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Machine learning-based design exploration of clamshell telescope enclosure structure

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This study presents an innovative procedure using generative design in combination with machine learning. A new workflow is developed to approximate the responses of individual model evaluations and combine them in a unified environment from which design solutions are searched. This ensures that all design considerations, constraints and objectives are taken into account simultaneously. The proposed workflow is validated on the design of the enclosure for the New Robotic Telescope (NRT), the world's largest robotic, fully autonomous, optical telescope of the four-metre-class. The proposed design for the enclosure is a curved clamshell structure with a 19-metre internal floor diameter, consisting of six segments, three on each side. The results of the study have provided insights into the behaviour of the structure and made it possible to propose final solutions that show significant improvements over the concept design in terms of total mass and operating forces.

1. Introduction

Despite the technological advancements that are driving the construction industry towards digitalization, designers continue to encounter certain limitations and

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challenges. During the design process, designers must deal with various requirements and constraints while trying to find suitable solutions that consider all aspects of the design. These solutions are typically found iteratively at the cost of repetitive work, collaboration and time. Finding a suitable solution iteratively means adopting a solution, analyzing it, and verifying its suitability until all design constraints and objectives are met. Although this process is streamlined for known and similar problems, it can stall for new and unknown design challenges. In this study, a complex structure for enclosing a telescope is designed and optimal solutions are sought. For this purpose, a comprehensive design investigation and exploration is required to understand the problem and its challenges. To this end, alternative methods and approaches are considered, including generative design and machine learning.

In the generative design paradigm, the focus shifts from the solution to the problem. In this approach, the main element is a computational model that represents a real-world problem. Through the process of automated generation and testing, the insights of the model are obtained, which allows the designer to find the most appropriate solution [1,2]. This approach has been applied to many problems in engineering [3–6], including optimization of urban layouts [7] and building design [8].

The application of machine learning techniques in the field of structural engineering is not a novel concept. In their early stages, these techniques were mainly used to analyze simple structures with the aim to predict structural responses [9–11] and optimize them [12,13]. These predictions were typically centred on specific locations that were predetermined based on the insights and expertise of engineers. As the discipline progressed, its scope expanded to include the analysis of larger structures [14,15]. Nevertheless, the application of such techniques remained limited to predicting the direct structural responses of individual elements or systems rather than assessing the overall integrity of the structure, primarily due to the complexity and nonlinearity of the problem [16].

We aim to develop a system capable of taking into account multiple considerations and evaluating the entire design, regardless of the number of analyses or simulations needed. This system will be tested in the design of the complex telescope enclosure structure.

The New Robotic Telescope (NRT) will be the world's largest four-metre-class optical, robotic-autonomous telescope, located at the Roque de los Muchachos Observatory (ORM) in La Palma, Canary Islands, Spain, and housed in a clamshell enclosure. It includes a novel, first-generation instrumentation suite, designed to conduct spectroscopic, polarimetric and photometric observations driven by user requirements. The science case is driven by transient classification and fast follow-up, with the telescope capable of starting observations within 30 s of receiving the trigger. This enables the observation of faint and rapidly fading transient sources that other optical facilities cannot capture [17].

The design follows in the footsteps of the highly successful Liverpool Telescope (LT), which, like some of its sister telescopes, the Faulkes Telescope North (FTN) in Hawaii and the Faulkes Telescope South (FTS) in Australia [18,19], uses a clamshell enclosure. LT, FTN and FTS are two-metre-class telescopes. Each is housed in a novel clamshell enclosure that folds down to give the telescope an unobstructed view over its entire operating range down to approximately 20° above the horizon and is designed to operate in wind speeds of up to 180 km h^{-1} [20]. They also provide space to place additional 40 cm telescopes on elevated platforms within the two-metre enclosure [21]. Similar clamshell enclosures with diameters of 7 and 9 m have been built for the high-resolution solar telescopes Dutch Open Telescope (EGOR) with a 45 cm primary mirror and GREGOR with a 1.5 m primary mirror, both located in the Canary Islands [22]. It is now widely recognized that large future telescopes will benefit from clamshell enclosures and its features. Another telescope currently in the design stage is the European Solar Telescope (EST), a four-metre-class telescope for which a clamshell type enclosure is also being considered [23,24].

Clamshell enclosure allows full access to the sky without rotating the dome and protects the telescope when not in operation. However, many four-metre-class telescopes use a conventional dome enclosure. Examples include: The Discovery Channel Telescope [25] in Arizona; the Visible and Infrared Survey Telescope for Astronomy [26] and the Victor M. Blanco Telescope, both

in Chile; Southern Astrophysical Research Telescope [27]; and finally, the William Herschel Telescope on the island of La Palma in the Canary Islands, Spain. However, the dome enclosures account for a significant portion of the project budget at about 8% [28]. They require constant slewing as the telescope moves, causing vibrations that affect image quality. Minor problems with water leaks and moderate electrical and control problems have also been reported [26]. Due to the growing institutional demand for observatories, high quality domes for telescopes of class up to 2 m are commercially available. These come equipped with an electric shutter and a motorized dome rotation system [29]. However, the NRT is a four-metre-class telescope [30], and domes are reportedly more prone to failure due to their longer cycle time and other disadvantages mentioned above. Therefore, the NRT will be the first telescope in its size class to use a clamshell enclosure.

The aim of this research is to investigate the potential of generative design, complemented by machine learning, in the design exploration of a complex engineering problem such as the NRT enclosure. When many constraints are imposed on the design and the optimal solution is further constrained by the interactions of important structural elements, which may be inversely proportional, exploring possible yet efficient design solutions become challenging. Conventional methods reach their limits in such designs due to the immense number of possible solutions and at the same time run the risk of overlooking potentially better alternatives. The generative approach allows the designer to concentrate on defining the design while the algorithms search for the solution. By varying the design parameters, several different solutions are generated and analyzed to better understand the design and predict its behaviour. This knowledge can be used to revise and improve the design description or to choose a solution that fulfills all considered objectives. Due to the complexity of the clamshell design problem, it was necessary to include machine learning in this process to properly model behaviour and explore possible designs.

