.0030138	0.00	0.01909		X			
2918	0.0032636	0.00	-0.01677		X			
2964	0.0038778	0.00	-0.00952		X			
2987	0.0036831	0.00	0.02354		X			
2988	0.0047907	0.00	0.03013		X			
2995	0.0167044	0.18	-1.05042	R	X			
2996	0.0040587	0.12	-0.86678	R	X			
3084	0.0171543	0.06	0.61232	R	X			
3085	0.0167305	0.03	-0.40013	R	X			
3185	0.0169612	0.05	0.53251	R	X			
3186	0.0058463	0.01	0.27396	R	X			
3254	0.0167261	0.04	0.48936	R	X			
3255	0.0130432	0.05	0.57465	R	X			
3275	0.0176750	0.23	-1.19125	R	X			
3302	0.0079478	0.00	0.05046		X			
3419	0.0043139	0.00	0.02772		X			

3442	0.0167213	0.00	-0.11096		X
3445	0.0180882	0.88	2.34886	R	X
3446	0.0170292	1.01	2.53064	R	X
3449	0.0173806	0.23	1.18784	R	X
3595	0.0033285	0.00	-0.01181		X
3619	0.0031731	0.00	-0.01299		X
3661	0.0167322	0.40	1.57072	R	X
3683	0.0167284	0.01	0.28239	R	X
3684	0.0070304	0.06	0.57719	R	X
3687	0.0029610	0.00	-0.00924		X
3729	0.0168963	0.63	-1.97262	R	X
3730	0.0075469	0.00	0.03128		X
3826	0.0115870	0.00	-0.00499		X
3850	0.0168663	0.06	-0.61034	R	X
3873	0.0169448	0.40	-1.55839	R	X
3874	0.0022222	0.03	0.39362	R	
3921	0.0049061	0.00	0.03066		X
4051	0.0166652	0.06	-0.58628	R	X
4052	0.0032318	0.08	-0.68919	R	X
4236	0.0168672	0.20	1.10551	R	X
4237	0.0033408	0.11	0.83708	R	X
4243	0.0114825	0.01	-0.17541		X
4262	0.0037820	0.00	0.02400		X
4284	0.0040347	0.00	0.02596		X
4305	0.0045087	0.00	0.02795		X
4507	0.0166448	0.15	-0.94153	R	X
4508	0.0037849	0.11	-0.81191	R	X
4525	0.0030176	0.00	-0.01567		X
4556	0.0083954	0.49	-1.75916	R	X
4835	0.0170287	0.08	-0.68708	R	X
4836	0.0023988	0.05	0.57581	R	
4840	0.0166714	0.02	0.30405	R	X
4841	0.0029514	0.00	-0.00929		X
4914	0.0170656	0.24	-1.21708	R	X
4934	0.0033520	0.00	-0.01746		X
4963	0.0029409	0.00	-0.01032		X
4977	0.0046573	0.00	0.02918		X
5034	0.0168357	0.31	-1.36961	R	X
5035	0.0067531	0.06	-0.59241	R	X
5052	0.0034803	0.00	0.02145		X
5054	0.0033376	0.00	-0.01058		X
5056	0.0033001	0.00	-0.00891		X
5058	0.0167504	0.04	0.49764	R	X
5059	0.0108115	0.06	-0.59121	R	X
5078	0.0179344	0.36	1.48176	R	X
5081	0.0166870	0.14	-0.92207	R	X
5082	0.0123149	0.01	-0.19553		X

5102	0.0168790	0.02	-0.30982	R	X
5130	0.0166716	0.09	-0.71984	R	X
5362	0.0166963	0.01	-0.28956	R	X
5365	0.0167011	0.03	0.42829	R	X
5366	0.0037583	0.06	0.60111	R	X
5385	0.0045377	0.00	0.02830		X
5443	0.0031075	0.00	-0.01093		X
5605	0.0034500	0.00	0.01835		X
5628	0.0027244	0.03	0.41328	R	
5650	0.0057251	0.00	0.03650		X
5724	0.0174730	0.72	2.12755	R	X
5725	0.0084722	0.42	1.63013	R	X
5729	0.0175604	0.30	1.34823	R	X
5774	0.0048213	0.00	0.03050		X
5824	0.0168256	0.03	0.41492	R	X
5825	0.0157490	0.00	-0.11922		X
5843	0.0051408	0.00	0.03241		X
5899	0.0029814	0.00	-0.01053		X
5985	0.0038614	0.00	0.02351		X
6080	0.0030120	0.00	0.01756		X
6109	0.0033821	0.00	-0.00578		X
6111	0.0167528	0.19	1.08415	R	X
6134	0.0060340	0.00	-0.01994		X
6137	0.0169519	0.01	-0.23566		X
6138	0.0072496	0.10	0.79459	R	X
6181	0.0031342	0.00	-0.01604		X
6307	0.0033856	0.00	-0.01272		X
6355	0.0029726	0.00	-0.01112		X
6369	0.0035763	0.00	0.02052		X
6396	0.0031082	0.00	-0.01595		X
6540	0.0037752	0.00	-0.01945		X
6541	0.0031295	0.00	-0.01569		X
6635	0.0085053	0.00	0.05425		X
6708	0.0033329	0.00	-0.01701		X
6805	0.0032213	0.00	0.01525		X
6807	0.0022386	0.02	0.37806	R	
6896	0.0030080	0.00	0.01759		X
6970	0.0036217	0.00	0.02263		X
7016	0.0030695	0.00	0.01798		X
7027	0.0169571	0.03	-0.44087	R	X
7028	0.0050436	0.18	-1.06946	R	X
7166	0.0022324	0.02	0.38221	R	
7171	0.0030643	0.00	-0.01115		X
7267	0.0033107	0.00	-0.01206		X
7291	0.0034301	0.00	-0.01251		X
7305	0.0031529	0.00	0.01797		X
7328	0.0032555	0.00	0.01904		X

7399	0.0061584	0.21	-1.13371	R	X
7580	0.0035750	0.09	-0.73706	R	X
7603	0.0170802	0.58	-1.89060	R	X
7691	0.0042194	0.00	0.02606		X
7747	0.0038296	0.00	-0.01390		X
7761	0.0043714	0.00	0.02644		X
7762	0.0037645	0.00	0.02203		X
8003	0.0056428	0.00	0.03484		X
8026	0.0041406	0.00	0.02367		X
8083	0.0030234	0.00	-0.01077		X
8127	0.0029929	0.00	0.00249		X
8145	0.0053731	0.00	0.03369		X
8203	0.0032135	0.00	-0.01147		X
8216	0.0032859	0.00	0.01906		X
8251	0.0032284	0.00	-0.01149		X
8295	0.0036661	0.00	-0.00996		X
8296	0.0173371	0.02	0.33450	R	X
8297	0.0137586	0.00	0.08752		X
8408	0.0029355	0.00	0.01671		X
8456	0.0032677	0.00	0.01882		X
8467	0.0039143	0.00	-0.01415		X
8510	0.0178773	0.30	1.36165	R	X
8515	0.0080081	0.01	-0.18873	R	X
8611	0.0033859	0.00	-0.01205		X
8625	0.0060268	0.00	0.03784		X
8683	0.0030152	0.00	-0.01067		X
8707	0.0032305	0.00	-0.01153		X

R Large residual

X Unusual *X*

Fits and Diagnostics for Unusual Observations

Test Set

Obs	TELS (kW)	Fit	SE Fit	95% CI	Resid	Std Resid	HI		
1237	45.5362	38.1904	0.0524	(38.0876, 38.2932)	7.3458	7.83	0.0031328	R	X
1429	15.4832	15.7576	0.0552	(15.6494, 15.8657)	-0.2744	-0.29	0.0034676		X
1456	25.3892	27.5458	0.1222	(27.3062, 27.7853)	-2.1566	-2.28	0.0170243	R	X
1478	44.9291	27.5989	0.1228	(27.3582, 27.8396)	17.3302	18.35	0.0171855	R	X
1787	26.0871	27.6280	0.1214	(27.3900, 27.8660)	-1.5409	-1.63	0.0168026		X
1788	26.6797	15.9803	0.0715	(15.8402, 16.1205)	10.6994	11.39	0.0058239	R	X
2155	19.6952	20.8837	0.0920	(20.7034, 21.0640)	-1.1885	-1.26	0.0096442		X
2289	15.1101	14.7755	0.0530	(14.6716, 14.8793)	0.3346	0.36	0.0031988		X
2459	35.0577	35.2362	0.0578	(35.1228, 35.3495)	-0.1785	-0.19	0.0038091		X
2697	16.0906	15.7242	0.0580	(15.6105, 15.8379)	0.3664	0.39	0.0038338		X
2842	18.4191	18.0819	0.0528	(17.9784, 18.1855)	0.3372	0.36	0.0031823		X

2917	20.3704	20.6325	0.0518	(20.5310, 20.7341)	-0.2621	-0.28	0.0030592	X
2967	43.8369	43.5234	0.0586	(43.4086, 43.6382)	0.3135	0.33	0.0039092	X
3089	23.4981	27.5522	0.1215	(27.3141, 27.7903)	-4.0541	-4.29	0.0168175	R X
3279	37.2814	27.6374	0.1211	(27.4000, 27.8749)	9.6440	10.21	0.0167257	R X
3450	31.8812	24.2929	0.1076	(24.0819, 24.5038)	7.5883	8.05	0.0131959	R X
3662	28.3571	16.0588	0.0759	(15.9100, 16.2076)	12.2983	13.09	0.0065651	R X
3686	36.2538	36.4152	0.0561	(36.3053, 36.5251)	-0.1614	-0.17	0.0035821	X
3688	31.0962	27.7268	0.1218	(27.4881, 27.9656)	3.3694	3.57	0.0169138	R X
3689	23.9494	27.6078	0.1209	(27.3708, 27.8448)	-3.6584	-3.87	0.0166600	R X
3707	24.6166	27.4487	0.1243	(27.2051, 27.6923)	-2.8321	-3.00	0.0175994	R X
3805	32.0025	27.5343	0.1222	(27.2948, 27.7739)	4.4682	4.73	0.0170204	R X
3825	14.5796	27.5024	0.1221	(27.2630, 27.7417)	-12.9228	-13.68	0.0169937	R X
3905	24.8149	27.5239	0.1219	(27.2848, 27.7629)	-2.7090	-2.87	0.0169492	R X
4242	24.5046	27.6434	0.1209	(27.4064, 27.8805)	-3.1388	-3.32	0.0166637	R X
4549	40.6311	27.6573	0.1212	(27.4198, 27.8948)	12.9738	13.74	0.0167332	R X
4555	21.7795	27.6111	0.1209	(27.3741, 27.8480)	-5.8316	-6.18	0.0166548	R X
4857	12.7418	12.3614	0.0613	(12.2411, 12.4816)	0.3804	0.41	0.0042884	X
5055	37.8163	27.7718	0.1226	(27.5315, 28.0121)	10.0445	10.63	0.0171306	R X
5077	20.5882	27.5900	0.1210	(27.3527, 27.8272)	-7.0018	-7.41	0.0166934	R X
5079	27.2651	27.4538	0.0512	(27.3534, 27.5543)	-0.1887	-0.20	0.0029937	X
5106	25.3586	27.5493	0.1215	(27.3111, 27.7875)	-2.1907	-2.32	0.0168349	R X
5123	33.7422	27.6808	0.1211	(27.4434, 27.9181)	6.0614	6.42	0.0167144	R X
5124	39.3274	39.4756	0.0575	(39.3630, 39.5882)	-0.1482	-0.16	0.0037634	X
5125	36.4926	27.7013	0.1213	(27.4635, 27.9390)	8.7913	9.31	0.0167702	R X
5129	29.1936	27.6863	0.1212	(27.4487, 27.9239)	1.5073	1.60	0.0167480	X
5368	35.2421	35.4327	0.0588	(35.3175, 35.5479)	-0.1906	-0.20	0.0039369	X
5601	18.0823	27.5543	0.1214	(27.3163, 27.7923)	-9.4720	-10.03	0.0168066	R X
5602	23.2688	19.8602	0.0872	(19.6893, 20.0310)	3.4086	3.62	0.0086599	R X
5726	33.9992	34.1606	0.0539	(34.0548, 34.2663)	-0.1614	-0.17	0.0033157	X
5730	19.2939	20.5379	0.0901	(20.3613, 20.7145)	-1.2440	-1.32	0.0092525	X
5819	33.7390	27.6624	0.1211	(27.4250, 27.8999)	6.0766	6.43	0.0167242	R X
5964	23.2240	22.8860	0.0536	(22.7809, 22.9911)	0.3380	0.36	0.0032768	X
5966	31.9371	27.6375	0.1211	(27.4001, 27.8749)	4.2996	4.55	0.0167188	R X
6061	10.5455	10.8533	0.0593	(10.7370, 10.9695)	-0.3078	-0.33	0.0040105	X
6204	42.7827	20.5066	0.0915	(20.3273, 20.6858)	22.2761	23.67	0.0095361	R X
6368	1.7239	1.4047	0.0544	(1.2980, 1.5114)	0.3192	0.34	0.0033794	X
6440	1.7026	1.3727	0.0561	(1.2627, 1.4827)	0.3299	0.35	0.0035887	X
6542	13.1447	13.4449	0.0582	(13.3309, 13.5589)	-0.3002	-0.32	0.0038554	X
6594	30.0034	30.1903	0.0541	(30.0841, 30.2964)	-0.1869	-0.20	0.0033398	X
6657	19.7720	19.4381	0.0537	(19.3327, 19.5434)	0.3339	0.36	0.0032908	X
6951	49.0090	41.4636	0.0435	(41.3783, 41.5490)	7.5454	8.05	0.0021618	R
7147	28.5451	28.7463	0.0552	(28.6381, 28.8544)	-0.2012	-0.21	0.0034690	X
7185	18.2547	17.9333	0.0540	(17.8275, 18.0391)	0.3214	0.34	0.0033198	X
7285	44.9198	44.6742	0.0542	(44.5680, 44.7804)	0.2456	0.26	0.0033447	X
7398	1.6505	25.6156	0.1189	(25.3824, 25.8487)	-23.9651	-25.38	0.0161260	R X
7547	17.3611	17.6176	0.0515	(17.5166, 17.7187)	-0.2565	-0.27	0.0030285	X
7579	25.7780	27.7023	0.1225	(27.4622, 27.9424)	-1.9243	-2.04	0.0170965	R X

7597	39.3274	27.7035	0.1222	(27.4639, 27.9431)	11.6239	12.31	0.0170334	R	X
7604	0.1982	18.2124	0.0859	(18.0439, 18.3808)	-18.0142	-19.15	0.0084153	R	X
7714	23.6395	23.2439	0.0688	(23.1091, 23.3788)	0.3956	0.42	0.0053933		X
8002	21.7966	21.3712	0.0683	(21.2373, 21.5052)	0.4254	0.45	0.0053235		X
8025	19.5723	19.2427	0.0539	(19.1371, 19.3483)	0.3296	0.35	0.0033081		X
8031	8.4401	8.7014	0.0530	(8.5976, 8.8053)	-0.2613	-0.28	0.0031995		X
8096	1.6355	1.3190	0.0545	(1.2121, 1.4259)	0.3165	0.34	0.0033905		X
8193	21.0726	20.7122	0.0585	(20.5974, 20.8269)	0.3604	0.38	0.0039073		X
8265	18.0593	17.6452	0.0665	(17.5149, 17.7755)	0.4141	0.44	0.0050343		X
8292	44.1740	22.3078	0.0960	(22.1197, 22.4959)	21.8662	23.22	0.0104986	R	X
8361	14.4536	14.0369	0.0673	(13.9049, 14.1689)	0.4167	0.44	0.0051662		X
8508	34.7799	27.6673	0.1225	(27.4270, 27.9075)	7.1126	7.53	0.0171160	R	X
8514	23.8753	27.6231	0.1224	(27.3831, 27.8631)	-3.7478	-3.97	0.0170908	R	X

R Large residual

X Unusual X

Durbin-Watson Statistic

Durbin-Watson Statistic = 1.59523

Appendix B: Regression Model Results – Simplified Awka Scenario

Method

Test set fraction 30.0%

Regression Equation

$$\begin{aligned} \text{TELS (kW)} = & 0.950048 * \text{Inverter Power Input (kW)} \\ & - 0.00846 * \text{Battery Input Power (kW)} \\ & + 0.48188 * \text{DGen Power Output (kW)} \end{aligned}$$

Coefficients

Term	Coef	SE Coef	95% CI	T-Value	P-Value	VIF
Inverter Power Input (kW)	0.950048	0.000669	(0.948736, 0.951360)	1419.81	0.000	1.03
Battery Input Power (kW)	-0.00846	0.00173	(-0.01185, -0.00506)	-4.88	0.000	1.33
DGen Power Output (kW)	0.48188	0.00238	(0.47722, 0.48654)	202.77	0.000	1.30

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC	Test S	Test R-sq
0.938560	99.71%	99.71%	5519.65	99.71%	16629.23	16656.11	1.20795	99.52%

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value
Regression	3	1879910	99.71%	1879910	626637	711363.16
Inverter Power Input (kW)	1	1834012	97.28%	1775775	1775775	2015873.99
Battery Input Power (kW)	1	9681	0.51%	21	21	23.81
DGen Power Output (kW)	1	36217	1.92%	36217	36217	41114.07
Error	6129	5399	0.29%	5399	1	
Lack-of-Fit	6122	5399	0.29%	5399	1	*
Pure Error	7	0	0.00%	0	0	
Total	6132	1885309	100.00%			
Source	P-Value					
Regression	0.000					
Inverter Power Input (kW)	0.000					

Battery Input Power (kW)	0.000
DGen Power Output (kW)	0.000
Error	
Lack-of-Fit	*
Pure Error	
Total	

Fits and Diagnostics for Unusual Observations

Training Set

Obs	TELS (kW)	Fit	SE Fit	95% CI	Resid	Std Resid	Del Resid
19	24.7541	24.9756	0.0455	(24.8864, 25.0649)	-0.2215	-0.24	-0.24
32	1.7287	1.5482	0.0372	(1.4752, 1.6212)	0.1805	0.19	0.19
80	1.7591	1.5732	0.0384	(1.4980, 1.6484)	0.1859	0.20	0.20
91	24.0933	24.3090	0.0443	(24.2221, 24.3959)	-0.2157	-0.23	-0.23
139	25.7837	26.0145	0.0474	(25.9215, 26.1074)	-0.2308	-0.25	-0.25
153	10.2610	10.0355	0.0481	(9.9413, 10.1298)	0.2255	0.24	0.24
187	23.6441	23.8558	0.0435	(23.7706, 23.9411)	-0.2117	-0.23	-0.23
202	36.6741	36.5663	0.0370	(36.4937, 36.6389)	0.1078	0.11	0.11
211	26.9764	27.2179	0.0496	(27.1206, 27.3151)	-0.2415	-0.26	-0.26
225	15.0924	14.8648	0.0498	(14.7672, 14.9623)	0.2276	0.24	0.24
283	21.6984	21.8926	0.0399	(21.8144, 21.9709)	-0.1942	-0.21	-0.21
331	24.5966	24.8167	0.0452	(24.7280, 24.9054)	-0.2201	-0.23	-0.23
403	23.9927	24.1667	0.0365	(24.0951, 24.2383)	-0.1740	-0.19	-0.19
803	21.6173	21.4145	0.0469	(21.3226, 21.5063)	0.2028	0.22	0.22
873	16.6297	16.4701	0.0368	(16.3980, 16.5421)	0.1596	0.17	0.17
907	26.0409	26.2460	0.0426	(26.1624, 26.3295)	-0.2051	-0.22	-0.22
949	38.5590	38.7645	0.0457	(38.6749, 38.8541)	-0.2055	-0.22	-0.22
952	34.0695	27.6264	0.1211	(27.3890, 27.8637)	6.4431	6.92	6.95
955	25.4962	27.6623	0.1213	(27.4246, 27.9001)	-2.1661	-2.33	-2.33
956	0.3547	13.5026	0.0611	(13.3828, 13.6223)	-13.1479	-14.04	-14.27
970	29.0827	29.2877	0.0432	(29.2030, 29.3724)	-0.2050	-0.22	-0.22
979	21.3771	27.6085	0.1211	(27.3710, 27.8459)	-6.2314	-6.70	-6.72
1003	26.1109	26.3048	0.0406	(26.2252, 26.3843)	-0.1939	-0.21	-0.21
1075	25.3627	25.5459	0.0385	(25.4705, 25.6214)	-0.1832	-0.20	-0.20
1099	27.2198	27.4263	0.0431	(27.3418, 27.5108)	-0.2065	-0.22	-0.22
1171	28.1982	28.4049	0.0433	(28.3199, 28.4898)	-0.2067	-0.22	-0.22
1219	26.2989	26.4718	0.0368	(26.3996, 26.5440)	-0.1729	-0.18	-0.18
1267	25.3382	25.5325	0.0405	(25.4531, 25.6120)	-0.1943	-0.21	-0.21
1291	23.6417	23.8201	0.0373	(23.7471, 23.8932)	-0.1784	-0.19	-0.19
1411	24.7890	24.9665	0.0373	(24.8933, 25.0396)	-0.1775	-0.19	-0.19
1473	18.0735	27.6239	0.1211	(27.3866, 27.8612)	-9.5504	-10.26	-10.35
1474	15.9347	15.4108	0.0682	(15.2771, 15.5444)	0.5239	0.56	0.56
1479	37.5570	37.7195	0.0385	(37.6440, 37.7950)	-0.1625	-0.17	-0.17
1526	45.8271	38.2471	0.0372	(38.1742, 38.3201)	7.5800	8.08	8.13

1531	24.2952	24.4837	0.0393	(24.4068, 24.5607)	-0.1885	-0.20	-0.20
1546	19.3239	19.1054	0.0492	(19.0089, 19.2018)	0.2185	0.23	0.23
1603	25.0769	25.2708	0.0404	(25.1916, 25.3499)	-0.1939	-0.21	-0.21
1791	26.0198	26.2398	0.0454	(26.1508, 26.3288)	-0.2200	-0.23	-0.23
1793	22.1665	27.5852	0.1214	(27.3473, 27.8232)	-5.4187	-5.82	-5.84
1794	11.4136	15.0935	0.0664	(14.9634, 15.2236)	-3.6799	-3.93	-3.94
2000	1.6754	1.4972	0.0367	(1.4251, 1.5692)	0.1782	0.19	0.19
2059	26.7424	26.9599	0.0451	(26.8716, 27.0483)	-0.2175	-0.23	-0.23
2107	26.5342	26.7446	0.0437	(26.6589, 26.8303)	-0.2104	-0.22	-0.22
2131	26.4664	26.6703	0.0425	(26.5870, 26.7536)	-0.2039	-0.22	-0.22
2146	23.9480	27.6102	0.1211	(27.3727, 27.8476)	-3.6622	-3.93	-3.94
2148	30.9132	31.0987	0.0402	(31.0200, 31.1775)	-0.1855	-0.20	-0.20
2150	29.7610	29.9313	0.0372	(29.8582, 30.0043)	-0.1703	-0.18	-0.18
2151	29.0762	27.6167	0.1211	(27.3793, 27.8541)	1.4595	1.57	1.57
2153	32.4432	32.6258	0.0401	(32.5472, 32.7044)	-0.1826	-0.19	-0.19
2154	27.4252	27.6548	0.1212	(27.4172, 27.8923)	-0.2296	-0.25	-0.25
2196	40.6341	40.8121	0.0420	(40.7297, 40.8944)	-0.1780	-0.19	-0.19
2197	26.1070	25.9390	0.0420	(25.8567, 26.0213)	0.1680	0.18	0.18
2275	24.0824	24.2762	0.0402	(24.1974, 24.3550)	-0.1938	-0.21	-0.21
2316	38.1377	37.9979	0.0428	(37.9140, 38.0818)	0.1398	0.15	0.15
2317	25.1704	24.9988	0.0422	(24.9160, 25.0816)	0.1716	0.18	0.18
2338	25.3576	25.0687	0.0650	(24.9414, 25.1961)	0.2889	0.31	0.31
2371	22.1932	22.3756	0.0377	(22.3016, 22.4496)	-0.1824	-0.19	-0.19
2443	29.0894	29.3293	0.0496	(29.2320, 29.4267)	-0.2399	-0.26	-0.26
2461	27.9440	27.7244	0.0524	(27.6217, 27.8271)	0.2196	0.23	0.23
2467	22.6820	22.8657	0.0381	(22.7911, 22.9403)	-0.1837	-0.20	-0.20
2481	17.4076	17.2119	0.0441	(17.1254, 17.2983)	0.1957	0.21	0.21
2528	1.6895	1.4985	0.0394	(1.4213, 1.5757)	0.1910	0.20	0.20
2603	29.4913	27.6295	0.1211	(27.3922, 27.8669)	1.8618	2.00	2.00
2604	33.0534	33.2650	0.0453	(33.1763, 33.3537)	-0.2116	-0.23	-0.23
2607	32.9489	27.6116	0.1211	(27.3742, 27.8490)	5.3373	5.73	5.75
2608	28.0112	17.0611	0.0757	(16.9127, 17.2095)	10.9501	11.71	11.84
2624	1.7120	1.4979	0.0441	(1.4114, 1.5844)	0.2141	0.23	0.23
2635	25.0883	25.2985	0.0434	(25.2133, 25.3836)	-0.2102	-0.22	-0.22
2683	25.4208	25.6355	0.0443	(25.5486, 25.7224)	-0.2147	-0.23	-0.23
2793	9.7334	9.5175	0.0460	(9.4272, 9.6077)	0.2159	0.23	0.23
2865	14.6407	14.4284	0.0466	(14.3371, 14.5197)	0.2123	0.23	0.23
2875	21.0917	21.2689	0.0366	(21.1972, 21.3407)	-0.1772	-0.19	-0.19
2888	1.7747	1.5964	0.0368	(1.5243, 1.6685)	0.1783	0.19	0.19
2912	1.6446	1.4660	0.0369	(1.3937, 1.5382)	0.1786	0.19	0.19
2923	21.7839	21.9754	0.0394	(21.8982, 22.0527)	-0.1915	-0.20	-0.20
2964	40.3511	40.6036	0.0542	(40.4973, 40.7099)	-0.2525	-0.27	-0.27
2987	23.7945	23.5866	0.0486	(23.4913, 23.6819)	0.2079	0.22	0.22
2988	31.9926	31.7772	0.0532	(31.6729, 31.8815)	0.2154	0.23	0.23
2990	36.3820	36.5528	0.0394	(36.4756, 36.6300)	-0.1708	-0.18	-0.18
2995	20.1617	27.6315	0.1211	(27.3941, 27.8688)	-7.4698	-8.03	-8.07
2996	0.2144	12.7856	0.0579	(12.6721, 12.8990)	-12.5712	-13.42	-13.62

