Data Driven Model Improved by Multi-Objective Optimisation for Prediction of Building Energy Loads

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Abstract

Machine learning (ML) has been recognised as a powerful method for modelling building energy consumption. The capability of ML to provide a fast and accurate prediction of energy loads makes it an ideal tool for decision-making tasks related to sustainable design and retrofit planning. However, the accuracy of these ML models is dependent on the selection of the right hyper-parameters for a specific building dataset. This paper proposes a method for optimising ML models for forecasting both heating and cooling loads. The technique employs multi-objective optimisation with evolutionary algorithms to search the space of possible parameters. The proposed approach not only tunes single model to precisely predict building energy loads but also accelerates the process of model optimisation. The study utilises simulated building energy data generated in EnergyPlus to validate the proposed method, and compares the outcomes with the regular ML tuning procedure (i.e. grid search). The optimised model provides a reliable tool for building designers and engineers to explore a large space of the available building materials and technologies.

Keywords: Building energy loads, Building energy prediction, Machine learning, Model optimisation, Energy performance

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1. Introduction

There have been several approaches proposed to enhance the energy efficiency of buildings in many countries in recent decades. For instance in Europe, it was estimated in 2010 that 60 billion Euros could be saved annually by improving EU buildings' energy performance by 20 per cent [1].

Every attempt to optimise the energy performance of buildings involves a series of calculations to estimate the energy consumption and create an index, such as an 'energy performance indicator' or 'use intensity' from the measured data [2, 3]. Most prevailing optimisation methods are simulation-based where the energy-related objectives (i.e. energy consumption or gas emissions) are calculated by a Building Performance Simulation (BPS) tool such as EnergyPlus, TRNSYS and ESP-r. This approach restricts the computing complexity of the algorithms to BPSs' calculation time. As such, when a vast range of solutions are defined, the calculation and optimisation process may become extremely costly and cumbersome. For this reason, most of the studies which focused on decision making for energy performance improvement of buildings either investigated basic and simple optimisation models or targeted retrofitting only one or two parts of envelopes to pare-down total calculation time and cost. It should also be noted that the majority of studies targeted residential buildings, and there are only a few examples of research related to tertiary buildings. A key component of achieving global development and meeting climate change mitigation targets is the optimisation of the entire building stock. This process requires significant testing and planning to deliver.

With the tremendous growth in the amount of valid and attainable datasets of buildings and collection of Big Data from smart buildings, there is an increasing interest in the employment of Artificial Intelligent (AI) methods specifically Machine Learning (ML) techniques for analysing, modelling, and predicting building data [4, 5].

The precision and suitability of the data and the relationships inferred from it become a critical fact in the successful application of ML models. As ML methods build a model over a historical dataset, the main and most important step for having accurate predictions is the extraction of relevant features. Depending on the nature of predictions (the energy indicator and forecasting period), this variable could include simple basic weather indices

(e.g. temperature and humidity) or complex building characteristics and climate parameters. Previous research has demonstrated that rather than feature extraction the process of tuning a model itself not only increases the predictive accuracy but also reduces model complexity, ease of use, and consistency of predictions [6]. It has been argued that considering occupancy in retrofit decision-making, particularly in populated real estate properties such as higher education buildings, could leverage energy efficiency [7].

ML techniques have been widely used for modelling building energy loads and performance. Traditionally, the default values for hyper-parameters have been used in this field. However, in recent years researchers have started to tune the ML models to have more accurate predictions of energy metrics [8, 9, 10, 11]. Tuning ML model hyper-parameters using a grid search can be time-consuming when a complex method is chosen such as Artificial Neural Networks (ANN) or models based on decision trees.

When MLs are utilised for forecasting multiple measures such as heating and cooling loads, models need to be optimised for both the targets [12, 13]. This procedure, in turn, increases the time required for processing and improves the usability of MLs.

In the proposed method, evolutionary-based multi-objective optimisation (MOO) algorithm was employed to smartly explore the ML model’s configuration parameters space and suggest a set of packages for maximising ML accuracy for both heating and cooling load predictions. This study applied a Random-Forest (RF) model because a python implementation is capable of providing the multivariate forecasting.

