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Daisy: A Data-Driven Multi-Objective Design Tool

Abstract: Meeting climate pledges demands that building performance for new construction is optimized in a multi-objective manner that minimizes operational energy and embodied carbon whilst balancing architectural objectives such as daylight. Daisy is a performance-driven, parametric design tool which harnesses machine learning to enable designers to navigate the design space for multi-objective optimization which has rarely been attempted at the concept stage. In this paper we explore a case study design for a 63-storey commercial building in central London. This paper highlights how early-staged design space exploration facilitates higher performing engineering and architectural performance providing optimized whole-life carbon design. The Daisy workflow allows the relative importance of early-stage design input parameters relating to the building's shape, size, orientation, structure, façade and building service systems to be estimated by harnessing data science techniques. Daisy was able to demonstrate the design improvement potential from the benchmark design with two clear trade-off strategies. First, by reducing the spatial daylight autonomy from 63.5 % to 52.9 %, the energy use intensity can be reduced by 4.1 % without increasing building embodied carbon. Secondly, by increasing the spatial daylight autonomy by 14.7 % and accepting an increase in building embodied carbon, the energy use intensity of the design can be reduced by 7.1 %. The application and benefits of surrogate modelling for interactive design exploration and design variable importance is discussed.

1 Introduction

To meet the challenge of the carbon emergency requires a step-change in how buildings are designed. Multi-objective optimization as part of early-stage design of buildings has the potential to significantly reduce building embodied carbon associated with material use and whole life operational carbon emissions associated with a building's energy use. Such reductions may greatly outweigh carbon savings which are potential later in the design process. However, despite an increased emphasis on building performance (Lützkendorf 2015; Swan et al. 2015; LETI 2020) little work has explored the potential for optimization in early-stage conceptual design. Effective early-stage design optimization requires balancing conflicting performance objectives including energy use associated with operation and maintenance of the building, the carbon emissions arising from the structural materials, and user-comfort criteria such as achieving a target illuminance level during operational hours. Balancing design trade-offs can

https://doi.org/10.1515/9783111162683-009

be achieved through multi-objective optimization (MOO) which simultaneously maximizes a set of performance objectives through searching a multi-dimensional design parameter space (Deb 2011; Evins 2012). Rather than identifying a single "globally optimal" design, MOO is used to identify the pareto front; designs which have optimal performance for one objective without negatively impacting the performance of any other objective (Deb 2011).

Despite advances in parametric design and MOO for building structures (Machairas et al. 2014; Samuelson et al. 2016; Brown and Mueller 2016; Gehry et al. 2020; Brown et al. 2020; Gauch et al. 2023), limited work has explored MOO for simultaneous optimization of building embodied carbon, operational energy use and user-comfort metrics such as spatial daylight autonomy.

1.1 Daisy

This work introduces Daisy, a performance MOO parametric design tool incorporating machine learning and data- driven computational workflows for designer-led optimization as part of early-stage building design. A workflow of Daisy is presented in Fig. 1, highlighting how it incorporates parametric design (Jabi 2013) and design cataloguing (Brown et al. 2020).

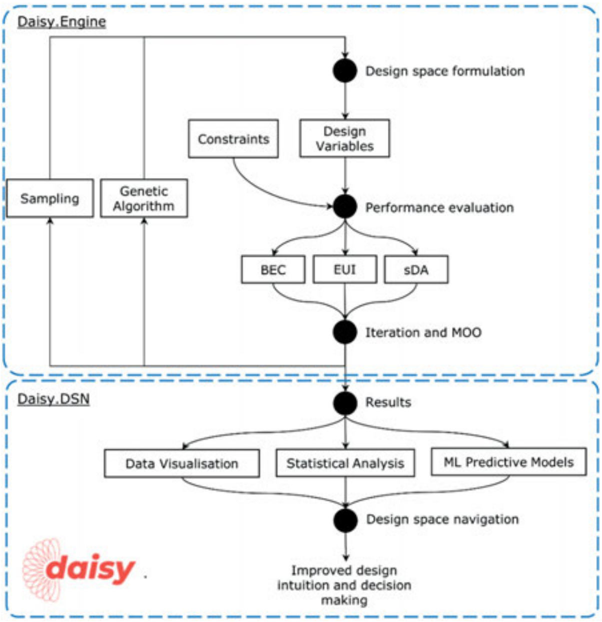

Fig. 1: Daisy design methodology flowchart. Chauhan et al. (2023).