This introduces an alternative approach that seamlessly integrates generative design and machine learning by incorporating surrogate models into a unified optimization framework. This approach resolves interoperability problems and enables efficient exploration of large design spaces. Applied to complex engineering challenges such as the observatory enclosure, it significantly helps in the search for efficient engineering solutions. The structure of this paper is as follows: in §2, we present the location and details of the NRT design; in §3, we outline the research methodology; in §4, we describe the experimental set-up; in §5, we present the results of the design exploration and discuss the findings; and finally, in §6, we conclude the paper.

2. Telescope enclosure design

(a) Site specifications

The NRT is set to be built next to the William Herschel Telescope (WHT), on the site of the now decommissioned Automatic Transit Circle (ATC) at the ORM on La Palma, Canary Islands, Spain. The proposed site drives the following environmental conditions for consideration [31]:

Altitude: 2325 m

- Temperature Range: -10 – 30°C (operational); -15 – 40°C (survival).
- Wind loading: 30 km h^{-1} with gusts up to 80 km h^{-1} (operational); 85 km h^{-1} with gusts up to 125 km h^{-1} (survival).
- Snow loading: up to 300 mm evenly covered.
- Ice loading: up to 75 mm evenly covered.
- Seismic activity: 0.06 g in any direction.

The ORM offers excellent and stable weather conditions for observations. A study of the WHT between 1990 and 2007 found that in May and August it had the lowest weather downtime—less than 10%. While in November, December and January, the weather downtime was around

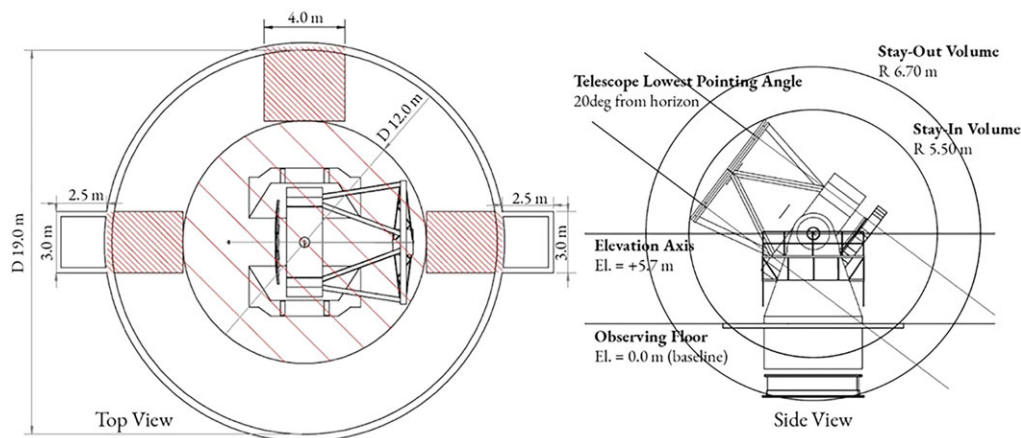


Figure 1. Top (a) and side view (b) of the early telescope clear-sweep and telescope constraints defined by the NRT project team.

40% [32]. The site of the decommissioned ATC was selected for this project due to its favourable observing conditions, lower costs and quicker planning permission.

(b) Design considerations

The design of the enclosure must ensure that the telescope is protected under extreme weather conditions and that it works reliably and autonomously under the operating conditions of the proposed site. To avoid any interference with the telescope from wind or installed machinery, the enclosure should be isolated from the pier on which the telescope sits. The enclosure should also be large enough to allow free movement of the telescope in either open or closed state. The NRT concept of operations drove the following key criteria, which directly influenced the choice of the enclosure:

- The enclosure should satisfy the telescope's space constraints, dimensions and elevation to avoid dome and shell seeing [33] (figure 1), and it should fit within the site constraints.
- The enclosure should exhibit robustness to the unexpected environmental conditions at the site and reliable for autonomous observation in unmanned operation with minimal routine maintenance schedules.
- It should provide access for maintenance in both open and closed positions and allow full access to the sky for observation at all elevations greater than 20° above the horizon (figure 1b).
- It should provide a balanced thermal environment.
- The opening and closing time of the enclosure should be less than 2 min.
- The design of enclosure should be cost-effectiveness, so that most of the budget could be targeted towards science.

(c) Enclosure selection

In the concept design phase, various enclosure types were considered, such as a dome, a roll-off roof, a polygonal and a curved clamshell enclosure. An initial estimate showed that the dome was ruled out as it could not meet the requirements for fast follow-up of a slewing speed greater than 6° s^{-1} . A roll-off roof, as used for the QUIJOTE CMB experiment [34] and the Sloan Digital Sky Survey telescope [35,36], would allow a significant cost reduction. However, neither of these telescopes is a four-metre-class and such types of enclosure would not fit within the

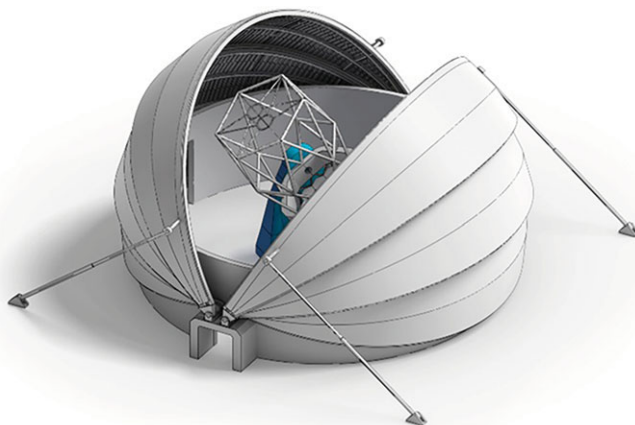


Figure 2. The proposed clamshell enclosure design for the NRT project.

site constraints. The negative effect of the dome is that it tends to form air bubbles of deviating temperature, as it is practically impossible to keep nearby object at a temperature within 0.1°C with the surrounding air. Deviations of 0.1°C in the air produce motion of the image, blurring effects and indicate image degradation [37].

