Generative Machine Learning for Energy Predictions of Existing Buildings

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Abstract. Buildings consume a substantial amount of energy, with a significant portion dedicated to maintaining thermal comfort. However, predicting energy requirements is challenging due to the influence of numerous uncertain and difficult-to-measure building characteristics. This uncertainty hampers the analysis of potential energy improvement opportunities. We propose a novel approach based on generative machine learning (ML) to estimate values of energy related characteristics such as heat transfer coefficients, permeability, and occupants. Training the generative ML network requires geometrical information, ranges for uncertain values of building characteristics, and energy consumption data. The ML network generates sets of possible values for the characteristics. We tested our approach on an office building to predict its energy characteristics. Our approach utilizing generative ML provides a promising solution for estimating relevant building characteristics. By reducing uncertainty in energy predictions, this approach can inform decision-making processes and facilitate the development of more effective strategies to achieve energy efficiency.

1. Introduction

Energy-efficient buildings are essential for reducing energy use for a sustainable built world. While it is important to design new buildings to be energy efficient, it is even more important to operate and retrofit existing buildings to achieve their energy saving potential. In the European Union, buildings contribute to 40% of the total energy use and are the single largest consumer of energy (European Commission, 2019). As of 2020, 75% of the existing building stock is energy inefficient. Thus, energy retrofits and efficient building operation are inevitable challenges to achieve sustainability in the built world.

Any intervention to improve energy performance starts with understanding existing conditions and developing potential solutions, followed by analysing the effects of such on energy performance to assess their suitability. Much information about the existing building is required for assessing the effects of interventions on energy use using dynamic simulations (Schlueter and Geyer, 2018). Geometry, thermal properties such as heat transfer coefficients (u-values), and occupants are examples of characteristics that needs to be quantified to predict energy use (Singh and Geyer, 2020). While some characteristics, such as geometry, can be measured easily and with a reasonable accuracy, values of other characteristics are difficult to estimate. Uncertainty is typically addressed by sampling the characteristics in a large range to predict probabilistic energy use (Van Gelder, Janssen and Roels, 2014).

Model refutation is a commonly used method to estimate values of characteristics of civil infrastructure, for example, Cao, Koh and Smith, (2021). The method uses physical principles to model relationships between uncertain characteristics and measurable variables. First, it populates sets of values of characteristics within constraints, followed by predicting values of measured variables using the model, and finally, retaining the sets of values of characteristics corresponding to the measured values of variables. Another method calibrates values of energy related characteristics based on actual energy use (Cho and Kim, 2019). More generally, the residual minimisation method finds the values for uncertain characteristics that lead to lower error values between measured and predicted values of variables (Sanayei et al., 2015). These methods often suffer from either low precision or low accuracy.

We propose a novel approach based on generative machine learning (ML) to estimate the value sets for uncertain characteristics. In our approach, two ML networks are trained. The first network (section 3.1) is trained on the data from physical-principle models and predicts energy uses based on the values of characteristics. This is often called surrogate modelling. The second network (section 3.2) is a generative ML network that generates sets of values for building characteristics that have energy use predictions that are similar to measured values. The generative ML network is trained to predict sets of values of uncertain characteristics to minimise errors between predicted and measured values of energy use.

2. Methods to estimate values of building characteristics

Estimating values of characteristics of existing buildings is an important subtask when estimating current performance and the effects of proposed interventions. While a few characteristics require simple measuring tools, others require complex investigative methods. Moreover, values of many characteristics related to building operation remain uncertain. The most relevant characteristics, required for energy modelling, are summarised, as follows:

Geometry: Energy modelling requires size and location of walls, floors, ceilings, roofs, and windows. This information is usually collected in the three-dimensional coordinate system using either simple measuring tapes or advanced laser scanners. Advanced handheld devices allow this information to be exported for performance analysis (Mêda, Calvetti and Sousa, 2023).

Thermal characteristics: The most relevant characteristics for energy modelling are u-values, solar heat gain coefficients (g-values), and air permeability. u-values are determined by measuring thicknesses of each material layer and their thermal conductivity. The calculated values do not consider variation caused by deficient construction and deterioration. The g-value of transparent elements is determined by manufacturer specifications. In Germany, air permeability is mostly determined based on construction quality (DIN Normung, 2016).