Daisy.engine utilizes Rhinoceros 3D (Robert McNeel & Associates, 2020) and Grasshopper modelling tools (Akos et al. 2014) for performance-based parametric design, while Daisy Design Space Navigator (Daisy.DSN) utilizes surrogate models, statistical approximations of the non-linear design space, which enable users to intuitively navigate the design space and generate near real-time predictions of performance objectives. Daisy allows designers to simulate how changes in design parameters impact the global performance of the building and allows sets of designs which fall on the pareto front to be identified. In Daisy.engine, parametric design variables are selected through Latin Hypercube sampling (selecting sets of parameters from an n-dimensional grid, Loh 1996) and the NSGA-II genetic algorithm (Deb 2011), implemented using the Wallacei plugin (Makki et al. 2018).

For this study the three performance indicators for the MOO in Daisy are:

1. Building embodied carbon (BEC) per square meter of gross internal floor area
2. Energy use intensity (EUI) per square meter of gross internal floor area
3. Spatial daylight autonomy (sDA)

1.1.1 Daisy.DSN

Daisy is designed to seamlessly integrate with the existing user-orientated design process through tools such as a web-hosted dashboard, which allows designers and clients to explore the design space and form an intuitive understanding of the relationships between design variable and performance objectives.

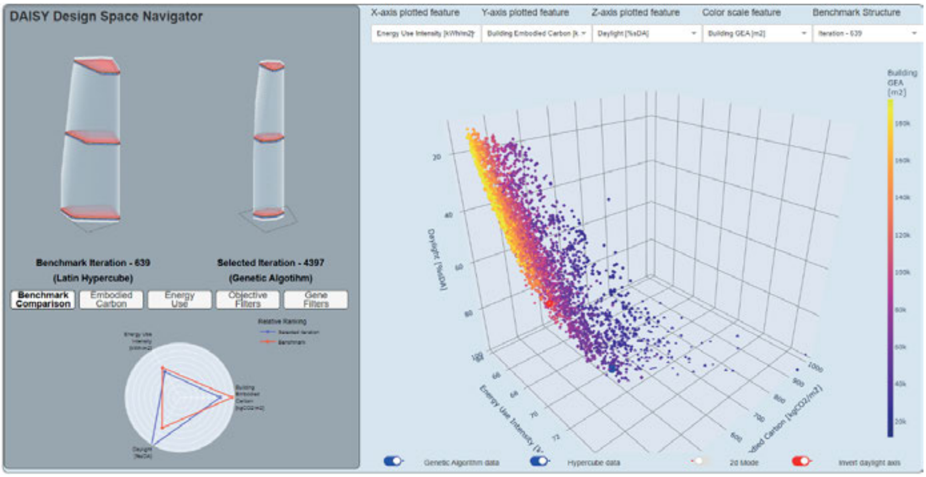

Fig. 2: Daisy.DSN web hosted dashboard.

To further strengthen designer understanding of the design space, Daisy.DSN implements surrogate models including quantile regression models (Fahrmeir et al. 2013) and random forests (Williams and Cremaschi 2019). These models enable informed navigation of the design space, highlighting to users the relative impact of changes on design variables on the performance of a benchmark structure, and allow approximated near real-time design simulation.

2 Case Study Methodology

In this paper Daisy is applied to the design of a real-world 63-storey commercial building. Surrogate modelling is demonstrated as an efficient way to aid user-led design exploration and communicate to clients the factors involved when weighing design decisions. The case study building, initially designed using a conventional design methodology, is a 63-storey, reinforced concrete framed, commercial building in central London and is typical of modern tall urban buildings. The results presented in this paper are anonymized with a benchmark design selected which has similar EUI, BEC and sDA selected for benchmarking relative performance.

2.1 Design space formulation

Histograms of the 13 building façade and shape variables used in the Daisy.engine design simulations and which define the design space for optimization are presented in Fig. 3. Further details of the implementation of the analysis in Daisy.engine are provided in Chauhan et al. (2023).

2.2 Performance evaluation

At the client's request, all design objectives used within the case study are normalized per square meter of internal floor area. This was carried out to investigate the effects of a varying floor area on design trade-offs between performance objectives.

Objective 1 – Embodied Carbon of Structure and Façade
Eurocode compliant structural frame designs are generated through an internal calculation engine, with accompanying embodied emissions calculated using BS EN 15978:2011 (BSI 2011). Emission coefficients, including construction and transport contributions, are derived from the ICE database (Hammond and Jones, 2008).

