Net-Zero Navigator:
A platform for interactive net-zero building design using surrogate modelling

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Abstract

The design of high-performance buildings requires rapid iteration over many highly-integrated choices. These must be made early the design process, as certain performance targets like net-zero energy consumption may not be achievable at later stage. Existing high-resolution simulation approaches are not easily able to deliver fast, integrated design iterations.

In this paper we introduce the Net-Zero Navigator, an open-source platform for conceptual building performance design based on surrogate modelling. It leverages state-of-the-art machine learning techniques to provide surrogate models which emulate high-fidelity building performance simulation results, providing accurate design performance estimates instantly. Results are given to quantify the performance of the surrogate modelling approach, which achieved R^2 values of over 96%.

The platform builds on a suite of existing software tools (EnergyPlus, TensorFlow, KERAS API) as well as the codebase of the Building and Energy Simulation, Optimization and Surrogate-modelling (BESOS) platform. Overall, the Net-Zero Navigator platform provides a fast, interactive way to undertake concept-stage building design.

Introduction

Performance-based building design

In performance-based building design, energy metrics are used to quantify how much a design fulfils single or multiple design objectives (Kalay, 1999). This paradigm spread rapidly in recent years and as a result there are a proliferation of building energy simulation software options to address this need (Attia, 2010).

Energy performance analysis tools are used throughout the design process, from conceptual to detailed design (Östman, 2005). The Net-Zero Navigator is currently targeted to support guidance in the early design stages, where the design is most flexible and decisions have the highest impact on final performance. At this stage, absolute accuracy can be sacrificed in favour of flexibility, breadth and speed of design space exploration. this fits well with the surrogate-modelling based approach.

Conceptual design analysis tools

Existing energy simulation software tools apply building physics equations with varying level of detail. More detailed tools require careful building model implementation and potentially have long simulation run times. This mismatches the need for fast feedback during the highly dynamic process of the early design stage, where multiple, strongly differing design concepts are to be explored (Petersen, 2011).

For that reason a subfield of tools is developing which aims at low computational cost, limited number of user input requirements, and a high degree of interactivity. The underlying performance estimates are either based on *simplified physics* models or collected from *a database of pre-run parametric simulations*. Recently, the use of statistical simulation *surrogate models*, also called emulators or meta-models, gained increasing attention (Westermann and Evins, 2019). Examples include tools from Nielsen (2005) who developed a dynamic, single-thermal-zone, lumped parameter model to estimate energy demand and indoor comfort, and from Gratia and De Herde (2002) who developed OPTI, a tool which provides annual thermal needs and thermal comfort estimates by accessing a database of pre-run simulations.

In comparison to the previous methods, Ritter et al. (2015) used a statistical emulator of a detailed, dynamic simulation tool to provide performance estimates in their DSEAM tool. Although the model is a rather simplistic second order linear regression model fitted to simulation output data it has multiple advantages over the approaches mentioned above.

First, no simplification of building physics is done, and only a small error of the statistical model is introduced. Given recent advances in machine learning even very complex physical phenomena can be emulated (Kasim et al., 2020). Second, no parametric data must be stored and the tool uses a continuous function providing the user with performance esti-

mates for a continuous set of a large set of design inputs. The latter in particular allows design space exploration and "recognizes that different (building) forms can successfully achieve similar functions" and performances (Kalay, 1999).
When we analyse design spaces spanned by large number of parameters, advanced visualization techniques are required. Ritter et al. use parallel-coordinate plots (PCP) which were also found popular in industry with multiple trials to develop interactive tools to building designers [1].