After an extensive study of available enclosures for housing a four-metre-class telescope, the NRT team, supported by a trade-off report provided by IDOM, selected a novel curved clamshell enclosure for the NRT project, rejecting conventional dome enclosure and a roll-off roof. The curved clamshell enclosure meets all the key requirements: robustness, thermal equilibrium, reliability, accessibility, size and cost. In addition, the decision was also based on the very good experiences with the polygonal clamshell from LT, which has been in use for 17 years and has had only three recorded failures. The proposed design for the NRT project design is an optimized version of the LT clamshell enclosure, using arched beams to form curved segments that can achieve similar strength with much less mass. Furthermore, the clamshell structure (figure 2) should consist of three segments for each half, six in total. An eight-segment design (four segments for each half) was considered, but preliminary analysis showed that by increasing the number of segments the outer diameter increases, leading to increased mass and thus cost. Conversely, the four-segment design (two segments for each half) showed that this would result in a reduced field of view, thereby, failing to fulfil the requirement of sky access for elevations of 20° above the horizon.

(d) Specifications of a proposed clamshell enclosure design

The proposed design for the enclosure was initially developed by IDOM for the NRT project. This formed the starting concept for the analysis and further development. The design is a curved clamshell structure with six segments, three on each side. The structure of each segment consists of three principal arches connected by nine crossbeams made of standard Eurocode steel rectangular hollow sections (RHS). The portal segment contains an additional outer beam that seals the two halves together (figure 3). To increase rigidity, a 2 mm thick metal deck covers the beams, insulated and protected with a waterproof cladding. Each segment is connected with locking pin joints so that the lower segments can follow the upper portal segment into a closed and open position. In this way, each half is driven by a pair of hydraulic cylinders attached on each side of the portal segments. When opening, the segments follow under gravity and when closing, the segments are pulled upwards by the portal segment and the pin joints. This design allows observations at elevations greater than 13° above the horizon, which is an improvement on the initial constraint, though as a seeing limited telescope air mass values at this elevation probably rule out useful observations.

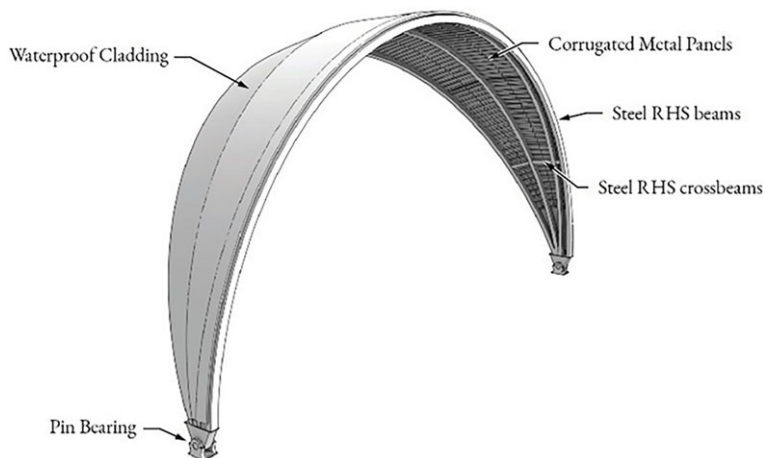


Figure 3. Portal segment and its elements.

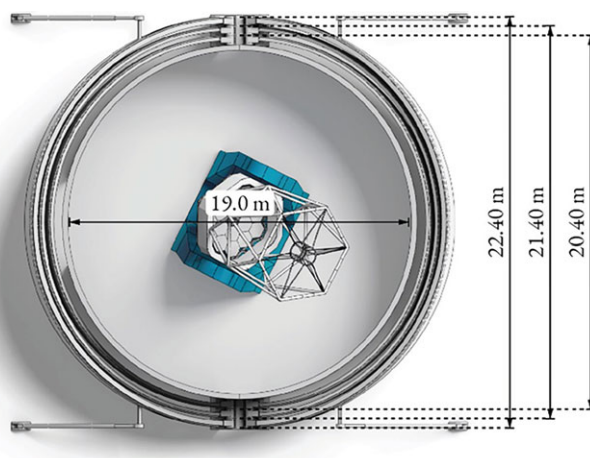


Figure 4. Clamshell enclosure in the open state with the associated dimensions.

The fixed structure has a circular shape with an internal floor diameter of 19 m, while the outer diameters of the segments range from 20.4 to 22.4 m (figure 4). It has two 2.1 m high pedestrian entrances located at both ends of the structure, leading directly to the observation floor level. The pin bearings of the individual segments sit on top of these two entrances. There is also a 4 m high maintenance access located at a 90° angle to the pedestrian accesses (figure 5). Each hydraulic cylinder is attached to the foundations, which are connected to the fixed main base. The estimated weight of the entire enclosure is 105 tonnes, with the movable section weighing 56 tonnes and the fixed structure weighing 49 tonnes. This design solution will serve as a reference point and the mass of the movable part will be used as a benchmark for the optimization process. For comparison, the 23-metre version of the EST clamshell enclosure has an estimated weight of 58 tonnes [24].

3. Methodology

To address complex design problems while considering all constraints, limitations and assemblies, a combination of the generative design approach and machine learning is employed.