3019	22.6339	22.8328	0.0409	(22.7526, 22.9129)	-0.1989	-0.21	-0.21
3034	13.3408	13.1711	0.0377	(13.0972, 13.2450)	0.1697	0.18	0.18
3083	21.4507	21.6388	0.0387	(21.5629, 21.7147)	-0.1881	-0.20	-0.20
3084	32.0562	27.7208	0.1226	(27.4805, 27.9611)	4.3354	4.66	4.67
3085	24.8111	27.6614	0.1213	(27.4236, 27.8991)	-2.8503	-3.06	-3.06
3087	34.2608	34.4694	0.0450	(34.3811, 34.5577)	-0.2086	-0.22	-0.22
3091	22.8903	23.0900	0.0411	(23.0094, 23.1706)	-0.1997	-0.21	-0.21
3105	24.6084	24.4525	0.0391	(24.3758, 24.5292)	0.1559	0.17	0.17
3106	25.0998	24.9348	0.0410	(24.8544, 25.0152)	0.1650	0.18	0.18
3185	31.3048	27.5510	0.1221	(27.3117, 27.7903)	3.7538	4.03	4.04
3186	19.6102	16.2660	0.0713	(16.1263, 16.4058)	3.3442	3.57	3.58
3224	1.6546	1.4768	0.0367	(1.4049, 1.5487)	0.1778	0.19	0.19
3254	31.1583	27.6576	0.1212	(27.4200, 27.8952)	3.5007	3.76	3.77
3255	29.0387	24.3697	0.1069	(24.1601, 24.5794)	4.6690	5.01	5.02
3259	21.5518	21.7303	0.0369	(21.6579, 21.8027)	-0.1785	-0.19	-0.19
3275	19.2389	27.4965	0.1240	(27.2534, 27.7396)	-8.2576	-8.88	-8.93
3276	36.4180	36.6278	0.0458	(36.5380, 36.7176)	-0.2098	-0.22	-0.22
3302	35.1012	34.7968	0.0713	(34.6570, 34.9365)	0.3044	0.33	0.33
3345	15.0277	14.8550	0.0388	(14.7789, 14.9310)	0.1727	0.18	0.18
3393	8.8797	8.7093	0.0366	(8.6375, 8.7811)	0.1704	0.18	0.18
3419	20.0159	19.7688	0.0550	(19.6610, 19.8767)	0.2471	0.26	0.26
3442	26.7913	27.5940	0.1213	(27.3563, 27.8317)	-0.8027	-0.86	-0.86
3443	31.4892	31.7206	0.0485	(31.6255, 31.8157)	-0.2314	-0.25	-0.25
3445	43.5563	27.7759	0.1248	(27.5312, 28.0206)	15.7804	16.96	17.38
3446	45.0966	27.6791	0.1215	(27.4409, 27.9173)	17.4175	18.72	19.27
3448	35.3621	35.5520	0.0421	(35.4694, 35.6346)	-0.1899	-0.20	-0.20
3449	36.0360	27.7381	0.1232	(27.4966, 27.9795)	8.2979	8.92	8.98
3464	1.6331	1.4444	0.0389	(1.3682, 1.5207)	0.1887	0.20	0.20
3488	1.6354	1.4475	0.0387	(1.3715, 1.5234)	0.1879	0.20	0.20
3499	23.3521	23.5451	0.0399	(23.4668, 23.6233)	-0.1930	-0.21	-0.21
3512	1.6444	1.4665	0.0367	(1.3945, 1.5384)	0.1779	0.19	0.19
3547	21.6787	21.8555	0.0366	(21.7837, 21.9273)	-0.1768	-0.19	-0.19
3571	22.5152	22.7046	0.0391	(22.6279, 22.7813)	-0.1894	-0.20	-0.20
3588	40.3755	40.5335	0.0390	(40.4571, 40.6099)	-0.1580	-0.17	-0.17
3595	30.4283	30.6833	0.0527	(30.5800, 30.7865)	-0.2550	-0.27	-0.27
3612	41.6835	41.5648	0.0415	(41.4833, 41.6462)	0.1187	0.13	0.13
3619	28.6086	28.8623	0.0522	(28.7600, 28.9646)	-0.2537	-0.27	-0.27
3633	17.5426	17.3506	0.0434	(17.2655, 17.4357)	0.1920	0.20	0.20
3659	27.6584	27.8452	0.0396	(27.7676, 27.9228)	-0.1868	-0.20	-0.20
3660	26.7883	26.9686	0.0383	(26.8936, 27.0436)	-0.1803	-0.19	-0.19
3661	38.7352	27.6378	0.1211	(27.4005, 27.8752)	11.0974	11.92	12.06
3683	29.5949	27.5880	0.1213	(27.3501, 27.8259)	2.0069	2.16	2.16
3684	24.2310	17.8363	0.0785	(17.6825, 17.9901)	6.3947	6.84	6.86
3687	31.3658	31.6000	0.0490	(31.5040, 31.6960)	-0.2342	-0.25	-0.25
3691	22.2066	22.3901	0.0380	(22.3157, 22.4645)	-0.1835	-0.20	-0.20
3729	13.7989	27.5854	0.1214	(27.3475, 27.8234)	-13.7865	-14.81	-15.08
3730	18.5824	18.2637	0.0814	(18.1042, 18.4232)	0.3187	0.34	0.34

3752	1.6663	1.4907	0.0362	(1.4197, 1.5617)	0.1756	0.19	0.19
3779	23.7453	23.5885	0.0389	(23.5122, 23.6648)	0.1568	0.17	0.17
3787	20.4869	20.6613	0.0360	(20.5908, 20.7319)	-0.1744	-0.19	-0.19
3804	31.9653	32.1451	0.0395	(32.0677, 32.2225)	-0.1798	-0.19	-0.19
3826	22.9493	22.9990	0.1010	(22.8010, 23.1969)	-0.0497	-0.05	-0.05
3850	23.2149	27.5673	0.1217	(27.3288, 27.8059)	-4.3524	-4.68	-4.68
3851	23.1456	22.9788	0.0405	(22.8993, 23.0583)	0.1668	0.18	0.18
3858	25.5750	25.7795	0.0424	(25.6963, 25.8627)	-0.2045	-0.22	-0.22
3859	20.7314	20.9100	0.0368	(20.8378, 20.9821)	-0.1786	-0.19	-0.19
3873	16.6129	27.5687	0.1217	(27.3302, 27.8072)	-10.9558	-11.77	-11.91
3874	16.6026	8.8584	0.0435	(8.7731, 8.9437)	7.7442	8.26	8.31
3907	24.6399	24.8418	0.0418	(24.7598, 24.9237)	-0.2019	-0.22	-0.22
3920	1.6678	1.4883	0.0370	(1.4157, 1.5609)	0.1795	0.19	0.19
3921	14.5710	14.2831	0.0618	(14.1620, 14.4041)	0.2879	0.31	0.31
3979	23.6029	23.7929	0.0394	(23.7157, 23.8701)	-0.1900	-0.20	-0.20
3992	1.6780	1.4955	0.0376	(1.4218, 1.5693)	0.1825	0.19	0.19
4027	22.7946	22.9773	0.0379	(22.9030, 23.0516)	-0.1827	-0.19	-0.19
4047	32.8091	32.9810	0.0384	(32.9057, 33.0563)	-0.1719	-0.18	-0.18
4049	31.9034	32.0713	0.0375	(31.9979, 32.1448)	-0.1679	-0.18	-0.18
4051	23.4658	27.6494	0.1211	(27.4119, 27.8869)	-4.1836	-4.50	-4.50
4052	0.1811	11.4251	0.0517	(11.3237, 11.5265)	-11.2440	-12.00	-12.14
4137	13.0252	12.8382	0.0411	(12.7577, 12.9187)	0.1870	0.20	0.20
4138	14.5078	14.3144	0.0428	(14.2306, 14.3982)	0.1934	0.21	0.21
4195	23.8039	23.9927	0.0392	(23.9158, 24.0696)	-0.1888	-0.20	-0.20
4236	35.5215	27.6842	0.1216	(27.4458, 27.9226)	7.8373	8.42	8.47
4237	33.6421	20.3451	0.0542	(20.2389, 20.4514)	13.2970	14.19	14.43
4243	21.4263	22.9367	0.1005	(22.7396, 23.1338)	-1.5104	-1.62	-1.62
4262	27.5971	27.3988	0.0482	(27.3043, 27.4934)	0.1983	0.21	0.21
4284	21.1144	20.8808	0.0527	(20.7774, 20.9841)	0.2336	0.25	0.25
4305	11.8381	11.5571	0.0597	(11.4401, 11.6742)	0.2810	0.30	0.30
4404	32.6195	32.4903	0.0382	(32.4155, 32.5652)	0.1292	0.14	0.14
4474	15.8112	15.6535	0.0361	(15.5827, 15.7242)	0.1577	0.17	0.17
4496	1.7036	1.5245	0.0370	(1.4521, 1.5969)	0.1791	0.19	0.19
4507	20.9238	27.6267	0.1211	(27.3894, 27.8641)	-6.7029	-7.20	-7.23
4508	0.1986	12.4051	0.0562	(12.2950, 12.5152)	-12.2065	-13.03	-13.21
4556	1.3127	18.7239	0.0844	(18.5585, 18.8893)	-17.4112	-18.63	-19.18
4714	19.0314	18.8599	0.0399	(18.7817, 18.9381)	0.1715	0.18	0.18
4723	22.7308	22.9034	0.0360	(22.8328, 22.9740)	-0.1726	-0.18	-0.18
4835	22.6712	27.5469	0.1222	(27.3074, 27.7864)	-4.8757	-5.24	-5.25
4836	25.2073	14.3394	0.0456	(14.2500, 14.4287)	10.8679	11.59	11.72
4837	29.9695	30.1585	0.0405	(30.0790, 30.2379)	-0.1890	-0.20	-0.20
4840	29.7767	27.6058	0.1211	(27.3683, 27.8433)	2.1709	2.33	2.33
4841	31.2874	31.5215	0.0490	(31.4256, 31.6175)	-0.2341	-0.25	-0.25
4858	17.0197	16.8478	0.0393	(16.7708, 16.9248)	0.1719	0.18	0.18
4914	18.9783	27.5488	0.1221	(27.3093, 27.7882)	-8.5705	-9.21	-9.27
4915	24.5219	24.7103	0.0393	(24.6333, 24.7873)	-0.1884	-0.20	-0.20
4929	16.3092	16.0987	0.0467	(16.0071, 16.1902)	0.2105	0.22	0.22

4963	30.1625	30.4006	0.0495	(30.3036, 30.4975)	-0.2381	-0.25	-0.25
4977	15.0561	14.7784	0.0598	(14.6612, 14.8956)	0.2777	0.30	0.30
5026	19.8669	19.7160	0.0363	(19.6449, 19.7871)	0.1509	0.16	0.16
5034	17.9030	27.5848	0.1214	(27.3468, 27.8227)	-9.6818	-10.40	-10.50
5035	10.6775	17.3873	0.0767	(17.2369, 17.5377)	-6.7098	-7.17	-7.20
5052	31.3154	31.1495	0.0439	(31.0635, 31.2355)	0.1659	0.18	0.18
5054	33.1157	33.3648	0.0521	(33.2628, 33.4669)	-0.2491	-0.27	-0.27
5056	36.1530	36.3916	0.0508	(36.2920, 36.4911)	-0.2386	-0.25	-0.25
5058	31.2290	27.6677	0.1213	(27.4298, 27.9055)	3.5613	3.83	3.83
5059	16.9580	22.2265	0.0975	(22.0354, 22.4176)	-5.2685	-5.64	-5.66
5076	27.5993	27.8207	0.0459	(27.7306, 27.9107)	-0.2214	-0.24	-0.24
5078	37.9320	27.7757	0.1248	(27.5311, 28.0204)	10.1563	10.92	11.02
5080	25.0349	25.2407	0.0426	(25.1572, 25.3241)	-0.2058	-0.22	-0.22
5081	21.0463	27.6201	0.1211	(27.3828, 27.8575)	-6.5738	-7.06	-7.09
5082	22.1261	23.7575	0.1041	(23.5534, 23.9615)	-1.6314	-1.75	-1.75
5100	37.0991	37.2502	0.0367	(37.1784, 37.3221)	-0.1511	-0.16	-0.16
5102	25.3452	27.5642	0.1218	(27.3255, 27.8029)	-2.2190	-2.38	-2.39
5107	24.1631	24.3488	0.0387	(24.2730, 24.4247)	-0.1857	-0.20	-0.20
5128	25.6555	25.8290	0.0368	(25.7568, 25.9011)	-0.1735	-0.18	-0.18
5130	22.4972	27.6360	0.1211	(27.3986, 27.8733)	-5.1388	-5.52	-5.53
5179	24.3504	24.5367	0.0388	(24.4605, 24.6128)	-0.1863	-0.20	-0.20
5250	33.0651	33.2325	0.0377	(33.1585, 33.3065)	-0.1674	-0.18	-0.18
5275	23.0867	23.2620	0.0366	(23.1903, 23.3337)	-0.1753	-0.19	-0.19
5323	28.9792	29.2103	0.0480	(29.1163, 29.3043)	-0.2311	-0.25	-0.25
5339	20.6618	20.5108	0.0366	(20.4391, 20.5825)	0.1510	0.16	0.16
5340	17.0887	16.9078	0.0411	(16.8273, 16.9883)	0.1809	0.19	0.19
5362	25.5891	27.6528	0.1212	(27.4152, 27.8903)	-2.0637	-2.22	-2.22
5364	30.9594	31.1784	0.0461	(31.0880, 31.2688)	-0.2190	-0.23	-0.23
5365	30.6578	27.6023	0.1212	(27.3647, 27.8398)	3.0555	3.28	3.29
5366	21.0462	11.9590	0.0570	(11.8473, 12.0707)	9.0872	9.70	9.77
5385	12.1132	11.8345	0.0593	(11.7183, 11.9508)	0.2787	0.30	0.30
5386	19.3626	19.1662	0.0449	(19.0783, 19.2541)	0.1964	0.21	0.21
5443	30.4977	30.7420	0.0507	(30.6426, 30.8414)	-0.2443	-0.26	-0.26
5491	23.3102	23.4950	0.0384	(23.4197, 23.5703)	-0.1848	-0.20	-0.20
5584	37.5068	37.7000	0.0434	(37.6150, 37.7850)	-0.1932	-0.21	-0.21
5605	42.1661	42.0560	0.0406	(41.9765, 42.1356)	0.1101	0.12	0.12
5628	45.5365	38.0254	0.0392	(37.9485, 38.1022)	7.5111	8.01	8.05
5650	22.6825	22.3974	0.0634	(22.2731, 22.5217)	0.2851	0.30	0.30
5724	42.3287	27.7319	0.1229	(27.4909, 27.9729)	14.5968	15.69	16.01
5725	35.5312	19.4179	0.0851	(19.2510, 19.5848)	16.1133	17.24	17.67
5729	37.1014	27.7484	0.1236	(27.5062, 27.9906)	9.3530	10.05	10.14
5755	22.5790	22.7613	0.0378	(22.6872, 22.8353)	-0.1823	-0.19	-0.19
5774	25.2044	24.9562	0.0569	(24.8446, 25.0678)	0.2482	0.26	0.26
5824	30.6434	27.6754	0.1215	(27.4373, 27.9135)	2.9680	3.19	3.19
5825	25.9036	26.7681	0.1176	(26.5377, 26.9986)	-0.8645	-0.93	-0.93
5826	21.6252	21.8155	0.0392	(21.7387, 21.8922)	-0.1903	-0.20	-0.20
5843	15.8412	15.5537	0.0620	(15.4323, 15.6752)	0.2875	0.31	0.31

5851	22.3345	22.5194	0.0382	(22.4444, 22.5944)	-0.1849	-0.20	-0.20
5899	28.6252	28.8640	0.0494	(28.7673, 28.9608)	-0.2388	-0.25	-0.25
5914	12.0041	11.8369	0.0368	(11.7648, 11.9091)	0.1672	0.18	0.18
5985	13.2701	13.0155	0.0547	(12.9083, 13.1227)	0.2546	0.27	0.27
6056	1.7411	1.5324	0.0430	(1.4480, 1.6167)	0.2087	0.22	0.22
6080	1.6730	1.4375	0.0485	(1.3425, 1.5326)	0.2355	0.25	0.25
6106	21.7308	21.5685	0.0391	(21.4918, 21.6452)	0.1623	0.17	0.17
6109	41.7481	41.9633	0.0483	(41.8686, 42.0580)	-0.2152	-0.23	-0.23
6110	39.7839	39.9635	0.0419	(39.8813, 40.0457)	-0.1796	-0.19	-0.19
6111	35.3187	27.6192	0.1211	(27.3818, 27.8565)	7.6995	8.27	8.32
6130	15.6179	15.4180	0.0444	(15.3311, 15.5050)	0.1999	0.21	0.21
6134	42.9255	43.2615	0.0699	(43.1245, 43.3985)	-0.3360	-0.36	-0.36
6137	25.8752	27.5629	0.1218	(27.3241, 27.8016)	-1.6877	-1.81	-1.81
6138	26.6670	18.0099	0.0790	(17.8551, 18.1647)	8.6571	9.26	9.32
6152	1.6638	1.4812	0.0377	(1.4073, 1.5550)	0.1826	0.19	0.19
6163	26.3906	26.6268	0.0485	(26.5316, 26.7219)	-0.2362	-0.25	-0.25
6177	19.3609	19.2045	0.0371	(19.1317, 19.2772)	0.1564	0.17	0.17
6235	20.3645	20.5468	0.0375	(20.4734, 20.6202)	-0.1823	-0.19	-0.19
6307	28.6748	28.9315	0.0527	(28.8281, 29.0349)	-0.2567	-0.27	-0.27
6321	12.3511	12.1599	0.0417	(12.0781, 12.2416)	0.1912	0.20	0.20
6355	26.7491	26.9885	0.0492	(26.8921, 27.0849)	-0.2394	-0.26	-0.26
6369	15.9284	15.6836	0.0534	(15.5789, 15.7883)	0.2448	0.26	0.26
6392	1.7180	1.5347	0.0378	(1.4606, 1.6088)	0.1833	0.20	0.20
6416	1.7636	1.5447	0.0451	(1.4563, 1.6331)	0.2189	0.23	0.23
6427	25.2651	25.4913	0.0465	(25.4002, 25.5824)	-0.2262	-0.24	-0.24
6475	23.2357	23.4438	0.0427	(23.3600, 23.5275)	-0.2081	-0.22	-0.22
6488	1.7509	1.5673	0.0379	(1.4930, 1.6416)	0.1836	0.20	0.20
6523	21.6581	21.8520	0.0398	(21.7739, 21.9301)	-0.1939	-0.21	-0.21
6547	20.7650	20.9509	0.0382	(20.8760, 21.0258)	-0.1859	-0.20	-0.20
6635	24.2643	23.9120	0.0772	(23.7606, 24.0635)	0.3523	0.38	0.38
6704	1.4574	1.2300	0.0468	(1.1383, 1.3218)	0.2274	0.24	0.24
6752	1.7158	1.5306	0.0382	(1.4558, 1.6055)	0.1852	0.20	0.20
6805	44.4848	44.3741	0.0420	(44.2917, 44.4565)	0.1107	0.12	0.12
6807	46.8790	39.3680	0.0397	(39.2902, 39.4457)	7.5110	8.01	8.05
6811	24.5910	24.8112	0.0452	(24.7225, 24.8998)	-0.2202	-0.23	-0.23
6824	1.6882	1.4838	0.0421	(1.4012, 1.5664)	0.2044	0.22	0.22
6825	7.4805	7.2946	0.0394	(7.2174, 7.3719)	0.1859	0.20	0.20
6859	20.8553	21.0419	0.0384	(20.9668, 21.1171)	-0.1866	-0.20	-0.20
6883	24.9345	25.1577	0.0459	(25.0678, 25.2476)	-0.2232	-0.24	-0.24
6896	1.6527	1.4231	0.0473	(1.3304, 1.5158)	0.2296	0.24	0.24
6931	22.8167	23.0210	0.0420	(22.9387, 23.1032)	-0.2043	-0.22	-0.22
6955	26.1465	26.3805	0.0481	(26.2863, 26.4748)	-0.2340	-0.25	-0.25
6969	16.5290	16.3717	0.0363	(16.3005, 16.4428)	0.1573	0.17	0.17
6970	23.2940	23.0940	0.0469	(23.0020, 23.1860)	0.2000	0.21	0.21
7003	23.5124	23.7228	0.0432	(23.6380, 23.8076)	-0.2104	-0.22	-0.22
7016	1.7439	1.5127	0.0476	(1.4194, 1.6061)	0.2312	0.25	0.25
7025	30.9988	31.1972	0.0425	(31.1140, 31.2805)	-0.1984	-0.21	-0.21

7026	24.6400	24.8226	0.0382	(24.7477, 24.8975)	-0.1826	-0.19	-0.19
7027	24.5710	27.6807	0.1215	(27.4424, 27.9189)	-3.1097	-3.34	-3.34
7028	0.2637	14.1150	0.0639	(13.9897, 14.2402)	-13.8513	-14.79	-15.06
7051	22.7599	22.9637	0.0419	(22.8816, 23.0457)	-0.2038	-0.22	-0.22
7088	1.7170	1.5284	0.0389	(1.4521, 1.6046)	0.1886	0.20	0.20
7161	19.8228	19.6518	0.0401	(19.5732, 19.7304)	0.1710	0.18	0.18
7166	50.9380	43.4271	0.0412	(43.3463, 43.5078)	7.5109	8.01	8.05
7171	26.6669	26.9056	0.0490	(26.8094, 27.0017)	-0.2387	-0.25	-0.25
7195	21.1437	21.3330	0.0389	(21.2568, 21.4093)	-0.1893	-0.20	-0.20
7232	1.7157	1.5168	0.0410	(1.4365, 1.5972)	0.1989	0.21	0.21
7257	13.1477	12.9752	0.0382	(12.9003, 13.0501)	0.1725	0.18	0.18
7267	27.7536	28.0020	0.0510	(27.9020, 28.1021)	-0.2484	-0.27	-0.27
7291	28.2787	28.5318	0.0520	(28.4298, 28.6338)	-0.2531	-0.27	-0.27
7304	1.6773	1.4567	0.0454	(1.3677, 1.5458)	0.2206	0.24	0.24
7305	13.1399	12.9145	0.0488	(12.8189, 13.0101)	0.2254	0.24	0.24
7315	22.8114	23.0156	0.0420	(22.9334, 23.0978)	-0.2042	-0.22	-0.22
7328	1.4543	1.2175	0.0487	(1.1219, 1.3130)	0.2368	0.25	0.25
7352	1.6749	1.4640	0.0434	(1.3788, 1.5492)	0.2109	0.22	0.22
7363	21.8750	22.0708	0.0402	(21.9919, 22.1497)	-0.1958	-0.21	-0.21
7384	28.6109	28.7772	0.0363	(28.7061, 28.8483)	-0.1663	-0.18	-0.18
7399	1.7306	15.0415	0.0703	(14.9037, 15.1793)	-13.3109	-14.22	-14.46
7411	19.8004	19.9776	0.0364	(19.9062, 20.0490)	-0.1772	-0.19	-0.19
7425	9.6448	9.4784	0.0360	(9.4078, 9.5490)	0.1664	0.18	0.18
7520	1.7103	1.4991	0.0435	(1.4138, 1.5844)	0.2112	0.23	0.23
7531	25.2527	25.4788	0.0464	(25.3877, 25.5698)	-0.2261	-0.24	-0.24
7544	1.6344	1.4556	0.0369	(1.3833, 1.5279)	0.1788	0.19	0.19
7577	31.8422	32.0507	0.0444	(31.9636, 32.1378)	-0.2085	-0.22	-0.22
7580	0.1574	11.5790	0.0524	(11.4762, 11.6818)	-11.4216	-12.19	-12.34
7603	14.4453	27.5993	0.1212	(27.3617, 27.8369)	-13.1540	-14.13	-14.37
7627	20.0558	20.2354	0.0369	(20.1631, 20.3077)	-0.1796	-0.19	-0.19
7675	22.2145	22.4134	0.0409	(22.3333, 22.4935)	-0.1989	-0.21	-0.21
7691	24.8250	24.6117	0.0500	(24.5136, 24.7098)	0.2133	0.23	0.23
7713	8.4553	8.2670	0.0401	(8.1884, 8.3457)	0.1883	0.20	0.20
7723	21.2591	21.4494	0.0391	(21.3728, 21.5261)	-0.1903	-0.20	-0.20
7747	29.7016	29.9675	0.0546	(29.8604, 30.0746)	-0.2659	-0.28	-0.28
7761	7.0124	6.7430	0.0563	(6.6326, 6.8534)	0.2694	0.29	0.29
7762	12.0875	11.8427	0.0524	(11.7399, 11.9455)	0.2448	0.26	0.26
7795	20.4209	20.6037	0.0376	(20.5301, 20.6773)	-0.1828	-0.19	-0.19
7808	1.6290	1.4180	0.0435	(1.3327, 1.5032)	0.2110	0.23	0.23
7867	22.9113	23.1164	0.0421	(23.0338, 23.1990)	-0.2051	-0.22	-0.22
7891	21.0482	21.2366	0.0387	(21.1607, 21.3125)	-0.1884	-0.20	-0.20
7904	1.6571	1.4572	0.0412	(1.3764, 1.5380)	0.1999	0.21	0.21
7915	23.4190	23.6287	0.0431	(23.5442, 23.7131)	-0.2097	-0.22	-0.22
7928	1.6593	1.4702	0.0390	(1.3938, 1.5466)	0.1891	0.20	0.20
7939	21.8659	22.0616	0.0402	(21.9828, 22.1404)	-0.1957	-0.21	-0.21
7963	22.0589	22.2564	0.0406	(22.1768, 22.3359)	-0.1975	-0.21	-0.21
7980	36.6314	36.5080	0.0394	(36.4307, 36.5852)	0.1234	0.13	0.13