Contributions of this paper

The Net-Zero Navigator will be the first tool to allow building designers who are not machine learning experts to leverage advancements in surrogate modelling to drastically improve their ability to find high performance building designs.
The platform features a holistic set of building archetype surrogate models, which can be accessed using intuitive visualizations hosted on a web-platform. Beyond that, an advanced user interface allows users to access the underlying codebase and Jupyter Notebooks, such that the process of surrogate modelling and visualiziation of building design spaces can be customized if needed.
Computational optimization of buildings has been an increasing focus of research in recent years, as detailed in Evins (2013). The Net-Zero-Navigator (NZN) platform builds upon this work to deliver a practical, usable tool for design space exploration, which was often the underlying intent of many optimization studies.
The NZN platform goes beyond existing Canadian energy compliance tools (CANQuest, HOT2000 etc.) by providing rigorous simulation, multi-objective optimization, and visual exploration of design implications. It goes beyond previous simplified compliance guidance (e.g. screeningtool.ca) by providing much greater breadth and detail in results exploration. It goes beyond HTAP and BTAP (developed by Canmet) in providing surrogate modelling coupled with a user-friendly interface.
The Net-Zero Navigator is the first platform to provide visual exploration and optimization of buildings in an accessible online environment. It spearheads the application of modern computational techniques (cloud computing, machine learning, interactive visualization) to this domain.

The platform

The platform is composed of a *core* and an *advanced interfaces*. The software architecture diagram is presented in Figure 1.
The main features and the way they work together is detailed below. EnergyPlus simulations capture the whole building-level interactions between different

[1]Building Pathfinder (`http://www.buildingpathfinder.com/`), BTAP (`https://canmet-energy.github.io/parallel-coordinates/`), Canmet-Energy (2020)

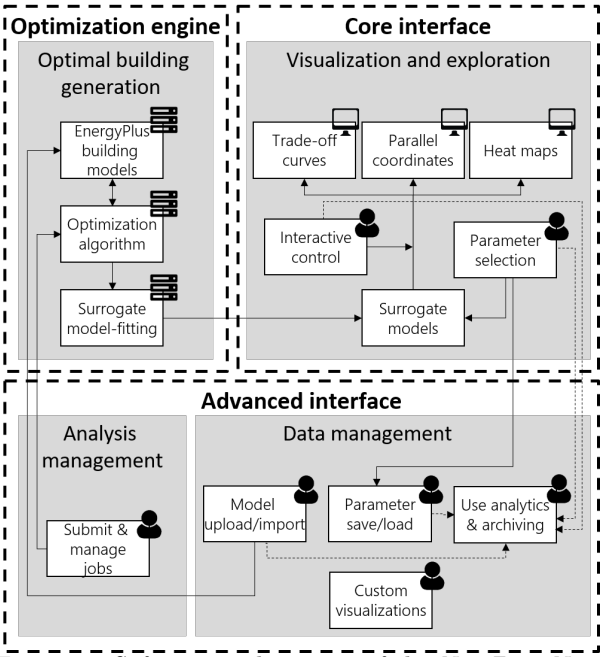

Figure 1: Software architecture of the Net-Zero Navigator platform.

elements and systems. Results are used to generate surrogate models (fitted statistical representations of optimization data) for effective deployment as an online platform. Optimization algorithms can then be applied to find synergies across many objectives. A prototype advanced interface allows optimization and exploration using user-uploaded models, calibration of models to measured building data prior to exploration, and user data analytics. The platform combines the best available technologies in each area to provide a user-friendly, open-source interface for optimization and visualization.
The core methodologies employed are detailed building energy simulation, multi-objective optimization, surrogate modelling and web-based interactive visual data exploration, brought together through an API-based modular software implementation, as shown in the software architecture diagram in Figure 1. Icons indicate user interface modules, cluster-based computation modules, and visualization modules.
The interfaces as well as the process to fit surrogate models are described in more detail in the following sections.