The façade embodied carbon is calculated individually for each façade orientation through a weighted average of a typical façade bay, adjusted for the design space

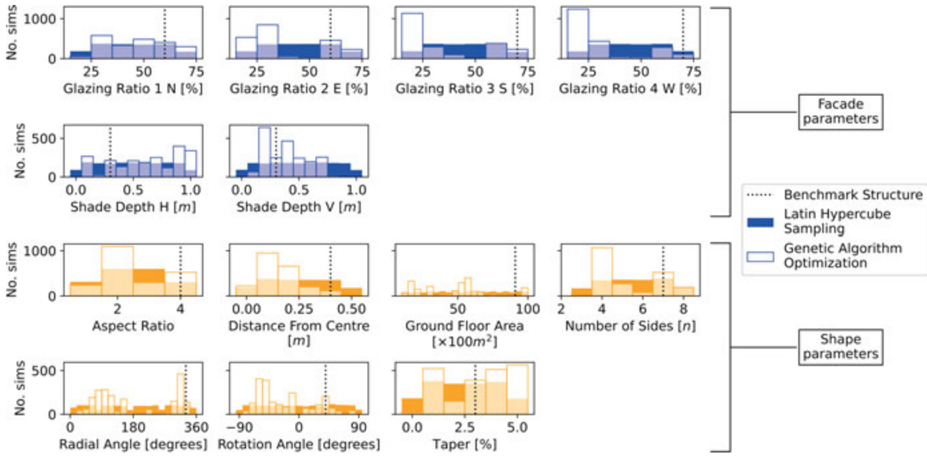

Fig. 3: Histograms of variables used in design optimization of case study building.

variables, following the standard for systemized building envelopes (Centre for Window and Cladding Technology 2006). Cradle-to-gate global warming potential of all façade components are assessed through environmental product declarations using the methodologies specified in BS EN 15804 (BSI 2012) and BS EN 15978 (BSI 2011).

Objective 2 – Operational Energy Use

Dynamic thermal models are implemented in Grasshopper using the Honeybee plugin (Roudsari et al. 2013). Within the models, ceiling and floors are modelled as adiabatic and each floor is separated into a core zone surrounded by a perimeter zone of 4.5 m depth. Heating and cooling units located at the edge of the perimeter zone are assumed to minimize mixing between perimeter and core zones, with an assumption of zero convective loss between regions. A closed cavity system with fixed U-values and G-values are used across the designs.

Simplified mass site context, derived from OpenStreetMap (OpenStreetMap contributors 2022), is used for modelling of shading provided by surrounding buildings. Lighting use is modelled as dynamically controlled. Operational energy use is calculated through a weighted average of the energy use for the ground floor, top floor, and a floor at mid-height of the building. For each floor, an area weighted operational energy use is calculated for each façade orientation. HVAC systems are modelled as air handling units with thermal wheel heat recovery which supplied demand controlled minimum fresh air to fan coil units. Heat pumps and air-cooled chillers, with dynamic efficiencies following ASHRAE limiting performance curves (RANSI 2020), are used for heating and cooling calculations.

Objective 3 – Spatial Daylight Autonomy
Spatial daylight autonomy (sDA), the percentage of floor area which achieves a target illuminance level exceeding 300 lux for 50 % of occupied hours, is used to measure access to daylight in the building. sDA is used in the WELL building standard (WELL Building Institute 2014) and the Leadership in Energy and Environmental Design (LEED) green building certification (Kubba 2016) and accounts for local weather data and site context building geometry. The sDA is calculated using a 2 m sensor grid, at height 1.2 m, with the perimeter core scaled by 25 % and internal partition zones removed to account for daylight within the central core area.

3 Case study results

Plotted in Fig. 4 are comparisons of the performance indicators calculated in Daisy.engine for the genetic algorithm (GA) optimization and the hypercube sampling, and data from the simulated benchmark structure. The pareto fronts for each combination of performance indicators are shown independently in the 2D subplots, with a global pareto front calculated from the combined GA and hypercube data shown in the 3D subplot.