Internal conditions: Energy use varies greatly due to internal conditions and occupant behaviour (Gaetani, Hoes and Hensen, 2018). Primarily, building use, number of occupants, ventilation requirement, temperature setpoints, light and equipment heat gains, as well as internal mass affect the energy use. These characteristics are difficult to be quantified even with the most sophisticated methods. Moreover, manual control leads to higher uncertainties.

Coefficient of performance (COP): The nominal efficiency of equipment is usually provided by manufacturers. However, variations may occur due to environmental conditions.

Thus, we assume geometry to be deterministic while thermal characteristics, internal conditions, and COP are taken to be uncertain within given ranges for energy modelling. Further, we assume that the energy use is measured for some time intervals.

2.1. Model refutation and residual minimisation to estimate uncertain characteristics

One of the methods for estimating existing characteristics is based on model refutation (Smith, 2016). In this method, target parameters, which can be measured, are identified. The method assumes that relationships between characteristics and target parameters can be modelled using physical-principle models. It further assumes that values of the existing characteristics are defined by ranges of possibilities. These ranges are used for sampling the values of characteristics and the model predicts values of target variables. Using these predictions, the measured values of target variables, and estimations of uncertainty ranges, the method refutes sets of values of characteristics. This method is widely used in structural health monitoring (Goulet, Kripakaran and Smith, 2010; Goulet and Smith, 2013; Pai and Smith, 2022).

While model refutation requires generating sets of values for characteristics in given ranges to find suitable sets, residual minimisation tunes the model parameters such that the error residuals between the measured and model estimated values of target variables are minimised (Sanayei *et al.*, 2015). However, the residual minimisation method is not model independent. Most importantly, an implicit assumption is the absence of systematic errors, which is rarely the case.

2.2.Estimation of building characteristics for energy modelling

Primary data sources for estimating energy related characteristics in the existing building are technical drawings, standards, manufacture specifications, and on-site audits. (Cho and Kim, 2019) used this information with measured energy use to calibrate energy related characteristics. The energy related characteristics are calibrated in a physical model so that it predicts the same energy use as measured. The approach can be extended to residual minimisation to find sets of values for building characteristics that have the same energy use as measured. However, without inclusion of systematic modelling errors, inaccurate results are expected, particularly when extrapolating. The alternative strategy is also challenging; the model refutation method often requires exploring large population spaces, which is computationally inefficient using dynamic energy simulations.

3. Generative ML approach to predict values of building characteristics

This paper presents a model independent approach to predict values of characteristics using generative ML. The presented approach replaces dynamic energy simulations by an ML network that models relationships between uncertain characteristics and measured variables. Further, it trains a generative ML network that produces sets of values for characteristics that minimises error residuals between the predicted and measured values of target variables. The generative ML approach can be divided in two steps, as follows:

3.1.Data collection and the regressor network

We assume that energy analysts collect geometrical information with a handheld device. Further, they provide additional information such as u-values, occupancy, etc. in the form of ranges of values since these characteristics are difficult to determine with certainty. We sampled these uncertain characteristics and used their values with geometrical details to create energy models in the dynamic simulation tool EnergyPlus (National Renewable Energy Laboratory, 2022). The run periods are defined based on available information about energy use. We treat energy use for several run periods as different ‘target variables’. For example, energy uses for January and February, are treated as two target variables.

First, we need a network that predicts energy use, i.e., target variables based on the values of characteristics. We refer to this network as ‘regressor’ which is trained on the simulation data, as shown in Figure 1. A two-layer neural network is used for the regressor. We used L2 regularisation and early stopping to prevent overfitting. We experimented with a number of hyperparameters, namely, the number of layers and neurons, the regularisation coefficient, and the learning rate. The hyperparameters are tuned using the hold-out validation (Yadav and Shukla, 2016). A network with the least validation loss (mean squared error) is considered for further evaluation. A naive approach to predict values of uncertain characteristics will be to invert this model. The inverted model takes the measured energy use as input and predicts the values of uncertain characteristics. The naive approach predicts only one value for each characteristic while causal effect diagnosis requires generating sets of values for characteristics.