User Centered Design

A core objective of the NZN project is the practical integration of surrogate modelling methods into the work processes of industry user groups and stakeholders, creating a platform to leverage the domain-knowledge of building designers and planners using more robust parametric modelling tool sets. This involves developing a refined interface for defining simulation parameters, interrogating sub-model analyses, and visualizing surrogate output. Feedback and testing by users will be central to the iterative

refinement of the methods and development of an interface for practical application of these surrogate modelling modules.
Prototype interface and visualizations will be developed in JavaScript in order to interface easily with the computational modules developed in for the underlying surrogate modelling. The interface design will be refined through an iterative process involving user-group testing. The overall methodology and module structures will be documented and reported using user interface design and open source best practices. This will include development and implementation of training modules, workshops and information sessions that will aim to expand the user base and foster a collaborative environment for continued development of the tools and methods.
A summary of the intended user definitions, functionality and outputs are shown in Figure 2.

Due to the open and adaptive development structure of NZN, the overall scope of the NZN project encompasses a broad range of potential user groups and use cases. To address the gaps in conventional building simulation practice, and to leverage the surrogate modelling framework developed for BESOS, the design focus of the NZN platform divided between two main interface modes: *core* and *advanced*.

Core Interface

The *core interface* provides interactive visualization for design exploration. The surrogate models resulting from model-fitting are provided via a cloud-based service to allow real-time optimization via an online interactive visualization interface. This core tool will allow designers to refine parameters and observe the impacts in real time, quickly gaining an understanding of the best paths to high performance for a given building type and context.
The core interface is intended to serve segments of the user group interested in quickly exploring the building design space for a predefined set of building archetypes (based on the representation in typical Canadian building stock), providing feedback on performance under selected metrics. Inputs are intuitive and adaptive, requiring minimal time from the user to generate meaningful results. Among the driving design principles for the core interface are interactivity, adaptability and intuitiveness: providing a comprehensive (but curated) range of functionality, while enabling the user to hide unnecessary information and controls, interact directly with the inputs and results, and dynamically hone in on their primary objectives.

Context variables

A variety of contextual inputs for these archetypes can be modified by the user to customize the building to suit their needs. Areas of control influencing building performance include building program (occupancy, space types, operational schedules, etc.), building geometry (floor area, height, aspect ratios, etc.), and weather (location, current or future climate conditions, etc.). Additional inputs for life cycle analysis will also be available including initial impacts (capital costs, embodied carbon, etc.), operational costs (fuel prices, emissions intensities, etc.), and financial assumptions (escalation rates, debt leveraging, interest rates, etc.). The full set of contextual inputs will be refined through exhaustive sensitivity analysis and user testing.