8003	30.3711	30.1335	0.0567	(30.0223, 30.2448)	0.2376	0.25	0.25
8026	17.2313	16.9800	0.0551	(16.8720, 17.0880)	0.2513	0.27	0.27
8083	25.7428	25.9733	0.0473	(25.8804, 26.0661)	-0.2305	-0.25	-0.25
8120	1.6290	1.4482	0.0373	(1.3750, 1.5213)	0.1808	0.19	0.19
8145	15.8395	15.5628	0.0598	(15.4456, 15.6800)	0.2767	0.30	0.30
8178	28.0541	28.2445	0.0403	(28.1654, 28.3236)	-0.1904	-0.20	-0.20
8192	1.7172	1.5074	0.0432	(1.4226, 1.5922)	0.2098	0.22	0.22
8203	26.5624	26.8003	0.0489	(26.7045, 26.8960)	-0.2379	-0.25	-0.25
8216	1.7647	1.5354	0.0472	(1.4429, 1.6280)	0.2293	0.24	0.24
8251	26.5847	26.8227	0.0489	(26.7268, 26.9185)	-0.2380	-0.25	-0.25
8295	35.3122	35.5526	0.0509	(35.4528, 35.6525)	-0.2404	-0.26	-0.26
8296	30.0714	27.7028	0.1220	(27.4636, 27.9420)	2.3686	2.55	2.55
8297	25.4553	24.7598	0.1085	(24.5472, 24.9725)	0.6955	0.75	0.75
8299	20.1223	20.3025	0.0370	(20.2299, 20.3750)	-0.1802	-0.19	-0.19
8312	1.7494	1.5423	0.0427	(1.4585, 1.6260)	0.2071	0.22	0.22
8347	24.6092	24.8296	0.0453	(24.7408, 24.9183)	-0.2204	-0.24	-0.24
8395	21.4706	21.6628	0.0395	(21.5854, 21.7402)	-0.1922	-0.20	-0.20
8408	1.6908	1.4788	0.0437	(1.3932, 1.5645)	0.2120	0.23	0.23
8432	1.7310	1.5231	0.0429	(1.4391, 1.6071)	0.2079	0.22	0.22
8456	1.6826	1.4565	0.0466	(1.3652, 1.5478)	0.2261	0.24	0.24
8467	29.5254	29.7896	0.0543	(29.6832, 29.8961)	-0.2642	-0.28	-0.28
8481	13.9491	13.7825	0.0373	(13.7095, 13.8556)	0.1666	0.18	0.18
8509	28.4593	28.6582	0.0420	(28.5759, 28.7405)	-0.1989	-0.21	-0.21
8510	37.1022	27.7425	0.1233	(27.5007, 27.9842)	9.3597	10.06	10.14
8515	16.6047	18.5554	0.0815	(18.3956, 18.7151)	-1.9507	-2.09	-2.09
8611	27.0062	27.2480	0.0497	(27.1506, 27.3453)	-0.2418	-0.26	-0.26
8624	1.7238	1.5464	0.0366	(1.4747, 1.6181)	0.1774	0.19	0.19
8625	21.3639	21.0889	0.0610	(20.9694, 21.2085)	0.2750	0.29	0.29
8683	25.1327	25.3577	0.0462	(25.2671, 25.4483)	-0.2250	-0.24	-0.24
8707	26.1930	26.4275	0.0482	(26.3331, 26.5219)	-0.2345	-0.25	-0.25
8720	1.6134	1.4265	0.0385	(1.3509, 1.5020)	0.1869	0.20	0.20
8755	23.9876	24.2023	0.0441	(24.1158, 24.2888)	-0.2147	-0.23	-0.23
Obs	HI	Cook's D	DFITS				
19	0.0023530	0.00	-0.01148		X		
32	0.0015749	0.00	0.00764		X		
80	0.0016701	0.00	0.00811		X		
91	0.0022290	0.00	-0.01087		X		
139	0.0025528	0.00	-0.01245		X		
153	0.0026241	0.00	0.01234		X		
187	0.0021467	0.00	-0.01047		X		
202	0.0015580	0.00	0.00454		X		
211	0.0027944	0.00	-0.01364		X		
225	0.0028104	0.00	0.01289		X		
283	0.0018079	0.00	-0.00881		X		
331	0.0023231	0.00	-0.01133		X		
403	0.0015145	0.00	-0.00723		X		
803	0.0024931	0.00	0.01082		X		

873	0.0015346	0.00	0.00667		X
907	0.0020620	0.00	-0.00994		X
949	0.0023719	0.00	-0.01069		X
952	0.0166376	0.27	0.90393	R	X
955	0.0166951	0.03	-0.30338	R	X
956	0.0042350	0.28	-0.93052	R	X
970	0.0021183	0.00	-0.01007		X
979	0.0166550	0.25	-0.87447	R	X
1003	0.0018695	0.00	-0.00895		X
1075	0.0016809	0.00	-0.00802		X
1099	0.0021091	0.00	-0.01012		X
1171	0.0021311	0.00	-0.01019		X
1219	0.0015402	0.00	-0.00724		X
1267	0.0018632	0.00	-0.00895		X
1291	0.0015764	0.00	-0.00756		X
1411	0.0015805	0.00	-0.00753		X
1473	0.0166382	0.59	-1.34625	R	X
1474	0.0052771	0.00	0.04076		X
1479	0.0016845	0.00	-0.00712		X
1526	0.0015731	0.03	0.32252	R	X
1531	0.0017492	0.00	-0.00842		X
1546	0.0027476	0.00	0.01224		X
1603	0.0018502	0.00	-0.00890		X
1791	0.0023407	0.00	-0.01137		X
1793	0.0167232	0.19	-0.76135	R	X
1794	0.0049999	0.03	-0.27896	R	X
2000	0.0015329	0.00	0.00745		X
2059	0.0023054	0.00	-0.01115		X
2107	0.0021689	0.00	-0.01046		X
2131	0.0020492	0.00	-0.00986		X
2146	0.0166520	0.09	-0.51264	R	X
2148	0.0018321	0.00	-0.00848		X
2150	0.0015748	0.00	-0.00721		X
2151	0.0166432	0.01	0.20403		X
2153	0.0018229	0.00	-0.00832		X
2154	0.0166727	0.00	-0.03211		X
2196	0.0020034	0.00	-0.00850		X
2197	0.0020009	0.00	0.00802		X
2275	0.0018343	0.00	-0.00886		X
2316	0.0020800	0.00	0.00681		X
2317	0.0020257	0.00	0.00825		X
2338	0.0047892	0.00	0.02140		X
2371	0.0016177	0.00	-0.00783		X
2443	0.0027981	0.00	-0.01356		X
2461	0.0031152	0.00	0.01310		X
2467	0.0016452	0.00	-0.00795		X
2481	0.0022067	0.00	0.00982		X

2528	0.0017598	0.00	0.00855		X
2603	0.0166377	0.02	0.26026	R	X
2604	0.0023255	0.00	-0.01090		X
2607	0.0166498	0.19	0.74815	R	X
2608	0.0065046	0.30	0.95780	R	X
2624	0.0022093	0.00	0.01074		X
2635	0.0021409	0.00	-0.01038		X
2683	0.0022290	0.00	-0.01082		X
2793	0.0024052	0.00	0.01131		X
2865	0.0024608	0.00	0.01125		X
2875	0.0015207	0.00	-0.00737		X
2888	0.0015364	0.00	0.00746		X
2912	0.0015417	0.00	0.00748		X
2923	0.0017631	0.00	-0.00858		X
2964	0.0033402	0.00	-0.01560		X
2987	0.0026848	0.00	0.01151		X
2988	0.0032129	0.00	0.01305		X
2990	0.0017610	0.00	-0.00765		X
2995	0.0166383	0.36	-1.04941	R	X
2996	0.0038038	0.23	-0.84162	R	X
3019	0.0018997	0.00	-0.00925		X
3034	0.0016128	0.00	0.00727		X
3083	0.0017013	0.00	-0.00828		X
3084	0.0170517	0.13	0.61469	R	X
3085	0.0166919	0.05	-0.39928	R	X
3087	0.0023024	0.00	-0.01069		X
3091	0.0019198	0.00	-0.00934		X
3105	0.0017368	0.00	0.00694		X
3106	0.0019089	0.00	0.00770		X
3185	0.0169174	0.09	0.52982	R	X
3186	0.0057677	0.02	0.27243	R	X
3224	0.0015269	0.00	0.00741		X
3254	0.0166804	0.08	0.49042	R	X
3255	0.0129805	0.11	0.57535	R	X
3259	0.0015474	0.00	-0.00749		X
3275	0.0174566	0.47	-1.19068	R	X
3276	0.0023827	0.00	-0.01093		X
3302	0.0057681	0.00	0.02478		X
3345	0.0017085	0.00	0.00762		X
3393	0.0015228	0.00	0.00710		X
3419	0.0034375	0.00	0.01549		X
3442	0.0166913	0.00	-0.11237		X
3443	0.0026696	0.00	-0.01277		X
3445	0.0176864	1.73	2.33148	R	X
3446	0.0167641	1.99	2.51651	R	X
3448	0.0020160	0.00	-0.00910		X
3449	0.0172194	0.46	1.18812	R	X

3464	0.0017183	0.00	0.00835		X
3488	0.0017044	0.00	0.00828		X
3499	0.0018095	0.00	-0.00876		X
3512	0.0015293	0.00	0.00742		X
3547	0.0015238	0.00	-0.00736		X
3571	0.0017371	0.00	-0.00842		X
3588	0.0017237	0.00	-0.00700		X
3595	0.0031493	0.00	-0.01529		X
3612	0.0019589	0.00	0.00561		X
3619	0.0030890	0.00	-0.01507		X
3633	0.0021381	0.00	0.00948		X
3659	0.0017795	0.00	-0.00841		X
3660	0.0016612	0.00	-0.00784		X
3661	0.0166426	0.80	1.56934	R	X
3683	0.0167123	0.03	0.28121	R	X
3684	0.0069866	0.11	0.57565	R	X
3687	0.0027239	0.00	-0.01306		X
3691	0.0016354	0.00	-0.00792		X
3729	0.0167223	1.24	-1.96719	R	X
3730	0.0075178	0.00	0.02966		X
3752	0.0014890	0.00	0.00723		X
3779	0.0017183	0.00	0.00694		X
3787	0.0014706	0.00	-0.00714		X
3804	0.0017685	0.00	-0.00807		X
3826	0.0115780	0.00	-0.00576		X
3850	0.0168108	0.12	-0.61258	R	X
3851	0.0018663	0.00	0.00769		X
3858	0.0020445	0.00	-0.00987		X
3859	0.0015379	0.00	-0.00747		X
3873	0.0168028	0.79	-1.55655	R	X
3874	0.0021502	0.05	0.38555	R	X
3907	0.0019837	0.00	-0.00960		X
3920	0.0015563	0.00	0.00756		X
3921	0.0043299	0.00	0.02027		X
3979	0.0017618	0.00	-0.00851		X
3992	0.0016075	0.00	0.00781		X
4027	0.0016309	0.00	-0.00787		X
4047	0.0016738	0.00	-0.00751		X
4049	0.0015939	0.00	-0.00715		X
4051	0.0166603	0.11	-0.58602	R	X
4052	0.0030379	0.15	-0.67018	R	X
4137	0.0019138	0.00	0.00873		X
4138	0.0020748	0.00	0.00941		X
4195	0.0017448	0.00	-0.00842		X
4236	0.0167904	0.40	1.10683	R	X
4237	0.0033346	0.22	0.83460	R	X
4243	0.0114758	0.01	-0.17442		X

4262	0.0026400	0.00	0.01088		X
4284	0.0031566	0.00	0.01403		X
4305	0.0040473	0.00	0.01912		X
4404	0.0016551	0.00	0.00561		X
4474	0.0014793	0.00	0.00647		X
4496	0.0015500	0.00	0.00752		X
4507	0.0166376	0.29	-0.94069	R	X
4508	0.0035813	0.20	-0.79208	R	X
4556	0.0080805	0.94	-1.73073	R	X
4714	0.0018075	0.00	0.00778		X
4723	0.0014731	0.00	-0.00707		X
4835	0.0169479	0.16	-0.68944	R	X
4836	0.0023576	0.11	0.56980	R	X
4837	0.0018657	0.00	-0.00871		X
4840	0.0166602	0.03	0.30372	R	X
4841	0.0027204	0.00	-0.01305		X
4858	0.0017502	0.00	0.00767		X
4914	0.0169338	0.49	-1.21710	R	X
4915	0.0017508	0.00	-0.00841		X
4929	0.0024741	0.00	0.01118		X
4963	0.0027784	0.00	-0.01341		X
4977	0.0040592	0.00	0.01892		X
5026	0.0014933	0.00	0.00622		X
5034	0.0167250	0.61	-1.36878	R	X
5035	0.0066827	0.12	-0.59079	R	X
5052	0.0021857	0.00	0.00828		X
5054	0.0030769	0.00	-0.01477		X
5056	0.0029282	0.00	-0.01379		X
5058	0.0167141	0.08	0.49945	R	X
5059	0.0107866	0.12	-0.59084	R	X
5076	0.0023941	0.00	-0.01157		X
5078	0.0176837	0.72	1.47923	R	X
5080	0.0020591	0.00	-0.00997		X
5081	0.0166402	0.28	-0.92249	R	X
5082	0.0122982	0.01	-0.19519		X
5100	0.0015257	0.00	-0.00630		X
5102	0.0168293	0.03	-0.31208	R	X
5107	0.0017004	0.00	-0.00817		X
5128	0.0015369	0.00	-0.00726		X
5130	0.0166409	0.17	-0.71998	R	X
5179	0.0017132	0.00	-0.00823		X
5250	0.0016165	0.00	-0.00718		X
5275	0.0015189	0.00	-0.00729		X
5323	0.0026103	0.00	-0.01261		X
5339	0.0015185	0.00	0.00628		X
5340	0.0019138	0.00	0.00845		X
5362	0.0166678	0.03	-0.28877	R	X

5364	0.0024160	0.00	-0.01150		X
5365	0.0166682	0.06	0.42778	R	X
5366	0.0036865	0.12	0.59457	R	X
5385	0.0039914	0.00	0.01883		X
5386	0.0022840	0.00	0.01002		X
5443	0.0029180	0.00	-0.01410		X
5491	0.0016734	0.00	-0.00807		X
5584	0.0021346	0.00	-0.00953		X
5605	0.0018682	0.00	0.00508		X
5628	0.0017447	0.04	0.33660	R	X
5650	0.0045636	0.00	0.02061		X
5724	0.0171562	1.43	2.11537	R	X
5725	0.0082242	0.82	1.60921	R	X
5729	0.0173335	0.59	1.34617	R	X
5755	0.0016206	0.00	-0.00783		X
5774	0.0036773	0.00	0.01609		X
5824	0.0167466	0.06	0.41651	R	X
5825	0.0156877	0.00	-0.11720		X
5826	0.0017407	0.00	-0.00847		X
5843	0.0043591	0.00	0.02031		X
5851	0.0016604	0.00	-0.00804		X
5899	0.0027659	0.00	-0.01342		X
5914	0.0015368	0.00	0.00699		X
5985	0.0033956	0.00	0.01586		X
6056	0.0021008	0.00	0.01021		X
6080	0.0026698	0.00	0.01300		X
6106	0.0017377	0.00	0.00722		X
6109	0.0026472	0.00	-0.01183		X
6110	0.0019972	0.00	-0.00857		X
6111	0.0166409	0.39	1.08214	R	X
6130	0.0022339	0.00	0.01009		X
6134	0.0055452	0.00	-0.02680		X
6137	0.0168374	0.02	-0.23736		X
6138	0.0070771	0.20	0.78694	R	X
6152	0.0016108	0.00	0.00782		X
6163	0.0026744	0.00	-0.01305		X
6177	0.0015640	0.00	0.00660		X
6235	0.0015925	0.00	-0.00776		X
6307	0.0031574	0.00	-0.01542		X
6321	0.0019732	0.00	0.00907		X
6355	0.0027475	0.00	-0.01341		X
6369	0.0032376	0.00	0.01489		X
6392	0.0016228	0.00	0.00788		X
6416	0.0023086	0.00	0.01123		X
6427	0.0024511	0.00	-0.01196		X
6475	0.0020732	0.00	-0.01011		X
6488	0.0016293	0.00	0.00791		X

6523	0.0018012	0.00	-0.00878		X
6547	0.0016557	0.00	-0.00807		X
6635	0.0067732	0.00	0.03110		X
6704	0.0024866	0.00	0.01211		X
6752	0.0016556	0.00	0.00804		X
6805	0.0020068	0.00	0.00529		X
6807	0.0017864	0.04	0.34060	R	X
6811	0.0023221	0.00	-0.01133		X
6824	0.0020159	0.00	0.00980		X
6825	0.0017637	0.00	0.00833		X
6859	0.0016702	0.00	-0.00814		X
6883	0.0023874	0.00	-0.01164		X
6896	0.0025377	0.00	0.01235		X
6931	0.0019991	0.00	-0.00975		X
6955	0.0026251	0.00	-0.01281		X
6969	0.0014948	0.00	0.00649		X
6970	0.0024995	0.00	0.01068		X
7003	0.0021228	0.00	-0.01035		X
7016	0.0025747	0.00	0.01253		X
7025	0.0020461	0.00	-0.00958		X
7026	0.0016581	0.00	-0.00794		X
7027	0.0167718	0.06	-0.43676	R	X
7028	0.0046343	0.34	-1.02777	R	X
7051	0.0019891	0.00	-0.00970		X
7088	0.0017188	0.00	0.00835		X
7161	0.0018234	0.00	0.00779		X
7166	0.0019246	0.04	0.35358	R	X
7171	0.0027307	0.00	-0.01333		X
7195	0.0017167	0.00	-0.00837		X
7232	0.0019078	0.00	0.00927		X
7257	0.0016556	0.00	0.00749		X
7267	0.0029578	0.00	-0.01444		X
7291	0.0030707	0.00	-0.01499		X
7304	0.0023440	0.00	0.01140		X
7305	0.0026996	0.00	0.01251		X
7315	0.0019982	0.00	-0.00974		X
7328	0.0026978	0.00	0.01314		X
7352	0.0021425	0.00	0.01042		X
7363	0.0018375	0.00	-0.00896		X
7384	0.0014920	0.00	-0.00685		X
7399	0.0056092	0.38	-1.08615	R	X
7411	0.0015055	0.00	-0.00734		X
7425	0.0014719	0.00	0.00681		X
7520	0.0021495	0.00	0.01045		X
7531	0.0024487	0.00	-0.01195		X
7544	0.0015440	0.00	0.00750		X
7577	0.0022413	0.00	-0.01054		X

7580	0.0031216	0.16	-0.69040	R	X
7603	0.0166757	1.13	-1.87112	R	X
7627	0.0015446	0.00	-0.00753		X
7675	0.0018950	0.00	-0.00924		X
7691	0.0028423	0.00	0.01215		X
7713	0.0018272	0.00	0.00859		X
7723	0.0017355	0.00	-0.00846		X
7747	0.0033876	0.00	-0.01655		X
7761	0.0036019	0.00	0.01729		X
7762	0.0031217	0.00	0.01462		X
7795	0.0016013	0.00	-0.00781		X
7808	0.0021474	0.00	0.01044		X
7867	0.0020157	0.00	-0.00983		X
7891	0.0017012	0.00	-0.00829		X
7904	0.0019266	0.00	0.00937		X
7915	0.0021060	0.00	-0.01027		X
7928	0.0017254	0.00	0.00838		X
7939	0.0018359	0.00	-0.00895		X
7963	0.0018685	0.00	-0.00911		X
7980	0.0017624	0.00	0.00553		X
8003	0.0036542	0.00	0.01536		X
8026	0.0034437	0.00	0.01577		X
8083	0.0025447	0.00	-0.01242		X
8120	0.0015796	0.00	0.00767		X
8145	0.0040592	0.00	0.01886		X
8178	0.0018468	0.00	-0.00873		X
8192	0.0021229	0.00	0.01032		X
8203	0.0027093	0.00	-0.01323		X
8216	0.0025327	0.00	0.01232		X
8251	0.0027139	0.00	-0.01324		X
8295	0.0029443	0.00	-0.01394		X
8296	0.0169071	0.04	0.33394	R	X
8297	0.0133613	0.00	0.08681		X
8299	0.0015548	0.00	-0.00758		X
8312	0.0020702	0.00	0.01006		X
8347	0.0023255	0.00	-0.01135		X
8395	0.0017702	0.00	-0.00863		X
8408	0.0021659	0.00	0.01053		X
8432	0.0020844	0.00	0.01013		X
8456	0.0024621	0.00	0.01198		X
8467	0.0033475	0.00	-0.01634		X
8481	0.0015757	0.00	0.00706		X
8509	0.0019999	0.00	-0.00950		X
8510	0.0172666	0.59	1.34446	R	X
8515	0.0075393	0.01	-0.18188	R	X
8611	0.0028006	0.00	-0.01367		X
8624	0.0015204	0.00	0.00738		X

8625	0.0042212	0.00	0.01911	X
8683	0.0024255	0.00	-0.01183	X
8707	0.0026345	0.00	-0.01286	X
8720	0.0016856	0.00	0.00819	X
8755	0.0022095	0.00	-0.01078	X

R Large residual

X Unusual *X*

Fits and Diagnostics for Unusual Observations

Test Set

Obs	TELS (kW)	Fit	SE Fit	95% CI	Resid	Std Resid	HI		
660	27.2286	27.0911	0.0369	(27.0186, 27.1635)	0.1375	0.15	0.0015493	X	
811	24.0578	24.2342	0.0370	(24.1617, 24.3067)	-0.1764	-0.19	0.0015526	X	
1237	45.5362	38.0251	0.0392	(37.9482, 38.1019)	7.5111	8.00	0.0017447	R	X
1456	25.3892	27.5711	0.1216	(27.3327, 27.8095)	-2.1819	-2.31	0.0167898	R	X
1477	39.0421	39.2239	0.0420	(39.1415, 39.3063)	-0.1818	-0.19	0.0020043		X
1478	44.9291	27.5549	0.1220	(27.3158, 27.7940)	17.3742	18.36	0.0168896	R	X
1498	23.0862	22.9313	0.0383	(22.8562, 23.0064)	0.1549	0.16	0.0016649		X
1627	24.8257	25.0186	0.0402	(24.9399, 25.0973)	-0.1929	-0.21	0.0018306		X
1675	24.2582	24.4404	0.0381	(24.3658, 24.5150)	-0.1822	-0.19	0.0016453		X
1787	26.0871	27.6344	0.1211	(27.3971, 27.8718)	-1.5473	-1.64	0.0166398		X
1788	26.6797	15.9472	0.0701	(15.8099, 16.0845)	10.7325	11.40	0.0055710	R	X
1891	25.7844	25.9745	0.0398	(25.8964, 26.0525)	-0.1901	-0.20	0.0017993		X
2011	27.0357	27.2516	0.0448	(27.1638, 27.3395)	-0.2159	-0.23	0.0022808		X
2155	19.6952	20.8836	0.0915	(20.7041, 21.0630)	-1.1884	-1.26	0.0095117		X
2247	39.0210	39.1865	0.0395	(39.1090, 39.2640)	-0.1655	-0.18	0.0017740		X
2289	15.1101	14.8949	0.0473	(14.8022, 14.9876)	0.2152	0.23	0.0025369		X
2299	20.9105	21.0872	0.0365	(21.0157, 21.1587)	-0.1767	-0.19	0.0015107		X
2389	25.5277	25.3745	0.0390	(25.2980, 25.4510)	0.1532	0.16	0.0017279		X
2419	26.3534	26.5681	0.0445	(26.4809, 26.6553)	-0.2147	-0.23	0.0022461		X
2459	35.0577	35.3212	0.0551	(35.2133, 35.4292)	-0.2635	-0.28	0.0034433		X
2577	19.7668	19.5831	0.0425	(19.4998, 19.6664)	0.1837	0.20	0.0020510		X
2587	23.3119	23.5034	0.0396	(23.4257, 23.5810)	-0.1915	-0.20	0.0017817		X
2697	16.0906	15.8498	0.0527	(15.7465, 15.9530)	0.2408	0.26	0.0031494		X
2731	23.2568	23.4543	0.0408	(23.3745, 23.5342)	-0.1975	-0.21	0.0018851		X
2842	18.4191	18.2126	0.0465	(18.1214, 18.3038)	0.2065	0.22	0.0024569		X
2967	43.8369	43.7346	0.0405	(43.6553, 43.8140)	0.1023	0.11	0.0018605		X
2971	24.3733	24.5811	0.0429	(24.4971, 24.6652)	-0.2078	-0.22	0.0020865		X
2994	23.4514	23.6332	0.0379	(23.5590, 23.7074)	-0.1818	-0.19	0.0016266		X
3089	23.4981	27.5807	0.1214	(27.3427, 27.8188)	-4.0826	-4.31	0.0167422	R	X
3152	1.7941	1.6060	0.0388	(1.5300, 1.6821)	0.1881	0.20	0.0017085		X
3163	22.3735	22.5617	0.0389	(22.4855, 22.6379)	-0.1882	-0.20	0.0017139		X
3183	30.4346	30.6659	0.0483	(30.5713, 30.7605)	-0.2313	-0.25	0.0026429		X
3253	32.6920	32.8630	0.0382	(32.7881, 32.9379)	-0.1710	-0.18	0.0016571		X
3279	37.2814	27.6072	0.1211	(27.3698, 27.8447)	9.6742	10.22	0.0166573	R	X
3283	22.4042	22.5923	0.0389	(22.5162, 22.6685)	-0.1881	-0.20	0.0017139		X