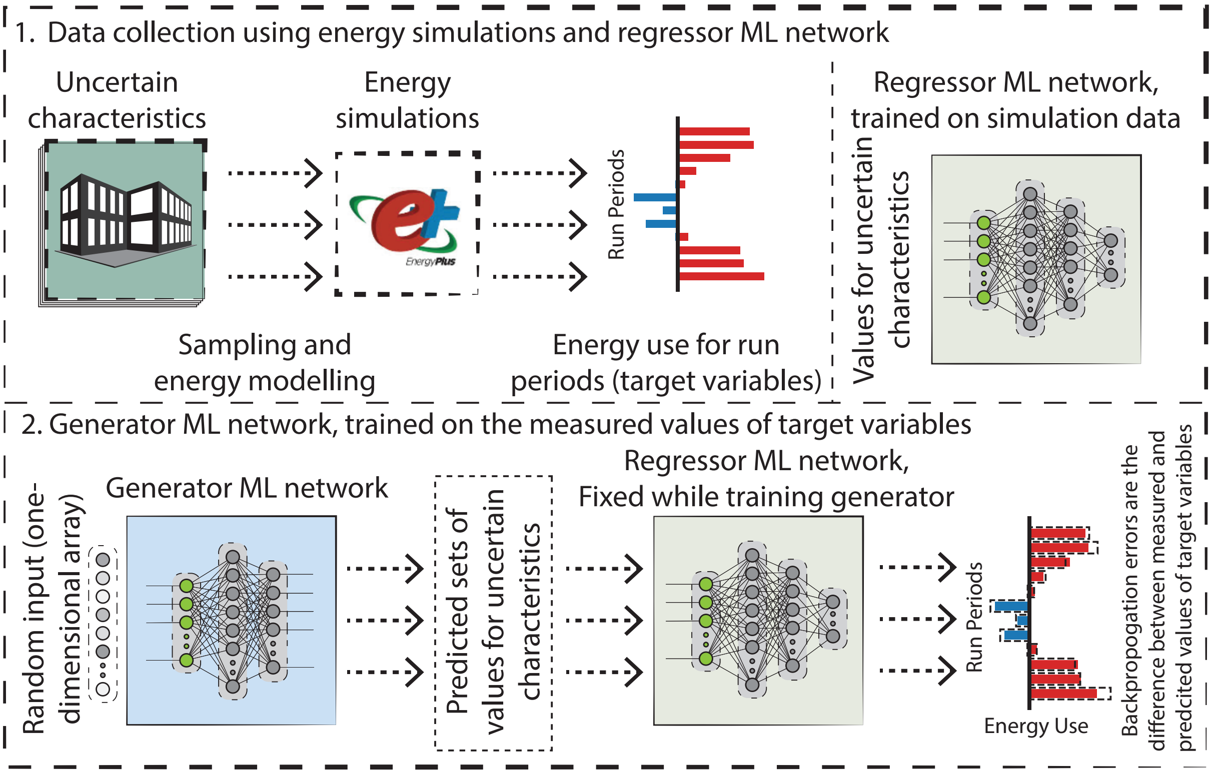

Figure 1: A generative ML model to predict set of values for energy related characteristics

3.2.The generator network for predicting the values of building characteristics

The generator network takes a one-dimensional random array as input and predicts sets of values for the uncertain parameters. The predicted sets of values are fed to the 'regressor' that predicts target variables. Based on the difference between observed and predicted values, errors are calculated, and the 'generator' is trained. The generator is a neural network with a maximum of two layers. We adopted two strategies to ensure that the generator does not predict values of characteristics outside their defined ranges. The output of the last layer is fed to a 'hard sigmoid' activation layer with a custom activity regulariser on its output. Hard sigmoid activation, $f(x)$, linearly maps the values between (-2.5, 2.5) to (0, 1), $x < -2.5$ to 0, and $x > -2.5$ to 1, as described in Equation 1.

$$f(x) = max\ (0, min(1, \frac{x+1}{2})) \qquad \ldots (1)$$

However, just using this activation function has a drawback: the last layer can still predict values outside the range of (-2.5, 2.5) and the activation layer will assign (0, 1), respectively. Therefore, we used an activity regulariser that adds a penalty, 'P', whenever the output of the last layer is outside the range of (-2.5, 2.5). 100 is the regularization coefficient. This activation function penalises any predictions outside the selected range, see Equation 2.