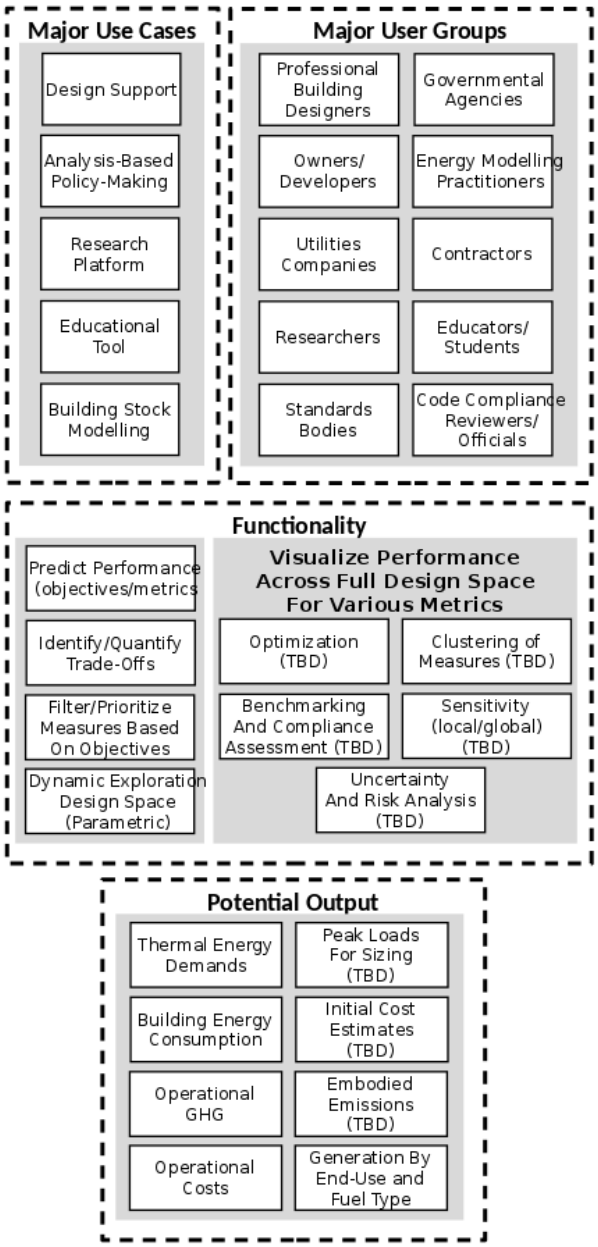

Figure 2: Summary of Intended User Definitions, Functionality and Outputs

Measures and Parameters

The user can then choose a subset of measures for consideration – to evaluate their impact on selected

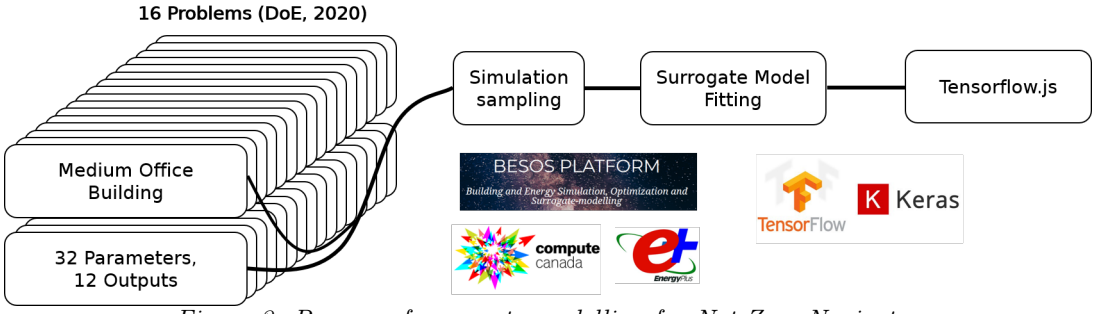

Figure 3: Process of surrogate modelling for Net-Zero Navigator

metrics and outputs – adding dimensions to the problem space. The combination of the baseline building definition and measures defines the overall design space, which is constructed on the underlying surrogate models that make up the engine of NZN. Interactive modules will be incorporated that enable a variety of functionality, including assessment of specific design configurations, filtering and adjustment of measures, or optimization based on selected metrics (such as operational energy, emissions or cost).

Outputs and Visualization

Outputs may include pre-set energy reports, data files, LCC assessment summaries, or peak sizing information for design support. Users will have the option to export EnergyPlus IDFs for specific design configurations for more explicit analysis. Results will be dynamically updated and presented to the user through interactive widgets. Visualization options include parallel coordinates plots, star diagrams, and conventional graphs. These components of interface design will be refined through an iterative process that will involve prototyping, user testing and stakeholder engagement.
The tool is designed to account for any combination of user inputs and default assumptions. The surrogate models used for the core interface are developed to provide a robust foundation for rapid, exhaustive design space exploration, and accuracy has been shown to be sufficient for this purpose; however, more detailed customization is possible in the advanced interface, which can be used to improve precision.

Advanced Interface

An *advanced interface* is proposed for energy modelling professionals as well as researchers. It provides a means to directly generate and interrogate underlying EnergyPlus and surrogate models, providing access to the full functionality of BESOS.
An advanced interface is proposed for energy modelling professionals as well as researchers. It provides the following functionalities:

- import/export EnergyPlus models,
- modify and sample EnergyPlus models,
- fit a surrogate model,
- optimize the design of a building according to various criteria,
- analyse the results using the same advanced visualization tools as for the core interface,
- customize its own visualization tool.