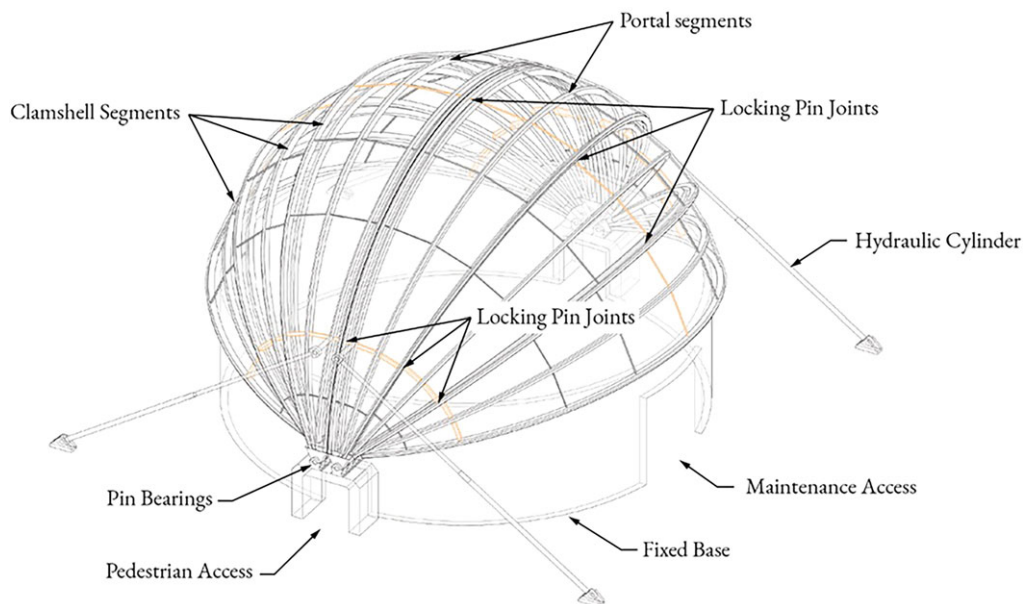


Figure 5. Closed clamshell enclosure with the named structural elements and accesses.

In generative design, a parametric computational model is developed to simulate the behaviour of the design problem. Such models are a collection of instructions and algorithms that describe and simulate the design problem. They are also parametric to allow the generation of design alternatives by changing parameter values, which are studied with the aim of finding the best fitting solution [38]. However, it is often impossible to capture the entire behaviour of the structure in a single model. Consequently, multiple models and simulations are required to analyze the overall structural behaviour. However, this is a challenging process as there is often a lack of effective communication between the various computational models. In our application, machine learning models are used to bridge this gap. Specifically, the machine learning models are trained to act as computational models and provide predicted results based on the given parameters. This is known as surrogate modelling [39] or metamodeling [40]. Such models are inherently much faster and more resource-efficient, so many more executions can be performed. In this way, different simulation results can be combined in one environment and the optimization for the entire design is derived from there. However, surrogate models have some limitations: first, they require data to train and second, they are only an approximation of the original model, which can lead to different outputs [41]. Despite this, they can quickly generate many results, which can be used to identify trends that are valuable for the problem-solving process.

The workflow consists of three distinct parts. First, parametric computational models are developed to simulate the responses for a given structural design. This is done using Dynamo [42], an open-source environment for computational design. This environment enables the integration of various functions, parameters, equations or other blocks of code that collectively describe the shape and behaviour of the associated design model. In addition, Dynamo supports integration with Python, facilitating structural analysis through OpenSees [43], an open-source package that provides a framework for finite element simulations. Using a solver, in this case a genetic algorithm, optimization is performed for each evaluation. From this, a set of simulated responses is extracted by obtaining both the non-optimal and optimal data. The resulting data contain the model configurations as input variables and the model responses as output variables. These data are analyzed to extract useful knowledge for further development of the computational model.

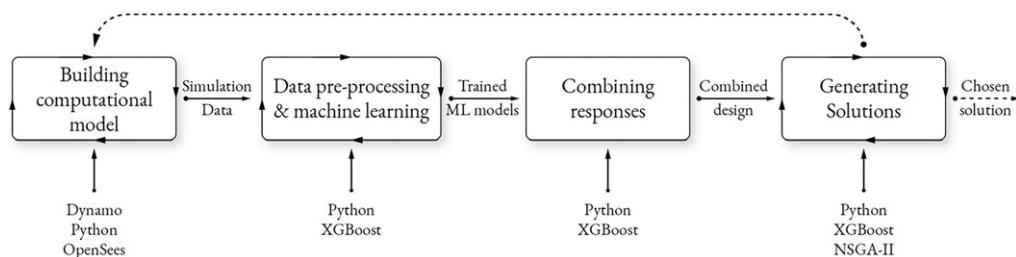


Figure 6. Graphical illustration of the described method.

Next, the simulated data are used to train supervised machine learning models. For this purpose, the data are pre-processed for the training process by identifying the most important variables and modifying some to improve the predictive performance. For instance, the structural responses are combined into a single variable ‘named utilization ratio’, which has two possible classes: positive if all the structural responses are below the maximum allowed, and negative if any of the structural responses exceeds the associated capacities. This is done using the Python environment with the extreme gradient boosting (XGBoost) [44] package for developing machine learning models. The tests showed comparable performance between neural networks and tree-based XGBoost models. However, the XGBoost models were preferred due to their simplicity, requiring fewer hyperparameter settings compared to neural networks [45]. Moreover, these models showed slightly faster prediction speed in our tests.

Finally, the trained machine learning models serve as objective functions in a multi-objective optimization task. This ensures that an overall structural design is considered when exploring the design space and searching for an optimal solution. For this purpose, the implementation of the genetic algorithm NSGA-II [46] in a Python environment is used. In this way, the responses from the different simulations are unified in a single environment where they can be evaluated together. The result of the multi-objective optimization is a set of Pareto-optimal solutions that are used to identify the trade-offs between the objectives. Since the optimization uses surrogate models, which are only an approximation of the original models, it is necessary to verify solutions with the computational models.

Note that this is an iterative process until a computational model is developed that can generate a suitable solution. The process described is shown in figure 6.

4. Case study

The most complex and heaviest component of the enclosure is the moving clamshell structure, making it the primary target for optimization to achieve cost-effectiveness. Key variables for optimization include: determining the overall mass; the differentiation and manufacturability of the segment beams and their degree of utilization; and determining the required position, force, and length of the hydraulic cylinders. The aim of this optimization is to explore possible design alternatives before engaging a construction design partner to ensure that the trade study implications are well understood by the project team.