$$P(x) = \begin{cases} 0 \quad if \ -2.5 \le x \le 2.5 \ else \\ 100 \times \ln(abs(0.4 \times x)) \end{cases} \qquad \ldots (2)$$

We used a custom loss function that defines the loss as the minimum of mean square errors between the predicted and observed values of the target variables, see Equation 3. K is the number of target variables, n is the number of training samples, y is the measured value and $\hat{y}$ is the predicted value of a target variable. This loss function reduces the error for any of the target variables; thus, allowing the network to match the observed and predicted values for one target variable at any iteration.

$$Loss\ function = \min_{a = 1\ to\ K} \sum_{i=1}^{n} (y_i^a - \hat{y}_i^a)^2 \qquad \ldots (3)$$

Once the generator network is trained, it predicts sets of values of characteristics that satisfy their pre-defined constraints, and the measured energy uses. Since we found that one generator network does not predict significantly different sets by changing random input, we trained many generators with different values of hyperparameters. Since many models are required, we cannot select the model with the least validation loss. We used 80% of the best performing generators to predict sets of values for uncertain characteristics.

4. Tausendpfund building

We tested the proposed approach for the office building ‘Tausendpfund’ in Regensburg, Germany (Vollmer *et al.*, 2019). The building has three floors with an approximate floor area of 1200 m^2. Figure 2 shows the zones of the building, as in the energy model.

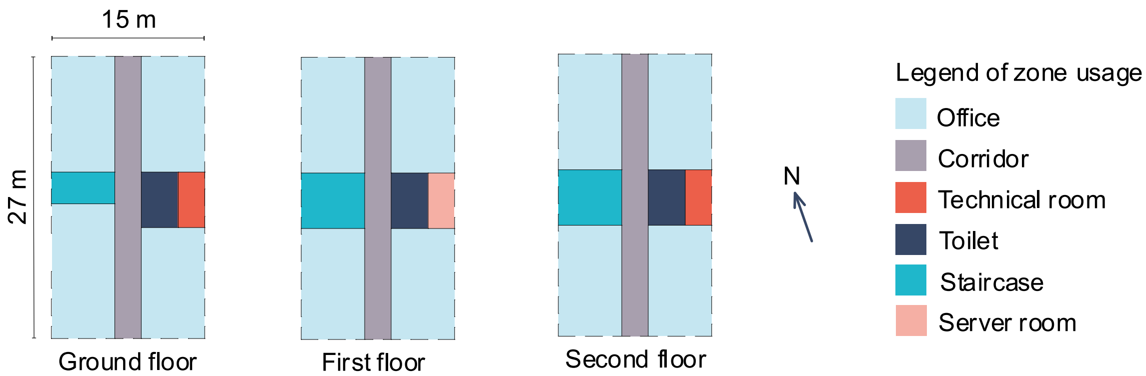

Figure 2: Floor plans of the testcase building

The construction of walls, windows, floors, and roof are modelled as built and described in (Vollmer *et al.*, 2019). We assumed uncertain u-values since as-built information is mostly unavailable. The u-values are sampled within the possible value ranges and the thickness of insulation layer is varied to achieve sampled u-values in the energy model. A generic classification of Type-II buildings corresponds to an air permeability of around 6 m^3/m^2h. We assumed a fixed schedule for occupancy, lighting, equipment, and setpoints; however, uncertainty in their values, as mentioned in Table 1 is considered. The building has a heat pump that supplies heat through an underfloor heating system. We used a heat pump object in EnergyPlus model that supplies air to individual zones to mimic the system. The COP of the heat pump is the most relevant parameter in this regard. Table 1 summarizes energy-related characteristics, their possible ranges of values, and measured values (if available). Using the naive approach, we also predicted values of building characteristics corresponding to energy use in 2017 and 2018.