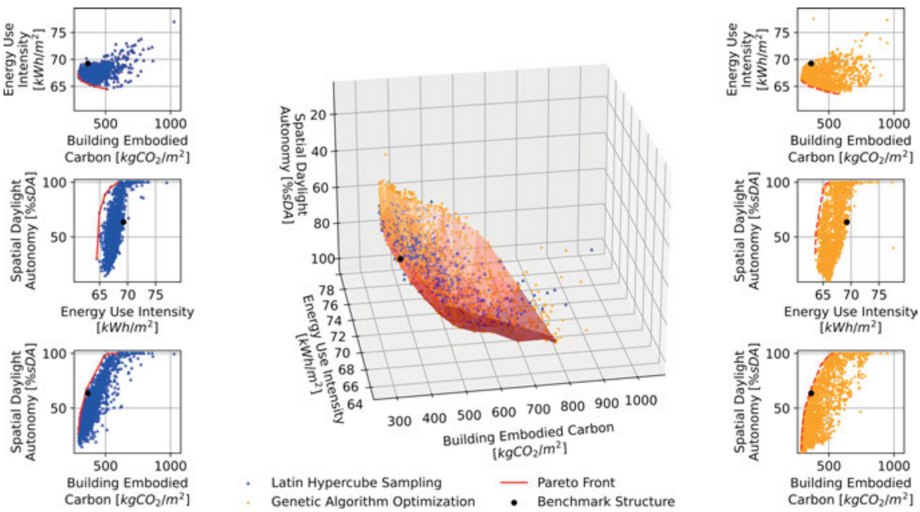

Fig. 4: BEC, EUI and sDA for hypercube sampling (blue triangles, left) and GA optimization (yellow dots, right). Performance of benchmark structure highlighted in red.

Figure 4 highlights that greater mapping of the solution space and higher average performance was achieved through GA optimization than hypercube sampling, as shown through comparison of the pareto fronts. This suggests that the GA successfully improved the performance of the building designs whilst maintaining diversity within the design parameters.

4 Discussion

For individual performance indicators, designs are identified with a BEC of 287.7 kg CO_2/m^2, 25.1 % lower than the median value, or an EUI of 63.6 kWh/m^2, 5.2 % lower than the median value. Numerous designs are identified with a sDA of 100 %, 2.17 % higher than the median. These designs are extremities of the pareto front identified by Daisy; while they maximize performance for one objective this is often at the expense of other performance indicators. Other designs, while not maximizing a single performance indicator, may offer more palatable design trade-offs that balance the competing needs of reducing EUI and BEC, whilst maximizing sDA. Note, potential reductions in EUI are limited due to a range of fixed energy uses within the building which reflect typical commercial buildings. This provides a lower bound EUI which can be achieved.

4.1 Benchmark structure performance

Relative to other designs, the benchmark structure has a high external window area and a low form factor, as demonstrated in Fig. 5. While the benchmark structure is pareto efficient, as shown in Fig. 4, with an sDA higher than 72.3 % of designs simulated and a BEC lower than 60.4 % of designs simulated, the benchmark structure's EUI is higher than 94.1 % of other designs.

4.2 Balancing performance objectives

Figure 6 presents the normalized performance indicators relative to the gross internal area (GIA) of the designs obtained from hypercube and GA sampling. The results highlight that, while a building which maximizes GIA allows for reductions in BEC through minimizing the area of carbon intensive façade required, this severely limits the maximum sDA which can be achieved. A lower sDA results is an increased EUI, due to the need for artificial lighting. To achieve a high sDA, the GIA must be smaller. However, as the GIA decreases, other design parameters must be holistically selected to avoid an increased EUI arising from higher peak cooling and heating requirements due to factors such as high glazing ratios or aspect ratios.

