Micro-generation technologies and consumption of resources: a complex systems' exploration

Tonci Grubic[a], Liz Varga[b], Yukun Hu[b*], Anurag Tewari[c]

[a] Business School, Liverpool John Moores University, Liverpool L3 5UG, UK
[b] Department of Civil, Environmental & Geomatic Engineering, University College London, London WC1E 6BT, UK
[c] School of Management, Cranfield University, Bedford MK43 0AL, UK

Abstract
This study is motivated by a research gap in the systemic implications that wider adoption of multiple micro-generation technologies may bring to interdependent infrastructures. It explores how the adoption of battery electric vehicles, solar photovoltaics, solar thermal water heating, rain water harvesting, grey water recycling, and waste heat recovery affect system-level consumption of water, gas, gasoline, electricity, CO_2 emissions, and electricity generation cost. The simulations based on a new agent-based model show that grey water recycling and rain water harvesting reduce water and solar thermal water heating and rain water harvesting reduce gas demand respectively. A wider adoption of battery electric vehicle and solar photovoltaics have no effect while a reduction in the number of gasoline cars and gas users leads to higher electricity consumption, CO_2 emissions, and electricity generation cost. The following policy implications are identified: grey water recycling and rain water harvesting should be actively promoted; improvements in the design and use of gas boilers may be better options than solar thermal water heating and rain water harvesting; battery electric vehicle should be adopted together with solar photovoltaics; solar photovoltaics should not be supported with feed-in-tariffs. If the last two implications are not addressed, then a more complementary electricity generation mix is necessary otherwise policies that promote replacement of gasoline cars by battery electric vehicles may result in negative systemic impacts.

Keywords: Micro-generation; technologies; resource consumption; agent-based model; simulation

1. Introduction

The problems of deteriorating and aging infrastructures are only exacerbated by their ever increasing interdependencies (Rinaldi et al., 2001). An area expected to bring relief to the UK's challenged national infrastructures would be a large-scale adoption of household water and energy generation technologies since the domestic sector is responsible for a significant part of the country's energy and water consumption. Annually, the UK domestic sector consumes 29% of total energy consumption (DECC, 2014) and accounts for more than a quarter of CO_2 emissions (Bergman and Eyre, 2011). In relation to water, 154 litres of water per person per day are consumed (DEFRA, 2011) and water sector (treatment and distribution) is fourth most energy intensive industry (Gallagher et al., 2015). Adoption of micro-generation (Sauter and Watson, 2007; Balcombe et al., 2014) or distributed generation (Allan et al, 2015; Theo et al., 2017; Mehigan et al. 2018) technologies, such as solar photovoltaics, solar thermal water heating or heat pumps, promises to alleviate some of that consumption. Having in mind that they cover a wide variety of generation technologies with no consensus existing on their precise definition

[*] Corresponding author. E-mail address: yukun.hu@ucl.ac.uk (Y. Hu)

(Allan et al, 2015; Mehigan et al. 2018), the authors define micro-generation technologies (MGTs) as generation technologies installed in individual households (Sauter and Watson, 2007) which can either be stand-alone or grid-connected (Allan et al, 2015). According to (Sauter and Watson, 2007) such technologies could have a substantial share in the UK's future energy generation mix. Reduction in greenhouse gas emissions is the predominant driver for the deployment of MGTs (Mehigan et al. 2018). UK government sees distributed energy generation as potentially bringing a positive contribution to reducing UK's CO_2 emissions (Woodman and Baker, 2008). Watson et al. (2008) state that micro-generation of electricity and heat could contribute as much as 40% of UK electricity demand and reduce CO_2 emissions by 15% by 2050. Further benefits of wider adoption of MGTs include (Sauter and Watson, 2007; Balcombe et al., 2014; Woodman and Baker, 2008): diversification of sources of energy, fuel autonomy, improve energy security, and reduction of fuel poverty.

The impact of the wider adoption of MGTs upon on interdependent infrastructures as measured by the ensuing resource consumption, CO_2 emissions, and cost, is a little-known phenomenon. In a recent review of literature on distributed generation Mehigan et al. (2018) found that there is a gap in the literature in considering the role of distributed generation within the long-tem context of the entire electricity system and the wider energy sector. For example, diffusion of electric vehicles is likely to have a strong impact on power system (Schill and Gerbaulet, 2015), however this has mainly been studied in the context of short-term planning leaving the long-term impact of electric vehicles inadequately investigated (Koltsaklis and Dagoumas, 2018). Furthermore, the most prevalently used energy systems models, such as MARKAL and its variants (Hall and Buckley, 2016), cannot represent the intricacies of electricity sector transformation (Boßmann and Staffell, 2015). There is also a lack of understanding about the *combined effects* which adoption of a variety of MGTs may bring to a wider range of infrastructures. In a recent review of literature Allan et al. (2015) found only a handful of examples that look into system-wide impacts of the wider adoption of MGTs. They also identified that the general trend in MGT literature is to focus on microeconomic analysis of *individual* technologies. In another review of literature on MGTs, Juntunen and Hyysalo (2015) found that majority of research is done in relation to technical and economic aspects and little attention have been devoted to how these technologies impact electricity production. At the same time, MGTs are widely understood to include the generation of heat or electricity or both (Balcombe et al., 2014; Mehigan et al., 2018; Juntunen and Hyysalo, 2015) thus almost completely *ignoring* water technologies from the analysis. On the other hand, research into infrastructures has generally focused on a single sector looking into specific system elements rather than the whole, and has predominately been concerned with optimisation rather than transitions (Loorbach et al., 2010).

This study investigates the effects of wider adoption of multiple MGTs by UK households upon their consumption of infrastructure resources, CO_2 emissions, and electricity costs that derive from this. It is important to state clearly what is meant by an infrastructure resource. By that it means water, gas, gasoline (petrol and diesel), and electricity, as consumed by the households, and not resources, such as money, materials, electricity, water, etc., needed to e.g. build, operate, and maintain the networks and physical infrastructure to deliver these. This study aims to explore whether more MGTs result in lower consumption of resources, and consequently in lower costs and CO_2 emissions. To realise this, an agent-based model (ABM) has been developed and tested. The rest of the paper is structured as follows. The Section 2 introduces the research design and specific methods. In Section 3 simulation results are presented and in Section 4 their implications for policy are discussed. In the conclusion, the key points are summarised.

2. Research design

The ABM method was selected in this study as it provides distinct benefits for modelling interdependent infrastructures as argued by (Rinaldi et al., 2001; Heller, 2001; Rigole and Deconinck, 2006; Chappin and Dijkema, 2010; Varga et al., 2014). Furthermore, ABM is increasingly being used to model and simulate energy systems (Hall and Buckley, 2016; Ringkjøb et al., 2018) and uptake processes of MGTs (Schwarz and Ernst, 2008; Yousefi et al., 2011; Shafiei et al., 2012; Sopha et al., 2013). In order to ensure sound model development, a framework by Chappin and Dijkema (2010) was adopted. This framework was specifically proposed to support development of ABMs in the context of infrastructure transitions. The framework consists of five main components (Figure 1): (1) system representation, (2) exogenous scenarios, (3) design variables for transition assemblages, (4) system evolution, and (5) impact assessment.

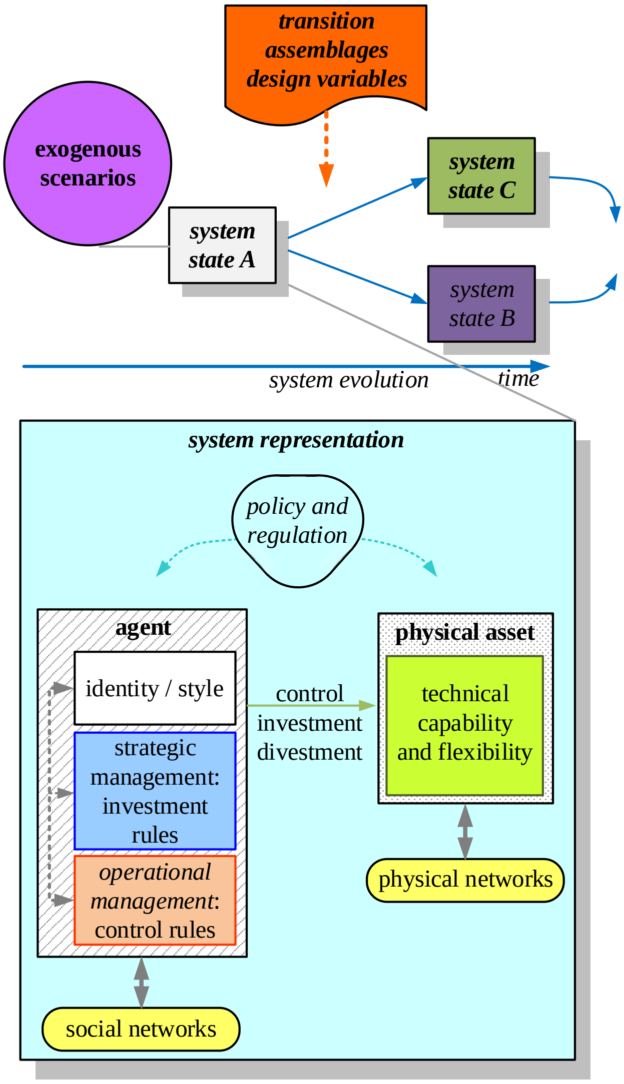

Figure 1. Framework for assessing system transitions with agent-based models (Chappin and Dijkema, 2010)

2.1 System representation

Developing a system representation is a process which identifies and represents key knowledge about the system. The key decisions to be made here are those that involve the system boundaries. This constitutes the most fundamental assumption, that there is a 'system' and an 'environment' (Allen, 2000). According to Midgley (2008) boundary judgements are linked with value judgements, i.e. the values adopted by a research team direct the drawing of boundaries around the phenomenon of interest, which in turn define what is perceived to be the pertinent knowledge. Given that complex systems are open, that is, they interact with other systems including their environment, it is noted that boundaries are not hard and even in defining boundaries key features may be missed which contribute to systemic outcomes. Richardson et al. (2001) argue that boundaries inferred are more a feature of the need in this study for a bounded description than the feature of the system itself; while Ulrich and Reynolds (2010) claim that the system concept is not needed at all if system boundaries are not handled critically. Guided by these ideas brainstorming of the expert opinions of stakeholders and other collaborators working on this research (see Acknowledgements) were used. Boundary definition was achieved through a number of events and discussions that involved experts from various infrastructures (energy, water and waste, telecommunication, transport) resolving the following boundary scoping questions:

1. What parts of the UK national infrastructures to consider?
2. What household characteristics and MGTs to consider?

In defining the pertinent infrastructures the lifelines concept (O'Rourke, 2007), which groups infrastructure into six principal systems: electric power, gas and liquid fuels, telecommunications, transportation, waste disposal, and water supply, was followed. The following infrastructures were selected (Table 1) as having the most relevance for MGTs: electric power generation, water treatment, distribution, and sewerage, and public transportation.