Section 2 provides an overview of the preceding studies with regards to tuning ML models with the purpose of building energy indicators forecasting. Afterwards, the RF method and the studied dataset are described in Section 3. Section 4 presents the results of the proposed ML optimisation approach. The final section provides detailed discussions and recommendations for future work.

2. Background and Motivations

Machine learning algorithms are categorised into two groups: supervised learning, in which the data is labelled, and unsupervised learning, where there is no target for the records in the dataset. Supervised learning is a regression analysis or a set of classifications linking inputs factors (X) to single or multiple “output” variables (Y). Whereas, in unsupervised learning, data is

72 organised into clusters by pulling out similarities between various samples
73 within the dataset. As such, unsupervised learning is applied to unlabelled
74 datasets. In contrast, in the supervised learning algorithms, the input-output
75 relationships are detected and used for the prediction of new records.

76 Kalogirou et al. [14] were the first team of researchers who employed ML
77 models to determine the heating loads of a building, taking into considera-
78 tion the building envelope features as well as the temperature outside. In
79 a related study, ANNs were used in estimating the electricity demand level
80 in a holiday residence, simulated in ZID software [15]. A more recent study
81 [16] also applied ANNs to forecast the heating loads of a simulated house in
82 Nicosia, Cyprus with the aim of finding a Pareto scenario when dealing with
83 various types of walls and roofs, with different constructional arrangements
84 and material types. They utilised TRaNsient SYstem (TRNSYS) as the en-
85 ergy evaluation engine for all building combinations. The model was then
86 validated by comparing the calculated energy consumption with the actual
87 measurement from the building. More recent studies have widely used ANN
88 for estimating building heating and cooling loads [17, 18, 19, 20], electricity
89 demand [21, 22, 23], and energy consumption [24, 25, 26].

90 Yalcintas [27, 28] created an ANN model for estimating energy bench-
91 marking considering tropical climate weather data and including chiller data.
92 These buildings included offices, classrooms, laboratory-type buildings, and
93 miscellaneous use buildings. The efficiency of ‘energy use intensity calcula-
94 tion’ is examined against multiple linear regression techniques indicating an
95 exceptional improvement over it. Hong [29] also used ANN for energy perfor-
96 mance evaluation of primary and secondary schools established in the UK by
97 computing electrical and heating usage. Although it was found that the ac-
98 curacy of ANN outperforms traditional statistical models, these predictions
99 were not as accurate as simulation and engineering calculations [30]. Wong
100 *et al.* [31] applied ANN on a commercial building, including day-lighting lo-
101 cated in Hong Kong to assess the dynamic energy performance. EnergyPlus
102 and methods for computation of interior reflection are utilised to produce
103 the building daily energy load. Nash–Sutcliffe Efficiency Coefficient is used
104 as the primary measurement to investigate ANN accuracy in predicting cool-
105 ing, heating, electric lighting and total electricity consumption. Ascione et
106 al. [32] trained ANN models to predict the energy performance of existing
107 and renovated buildings, along with the occupant thermal comfort.

108 Support Vector Machine (SVM) for prediction of building energy indica-
109 tors was introduced by Dong et al. [33] and adopted by a number of studies

110 for estimation of cooling and heating loads [34, 35, 36, 37], electricity con-
111 sumption [11, 38], and energy consumption [39, 40, 41, 9, 42, 43].

112 The use of ensemble ML models (e.g. RF and gradient boosted re-
113 gression trees) in the building energy domain is restricted to recent years
114 [44, 45, 46, 47, 6], despite an established track-record of utilisation in other
115 disciplines. Li et al. [48] compared SVM, ANN and ensemble models on pre-
116 diction of building energy performance by using trust metric to evaluate the
117 reliability of the models. The superiority of SVM and ML over the ensemble
118 and linear models was concluded. However, the authors did not optimise the
119 models to generate the Pareto frontier. In a recent study [6] which tuned and
120 compared the most commonly used models revealed the better performance
121 of ensemble models over others. Papadopoulos et al. [12] also compared
122 different ensemble models in estimation of the energy performance of res-
123 idential buildings (including 768 variations of a model building) evaluated
124 using Ecotect software.