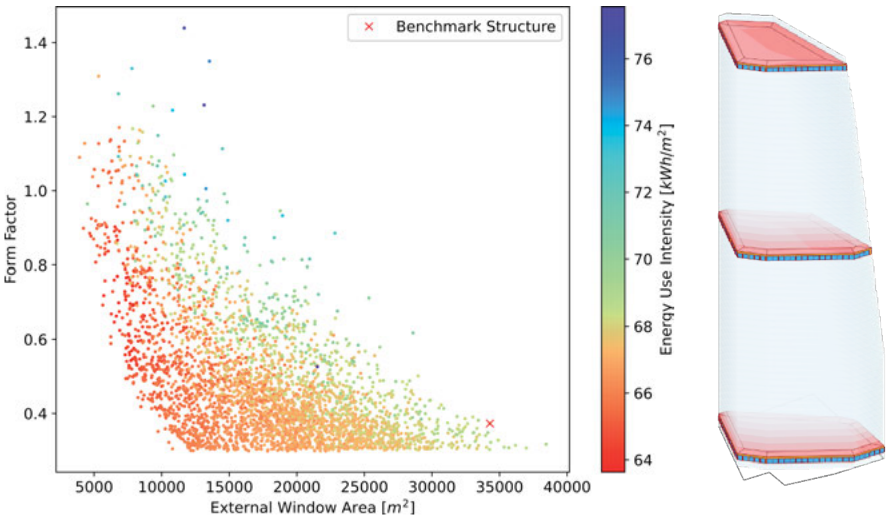

Fig. 5: Left: Comparison of EUI, form factor and external window area; Right: Simulated benchmark structure.

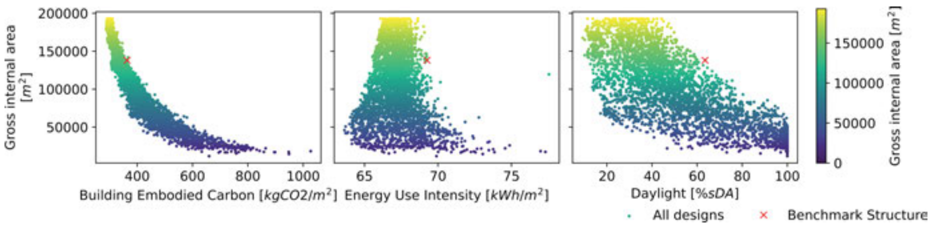

Fig. 6: GIA plotted against normalized performance indicators.

4.3 Random Forests: Pareto optimization and design compromises

Random forests (Williams and Cremaschi 2019) are used to identify roadmaps for improving global design efficiency, identify predictive variables for specific design performance, and enable informed navigation of the design space. Random forests of binary decision trees are implemented with the Scikit Learn Python package (Pedregosa et al. 2011), with 40 % of the data for model verification. Tree depth is increased sequentially to achieve 95 % training accuracy. No meaningful differences in classification accuracy between training and held back data was noted for the case study data, suggesting robustness of the fitted models.

The output from the random forests is the normalized feature importance's, the average total reduction in inaccurately classified designs arising from the use of the design parameter in the binary classification. These feature importance's provide a relative ranking that allow informed navigation of the design space.

Three design scenarios, shown in Fig. 7 and based on the real-world needs of the designers, are examined:

1. Characterizing designs with sDA < 40 %, the limit of good daylighting as defined in the LEED standard (Kubba 2016),
2. Identifying routes to reduce EUI of the benchmark structure through increasing sDA and BEC,
3. Identifying routes to reduce EUI of the benchmark structure through decreasing BEC and sDA whilst ensuring sDA > 40 % (Kubba 2016) or sDA > 55 % (WELL Building Institute 2014).

In relation to design scenarios 2 and 3, as the benchmark structure is already on the pareto front for BEC and sDA, to reduce the EUI compromises must be made in either the sDA or the BEC.

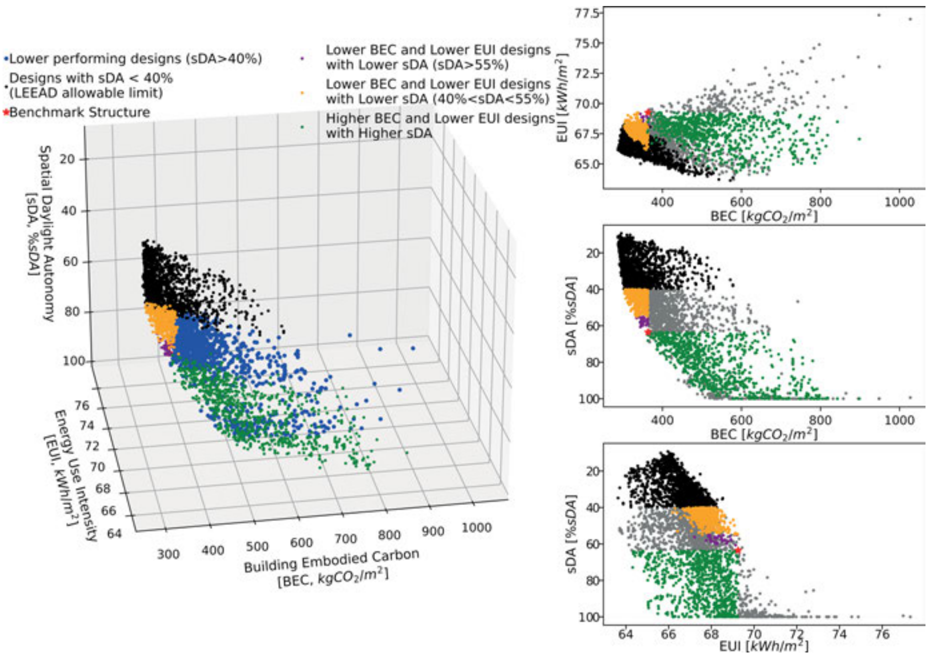

Fig. 7: Design scenarios explored through random forests; comparison of performance indicators.