Table 1: Possible value ranges and measured / calculated values of building characteristics

Building characteristic	Possible value range	Measured / calculated value	Predicted values (using the naive approach)	
			2017	2018
u-value: Walls (W/m^2K)	0.15 – 0.25	0.18	0.24	0.20
u-value: Floor (W/m^2K)	0.15 – 0.25	0.19	0.24	0.21
u-value: Roof (W/m^2K)	0.10 – 0.20	0.15	0.19	0.16
u-value: Window (W/m^2K)	0.60 – 1.00	0.87	1.00	0.78
g-value (-)	0.30 – 0.50	0.35	0.40	0.32
Permeability (m^3/m^2-h)	5.40 – 6.60	Not available	6.44	6.10
Occupancy (persons/sq. m.)	16 – 24	22 (as in layout)	21.18	21.04
Heating setpoint (°C)	19.0 – 23.0	21 (as documented)	26.33	20.90
Internal mass (kJ/m^2)	18.0 – 30.0	Not available	28.40	24.82
Light heat gain (W/m^2)	4.50 – 7.50	Not available	6.96	6.08
Equipment heat gain (W/m^2)	6.00 – 10.00	Not available	9.02	8.30
Coefficient of performance (-)	1.80 – 3.00	Not available	3.30	2.27

5. Results

We sampled 100 sets of uncertain characteristics and created energy models. We used energy use data of the heating seasons of 2017 and 2018. We defined four run periods in energy models, i.e., November, December, January, and February. An Apple M1 Max (10-cores) machine is used for this research to report times for different steps. It takes 6.4 minutes to create energy models and perform simulations. A 'regressor' network is trained on the simulation data. The regressor takes values of uncertain parameters as input and predicts the energy use for the run periods. We tuned hyperparameters of the regressor using one-holdout-cross-validation set. After training the regressor for 4 random sets of hyperparameters, we found a network with the least validation loss of 0.0019 sq. MWh (mean-squared-error). It takes around 1.15 minutes to train the regressor, which is saved and used further.

A 'generator' network takes random input and predicts values of the characteristics. The set of input parameter values is fed to the regressor that predicts the energy use for the selected run periods. We trained the generator with many sets of hyperparameters, as mentioned in Table 2:. Training the generator for one set of hyperparameters takes around 8 seconds. We trained 125 generators and used the top 80% (100) to predict 100 sets of values for the characteristics.

Table 2: Values of hyperparameters for generator

Hyperparameter	Values
Number of neurons (layer 1)	40, 60, 80, 100
Number of neurons (layer 2)	0 (no 2nd layer), 10, 20, 30
Learning rate	1e-2, 3e-3, 1e-3, 3e-4

Figure 3 shows the predicted sets of uncertain characteristics on a parallel axis plot. The axes show uncertain characteristics with their min-max values. A line shows a set of values for characteristics with the predicted energy use in the four months. The colour of a line shows the error between the measured and predicted values of target variables. A generator generates only one set of values of input parameters even with different random inputs; however, retraining the generator on a different set of hyperparameters yields different values of input parameters. One line in Figure 2 represents the predicted values of characteristics from one generator model. The possible values for the characteristics are distributed along the entire axes. It suggests that parameters can have any value between their defined ranges. However, we can find suitable sets of values that have similar energy use as measured. Further, there is a difference between the predicted and the measured energy use. A set of values may not be suitable for all run periods, and it may cause a significant difference from measured values for some run periods. On average, the target variables for predicted sets of values have a difference of 23.2% (November), 4.9% (December), 17.5% (January), and 9.3% (February) from their measured values.