Table 1: Infrastructures related characteristics

Infrastructure	***Characteristics***			
Electricity generation:	Coal	Gas	Nuclear	Wind
Technology mix[a]	40%	30%	20%	10%
Cost, £/kWh (Tidball et al., 2010)	0.03-0.047	0.032-0.039	0.034-0.067	0.051-0.091
CO_2 emission, g/kWh (Tidball et al., 2010)	900-1100	400-600	5-10	20-25
Water[b]:	Treatment	Distribution	Sewerage	
Energy consumption, kWh/m^3	0.135	0.44	0.07	
CO_2 emission, kgCO_2/m^3	0.327	0.126	0.583	
Public transportation (House 2005; Baseline, 2007):	Diesel Bus	Diesel Train	Electric train	
Energy consumption	41.86 km/litre	77.28 km/litre	9.259 km/pax.kWh	
CO_2 emission, kgCO_2/litre	2.2-3	2.2-3	No direct emission[c]	

[a] According to Ofgem data (2019) electricity generation mix for Q1 2013: Coal 40%, Gas 27%, Nuclear 17%, Wind (onshore and offshore) 7%, Bioenergy 4%, Net imports 3%, Hydro 1%, Oil 1%, Other fuels 1%. Technology mix considered here is based on adjusted figures that compensates for the exclusion of all the other fuel sources.
[b] These figures are results of an analysis from 69 water treatment plants of Yorkshire Water conducted by the authors' project team members working in Pennine Water Group, University of Sheffield.
[c] Refer to the CO_2 emission of electricity generation.

Since this study focuses on technology adoption, the model developed does not cover the distribution of electricity and it does not include distribution losses. However, the driver towards prosumerism means distribution losses are indirectly and very simplistically taken into account through MGT adoption rates. Total energy consumption for water treatment, distribution, and sewerage is corrected for the amount of electricity generated from sludge processing and other renewable sources (between 14% and 30%). These figures are based on a real-world case study of Yorkshire Water. Due to space limitations the end results are only presented and only those aspects of these which are relevant for the study.

The most pertinent MGTs include: battery electric vehicles (BEVs), solar photovoltaics (PVs), solar thermal water heating (STWH), rain water harvesting (RWH), grey water recycling (GWR), and waste heat recovery (WHR). While some of these technologies have been explored in isolation (Caird et al., 2008; Yousefi et al., 2011; Robinson et al., 2013; Steinhilber et al., 2013), their combination has rarely been explored. Interest in RWH and GWR has been limited (Hyde and Maradza, 2013). Even less interest has been raised by a claim made by Hofman et al. (2011), which is about the possibilities of saving heat lost via sewage which is around 40% of the total heat loss of a modern house. It further concluded that if consumers would save only 6% of warm water or recover 10% of the heat in sewage water, then the total energy demand of treatment can be offset. An example of technology that recovers heat from wastewater is shower heat exchanger. Therefore, together the six technologies have a potential to reduce domestic dependence on infrastructures for energy, water, and transport.

2.2 Exogenous scenarios

Once a system representation is defined, then everything that falls outside the system boundaries is categorised as exogenous. And everything that is exogenous but relevant is seen as potentially forming a scenario space. Three levels of complexity could be used to determine the scenario space, which are *exogenous scenario levels* (*ESLs*). The *ESL1* involves static parameter values where values of some exogenous parameters are varied only between the simulation runs, e.g. the price of natural gas. The *ESL2* concerns modelling exogenous scenario parameters as continuous or varying trends during the simulation runs. For example, a price trend for a natural gas rather than static value. The *ESL3* involves the use of mathematical or other simulation models, e.g. systems dynamics models, for providing scenario parameters. This last approach is more complicated than varying trends and is used only if scenario parameters are strongly correlated (Chappin and Dijkema, 2010). Exogenous scenario parameters are those related to the household characteristics and MGTs. They were identified during the brainstorming discussions of the project workshop (see Acknowledgements) and are listed in Table 2.

Table 2: Exogenous scenario parameters

Parameters	***Trend***
ESP1: Steady decrease in cost of MGTs	By 2050 almost half of households would be able to afford MGTs, whereas today this is possible only for less than 10% in case of BEVs or PVs. The reduction of cost may initially come from government subsidies, and later from innovation and efficiency improvements, and improvements in the standard of living.
ESP2: Steady increase in the number of households with environmental attribute	By 2050 number of households with environmental attribute would more than double, from around 30% today to 70%, meaning there will be more people who are prepared to actively participate in reducing their environmental effects, e.g. by adopting an MGT. This is to reflect the increasing awareness of climate change and issues it may bring.

ESP3: Steady increase in the BEV battery range	By 2050 the battery range would double relative to its contemporary value. This may result from further innovation and efficiency improvements.
ESP4: Steady proliferation of BEV charging stations	From almost negligible number of charging stations today, by 2050 it is expected on average 1 charging station for every 10 BEVs. This may initially result from government subsidies to stimulate adoption of BEVs by offering improvements in BEV usability and availability of supporting infrastructure.
ESP5: Steady increase in the number of journeys by electric trains	By 2050 there will be at least 20% more journeys by electric trains than today (around 60%). This also captures UK policy changes in relation to further electrification of its railways.
ESP6: Steady increase in the number of urban dwellers	By 2050 there will be at least 10% more people living in urban areas than today (around 80%). This reflects the current trends in ever more expanding urban living.

2.3 Design variables for transition assemblages

A transition assemblage can be understood as investigation and design of technical systems, policies, regulations, and investment strategies and their implementation, which will lead to infrastructure transitions (see Figure 1). Chappin and Dijkema (2010) have identified four different levels of transition assemblage designs, that is *transition assemblage levels (TALs)*. They are also clear that modellers should aim for *TAL3* or *4* in their designs. That is because in *TAL1* the structure of the model is designed as a fixed set of policies and regulations, implicitly set in the model; *TAL2* uses fixed system parameters that the model needs to be able to respond to during the simulation. In addition, at *TAL2*, the model is still impossible to assess the effect of transition assemblage but at least it is upgradable to *TAL3*. When the model is upgraded to *TAL3*, a policy can be any of the *ESLs*. Finally, *TAL4* involves endogenous system parameters where policy development is endogenous. This implies that the policy maker is an agent who decides on the content of the policy during a simulation run. This is the most effective level however; it requires understanding of decision-making processes of the policy maker. Considering the complexities involved here, an alternative is to model this as an exogenous scenario parameter (*ESL3*).

TAL3 provides the minimum sophistication necessary to investigate policy interventions for the six exogenous scenario parameters (see Table 2) and for the research problem, where the policy is seen as a set of scenario parameters exogenous to the system transition (Chappin and Dijkema, 2010). The following five policy intervention parameters are identified: electricity proposals until 2050 from coal, nuclear, and wind; reductions in use of gasoline cars to promote adoption of BEVs, and reduction in gas users by 2050. The last two policy intervention parameters reflect a shift away from fossil fuels as the primary sources for transport and energy.

Whereas exogenous scenarios (Table 2) are at *ESL2* (varying trends), the policy intervention parameters will be modelled at *ESL1*, i.e. varying parameter values only between simulation runs.

2.4 System evolution

By reacting to the exogenous scenarios and transition assemblages, the agents, the constituent elements of ABMs, drive the evolution of the system. Agents are modelled as interdependent and their aggregate behaviour emerges as the collective operation of the whole system from the interaction among many numbers of subsystems. In general terms, the system evolution occurs as agents adopt an MGT, which in turn brings changes to infrastructure consumption. Therefore, understanding the system evolution entails answering the following questions:

1. What factors determine household adoption process for an MGT?
2. What changes to infrastructure use result from MGT adoption?

This will allow the design of an ABM that will run the virtual system.

2.4.1 Factors determining MGT adoption process

The characteristics of early and mass adopters of MGTs were identified from the relevant literature as follows. Regarding the adoption of BEVs, the main adopters are identified as the people who are younger in age, of higher education and with higher income levels (Baca and Brausen, 1997; Shi et al., 2019); but beyond that, ownership and human factors can also determine the adoption of BEVs, such as one's identity (as a symbol of making a difference), maturity, intelligence and awareness, or as a way to 'stand out in the crowd' (Schuitema et al., 2013). Through semi structured interviews with non-commercial drivers, characteristics such as environmental concerns, social status and self-esteem when they determine the adoption of BEVs were revealed (Graham-Rowe et al., 2012). Moreover, Williams and Kurani (2006) further considered both exogenous and endogenous scenario parameters of adoption such as: longer commutes, married couples, additional vehicles, higher incomes, age, higher educational attainment, and higher expenditure in terms of utilities and mortgages.

Household generation focusing on PV and STWH in a like manner reaffirm the characteristics identified for BEVs. Claudy et al. (2011) reported on various socio-demographic factors that positively influence adoption, such as age, income levels and knowledge when discussing solar panels and water heaters. Comparable results are also found in other studies, such as energy-using appliances and energy saving features (O'Doherty et al., 2008), adoption of PVs and micro-wind technologies (Zarnikau, 2003; Arkesteijn and Oerlemans, 2005; Sauter and Watson, 2007), and utilisation of bio-energy (Nyrud et al., 2008).