3321	12.4665	12.2930	0.0382	(12.2181, 12.3678)	0.1735	0.18	0.0016556	X
3403	21.7642	21.9560	0.0395	(21.8787, 22.0333)	-0.1918	-0.20	0.0017668	X
3450	31.8812	24.2433	0.1073	(24.0330, 24.4536)	7.6379	8.09	0.0130660	R X
3560	1.5332	1.3355	0.0407	(1.2556, 1.4153)	0.1977	0.21	0.0018837	X
3611	21.9424	21.7722	0.0407	(21.6924, 21.8520)	0.1702	0.18	0.0018821	X
3662	28.3571	16.0471	0.0759	(15.8983, 16.1958)	12.3100	13.07	0.0065365	R X
3686	36.2538	36.5069	0.0534	(36.4022, 36.6116)	-0.2531	-0.27	0.0032378	X
3688	31.0962	27.6970	0.1219	(27.4580, 27.9359)	3.3992	3.59	0.0168671	R X
3689	23.9494	27.6234	0.1211	(27.3860, 27.8607)	-3.6740	-3.88	0.0166384	R X
3690	24.9254	25.1054	0.0378	(25.0313, 25.1795)	-0.1800	-0.19	0.0016214	X
3707	24.6166	27.4942	0.1241	(27.2509, 27.7375)	-2.8776	-3.04	0.0174857	R X
3714	24.3084	24.4884	0.0377	(24.4145, 24.5622)	-0.1800	-0.19	0.0016113	X
3753	17.3881	17.2207	0.0385	(17.1451, 17.2962)	0.1674	0.18	0.0016862	X
3754	20.4855	20.3221	0.0389	(20.2459, 20.3983)	0.1634	0.17	0.0017149	X
3805	32.0025	27.5404	0.1224	(27.3005, 27.7803)	4.4621	4.71	0.0170002	R X
3825	14.5796	27.5672	0.1217	(27.3287, 27.8058)	-12.9876	-13.72	0.0168113	R X
3827	29.5752	29.7623	0.0401	(29.6837, 29.8410)	-0.1871	-0.20	0.0018267	X
3835	21.9601	22.1403	0.0373	(22.0672, 22.2135)	-0.1802	-0.19	0.0015814	X
3905	24.8149	27.5535	0.1220	(27.3143, 27.7927)	-2.7386	-2.89	0.0168993	R X
4171	22.1417	22.3167	0.0364	(22.2454, 22.3880)	-0.1750	-0.19	0.0015005	X
4242	24.5046	27.6498	0.1211	(27.4123, 27.8873)	-3.1452	-3.32	0.0166610	R X
4473	13.4943	13.2810	0.0464	(13.1900, 13.3720)	0.2133	0.23	0.0024472	X
4549	40.6311	27.6122	0.1211	(27.3748, 27.8496)	13.0189	13.76	0.0166489	R X
4555	21.7795	27.6291	0.1211	(27.3917, 27.8664)	-5.8496	-6.18	0.0166377	R X
4771	24.1798	24.3649	0.0386	(24.2892, 24.4406)	-0.1851	-0.20	0.0016918	X
4857	12.7418	12.4711	0.0578	(12.3577, 12.5845)	0.2707	0.29	0.0037960	X
4939	23.0594	23.2372	0.0371	(23.1646, 23.3099)	-0.1778	-0.19	0.0015593	X
4976	1.6196	1.4400	0.0370	(1.3674, 1.5126)	0.1796	0.19	0.0015561	X
5030	30.7474	30.9345	0.0404	(30.8553, 31.0137)	-0.1871	-0.20	0.0018530	X
5055	37.8163	27.7118	0.1223	(27.4720, 27.9515)	10.1045	10.68	0.0169753	R X
5077	20.5882	27.6183	0.1211	(27.3809, 27.8556)	-7.0301	-7.43	0.0166417	R X
5079	27.2651	27.5086	0.0500	(27.4105, 27.6066)	-0.2435	-0.26	0.0028395	X
5106	25.3586	27.5709	0.1216	(27.3325, 27.8094)	-2.2123	-2.34	0.0167906	R X
5123	33.7422	27.6512	0.1212	(27.4137, 27.8887)	6.0910	6.44	0.0166641	R X
5124	39.3274	39.5794	0.0539	(39.4738, 39.6851)	-0.2520	-0.27	0.0032975	X
5125	36.4926	27.6593	0.1212	(27.4217, 27.8970)	8.8333	9.33	0.0166856	R X
5129	29.1936	27.6693	0.1214	(27.4314, 27.9072)	1.5243	1.61	0.0167205	X
5131	25.0901	25.2829	0.0402	(25.2042, 25.3617)	-0.1928	-0.21	0.0018328	X
5192	1.6213	1.4428	0.0368	(1.3706, 1.5149)	0.1785	0.19	0.0015381	X
5368	35.2421	35.5139	0.0566	(35.4029, 35.6249)	-0.2718	-0.29	0.0036407	X
5480	1.7218	1.5279	0.0400	(1.4495, 1.6062)	0.1939	0.21	0.0018150	X
5528	1.6250	1.4468	0.0367	(1.3748, 1.5188)	0.1782	0.19	0.0015329	X
5539	22.4306	22.6045	0.0362	(22.5335, 22.6755)	-0.1739	-0.19	0.0014891	X
5601	18.0823	27.5969	0.1212	(27.3593, 27.8346)	-9.5146	-10.05	0.0166824	R X
5602	23.2688	19.8405	0.0870	(19.6700, 20.0110)	3.4283	3.64	0.0085863	R X
5635	24.3412	24.5439	0.0419	(24.4618, 24.6261)	-0.2027	-0.22	0.0019940	X
5659	25.7998	26.0069	0.0430	(25.9227, 26.0911)	-0.2071	-0.22	0.0020947	X

5726	33.9992	34.2432	0.0513	(34.1426, 34.3437)	-0.2440	-0.26	0.0029866	X
5730	19.2939	20.5386	0.0900	(20.3623, 20.7150)	-1.2447	-1.32	0.0091909	X
5731	25.6488	25.8563	0.0430	(25.7720, 25.9406)	-0.2075	-0.22	0.0021004	X
5793	13.2293	13.0441	0.0407	(12.9642, 13.1239)	0.1852	0.20	0.0018835	X
5819	33.7390	27.6361	0.1211	(27.3987, 27.8734)	6.1029	6.45	0.0166410	R X
5964	23.2240	23.0323	0.0453	(22.9436, 23.1211)	0.1917	0.20	0.0023284	X
5966	31.9371	27.6215	0.1211	(27.3841, 27.8588)	4.3156	4.56	0.0166393	R X
5967	32.9176	33.1105	0.0420	(33.0282, 33.1927)	-0.1929	-0.21	0.0019992	X
6204	42.7827	20.4451	0.0905	(20.2677, 20.6226)	22.3376	23.69	0.0093031	R X
6210	24.6092	24.7858	0.0371	(24.7130, 24.8586)	-0.1766	-0.19	0.0015644	X
6259	20.2755	20.4570	0.0373	(20.3839, 20.5301)	-0.1815	-0.19	0.0015786	X
6272	1.6921	1.5105	0.0374	(1.4371, 1.5839)	0.1816	0.19	0.0015915	X
6331	23.0304	23.2365	0.0424	(23.1535, 23.3196)	-0.2061	-0.22	0.0020367	X
6345	18.8236	18.6455	0.0411	(18.5650, 18.7261)	0.1781	0.19	0.0019166	X
6368	1.7239	1.4752	0.0512	(1.3748, 1.5756)	0.2487	0.26	0.0029779	X
6440	1.7026	1.4460	0.0528	(1.3425, 1.5496)	0.2566	0.27	0.0031665	X
6513	13.7050	13.5361	0.0376	(13.4623, 13.6099)	0.1689	0.18	0.0016076	X
6536	1.5768	1.3713	0.0423	(1.2883, 1.4543)	0.2055	0.22	0.0020354	X
6594	30.0034	30.2536	0.0517	(30.1522, 30.3549)	-0.2502	-0.27	0.0030356	X
6656	1.6698	1.4798	0.0392	(1.4029, 1.5566)	0.1900	0.20	0.0017433	X
6657	19.7720	19.5671	0.0467	(19.4757, 19.6586)	0.2049	0.22	0.0024712	X
6667	20.3749	20.5573	0.0375	(20.4839, 20.6308)	-0.1824	-0.19	0.0015941	X
6691	21.1216	21.3106	0.0388	(21.2345, 21.3868)	-0.1890	-0.20	0.0017131	X
6776	1.6401	1.4417	0.0409	(1.3615, 1.5218)	0.1984	0.21	0.0018979	X
6921	16.7162	16.5417	0.0397	(16.4638, 16.6195)	0.1745	0.19	0.0017888	X
6944	1.7223	1.5076	0.0442	(1.4208, 1.5943)	0.2147	0.23	0.0022217	X
6951	49.0090	41.4981	0.0404	(41.4188, 41.5774)	7.5109	8.00	0.0018566	R X
7064	1.7236	1.5394	0.0380	(1.4649, 1.6139)	0.1842	0.20	0.0016391	X
7123	23.4439	23.6538	0.0431	(23.5692, 23.7383)	-0.2099	-0.22	0.0021105	X
7137	12.7071	12.5133	0.0423	(12.4304, 12.5963)	0.1938	0.21	0.0020319	X
7147	28.5451	28.8007	0.0525	(28.6977, 28.9036)	-0.2556	-0.27	0.0031289	X
7185	18.2547	18.0386	0.0484	(17.9438, 18.1334)	0.2161	0.23	0.0026569	X
7208	1.6116	1.4238	0.0387	(1.3480, 1.4997)	0.1878	0.20	0.0017005	X
7243	24.8223	25.0445	0.0457	(24.9550, 25.1340)	-0.2222	-0.24	0.0023660	X
7285	44.9198	44.8597	0.0361	(44.7890, 44.9305)	0.0601	0.06	0.0014793	X
7398	1.6505	25.7348	0.1160	(25.5073, 25.9622)	-24.0843	-25.47	0.0152804	R X
7448	1.5903	1.3872	0.0419	(1.3051, 1.4693)	0.2031	0.22	0.0019897	X
7579	25.7780	27.6903	0.1217	(27.4517, 27.9290)	-1.9123	-2.02	0.0168253	R X
7597	39.3274	27.6509	0.1212	(27.4134, 27.8884)	11.6765	12.34	0.0166635	R X
7604	0.1982	18.3021	0.0829	(18.1396, 18.4646)	-18.1039	-19.21	0.0078029	R X
7640	1.6035	1.4005	0.0418	(1.3185, 1.4825)	0.2030	0.22	0.0019866	X
7674	26.4010	26.6131	0.0440	(26.5269, 26.6994)	-0.2121	-0.23	0.0021981	X
7714	23.6395	23.3565	0.0633	(23.2325, 23.4805)	0.2830	0.30	0.0045444	X
7819	23.2907	23.4993	0.0428	(23.4153, 23.5832)	-0.2086	-0.22	0.0020830	X
8002	21.7966	21.5366	0.0581	(21.4227, 21.6506)	0.2600	0.28	0.0038376	X
8025	19.5723	19.3833	0.0435	(19.2981, 19.4685)	0.1890	0.20	0.0021452	X
8096	1.6355	1.4005	0.0484	(1.3056, 1.4953)	0.2350	0.25	0.0026591	X

8107	24.2382	24.4552	0.0446	(24.3678, 24.5426)	-0.2170	-0.23	0.0022559	X
8129	29.1912	29.3667	0.0380	(29.2922, 29.4412)	-0.1755	-0.19	0.0016389	X
8193	21.0726	20.8667	0.0473	(20.7741, 20.9594)	0.2059	0.22	0.0025373	X
8265	18.0593	17.8020	0.0565	(17.6912, 17.9128)	0.2573	0.27	0.0036265	X
8275	22.0444	22.2417	0.0405	(22.1622, 22.3212)	-0.1973	-0.21	0.0018660	X
8292	44.1740	22.2832	0.0942	(22.0985, 22.4680)	21.8908	23.21	0.0100831	R X
8294	36.8224	36.9886	0.0388	(36.9125, 37.0647)	-0.1662	-0.18	0.0017111	X
8361	14.4536	14.1814	0.0586	(14.0666, 14.2962)	0.2722	0.29	0.0038937	X
8384	1.6778	1.5012	0.0364	(1.4297, 1.5726)	0.1766	0.19	0.0015070	X
8483	29.0281	29.2030	0.0378	(29.1288, 29.2771)	-0.1749	-0.19	0.0016250	X
8508	34.7799	27.6350	0.1211	(27.3976, 27.8723)	7.1449	7.55	0.0166402	R X
8514	23.8753	27.6325	0.1211	(27.3952, 27.8698)	-3.7572	-3.97	0.0166387	R X
8563	21.3999	21.5915	0.0394	(21.5143, 21.6686)	-0.1916	-0.20	0.0017585	X
8696	1.6403	1.4515	0.0389	(1.3752, 1.5278)	0.1888	0.20	0.0017210	X
8731	23.9304	24.1446	0.0440	(24.0583, 24.2309)	-0.2142	-0.23	0.0021990	X

R Large residual

X Unusual *X*

Durbin-Watson Statistic

Durbin-Watson Statistic = 1.60088

Appendix C: Regression Model Results of SEM Reliability – Awka Scenario

Regression Equation

$$R_{SEM} = -0.003234 + 0.9993*R_{inv} + 0.003885*R_{pv} + 0.0000007064*R_{gen}$$

Coefficients

Term	Coef	SE Coef	95% CI	T-Value	P-Value	VIF
Constant	-0.003234	0.000000	(-0.003234, -0.003234)	*	*	
R_{inv}	0.9993	0.0000	(0.9993, 0.9993)	*	*	21418.32
R_{pv}	0.003885	0.000000	(0.003885, 0.003885)	*	*	20849.92
R_{gen}	0.000001	0.000000	(0.000001, 0.000001)	*	*	8.99

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC
0	100.00%	100.00%	7.77373E-12	100.00%	*	*

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	3	9.92573	100.00%	9.92573	3.30858	*	*
R_{inv}	1	9.92573	100.00%	0.00046	0.00046	*	*
R_{pv}	1	0.00000	0.00%	0.00000	0.00000	*	*
R_{gen}	1	0.00000	0.00%	0.00000	0.00000	*	*
Error	8756	0.00000	0.00%	0.00000	0.00000		
Total	8759	9.92573	100.00%				

Fits and Diagnostics for Unusual Observations

Obs	R_{SEM}	Fit	SE Fit	95% CI	Resid	Std Resid	Del Resid	HI	Cook's D
1	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00311919	*
2	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00310964	*
3	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00310011	*
4	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00309062	*
5	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00308115	*
6	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00307171	*
7	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00306230	*
8	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00305292	*
9	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00304356	*
10	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00303424	*
11	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00302494	*
12	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00301567	*

13	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00300643	*
14	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00299722	*
15	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00298803	*
16	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00297888	*
17	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00296975	*
18	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00296064	*
19	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00295157	*
20	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00294252	*
21	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00293350	*
22	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00292451	*
23	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00291555	*
24	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00290661	*
25	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00289770	*
26	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00288882	*
27	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00287996	*
28	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00287113	*
29	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00286233	*
30	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00285355	*
31	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00284480	*
32	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00283608	*
33	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00282739	*
34	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00281872	*
35	1.000	1.000	0.000	(1.000, 1.000)	0.000	*	*	0.00281008	*
36	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00280146	*
37	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00279287	*
38	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00278431	*
39	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00277577	*
40	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00276726	*
41	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00275878	*
42	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00275032	*
43	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00274189	*
44	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00273348	*
45	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00272510	*
46	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00271674	*
47	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00270841	*
48	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00270011	*
49	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00269183	*
50	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00268358	*
51	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00267535	*
52	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00266715	*
53	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00265897	*
54	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00265082	*
55	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00264269	*
56	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00263459	*
57	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00262651	*
58	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00261846	*
59	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00261044	*

60	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00260243	*
61	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00259446	*
62	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00258650	*
63	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00257858	*
64	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00257067	*
65	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00256280	*
66	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00255494	*
67	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00254711	*
68	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00253931	*
69	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00253152	*
70	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00252377	*
71	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00251603	*
72	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00250833	*
73	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00250064	*
74	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00249298	*
75	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00248534	*
76	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00247773	*
77	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00247014	*
78	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00246257	*
79	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00245503	*
80	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00244751	*
81	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00244002	*
82	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00243255	*
83	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00242510	*
84	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00241767	*
85	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00241027	*
86	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00240289	*
87	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00239554	*
88	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00238820	*
89	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00238090	*
90	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00237361	*
91	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00236635	*
92	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00235910	*
93	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00235189	*
94	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00234469	*
95	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00233752	*
96	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00233037	*
97	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00232324	*
98	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00231614	*
99	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00230905	*
100	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00230199	*
101	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00229495	*
102	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00228794	*
103	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00228095	*
104	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00227397	*
105	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00226702	*
106	0.999	0.999	0.000	(0.999, 0.999)	0.000	*	*	0.00226010	*

107	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00225319	*
108	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00224631	*
109	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00223945	*
110	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00223261	*
111	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00222579	*
112	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00221899	*
113	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00221222	*
114	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00220546	*
115	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00219873	*
116	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00219202	*
117	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00218533	*
118	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00217866	*
119	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00217202	*
120	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00216539	*
121	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00215879	*
122	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00215220	*
123	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00214564	*
124	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00213910	*
125	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00213258	*
126	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00212608	*
127	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00211960	*
128	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00211314	*
129	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00210671	*
130	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00210029	*
131	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00209389	*
132	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00208752	*
133	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00208116	*
134	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00207483	*
135	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00206851	*
136	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00206222	*
137	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00205594	*
138	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00204969	*
139	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00204346	*
140	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00203724	*
141	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00203105	*
142	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00202488	*
143	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00201872	*
144	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00201259	*
145	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00200648	*
146	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00200038	*
147	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00199431	*
148	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00198825	*
149	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00198222	*
150	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00197620	*
151	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00197021	*
152	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00196423	*
153	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00195828	*

154	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00195234	*
155	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00194642	*
156	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00194052	*
157	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00193464	*
158	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00192878	*
159	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00192294	*
160	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00191712	*
161	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00191131	*
162	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00190553	*
163	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00189976	*
164	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00189401	*
165	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00188829	*
166	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00188258	*
167	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00187689	*
168	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00187121	*
169	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00186556	*
170	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00185992	*
171	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00185431	*
172	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00184871	*
173	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00184313	*
174	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00183757	*
175	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00183203	*
176	0.998	0.998	0.000	(0.998, 0.998)	0.000	*	*	0.00182650	*
177	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00182099	*
178	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00181550	*
179	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00181003	*
180	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00180458	*
181	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00179915	*
182	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00179373	*
183	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00178833	*
184	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00178295	*
185	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00177759	*
186	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00177224	*
187	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00176691	*
188	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00176160	*
189	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00175631	*
190	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00175104	*
191	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00174578	*
192	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00174054	*
193	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00173532	*
194	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00173011	*
195	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00172492	*
196	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00171975	*
197	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00171460	*
198	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00170946	*
199	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00170434	*
200	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00169924	*

201	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00169416	*
202	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00168909	*
203	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00168404	*
204	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00167900	*
205	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00167399	*
206	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00166899	*
207	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00166400	*
208	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00165903	*
209	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00165408	*
210	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00164915	*
211	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00164423	*
212	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00163933	*
213	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00163445	*
214	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00162958	*
215	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00162473	*
216	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00161989	*
217	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00161507	*
218	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00161027	*
219	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00160548	*
220	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00160071	*
221	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00159596	*
222	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00159122	*
223	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00158650	*
224	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00158179	*
225	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00157710	*
226	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00157243	*
227	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00156777	*
228	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00156313	*
229	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00155850	*
230	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00155389	*
231	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00154929	*
232	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00154471	*
233	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00154015	*
234	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00153560	*
235	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00153107	*
236	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00152655	*
237	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00152205	*
238	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00151756	*
239	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00151309	*
240	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00150863	*
241	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00150419	*
242	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00149976	*
243	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00149535	*
244	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00149096	*
245	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00148658	*
246	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00148221	*
247	0.997	0.997	0.000	(0.997, 0.997)	0.000	*	*	0.00147786	*

248	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00147352	*
249	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00146920	*
250	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00146490	*
251	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00146061	*
252	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00145633	*
253	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00145207	*
254	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00144782	*
255	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00144359	*
256	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00143937	*
257	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00143517	*
258	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00143098	*
259	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00142680	*
260	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00142264	*
261	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00141850	*
262	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00141437	*
263	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00141025	*
264	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00140615	*
265	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00140206	*
266	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00139799	*
267	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00139393	*
268	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00138988	*
269	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00138585	*
270	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00138183	*
271	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00137783	*
272	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00137384	*
273	0.996	0.996	0.000	(0.996, 0.996)	0.000	*	*	0.00136986	*

Obs	DFITS	
1	*	X
2	*	X
3	*	X
4	*	X
5	*	X
6	*	X
7	*	X
8	*	X
9	*	X
10	*	X
11	*	X
12	*	X
13	*	X
14	*	X
15	*	X
16	*	X
17	*	X
18	*	X
19	*	X
20	*	X

21	*	X
22	*	X
23	*	X
24	*	X
25	*	X
26	*	X
27	*	X
28	*	X
29	*	X
30	*	X
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33	*	X
34	*	X
35	*	X
36	*	X
37	*	X
38	*	X
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40	*	X
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68	*	X
69	*	X
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145	*	X
146	*	X
147	*	X
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154	*	X
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160	*	X
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162	*	X
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240	*	X
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244	*	X
245	*	X
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247	*	X
248	*	X
249	*	X
250	*	X
251	*	X
252	*	X
253	*	X
254	*	X
255	*	X

256	*	X
257	*	X
258	*	X
259	*	X
260	*	X
261	*	X
262	*	X
263	*	X
264	*	X
265	*	X
266	*	X
267	*	X
268	*	X
269	*	X
270	*	X
271	*	X
272	*	X
273	*	X

X Unusual X

Appendix D: Regression Model Results – Liverpool Scenario

Method

Test set fraction 30.0%

Regression Equation

$$\begin{aligned} \text{TELS (kW)} = & 0.9020 + 1.172 * \text{Global Solar (kW/m}^2\text{)} \\ & + 0.51069 * \text{DGen Power Output (kW)} \\ & + 0.85298 * \text{Inverter Power Input (kW)} \\ & - 0.07454 * \text{Battery Input Power (kW)} \\ & + 0.0000161 * \text{Time (hr)} \end{aligned}$$

Coefficients

Term	Coef	SE Coef	95% CI	T-Value	P-Value
Constant	0.9020	0.0927	(0.7202, 1.0838)	9.73	0.000
Global Solar (kW/m ²)	1.172	0.130	(0.917, 1.428)	9.00	0.000
DGen Power Output (kW)	0.51069	0.00443	(0.50200, 0.51938)	115.17	0.000
Inverter Power Input (kW)	0.85298	0.00674	(0.83977, 0.86619)	126.60	0.000
Battery Input Power (kW)	-0.07454	0.00374	(-0.08187, -0.06722)	-19.96	0.000
Time (hr)	0.000016	0.000013	(-0.000009, 0.000041)	1.25	0.212
Term	VIF				
Constant					
Global Solar (kW/m ²)	1.76				
DGen Power Output (kW)	1.87				
Inverter Power Input (kW)	2.05				
Battery Input Power (kW)	1.53				
Time (hr)	1.00				

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)	AICc	BIC	Test S	Test R-sq
2.57204	82.19%	82.18%	40670.6	82.13%	28995.65	29042.68	2.51998	82.74%

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value
Regression	5	187070	82.19%	187070	37414	5655.62
Global Solar (kW/m ²)	1	44015	19.34%	536	536	81.00

DGen Power Output (kW)	1	33958	14.92%	87749	87749	13264.36
Inverter Power Input (kW)	1	106452	46.77%	106020	106020	16026.30
Battery Input Power (kW)	1	2635	1.16%	2635	2635	398.30
Time (hr)	1	10	0.00%	10	10	1.56
Error	6126	40526	17.81%	40526	7	
Total	6131	227596	100.00%			
Source	P-Value					
Regression	0.000					
Global Solar (kW/m ²)	0.000					
DGen Power Output (kW)	0.000					
Inverter Power Input (kW)	0.000					
Battery Input Power (kW)	0.000					
Time (hr)	0.212					
Error						
Total						

Fits and Diagnostics for Unusual Observations

Training Set

Obs	TELS (kW)	Fit	SE Fit	95% CI	Resid	Std Resid	Del Resid
10	13.644	10.744	0.158	(10.434, 11.054)	2.901	1.13	1.13
23	13.049	19.421	0.138	(19.152, 19.691)	-6.373	-2.48	-2.48
24	4.240	15.470	0.121	(15.232, 15.708)	-11.230	-4.37	-4.38
34	19.462	12.549	0.118	(12.319, 12.780)	6.913	2.69	2.69
42	20.579	11.412	0.095	(11.226, 11.598)	9.167	3.57	3.57
45	14.589	8.353	0.084	(8.188, 8.519)	6.236	2.43	2.43
58	19.910	16.820	0.155	(16.517, 17.124)	3.089	1.20	1.20
59	23.457	19.543	0.181	(19.188, 19.899)	3.913	1.53	1.53
65	15.825	8.985	0.086	(8.817, 9.153)	6.840	2.66	2.66
89	27.323	14.857	0.113	(14.637, 15.078)	12.466	4.85	4.86
90	17.489	9.835	0.088	(9.662, 10.008)	7.654	2.98	2.98
91	18.067	10.130	0.089	(9.956, 10.305)	7.937	3.09	3.09
106	18.613	15.506	0.156	(15.200, 15.812)	3.107	1.21	1.21
107	25.411	21.042	0.199	(20.652, 21.432)	4.369	1.70	1.70
113	15.545	8.843	0.085	(8.676, 9.009)	6.703	2.61	2.61
114	14.054	8.081	0.083	(7.918, 8.244)	5.973	2.32	2.32
115	14.362	8.238	0.084	(8.075, 8.402)	6.124	2.38	2.38
118	15.190	8.661	0.084	(8.496, 8.827)	6.529	2.54	2.54
119	15.402	8.769	0.085	(8.603, 8.935)	6.632	2.58	2.58
137	26.107	14.237	0.109	(14.024, 14.450)	11.870	4.62	4.63
138	19.909	11.072	0.092	(10.890, 11.253)	8.838	3.44	3.44

139	19.335	10.778	0.091	(10.600, 10.957)	8.557	3.33	3.33
143	17.968	10.080	0.089	(9.907, 10.254)	7.888	3.07	3.07
154	17.356	14.227	0.158	(13.916, 14.537)	3.129	1.22	1.22
161	17.701	9.944	0.088	(9.772, 10.117)	7.757	3.02	3.02
162	15.763	8.955	0.085	(8.788, 9.121)	6.808	2.65	2.65
186	16.274	9.216	0.085	(9.048, 9.383)	7.058	2.75	2.75
187	17.731	9.960	0.088	(9.788, 10.132)	7.771	3.02	3.03
190	17.222	9.700	0.087	(9.530, 9.871)	7.522	2.93	2.93
191	18.028	10.112	0.088	(9.939, 10.285)	7.916	3.08	3.08
202	28.992	16.831	0.203	(16.432, 17.229)	12.161	4.74	4.75
209	21.139	11.701	0.095	(11.516, 11.887)	9.438	3.67	3.68
210	17.855	10.024	0.088	(9.852, 10.196)	7.831	3.05	3.05
211	20.229	11.236	0.093	(11.055, 11.418)	8.993	3.50	3.50
214	18.460	10.333	0.089	(10.158, 10.507)	8.127	3.16	3.16
215	16.096	9.126	0.085	(8.959, 9.292)	6.971	2.71	2.71
226	20.428	17.104	0.162	(16.787, 17.422)	3.324	1.29	1.29
227	25.153	21.370	0.175	(21.027, 21.714)	3.783	1.47	1.47
233	18.608	10.409	0.089	(10.235, 10.584)	8.198	3.19	3.19
234	18.109	10.154	0.088	(9.981, 10.326)	7.955	3.09	3.10
270	6.286	18.946	0.141	(18.669, 19.224)	-12.660	-4.93	-4.94
271	6.974	18.995	0.141	(18.719, 19.271)	-12.021	-4.68	-4.69
274	19.237	15.824	0.167	(15.498, 16.151)	3.413	1.33	1.33
281	20.639	11.448	0.093	(11.266, 11.631)	9.191	3.58	3.58
287	19.103	10.662	0.090	(10.487, 10.838)	8.441	3.28	3.29
298	22.214	17.600	0.214	(17.181, 18.020)	4.614	1.80	1.80
306	16.402	9.283	0.085	(9.118, 9.449)	7.119	2.77	2.77
322	19.744	16.188	0.172	(15.851, 16.524)	3.556	1.39	1.39
328	27.381	25.649	0.144	(25.367, 25.931)	1.732	0.67	0.67
329	27.080	14.740	0.110	(14.524, 14.956)	12.339	4.80	4.81
335	16.682	10.078	0.086	(9.910, 10.247)	6.603	2.57	2.57
346	22.594	18.912	0.174	(18.570, 19.253)	3.683	1.44	1.44
354	15.859	9.007	0.083	(8.843, 9.170)	6.852	2.67	2.67
355	15.586	8.867	0.083	(8.705, 9.030)	6.719	2.61	2.61
370	20.493	16.804	0.176	(16.459, 17.149)	3.689	1.44	1.44
371	23.486	20.465	0.147	(20.177, 20.753)	3.021	1.18	1.18
377	24.817	13.586	0.103	(13.384, 13.789)	11.231	4.37	4.38
378	19.872	11.056	0.091	(10.879, 11.234)	8.815	3.43	3.43
379	15.524	8.836	0.083	(8.674, 8.998)	6.688	2.60	2.60
382	17.099	9.640	0.085	(9.473, 9.807)	7.458	2.90	2.90
383	20.575	11.415	0.092	(11.235, 11.596)	9.159	3.56	3.57
394	17.951	14.244	0.181	(13.889, 14.598)	3.707	1.44	1.45
401	26.090	14.238	0.107	(14.028, 14.447)	11.853	4.61	4.62
402	19.897	11.070	0.090	(10.893, 11.247)	8.827	3.43	3.44
403	17.992	10.097	0.087	(9.927, 10.266)	7.895	3.07	3.07
406	15.768	8.961	0.083	(8.799, 9.123)	6.807	2.65	2.65
407	19.728	10.983	0.090	(10.807, 11.160)	8.744	3.40	3.40
427	14.883	8.509	0.081	(8.350, 8.669)	6.373	2.48	2.48