To ensure successful optimization of the clamshell enclosure, it is necessary to consider its behaviour in different operating states, particularly in the closed and semi-closed states as these conditions exhibit different structural behaviours and consequently different optimal solutions. The semi-closed state represents the configuration where the roof is partially open and where the highest forces and utilization factors were observed. This occurs just before the last segment is released. When opening or closing, the structure is supported by the hydraulic cylinders in addition to the pin bearings at the segment ends. In the closed state, on the other hand, locking pin joints on the outside of the portal segment seal the two halves and relieve the actuators, which lock the hydraulic cylinder in position. Therefore, it is important to use an approach that allows

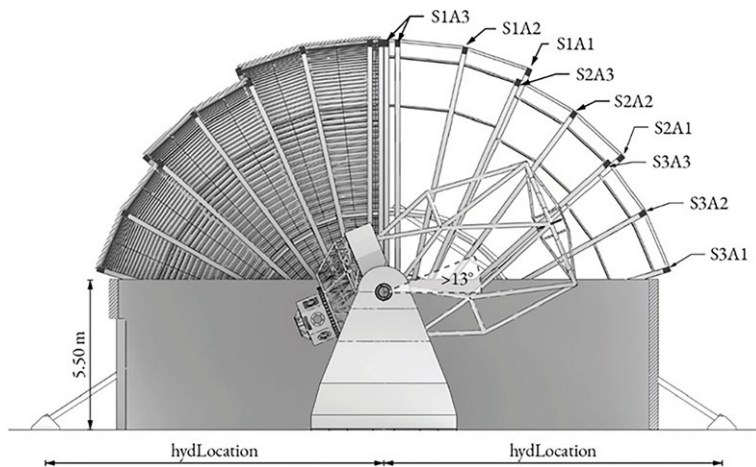


Figure 7. Side cross-section of the clamshell enclosure featuring the design parameters of beams and hydraulic cylinders.

multiple models or model responses to be integrated and used within the same optimization problem.

(a) Optimization set-up

The clamshell enclosure is optimized with three objectives in mind: minimizing the mass, minimizing the force in the hydraulic cylinder and tracking that the utilization ratio does not exceed 1.0, as shown in equation (4.1). The utilization ratio is defined in equation (4.2) as the ratio between the effects of design actions on the structure and the corresponding design resistance. The utilization calculations are derived from Eurocode 3 [47], which refers to the design of steel structures, and the maximum value between the ultimate limit state check is considered to be the utilization output. Deformations were also calculated, but they turned out not to be dominant. Furthermore, the following design parameters are considered: beam cross-sections (marked as 'S1A1'), crossbeam cross-sections (marked as 'C' and 'Ch'), crossbeam distribution along the segment, position of the hydraulic cylinder (marked as 'hydLocation') at the base and height of the hydraulic cylinder attachment (marked as 'hydHeight'), as shown in figures 7 and 8. To simplify the analysis and optimization process, only half of the structure is considered due to the symmetrical design. That is why the beam elements of only three segments are considered. These are named after the associated segment and their position within the segment. All crossbeams share the same cross-section, except for those in the second and penultimate positions, which are named 'Ch' due to being subjected to greater loading forces. For this reason, they are analyzed separately from the 'C' crossbeam members. This is also where the hydraulic cylinder is attached and where the side locking pin joints are located. The beam and crossbeam cross-sections parameters range from 112 possible pre-defined cross-section dimensions based on the RHS profiles according to Eurocode 3 [47],

$$\left. \begin{aligned} &\text{minimize } f_{\text{mass}}(x), f_{\text{force}}(x), \\ &\text{subject to } g_{\text{utilization}}(x) < 1 \\ &x \in X, \end{aligned} \right\} \quad (4.1)$$

and

where: $f(x)$ is the objective function; $g(x)$ is the constraint function and x are the design variables,

$$g_{\text{utilization}}(x) = \max \left(\frac{E_d}{R_d} \right), \quad (4.2)$$

where E_d are the design action effects and R_d is the design resistance.

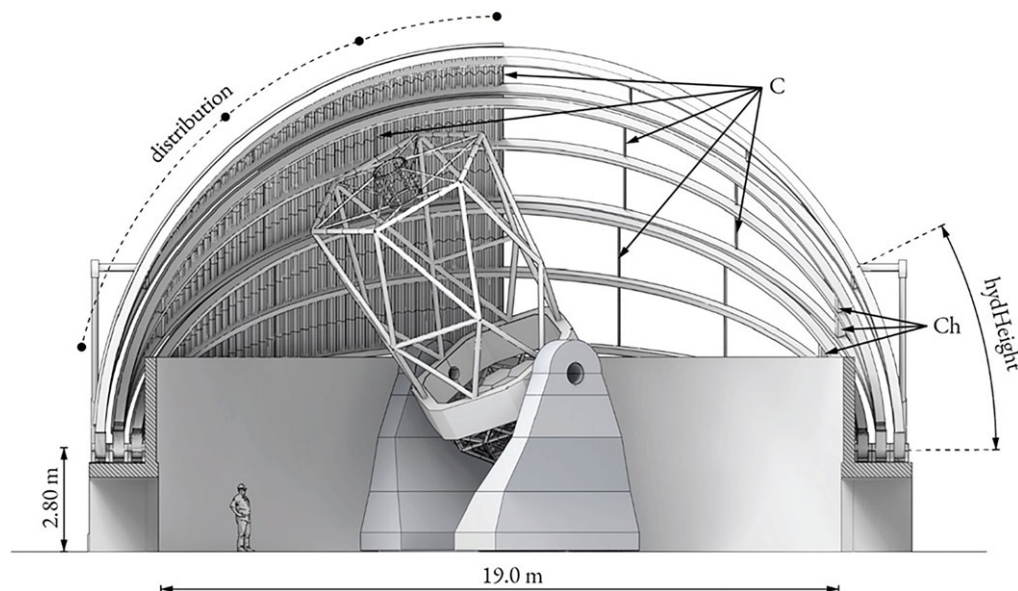


Figure 8. Front cross-section of the clamshell enclosure featuring the design parameters of crossbeams and hydraulic cylinders.

Considering all possible design parameters, the size of the search space amounted to 5.3×10^{33} of the total number of possible combinations, which makes a manual search impossible. To solve this problem, two approaches are used to effectively explore the search space. First, optimization algorithms are used to achieve reasonable convergence towards the optima. Second, surrogate models are used to approximate the responses much faster than the computational model.

(b) Computational model development

To analyze the behaviour of the clamshell enclosure, a parametric computational model is developed. This model includes the parameterized geometry of the enclosure, segmentation of geometry into finite elements, calculations of action exerted on the structure, structural analysis and visualization of the results. This allows us to modify the size and configuration of the clamshell enclosure, the sizing of the structural elements and the simulation of their responses to various loading.