In contrast, research into the characteristics of adopters with regard to water based technologies provided little additional insights, other than reaffirming the characteristics that are apparent with BEV adoption. That is, a higher level of educational attainment can be observed in those who choose to purchase such water based technologies (Berk et al., 1993; Gilg and Barr, 2006; Millock and Nauges, 2010). While the vast majority of the literature that was reviewed above assumed a quantitative approach to defining the characteristics of adopters, Schwarz and Ernst (2008) have taken a different approach when discussing water saving technologies. In their approach, people are clustered into lifestyle groups, such as post-materialists, social leaders, traditionalists, mainstream, and hedonistic, while the first two groups are seen as the main adopters of water saving technologies.

The papers reviewed above identify the diverse and complex decision-making processes that are utilised by adopters and that inform the characteristics of adopters in the realm of a single technology. These characteristics are often substantially compounded when diverse technologies are being assessed simultaneously. This claim is supported by McDonald et al. (2003) who endeavour to score adopters by the numbers of studies that reveal various characteristics, and this is also identified by Rogers (2003). The score is: higher education levels (supported by 74% of studies), higher social status (63%), higher income levels (68%), and more socially active (73%). Clearly, the identified characteristics of adopters are not uniformly accepted and vary in terms of the context and application. Hauser et al. (2006)

reiterates this claim that while some studies have indicated that innovators are wealthier, better educated, and younger, other studies (Gatignon and Robertson, 1991; Rogers, 2003) have failed to validate such findings. In fact, there is also a clear and discernible link between the established characteristics (Rogers, 2003). That is, higher education attainment is not mutually exclusive from both higher social status and higher income levels. This interrelationship further masks the value that could be attributed to any of these characteristics in isolation, and this makes modelling of these attributes problematic at best.

2.4.2 Changes to infrastructure use from MGT adoption

In conceptualising the changes to infrastructures arising from adoption of various MGTs, the typology of interdependencies proposed by Rinaldi et al. (2001) was applied in this study. They identified four principal classes of infrastructure interdependencies: physical, cyber, geographic, and logical. Physical interdependency between two infrastructures arises if the state of each is dependent on the material outputs of the other. Cyber interdependency is manifested in those cases when the state of an infrastructure depends on the information transmitted via information infrastructure. Geographic interdependencies occur when multiple infrastructures are in close spatial proximity. If each of infrastructures depends on the state of the other by ways other than physical, cyber or geographic; then they are interdependent logically, e.g. by means of a government policy. This typology of interdependencies was applied in this study to identify and map potential changes to infrastructure demand arising from the adoption of MGTs. A brainstorming session was held with other project members and stakeholders and the results are presented in Table 3.

Table 3: Potential changes to infrastructure demand brought by the adoption of MGTs

Technology	***Infrastructure(s) affected***	***Example***	***Infrastructure interdependencies***
Battery Electric Vehicle (BEV)	Electric infrastructure; gasoline infrastructure	Increase in demand for electricity, reduces gasoline consumption, may lead to adoption of PV.	Physical (e.g. wider adoption of BEV will increase demand for electricity and reduce gasoline consumption) and Logical (e.g. by means of government subsidies or other incentives, e.g. free charging stations, households are steered towards BEV and away from gasoline cars.)
Solar Photovoltaic (PV)	Electric infrastructure	Reduction of demand for electricity, may lead to adoption of BEV, may lead to adoption of STWH and other MGTs.	No foreseen infrastructure interdependencies – result is reduction of electricity demand. This technology can generate and export electricity to the electric infrastructure. However, it is assumed that no electricity generated in this way will be exported to the grid. Rationale: in this case distribution losses inherent in the electricity network need to be considered, which is outside the scope of the study.

Rain Water Harvesting (RWH)	Water treatment; water distribution	Reduction of demand for treated water, some reduction of pluvial volume and load into urban drainage systems, no change in domestic volume or load into sewerage systems (hence no change in sludge production), no change in domestic energy consumption (RWH is predominantly passive/gravity-fed).	No foreseen interdependencies - result is reduction of demand for water treatment and distribution.
Grey Water Recycling (GWR)	Water treatment; water distribution; sewerage infrastructure; electric infrastructure	Reduction of domestic volume into sewerage systems, minor reduction of domestic load (defined as density of other liquids, dissolved solids or bacteria in the unit of volume) into sewerage systems, reduced demand for treated water, increase in domestic energy consumption.	Physical - increase in domestic electricity consumption (assumed to be negligible), unforeseen effect on electricity demand for water treatment.
Solar Thermal Water Heating (STWH)	Electric infrastructure; gas infrastructure	Reduction of demand for electricity and gas	Physical
Waste Heat Recovery (WHR)	Gas infrastructure; electric infrastructure; sewerage infrastructure;	Reduction of demand for electricity and gas, minor reduction of domestic load whose overall effect on sewerage operations is hard to assess.	Physical – reduction of energy demand, and Logical – reduction of domestic load.

From Table 3, it can be seen that the adoption of an MGT has some (mainly physical) impacts on more than one infrastructure, which is usually a decrease in demand from infrastructure. The exception is BEV, which increases demand if implemented without PV. It should be noted that this is highly simplified and abstract representation of a real world as it lacks all the interdependencies that exist between various stakeholders, such as between electricity generation and water distribution, treatment, and sewerage (e.g. electricity generation requires water and produces waste water and heat). Therefore, producing more detailed and realistic representations of infrastructure interdependencies calls for wider study and more inclusive approaches (Varga et al., 2014), but this is beyond the scope of this paper. Here the focus is only on those infrastructure interdependencies affected by the adoption of six MGTs.

2.4.3 Translating considerations into an ABM design

The ABM model in this study was built using AnyLogic® in which agents are represented by households. The behaviour of households is modelled by means of statecharts, as shown in Figure 2.

The statechart consists of two elements: transitions and states. Transitions are represented as arrows and states these lead to and from are presented as yellow boxes. Transition to a new state is triggered when certain criteria are met. Triggers include: message arrival, elapse of time, or meeting a logical condition. In addition, each household is initialised and changes according to Table 4.

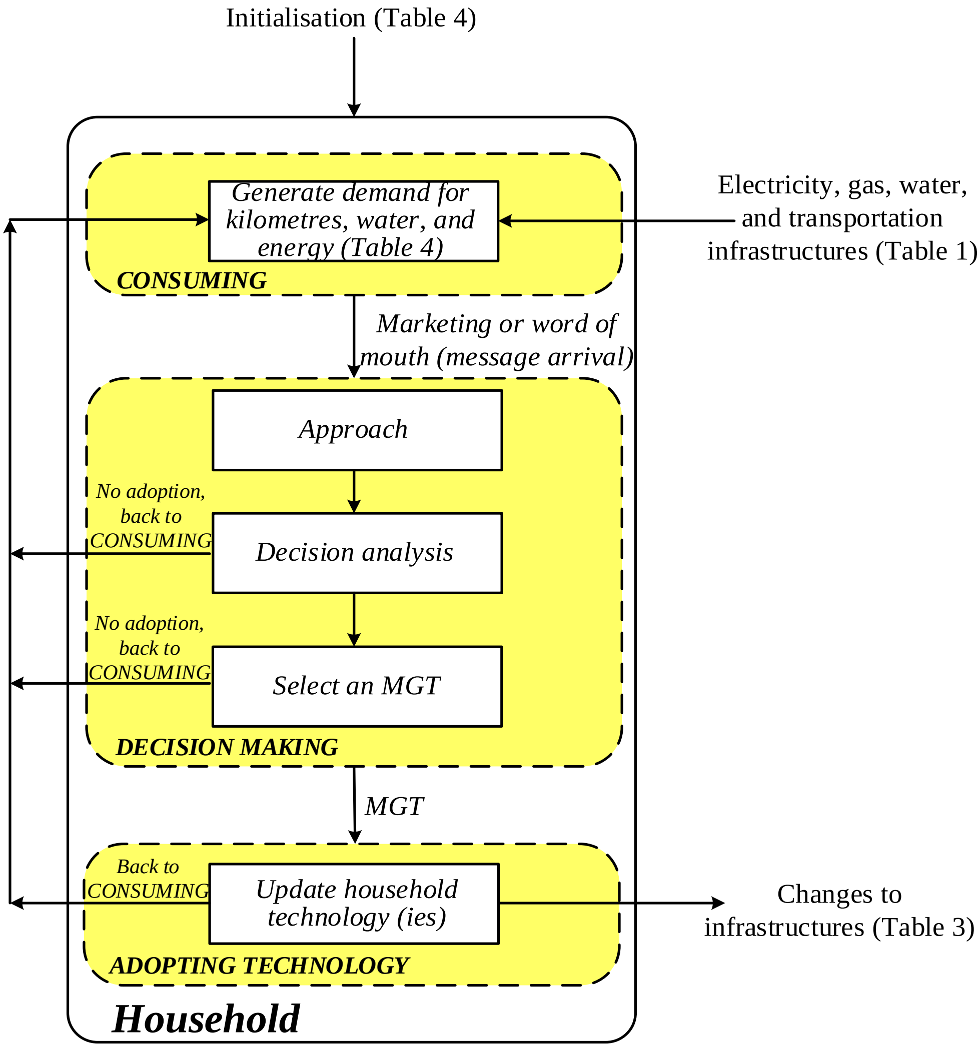

Figure 2. The logic behind household dynamics

Once initialised, the dynamics of each household follows the logic from the statechart diagram. There are three distinct states: consuming, decision making, and adopting technology (Figure 2).

When in the consuming state the household's demand for gasoline, electricity, water, and gas is generated according to Table 4. These utilities are used to meet the household's demand for transportation, water, and energy required for drinking and cooking, toilet flushing, hygiene, and washing (dishes and clothes). The process of decision making coded into the model is a quasi-rational approach, informed by literature review, characterised as follows:

C1. Interactions or links of adopters (both human and commercial marketing): this attribute enables us to reflect social activities such as knowledge and awareness, such as perceptions, socio-demographics, and housing attributes (Claudy et al., 2011), and higher education, social status and income (Rogers, 2003).

C2. The financial means to purchase: this attribute enables us to capture higher education and income levels (Rogers, 2003; Sauter and Watson, 2007).

C3. The desire to adopt renewable technology (Greenness "making the difference"): this attribute enables us to model social or greenness attributes of adopters (Sauter and Watson, 2007; Graham-Rowe et al., 2012; Schuitema et al., 2013).