442	15.786	11.934	0.193	(11.555, 12.313)	3.852	1.50	1.50
449	19.718	10.988	0.090	(10.812, 11.164)	8.730	3.40	3.40
466	18.400	14.412	0.192	(14.035, 14.789)	3.989	1.56	1.56
473	24.809	13.590	0.103	(13.388, 13.791)	11.219	4.37	4.37
475	16.765	9.471	0.084	(9.307, 9.636)	7.294	2.84	2.84
479	14.497	8.338	0.081	(8.180, 8.496)	6.159	2.40	2.40
497	19.574	10.920	0.089	(10.745, 11.095)	8.653	3.37	3.37
505	5.521	18.896	0.141	(18.620, 19.172)	-13.375	-5.21	-5.22
506	4.249	18.806	0.142	(18.527, 19.085)	-14.557	-5.67	-5.68
514	16.933	12.576	0.213	(12.158, 12.993)	4.357	1.70	1.70
521	17.207	9.711	0.084	(9.545, 9.876)	7.496	2.92	2.92
523	15.831	8.995	0.082	(8.835, 9.156)	6.836	2.66	2.66
524	14.581	8.357	0.080	(8.199, 8.514)	6.224	2.42	2.42
538	4.470	1.611	0.201	(1.217, 2.004)	2.860	1.12	1.12
551	13.007	19.427	0.135	(19.163, 19.691)	-6.420	-2.50	-2.50
552	3.246	18.736	0.144	(18.454, 19.017)	-15.490	-6.03	-6.05
562	14.553	10.327	0.215	(9.906, 10.749)	4.225	1.65	1.65
570	16.790	9.485	0.083	(9.323, 9.648)	7.304	2.84	2.84
586	14.195	10.474	0.192	(10.097, 10.851)	3.721	1.45	1.45
594	18.672	10.447	0.086	(10.278, 10.616)	8.225	3.20	3.20
610	12.850	9.713	0.170	(9.380, 10.047)	3.137	1.22	1.22
634	13.112	8.925	0.219	(8.496, 9.354)	4.187	1.63	1.63
641	26.233	18.688	0.088	(18.516, 18.861)	7.544	2.93	2.94
666	16.285	10.335	0.084	(10.172, 10.499)	5.950	2.31	2.32
689	27.003	19.186	0.090	(19.010, 19.361)	7.817	3.04	3.04
690	15.538	8.848	0.080	(8.691, 9.006)	6.690	2.60	2.60
706	12.379	8.755	0.195	(8.373, 9.136)	3.625	1.41	1.41
738	20.897	13.589	0.097	(13.399, 13.778)	7.308	2.84	2.85
753	13.282	17.689	0.170	(17.355, 18.023)	-4.407	-1.72	-1.72
754	11.211	4.983	0.130	(4.728, 5.238)	6.227	2.42	2.43
768	4.990	18.863	0.140	(18.587, 19.138)	-13.873	-5.40	-5.41
790	14.047	19.399	0.132	(19.139, 19.659)	-5.352	-2.08	-2.08
791	19.212	10.726	0.086	(10.557, 10.895)	8.486	3.30	3.30
802	13.153	10.414	0.150	(10.121, 10.708)	2.738	1.07	1.07
810	13.948	8.038	0.077	(7.886, 8.190)	5.910	2.30	2.30
845	8.025	19.079	0.137	(18.810, 19.347)	-11.054	-4.30	-4.31
846	4.495	18.829	0.141	(18.553, 19.105)	-14.334	-5.58	-5.60
858	18.557	12.257	0.089	(12.081, 12.432)	6.300	2.45	2.45
859	15.262	8.710	0.079	(8.556, 8.864)	6.552	2.55	2.55
860	14.007	8.069	0.077	(7.918, 8.220)	5.938	2.31	2.31
863	16.080	9.128	0.080	(8.971, 9.284)	6.952	2.70	2.71
898	11.569	8.424	0.177	(8.077, 8.771)	3.145	1.23	1.23
907	19.528	10.889	0.086	(10.721, 11.058)	8.639	3.36	3.36
910	20.441	11.356	0.088	(11.183, 11.528)	9.085	3.53	3.54
911	20.172	11.218	0.087	(11.047, 11.390)	8.954	3.48	3.49
945	11.832	16.424	0.215	(16.002, 16.847)	-4.593	-1.79	-1.79
955	19.119	10.681	0.085	(10.515, 10.848)	8.438	3.28	3.29

956	18.089	10.155	0.083	(9.993, 10.317)	7.934	3.09	3.09
978	15.671	8.921	0.078	(8.768, 9.074)	6.750	2.63	2.63
979	17.148	9.675	0.081	(9.517, 9.833)	7.473	2.91	2.91
983	14.789	8.470	0.077	(8.320, 8.621)	6.319	2.46	2.46
1007	17.029	11.237	0.084	(11.072, 11.401)	5.793	2.25	2.25
1026	14.566	8.358	0.076	(8.208, 8.508)	6.208	2.41	2.42
1040	7.646	19.064	0.136	(18.797, 19.331)	-11.418	-4.45	-4.45
1041	11.152	3.281	0.182	(2.924, 3.639)	7.871	3.07	3.07
1063	8.941	19.147	0.135	(18.882, 19.412)	-10.206	-3.97	-3.98
1064	3.890	18.801	0.140	(18.525, 19.076)	-14.910	-5.81	-5.82
1075	19.019	10.632	0.084	(10.468, 10.796)	8.387	3.26	3.27
1098	18.742	10.494	0.083	(10.332, 10.657)	8.248	3.21	3.21
1099	20.412	11.344	0.087	(11.174, 11.514)	9.068	3.53	3.53
1113	12.982	10.121	0.155	(9.817, 10.425)	2.861	1.11	1.11
1137	12.556	9.684	0.157	(9.376, 9.991)	2.872	1.12	1.12
1170	17.370	9.799	0.080	(9.643, 9.956)	7.571	2.95	2.95
1171	22.263	12.290	0.091	(12.112, 12.469)	9.973	3.88	3.88
1185	11.296	8.471	0.160	(8.157, 8.784)	2.825	1.10	1.10
1186	18.584	15.292	0.158	(14.982, 15.603)	3.291	1.28	1.28
1194	17.377	9.805	0.080	(9.649, 9.961)	7.572	2.95	2.95
1195	17.353	9.783	0.079	(9.627, 9.939)	7.570	2.94	2.95
1196	14.218	8.182	0.075	(8.036, 8.328)	6.036	2.35	2.35
1199	19.776	11.021	0.085	(10.855, 11.187)	8.755	3.41	3.41
1209	12.330	8.056	0.225	(7.616, 8.497)	4.274	1.67	1.67
1219	19.721	10.993	0.084	(10.828, 11.158)	8.728	3.40	3.40
1250	5.680	18.919	0.138	(18.650, 19.189)	-13.240	-5.15	-5.17
1257	10.833	7.988	0.163	(7.669, 8.307)	2.844	1.11	1.11
1267	20.118	11.197	0.085	(11.030, 11.363)	8.922	3.47	3.47
1269	14.716	8.438	0.075	(8.291, 8.584)	6.278	2.44	2.44
1281	9.292	6.636	0.162	(6.318, 6.954)	2.656	1.03	1.03
1290	13.589	7.877	0.074	(7.733, 8.021)	5.712	2.22	2.22
1291	17.729	9.977	0.080	(9.821, 10.133)	7.752	3.02	3.02
1295	14.209	8.407	0.074	(8.262, 8.552)	5.802	2.26	2.26
1305	7.489	5.251	0.153	(4.951, 5.551)	2.238	0.87	0.87
1314	19.795	11.056	0.084	(10.890, 11.221)	8.739	3.40	3.40
1329	10.261	7.494	0.163	(7.174, 7.814)	2.767	1.08	1.08
1411	19.893	11.820	0.085	(11.652, 11.988)	8.073	3.14	3.14
1415	19.780	13.765	0.093	(13.584, 13.947)	6.014	2.34	2.34
1425	12.221	9.588	0.148	(9.299, 9.877)	2.633	1.03	1.03
1435	14.234	8.194	0.073	(8.051, 8.338)	6.040	2.35	2.35
1445	9.922	19.223	0.133	(18.963, 19.483)	-9.301	-3.62	-3.62
1446	8.260	19.105	0.134	(18.842, 19.368)	-10.846	-4.22	-4.23
1459	15.928	9.060	0.075	(8.912, 9.207)	6.868	2.67	2.67
1463	21.330	13.462	0.092	(13.281, 13.643)	7.868	3.06	3.06
1483	18.088	10.539	0.080	(10.382, 10.695)	7.549	2.94	2.94
1487	16.381	10.987	0.080	(10.831, 11.143)	5.394	2.10	2.10
1531	18.219	10.231	0.079	(10.076, 10.386)	7.988	3.11	3.11

1545	13.753	10.843	0.154	(10.540, 11.146)	2.911	1.13	1.13
1559	14.528	8.687	0.073	(8.545, 8.830)	5.841	2.27	2.27
1583	18.430	11.257	0.081	(11.097, 11.416)	7.174	2.79	2.79
1593	12.943	10.194	0.152	(9.895, 10.492)	2.749	1.07	1.07
1603	18.805	10.531	0.080	(10.375, 10.688)	8.274	3.22	3.22
1637	7.894	19.082	0.134	(18.820, 19.345)	-11.188	-4.36	-4.36
1655	13.967	8.061	0.071	(7.922, 8.201)	5.905	2.30	2.30
1685	5.606	18.921	0.136	(18.654, 19.188)	-13.315	-5.18	-5.20
1707	6.723	19.001	0.135	(18.736, 19.265)	-12.277	-4.78	-4.79
1708	5.827	18.937	0.136	(18.671, 19.203)	-13.110	-5.10	-5.11
1723	16.224	9.215	0.074	(9.070, 9.360)	7.009	2.73	2.73
1736	4.624	2.796	0.147	(2.508, 3.083)	1.828	0.71	0.71
1757	6.164	18.962	0.135	(18.697, 19.227)	-12.798	-4.98	-4.99
1771	17.401	9.818	0.076	(9.669, 9.967)	7.583	2.95	2.95
1804	4.946	18.876	0.136	(18.609, 19.144)	-13.931	-5.42	-5.44
1819	16.139	9.176	0.073	(9.032, 9.320)	6.963	2.71	2.71
1823	18.867	11.396	0.081	(11.237, 11.554)	7.472	2.91	2.91
1833	14.360	11.493	0.153	(11.193, 11.794)	2.867	1.12	1.12
1846	18.000	10.124	0.077	(9.974, 10.274)	7.876	3.06	3.07
1867	15.598	8.904	0.072	(8.763, 9.046)	6.694	2.60	2.60
1880	3.769	4.055	0.141	(3.778, 4.331)	-0.285	-0.11	-0.11
1905	10.864	8.107	0.167	(7.779, 8.434)	2.757	1.07	1.07
1912	33.191	31.468	0.146	(31.182, 31.753)	1.723	0.67	0.67
1919	18.414	10.337	0.077	(10.186, 10.488)	8.077	3.14	3.14
1940	13.892	8.028	0.069	(7.892, 8.164)	5.864	2.28	2.28
1963	15.887	9.060	0.072	(8.919, 9.202)	6.827	2.66	2.66
1967	16.521	10.352	0.075	(10.205, 10.499)	6.169	2.40	2.40
1991	19.908	12.520	0.085	(12.354, 12.686)	7.388	2.87	2.88
2040	4.745	18.206	0.131	(17.950, 18.463)	-13.461	-5.24	-5.25
2059	21.171	11.767	0.084	(11.603, 11.930)	9.405	3.66	3.66
2107	19.898	11.196	0.079	(11.041, 11.352)	8.702	3.38	3.39
2131	19.847	11.378	0.080	(11.220, 11.536)	8.469	3.29	3.30
2193	5.348	3.177	0.169	(2.846, 3.508)	2.171	0.85	0.85
2206	18.637	10.923	0.077	(10.771, 11.074)	7.714	3.00	3.00
2207	14.771	8.481	0.069	(8.346, 8.616)	6.290	2.45	2.45
2231	15.632	8.921	0.070	(8.784, 9.058)	6.711	2.61	2.61
2240	4.318	2.610	0.149	(2.318, 2.901)	1.708	0.67	0.67
2275	18.059	10.359	0.074	(10.214, 10.504)	7.700	2.99	3.00
2303	14.388	8.287	0.068	(8.154, 8.420)	6.101	2.37	2.37
2360	4.014	2.312	0.151	(2.016, 2.609)	1.702	0.66	0.66
2371	16.643	9.996	0.066	(9.866, 10.126)	6.646	2.58	2.59
2384	2.983	1.651	0.140	(1.376, 1.926)	1.332	0.52	0.52
2428	6.566	19.001	0.133	(18.741, 19.261)	-12.435	-4.84	-4.85
2443	21.814	12.476	0.083	(12.313, 12.640)	9.338	3.63	3.64
2467	18.127	10.547	0.073	(10.404, 10.690)	7.580	2.95	2.95
2504	3.854	2.389	0.142	(2.111, 2.667)	1.464	0.57	0.57
2515	15.493	9.247	0.068	(9.113, 9.380)	6.246	2.43	2.43

2519	14.030	19.531	0.127	(19.282, 19.780)	-5.501	-2.14	-2.14
2544	5.564	18.932	0.134	(18.670, 19.194)	-13.368	-5.20	-5.22
2563	15.458	9.269	0.068	(9.135, 9.403)	6.189	2.41	2.41
2564	13.922	8.055	0.066	(7.926, 8.184)	5.868	2.28	2.28
2567	17.063	9.657	0.071	(9.518, 9.797)	7.406	2.88	2.88
2591	21.503	13.055	0.086	(12.887, 13.223)	8.448	3.29	3.29
2635	18.814	11.049	0.074	(10.904, 11.193)	7.765	3.02	3.02
2674	19.650	16.776	0.143	(16.495, 17.056)	2.875	1.12	1.12
2683	19.063	11.212	0.074	(11.068, 11.357)	7.850	3.05	3.06
2712	5.918	17.169	0.119	(16.936, 17.401)	-11.251	-4.38	-4.39
2734	14.623	8.414	0.066	(8.284, 8.543)	6.209	2.41	2.42
2735	19.649	10.980	0.076	(10.831, 11.130)	8.668	3.37	3.37
2744	5.282	3.269	0.164	(2.948, 3.591)	2.012	0.78	0.78
2803	15.072	9.385	0.068	(9.252, 9.518)	5.688	2.21	2.21
2851	15.003	9.286	0.065	(9.157, 9.414)	5.717	2.22	2.22
2854	13.669	7.929	0.064	(7.802, 8.055)	5.740	2.23	2.23
2855	17.678	9.976	0.071	(9.837, 10.116)	7.702	3.00	3.00
2888	8.704	4.655	0.147	(4.367, 4.943)	4.049	1.58	1.58
2918	6.288	7.977	0.143	(7.697, 8.258)	-1.689	-0.66	-0.66
2923	16.336	10.191	0.073	(10.048, 10.335)	6.144	2.39	2.39
2957	8.338	19.151	0.129	(18.897, 19.405)	-10.813	-4.21	-4.22
2999	12.735	19.447	0.126	(19.199, 19.695)	-6.712	-2.61	-2.61
3019	16.973	10.420	0.068	(10.287, 10.553)	6.553	2.55	2.55
3070	13.903	19.531	0.126	(19.285, 19.777)	-5.628	-2.19	-2.19
3104	5.200	3.341	0.162	(3.024, 3.657)	1.859	0.72	0.72
3128	4.591	3.129	0.144	(2.848, 3.411)	1.462	0.57	0.57
3144	5.309	14.807	0.101	(14.609, 15.005)	-9.498	-3.70	-3.70
3191	9.883	19.248	0.128	(18.998, 19.499)	-9.365	-3.65	-3.65
3224	4.279	3.224	0.140	(2.949, 3.498)	1.055	0.41	0.41
3246	6.174	18.819	0.134	(18.556, 19.083)	-12.645	-4.92	-4.93
3247	4.958	18.693	0.137	(18.425, 18.962)	-13.735	-5.35	-5.36
3288	5.574	18.945	0.132	(18.686, 19.203)	-13.371	-5.21	-5.22
3359	16.145	9.480	0.067	(9.349, 9.611)	6.665	2.59	2.59
3414	5.233	18.777	0.137	(18.509, 19.046)	-13.545	-5.27	-5.29
3443	25.188	19.921	0.124	(19.677, 20.164)	5.267	2.05	2.05
3444	12.488	18.870	0.134	(18.607, 19.133)	-6.382	-2.48	-2.49
3445	21.030	11.858	0.067	(11.727, 11.990)	9.172	3.57	3.57
3448	28.286	27.523	0.139	(27.249, 27.796)	0.763	0.30	0.30
3449	27.782	18.828	0.116	(18.600, 19.055)	8.954	3.48	3.49
3488	3.781	2.904	0.146	(2.617, 3.190)	0.877	0.34	0.34
3499	17.512	11.014	0.072	(10.872, 11.156)	6.498	2.53	2.53
3503	19.726	11.032	0.074	(10.887, 11.178)	8.694	3.38	3.38
3571	16.884	10.868	0.072	(10.728, 11.009)	6.016	2.34	2.34
3592	32.038	30.253	0.144	(29.972, 30.535)	1.785	0.69	0.69
3595	22.818	13.071	0.081	(12.913, 13.229)	9.747	3.79	3.80
3599	18.982	11.422	0.074	(11.276, 11.567)	7.560	2.94	2.94
3619	21.453	13.310	0.088	(13.138, 13.482)	8.144	3.17	3.17

3659	22.124	13.871	0.065	(13.744, 13.998)	8.252	3.21	3.21
3672	3.662	18.815	0.134	(18.553, 19.078)	-15.154	-5.90	-5.92
3695	13.368	19.503	0.125	(19.258, 19.748)	-6.135	-2.39	-2.39
3696	5.305	18.932	0.132	(18.674, 19.190)	-13.627	-5.31	-5.32
3719	12.792	19.463	0.125	(19.217, 19.708)	-6.671	-2.60	-2.60
3752	4.583	2.934	0.163	(2.615, 3.253)	1.649	0.64	0.64
3791	20.944	11.659	0.077	(11.508, 11.810)	9.285	3.61	3.62
3815	12.170	19.420	0.125	(19.174, 19.666)	-7.250	-2.82	-2.82
3859	15.546	9.111	0.062	(8.990, 9.232)	6.435	2.50	2.50
3862	18.549	10.437	0.070	(10.299, 10.575)	8.112	3.16	3.16
3911	19.391	13.935	0.085	(13.770, 14.101)	5.456	2.12	2.12
3935	15.209	10.034	0.066	(9.904, 10.163)	5.175	2.01	2.01
3963	7.973	19.125	0.129	(18.873, 19.377)	-11.152	-4.34	-4.35
3964	7.142	19.069	0.129	(18.815, 19.322)	-11.927	-4.64	-4.65
3972	14.937	16.066	0.141	(15.789, 16.343)	-1.129	-0.44	-0.44
3979	17.700	11.363	0.067	(11.232, 11.494)	6.337	2.46	2.47
4005	13.816	19.553	0.124	(19.309, 19.797)	-5.737	-2.23	-2.23
4103	17.719	10.017	0.068	(9.883, 10.151)	7.702	3.00	3.00
4184	3.715	3.045	0.141	(2.769, 3.322)	0.670	0.26	0.26
4189	10.256	11.925	0.164	(11.604, 12.245)	-1.668	-0.65	-0.65
4195	17.850	11.404	0.071	(11.264, 11.543)	6.447	2.51	2.51
4240	21.706	15.287	0.093	(15.103, 15.470)	6.419	2.50	2.50
4339	16.080	10.509	0.070	(10.371, 10.647)	5.571	2.17	2.17
4440	8.780	15.401	0.098	(15.208, 15.594)	-6.621	-2.58	-2.58
4472	2.958	1.997	0.142	(1.718, 2.275)	0.961	0.37	0.37
4525	5.928	7.703	0.147	(7.415, 7.990)	-1.775	-0.69	-0.69
4535	23.058	16.224	0.099	(16.030, 16.417)	6.834	2.66	2.66
4557	14.455	19.603	0.124	(19.360, 19.846)	-5.148	-2.00	-2.00
4559	11.828	17.619	0.111	(17.401, 17.837)	-5.791	-2.25	-2.25
4603	16.739	10.809	0.072	(10.668, 10.950)	5.930	2.31	2.31
4616	4.112	2.749	0.152	(2.451, 3.047)	1.363	0.53	0.53
4621	11.169	12.683	0.153	(12.383, 12.983)	-1.514	-0.59	-0.59
4708	6.820	19.056	0.130	(18.802, 19.310)	-12.236	-4.76	-4.77
4723	17.046	10.931	0.070	(10.794, 11.067)	6.115	2.38	2.38
4727	15.794	9.044	0.064	(8.918, 9.170)	6.750	2.63	2.63
4775	17.059	9.691	0.067	(9.560, 9.822)	7.368	2.87	2.87
4828	7.925	19.136	0.128	(18.884, 19.388)	-11.211	-4.36	-4.37
4829	6.857	19.057	0.130	(18.802, 19.311)	-12.200	-4.75	-4.76
4841	26.144	20.088	0.124	(19.845, 20.331)	6.056	2.36	2.36
4919	14.868	8.574	0.063	(8.451, 8.697)	6.294	2.45	2.45
4934	7.885	9.625	0.155	(9.322, 9.928)	-1.740	-0.68	-0.68
4955	28.643	25.249	0.154	(24.946, 25.551)	3.394	1.32	1.32
4963	23.736	13.780	0.084	(13.615, 13.944)	9.956	3.87	3.88
4967	18.013	10.903	0.071	(10.764, 11.041)	7.111	2.77	2.77
4980	10.992	12.435	0.144	(12.153, 12.716)	-1.442	-0.56	-0.56
5052	14.911	11.715	0.169	(11.384, 12.047)	3.195	1.24	1.25
5056	30.408	20.171	0.125	(19.927, 20.415)	10.238	3.99	3.99

5064	7.915	16.224	0.106	(16.017, 16.432)	-8.309	-3.23	-3.24
5078	18.963	13.162	0.080	(13.006, 13.318)	5.801	2.26	2.26
5080	20.025	12.096	0.065	(11.969, 12.224)	7.929	3.08	3.09
5087	11.950	19.425	0.125	(19.179, 19.671)	-7.475	-2.91	-2.91
5132	10.081	19.230	0.128	(18.980, 19.480)	-9.149	-3.56	-3.56
5135	16.497	9.410	0.066	(9.280, 9.539)	7.087	2.76	2.76
5158	17.577	10.836	0.070	(10.697, 10.974)	6.742	2.62	2.62
5179	18.260	11.488	0.077	(11.337, 11.638)	6.773	2.63	2.64
5227	16.126	10.183	0.067	(10.052, 10.314)	5.943	2.31	2.31
5230	14.394	19.600	0.124	(19.357, 19.844)	-5.206	-2.03	-2.03
5231	18.222	10.754	0.071	(10.615, 10.893)	7.467	2.90	2.91
5275	17.313	10.875	0.071	(10.735, 11.014)	6.438	2.50	2.51
5303	20.240	14.646	0.089	(14.471, 14.820)	5.595	2.18	2.18
5323	21.731	12.450	0.077	(12.299, 12.602)	9.281	3.61	3.61
5352	6.216	14.258	0.094	(14.073, 14.443)	-8.042	-3.13	-3.13
5382	5.761	19.070	0.131	(18.813, 19.327)	-13.309	-5.18	-5.19
5383	6.737	18.788	0.139	(18.514, 19.061)	-12.050	-4.69	-4.70
5403	7.256	19.098	0.130	(18.844, 19.352)	-11.842	-4.61	-4.62
5404	3.306	18.818	0.134	(18.555, 19.081)	-15.512	-6.04	-6.06
5443	22.870	13.555	0.085	(13.389, 13.722)	9.315	3.62	3.63
5447	21.897	12.172	0.080	(12.015, 12.329)	9.725	3.78	3.79
5472	5.544	16.245	0.110	(16.029, 16.461)	-10.701	-4.16	-4.17
5491	17.480	10.641	0.068	(10.508, 10.773)	6.839	2.66	2.66
5543	14.798	8.682	0.064	(8.557, 8.808)	6.115	2.38	2.38
5584	30.001	28.671	0.142	(28.393, 28.948)	1.330	0.52	0.52
5587	14.534	9.049	0.062	(8.926, 9.171)	5.485	2.13	2.13
5591	14.879	9.078	0.065	(8.951, 9.205)	5.801	2.26	2.26
5637	14.814	8.558	0.064	(8.432, 8.684)	6.256	2.43	2.43
5638	16.078	9.204	0.066	(9.074, 9.334)	6.875	2.67	2.68
5662	14.284	8.288	0.064	(8.163, 8.413)	5.996	2.33	2.33
5663	15.087	8.698	0.065	(8.571, 8.825)	6.389	2.48	2.49
5685	13.120	7.694	0.062	(7.572, 7.816)	5.426	2.11	2.11
5696	3.274	1.712	0.155	(1.409, 2.016)	1.562	0.61	0.61
5711	17.866	11.361	0.074	(11.217, 11.506)	6.505	2.53	2.53
5729	28.634	16.884	0.088	(16.713, 17.056)	11.750	4.57	4.58
5732	14.701	8.503	0.064	(8.377, 8.630)	6.197	2.41	2.41
5755	16.932	10.114	0.067	(9.983, 10.244)	6.818	2.65	2.65
5759	18.945	10.670	0.073	(10.527, 10.813)	8.275	3.22	3.22
5781	13.207	18.920	0.121	(18.683, 19.157)	-5.713	-2.22	-2.22
5807	19.445	10.999	0.074	(10.853, 11.145)	8.446	3.29	3.29
5824	23.319	12.488	0.077	(12.336, 12.639)	10.832	4.21	4.22
5825	20.720	12.667	0.067	(12.536, 12.798)	8.053	3.13	3.13
5826	17.334	10.112	0.067	(9.982, 10.243)	7.222	2.81	2.81
5831	13.982	19.581	0.125	(19.335, 19.827)	-5.599	-2.18	-2.18
5851	16.749	9.876	0.068	(9.743, 10.008)	6.873	2.67	2.67
5875	13.798	8.345	0.064	(8.220, 8.469)	5.453	2.12	2.12
5879	16.696	10.064	0.069	(9.928, 10.200)	6.632	2.58	2.58