Designs with sDA < 40 %

A random forest with a maximum depth six, identifies the external wall area as the greatest predictor of sDA < 40 % (feature importance = 0.810), as plotted in Fig. 8. This is followed by the minimum radius of the design (feature importance = 0.030) and a range of other parameters with smaller importance. Counterintuitively, the average window

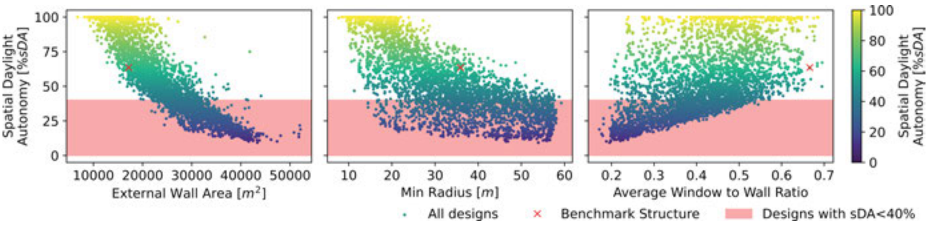

Fig. 8: Comparison of design parameters relative to sDA < 40 %.

to wall ratio of the building is a relatively poor predictor of designs with sDA < 40 % (feature importance = 0.003) as it fails to account for the combined effect of the building form and internal floor area.

Reducing EUI through increasing sDA and BEC

Increasing sDA of the design allows reductions in lighting and heating, potentially reducing the EUI of the design. However, due to the high BEC of the façade, there is a strong positive correlation between sDA and BEC and any increase in sDA is likely to increase BEC. The simulations demonstrate that increasing sDA can allow a reduction in EUI of the benchmark design of up to 7.1 %, from 69.2 kWh/m^2 to 64.3 kWh/m^2, moving the EUI from higher than 94.1 % of other simulated designs to lower than 98.8 % of simulated designs. The cost of this design decision is an increase in BEC of 220 kg CO_2/m^2, 60.9 % of the BEC of the benchmark structure. Through accepting smaller reductions in EUI more palatable designs can be identified through the Daisy.DSN design catalogue, an example of which is shown in Fig. 9. For example, there is a design which has an EUI lower than 70 % of other designs simulated, enabling a reduction in EUI of 3.7 %, but requires an increase in BEC of only 2.7 %.

Design parameters which enable reductions in EUI through increased sDA, as identified through a random forest with a maximum depth of five, are high external wall areas (feature importance 0.665), high minimum radii (feature importance 0.210), high window to wall ratios (feature importance 0.070) and a high surface area to volume ratio (feature importance 0.027), all plotted in Fig. 10. The key contribution of these features to the EUI efficiency are to significantly reduce the building's heating and lighting requirements.

Reducing EUI through decreasing sDA and BEC

Decreasing sDA improves the energy efficiency of the façade and decreases the cooling requirements for the building, enabling a lower EUI. In the context of carbon neutral buildings, this has the added advantage that, due to the strong correlation between sDA and BEC, reducing the sDA reduces the BEC. The limitation of this approach is that, to meet the LEED standard (40 % sDA), the maximum reduction in EUI which