Table 4: Household characteristics

Characteristic	***Definition***
Household size	Between 1 and 6 persons uniformly distributed. This assumption was made to reflect the lack of knowledge about correlation that may exist between the household size, house size (see importance of this in the roof area characteristic below), location (urban or rural), and kilometres demand per car in the household.
Electricity (100% at the moment), gas user (85% at the moment)	Energy sources used to meet energy demand for cooking, hygiene, and washing. Assumption, 11.2 kWh/m^3 of gas is obtained which generates 0.203 kgCO_2/kWh (Carbon footprint calculator, 2019).
The following figures are based on 2013 adoption levels: RWH (negligible or 0%, Rain water harvesting, 2019), WHR (0%), GWR (0%, Environment Agency, 2011), STWH (0.4%, Energy saving trust, 2019), PV (2%, Energy saving trust, 2019), BEV (negligible or 0%).	Generation technologies used by the household. Water and energy harvested through these technologies is used in meeting the household's demand for transportation, energy, and water. Assumptions behind are as follows: • RWH - annual rainfall in centimetres in England is 60-100 (Rain water harvesting, 2019). • WHR - around 40% of heat from hygiene and washing may be recovered (Hofman et al., 2011). • GWR - collected from water used for hygiene and toilet flushing. • STWH - annual useful energy delivered is 800-1750 kWh. • PV - standard solar panel of 1m^2 has an input rate of 1 kW/hr with 15-20% efficiency at best (Theecoexperts, 2019), further assumption: 2-6 hours of sun per day. • BEV - a modern BEV consumes 0.2-0.3 kWh/km.
Environmental priority, economic attribute, location of living, charging at work, roof area, PV area	Other household characteristics: • Environmental priority (Yes or No) • Economic attribute (0-1) – unit-less but relative measure of a wealth of a household which models the household's financial ability to buy a technology. When making a decision to adopt an MGT this attribute is considered (together with environmental priority and influence of noise used to model omissions and uncertainties (see *Section 2.4.3*) in relation to a current cost of a technology. The latter is modelled as a dynamic parameter to reflect the changing cost of MGTs (see ESP1 in Table 2). Its value can be affected either by government subsidies or reduced price due to innovation, efficiency improvements, economies of scale, etc. • Location of living (Urban or Rural) • Charging at work (Yes or No) • Roof area - average roof area of a house in England is 50-85 m^2 • PV area - area of installed PV panels is 4-10 m^2
Kilometres demand	The baseline demand is 80-322 km/week/car.

	This demand is corrected for the household's location of living (if urban then 30-60% below the baseline demand, if rural then 30-60% above the baseline demand). This demand is met either through private means, gasoline cars (equally split between petrol and diesel) and/or BEVs, or public transportation means, diesel buses, and trains (diesel and electric). If by public transport, it is then assumed that 50% will be met by diesel buses and 50% by trains (diesel and electric). Demand for these utilities is then recorded.
Water demand	Includes demand for drinking and cooking (250-300 litre/person/month), toilet flushing (1000-1500 litre/person/month), hygiene (800-1200L per person/month), and washing (1200-1500 litre/person/month). This data is based on published consumption figures by Waterwise (2019).
Energy demand	Includes demand for cooking (10-25 kWh/person/month), hygiene (10-20 kWh/person/month), and washing (40-90 kWh/person/month) (Palmer and Cooper, 2012; DECC, 2014).
Number of cars	Based on data about household car availability for period 1985/86-2010 (Department for Transport statistics, 2019): 0 cars/household - 25% of population; 1 car/household - 17% of population; 2 car/household - 49% of population; ≥3 car/household - 9% of population. The UK's average new car fuel consumption in 2010 was 5-7 litre/100km (5.4 for diesel vehicles and 6.4 for petrol) with 1 litre of petrol or diesel generating 2.2-3.0 kg of CO_2.

The quasi-rational approach is a three-step process starting with a household being approached either through the means of commercial marketing or word of mouth via one of its connections who have already adopted a household technology (C1). Next, the household needs to decide whether it has sufficient means and motivation to adopt a technology (C2 and C3). Even if the outcome of this analysis is positive, the final decision in the real world may be to not adopt. Adding noise allows accounting for the effects of omissions in the model and uncertainties arising from the model's decision-making simplifications. The notion of noise adopted in this study follows Edmunds' approach (Edmunds, 2000).

If the decision is to adopt, the last step involves the selection of an MGT. In the model, the household would randomly select one of the six technologies as long as the selected technology has not already been adopted by the household. This random approach is applied for two reasons. First, literature is rich in identifying factors that make a decision-making process which informs the characteristics of adopters in the realm of a single technology but is generally silent when diverse technologies are being assessed simultaneously. Second, selection of a particular MGT in the real world is influenced by specific household characteristics whose details are not readily available and are also constantly changing.

Once a random MGT is selected, further, technology specific, criteria will be considered before the household's final decision is made to adopt the MGT. In the case that BEV is randomly selected, access to charging at work facilities and battery range attributes would also be considered. If these final criteria are unmet, then the MGT will not be adopted. The algorithms of the ABM are provided in Technical Appendix.

Once selected and adopted by a household, the MGT should alleviate some of the transportation, water, and energy demands of the household and bring changes to infrastructures according to Table 3. The remainder of supply will come from respective macro infrastructures as shown in Table 1.

2.5 Impact assessment

The scenario space, formed of various parameter values, could be vast and for that reason a systematic approach is required for impact assessment. Such an approach is found in literature that deals with statistical design of experiments, that is, Factorial method (Montgomery, 2013). The use of this method involves devising a strategy to: determine which combinations of factors and their values to investigate; determine the most relevant factors and their values which may have impact on the system performance; and verify the findings and conclusions. After the development of the model and its testing, an experimental strategy was formulated that follows the Seven-step approach proposed by (Coleman and Montgomery, 1993). The steps are: (1) Statement of the problem, (2) Choice of factors and levels, (3) Selection of the response variable(s), (4) Choice of experimental design, (5) Conducting the experiment, (6) Data analysis, and (7) Recommendations. In some situations, steps 2 and 3 can be reversed (ibid) and in fact they are shown reversed here.

The main objective of the impact assessment is to gain insights on the potential impact of wider adoption of six MGTs on the consumption of resources (water, gas, gasoline, and electricity) by the households, CO_2 emissions, and electricity generation costs, in the context of identified policies and scenarios. Step 1, the problem statement, is "is the adoption of one or more MGTs beneficial for the whole system?" The following six response variables are considered for Step 3: water consumption (m^3), gas consumption (m^3), gasoline consumption (m^3), electricity consumption (MWh), CO_2 emissions (tonnes), and electricity generation cost (millions £ measured by levelised electricity generation cost). For Step 2, the selection of factors and their levels, should be those which promise to have the most significant effects on the (six) response variables. The five control factors (A-E) and the levels introduced in Table 5 are the natural choices since they are the policy intervention parameters discussed in the design of transition assemblages. By experimenting with these factors, the impact of potential future scenarios can be assessed regardless of MGTs (see the description of blocks below).

Table 5: Control factors of impact assessment

Factor	***Low level***	***High level***	***Centre point***	***Axial points***			
A. Reduction of number of gasoline cars by 2050	50%	100%	75%	63%	69%	88%	97%
B. Reduction of gas users by 2050	30%	60%	45%	38%	44%	53%	57%
C. Reduction in coal generated electricity by 2050	30%	60%	45%	38%	44%	53%	57%
D. Increase in wind generated electricity by 2050	5%	10%	7.5%	6%	8%	9%	
E. Increase in nuclear generated electricity by 2050	3%	6%	4.5%	4%	5%		

Changes in the amount of electricity generated by coal, wind, and nuclear (control factors C, D, and E in Table 5), would also affect the amount of electricity generated by gas. For example, reduction in coal generated electricity (C) is offset by the increase in wind (D), nuclear (E) and gas generated electricity. In practice other sources (e.g. hydro, solar, biomass) are also used to replace fossil-fuel generated electricity, however, the four considered here (gas, coal, wind and nuclear) are by far the most significant (see Table 1).

In addition to the five control factors, two blocks are also used to simulate the effects of those controllable noise factors that exert influence on response variables. Using blocks helps identify the most robust values for the control factors. The two blocks used are low and high adoption levels of six MGTs established prior to experimentation.

The experimental design based on the control factors, Step 4, chosen is a sequential one consisting of three steps:

- Full factorial design resulting in 96 runs (3 replications per 32 control factor combinations - low/high 2^5).
- Additional 10 runs for centre points.
- Additional 15 axial runs.

The latter two additional runs explore possible curvature effects, which manifest as discontinuities and may result from multiple-factor interactions and/or through their nonlinear main effects. Factor values for centre and axial runs are shown in Table 5. The alternative to this would be to conduct three-level either full or fractional factorial design but these designs are widely perceived to be least efficient and less effective in obtaining an indication of curvature effects to the experimental design adopted here (Montgomery, 2013).

Step 5 was to run the model with 1,000 households (agents) and the actual simulation time was from 2013 to 2050. Step 6, analysis, is presented in the following section and Step 7, recommendations, in Section 4.

3. Results and analysis

3.1 Statistical analysis

The results of 121 completely randomized experiments were analysed using Design-Expert® (2019) software. The analysis involved finding a mathematical model to explain the experimental results, evaluating that model for adequacy, and finally, identifying the factors (A-E in Table 5) and their levels which produce the most significant effects on the six system response variables. In evaluating the mathematical model for adequacy, techniques of normal probability plots were used that compare the distribution of the residuals to a normal distribution of residuals, residuals vs. predicted plots, residuals vs. simulation run, and predicted vs. actual response values. To analyse the effects of control factors the techniques of Analysis of Variance (ANOVA) and F-tests were applied. The analysis revealed no curvature effects. The lack of nonlinearity is probably due to limited understanding about the effects of concurrent adoption of multiple MGTs on infrastructures as captured in Table 3, rather than non-existence of such effects. Therefore, the following linear model (Eq. 1) was adopted:

$$y = \mu + \alpha \times A + \beta \times B + \gamma \times C + \delta \times D + \varepsilon \times E + \theta \qquad \text{(Eq. 1)}$$

The individual expression terms read as follows: μ is the overall experimental average, α to ε are main effects of factors A to E, and θ is error. y represents the adjusted average of the results. The results of ANOVA for the linear model for all six response variables are presented in Table 6. The p value addresses whether the observed effect from the model term stands out above the error. If p is less than 0.05, then the model term is statistically significant. The interpretation of simulation results is structured around factors found to have the most significant effects, both in statistical and real terms, on water, gas, gasoline, and electricity consumption, CO_2 emissions, and electricity generation cost.