5899	21.466	12.235	0.080	(12.079, 12.392)	9.230	3.59	3.59
6004	7.544	19.128	0.130	(18.873, 19.383)	-11.584	-4.51	-4.52
6005	9.178	19.244	0.129	(18.991, 19.496)	-10.065	-3.92	-3.92
6023	23.464	13.883	0.090	(13.707, 14.058)	9.581	3.73	3.73
6115	14.987	8.673	0.067	(8.542, 8.804)	6.313	2.46	2.46
6163	19.790	11.122	0.077	(10.972, 11.272)	8.668	3.37	3.37
6167	15.798	10.111	0.070	(9.975, 10.248)	5.687	2.21	2.21
6239	16.066	9.207	0.069	(9.073, 9.342)	6.859	2.67	2.67
6291	6.940	19.090	0.131	(18.832, 19.347)	-12.150	-4.73	-4.74
6292	5.306	18.974	0.133	(18.713, 19.235)	-13.668	-5.32	-5.33
6307	22.621	12.557	0.085	(12.391, 12.723)	10.064	3.91	3.92
6335	21.631	13.255	0.086	(13.087, 13.424)	8.376	3.26	3.26
6355	20.059	11.248	0.078	(11.096, 11.401)	8.811	3.43	3.43
6365	7.099	19.102	0.131	(18.845, 19.360)	-12.003	-4.67	-4.68
6390	7.557	19.135	0.131	(18.878, 19.392)	-11.578	-4.51	-4.51
6391	6.404	18.283	0.150	(17.989, 18.577)	-11.879	-4.63	-4.63
6411	6.819	19.083	0.132	(18.825, 19.341)	-12.264	-4.77	-4.78
6412	5.699	19.004	0.133	(18.743, 19.265)	-13.305	-5.18	-5.19
6453	14.928	8.629	0.068	(8.497, 8.762)	6.298	2.45	2.45
6454	20.539	11.495	0.079	(11.339, 11.651)	9.044	3.52	3.52
6455	18.536	10.472	0.074	(10.326, 10.618)	8.064	3.14	3.14
6464	3.572	2.052	0.145	(1.768, 2.336)	1.520	0.59	0.59
6475	17.424	9.905	0.072	(9.763, 10.046)	7.520	2.92	2.93
6500	15.181	8.759	0.068	(8.626, 8.893)	6.422	2.50	2.50
6503	13.200	19.536	0.127	(19.287, 19.785)	-6.337	-2.47	-2.47
6512	2.473	0.960	0.153	(0.660, 1.260)	1.513	0.59	0.59
6523	16.241	9.301	0.070	(9.164, 9.439)	6.940	2.70	2.70
6547	15.571	8.960	0.069	(8.824, 9.095)	6.612	2.57	2.57
6573	14.471	19.628	0.127	(19.379, 19.876)	-5.156	-2.01	-2.01
6574	17.658	10.608	0.074	(10.463, 10.754)	7.050	2.74	2.74
6575	18.838	10.628	0.076	(10.480, 10.777)	8.210	3.19	3.20
6584	4.488	2.723	0.148	(2.432, 3.013)	1.765	0.69	0.69
6623	9.720	16.316	0.107	(16.106, 16.526)	-6.596	-2.57	-2.57
6632	4.722	2.817	0.152	(2.518, 3.115)	1.905	0.74	0.74
6645	14.055	19.599	0.127	(19.350, 19.848)	-5.544	-2.16	-2.16
6704	4.604	2.946	0.143	(2.665, 3.228)	1.658	0.65	0.65
6728	4.503	2.823	0.145	(2.539, 3.106)	1.680	0.65	0.65
6761	29.292	27.539	0.145	(27.255, 27.824)	1.753	0.68	0.68
6763	13.242	7.774	0.067	(7.642, 7.905)	5.469	2.13	2.13
6800	8.123	5.651	0.159	(5.339, 5.964)	2.472	0.96	0.96
6810	18.812	10.625	0.077	(10.474, 10.776)	8.188	3.18	3.19
6811	18.441	10.429	0.076	(10.280, 10.578)	8.012	3.12	3.12
6812	15.568	8.962	0.071	(8.824, 9.100)	6.606	2.57	2.57
6814	16.955	9.670	0.073	(9.527, 9.813)	7.284	2.83	2.83
6815	22.149	12.323	0.085	(12.155, 12.490)	9.826	3.82	3.83
6834	13.846	8.087	0.068	(7.953, 8.221)	5.759	2.24	2.24
6872	5.356	2.837	0.177	(2.490, 3.184)	2.518	0.98	0.98

6883	18.698	10.562	0.077	(10.411, 10.713)	8.136	3.16	3.17
6896	5.720	3.957	0.140	(3.682, 4.231)	1.764	0.69	0.69
6907	15.707	9.035	0.071	(8.895, 9.174)	6.672	2.60	2.60
6930	13.810	8.067	0.069	(7.932, 8.201)	5.744	2.23	2.23
6931	17.110	9.752	0.074	(9.607, 9.896)	7.359	2.86	2.86
6932	13.209	7.759	0.068	(7.626, 7.893)	5.450	2.12	2.12
6954	18.074	10.244	0.076	(10.095, 10.393)	7.830	3.05	3.05
6955	19.607	11.027	0.079	(10.871, 11.183)	8.580	3.34	3.34
7013	4.402	18.922	0.136	(18.654, 19.189)	-14.519	-5.65	-5.67
7026	18.477	10.451	0.077	(10.300, 10.603)	8.026	3.12	3.12
7027	17.448	9.926	0.075	(9.778, 10.073)	7.522	2.93	2.93
7028	13.449	7.883	0.069	(7.748, 8.019)	5.565	2.16	2.17
7031	13.397	7.857	0.069	(7.722, 7.992)	5.540	2.15	2.16
7040	8.317	6.170	0.143	(5.890, 6.450)	2.147	0.84	0.84
7055	16.735	9.562	0.074	(9.417, 9.707)	7.173	2.79	2.79
7074	14.401	8.370	0.070	(8.233, 8.508)	6.031	2.35	2.35
7098	19.133	10.788	0.079	(10.633, 10.943)	8.346	3.25	3.25
7102	13.775	19.587	0.129	(19.335, 19.839)	-5.812	-2.26	-2.26
7112	5.116	3.228	0.148	(2.937, 3.519)	1.888	0.74	0.74
7169	26.573	25.360	0.140	(25.086, 25.634)	1.212	0.47	0.47
7171	19.997	11.230	0.082	(11.070, 11.390)	8.767	3.41	3.41
7172	13.663	7.995	0.070	(7.857, 8.132)	5.668	2.20	2.21
7173	18.365	10.396	0.078	(10.244, 10.549)	7.969	3.10	3.10
7174	18.234	10.329	0.078	(10.177, 10.481)	7.904	3.07	3.08
7175	18.921	10.680	0.079	(10.525, 10.835)	8.241	3.21	3.21
7195	15.856	9.115	0.073	(8.972, 9.259)	6.740	2.62	2.62
7209	9.212	7.028	0.144	(6.746, 7.311)	2.184	0.85	0.85
7224	5.441	18.999	0.136	(18.733, 19.264)	-13.558	-5.28	-5.29
7242	19.369	14.051	0.092	(13.872, 14.231)	5.318	2.07	2.07
7247	17.481	9.946	0.076	(9.796, 10.096)	7.535	2.93	2.93
7257	9.881	6.974	0.174	(6.632, 7.315)	2.908	1.13	1.13
7264	28.778	27.131	0.140	(26.855, 27.406)	1.648	0.64	0.64
7281	14.137	10.645	0.184	(10.284, 11.006)	3.492	1.36	1.36
7291	21.206	11.849	0.085	(11.682, 12.016)	9.357	3.64	3.64
7295	16.177	9.281	0.074	(9.135, 9.426)	6.896	2.68	2.68
7305	10.062	7.515	0.157	(7.208, 7.822)	2.547	0.99	0.99
7314	15.704	9.730	0.075	(9.583, 9.876)	5.975	2.32	2.32
7315	17.106	9.756	0.076	(9.606, 9.905)	7.350	2.86	2.86
7337	20.995	11.765	0.085	(11.598, 11.932)	9.230	3.59	3.59
7363	16.404	9.398	0.075	(9.250, 9.545)	7.006	2.73	2.73
7385	17.341	9.885	0.077	(9.734, 10.036)	7.456	2.90	2.90
7401	11.658	8.018	0.201	(7.624, 8.412)	3.640	1.42	1.42
7409	25.168	13.886	0.097	(13.695, 14.077)	11.282	4.39	4.40
7410	18.381	10.408	0.079	(10.253, 10.564)	7.973	3.10	3.10
7411	14.848	8.604	0.073	(8.461, 8.747)	6.244	2.43	2.43
7425	7.919	4.692	0.199	(4.301, 5.082)	3.227	1.26	1.26
7433	26.337	14.480	0.101	(14.282, 14.678)	11.857	4.61	4.62

7434	18.049	10.239	0.079	(10.085, 10.393)	7.810	3.04	3.04
7449	11.845	8.354	0.193	(7.975, 8.733)	3.491	1.36	1.36
7457	20.959	11.733	0.086	(11.565, 11.901)	9.226	3.59	3.59
7481	16.401	9.406	0.076	(9.257, 9.555)	6.995	2.72	2.72
7486	14.921	8.642	0.074	(8.498, 8.787)	6.278	2.44	2.44
7497	11.118	7.881	0.184	(7.520, 8.243)	3.236	1.26	1.26
7505	27.632	15.139	0.106	(14.932, 15.346)	12.494	4.86	4.87
7506	17.452	9.936	0.078	(9.783, 10.088)	7.517	2.92	2.93
7509	14.004	8.175	0.073	(8.032, 8.317)	5.829	2.27	2.27
7510	17.487	9.953	0.078	(9.800, 10.106)	7.533	2.93	2.93
7529	15.918	9.156	0.076	(9.008, 9.304)	6.762	2.63	2.63
7553	22.353	12.442	0.090	(12.266, 12.618)	9.912	3.86	3.86
7559	13.490	19.116	0.127	(18.867, 19.365)	-5.626	-2.19	-2.19
7569	11.592	7.807	0.208	(7.398, 8.215)	3.786	1.48	1.48
7577	25.470	14.033	0.099	(13.839, 14.227)	11.437	4.45	4.46
7578	15.392	8.885	0.075	(8.738, 9.032)	6.508	2.53	2.53
7593	12.147	9.679	0.144	(9.397, 9.962)	2.467	0.96	0.96
7594	11.662	9.086	0.153	(8.787, 9.385)	2.576	1.00	1.00
7601	16.938	9.676	0.078	(9.524, 9.828)	7.262	2.82	2.83
7608	4.565	18.943	0.138	(18.672, 19.213)	-14.378	-5.60	-5.61
7617	9.473	5.828	0.211	(5.414, 6.243)	3.645	1.42	1.42
7626	20.224	11.353	0.085	(11.187, 11.519)	8.871	3.45	3.45
7627	16.157	9.276	0.077	(9.126, 9.426)	6.881	2.68	2.68
7641	11.669	9.274	0.143	(8.994, 9.554)	2.395	0.93	0.93
7649	24.120	13.343	0.095	(13.157, 13.530)	10.776	4.19	4.20
7665	8.936	5.936	0.183	(5.577, 6.294)	3.000	1.17	1.17
7675	16.659	9.533	0.078	(9.381, 9.685)	7.126	2.77	2.77
7689	11.784	9.248	0.149	(8.956, 9.540)	2.535	0.99	0.99
7713	7.126	4.275	0.185	(3.912, 4.638)	2.851	1.11	1.11
7737	12.143	9.692	0.144	(9.410, 9.975)	2.450	0.95	0.95
7745	29.219	15.949	0.112	(15.729, 16.168)	13.271	5.16	5.18
7747	22.273	12.401	0.091	(12.224, 12.579)	9.872	3.84	3.84
7751	17.322	11.322	0.083	(11.160, 11.484)	6.000	2.33	2.33
7769	17.374	9.900	0.080	(9.744, 10.056)	7.474	2.91	2.91
7771	13.845	8.098	0.074	(7.952, 8.244)	5.747	2.24	2.24
7782	7.605	19.161	0.135	(18.895, 19.426)	-11.556	-4.50	-4.51
7783	5.891	19.039	0.137	(18.771, 19.308)	-13.148	-5.12	-5.13
7794	18.298	10.372	0.082	(10.212, 10.532)	7.926	3.08	3.09
7795	15.314	8.848	0.076	(8.698, 8.998)	6.466	2.51	2.52
7810	15.384	11.498	0.201	(11.105, 11.891)	3.886	1.52	1.52
7823	15.167	8.773	0.076	(8.624, 8.923)	6.393	2.49	2.49
7833	8.261	6.193	0.143	(5.913, 6.473)	2.068	0.81	0.81
7848	4.429	18.937	0.139	(18.664, 19.210)	-14.507	-5.65	-5.66
7865	18.784	10.622	0.083	(10.459, 10.784)	8.163	3.18	3.18
7882	12.328	8.532	0.208	(8.124, 8.940)	3.797	1.48	1.48
7891	15.784	9.090	0.078	(8.937, 9.242)	6.694	2.60	2.61
7895	17.948	11.295	0.084	(11.130, 11.460)	6.653	2.59	2.59

7913	21.513	12.016	0.090	(11.840, 12.192)	9.497	3.69	3.70
7925	6.106	19.057	0.138	(18.787, 19.326)	-12.951	-5.04	-5.05
7926	5.609	19.022	0.138	(18.751, 19.292)	-13.413	-5.22	-5.23
7936	26.439	25.256	0.140	(24.982, 25.531)	1.182	0.46	0.46
7937	24.539	16.406	0.110	(16.191, 16.621)	8.133	3.17	3.17
7939	16.397	9.404	0.079	(9.249, 9.559)	6.993	2.72	2.72
7954	15.537	11.087	0.227	(10.642, 11.532)	4.450	1.74	1.74
7961	16.512	9.463	0.079	(9.307, 9.618)	7.049	2.74	2.74
7968	4.265	14.079	0.105	(13.873, 14.286)	-9.814	-3.82	-3.82
7978	19.781	15.104	0.225	(14.664, 15.545)	4.676	1.83	1.83
7986	16.344	9.377	0.079	(9.221, 9.533)	6.967	2.71	2.71
8009	20.132	12.315	0.090	(12.139, 12.491)	7.817	3.04	3.04
8016	5.569	19.020	0.138	(18.749, 19.292)	-13.451	-5.24	-5.25
8026	11.804	8.493	0.187	(8.126, 8.860)	3.311	1.29	1.29
8033	23.509	13.037	0.096	(12.849, 13.225)	10.472	4.07	4.08
8040	3.229	17.471	0.131	(17.214, 17.728)	-14.242	-5.54	-5.56
8050	23.993	19.757	0.199	(19.367, 20.146)	4.237	1.65	1.65
8057	23.906	15.611	0.106	(15.403, 15.819)	8.295	3.23	3.23
8058	16.352	9.382	0.080	(9.226, 9.539)	6.969	2.71	2.71
8074	18.611	14.585	0.198	(14.196, 14.973)	4.026	1.57	1.57
8081	18.813	10.639	0.085	(10.474, 10.805)	8.173	3.18	3.18
8154	15.420	8.908	0.079	(8.753, 9.064)	6.512	2.53	2.53
8170	14.336	10.725	0.192	(10.349, 11.101)	3.611	1.41	1.41
8177	22.452	12.500	0.094	(12.316, 12.683)	9.952	3.87	3.88
8178	21.038	11.777	0.090	(11.600, 11.954)	9.260	3.60	3.61
8182	15.709	9.056	0.080	(8.899, 9.213)	6.653	2.59	2.59
8183	18.232	10.345	0.084	(10.180, 10.510)	7.888	3.07	3.07
8194	20.099	16.456	0.179	(16.105, 16.807)	3.642	1.42	1.42
8200	27.298	26.524	0.151	(26.228, 26.821)	0.774	0.30	0.30
8202	15.360	8.878	0.080	(8.722, 9.034)	6.482	2.52	2.52
8203	19.919	11.206	0.088	(11.034, 11.379)	8.712	3.39	3.39
8207	17.191	10.081	0.083	(9.919, 10.244)	7.110	2.77	2.77
8218	20.491	16.902	0.177	(16.556, 17.248)	3.589	1.40	1.40
8219	23.615	20.364	0.160	(20.050, 20.678)	3.251	1.27	1.27
8227	14.554	8.467	0.079	(8.313, 8.621)	6.087	2.37	2.37
8230	14.379	19.648	0.133	(19.387, 19.908)	-5.269	-2.05	-2.05
8231	17.308	10.867	0.085	(10.701, 11.033)	6.441	2.51	2.51
8250	19.729	11.110	0.088	(10.938, 11.282)	8.619	3.35	3.36
8251	21.053	11.786	0.091	(11.608, 11.964)	9.267	3.61	3.61
8254	13.693	19.600	0.133	(19.338, 19.861)	-5.907	-2.30	-2.30
8255	18.385	10.444	0.085	(10.278, 10.611)	7.941	3.09	3.09
8266	17.191	12.439	0.236	(11.975, 12.902)	4.753	1.86	1.86
8279	15.101	8.747	0.080	(8.591, 8.904)	6.354	2.47	2.47
8290	20.636	16.922	0.183	(16.564, 17.281)	3.713	1.45	1.45
8291	20.814	18.101	0.141	(17.824, 18.378)	2.713	1.06	1.06
8296	22.862	15.880	0.077	(15.729, 16.032)	6.981	2.72	2.72
8297	20.361	11.434	0.089	(11.258, 11.609)	8.927	3.47	3.48

8303	17.050	9.743	0.083	(9.581, 9.906)	7.307	2.84	2.84
8314	17.466	14.202	0.168	(13.873, 14.531)	3.264	1.27	1.27
8315	21.190	18.254	0.148	(17.963, 18.545)	2.936	1.14	1.14
8321	27.593	17.572	0.120	(17.337, 17.808)	10.021	3.90	3.90
8322	16.968	9.701	0.083	(9.539, 9.864)	7.267	2.83	2.83
8335	9.104	19.276	0.136	(19.008, 19.543)	-10.172	-3.96	-3.97
8336	6.504	19.092	0.139	(18.820, 19.364)	-12.587	-4.90	-4.91
8346	17.303	9.873	0.084	(9.709, 10.037)	7.430	2.89	2.89
8347	18.454	10.461	0.086	(10.293, 10.629)	7.993	3.11	3.11
8351	17.623	11.587	0.088	(11.415, 11.759)	6.036	2.35	2.35
8362	14.813	11.718	0.167	(11.390, 12.046)	3.095	1.21	1.21
8383	7.418	19.157	0.138	(18.886, 19.428)	-11.739	-4.57	-4.58
8393	18.937	10.708	0.087	(10.537, 10.879)	8.229	3.20	3.20
8395	16.101	9.260	0.082	(9.099, 9.421)	6.841	2.66	2.66
8410	18.001	13.556	0.220	(13.125, 13.988)	4.445	1.73	1.73
8417	24.325	17.153	0.116	(16.926, 17.381)	7.172	2.79	2.79
8418	18.240	10.353	0.086	(10.184, 10.521)	7.888	3.07	3.07
8422	13.252	19.571	0.134	(19.308, 19.834)	-6.319	-2.46	-2.46
8434	18.533	15.482	0.158	(15.172, 15.792)	3.051	1.19	1.19
8441	20.750	11.635	0.091	(11.456, 11.814)	9.115	3.55	3.55
8442	14.427	8.406	0.080	(8.248, 8.563)	6.022	2.34	2.34
8446	14.377	8.380	0.080	(8.223, 8.538)	5.997	2.33	2.33
8447	17.750	10.103	0.085	(9.935, 10.270)	7.647	2.97	2.98
8458	16.674	13.715	0.157	(13.407, 14.023)	2.959	1.15	1.15
8466	14.530	8.459	0.081	(8.300, 8.617)	6.071	2.36	2.36
8467	23.258	12.916	0.098	(12.724, 13.108)	10.342	4.02	4.03
8482	16.588	16.229	0.231	(15.777, 16.682)	0.359	0.14	0.14
8506	18.586	7.533	0.159	(7.221, 7.844)	11.053	4.31	4.31
8513	22.452	13.468	0.099	(13.274, 13.662)	8.984	3.50	3.50
8517	14.158	19.637	0.134	(19.373, 19.900)	-5.479	-2.13	-2.13
8554	9.123	6.234	0.202	(5.838, 6.631)	2.889	1.13	1.13
8561	22.762	16.500	0.113	(16.279, 16.721)	6.262	2.44	2.44
8567	18.356	10.414	0.087	(10.243, 10.585)	7.942	3.09	3.09
8578	18.036	15.188	0.151	(14.892, 15.484)	2.848	1.11	1.11
8579	16.900	14.087	0.151	(13.792, 14.382)	2.813	1.10	1.10
8585	27.781	15.626	0.113	(15.404, 15.849)	12.154	4.73	4.74
8586	16.865	9.653	0.085	(9.487, 9.819)	7.212	2.81	2.81
8587	13.444	7.906	0.081	(7.748, 8.064)	5.538	2.15	2.15
8602	21.896	11.683	0.151	(11.388, 11.979)	10.213	3.98	3.98
8611	21.369	11.954	0.094	(11.769, 12.138)	9.416	3.66	3.67
8626	15.058	8.654	0.119	(8.420, 8.888)	6.404	2.49	2.49
8639	14.518	19.664	0.135	(19.400, 19.928)	-5.146	-2.00	-2.00
8650	7.871	4.939	0.189	(4.569, 5.310)	2.932	1.14	1.14
8651	16.717	13.782	0.157	(13.474, 14.089)	2.935	1.14	1.14
8657	15.561	8.988	0.084	(8.825, 9.152)	6.573	2.56	2.56
8674	20.137	16.628	0.216	(16.205, 17.051)	3.509	1.37	1.37
8681	20.099	11.306	0.092	(11.126, 11.486)	8.793	3.42	3.42

8705	17.146	9.799	0.086	(9.630, 9.968)	7.348	2.86	2.86
8706	18.721	10.603	0.089	(10.428, 10.777)	8.118	3.16	3.16
8707	20.759	11.644	0.093	(11.461, 11.827)	9.116	3.55	3.55
8711	18.371	11.684	0.091	(11.505, 11.863)	6.687	2.60	2.60
8722	13.303	10.584	0.157	(10.276, 10.892)	2.719	1.06	1.06
8723	23.511	20.140	0.167	(19.813, 20.466)	3.371	1.31	1.31
8729	16.371	10.789	0.088	(10.617, 10.961)	5.582	2.17	2.17
8730	17.915	10.191	0.088	(10.019, 10.364)	7.723	3.00	3.01
8746	20.189	16.598	0.217	(16.173, 17.023)	3.590	1.40	1.40
8753	18.919	10.704	0.090	(10.528, 10.881)	8.214	3.20	3.20
8754	14.717	8.559	0.083	(8.396, 8.722)	6.158	2.40	2.40
8755	17.988	10.229	0.088	(10.057, 10.402)	7.759	3.02	3.02
8758	18.933	10.712	0.090	(10.536, 10.888)	8.221	3.20	3.20
8759	14.430	8.412	0.083	(8.249, 8.575)	6.018	2.34	2.34
Obs	HI	Cook's D	DFITS				
10	0.00378138	0.00	0.069613		X		
23	0.00285888	0.00	-0.132913	R			
24	0.00222575	0.01	-0.206758	R			
34	0.00208885	0.00	0.123153	R			
42	0.00135537	0.00	0.131514	R			
45	0.00107616	0.00	0.079652	R			
58	0.00361651	0.00	0.072491		X		
59	0.00497609	0.00	0.107880		X		
65	0.00111173	0.00	0.088818	R			
89	0.00191380	0.01	0.212833	R			
90	0.00117440	0.00	0.102169	R			
91	0.00120174	0.00	0.107180	R			
106	0.00367994	0.00	0.073559		X		
107	0.00598130	0.00	0.132177		X		
113	0.00109128	0.00	0.086221	R			
114	0.00104641	0.00	0.075226	R			
115	0.00105434	0.00	0.077420	R			
118	0.00107834	0.00	0.083481	R			
119	0.00108509	0.00	0.085073	R			
137	0.00178062	0.01	0.195417	R			
138	0.00129241	0.00	0.123794	R			
139	0.00125855	0.00	0.118267	R			
143	0.00118545	0.00	0.105785	R			
154	0.00378533	0.00	0.075144		X		
161	0.00116875	0.00	0.103289	R			
162	0.00108822	0.00	0.087460	R			
186	0.00110201	0.00	0.091243	R			
187	0.00116449	0.00	0.103287	R			
190	0.00114054	0.00	0.098941	R			
191	0.00117797	0.00	0.105833	R			
202	0.00624373	0.02	0.376619	R	X		
209	0.00135585	0.00	0.135436	R			

210	0.00116549	0.00	0.104140	R	
211	0.00129620	0.00	0.126162	R	
214	0.00119477	0.00	0.109430	R	
215	0.00108902	0.00	0.089581	R	
226	0.00396088	0.00	0.081653		X
227	0.00464170	0.00	0.100693		X
233	0.00119872	0.00	0.110575	R	
234	0.00117272	0.00	0.106113	R	
270	0.00301975	0.01	-0.271821	R	X
271	0.00298968	0.01	-0.256761	R	X
274	0.00419474	0.00	0.086309		X
281	0.00130783	0.00	0.129520	R	
287	0.00121372	0.00	0.114561	R	
298	0.00692376	0.00	0.150340		X
306	0.00108150	0.00	0.091170	R	
322	0.00445919	0.00	0.092753		X
328	0.00312236	0.00	0.037745		X
329	0.00183821	0.01	0.206442	R	
335	0.00111486	0.00	0.085858	R	
346	0.00459817	0.00	0.097551		X
354	0.00105095	0.00	0.086501	R	
355	0.00104109	0.00	0.084414	R	
370	0.00466912	0.00	0.098482		X
371	0.00325680	0.00	0.067252		X
377	0.00161085	0.01	0.175794	R	
378	0.00123914	0.00	0.120906	R	
379	0.00103399	0.00	0.083739	R	
382	0.00109462	0.00	0.096104	R	
383	0.00128180	0.00	0.127781	R	
394	0.00494400	0.00	0.101856		X
401	0.00172507	0.01	0.192047	R	
402	0.00123573	0.00	0.120904	R	
403	0.00113160	0.00	0.103447	R	
406	0.00103696	0.00	0.085352	R	
407	0.00122458	0.00	0.119221	R	
427	0.00100344	0.00	0.078605	R	
442	0.00564140	0.00	0.113137		X
449	0.00121896	0.00	0.118744	R	
466	0.00558566	0.00	0.116562		X
473	0.00159302	0.01	0.174634	R	
475	0.00106147	0.00	0.092540	R	
479	0.00098210	0.00	0.075141	R	
497	0.00120275	0.00	0.116920	R	
505	0.00300605	0.01	-0.286593	R	X
506	0.00306950	0.02	-0.315334	R	X
514	0.00685429	0.00	0.141247		X
521	0.00107593	0.00	0.095757	R	