125 Table 1 outlines ML application on the prediction of building energy
126 usage.

Table 1: ML modelling for prediction of building energy loads and performance.

ML	Term	Building	Features	Ref
ANN	Month	schools in England and Wales	Construction year, Phase of education, No. of pupils, Internal conditioning, Orientation, Facade adjacency, Floor area, Depth ratio, Compactness ratio, Glazing ratio & type, Roof shape & glazing, Heating & Cooling degree-days	[29]
ANN	-	Educational building	Operation hours, Age, Square feet area, Yearly electricity usage, Percentage electricity used for lighting, air conditioning, plug loads	[28]
ANN	Year	Office buildings	geometry(9), envelope(30), operation (6) and HVAC (3)	[32]
ANN	Year	Schools in UK	Glazing ratio, Glazing type, Roof shape, Roof glazing, Heating degree days, Cooling degree days	[18]
ANN	-	Residential buildings	Degree days, Net volume & floor area, Dispersant surface, Opaque to glazed ratio, Construction year & period, Thermal conductivity, Average floor height, Opaque & glazed surface area, Non-linear features	[49]
ANN	Day	Reference office building	External weather conditions, Building envelope designs, Day type	[31]
ANN	Hour	Simulation models	Solar radiation, Wind speed, Outside temperature & mass flow rate of hot water of previous 24h, Hot water temperature	[50]

SVM	Day	Single-story mass-built buildings	Dry bulb and relative humidity, Wind speed, Direct solar, Ground temperature, Outdoor air density, Water mains temperature, No. of occupants, Heat gain of lights, electric equipment and window, Heat loss for walls, Infiltration volume, Heating outlet temp	[51]
SVM, Year ANN		59 residential buildings in China	Mean heat transfer coefficient of building walls, Mean thermal inert index of walls, Roof heat transfer coefficient, Building size coefficient, Absorption coefficient for solar radiation of exterior walls, Window to wall ratio, Shading coefficient of window, Integrated shading coefficient	[40]
ANN	Hour	An institutional facility	Outside temperature and relative humidity, Boiler outlet water temperature and flow-rate, Chiller outlet water temperature and flow-rate, Supply air temperatures for hot, cold duct, Supply and return control settings, Indoor temperatures of different zones	[22]
RF, GBRT	Year	Model building	Relative compactness, Surface area, Wall area, Roof area, Overall height, Orientation, Glazing area, Glazing area distribution	[44, 45]

127 2.1. Research Gap

128 Recently, researchers working in modelling building energy have identified
129 the potential of ML model [52, 53, 54, 8, 12]. The main role of extracting
130 logically appropriate feature of building physics, conditions and environments
131 in the accuracy of surrogates models is clear. However, without tuning the
132 ML models, it is not possible to get the real benefit from them.

Simple models with few parameters like SVM are easy to optimise, but when the number of hyper-parameters is increased the search space grows exponentially. For example, to tune an RF with six parameters, a grid search will explore more than four thousands possible configurations. That is why traditionally, the researchers mostly relied on default values for those hyper-parameters. However, such models provide far more accurate results by precisely tuning in comparison with SVM or Gaussian process regression [6].

Forecasting two or more building energy measures such as heating and cooling loads simultaneously requires even more expertise and investigation. The use of complex model and grid search for such applications is not a viable solution, due to the complexity in processing time as well as the selection of the ideal model.

This study outlines a detailed method to train one single model for prediction of both heating and cooling loads of buildings and maximise the ML model's efficiency. Though the demonstration presented here are from simulated data, the approach is also applicable to measured energy data.

3. Methodology

ML models work as black boxes, meaning that the detailed relations of energy performance and building characteristics and weather data are not provided. As mentioned earlier, the initial phase of data-driven modelling is the extraction of a feature set for representing the energy system. Surrogate methods model a system with fewer features than engineering approaches. However, formulating a logical set of variables for these models is both essential and laborious, particularly when modelling complex systems such as the energy efficiency of commercial buildings. The determined features might be building characteristics or weather data or complex parameters computed from primary ones, for example, median dew point temperature [5]. After feature engineering, which also includes imputation/elimination of missing data and normalisation, the next step is to optimise the model itself. In this phase, the hyper-parameters of ML models are tuned in a way to achieve the highest possible accuracy. There are no explicit rules to guide the selection of these parameters by considering the dataset detail such as the number of records or input variables. Hence, the best dataset can be selected using a brute-force search. Another way to find the best feature is to use evolutionary algorithms such as a genetic algorithm. This not only reduces the processing time of the search procedure but also provides better performance.