The advanced interface also allows custom metrics to be implemented, letting policy-makers explore the impact of measures across the design space.
All the features are accessible through Jupyter Notebooks and Python code. Moreover Net-Zero Navigator advanced interface benefits from the same functionalities as BESOS, also developed by our team, allowing an easy share of the work and an access to Compute Canada supercomputer to fasten the calculations.

Surrogate modelling procedure

The surrogate modelling procedure underlying the Net-Zero Navigator platform is shown in Figure 3. It consists of

- defining the design problem, i.e. the free design parameters and the design objectives,
- running simulation samples,
- fitting the surrogate model and exporting it as a TensorflowJS object, such that the model can be embedded into the NZN browser application.

The core objective of the process is to derive a surrogate model with a large application scope. This allows one surrogate to cover many design problems. The problem definition stage is a crucial in that regard. We approach it by collecting a holistic set of design parameters and performance metrics in an iterative process. We integrate form (window-to-wall ratio, building storeys, overhangs, orientation), materials (U-Values, Solar-Heat-Gain-coefficient, thickness), loads (people, plug, server, lighting), controls (set point schedules, area covered by daylighting sensors) and HVAC parameters (air rate, pumping rate, plant performance, DHW, heat recovery eff.).
The design parameters span a large combinatorial space. We explore it by collecting building performance simulation samples from within that space, where we aim to maximise the information gain per

simulation run. Therefore, we use Latin-Hypercube sampling (LHS). The platform offers all tools for surrogate derivation, including a Python EnergyPlus API (based on EPPy), and access to computational hardware from Compute Canada. The latter enables us to run thousands of simulations within a reasonable amount of time, and to leverage GPU resources to train deep neural network surrogate models.

To train the surrogate model, we use the machine learning toolbox Keras, which uses TensorFlow as a backend. TensorFlow is a toolbox specifically designed to train neural networks. In the NZN core interface, we are mostly concerned with predicting aggregated annual performance metrics, not time series results. This allows us to limit the complexity of the networks to relatively shallow, multi-output feed-forward neural nets ($\leq$ 3 hidden layers, $\leq$ 512 neurons per layer), which have proven to emulate aggregated simulation outcomes well (Westermann and Evins, 2019).

Once the model is trained and its accuracy validated using simulation runs not included in the training data, we export the neural network architecture and trained weights as a JavaScript file to be embedded into the NZN browser-based application, which uses TensorFlow.js to perform all surrogate model evaluations directly in the user's web-browser.

In the next section we go through all the steps above for an example case which is present in the platform, and investigate the accuracy of the surrogate model. NZN also allows the user to go through these steps for bespoke problems using the *advanced interface*.

Parameter List Problem 1, Thermal Loads	
1.-3.	Wall, Roof, Window U-Value
4.	Window SHGC
5.	Infiltration rate
6.-7.	Ventilation effectiveness (htg., and cooling)
5.	Horizontal shading depth
6.	Wall, floor thermal mass
7.	Daylighting sensors
8.	People
9.-11.	Plug, Lighting, Server-Roam Loads
12.-15.	Humidity, temp. Setpoint (min, max)
16.-19.	WWR (North, East, South, West)
20.	Orientation
21.	Number of Storeys
22.-23.	Heat Recovery (Sensible, Latent)
23.-25.	Plant Performance (Heating-Fuel, Heating-Elec., Cooling)
26.-27.	Fan-power (air rate, conditioning share)
28.-29.	Heating plant fuel mix (share of total, Biofuel Share)
30.-31.	Pumping (rate, hydronic Share)
32.	Domestic hot water (Share)
35.	PV system capacity

Table 1: List of design parameters for Problem 1, Medium office)

Example case

In this section, we explain how we derive a surrogate model for one of the 16 DoE archetype buildings and explain how the user can interact with it. We briefly describe the base building model (a medium-sized office (Canmet-Energy, 2020)), provide accuracy estimates of the surrogate model for each individual performance objective, and present the parallel coordinate plot as example of a visualization tools.