For the structural analysis, the design situations according to Eurocode 0 [48] are considered. In particular, the closed state is analyzed for persistent and accidental situations under gravity, snow and wind loads. The semi-closed state is analyzed for transient and accidental situations in case of sudden wind gust during operational state or in temporary state during suspension for repairs. Calculations are performed in OpenSees using a linear static analysis with line elements for the curved beams and shell elements for the connecting roof structure. Since OpenSees does not directly support distributed loads in the global coordinate system, uniform loads were replaced by point loads at the element joints, neglecting equivalent moments. To minimize errors introduced by this approximation, the mesh density was increased until no noticeable changes in the responses were observed. In addition to gravity and ice/snow loading, three different uniform wind loads are considered: wind pressure, where the headwind acts on the roof structure against the normal direction of the surface; headwind suction, where the wind acts in the direction normal to the surface; and crosswind, where one half of the roof experiences pressure and the other half experiences suction. In addition, the study includes a total of six case studies divided into three different configurations of beam profiles and two design types to facilitate future trade-offs between manufacturability and raw material costs since manufacturing cost data was not available at this stage of the design process.

Table 1. Size of training datasets.

case study	mass	force	utilization (closed)	utilization (semi-closed)
1.a/2.a	24 363	7774	7596	7774
3.a	31 939	7733	13 808	7733
1.b/2.b	24 363	4530	4583	4530
3.b	31 939	6037	4586	6037

Table 2. Performance of various predictive models on the validation dataset.

model	metric	1.a/2.a	3.a	1.b/2.b	3.b
mass	R^2	0.999	0.998	0.999	0.998
	RMSE	0.20	0.30	0.20	0.30
force	R^2	0.995	0.987	0.991	0.987
	RMSE	3.60	3.50	4.22	4.55
utilization (closed)	Acc	0.968	0.940	0.983	0.975
	Pr	0.920	0.943	0.976	0.997
utilization (semi-closed)	Acc	0.967	0.959	0.979	0.978
	Pr	0.978	0.976	0.995	0.995

(c) Machine learning development

For all case studies, the data for the closed and semi-closed states are generated through the computational model. To this end, optimization was performed for each state to obtain data from the non-optimal and optimal data generated by the genetic algorithm. The generated data included the structural analysis responses and their parameter values as input–output pairs. Specifically, the input data included the design parameters considered, while the output data included the values of the total mass, the force in the hydraulic cylinder and the maximum utilization of the structure, respectively, for the closed and semi-closed states. Sizes of the datasets are listed in [table 1](#).

The machine learning models were developed by dividing the data into 80/20 sets for training and validation, respectively. For each scenario within the case studies, four different supervised predictive models were created, each targeting a specific output in the data. These models include: a regression model to estimate the total mass of the enclosure; another regression model to determine the force in the hydraulic cylinder; and two classification models, one to determine if the utilization ratio exceeds 1.0 in the closed state, and another for the semi-closed state. The models were formulated using the XGBoost framework, which uses tree-based predictive models based on the gradient boosting training method. During implementation, only three hyperparameters were changed from the default settings: the tree depth, ranging from three to five levels; the number of gradient-boosting rounds, ranging from 250 to 1500 in increments of 250; and the evaluation metric, which takes the mean square error for regression models and the area under the precision-recall curve for classification models. The performance of these models is listed in [table 2](#).

These predictive models were used as surrogate objective functions in multi-objective optimization. To obtain solutions that would satisfy utilization constraint, both utilization models were combined into one function by obtaining the minimum prediction probability that the utilization exceeds the threshold. These predictive models served as surrogate objective functions within multi-objective optimization. To derive solutions that satisfy the utilization constraint,

both utilization models were combined into one function. This was achieved by taking the minimum value of the two prediction probabilities that the utilization does not exceed the threshold.

As the last step, the validity of the optimal solutions is confirmed through structural analysis in the computational model. These results are then used to gain insight into the behaviour of the entire clamshell enclosure. Based on those results, the final solutions are selected,

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}, \quad (4.3)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum (y_i - \hat{y}_i)^2}, \quad (4.4)$$

$$\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.5)$$

and

$$\text{Pr} = \frac{TP}{TP + FP}, \quad (4.6)$$

where y_i is the true value; $\hat{y}_i$ is the predicted value; $\bar{y}$ is the mean of actual values; TP is the number of true positives; TN is the number of true negatives; FP is the number of false positives and FN is the number of false negatives.

5. Results

(a) Parameter analysis

(i) Prevailing wind loading

The effect of wind loading on the clamshell enclosure is significant and varies depending on whether it is subjected to a wind from a headwind or crosswind direction. In a headwind, the clamshell enclosure is protected by a full half and braced by the hydraulic cylinders, whereas in a crosswind, each half is subjected to pressure on one side and suction on the other, causing the segments to deform in the form of an in-plane buckling arch. Due to this reason, three different wind load cases are considered: headwind pressure, headwind suction and crosswind with asymmetric pressure and suction. In addition to these three different wind load cases, a snow or ice loading is applied. The preliminary analysis shows that the utilization ratio is first exceeded in buckling in bending and axial compression. This is mainly attributed to the buckling resistance of the beams, which decreases during the optimization process. This is due to the cross-sections of the beams being reduced to lower their mass. As such, the buckling is considered as authoritative, which is also reflected in the results.