169 In traditional Grid-search method, a specified set of possible values for each
170 parameter is required. However, evolutionary algorithms are able to select
171 the values from a determined continuous space or a discrete set.

172 In the proposed method, a MOO technique is utilised to exploit genetic
173 algorithm in the optimisation of ML models for prediction of heating and
174 cooling loads of buildings. Figure 1 demonstrates the proposed optimisation
175 procedure for selecting the best hyper-parameters. Here, the ML param-
176 eters are defined as the MOO variables to generate several sets with which
177 ML model accuracy is maximised for forecasting both energy loads. Most
178 implementations of the established ML models such as NN and RF support
179 the concurrent prediction of multiple targets. However, choosing a set of
180 hyper-parameters might improve the prediction accuracy of one target but
181 less the accuracy of the other objective function [6].

182 First, MOO is initiated with pre-set values (in this study, we used default
183 values suggested by the Python library) to create a model. This is evaluated
184 using a 10-fold cross validation method. In this approach, the dataset is
185 divided into 10 equal segments. Then a model is trained using 9 parts and
186 tested on the remaining one, and this procedure is repeated until the accuracy
187 of the model is assessed covering all parts. Finally, the average values of the
188 model performance (e.g. mean absolute error) of all 10 folds is sent to the
189 MOO. It continues generating new samples and evaluating models until it
190 reaches 500 iterations.

191 In the following section, the dataset, RF model and the utilised MOO
192 methods are elaborated.

193 3.1. Dataset

194 In this study, a dataset including residential and commercial building
195 models whose energy loads are calculated using EnergyPlus software is utilised.
196 The data comprises 460,000 records characterised by seven structural, six-
197 teen climate and three mixed features as presented in Table 2. The buildings'
198 attributes were adopted from models obtained from US DOE commercial
199 building reference databases and residential houses in Geneva, Switzerland
200 and north of Germany. To enrich the dataset, the variation of those mod-
201 els are simulated in various climate conditions collected from meteorological
202 data of metropolitan areas from all around the world and a generated syn-
203 thetic weather data [55]. For detail of the features refer to Table 3 presented
204 in [6]

Figure 1: Schematic diagram of the proposed ML optimisation method.

Figure 2 illustrates the frequency plot of the selected features from the EnergyPlus simulated dataset. It can be noted that almost all variables are somewhat spread over the feasible predetermined values. The correlation heat-map matrix provided in Figure 3 presents the independency of different features from each other particularly the ones associated with building physics.

3.2. RF

RF is an ensemble of randomised decision trees (DTs). A DT encompasses the establishment of an ML model in a tree structure form by a non-parametric algorithm. DT progressively divides the given data into elemental subsets until reaching a single sample residing in each sub-group. The inner and outer sets are called nodes and leaf nodes. The accuracy of DT is significantly dependent on the samples' distribution in the learning dataset. As such, DT is always introduced as an unsteady method, where even minor

Figure 2: Distribution of the selected features for building energy data.

Figure 2 (Cont.): Distribution of the selected features for building energy data.

Figure 3: EnergyPlus data features correlation map.