Table 6: ANOVA tables for six system response variables

Source	***Sum of squares***	***df***	***Mean square***	***F value***	***p value (Prob>F)***
ANOVA for water consumption, m^3					
Block	1.524E+11	1	1.524E+11		
Model	8.352E+10	5	1.670E+10	1.81	0.1160
A	1.797E+10	1	1.797E+10	1.95	0.1654
B	4.515E+09	1	4.515E+09	0.49	0.4854
C	3.788E+09	1	3.788E+09	0.41	0.5228
D	4.013E+08	1	4.013E+08	0.044	0.8351
E	5.562E+10	1	5.562E+10	6.03	0.0155*
Residual	1.051E+12	114	9.218E+09		
Lack of fit	3.899E+11	36	1.083E+10	1.28	0.1830
Pure error	6.610E+11	78	8.474E+09	1.81	0.1160
Total	1.287E+12	120	1.524E+11	1.95	
R-squared					0.0736
Adjusted R-squared					0.0330
Predicted R-squared					-0.0403
Linear model in terms of actual factors: N/A					
ANOVA for gas consumption, m^3					
Block	5.166E+06	1	5.166E+06		
Model	8.356E+12	5	1.671E+12	214.47	< 0.0001*
A	2.092E+10	1	2.092E+10	2.68	0.1041
B	8.303E+12	1	8.303E+12	1065.48	< 0.0001*
C	4.007E+09	1	4.007E+09	0.51	0.4748
D	2.656E+09	1	2.656E+09	0.34	0.5605
E	1.637E+10	1	1.637E+10	2.10	0.1500
Residual	8.884E+11	114	7.793E+09		
Lack of fit	2.994E+11	36	8.316E+09	1.10	0.3541
Pure error	5.890E+11	78	7.551E+09		
Total	9.245E+12	120			
R-squared					0.9039
Adjusted R-squared					0.8997
Predicted R-squared					0.8932
Linear model in terms of actual factors: y = 3720000-18640.52×B					
ANOVA for gasoline consumption, m^3					
Block	3.804E+05	1	3.804E+05		
Model	3.304E+08	5	6.609E+07	326.01	< 0.0001*
A	3.289E+08	1	3.289E+08	1622.68	< 0.0001*
B	3.464E+01	1	3.464E+01	0.0001709	0.9896
C	2.587E+04	1	2.587E+04	0.13	0.7216
D	6.829E+05	1	6.829E+05	3.37	0.0690
E	2.792E+05	1	2.792E+05	1.38	0.2430
Residual	2.311E+07	114	2.027E+05		
Lack of fit	7.466E+06	36	2.074E+05	1.03	0.4395
Pure error	1.564E+07	78	2.006E+05		
Total	3.539E+08	120			
R-squared					0.9346
Adjusted R-squared					0.9318

Predicted R-squared					0.9265
Linear model in terms of actual factors: y = 19047.37-69.98×A					
ANOVA for electricity consumption, MWh					
Block	1.121E+05	1	1.121E+05		
Model	1.212E+09	5	2.425E+08	58.53	< 0.0001*
A	1.797E+08	1	1.797E+08	43.39	< 0.0001*
B	9.786E+08	1	9.786E+08	236.25	< 0.0001*
C	4.095E+06	1	4.095E+06	0.99	0.3222
D	2.340E+06	1	2.340E+06	0.56	0.4539
E	3.850E+07	1	3.850E+07	9.29	0.0029*
Residual	4.722E+08	114	4.142E+06		
Lack of fit	1.677E+08	36	4.658E+06	1.19	0.2551
Pure error	3.045E+08	78	3.904E+06		
Total	1.685E+09	120			
R-squared					0.7197
Adjusted R-squared					0.7074
Predicted R-squared					0.6854
Linear model in terms of actual factors: y = 114000+51.72×A+202.37×B+396.95×E					
ANOVA for CO_2 emissions, tonne					
Block	5.580E+03	1	5.580E+03		
Model	6.158E+08	5	1.232E+08	91.49	< 0.0001*
A	4.549E+07	1	4.549E+07	33.80	< 0.0001*
B	5.899E+07	1	5.899E+07	43.82	< 0.0001*
C	4.198E+08	1	4.198E+08	311.88	< 0.0001*
D	7.650E+07	1	7.650E+07	56.83	< 0.0001*
E	1.772E+06	1	1.772E+06	1.32	0.2537
Residual	1.535E+08	114	1.346E+06		
Lack of fit	5.261E+07	36	1.461E+06	1.13	0.3208
Pure error	1.009E+08	78	1.293E+06		
Total	7.693E+08	120			
R-squared					0.8005
Adjusted R-squared					0.7918
Predicted R-squared					0.7763
Linear model in terms of actual factors: y = 79200.37+26.02×A+49.69×B-132.67×C-339.32×D					
ANOVA for electricity generation cost, millions £					
Block	2.904E-08	1	2.904E-08		
Model	2.780E-00	5	5.600E-01	61.58	< 0.0001*
A	3.300E-01	1	3.300E-01	36.56	< 0.0001*
B	2.000E-00	1	2.000E-00	221.58	< 0.0001*
C	3.900E-02	1	3.900E-02	4.37	0.0388*
D	2.200E-01	1	2.200E-01	24.84	< 0.0001*
E	1.600E-01	1	1.600E-01	17.82	< 0.0001*
Residual	1.030E-00	114	9.033E-03		
Lack of fit	3.800E-01	36	1.100E-02	1.29	0.1778
Pure error	6.500E-01	78	8.287E-03		
Total	3.810E-00	120			
R-squared					0.7298
Adjusted R-squared					0.7179
Predicted R-squared					0.6960
Linear model in terms of actual factors: y = 4.93+0.00222×A+0.00915×B-0.00129×C+0.02×D+0.03×E					

*The model term is statistically significant.

3.1.1 Effects on water, gas, and gasoline consumption

The linear model for water consumption is not statistically significant. Its goodness-of-fit measures (R-squared, adjusted R-squared, and predicted R-squared) show that the model explains little of the variability in water consumption. This means that none of the five control factors has any effect on water consumption. This is understandable because variability in water consumption is mainly affected by the adoption of water-related MGTs (see Section 3.2). The only factor found to have a significant effect on gas consumption, both in statistical and real terms, is a reduction of gas users. The greatest reduction ($11m^3$ per household) in gas consumption is achieved when this factor is set at a high level (60%). Similarly, the findings show that a reduction of number of gasoline cars has the most significant effect on overall gasoline consumption. The greatest reduction in gasoline consumption is achieved when this factor is set at a high level (100%). The reason for such straightforward findings on gas and gasoline consumption may be found in the modelling assumptions, which take into account demand of households for the only two infrastructures and assume an unchanging population. With improved mapping (Table 3) of the effects of MGTs on all infrastructures the results may well be different.

3.1.2 Effects on electricity consumption

Factors found to have statistically significant effects on electricity consumption are: reduction of number of gasoline cars, reduction of gas users, and increase in nuclear generated electricity. However, their real effect on electricity consumption varies. A reduction of number of gasoline cars and an increase in nuclear generated electricity have lesser effects on electricity consumption. By far the greatest effect comes from the reduction of gas users. A reduction of number of gasoline cars creates more demand for electricity arising from more people adopting BEVs and/or taking more journeys by electric trains. With every percentage reduction of gasoline-cars electricity consumption is increased by 0.51kWh per household. On the other hand, a percentage reduction of gas users increases electricity consumption by 2.02kWh per household. Hence, reduction of number of gasoline cars and of gas users should be set to 50% and 30% respectively. Increase in nuclear generated electricity should be set to 3%.

3.1.3 Effects on CO_2 emissions

Apart from an increase in the nuclear generated electricity, all the remaining four factors are found to significantly affect CO_2 emissions. Arranged in order of ever decreasing effect on CO_2 emissions, the remaining factors are: reduction in coal generated electricity, increase in wind generated electricity, reduction of gas users, and reduction of number of gasoline cars. The greatest impact on the reduction of CO_2 emissions (0.08 tonnes per household) occurs if the amount of electricity generated by coal is reduced by 60%. This finding is reasonable given the known emissions from coal generating plants. Further reduction (0.034 tonnes per household) could be achieved if the amount of electricity generated by wind is increased by 10%. This again makes sense as the electricity generation capacity lost from coal would be better replaced by wind rather than gas.

Third largest impact on CO_2 emissions (increase of 0.015 tonnes per household) comes from the 30% reduction of gas users since a 60% reduction is worse because of grid mix. This means that gas is still better option than electricity. Surprisingly, lesser effect on CO_2 emissions is achieved from 50% (increase of 0.013 tonnes per household) rather than 100% reduction in gasoline cars. These findings suggest that reduction in CO_2 emissions achieved from increasing wind generated electricity by 10% would be more than cancelled by the increase in CO_2 emissions that result from reducing gas users by 60% (increase of 0.03 tonnes per household) and gasoline cars by 100% (increase of 0.026 tonnes per household). Similar applies to reduction in CO_2 emissions achieved by reducing coal generated electricity by 60%. Seventy percent of this reduction (0.056 tonnes per household) would be cancelled if number of gas users and gasoline cars are reduced by 60% and 100% respectively.

3.1.4 Effects on electricity generation cost

The costs considered here are those of electricity generation as described in Table 1. All five factors are found to have statistically significant effects on electricity generation cost although in real terms the reduction of gas users has the greatest effect. Greater cost savings (£2.75 per household) result when the reduction of gas users is on low level (30%) rather than when on high level (60%). This may be explained by higher generation costs of alternative technologies; due to coal generation being replaced by more expensive wind and nuclear. Further reductions in overall electricity generation cost follow if values for reduction of number of gasoline cars, reduction in coal, increase in wind and nuclear generated electricity are set to 50%, 60%, 5%, and 3% respectively. The cost of reducing gasoline cars is higher when set on 100% (£2.22 per household) than when set on 50% (£1.11 per household). This may be explained by the higher dependency on electricity for transport this scenario would bring, either for charging BEVs and/or train journeys. The cost saved by replacing coal generated electricity by 60% (£0.774 per household) is negligible compared to the increase in electricity generation cost that results with the increase of wind and nuclear generated electricity to offset some of the capacity lost from coal. The simulations show that any percentage increase of either wind or nuclear generated electricity would increase the electricity generation cost by £0.2 per household and £0.3 per household respectively. Hence, the values for the increase in wind (5%) and nuclear (3%) generated electricity.