(ii) Feature importance

The aim of the analysis of the simulated data is to gain insight into the behaviour of the structure. Feature importance is used to determine which design parameters have the greatest effect on the utilization ratio for the basic design type. For the closed state (figure 9a), the results show that all beams have high importance, with some variation. In the portal segment, the middle beam (S1A2) had the highest importance, probably due to bearing the majority of the vertical load of the segment. This is in contrast with the second segment, where the end beams (S2A1 and S2A3) have greater importance. The reason for this is that the locking pin joints are located at the end beams. In the third segment, all beams show similar importance. On the other hand, the crossbeams have low importance, while their distribution indicated some effect on the utilization ratio. The distribution of the crossbeam has very limited importance and due to that reason, it is decided to maintain a uniform distribution of the crossbeams and treat it as a fixed parameter in the further optimization phases. In the semi-closed state (figure 9b), the most important elements are identified as the S1A3 portal beams and the Ch crossbeams. The reason for this is that in

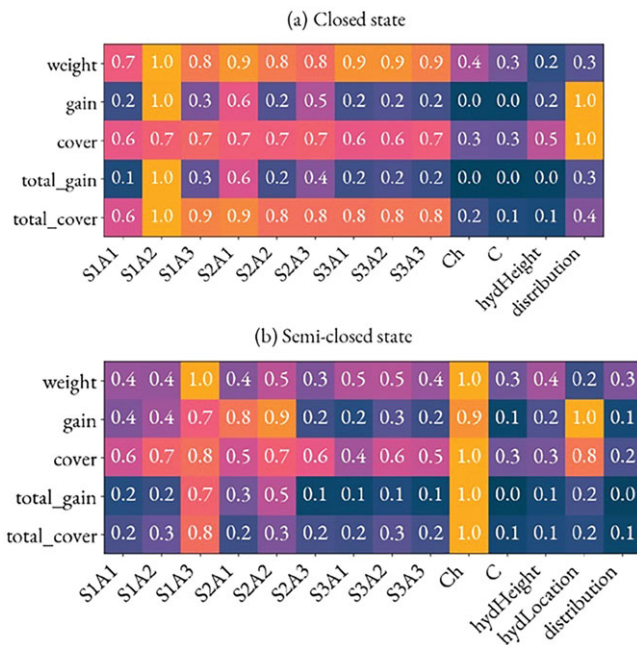


Figure 9. Relative feature importance scores based on the utilization ratio predictive model for the (a) closed state and (b) semi-closed state.

those beams the stresses are concentrated due to the transfer of the loading forces to the base supports of the hydraulic cylinders. In addition, both the base location and the attachment height of the cylinder are important factors, since their configuration dictates the bracing of the clamshell enclosure. Both parameters are considered of equal importance, although the results suggest that the hydraulic base location (named *hydLocation*) is more important. This is due to the wide range of values of the base location parameter, which may cause the feature importance algorithms to prioritize this parameter over the height of the cylinder with a smaller number of possible configurations.

(b) Structural optimization

The aim of optimization is to identify trade-off trends between design objectives and find the best possible solutions. The results of the optimization show that there is more than one optimal solution, as expected in multi-objective optimization. The trade-off trends between the mass, the utilization ratio and the forces in the hydraulic cylinder can be seen in [figure 10](#). The relationship between the mass and the utilization ratio is simple: when the mass decreases, the utilization ratio increases and vice versa. In contrast, the force in the hydraulic cylinder is more complex due to the variability of the forces in the hydraulic arm. Multiple iterations are performed with optimization algorithms to find the balance between these trade-off trends.

Several observations can be derived from the resulting parameter values shown in [figure 11](#). The optimization algorithms favoured beam cross-sections with greater height and less thickness, resulting in a greater second moment of area with the smallest cross-sectional area, thus achieving the required bending capacity with less mass. It is found that the largest cross-sections are required for the beams at the lower end of the segments (named A1), as they have to resist wind loads in the direction of the major axis as well as segment gravity and snow loads in the direction of the minor axis. In addition to these beams, the upper beam in the portal segment (S1A3) also requires a larger cross-section due to the attachment of the hydraulic cylinder. Furthermore, the

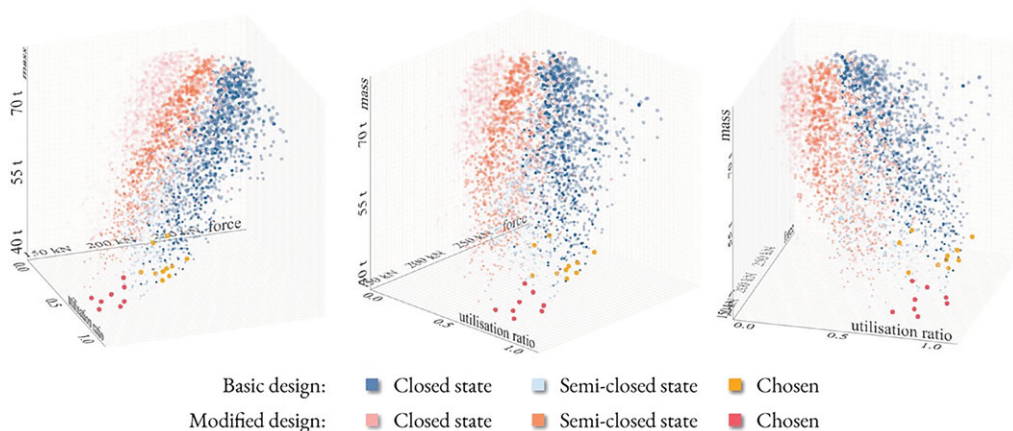


Figure 10. Trade-off comparison between different design alternatives based on the three optimization objectives.

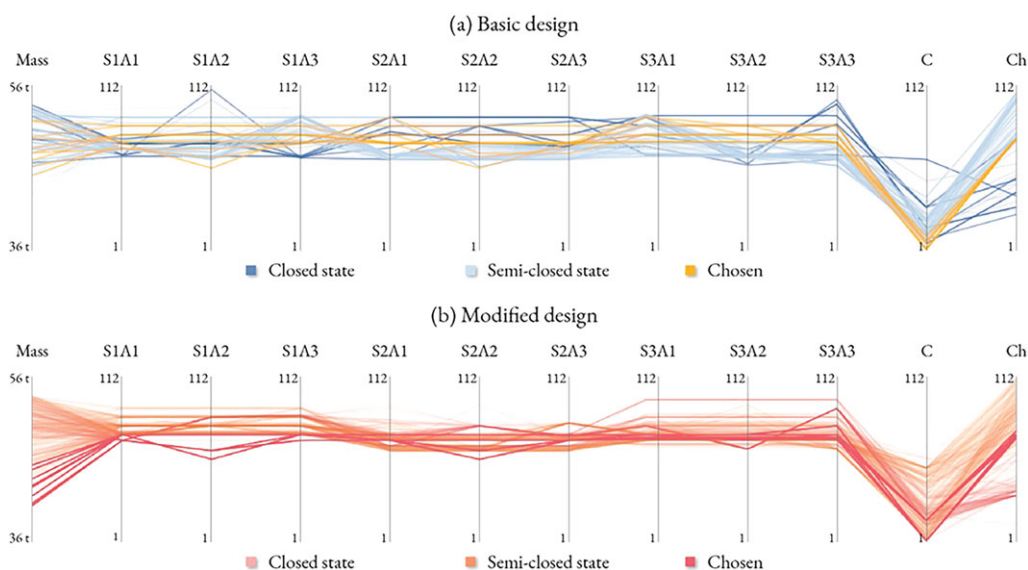


Figure 11. Parallel coordinates plot of the chosen solutions compared to the possible solutions for the closed and semi-closed states for (a) basic design and (b) modified design. The design parameters indicate the type of pre-defined RHS profiles used in the solution, with lower numbers representing smaller cross-sections.