Table 2: List of EnrgyPlus features extracted for model training

Feature	Code	Feature	Code
Average U-value of envelope	<i>uval</i>	Sum of thermal storage capacity	<i>tmass</i>
Ratio of window area to wall area	<i>WWR</i>	Ratio of window area to floor area	<i>WFR</i>
Form Factor (Volume / Wall Area)	<i>ff</i>	Median relative humidity	<i>medrh</i>
Roof Ratio (Roof / Wall Area)	<i>rr</i>	Average sunlit percentage of envelope	<i>avgsunperc</i>
Annual sum of energy gained due to infiltration	<i>suminfgain</i>	Annual sum of energy lost due to infiltration	<i>suminfloss</i>
Annual sum of Internal Heat Gain	<i>sumIHG</i>	Annual sum of cooling degree days	<i>cdd</i>
Annual sum of heating degree days	<i>hdd</i>	Annual average of dry bulb temperature	<i>avgtdb</i>
Median dry bulb temperature	<i>medtdb</i>	Inter-quartile range of dry bulb temperature	<i>iqrtdb</i>
Annual average of dry point temperature	<i>avgtdb</i>	Median dew point temperature	<i>medtdb</i>
Inter-quartile range of dew point temperature	<i>iqrtdb</i>	Annual average of global horizontal irradiation	<i>avgghi</i>
Annual sum of global horizontal irradiation	<i>sumdni</i>	Inter-quartile range of global horizontal irradiation	<i>iqrdni</i>
Annual average of direct normal irradiation	<i>avgghi</i>	Annual sum of direct normal irradiation	<i>sumdni</i>
Inter-quartile range of direct normal irradiation	<i>iqrdni</i>	Annual average of relative humidity	<i>avgrh</i>

219 alteration in the input data can change the whole structure. A set of DTs
 220 are often employed in conjunction with each other, and calculated average
 221 representative estimated values, in order to address the aforementioned is-
 222 sue. In other words, bagging and optionally bootstrapping are applied in RF
 223 with the aim of combining the separate models containing a similar set of

224 information and generating a linear combination from various independent
 225 trees. The RF training procedure mechanism is illustrated in Figure 4.

Figure 4: Diagram of an RF model with n independent trees.

226 Determining several hyper-parameters is a prerequisite to adopting RF.
 227 The first parameter to determine here is the number of independent trees
 228 of the forest. The precision of the model and training is always negatively
 229 related to predicting computational complexity; therefore, an optimal model
 230 is achieved through balancing these together. There are also other settings
 231 to be considered. This includes the number of variables while seeking the
 232 best split, whether or not apply bootstrapping while creating independent
 233 trees, and a minimum number of a data sample to split on nodes.

234 3.3. MOO

235 There are several tuning methods for optimising the MLs for accurate
 236 predictions. These approaches include grid and random search techniques,
 237 evolutionary algorithms or Bayesian optimisation. Generally, these methods
 238 are applied to optimise a single objective criterion. However, in applications
 239 where two or more objective functions (i.e. heating and cooling loads) are
 240 optimised, those approaches are not adequate to designate the behaviour
 241 of the ML, and the Pareto front of multiple criteria has to be considered.
 242 Usually, for each objective, an ML is independently tuned to get the best

hyper-parameters, and the most accurate model and its configuration are selected eventually. The main disadvantage of this strategy is the high time-complexity of tuning the separate models. We propose a MOO method for automated hyper-parameter selection in modelling the heating and cooling loads of a building. The proposed method reduces the time required for tuning, speeds up the model predictions and decreases human effort for implementing ML. The general MOO problem is presented mathematically as:

Minimise:

$$F(\hat{x}) = [f_1(\hat{x}), f_2(\hat{x}), \dots, f_m(\hat{x})]^T$$

Subject to:

$$g(\hat{x}) \leq 0$$

$$h(\hat{x}) = 0$$

where

$$x_i^{min} \leq x_i \leq x_i^{max} (i = 1, 2, \dots, n)$$

$$x = [x_1, x_2, \dots, x_n]^T \in \Theta$$

$$y = [y_1, y_2, \dots, y_n]^T \in \Psi$$

Here m is the number of objective functions which is three in this case. Θ is the search space with n dimensions and identified by upper and lower bounds of decision variables $x_i (i = 1, 2, \dots, n)$.

$$x^{max} = [x_1^{max}, x_2^{max}, \dots, x_n^{max}]^T$$

$$x^{min} = [x_1^{min}, x_2^{min}, \dots, x_n^{min}]^T$$

Ψ is an m -dimensional vector space of objective functions and defined by Θ and the objective function $f(x) \cdot g_j(\vec{x}) \leq 0 (j = 1, 2, \dots, p)$ and $h(\vec{x}) = 0 (j = 1, 2, \dots, q)$ denotes p and q which are respectively the number of inequality and equality constraints. If both p and q are equal to zero, then the problem is simplified as an unconstrained optimization problem.