523	0.00101565	0.00	0.084832	R	
524	0.00097504	0.00	0.075667	R	
538	0.00608846	0.00	0.087294		X
551	0.00274676	0.00	-0.131238	R	
552	0.00311479	0.02	-0.338140	R	X
562	0.00698407	0.00	0.138275		X
570	0.00104360	0.00	0.091889	R	
586	0.00559360	0.00	0.108823		X
594	0.00112793	0.00	0.107598	R	
610	0.00437298	0.00	0.081014		X
634	0.00724355	0.00	0.139572		X
641	0.00116850	0.00	0.100444	R	
666	0.00105510	0.00	0.075244	R	
689	0.00121141	0.00	0.105981	R	
690	0.00097285	0.00	0.081244	R	
706	0.00573088	0.00	0.107306		X
738	0.00141875	0.00	0.107240	R	
753	0.00438125	0.00	-0.113926		X
754	0.00256163	0.00	0.122907	R	
768	0.00298024	0.01	-0.296014	R	X
790	0.00265131	0.00	-0.107454	R	
791	0.00111982	0.00	0.110621	R	
802	0.00338854	0.00	0.062187		X
810	0.00090343	0.00	0.069148	R	
845	0.00283260	0.01	-0.229721	R	
846	0.00299062	0.02	-0.306430	R	X
858	0.00120765	0.00	0.085257	R	
859	0.00093217	0.00	0.077882	R	
860	0.00089577	0.00	0.069183	R	
863	0.00096008	0.00	0.083874	R	
898	0.00472731	0.00	0.084477		X
907	0.00111662	0.00	0.112452	R	
910	0.00117149	0.00	0.121159	R	
911	0.00115447	0.00	0.118527	R	
945	0.00701729	0.00	-0.150667		X
955	0.00108487	0.00	0.108260	R	
956	0.00103062	0.00	0.099195	R	
978	0.00092477	0.00	0.079922	R	
979	0.00098274	0.00	0.091227	R	
983	0.00089528	0.00	0.073602	R	
1007	0.00106626	0.00	0.073643	R	
1026	0.00088157	0.00	0.071755	R	
1040	0.00280747	0.01	-0.236243	R	
1041	0.00502416	0.01	0.218158	R	X
1063	0.00275997	0.01	-0.209302	R	
1064	0.00297621	0.02	-0.318054	R	X
1075	0.00105841	0.00	0.106282	R	

1098	0.00104065	0.00	0.103634	R	
1099	0.00113653	0.00	0.119104	R	
1113	0.00362898	0.00	0.067264		X
1137	0.00372218	0.00	0.068390		X
1170	0.00096268	0.00	0.091478	R	
1171	0.00125152	0.00	0.137498	R	
1185	0.00386828	0.00	0.068586		X
1186	0.00379086	0.00	0.079094		X
1194	0.00095980	0.00	0.091346	R	
1195	0.00095499	0.00	0.091093	R	
1196	0.00084302	0.00	0.068216	R	
1199	0.00108079	0.00	0.112129	R	
1209	0.00762260	0.00	0.146210		X
1219	0.00107425	0.00	0.111440	R	
1250	0.00286130	0.01	-0.276716	R	
1257	0.00400265	0.00	0.070247		X
1267	0.00109034	0.00	0.114767	R	
1269	0.00084498	0.00	0.071042	R	
1281	0.00397075	0.00	0.065340		X
1290	0.00081743	0.00	0.063565	R	
1291	0.00095669	0.00	0.093375	R	
1295	0.00083088	0.00	0.065094	R	
1305	0.00354264	0.00	0.051963		X
1314	0.00107301	0.00	0.111513	R	
1329	0.00402229	0.00	0.068518		X
1411	0.00110477	0.00	0.104515	R	
1415	0.00130127	0.00	0.084489	R	
1425	0.00329426	0.00	0.058945		X
1435	0.00080554	0.00	0.066728	R	
1445	0.00266472	0.01	-0.187360	R	
1446	0.00272116	0.01	-0.220869	R	
1459	0.00085515	0.00	0.078196	R	
1463	0.00128894	0.00	0.110040	R	
1483	0.00096313	0.00	0.091228	R	
1487	0.00095854	0.00	0.065007	R	
1531	0.00094348	0.00	0.095553	R	
1545	0.00360827	0.00	0.068222		X
1559	0.00080253	0.00	0.064408	R	
1583	0.00100146	0.00	0.088401	R	
1593	0.00350183	0.00	0.063478		X
1603	0.00096331	0.00	0.100013	R	
1637	0.00270623	0.01	-0.227241	R	
1655	0.00076631	0.00	0.063629	R	
1685	0.00279756	0.01	-0.275160	R	
1707	0.00274393	0.01	-0.251177	R	
1708	0.00278391	0.01	-0.270242	R	
1723	0.00082797	0.00	0.078514	R	

1736	0.00325343	0.00	0.040673		X
1757	0.00276154	0.01	-0.262707	R	
1771	0.00087081	0.00	0.087131	R	
1804	0.00281292	0.01	-0.288740	R	
1819	0.00081257	0.00	0.077275	R	
1823	0.00098750	0.00	0.091433	R	
1833	0.00354639	0.00	0.066614		X
1846	0.00088842	0.00	0.091412	R	
1867	0.00078801	0.00	0.073150	R	
1880	0.00300996	0.00	-0.006106		X
1905	0.00421783	0.00	0.069914		X
1912	0.00320393	0.00	0.038040		X
1919	0.00089959	0.00	0.094344	R	
1940	0.00072619	0.00	0.061509	R	
1963	0.00078850	0.00	0.074629	R	
1967	0.00085186	0.00	0.070088	R	
1991	0.00108354	0.00	0.094712	R	
2040	0.00258370	0.01	-0.267287	R	
2059	0.00105407	0.00	0.118962	R	
2107	0.00095081	0.00	0.104510	R	
2131	0.00097890	0.00	0.103202	R	
2193	0.00430810	0.00	0.055638		X
2206	0.00090229	0.00	0.090230	R	
2207	0.00071764	0.00	0.065587	R	
2231	0.00074253	0.00	0.071187	R	
2240	0.00334168	0.00	0.038524		X
2275	0.00082615	0.00	0.086176	R	
2303	0.00069608	0.00	0.062652	R	
2360	0.00345900	0.00	0.039053		X
2371	0.00066196	0.00	0.066560	R	
2384	0.00297633	0.00	0.028334		X
2428	0.00266114	0.01	-0.250536	R	
2443	0.00105313	0.00	0.118055	R	
2467	0.00080289	0.00	0.083624	R	
2504	0.00304550	0.00	0.031515		X
2515	0.00070138	0.00	0.064389	R	
2519	0.00243185	0.00	-0.105752	R	
2544	0.00269481	0.01	-0.271115	R	
2563	0.00070527	0.00	0.063973	R	
2564	0.00065784	0.00	0.058571	R	
2567	0.00076303	0.00	0.079644	R	
2591	0.00110814	0.00	0.109554	R	
2635	0.00081903	0.00	0.086528	R	
2674	0.00309735	0.00	0.062399		X
2683	0.00082234	0.00	0.087658	R	
2712	0.00212838	0.01	-0.202538	R	
2734	0.00066031	0.00	0.062100	R	

2735	0.00087880	0.00	0.100080	R	
2744	0.00407085	0.00	0.050125		X
2803	0.00069654	0.00	0.058422	R	
2851	0.00064707	0.00	0.056600	R	
2854	0.00062567	0.00	0.055880	R	
2855	0.00076506	0.00	0.082948	R	
2888	0.00326793	0.00	0.090294		X
2918	0.00309780	0.00	-0.036661		X
2923	0.00080802	0.00	0.067985	R	
2957	0.00253338	0.01	-0.212436	R	
2999	0.00241182	0.00	-0.128522	R	
3019	0.00069423	0.00	0.067209	R	
3070	0.00238550	0.00	-0.107158	R	
3104	0.00394378	0.00	0.045573		X
3128	0.00311793	0.00	0.031828		X
3144	0.00154043	0.00	-0.145312	R	
3191	0.00247089	0.01	-0.181618	R	
3224	0.00296357	0.00	0.022393		X
3246	0.00273345	0.01	-0.258233	R	
3247	0.00284023	0.01	-0.286061	R	
3288	0.00263360	0.01	-0.268055	R	
3359	0.00067507	0.00	0.067409	R	
3414	0.00283131	0.01	-0.281623	R	
3443	0.00233122	0.00	0.099134	R	
3444	0.00272425	0.00	-0.129922	R	
3445	0.00067625	0.00	0.092883	R	
3448	0.00294021	0.00	0.016135		X
3449	0.00202861	0.00	0.157263	R	
3488	0.00323098	0.00	0.019451		X
3499	0.00079070	0.00	0.071126	R	
3503	0.00083061	0.00	0.097580	R	
3571	0.00077538	0.00	0.065204	R	
3592	0.00311794	0.00	0.038862		X
3595	0.00098536	0.00	0.119207	R	
3599	0.00083143	0.00	0.084880	R	
3619	0.00116289	0.00	0.108176	R	
3659	0.00063490	0.00	0.080958	R	
3672	0.00271081	0.02	-0.308443	R	
3695	0.00235812	0.00	-0.116145	R	
3696	0.00262500	0.01	-0.272765	R	
3719	0.00236798	0.00	-0.126564	R	
3752	0.00399575	0.00	0.040680		X
3791	0.00089445	0.00	0.108169	R	
3815	0.00237740	0.00	-0.137845	R	
3859	0.00057700	0.00	0.060159	R	
3862	0.00075113	0.00	0.086570	R	
3911	0.00108141	0.00	0.069854	R	

3935	0.00065950	0.00	0.051719	R	
3963	0.00249976	0.01	-0.217644	R	
3964	0.00253177	0.01	-0.234317	R	
3972	0.00301187	0.00	-0.024161		X
3979	0.00067039	0.00	0.063858	R	
4005	0.00233648	0.00	-0.108108	R	
4103	0.00070420	0.00	0.079574	R	
4184	0.00300427	0.00	0.014324		X
4189	0.00405280	0.00	-0.041462		X
4195	0.00076559	0.00	0.069434	R	
4240	0.00132087	0.00	0.090864	R	
4339	0.00074681	0.00	0.059252	R	
4440	0.00146097	0.00	-0.098588	R	
4472	0.00305076	0.00	0.020705		X
4525	0.00325626	0.00	-0.039509		X
4535	0.00147571	0.00	0.102275	R	
4557	0.00232088	0.00	-0.096680	R	
4559	0.00187182	0.00	-0.097632	R	
4603	0.00078123	0.00	0.064512	R	
4616	0.00348844	0.00	0.031411		X
4621	0.00353721	0.00	-0.035136		X
4708	0.00253887	0.01	-0.240744	R	
4723	0.00073205	0.00	0.064399	R	
4727	0.00062333	0.00	0.065596	R	
4775	0.00067335	0.00	0.074433	R	
4828	0.00249541	0.01	-0.218609	R	
4829	0.00254097	0.01	-0.240135	R	
4841	0.00231743	0.00	0.113649	R	
4919	0.00059662	0.00	0.059832	R	
4934	0.00361565	0.00	-0.040827		X
4955	0.00359815	0.00	0.079444		X
4963	0.00106293	0.00	0.126485	R	
4967	0.00075897	0.00	0.076264	R	
4980	0.00312033	0.00	-0.031423		X
5052	0.00432293	0.00	0.082038		X
5056	0.00234414	0.01	0.193401	R	
5064	0.00169211	0.00	-0.133221	R	
5078	0.00096150	0.00	0.070032	R	
5080	0.00063793	0.00	0.077963	R	
5087	0.00237685	0.00	-0.142121	R	
5132	0.00245793	0.01	-0.176959	R	
5135	0.00065892	0.00	0.070820	R	
5158	0.00075074	0.00	0.071906	R	
5179	0.00088839	0.00	0.078592	R	
5227	0.00067270	0.00	0.059987	R	
5230	0.00233610	0.00	-0.098090	R	
5231	0.00076289	0.00	0.080299	R	

5275	0.00076505	0.00	0.069316	R	
5303	0.00119518	0.00	0.075315	R	
5323	0.00089861	0.00	0.108373	R	
5352	0.00134438	0.00	-0.114880	R	
5382	0.00259956	0.01	-0.265071	R	
5383	0.00294027	0.01	-0.255235	R	X
5403	0.00253870	0.01	-0.232955	R	
5404	0.00273048	0.02	-0.316936	R	
5443	0.00108748	0.00	0.119675	R	
5447	0.00097085	0.00	0.118052	R	
5472	0.00183427	0.01	-0.178747	R	
5491	0.00069109	0.00	0.069986	R	
5543	0.00062113	0.00	0.059314	R	
5584	0.00302983	0.00	0.028555		X
5587	0.00058702	0.00	0.051714	R	
5591	0.00063581	0.00	0.056928	R	
5637	0.00062416	0.00	0.060827	R	
5638	0.00066604	0.00	0.069059	R	
5662	0.00061095	0.00	0.057680	R	
5663	0.00063393	0.00	0.062609	R	
5685	0.00058591	0.00	0.051110	R	
5696	0.00361956	0.00	0.036670		X
5711	0.00081814	0.00	0.072433	R	
5729	0.00115912	0.00	0.155963	R	
5732	0.00062733	0.00	0.060411	R	
5755	0.00067019	0.00	0.068705	R	
5759	0.00080344	0.00	0.091340	R	
5781	0.00220658	0.00	-0.104606	R	
5807	0.00083833	0.00	0.095237	R	
5824	0.00090556	0.00	0.127021	R	
5825	0.00067638	0.00	0.081545	R	
5826	0.00066924	0.00	0.072727	R	
5831	0.00237215	0.00	-0.106312	R	
5851	0.00068956	0.00	0.070252	R	
5875	0.00060975	0.00	0.052397	R	
5879	0.00072724	0.00	0.069617	R	
5899	0.00096012	0.00	0.111416	R	
6004	0.00256228	0.01	-0.228929	R	
6005	0.00250218	0.01	-0.196471	R	
6023	0.00121426	0.00	0.130103	R	
6115	0.00067134	0.00	0.063670	R	
6163	0.00088768	0.00	0.100584	R	
6167	0.00073495	0.00	0.060003	R	
6239	0.00070986	0.00	0.071135	R	
6291	0.00261031	0.01	-0.242399	R	
6292	0.00268445	0.01	-0.276683	R	
6307	0.00108454	0.00	0.129149	R	

6335	0.00111966	0.00	0.109177	R	
6355	0.00091431	0.00	0.103766	R	
6365	0.00261031	0.01	-0.239466	R	
6390	0.00259397	0.01	-0.230230	R	
6391	0.00339542	0.01	-0.270490	R	X
6411	0.00262639	0.01	-0.245446	R	
6412	0.00267667	0.01	-0.268911	R	
6453	0.00069214	0.00	0.064496	R	
6454	0.00095351	0.00	0.108784	R	
6455	0.00083889	0.00	0.090951	R	
6464	0.00317336	0.00	0.033398		X
6475	0.00078747	0.00	0.082158	R	
6500	0.00070463	0.00	0.066349	R	
6503	0.00244045	0.00	-0.122058	R	
6512	0.00353451	0.00	0.035102		X
6523	0.00074361	0.00	0.073672	R	
6547	0.00072219	0.00	0.069165	R	
6573	0.00242718	0.00	-0.099032	R	
6574	0.00083634	0.00	0.079374	R	
6575	0.00086691	0.00	0.094133	R	
6584	0.00331989	0.00	0.039672		X
6623	0.00173395	0.00	-0.107027	R	
6632	0.00351216	0.00	0.044056		X
6645	0.00244066	0.00	-0.106788	R	
6704	0.00311119	0.00	0.036060		X
6728	0.00315825	0.00	0.036818		X
6761	0.00318452	0.00	0.038582		X
6763	0.00068360	0.00	0.055645	R	
6800	0.00384532	0.00	0.059828		X
6810	0.00089432	0.00	0.095354	R	
6811	0.00087255	0.00	0.092156	R	
6812	0.00075150	0.00	0.070494	R	
6814	0.00080409	0.00	0.080420	R	
6815	0.00110197	0.00	0.127098	R	
6834	0.00070649	0.00	0.059578	R	
6872	0.00473825	0.00	0.067723		X
6883	0.00089439	0.00	0.094760	R	
6896	0.00297105	0.00	0.037491		X
6907	0.00076763	0.00	0.071964	R	
6930	0.00071589	0.00	0.059813	R	
6931	0.00082478	0.00	0.082281	R	
6932	0.00070319	0.00	0.056243	R	
6954	0.00087164	0.00	0.090014	R	
6955	0.00095314	0.00	0.103172	R	
7013	0.00280648	0.01	-0.300660	R	
7026	0.00090079	0.00	0.093808	R	
7027	0.00085166	0.00	0.085476	R	

7028	0.00072019	0.00	0.058129	R	
7031	0.00071950	0.00	0.057837	R	
7040	0.00309210	0.00	0.046558		X
7055	0.00082485	0.00	0.080207	R	
7074	0.00074888	0.00	0.064238	R	
7098	0.00094482	0.00	0.099913	R	
7102	0.00249874	0.00	-0.113267	R	
7112	0.00332962	0.00	0.042500		X
7169	0.00295036	0.00	0.025675		X
7171	0.00100411	0.00	0.108218	R	
7172	0.00074390	0.00	0.060168	R	
7173	0.00091449	0.00	0.093845	R	
7174	0.00090807	0.00	0.092756	R	
7175	0.00094357	0.00	0.098583	R	
7195	0.00081016	0.00	0.074689	R	
7209	0.00314476	0.00	0.047762		X
7224	0.00278205	0.01	-0.279422	R	
7242	0.00126947	0.00	0.073781	R	
7247	0.00088258	0.00	0.087165	R	
7257	0.00458133	0.00	0.076872		X
7264	0.00298224	0.00	0.035087		X
7281	0.00512286	0.00	0.097683		X
7291	0.00109745	0.00	0.120770	R	
7295	0.00083574	0.00	0.077613	R	
7305	0.00370676	0.00	0.060514		X
7314	0.00084492	0.00	0.067602	R	
7315	0.00087573	0.00	0.084695	R	
7337	0.00110159	0.00	0.119355	R	
7363	0.00085411	0.00	0.079717	R	
7385	0.00089975	0.00	0.087088	R	
7401	0.00610372	0.00	0.111255		X
7409	0.00143292	0.00	0.166527	R	
7410	0.00094880	0.00	0.095639	R	
7411	0.00080838	0.00	0.069107	R	
7425	0.00599639	0.00	0.097756		X
7433	0.00154485	0.01	0.181774	R	
7434	0.00093600	0.00	0.093048	R	
7449	0.00564130	0.00	0.102526		X
7457	0.00110874	0.00	0.119689	R	
7481	0.00087481	0.00	0.080552	R	
7486	0.00082175	0.00	0.070059	R	
7497	0.00514326	0.00	0.090712		X
7505	0.00168494	0.01	0.200096	R	
7506	0.00091907	0.00	0.088736	R	
7509	0.00080053	0.00	0.064200	R	
7510	0.00092120	0.00	0.089035	R	
7529	0.00086239	0.00	0.077309	R	

7553	0.00121812	0.00	0.134815	R	
7559	0.00243475	0.00	-0.108220	R	
7569	0.00656756	0.00	0.120077		X
7577	0.00148075	0.00	0.171628	R	
7578	0.00085059	0.00	0.073886	R	
7593	0.00314162	0.00	0.053936		X
7594	0.00351890	0.00	0.059611		X
7601	0.00091223	0.00	0.085404	R	
7608	0.00288108	0.02	-0.301669	R	
7617	0.00675483	0.00	0.117264		X
7626	0.00108457	0.00	0.113813	R	
7627	0.00088490	0.00	0.079695	R	
7641	0.00308282	0.00	0.051856		X
7649	0.00137207	0.00	0.155620	R	
7665	0.00506026	0.00	0.083404		X
7675	0.00091189	0.00	0.083782	R	
7689	0.00335513	0.00	0.057291		X
7713	0.00518085	0.00	0.080196		X
7737	0.00313699	0.00	0.053521		X
7745	0.00189472	0.01	0.225487	R	
7747	0.00124192	0.00	0.135578	R	
7751	0.00103301	0.00	0.075084	R	
7769	0.00095737	0.00	0.090053	R	
7771	0.00083854	0.00	0.064782	R	
7782	0.00277048	0.01	-0.237516	R	
7783	0.00284423	0.01	-0.273971	R	
7794	0.00100495	0.00	0.097852	R	
7795	0.00088314	0.00	0.074803	R	
7810	0.00608190	0.00	0.118569		X
7823	0.00088320	0.00	0.073968	R	
7833	0.00309007	0.00	0.044822		X
7848	0.00292655	0.02	-0.306806	R	
7865	0.00104182	0.00	0.102619	R	
7882	0.00654488	0.00	0.120215		X
7891	0.00091512	0.00	0.078843	R	
7895	0.00106708	0.00	0.084625	R	
7913	0.00121580	0.00	0.129042	R	
7925	0.00285809	0.01	-0.270505	R	
7926	0.00288129	0.01	-0.281337	R	
7936	0.00296809	0.00	0.025118		X
7937	0.00182453	0.00	0.135418	R	
7939	0.00094588	0.00	0.083747	R	
7954	0.00778450	0.00	0.153873		X
7961	0.00095418	0.00	0.084787	R	
7968	0.00167749	0.00	-0.156719	R	
7978	0.00763331	0.00	0.160103		X
7986	0.00095208	0.00	0.083698	R	

8009	0.00121569	0.00	0.106168	R	
8016	0.00289871	0.01	-0.282999	R	
8026	0.00530136	0.00	0.094247		X
8033	0.00138603	0.00	0.151981	R	
8040	0.00259599	0.01	-0.283549	R	
8050	0.00597514	0.00	0.128107		X
8057	0.00170468	0.00	0.133493	R	
8058	0.00096523	0.00	0.084309	R	
8074	0.00593444	0.00	0.121322		X
8081	0.00108126	0.00	0.104681	R	
8154	0.00094983	0.00	0.078138	R	
8170	0.00557007	0.00	0.105389		X
8177	0.00133022	0.00	0.141475	R	
8178	0.00123115	0.00	0.126608	R	
8182	0.00096469	0.00	0.080452	R	
8183	0.00107038	0.00	0.100507	R	
8194	0.00484219	0.00	0.099032		X
8200	0.00345951	0.00	0.017751		X
8202	0.00095682	0.00	0.078060	R	
8203	0.00116573	0.00	0.115889	R	
8207	0.00103749	0.00	0.089184	R	
8218	0.00470983	0.00	0.096231		X
8219	0.00387074	0.00	0.078951		X
8227	0.00093750	0.00	0.072558	R	
8230	0.00266719	0.00	-0.106108	R	
8231	0.00108598	0.00	0.082644	R	
8250	0.00116341	0.00	0.114525	R	
8251	0.00124587	0.00	0.127453	R	
8254	0.00268208	0.00	-0.119292	R	
8255	0.00109247	0.00	0.102231	R	
8266	0.00845120	0.00	0.171356		X
8279	0.00096327	0.00	0.076775	R	
8290	0.00505552	0.00	0.103188		X
8291	0.00302529	0.00	0.058187		X
8296	0.00090651	0.00	0.081841	R	
8297	0.00121036	0.00	0.121011	R	
8303	0.00103899	0.00	0.091724	R	
8314	0.00427003	0.00	0.083286		X
8315	0.00333101	0.00	0.066112		X
8321	0.00218196	0.01	0.182606	R	
8322	0.00103919	0.00	0.091223	R	
8335	0.00281321	0.01	-0.210605	R	
8336	0.00291458	0.01	-0.265482	R	
8346	0.00105816	0.00	0.094126	R	
8347	0.00111269	0.00	0.103858	R	
8351	0.00116538	0.00	0.080233	R	
8362	0.00424037	0.00	0.078706		X

8383	0.00288512	0.01	-0.246265	R	
8393	0.00114681	0.00	0.108553	R	
8395	0.00101947	0.00	0.085053	R	
8410	0.00733911	0.00	0.149168		X
8417	0.00203706	0.00	0.126173	R	
8418	0.00111594	0.00	0.102630	R	
8422	0.00272186	0.00	-0.128584	R	
8434	0.00377575	0.00	0.073173		X
8441	0.00126303	0.00	0.126231	R	
8442	0.00097587	0.00	0.073233	R	
8446	0.00097534	0.00	0.072914	R	
8447	0.00109823	0.00	0.098701	R	
8458	0.00373741	0.00	0.070589		X
8466	0.00098344	0.00	0.074126	R	
8467	0.00144803	0.00	0.153424	R	
8482	0.00805357	0.00	0.012631		X
8506	0.00381849	0.01	0.266952	R	X
8513	0.00148204	0.00	0.134786	R	
8517	0.00272573	0.00	-0.111545	R	
8554	0.00617840	0.00	0.088830		X
8561	0.00191888	0.00	0.106899	R	
8567	0.00115177	0.00	0.104986	R	
8578	0.00344239	0.00	0.065197		X
8579	0.00342756	0.00	0.064262		X
8585	0.00194042	0.01	0.208930	R	
8586	0.00108775	0.00	0.092631	R	
8587	0.00098205	0.00	0.067560	R	
8602	0.00343072	0.01	0.233662	R	X
8611	0.00133847	0.00	0.134244	R	
8626	0.00214789	0.00	0.115687	R	
8639	0.00274547	0.00	-0.105153	R	
8650	0.00540151	0.00	0.084225		X
8651	0.00371290	0.00	0.069802		X
8657	0.00105402	0.00	0.083093	R	
8674	0.00703906	0.00	0.115298		X
8681	0.00127167	0.00	0.122172	R	
8705	0.00112452	0.00	0.095963	R	
8706	0.00119945	0.00	0.109522	R	
8707	0.00131832	0.00	0.128975	R	
8711	0.00126011	0.00	0.092450	R	
8722	0.00373064	0.00	0.064815		X
8723	0.00420063	0.00	0.085305		X
8729	0.00116379	0.00	0.074149	R	
8730	0.00116448	0.00	0.102657	R	
8746	0.00710575	0.00	0.118520		X
8753	0.00121993	0.00	0.111766	R	
8754	0.00104863	0.00	0.077647	R	