crossbeam Ch, which is located next to the hydraulic arm, also requires a large cross-section. All other crossbeams have smaller cross-sections.

A total of 10 solutions are chosen for the basic design and eight for the modified design. These solutions ranged in mass from 45.2 to 52.2 tonnes for the basic design and from 40.4 to 45.4 tonnes for the modified design. Similarly, the forces in the hydraulic cylinder range from 183 to 206 kN for the basic design and from 142 to 166 kN for the modified design. Compared to the benchmark design with a mass of 56 tonnes and a force in the hydraulic cylinder of 220 kN, the selected solutions show an improvement in mass, which can be reduced by 19% for the best solution and 7% for the worst solution for the basic design. For the modified design, the given solutions are even better and the mass is reduced by 28% for the best solution and 19% for the worst solution. For the forces in the hydraulic cylinder, the force reduction is 17% for the best solution and 6%

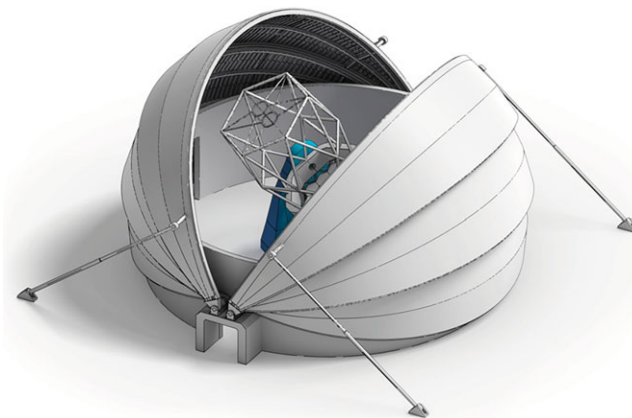


Figure 12. Final clamshell enclosure design.

for the worst solution in the basic design. In the modified design, the solutions are even better, as the force in the hydraulic cylinder is reduced by 35% in the best solution and 25% in the worst solution.

The solutions given have various degrees of utilization ratio. With the highest degree of utilization, the lowest masses and forces are achieved. Solutions with decreasing levels of the utilization ratio are also included as they are considered safer solutions. However, these solutions have increased mass and force in the hydraulic cylinder compared to the best solutions. The multiple solutions allow the design partner to test the most optimal option and proceed with subsequent alternatives if the test fails, continuing until all design criteria are met and the final design is selected (figure 12).

6. Conclusion

The method presented has proven to be very effective, as it substantially narrows the scope and number of feasible solutions that meet all criteria and constraints. This was achieved by combining multiple analyses into one evaluation model through the use of machine learning-based surrogates. This approach addresses interoperability issues in generative design and optimization problems.

The results of applying this method to the design of the NRT enclosure show a significant improvement in design performance. They show that for the best given solutions the mass and forces in the hydraulic cylinder were significantly reduced. It is also important to emphasize that even the least favourable solutions still contribute to the reduction of the mass of the enclosure and the forces in the hydraulic cylinder.

The aim of this design exploration was to identify potential design alternatives before engaging a design partner, allowing for more efficient project development. This resulted in a variety of efficient solutions with varying degrees of utilization, mass and force, serving as baseline options for the clamshell enclosure design in the next phase of project development. The design partner can use the results of this study to immediately focus on the design work without spending time understanding the implications for the telescope.

Although the methodology has inherent limitations, particularly in terms of precision due to its reliance on surrogate models, which are approximations of the original computational models, these limitations are manageable and justified by the method's flexibility. To ensure reliable results, surrogate models must be validated against the original computational models. Achieving high accuracy usually requires a large amount of simulated data, which can be time-consuming and resource intensive. Alternatively, less precise surrogate models can be used; however, this

often necessitates manual corrections to ensure that all design criteria are met. Despite these constraints, a key strength of the methodology is its extensibility. Additional analyses can be integrated at any point by incorporating new surrogate models. These models can then be used in renewed optimization runs without re-running earlier simulations, enabling efficient updates and expanded design exploration throughout the development process.

Data accessibility. The complete dataset and code base of this study are not publicly available as they remain in an experimental and fragmented state. They consist of numerous interdependent scripts, raw data and intermediate files that lack the structure, documentation and contextual framework required for meaningful external use. Without the specific explanations and methodological context contained in this manuscript, it would be difficult to interpret or reliably reproduce these materials.

However, we are committed to supporting scholarly verification and collaboration. Upon reasonable request, we are willing to provide access to key raw data (including raw hydraulics measurements, mass data and enclosure specifications) and key analysis scripts (e.g. for mass prediction, enclosure classification and hydraulics categorisation) to qualified researchers for academic purposes. Requests should be directed to the corresponding author and may be subject to a brief material transfer agreement to ensure appropriate use.

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. L.G.: investigation, methodology, resources, software, validation, visualization, writing—original draft; T.MC.: conceptualization, data curation, formal analysis, investigation, methodology, resources, software, supervision, validation, visualization, writing—original draft, writing—review and editing; D.C.: conceptualization, data curation, funding acquisition, project administration; A.M.: conceptualization, data curation, funding acquisition, project administration; M.D.: conceptualization, data curation, formal analysis, funding acquisition, investigation, project administration, validation, visualization; R.K.: conceptualization, investigation, supervision, validation, visualization, writing—original draft, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

Conflict of interest declaration. We declare we have no competing interests.

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