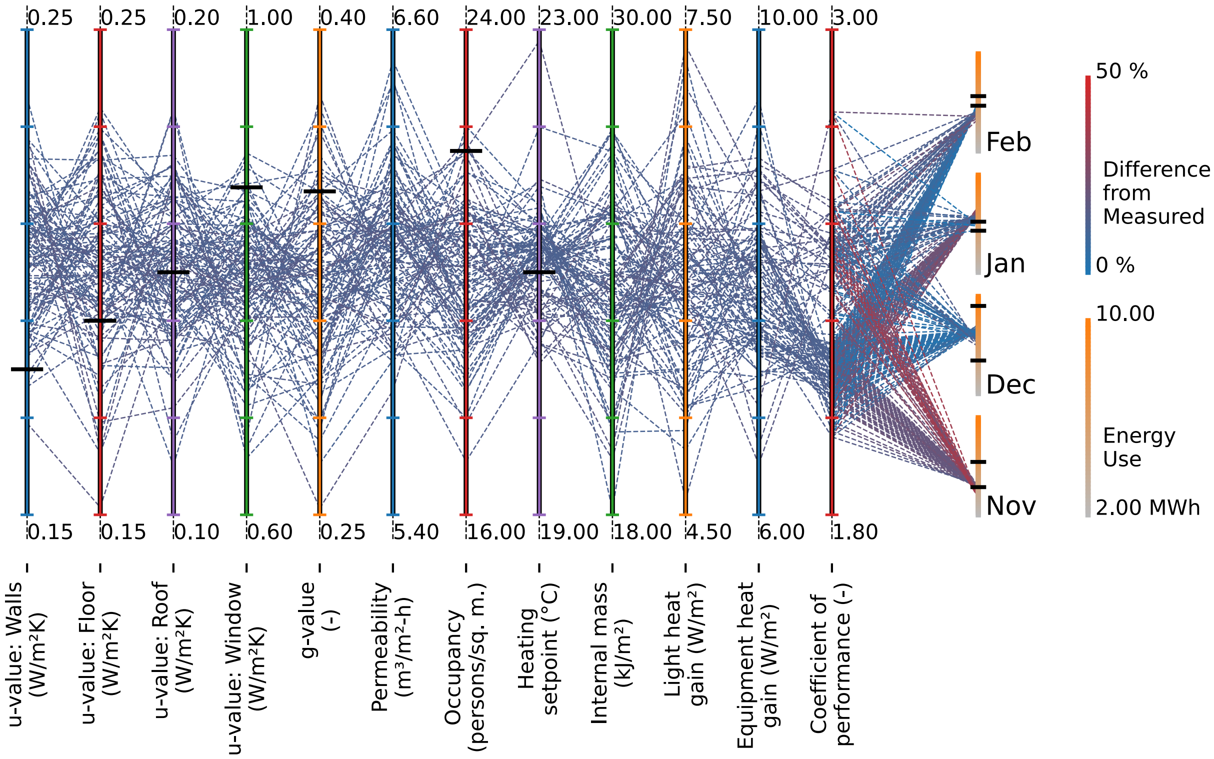

Figure 3: Predicted sets of values of parameters to achieve observed energy performances

The most generic approach is to sample uncertain characteristics in specified ranges and make probabilistic energy use predictions. The ML approach trained the generator network so that it only predicts the set of values to achieve the measured energy use. The energy predictions have a lesser uncertainty when using the predicted sets of values for uncertain characteristics than random sampling. Figure 4: shows the distribution of values of target variables. The left side of violin plots shows the distribution of the energy use values when the values of characteristics are randomly sampled, and the right side shows when the values of characteristics are predicted by the generator. It shows that energy use is more uncertain for random sampling than for ML predicted sets. Further, we calculated the 95% confidence interval for both the approaches, as mentioned in Table 3: We found that the confidence interval is smaller for ML predicted sets than for random samples of uncertain characteristics. However, there is a significant difference between the measured and predicted values.

Table 3: 95% confidence interval of target variables using random sampling and ML predicted sets

Run period	Random sampling	ML predicted sets
November	2.83-4.87	3.41-4.35
December	5.43-8.39	6.09-7.38
January	5.31-8.09	5.92-7.13
February	4.30-6.49	4.85-5.81