8755	0.00117333	0.00	0.103521	R	
8758	0.00122179	0.00	0.111949	R	
8759	0.00104181	0.00	0.075623	R	

R Large residual

X Unusual X

Fits and Diagnostics for Unusual Observations

Test Set

Obs	TELS (kW)	Fit	SE Fit	95% CI	Resid	Std Resid	HI		
11	19.321	16.212	0.154	(15.910, 16.513)	3.109	1.21	0.00357375		X
41	19.266	10.742	0.092	(10.561, 10.922)	8.524	3.31	0.00127629	R	
82	17.736	16.252	0.227	(15.808, 16.696)	1.484	0.57	0.00775689		X
130	15.580	8.613	0.135	(8.349, 8.878)	6.967	2.70	0.00274697	R	
178	21.251	10.365	0.189	(9.995, 10.735)	10.886	4.22	0.00537721	R	X
185	23.483	12.898	0.101	(12.700, 13.095)	10.585	4.11	0.00153579	R	
240	6.884	15.589	0.117	(15.360, 15.818)	-8.704	-3.38	0.00206196	R	
250	13.846	10.606	0.172	(10.269, 10.943)	3.240	1.26	0.00446578		X
257	22.915	12.610	0.099	(12.416, 12.803)	10.305	4.00	0.00147528	R	
305	29.392	15.920	0.118	(15.689, 16.151)	13.472	5.23	0.00209676	R	
323	21.984	18.735	0.156	(18.430, 19.040)	3.249	1.26	0.00366748		X
334	13.277	19.443	0.136	(19.176, 19.709)	-6.166	-2.39	0.00278644	R	
353	15.650	8.904	0.083	(8.741, 9.067)	6.746	2.62	0.00104508	R	
359	19.135	10.680	0.089	(10.505, 10.854)	8.455	3.29	0.00120041	R	
418	14.923	11.181	0.191	(10.807, 11.555)	3.742	1.45	0.00550934		X
425	22.694	12.507	0.097	(12.316, 12.697)	10.188	3.96	0.00142585	R	
426	16.658	9.416	0.084	(9.251, 9.581)	7.242	2.81	0.00106698	R	
450	16.018	9.089	0.083	(8.927, 9.252)	6.928	2.69	0.00103710	R	
474	14.962	8.550	0.081	(8.391, 8.710)	6.411	2.49	0.00099636	R	
490	22.738	18.572	0.193	(18.194, 18.949)	4.166	1.62	0.00561127		X
522	14.408	8.268	0.080	(8.111, 8.426)	6.140	2.39	0.00097059	R	
527	13.946	8.032	0.080	(7.876, 8.188)	5.913	2.30	0.00095749	R	
569	21.654	11.986	0.094	(11.803, 12.170)	9.667	3.76	0.00132386	R	
593	15.589	8.894	0.081	(8.735, 9.054)	6.695	2.60	0.00100103	R	
600	5.461	15.374	0.115	(15.148, 15.600)	-9.912	-3.85	0.00200911	R	
617	22.175	15.587	0.076	(15.438, 15.737)	6.587	2.56	0.00087589	R	
658	16.531	12.171	0.214	(11.751, 12.590)	4.360	1.69	0.00692362		X
682	14.378	10.505	0.199	(10.115, 10.894)	3.873	1.50	0.00597146		X
730	15.080	11.182	0.197	(10.795, 11.569)	3.898	1.51	0.00589003		X
778	14.981	11.136	0.195	(10.754, 11.518)	3.845	1.49	0.00574049		X
787	16.291	9.234	0.081	(9.076, 9.392)	7.057	2.74	0.00098210	R	
811	18.041	10.128	0.084	(9.965, 10.292)	7.912	3.07	0.00105450	R	
826	20.046	15.744	0.201	(15.350, 16.139)	4.302	1.67	0.00611849		X
851	31.538	29.755	0.147	(29.467, 30.044)	1.783	0.69	0.00327192		X
874	15.570	12.851	0.141	(12.575, 13.128)	2.718	1.06	0.00301665		X
906	17.277	9.740	0.081	(9.580, 9.900)	7.537	2.93	0.00100144	R	
969	10.855	7.982	0.164	(7.661, 8.303)	2.873	1.11	0.00405674		X

993	9.312	6.872	0.151	(6.576, 7.167)	2.440	0.95	0.00343849		X
1017	17.022	14.213	0.143	(13.933, 14.492)	2.809	1.09	0.00307943		X
1050	19.477	10.867	0.085	(10.701, 11.033)	8.610	3.35	0.00108899	R	
1074	19.783	11.025	0.085	(10.857, 11.192)	8.758	3.40	0.00110316	R	
1089	9.198	6.436	0.167	(6.109, 6.762)	2.762	1.07	0.00420236		X
1103	18.817	10.918	0.084	(10.753, 11.082)	7.899	3.07	0.00106459	R	
1161	10.570	7.769	0.162	(7.452, 8.087)	2.801	1.09	0.00397213		X
1218	19.803	11.050	0.085	(10.884, 11.216)	8.753	3.40	0.00108544	R	
1223	15.593	9.990	0.078	(9.837, 10.143)	5.603	2.18	0.00092460	R	
1233	11.555	8.742	0.159	(8.431, 9.053)	2.813	1.09	0.00380122		X
1249	5.628	18.916	0.138	(18.646, 19.185)	-13.287	-5.16	0.00286388	R	
1266	20.142	11.226	0.085	(11.059, 11.393)	8.916	3.46	0.00109905	R	
1268	16.763	9.483	0.078	(9.330, 9.636)	7.280	2.83	0.00091756	R	
1353	11.092	8.269	0.161	(7.953, 8.585)	2.823	1.10	0.00393058		X
1367	16.892	10.888	0.080	(10.730, 11.045)	6.004	2.33	0.00097813	R	
1555	13.970	8.062	0.072	(7.921, 8.202)	5.909	2.30	0.00078081	R	
1579	15.869	9.032	0.074	(8.886, 9.177)	6.838	2.66	0.00083517	R	
1627	18.617	10.435	0.079	(10.280, 10.591)	8.181	3.18	0.00094986	R	
1638	5.223	18.893	0.137	(18.625, 19.161)	-13.670	-5.31	0.00282275	R	
1654	15.031	8.605	0.073	(8.463, 8.747)	6.426	2.50	0.00079622	R	
1675	18.191	10.219	0.078	(10.066, 10.372)	7.972	3.10	0.00092126	R	
1684	6.672	18.997	0.135	(18.732, 19.261)	-12.324	-4.79	0.00274942	R	
1758	5.440	18.910	0.136	(18.644, 19.177)	-13.470	-5.23	0.00279512	R	
1775	14.436	8.303	0.071	(8.164, 8.442)	6.133	2.38	0.00076198	R	
1803	7.718	19.073	0.133	(18.811, 19.334)	-11.355	-4.41	0.00268955	R	
1843	14.966	8.579	0.071	(8.439, 8.719)	6.387	2.48	0.00076968	R	
1847	17.346	9.790	0.075	(9.642, 9.938)	7.556	2.94	0.00085768	R	
1879	7.977	18.271	0.150	(17.977, 18.564)	-10.294	-4.00	0.00338437	R	X
1891	19.336	10.814	0.080	(10.658, 10.970)	8.521	3.31	0.00095583	R	
1915	15.784	9.002	0.072	(8.861, 9.144)	6.781	2.64	0.00078925	R	
1918	16.108	9.159	0.073	(9.017, 9.301)	6.949	2.70	0.00079746	R	
1939	14.323	8.259	0.070	(8.122, 8.396)	6.064	2.36	0.00074134	R	
1943	15.096	8.643	0.071	(8.504, 8.782)	6.453	2.51	0.00075938	R	
1987	14.987	8.605	0.071	(8.466, 8.743)	6.382	2.48	0.00075673	R	
2011	21.578	12.523	0.086	(12.354, 12.693)	9.054	3.52	0.00113014	R	
2083	13.385	7.793	0.068	(7.659, 7.927)	5.592	2.17	0.00070511	R	
2132	14.139	8.157	0.068	(8.023, 8.291)	5.982	2.33	0.00070886	R	
2135	18.369	10.317	0.076	(10.168, 10.466)	8.052	3.13	0.00087063	R	
2155	14.769	8.602	0.069	(8.467, 8.736)	6.168	2.40	0.00071328	R	
2159	15.157	8.677	0.070	(8.541, 8.814)	6.480	2.52	0.00073501	R	
2265	7.718	5.483	0.159	(5.171, 5.795)	2.235	0.87	0.00383693		X
2299	15.681	9.454	0.065	(9.327, 9.582)	6.227	2.42	0.00063945	R	
2327	8.552	16.490	0.111	(16.273, 16.707)	-7.938	-3.08	0.00185191	R	
2409	14.378	11.489	0.158	(11.180, 11.799)	2.888	1.12	0.00375798		X
2419	19.762	11.396	0.078	(11.244, 11.549)	8.366	3.25	0.00091494	R	
2429	9.117	19.182	0.130	(18.926, 19.437)	-10.065	-3.91	0.00256205	R	
2456	3.439	2.394	0.140	(2.120, 2.668)	1.045	0.41	0.00295171		X

2576	6.409	4.599	0.143	(4.318, 4.879)	1.811	0.70	0.00308939		X
2587	17.481	10.327	0.072	(10.187, 10.468)	7.154	2.78	0.00077548	R	
2696	5.504	3.871	0.141	(3.594, 4.148)	1.633	0.63	0.00301306		X
2731	18.558	11.053	0.075	(10.905, 11.200)	7.505	2.92	0.00085716	R	
2887	7.305	18.762	0.149	(18.471, 19.053)	-11.457	-4.45	0.00333542	R	X
2904	5.953	18.461	0.128	(18.209, 18.712)	-12.507	-4.86	0.00248544	R	
2917	10.184	11.651	0.144	(11.368, 11.935)	-1.468	-0.57	0.00315385		X
2956	7.658	19.087	0.130	(18.831, 19.342)	-11.428	-4.44	0.00256666	R	
2971	19.395	11.244	0.075	(11.098, 11.391)	8.150	3.17	0.00084395	R	
3024	5.836	14.508	0.098	(14.316, 14.701)	-8.672	-3.37	0.00145892	R	
3057	9.796	6.783	0.189	(6.413, 7.154)	3.012	1.17	0.00540058		X
3095	12.733	19.448	0.126	(19.201, 19.696)	-6.716	-2.61	0.00240467	R	
3163	16.778	10.429	0.071	(10.290, 10.568)	6.349	2.47	0.00075779	R	
3167	14.049	19.543	0.125	(19.297, 19.789)	-5.493	-2.13	0.00237631	R	
3214	14.894	8.560	0.065	(8.433, 8.687)	6.334	2.46	0.00063212	R	
3264	4.538	15.142	0.104	(14.937, 15.347)	-10.604	-4.12	0.00164954	R	
3310	19.124	13.887	0.085	(13.720, 14.054)	5.238	2.04	0.00109965	R	
3311	15.215	8.726	0.065	(8.598, 8.853)	6.490	2.52	0.00063619	R	
3392	5.077	3.653	0.141	(3.377, 3.929)	1.425	0.55	0.00300122		X
3403	17.625	11.878	0.085	(11.711, 12.045)	5.747	2.23	0.00109614	R	
3413	5.224	18.932	0.132	(18.672, 19.191)	-13.708	-5.32	0.00264724	R	
3450	25.025	17.180	0.066	(17.051, 17.309)	7.845	3.05	0.00065610	R	
3575	19.294	12.641	0.079	(12.486, 12.796)	6.653	2.59	0.00094364	R	
3623	21.186	13.639	0.085	(13.473, 13.806)	7.546	2.93	0.00108927	R	
3827	25.147	19.868	0.124	(19.626, 20.111)	5.278	2.05	0.00231571	R	
3828	15.676	11.662	0.162	(11.344, 11.980)	4.014	1.56	0.00398563		X
3863	14.233	8.233	0.062	(8.111, 8.355)	6.000	2.33	0.00058312	R	
4151	13.667	7.948	0.061	(7.829, 8.068)	5.718	2.22	0.00056261	R	
4483	16.449	10.684	0.072	(10.543, 10.824)	5.766	2.24	0.00077752	R	
4558	13.859	19.552	0.124	(19.308, 19.795)	-5.692	-2.21	0.00233200	R	
4589	7.586	19.154	0.129	(18.902, 19.406)	-11.568	-4.49	0.00249907	R	
4590	5.487	19.145	0.134	(18.883, 19.407)	-13.659	-5.30	0.00270196	R	
4607	13.985	19.561	0.124	(19.318, 19.805)	-5.577	-2.17	0.00233015	R	
4684	6.309	19.019	0.130	(18.764, 19.274)	-12.710	-4.94	0.00256097	R	
4685	3.378	18.721	0.136	(18.455, 18.988)	-15.344	-5.96	0.00278731	R	
4709	7.472	19.142	0.129	(18.890, 19.395)	-11.670	-4.53	0.00250289	R	
4771	19.250	12.280	0.067	(12.150, 12.411)	6.969	2.71	0.00067176	R	
4784	3.910	2.662	0.145	(2.377, 2.947)	1.248	0.48	0.00318729		X
4939	17.292	11.238	0.061	(11.118, 11.359)	6.054	2.35	0.00057091	R	
4997	3.794	18.807	0.134	(18.543, 19.070)	-15.013	-5.83	0.00272267	R	
4998	4.545	18.662	0.138	(18.391, 18.933)	-14.118	-5.48	0.00289160	R	
5040	4.488	18.896	0.133	(18.636, 19.156)	-14.408	-5.59	0.00265436	R	
5079	13.631	7.977	0.061	(7.858, 8.097)	5.653	2.20	0.00056171	R	
5112	4.133	15.006	0.103	(14.804, 15.208)	-10.873	-4.22	0.00160400	R	
5368	28.190	18.675	0.078	(18.521, 18.828)	9.515	3.70	0.00092314	R	
5444	13.941	8.242	0.062	(8.121, 8.364)	5.698	2.21	0.00057803	R	
5515	16.178	10.142	0.062	(10.021, 10.262)	6.036	2.35	0.00057236	R	

5539	16.821	10.363	0.069	(10.227, 10.499)	6.457	2.51	0.00072865	R	
5615	20.819	11.625	0.077	(11.473, 11.776)	9.195	3.57	0.00090614	R	
5624	5.674	4.088	0.140	(3.814, 4.362)	1.586	0.62	0.00294545		X
5635	18.253	11.984	0.055	(11.877, 12.091)	6.270	2.44	0.00045105	R	
5636	13.536	7.909	0.063	(7.786, 8.032)	5.627	2.19	0.00059294	R	
5639	17.636	9.999	0.070	(9.863, 10.135)	7.637	2.97	0.00073067	R	
5659	19.347	11.425	0.074	(11.280, 11.570)	7.922	3.08	0.00082527	R	
5707	14.048	8.666	0.064	(8.541, 8.790)	5.382	2.09	0.00061268	R	
5731	20.351	14.249	0.087	(14.078, 14.420)	6.103	2.37	0.00114913	R	
5735	19.523	10.965	0.074	(10.819, 11.110)	8.559	3.33	0.00083407	R	
5768	4.796	3.035	0.153	(2.735, 3.335)	1.761	0.68	0.00354153		X
5803	15.688	9.357	0.065	(9.229, 9.485)	6.331	2.46	0.00064500	R	
5827	15.630	9.117	0.065	(8.990, 9.244)	6.513	2.53	0.00063131	R	
5864	5.721	3.897	0.149	(3.606, 4.188)	1.824	0.71	0.00333479		X
5923	15.417	9.122	0.066	(8.993, 9.251)	6.295	2.45	0.00065537	R	
5971	14.846	8.784	0.065	(8.656, 8.911)	6.062	2.36	0.00064096	R	
6006	5.198	14.249	0.097	(14.059, 14.439)	-9.051	-3.52	0.00142330	R	
6057	6.637	4.869	0.160	(4.555, 5.183)	1.768	0.69	0.00387419		X
6096	4.473	15.271	0.106	(15.064, 15.479)	-10.798	-4.19	0.00169605	R	
6143	18.469	10.433	0.073	(10.290, 10.576)	8.036	3.12	0.00080692	R	
6200	4.704	3.011	0.145	(2.727, 3.295)	1.693	0.66	0.00317770		X
6224	4.543	2.240	0.177	(1.894, 2.586)	2.303	0.89	0.00470975		X
6259	16.322	10.023	0.070	(9.885, 10.161)	6.299	2.45	0.00074914	R	
6263	15.462	9.992	0.070	(9.855, 10.128)	5.470	2.13	0.00073164	R	
6331	17.270	10.287	0.072	(10.145, 10.428)	6.984	2.71	0.00078709	R	
6366	3.906	18.876	0.135	(18.611, 19.141)	-14.970	-5.81	0.00276270	R	
6379	13.998	8.153	0.066	(8.024, 8.283)	5.844	2.27	0.00065966	R	
6428	14.271	8.294	0.067	(8.163, 8.424)	5.977	2.32	0.00067131	R	
6438	8.144	19.177	0.131	(18.921, 19.433)	-11.034	-4.28	0.00257575	R	
6439	5.097	18.126	0.154	(17.824, 18.429)	-13.030	-5.06	0.00359885	R	X
6479	17.116	9.747	0.072	(9.607, 9.888)	7.369	2.86	0.00077438	R	
6536	2.256	0.745	0.155	(0.442, 1.048)	1.511	0.59	0.00361117		X
6559	6.944	17.788	0.164	(17.465, 18.110)	-10.844	-4.21	0.00408705	R	X
6600	4.771	18.941	0.135	(18.677, 19.205)	-14.170	-5.50	0.00274048	R	
6671	17.757	11.384	0.077	(11.233, 11.535)	6.373	2.48	0.00089885	R	
6680	6.746	4.046	0.179	(3.696, 4.396)	2.700	1.05	0.00482679		X
6690	18.479	10.468	0.076	(10.319, 10.617)	8.010	3.11	0.00087089	R	
6691	15.839	9.098	0.070	(8.961, 9.236)	6.740	2.62	0.00074696	R	
6738	18.042	10.235	0.075	(10.088, 10.382)	7.806	3.03	0.00084939	R	
6762	16.407	9.400	0.072	(9.259, 9.541)	7.007	2.72	0.00078033	R	
6776	5.393	3.670	0.141	(3.395, 3.946)	1.722	0.67	0.00298634		X
6786	15.455	8.912	0.070	(8.774, 9.050)	6.544	2.54	0.00074788	R	
6809	34.042	31.774	0.179	(31.422, 32.126)	2.268	0.88	0.00486538		X
6813	14.461	8.397	0.069	(8.262, 8.532)	6.064	2.36	0.00071801	R	
6840	5.413	17.470	0.123	(17.229, 17.710)	-12.057	-4.68	0.00227657	R	
6882	13.228	7.770	0.068	(7.636, 7.903)	5.458	2.12	0.00069802	R	
6906	15.595	8.978	0.071	(8.839, 9.117)	6.617	2.57	0.00076394	R	

6911	13.344	19.553	0.128	(19.302, 19.804)	-6.209	-2.41	0.00248235	R	
6920	8.725	6.102	0.164	(5.781, 6.423)	2.623	1.02	0.00404527		X
6959	20.998	12.982	0.087	(12.812, 13.153)	8.016	3.11	0.00114222	R	
6968	6.155	3.600	0.174	(3.259, 3.941)	2.555	0.99	0.00457001		X
6983	12.780	19.514	0.129	(19.262, 19.767)	-6.735	-2.62	0.00250176	R	
6992	5.299	2.764	0.178	(2.415, 3.112)	2.536	0.98	0.00477843		X
7012	6.509	19.071	0.134	(18.808, 19.333)	-12.562	-4.88	0.00270552	R	
7137	8.470	6.290	0.148	(6.000, 6.580)	2.181	0.85	0.00330789		X
7146	15.912	9.143	0.073	(9.000, 9.286)	6.769	2.63	0.00080552	R	
7147	21.406	11.949	0.085	(11.782, 12.115)	9.457	3.67	0.00109119	R	
7233	10.179	7.074	0.183	(6.715, 7.434)	3.105	1.20	0.00507302		X
7243	19.732	11.095	0.081	(10.936, 11.255)	8.636	3.36	0.00099826	R	
7288	29.758	27.988	0.148	(27.697, 28.279)	1.770	0.69	0.00333003		X
7329	8.427	5.082	0.203	(4.684, 5.480)	3.345	1.30	0.00623390		X
7340	15.712	9.044	0.074	(8.899, 9.189)	6.668	2.59	0.00082554	R	
7343	15.254	8.810	0.073	(8.667, 8.954)	6.444	2.50	0.00081083	R	
7353	9.097	5.748	0.200	(5.357, 6.139)	3.349	1.30	0.00602241		X
7361	24.227	13.407	0.094	(13.222, 13.592)	10.820	4.20	0.00134460	R	
7362	14.778	8.568	0.073	(8.425, 8.710)	6.211	2.41	0.00079916	R	
7367	15.946	10.560	0.077	(10.408, 10.711)	5.386	2.09	0.00089974	R	
7377	10.204	7.121	0.181	(6.767, 7.476)	3.083	1.20	0.00493300		X
7473	13.822	10.000	0.201	(9.606, 10.394)	3.822	1.48	0.00611758		X
7487	19.261	10.859	0.082	(10.699, 11.019)	8.402	3.27	0.00100685	R	
7521	11.954	8.863	0.174	(8.522, 9.205)	3.091	1.20	0.00458108		X
7545	12.083	9.116	0.168	(8.788, 9.445)	2.967	1.15	0.00424452		X
7546	16.953	14.259	0.140	(13.984, 14.535)	2.693	1.05	0.00297688		X
7579	18.353	10.397	0.080	(10.239, 10.554)	7.956	3.09	0.00097303	R	
7625	20.072	11.276	0.084	(11.111, 11.442)	8.796	3.42	0.00107564	R	
7631	21.159	11.830	0.087	(11.660, 12.001)	9.328	3.62	0.00114515	R	
7650	19.440	10.953	0.083	(10.790, 11.116)	8.487	3.30	0.00104220	R	
7672	27.164	25.524	0.142	(25.245, 25.802)	1.640	0.64	0.00305118		X
7673	21.875	12.197	0.089	(12.022, 12.372)	9.678	3.76	0.00120129	R	
7674	20.915	11.707	0.087	(11.537, 11.877)	9.209	3.58	0.00113593	R	
7697	19.130	10.796	0.083	(10.634, 10.958)	8.334	3.24	0.00103255	R	
7727	17.646	10.567	0.081	(10.409, 10.725)	7.079	2.75	0.00098761	R	
7746	19.714	11.094	0.084	(10.929, 11.260)	8.619	3.35	0.00107342	R	
7770	17.180	9.800	0.079	(9.645, 9.956)	7.379	2.87	0.00094905	R	
7793	19.299	10.883	0.084	(10.719, 11.047)	8.416	3.27	0.00105756	R	
7817	19.834	11.157	0.085	(10.990, 11.324)	8.677	3.37	0.00109225	R	
7841	16.101	9.251	0.078	(9.098, 9.403)	6.850	2.66	0.00091791	R	
7858	17.547	14.569	0.153	(14.270, 14.869)	2.978	1.16	0.00352594		X
7889	17.469	10.858	0.082	(10.697, 11.020)	6.610	2.57	0.00102749	R	
7890	13.791	8.072	0.075	(7.924, 8.219)	5.719	2.22	0.00085742	R	
7938	15.350	8.869	0.078	(8.717, 9.021)	6.481	2.52	0.00090873	R	
7985	19.916	11.201	0.086	(11.032, 11.371)	8.715	3.39	0.00112596	R	
8002	15.228	10.997	0.218	(10.570, 11.424)	4.231	1.64	0.00716580		X
8010	14.553	8.463	0.077	(8.312, 8.614)	6.090	2.37	0.00089765	R	

8098	16.695	12.781	0.198	(12.392, 13.170)	3.914	1.52	0.00594117		X
8118	7.020	19.125	0.137	(18.855, 19.394)	-12.105	-4.70	0.00285201	R	
8119	4.170	18.923	0.141	(18.647, 19.199)	-14.753	-5.73	0.00298707	R	X
8129	23.350	12.957	0.096	(12.769, 13.145)	10.392	4.04	0.00139057	R	
8146	18.397	14.634	0.187	(14.267, 15.001)	3.763	1.46	0.00529278		X
8153	24.712	15.898	0.109	(15.685, 16.111)	8.814	3.42	0.00178663	R	
8176	30.681	22.868	0.106	(22.659, 23.076)	7.813	3.04	0.00171092	R	
8206	14.205	19.635	0.133	(19.375, 19.895)	-5.430	-2.11	0.00266522	R	
8226	16.388	9.404	0.081	(9.244, 9.563)	6.984	2.71	0.00099762	R	
8242	19.078	15.588	0.174	(15.246, 15.930)	3.490	1.35	0.00460152		X
8273	19.388	11.774	0.089	(11.600, 11.949)	7.613	2.96	0.00120223	R	
8300	15.480	8.941	0.080	(8.783, 9.099)	6.539	2.54	0.00097937	R	
8370	18.660	10.566	0.086	(10.397, 10.736)	8.094	3.15	0.00112774	R	
8384	5.999	19.057	0.140	(18.783, 19.330)	-13.058	-5.07	0.00294646	R	X
8394	13.354	7.857	0.079	(7.702, 8.012)	5.497	2.14	0.00094115	R	
8399	17.352	9.899	0.084	(9.734, 10.064)	7.453	2.90	0.00107072	R	
8419	13.515	7.939	0.079	(7.784, 8.095)	5.575	2.17	0.00094944	R	
8423	17.994	10.756	0.087	(10.586, 10.925)	7.239	2.81	0.00113117	R	
8443	13.299	7.830	0.079	(7.674, 7.985)	5.470	2.13	0.00094978	R	
8459	16.181	13.285	0.155	(12.980, 13.589)	2.896	1.12	0.00364771		X
8495	14.394	19.653	0.134	(19.390, 19.916)	-5.259	-2.04	0.00271797	R	
8505	10.825	19.421	0.136	(19.155, 19.687)	-8.596	-3.34	0.00278772	R	
8514	17.904	10.182	0.086	(10.014, 10.351)	7.721	3.00	0.00111894	R	
8530	16.291	16.265	0.229	(15.815, 16.714)	0.027	0.01	0.00796124		X
8537	15.972	9.196	0.083	(9.033, 9.359)	6.776	2.63	0.00104333	R	
8591	19.709	11.106	0.090	(10.929, 11.283)	8.604	3.34	0.00122982	R	
8610	19.390	10.943	0.090	(10.767, 11.118)	8.447	3.28	0.00121549	R	
8698	18.824	16.529	0.220	(16.099, 16.960)	2.294	0.89	0.00729261		X
8731	17.945	10.207	0.088	(10.035, 10.379)	7.738	3.01	0.00116614	R	

R Large residual

X Unusual *X*

Durbin-Watson Statistic

Durbin-Watson Statistic = 1.46874