Building details, parameters and objectives

The baseline building definition presented in this research leveraged the work of National Resources Canada (NRCan), who have developed a platform called BTAP to generate NECB versions of the Commercial Prototype Building Models originally created by Canmet-Energy (2020). For the purposes of this illustrative case study, the Medium Office archetype was selected.

Baseline assumptions for building program, space loads, basic controls, geometry and enclosure performance were directly derived from the NECB 2015 requirements. An alternative approach was taken to represent the mechanical systems, with the intention of capturing a wide variety of configurations and parameters through direct manipulation of air-side system and plant equipment performance in the EnergyPlus Energy Management System. This allows high-level exploration of a vast HVAC system design space through variation of a subset of core parameters, set up independently of any specific proposed design, while maintaining a consistent basis for generating building demands.

Sampling

We generate 10,000 simulation samples using the widely applied latin-hypercube sampling, which strat-

Output List Problem 1			
1.	Heating Supply, Gas	**7.**	Interior Lights
2.	Heating Supply, Electricity	**8.**	Pumps Power
3.	Heating Supply, Other	**9.**	Fan Power
4.	Cooling Supply, Electricity	**10.**	PV Generation
5.	Water Heating, Gas	**11.**	Heating Demand
6.	Interior Equipment	**12.**	Cooling Demand

Table 2: List of surrogate model outputs for Problem 1, Medium office)

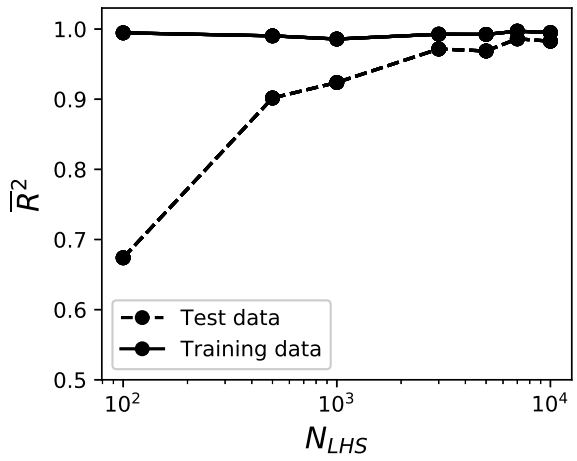

Figure 4: Number of samples vs. surrogate model accuracy.

ifies the design parameter space into equally large hypercubes and randomly collects samples from within each hypercube. We run the 10,000 samples on an HPC cluster (250 jobs with 1 CPU and 2Gb RAM running for 2 hours each).

We fit a 2-layered feed-forward neural network on the retrieved simulation results using the Adam optimizer minimizing the mean-squared-error (MSE), where we specified the learning rate schedule parameters with $\beta_1 = 0.9$, $\beta_2 = 0.999$. Other training hyperparameters were determined in a grid search (l2-regularization coefficient α, number of neurons per layer $n_{neurons}$). To control for the variation introduced by random weight normalization, we repeat each run of the grid search three times. For more details on feed-forward neural network training see (Bishop, 2006).

In this section, we only present the surrogate modelling performance for one of the 16 considered buildings. To efficiently run simulations for all other archetype buildings, we investigated the number of samples required to reach a satisfying surrogate model performance. In Figure 4 the accuracy as a function of the number of samples is shown. On the y-axis we plot the R^2 score, averaged over all outputs, and on the x-axis we plot the number of simulation samples, where 80% is used for training and 20% for testing and hence, corresponds to the total number of samples required to train and validate a surrogate model.The plot highlights that the increase in accuracy levels off after $N_{LHS} = 3000$ samples. However, it keeps increasing slightly for higher numbers of samples. We suggest that more than 100 samples per parameter are required, which compares well to existing literature (Westermann and Evins, 2019).

Surrogate model fitting

The final surrogate model is fitted using 8,000 simulation samples (plus 2,000 more for testing). The optimal 2-layered network architecture has 256 neurons per layer, where the weights are l2-regularized with $\alpha = 10^{-1}$. It achieves a mean $\overline{R}^2 = 0.986$ on the test data averaged over all outputs when predicting annual aggregated performance metrics.