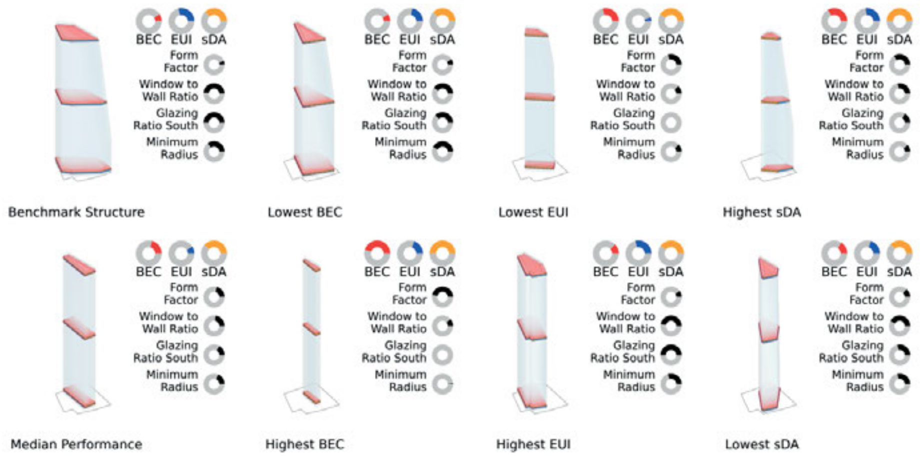

Fig. 9: Partial design catalogue for reducing EUI, through increasing sDA and/or increasing BEC. Radial dials show performance of designs relative to combined hypercube and GA datasets, scaled to have a minimum value of zero and a maximum value of one.

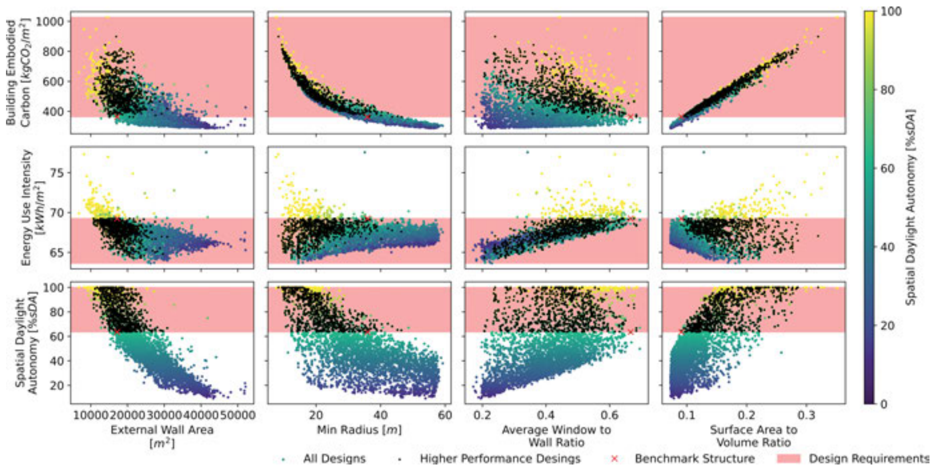

Fig. 10: Comparison of design parameters with a reduced EUI, increased sDA and increased BEC relative to the benchmark structure.

can be achieved is 4.4 % (69.2 kWh/m^2 to 66.2 kWh/m^2), lower than that which could be achieved when increasing the sDA. However, the EUI of this design remains lower than 76.3 % of other designs and allows for a BEC which is lower than 62.8 % of other designs simulated. As with reducing EUI through increasing sDA, there are a range of designs which enable a reduced EUI through decreased sDA, select examples of which are presented in Fig. 11.

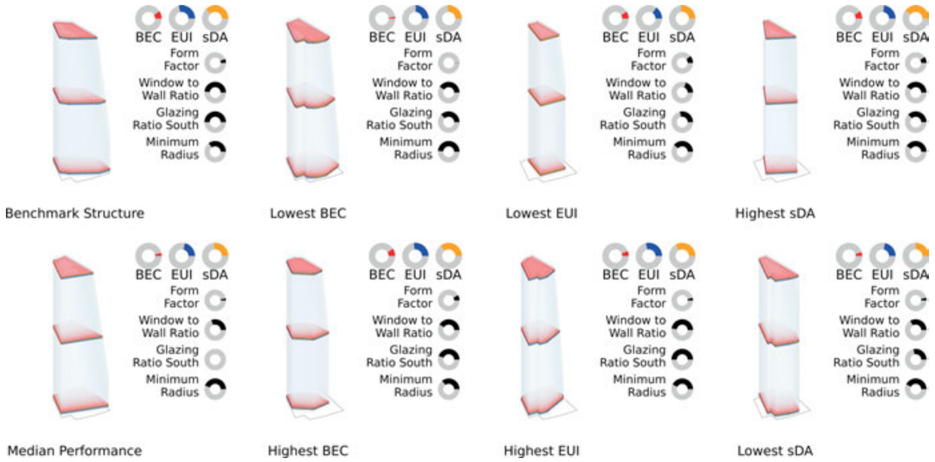

Fig. 11: Partial design catalogue for reducing EUI, through decreasing sDA and/or decreasing BEC.