3.2 Evaluation experiments

Sections 3.1.1 – 3.1.4 demonstrate that the five control factors have different effects on six system response variables. This is summarised in Table 7. By reflecting on these results a picture emerges about factor combinations and their values that promise to result in lower water, gas, gasoline, and electricity consumption, and lower CO_2 emissions and electricity generation cost.

Table 7: Summary of main effects of five control factors on six system response variables

System response variable	***A***	***B***	***C***	***D***	***E***
Water consumption	No effect	No effect	No effect	No effect	No effect
Gas consumption	No effect	60%	No effect	No effect	No effect
Gasoline consumption	100%	No effect	No effect	No effect	No effect
Electricity consumption	50%	30%	No effect	No effect	3%
CO_2 emissions	50%	30%	60%	10%	No effect
Electricity generation cost	50%	30%	60%	5%	3%

Two factors have consistent settings: a 60% reduction in coal generated electricity (C) and a 3% increase in nuclear generated electricity (E). The situation is not so clear with the remaining three factors. From the perspective of overall gasoline consumption, a reduction in gasoline cars (A) is better when set on 100%, however, when set to a 50% reduction it leads to lower electricity consumption, CO_2 emissions, and electricity generation cost. For these reasons the latter value is chosen. Following the same logic for a reduction of gas users (B), 30% is selected. Finally, both 5% and 10% values are selected for increase in wind generated electricity factor (D). This results in two factor combinations, 1: A(50%), B(30%), C(60%), D(5%), E(3%) and 2: A(50%), B(30%), C(60%), D(10%), E(3%).

Next stage involved the evaluation of the two proposed factor combinations. These have been subjected to 6 exogenous scenario parameters (Table 2) and run with both high (15%) and low (5%) adoption level of the six MGTs. Table 8 presents the simulation results for the four proposed configurations (*PC1-4*) each with 10 runs per configuration. It shows the average, highest, lowest values, and their differences, for all six system response variables and the six MGTs considered here.

Table 8: Proposed configurations – evaluation results

System response variable (per 1000 households)	***PC1***	***PC2***	***PC3***	***PC4***	***Highest - Lowest***	***PC2 – PC1***	***PC4 – PC3***
Water consumption, $\times 10^3$ m^3	6060	5978	6079	5965	114	-82	-114
Gas consumption, $\times 10^3$ m^3	3324	3255	3319	3264	69	-69	-55
Gasoline consumption, $\times 10^3$ m^3	16.17	15.92	15.88	16.01	0.29	-0.25	0.13
Electricity consumption, $\times 10^3$ MWh	122.8	123.6	123.6	123.5	0.8	0.8	-0.1
CO_2 emissions, tonnes	7.227	7.246	7.125	7.103	1430	190	-220
Electricity generation cost, millions £	5.411	5.435	5.537	5.556	0.145	0.024	0.019
Average number of BEVs	27	182	30	178	155	155	148
Average number of STWHs	23	108	23	107	85	85	84
Average number of PVs	35	133	38	137	102	98	99
Average number of GWRs	47	241	50	254	207	194	204
Average number of WHRs	14	74	16	78	64	60	62
Average number of RWHs	44	223	49	230	186	179	181

PC1, proposed with low adoption rate and wind increase of 5%.
PC2, proposed with high adoption rate and wind increase of 5%.
PC3, proposed with low adoption rate and wind increase of 10%.
PC4, proposed with high adoption rate and wind increase of 10%.

Arranged in order from the highest to the lowest, the evaluation results reveal that water-related technologies (GWR and RWH) are the most widely adopted MGTs, which are followed by BEV and then by PV and STWH. The least frequently adopted is WHR. Next stage of analysis involved a comparison between configurations with high (*PC2* and *PC4*) to those with low (*PC1* and *PC3*) levels of MGTs. This is presented in the last two columns of Table 8. It appears that more MGTs reduce water and gas consumption. This is expected because more water-related MGTs (GWR and RWH) should reduce water demand (see Table 3). Similarly, energy-related MGTs (STWH and WHR) should reduce gas demand (see Table 3). When it comes to establishing the effects of MGTs on the other four system response variables, no apparent pattern exists. That is because they have no apparent links, whilst water consumption is directly related to MGTs (GWR and RWH) and gas consumption is directly related to MGTs (STWH and WHR). What further obscures the analysis is potential effect that the increase of wind generated electricity may have on the system response variables, because the increase in wind generated electricity factor cannot set to a unique value. Namely, in addition to MGTs, the differences observed may also be due to this factor. Therefore, two-tailed t-tests were conducted to shed more light on the real reasons behind the differences observed. The differences can be found based on the p value in t-tests. The smaller the p value, the more significant the result. The results are presented in Table 9.

The t-tests show that the increase of wind generated electricity from 5% to 10% reduces average CO_2 emissions and increases average electricity generation cost, because they have small *p* value. This is expected and in agreement with Table 7. The factor has no effect on any of the other four system response variables. On the other hand, high level of MGTs seems only to reduce average water and gas consumption. This confirms that water-related technologies (GWR and RWH) and energy-related technologies (STWH and WHR) reduce water and gas consumption respectively, because they save more. The remaining MGTs, BEV and PV, have no statistically significant effect on average values of any of the other four system response variables.

Table 9: Proposed configurations – results of two-tailed t-tests

System response variable (per 1,000 households)		**Increase in wind generated electricity**		**Adoption level of MGTs**	
		5%	10%	Low	High
Water consumption, m^3	Mean×10^{-3}	6019	6022	6069	5971
	df	38		31	
	t-statistic	-0.08		3.30	
	p value (Prob T<=t)	0.9332		0.0024*	
Gas consumption, m^3	Mean×10^{-3}	3290	3292	3322	3260
	df	37		38	
	t-statistic	-0.08		2.56	
	p value (Prob T<=t)	0.9374		0.0144*	
Gasoline consumption, m^3	Mean×10^{-3}	16.04	15.94	16.02	15.96
	df	37		35	
	t-statistic	0.51		0.31	
	p value (Prob T<=t)	0.6132		0.7606	
Electricity consumption, MWh	Mean×10^{-3}	123.2	123.6	123.2	123.6
	df	38		34	
	t-statistic	-0.56		-0.56	
	p value (Prob T<=t)	0.5760		0.5768	
CO_2 emissions, tonnes	Mean×10^{-3}	72.367	71.14	71.76	71.75
	df	38		32	
	t-statistic	3.42		0.03	
	p value (Prob T<=t)	0.0015*		0.9762	
Electricity generation cost, millions £	Mean	5.423	5.547	5.474	5.495
	df	38		35	
	t-statistic	-4.14		-0.59	
	p value (Prob T<=t)	0.0002*		0.5559	

*The model term is statistically significant.

4. Discussion of findings and of their significance for policy

In this section possible implications of the findings for the UK policy is discussed.

GWR and RWH reduce water demand and have a potential for reducing electricity demand and CO_2 emissions, they should be more actively promoted: It is found that GWR and RWH significantly reduce demand for water. In scenarios with high adoption levels in which around 15% of population adopt either GWR or RWH, these technologies reduce water consumption between 82 and 114 m^3 per household (see Table 8). Considering that average per capita consumption in UK is around 154 litres of water per person per day (DEFRA, 2011) this translates to 4.5 to 6 months of water demand for a family of four. Given that the water sector (treatment and distribution) is fourth most energy intensive industry (Gallagher et al., 2015) this level of reduction should correspond to a significant reduction in electricity consumption and CO_2 emissions. Also, of all MGTs considered here, GWR and RWH are the most affordable. Therefore, GWR and RWH should be more actively promoted.

STWH and WHR have a limited potential for reducing energy demand, improvements in the design and use of gas boilers may be better options: Although STWH and WHR are the least widely adopted MGTs (see Table 8) it is found that they reduce demand for gas. It appears that the adoption levels of STWH and WHR observed here are sufficient to demonstrate their positive benefits for reducing gas demand. However, the reductions achieved are not sufficient enough to completely dispense of gas for energy. On average, these technologies save between 55 and 69 m^3 of gas per household (see Table 8). Given that 1 m^3 of gas delivers around 11 kWh of energy (see Table 4) and that average UK household consumes 12,000 kWh worth of gas energy per year (Typical Domestic Consumption Values, 2019), this translates to 23 days of gas consumption at best. This figure is almost identical to a result from a study of STWH in the UK by Bergman and Eyre (2011) who found that majority of installations achieved no more than 6% of energy savings. Therefore, unless significant improvements in efficiency of STWH and WHR are achieved, these technologies do not seem to have a potential to replace gas for energy and attempts to reduce gas users will have adverse effects. From this perspective, the model developed suggests gas dependency to be reasonable for the UK. Of all the factors considered, reduction of gas users contributes the most to the increase of electricity consumption, electricity generation cost, and CO_2 emissions. So policies that aim to reduce or even ban use of gas will have negative effects. However, necessary reductions in energy consumption and CO_2 emissions may come from elsewhere, such as improvements in the design and use of gas boilers. This resonates with Cullen and Allwood (Cullen and Allwood, 2010) who explored theoretical efficiency limits for energy conversion devices. Their analysis revealed that greater energy savings are available from focusing on e.g. gas burners than on efficiency improvements of e.g. gas-fired power stations. They estimated that prioritising efficiency measures for end-use conversion devices over fuel transformation and electricity generation might deliver more than five times the potential gain. Improvements need not necessarily come from technical solutions only; further improvements may also come from behavioural changes. It should be acknowledged that reducing energy demand is much more difficult than is commonly assumed. There is a misconception that energy efficiency improvements lead to proportional reductions in energy demand (Sorrell, 2015). The misconception ignores a so called 'rebound effect' (Herring, 1999) whereby it is recognised that improvements in energy efficiency often lead to greater energy consumption.