The surrogate model accuracy for each output is shown in Figure 5, where we compare simulation outcomes with surrogate model predictions. The red lines indicate the 0% and ±10% error borders.

The overall accuracy varies between $R^2 = 0.962$ when predicting the heating demand covered by natural gas, and achieves the highest accuracy when predicting the energy demand for water heating $R^2 = 0.999$. Alongside the explained variance, R^2, we also compute the mean absolute error for each of the models providing a slightly better physical insight.

Whereas the thermal demand can be accurately estimated, the supply causes a certain degree of inaccuracy of the model. All thermal supply outputs do not surpass an accuracy of $R^2 > 0.98$. As a core objective of net-zero buildings is the reduction of energy demand, we specifically highlight the accuracy of the surrogate for low-demand buildings. Therefore, we quantify the absolute percentage error (APE) and mean absolute percentage error (MAPE) for the 50% of the samples with the lowest demand for each output. This is visualized in the top left corner of each subplot. For completeness this metric is also computed for PV generation. In future, further refinement of the surrogate model is required to optimize the prediction of thermal sources.

Instant feedback for visualization

The major advantage of the surrogate model for the early design stage, is the instantaneous generation of simulation estimates. Here the model evaluates 100,000 inputs in 3.2s.

This allows for fast and interactive visualization. A popular example is the use of a parallel coordinates plot (e.g. see Figure 6). It features sliders to specify a favoured building design where the column on the right of the plot, here the heating demand, lets the user see the impact of design choices on some performance metric.

Other visualization techniques will be explored in Net-Zero Navigator platform, but are not discussed in this paper.

Outlook and Conclusions

In this paper we introduce the NetZero Navigator platform for early-stage design of low-energy buildings. We provide details on the software architecture, the application realm, and the underlying machine learning models.

In a case study on one of the buildings hosted on the core interface of the platform, we show how the underlying machine learning models are derived, report their accuracy to emulate simulation models and exemplify the design space visualization of that build-