Three features dominate the random forest for designs which enable reduced EUI, BEC and sDA, allowing the target classification accuracy of 95 % to be achieved with a maximum depth of 3. The key design parameter is external window area (feature importance = 0.526). Unexpectedly, designs which achieved a lower EUI through reduced sDA have a higher external window area than average. This arises due to the interaction with the other key design parameters of form factor (feature importance = 0.278) and external wall area (0.196). Designs with lower sDA and EUI have low form factors and moderate external wall areas, corresponding to stockier buildings with relatively high average window to wall areas, as shown in Fig. 12. However, these designs fall within local optima of EUI, balancing the competing needs of lighting, cooling, and heating.

5 Conclusion

The case study results have highlighted how Daisy, a multi-objective optimization (MOO) data-driven design methodology, enables generation of high-performance building designs that maximize spatial daylight autonomy (sDA), whilst minimizing energy use intensity (EUI) and building embodied carbon (BEC). Beyond this, surrogate modelling in the form of random forests, implemented as part of the Daisy design space navigator, allows designer-led optimization by quantifying relative feature importance, enabling informed navigation of the design space.

Through surrogate modelling, two roadmaps for reducing the EUI of the benchmark structure were identified, by increasing sDA and BEC, or reducing sDA and BEC. A broad range of designs fulfilling these criteria were identified allowing the creation of design catalogues whereby the user can weigh the trade-offs necessary to improve performance.

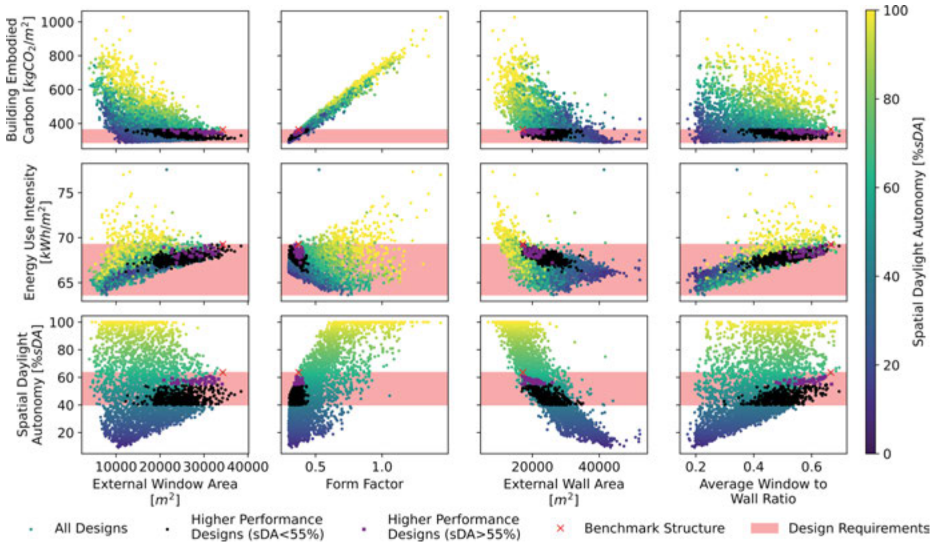

Fig. 12: Comparison of design parameters with a reduced EUI, decreased BEC relative to the benchmarkstructure and with sDA>40 % (LEED Standard) or sDA>55 % (WELL Building Standard).

In the context of the case study, this included whether a design which increased sDA and enabled a reduction of EUI of 3.7 %, to give an EUI lower than 70 % of other simulated designs, and required an associated increase in BEC of 2.1 %, was more attractive than a design which reduced EUI by 7.1 %, to give an EUI lower than 98.8 % of other simulated designs but required an increase of BEC in excess of 25 %. Alternatively, by reducing sDA, a reduction in EUI of 4.4 % relative to the benchmark could be achieved with a BEC which is lower than 61.8 % of other designs simulated. Quantifying these design trade-offs through multi-objective optimization allows for the user-informed, data driven decision making which is crucial in the move to a net-zero built environment.

The development of Daisy will continue to be driven by the needs of designers, for example by allowing limits on acceptable gross internal floor area to be defined by the user, allowing parallel simulation of multiple buildings within a single area, and allowing real-time approximated simulation of designs through surrogate modelling.

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