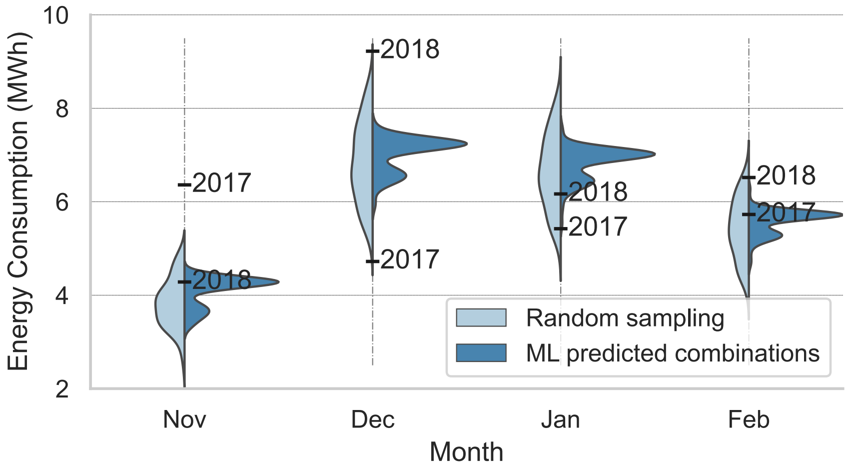

Figure 4: Distributions of energy use values using ML predicted sets and randomly sampled values

6. Discussion

The paper presents a method to determine values of energy related characteristics based on measured energy use. Using ML networks, we achieve computational efficiency and eliminate the need to randomly search the parameter space as required in model refutation approach. Moreover, physical principle models in other work are substituted by ML networks, making it model-independent. It can be used to determine the sets of values for any characteristics as long as an ML network can model the relationship between the characteristics and measurable variables. Challenges associated with determining energy related characteristics are described as follows.

Energy modelling: Creating energy simulation models to mimic real building conditions is a challenging task due to lack of information and modelling complexity. For example, we considered heating setpoint of office spaces will be the same throughout the season. However, setpoints are adjusted by occupants and may not be recorded in many cases. Moreover, a manual control will be difficult to model. Further, parameterising energy models requires more simplification. The lack of information and needed simplification leads to a mismatch between simulated and actual energy performance. This prediction gap is a wide area of research that cannot be discussed in the scope of this article.

Weather data: We used publicly available historical weather data for the city (location), since more specific weather data may not be available for many buildings. This approach will not be suitable if energy use is measured for very short periods such as hourly, daily, or weekly. The periods should be sufficiently large so that minor variations do not affect simulation results. In the testcase, there are large differences between energy uses for the same months of two years. Since we used historical weather data, simulations predict the same values for both years.

Generative ML model: We used a hard sigmoid activation function and a custom activity regulariser to ensure that the values of characteristics are within the predefined ranges. The output of the generator is scaled back from 0-1 to min-max values and it is constrained to only generate values between 0-1. Further, we found that one generator provides only one set of values, irrespective of random input. It requires training many generators to find different sets of values for characteristics.

Comparison with other methods: The proposed approach reduces the residuals between measured and predicted values of target variables by training an ML network that generates the sets of values of uncertain characteristics. An ML network is used as a surrogate to achieve a higher computational efficiency and iteratively minimise errors by training parameters of the ML network. The approach is useful when we search for value sets using constraints. The iterative approach of model refutation can lead to either finding no solution or searching many possible sets. Opposed to this, assuming that the simulation is perfect with no uncertainty, the ML network can always find values of characteristics in desired ranges. However, large deviations from the measured values of target variables can occur, if the ranges of possible values of characteristics are unrealistic or incompatible. The naive approach (residual minimisation) may lead to incorrect values of existing characteristics since only one set of values for uncertain characteristics represents only one of many possibilities. In future work, the method to incorporate uncertainties in the simulation model will be investigated.

7. Conclusions

A physical principle simulation model is used to simulate the as-built scenario and collect data for training ML networks. It is important to ensure high precision in the simulation models to minimize discrepancies between simulated and actual performance, which could lead to higher errors. Additionally, domain knowledge is required to define the ranges of unknown or uncertain characteristics. The ML approach involves two components: a regressor and a generator. While training the regressor is relatively straightforward based on the least validation loss, training the generator is more complex. Automation of the training process based on predefined metrics helps facilitate the adoption of this approach by energy experts. The results demonstrate that this approach reduces uncertainty in the values of target variables compared to random sampling of uncertain characteristics. This reduction in uncertainty enables a more precise analysis of the effect of design interventions. The predicted sets of values for uncertain characteristics generated by the ML approach offer valuable insights for analysing the impact of design interventions on energy consumption. The approach outlined in this research paper has the potential to enhance the decision-making process in energy optimization and contribute to more sustainable and efficient design practices.

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