BEV should be adopted together with PV and the latter should not be supported with feed-in-tariffs: It is hypothesised that adoption of a BEV would lead to an increase in electricity demand and decrease in gasoline demand (see Table 3). Similarly, it is expected that adoption of a PV would lead to reduction in electricity demand. Surprisingly, the results in this study show that BEV and PV do not affect average gasoline and electricity consumption, CO_2 emissions, and electricity generation cost (see Table 9). This is not because BEV and PV have no effect but because their *combined* net effect is close to zero. For example, no change in gasoline consumption occurs because gasoline cars are not always replaced by BEVs. Due to their high cost, limited battery range and access to charging (see Table 2), much cheaper public transport (often diesel buses and trains) is probably the reason why gasoline cars are not replaced by BEVs. As a result, overall effect on gasoline consumption and CO_2 emissions is close to zero. Similar occurs in case of BEV and PV and their combined zero effect on electricity consumption and ensuing CO_2 emissions. The zero-effect observed here is because of two reasons. First, the electricity generated by PV is used mainly to meet the household's demand; it is not exported to the grid (see Table 3) as typically is the case. The second reason is due to a significant number of households adopting both BEV and PV, which in case of the model developed is more than 30% of households. This means that the negative effects of BEV are, to some extent, counterbalanced by positive effects of PV. The two reasons ensure that the increase in electricity demand by BEV is cancelled by reduction in electricity demand by PV, which results in zero effect on electricity consumption and CO_2 emissions.

The above has two implications for policy. First, adoption of BEV should be supported with adoption of PV. The importance of collocation of PV and BEV is also recognised by other studies (Donateo et al., 2015; Eser et al., 2018). The second implication is related to the policies that promote adoption of PV. If such policies are promoted with feed-in-tariffs (Balcombe et al., 2014), which encourage the export of electricity thus generated to the electric grid, then this will have negative effects. What such policies seem to promote are higher inefficiencies and CO_2 emissions, which are only exacerbated by BEVs. This reminds us of Frondel et al. (2014) who characterised the promotion of PVs by German government as an unfolding disaster. They argue that the government's support of PVs, in the form of feed-in tariffs, is an outstanding example of misguided political intervention that has little to show in terms of greenhouse gas reductions.

Investment in higher levels of wind, gas, and nuclear generated electricity: The alternative to previous two policy implications is a different electricity generation mix. This mix would be more complementary with policies that promote replacement of gasoline cars by BEVs. If not supported by such a mix, then reduction of number of gasoline cars, and their replacement by BEVs, would lead to an increase in electricity consumption, CO_2 emissions, and electricity generation costs. This finding is in agreement with other studies that investigate the impacts of the gasoline cars replacement programmes with BEVs.

For example, Schill and Gerbaulet (2015) study possible impacts of future BEV fleets (up to 2030) on the German power system. They found that CO_2 emissions of BEVs are substantially higher than those of the overall power system. Only in situations in which the introduction of BEVs is linked to a deployment of additional renewables, BEVs become largely CO_2 neutral. A study by Bellochhi et al. (2018) assesses the impact of progressively increasing shares of BEV in Italy in scenarios with different level of production from renewable sources. They found that with a tenfold increase in renewable electricity generation and a complete replacement of gasoline cars with BEVs, CO_2 emissions could be reduced by 20% compared to 2015 level. However, this comes at the price of high curtailments (43%) and costs (56% higher compared to 2015 level). Similar is reported in a study by Eser et. al. (2018) that investigates impacts of BEVs in the context of interconnected electricity system of 7 European countries (Poland, the Czech Republic, Austria, Germany, Switzerland, France, and Italy). The study found moderate potential for BEVs to reduce the curtailment of wind and solar. Because of this two thirds of electricity produced to charge BEVs is from fossil fuels, which results in 25% higher CO_2 emissions per km of BEVs compared to gasoline cars. An increase of CO_2 prices to at least 100 €/tonne would be necessary to achieve a CO_2 intensity of the BEVs that would be comparable to gasoline cars. In the case study of China, Hofmann et al. (2016) found that the gasoline vehicle replacement with BEVs, when powered by 80% coal, has no effect on overall emissions. This is because reduction in CO_2 emissions in the gasoline sector is offset by the increase in CO_2 emissions in the electricity generation sector. Almost identical is found by (Li et al., 2016).

The results are in agreement with other studies. In common is an idea that policies that promote reductions of gasoline cars and their replacement by BEVs should simultaneously be accompanied by more significant changes in the technology mix used to generate electricity. If not accompanied by such changes, then the proliferation of BEVs will fail to realise the potential of CO_2 emission reductions. Moreover, it is likely to result in adverse effects on electricity consumption, CO_2 emissions, and electricity generation costs. To overcome this, higher levels of wind, gas, and nuclear generated electricity are necessary. Gas may be necessary to compensate for the intermittency of wind. If a complete shift away from fossil fuels is sought, then the transition from gasoline cars to BEVs would have to be supported by even higher levels of wind and nuclear. This is congruent with Sithole et al. (2016) who argue that wind and nuclear technologies are going to play an indispensable role for the UK to meet its legally binding agreement to reduce CO_2 emissions by 80% by 2050.

5. Conclusion

This paper explored how consumption of resources, water, gas, gasoline, and electricity, by UK households together with CO_2 emissions and electricity generation costs, might be affected by the wider adoption of micro-generation technologies (MGTs) in the context of some planned UK policy changes and transition scenarios. The MGTs investigated include: battery electric vehicles (BEVs), solar photovoltaics (PVs), solar thermal water heating (STWH), rain water harvesting (RWH), grey water recycling (GWR), and waste heat recovery (WHR). To address the research aim, an agent-based model has been developed and tested. The simulations show that greater adoption of GWR and RWH reduces demand for water. Similarly, STWH and WHR reduce gas demand. A wider adoption of BEV and PV has no statistically significant effects on any of the system response variables. Furthermore, the simulations found that a reduction of number of gasoline cars and gas users lead to higher electricity consumption, CO_2 emissions, and electricity generation costs. Based on these results five implications for policy were identified.

The first argues that GWR and RWH not only reduce water demand but have a potential to reduce electricity demand and CO_2 emissions. Hence, GWR and RWH should be more actively promoted. The second implication for policy states that STWH and WHR have limited potential to replace gas for energy. Consequently, attempts to reduce gas users will have adverse effects. Improvements in the design and use of gas boilers seem to be better options. The third implication argues that adoption of BEV should be supported with a simultaneous adoption of PV. In this way the negative effects of BEV will, to some extent, be counterbalanced by positive effects of PV. This is also related to the fourth implication, which deals with policies that promote adoption of PV. It argues that policies that promote adoption of PV via feed-in-tariffs may have negative effects. The alternative to the previous two policy implications is more complementary electricity generation mix. If this is not addressed, then policies that promote adoption of BEVs by simultaneously reducing the number of gasoline cars may result in higher electricity consumption, CO_2 emissions, and electricity generation costs. This mix would have higher levels of wind, gas, and nuclear generated electricity. This constitutes the final implication for policy.

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References

Allan, G., Ermenko, I., Gilmartin, M., Kockar, I., McGregor, P., 2015. The economics of distributed energy generation: a literature review. Renewable and Sustainable Energy Reviews 42, 543-556.

Allen, P., 2000. Knowledge, ignorance, and learning. Emergence 2(4), 78-103.

Arkesteijn, K., Oerlemans, L., 2005. The early adoption of green power by Dutch households: An empirical exploration of factors influencing the early adoption of green electricity for domestic purposes. Energy Policy 33(2), 183-196.

Baca, P.V., Brausen, J., 1997. The electric vehicle market. Competitiveness Review 7(1),36-45.

Balcombe, P., Rigb,y D., Azapagic, A., 2014. Investigating the importance of motivations and barriers related to microgeneration uptake in the UK. Applied Energy 130, 403-418.

Baseline energy statement - energy consumption and carbon dioxide emissions on the railway' from March 2007 - The voice of the passenger railway.

Bellocchi, S., Gambini, M., Manno, M., Stilo, T., Vellini, M., 2018. Positive interactions between electric vehicles and renewable energy sources in CO_2-reduced energy scenarios: The Italian case. Energy 161, 172-82.

Bergman, N., Eyre, N., 2011. What role for microgeneration in a shift to a low carbon domestic energy sector in the UK? Energy Efficiency 4(3), 335–353.

Berk, R., Schulman, D., McKeever, M., Freeman, H., 1993. Measuring the impact of water conservation campaigns in California. Climate Change 24(3), 233–248.

Boßmann, T., Staffell, I., 2015. The shape of future electricity demand: exploring load curves in 2050s Germany and Britain. Energy 90, 1317-1333.

Caird, S., Roy, R., Herring, H., 2008. Improving the energy performance of UK households: Results from surveys of consumer adoption and use of low- and zero carbon technologies. Energy Efficiency 1(2), 149–166.

Carbon footprint calculator, 2019. www.carbonindependent.org.

Chappin, E.J., Dijkema, G.P., 2010. Agent-based modelling of energy infrastructure transitions. International Journal of Critical Infrastructures 6(2):106-130.

Claudy, M.C., Michelson, C., O'Driscoll, A., 2011. The diffusion of micro generation technologies – assessing the influence of perceived product characteristics on home owners' willingness to pay. Energy Policy 39(3), 1459-1469.

Coleman, D.E., Montgomery, D.C., 1993. A systematic approach to planning for a designed industrial experiment. Technometrics 35(1), 1-12.

Cullen, J.M., Allwood, J.M., 2010. Theoretical efficiency limits for energy conversion devices. Energy 35(5), 2059-2069.

DECC, 2014. Energy consumption in the United Kingdom, Department for Energy and Climate Change (DECC). https://www.gov.uk/government/publications/energy-consumption-in-the-uk.

DEFRA, 2011. Water for life, Department for Environment, Food and Rural Affairs, London.

Department for Transport statistics, 2019. https://www.gov.uk/government/organisations/department-for-transport/series/national-travel-survey-statistics

Design-Expert, 2019. https://www.statease.com/software/design-expert.

Donateo, T., Licci, F., D'elia, A., Colangelo, G., Laforgia, D., Ciancarelli, F., 2015. Evaluation of emissions of CO_2 and air pollutants from electric vehicles in Italian cities. Applied Energy 157, 675-87.