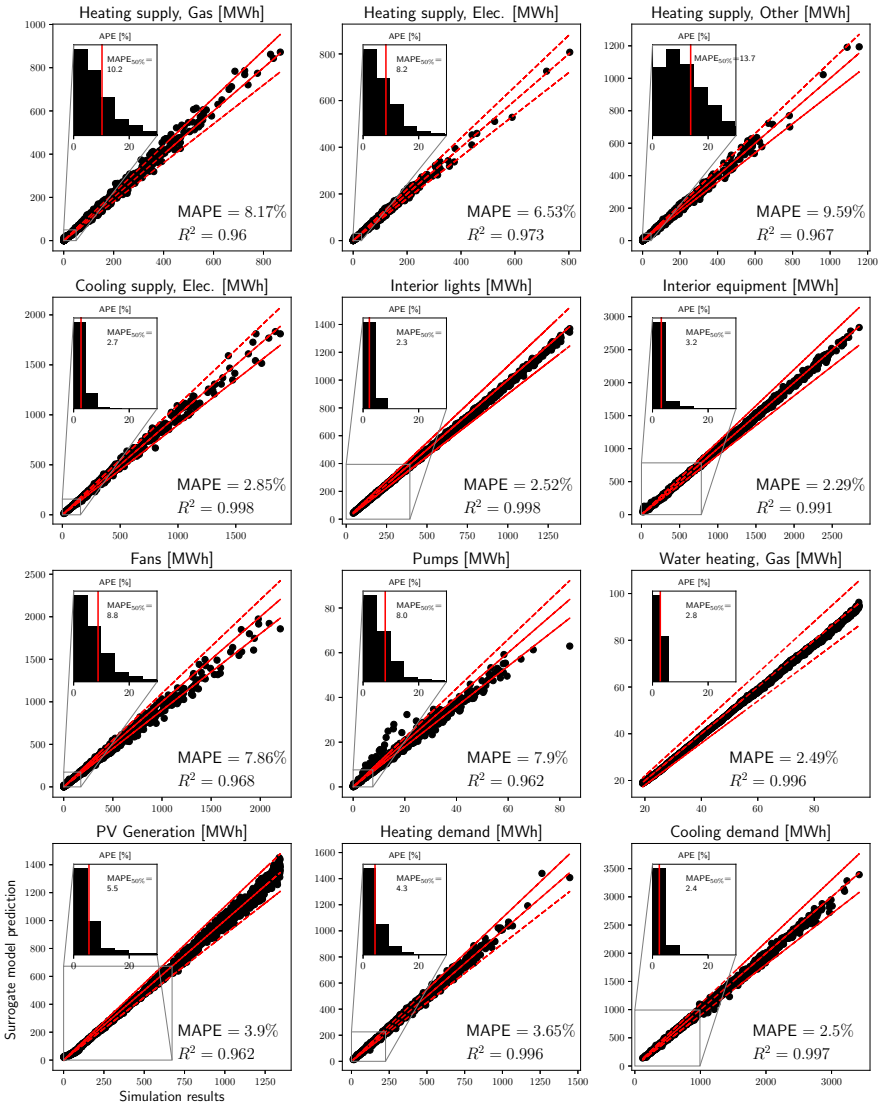

Figure 5: Surrogate model accuracy on test data for one of 16 buildings (Medium office) part of the NetZero Navigator platform.

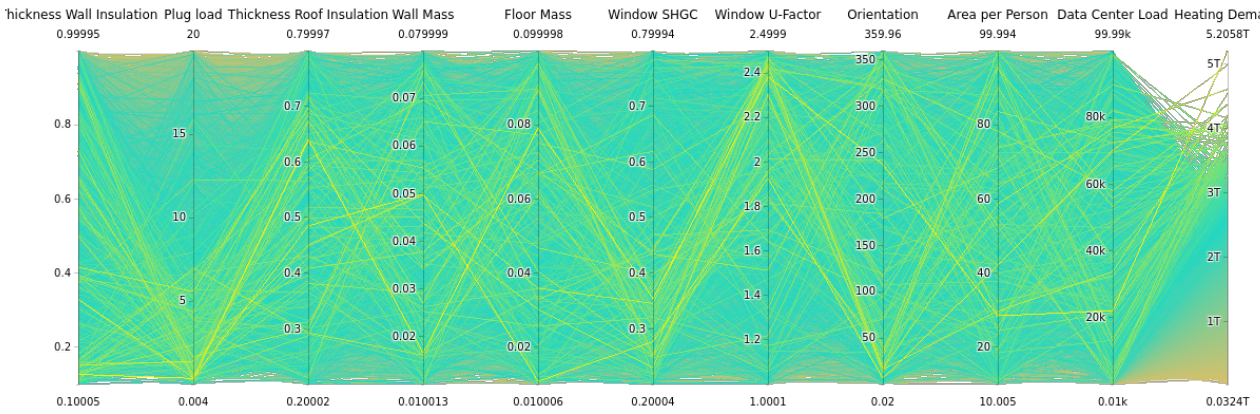

Figure 6: Parallel coordinate plot with 10 of the design parameters and heating demand as output.

ing using a parallel coordinates plot. For this case we show that surrogate models fitted using relatively few samples (8,000 for a 32 parameter problem) can achieve respectable accuracy ($R^2 \geq 96\%$), which is suitable for early-stage decision-making.
The platform will continue to be refined in alignment with user groups' needs. This includes better visualization of the building design spaces, higher accuracy of surrogate models, and refined input sets for the surrogate models. Many different archetype buildings and climates will be available in the core interface, and many parameter configuration and visualization options will be available in the advanced interface. Overall, this paper gives an introduction to the exciting developments that are available by combining machine-learning based surrogate models with online visualisation tools.

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