Edmunds, B., 2000. Complexity and scientific modelling. Foundations of Science 5(3), 379–390.

Energy saving trust, 2019. http://www.energysavingtrust.org.uk.

Environment Agency, 2011. Greywater for domestic users: an information guide, May. http://publications.environment-agency.gov.uk/PDF/GEHOO511BTWC-E-E.pdf.

Eser, P., Chokani, N., Abhari, R.S., 2018. Impacts of battery electric vehicles on renewable integration within the 2030 European power system. International Journal of Energy Research 42, 4142–56.

Frondel, M., Schmidt, C.M., Vance, C., 2014. Revisiting Germany's solar cell promotion: an unfolding disaster. Economic Analysis and Policy 44(1), 3-13.
Gallagher, J., Harris, I.M., Packwood, A.J., McNabola, A., Williams, A.P., 2015. A strategic assessment of micro-hydropower in the UK and Irish water industry: Identifying technical and economic constraints. Renewable Energy 81, 808-815.
Gatignon, H., Robertson, T., 1991. Innovative Decision Process, in: Thomas SR, Harold SK (eds.) Handbook on Consumer Behaviour, Prentice-Hall, Englewood Cliffs, NJ, 316-348.
Gilg, A., Barr, S., 2006. Behavioural attitudes towards water saving? Evidence from a study of environmental actions. Ecological Economics 57(3), 400–414.
Graham-Rowe, E., Gardiner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R., Stennard, J., 2012. Mainstream consumers driving plug-in battery-electric and plug-in hybrid cars: A qualitative analysis of responses and evaluations. Transportation Research: Part A 46(1), 140-153.
Hall, L.M., Buckley, A.R., 2016. A review of energy systems models in the UK: Prevalent usage and categorisation. Applied Energy 169, 607-628.
Hauser, J., Tellis, G.J., Griffin, A., 2006. Research on innovation: A review and agenda for marketing science. Marketing Science 25(6):687-717.
Heller, M., 2001. Interdependencies in civil infrastructure systems. The Bridge 31(4), 9-15.
Herring, H., 1999. Does energy efficiency save energy? The debate and its consequences. Applied Energy 63(3), 209-226.
Hofman, J., Hofman-Caris, R., Nederlof, M., Frijns, J., van Loosdrecht, M., 2011. Water and energy as inseparable twins for sustainable solutions. Water Science & Technology 63(1):88-92.
Hofmann, J., Guan, D., Chalvatzis, K., Huo, H., 2016. Assessment of electrical vehicles as a successful driver for reducing CO_2 emissions in China. Applied Energy 184, 995-1003.
House of Commons Hansard written answers for 20 July 2005.
Hyde, K., Maradza, E., 2013. An evaluation of the theoretical potential and practical opportunity for using recycled greywater for domestic purposes in Ghana. Journal of Cleaner Production 60, 195-200.
Juntunen, J.K., Hyysalo, S., 2015. Renewable micro-generation of heat and electricity – Review on common and missing socio-technical configurations. Renewable and Sustainable Energy Reviews 49,857-870.
Koltsaklis, N.E., Dagoumas, A.S., 2018 State-of-the-art generation expansion planning: A review. Applied Energy 230, 563-589.
Li, Y., Davis, C., Lukszo, Z., Weijnen, M., 2016. Electric vehicle charging in China's power system: Energy, economic and environmental trade-offs and policy implications. Applied Energy 173, 535-54.
Loorbach, D., Frantzeskaki, N., Thissen, W., 2010. Introduction to the special section: Infrastructures and transitions. Technological Forecasting & Social Change 77(8), 1195-1202.
McDonald, H., Corkindale, D., Sharp, B., 2003. Behavioural versus demographic predictors of early adoption: A critical analysis and comparative test. Journal of Marketing Theory and Practice 11(4), 84-95.
Mehigan, L., Deane, J.P., Gallachóir, B.Ó., Bertsch, V., 2018. A review of the role of distributed generation (DG) in future electricity systems. Energy 163, 822-836.
Midgley, G., 2008. Systems thinking, complexity and the philosophy of science. Emergence: Complexity and Organization 10(4),55-73.
Millock, K., Nauges, C., 2010. Household adoption of water-efficient equipment: The role of socio-economic factors, environmental attitudes and policy environmental and resource. Economics 46(4), 539-565.

Montgomery, D.C., 2013. Design and analysis of experiments (edition 8). John Wiley & Sons, Inc.

Nyrud, A.Q., Roos, A., Sande, J.B., 2008. Residential bio-energy heating: A study of consumer perceptions of improved wood stoves. Energy Policy 36(8), 3169-3176.

Ofgem data, 2019. https://www.ofgem.gov.uk/data-portal/electricity-generation-mix-quarter-and-fuel-source-gb.

O'Doherty, J., Lyons, S., Tol, R.S.J., 2008. Energy-using appliances and energy saving features: Determinants of ownership in Ireland. Applied Energy 85(7), 650-662.

O'Rourke, T.D., 2007. Critical infrastructure, interdependencies, and resilience. The Bridge 37(1), 22-29.

Palmer J, Cooper I, 2012. United Kingdom housing energy fact file, Department for Energy and Climate Change, December. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/201167/uk_housing_fact_file_2012.pdf.

Rain water harvesting, 2019. www.rainwaterharvesting.co.uk.

Richardson, K.A., Cilliers, P., Lissack, M., 2001. Complexity science: A "gray" science for the "stuff in between". Emergence 3(2), 6-18.

Rigole, T., Deconinck, G., 2006. A survey on modeling and simulation of interdependent critical infrastructures. 3rd IEEE Benelux young researches symposium in electrical power engineering, 27-28 April, Ghent Belgium 1-9.

Rinaldi, S.M., Peerenboom, J.P., Kelly, T.K., 2001. Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies. IEEE Control Systems Magazine 21(6), 11-25.

Ringkjøb, H.K., Haugan, P.M., Solbrekke, I.M., 2018. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renewable and Sustainable Energy Reviews 96, 440-459.

Robinson, A.P., Blythe, P.T., Bell, M.C., Hübner, Y., Hill, G.A., 2013. Analysis of electric vehicle driver recharging demand profiles and subsequent impacts on the carbon content of electric vehicle trips. Energy Policy 61, 337-348.

Rogers, E.M., 2003. Diffusion of Innovations: Simon and Schuster, New York.

Sauter, R., Watson, J., 2007. Strategies for the deployment of micro-generation: implications for social acceptance. Energy Policy 35, 2770-2779.

Schill, W.P., Gerbaulet, C., 2015. Power system impacts of electric vehicles in Germany: Charging with coal or renewables? Applied Energy 156, 185-196.

Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transportation Research: Part A 48, 39-49.

Schwarz, N., Ernst, A., 2008. Agent-based modeling of the diffusion of environmental innovations - An empirical approach. Technological Forecasting & Social Change 76(4), 497-511.

Shafiei, E., Thorkelsson, L., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. Technological Forecasting & Social Change 79(9), 1638-1653.

Shi, Y., Han, B., Han, L., Wei, Z., 2019. Uncovering the national and regional household carbon emissions in China using temporal and spatial decomposition analysis models. Journal of Cleaner Production 232, 966-979.

Sithole, H., Cockerill, T.T., Hughes, K.J., Ingham, D.B., Ma, L., Porter, R.T.J., Pourkashanian, M., 2016. Developing an optimal electricity generation mix for the UK 2050 future. Energy 100, 363-373.

Sopha, B.M., Klöckner, C.A., Hertwich, E.G., 2013. Adoption and diffusion of heating systems in Norway: Coupling agent-based modeling with empirical research. Environmental Innovation and Societal Transitions 8, 42-61.

Sorrell, S., 2015. Reducing energy demand: A review of issues, challenges and approaches. Renewable and Sustainable Energy Reviews 47, 74-82.

Steinhilber, S., Wells, P., Thankappan, S., 2013. Socio-technical inertia: Understanding the barriers to electric vehicles. Energy Policy 60, 531-539.

Theecoexperts, 2019. https://www.theecoexperts.co.uk.

Theo, W.L., Lim, J.S., Ho, W.S., Hashim, H., Lee, C.T., 2017. Review of distributed generation (DG) system planning and optimisation techniques: Comparison of numerical and mathematical modelling methods. Renewable and Sustainable Energy Reviews 67, 531-573.

Tidball, R., Bluestein, J., Rodriguez, N., Knoke, S., 2010. Cost and performance assumptions for modelling electricity generation technologies. National Renewable Energy Laboratory, NREL/SR-6A20-48595, U.S. Department of Energy.

Typical Domestic Consumption Values, 2019. https://www.ofgem.gov.uk/gas/retail-market/monitoring-data-and-statistics/typical-domestic-consumption-values.

Ulrich, W., Reynolds, M., 2010. Critical systems heuristics, in: Reynolds M, Holwell S, (Eds.) Systems Approaches to Managing Change: A Practical Guide, London: Springer, 243–292.

Varga, L., Grubic, T., Greening, P., Varga, S., Camci, F., Dolan, T., 2014. Characterizing conversion points and complex infrastructure systems: Creating a system representation for agent-based modeling. Complexity 19(6), 30-43.

Waterwise, 2019. Evidence Base, Waterwise. http://www.waterwise.org.uk/pages/at-home.html.

Watson, J., Sauter, R., Bahaj, B., James, P., Myers, L., Wing, R., 2008. Domestic micro generation: economic, regulatory and policy issues. Energy Policy 36(8), 3095-3106.

Williams, B.D., Kurani, K.S., 2006. Estimating the early household market for light-duty hydrogen-fuel-cell vehicles and other “Mobile Energy” innovations in California: A constraints analysis. Journal of Power Sources 160(1), 446-453.

Woodman, B., Baker, P., 2008. Regulatory frameworks for decentralised energy. Energy Policy 36(12), 4527-4531.

Yousefi, S., Moghaddam, M.P., Majd, V.J., 2011. Optimal real time pricing in an agent-based retail market using a comprehensive demand response model. Energy 36(9), 5716-5727.

Zarnikau, J., 2003. Consumer demand for ‘green power’ and energy efficiency. Energy Policy 31(15), 1661-1672.