Figure 5 shows a hypothetical Pareto frontier for the optimisation of two objective functions which are energy loads estimation errors. These solutions (set of ML hyper-parameters) have been enclosed by a vector of an ideal

262 solution and a vector of dominated results, delimiting the upper and the lower
 263 borders of optimal packages. An ideal or utopia point is a theoretical notion
 264 relative to an ideal target in which each objective is optimised without paying
 265 attention to the satisfaction of the others. MOO tries to produce solutions as
 266 close to the Pareto optimal front with a possible uniform distribution. When
 267 the non-dominated solutions are recognised, decision-makers choose one as a
 268 final answer in accordance with the problem and individual preferences.

Figure 5: An example Pareto frontier of minimising errors in heating and cooling loads predictions.

269 Our tuning method involves an improved multi-objective genetic algo-
 270 rithm (NSGA-II) [56]. Genetic algorithm is initiated by randomly generated
 271 solutions as a population and sorts them into fronts based on non-domination
 272 criteria. These solutions are evolved from one generation to another based
 273 on the objective evaluation, selection, crossover and mutation operators.

274 3.4. Evaluation criteria and optimisation variables

275 As mentioned earlier, the objective functions for the optimisation problem
 276 determine the accuracy of a model in the prediction of heating and cooling
 277 loads. Each model is evaluated using k-fold cross-validation in which the
 278 accuracy of each fold is calculated as root mean square error (RMSE) of the

prediction test set. The average RMSE value of heating and cooling loads in all folds is computed and regarded as the final value for the objective functions.

When the MOO algorithm generates a population, each solution contains a set of RF parameters. Table 3 summarises these variables.

Table 3: List of RF parameters which are considered as MOO variables

Parameter	Description	Type	Values
<i>n_estimator</i>	Count of independent trees in the formation of the forest	Integer	200 – 1200
<i>max_features</i>	Count of input variables in creating each independent tree	Category	26, 5
<i>max_depth</i>	The maximum depth of the tree	Integer	10 – 100
<i>min_samples_split</i>	The minimum samples in splitting an internal node	Integer	2 – 10
<i>min_samples_leaf</i>	The minimum number of samples required to be at a leaf node	Integer	1 – 10
<i>bootstrap</i>	Whether or not to apply bootstrapping samples while generating the trees	Boolean	True, False

4. Results

This study used Python programming language and packages for implementing the proposed algorithms. The study used a PC with Intel Core i7-6700 3.4GHz CPU, 32GB RAM (with no utilisation of GPU processing) for running the experiments.

Using conventional Grid search method requires further investigation to decide the topmost hyper-parameters for the ML model. Besides, the existing solutions are not developed to calculate the accuracy of predicting multiple targets. Hence, a custom function is needed to perform the task. The proposed method generates non-dominating solutions in which models accuracy in estimating heating and cooling loads are the highest. Furthermore, in a Grid search, it is not possible to search every potential value for the parameters in the grid due to the size of the vast search space. Therefore,

as the hyper-parameters are discretely introduced to the grid, the chance of success of the optimisation algorithm, which smartly selects the values from predefined intervals is higher to build a model with more reliable accuracy.

Figure 6 demonstrates the top 5 solutions, the ML parameters and models accuracies for heating and cooling loads in terms of RMSE. Among those, the two closest solutions to the utopian point are *S4* and *S5*. The number of trees in *S4* is lower than *S5* resulting in faster training and predictions. As such, *S4* is suggested as the final set of parameters for modelling energy loads of the selected building dataset.

Figure 6: Top solutions provided by MOO for predicting heating and cooling loads of buildings.

Performance of the selected model tested using the 10-fold cross-validation over 5,000 randomly selected samples along with the results from Grid search, and the original study is summarised in Table 4. It can be seen that the selection of the right ML model and optimising the parameters using a Grid search method, the accuracy of predicting energy loads is considerably increased. The proposed MOO approach not only reduces the tuning time but

also improves the performance of the models by precise tuning. The selection of 1,500 as the number of evolutionary algorithm iterations was based on a rule of thumb while the best model was identified at the 879th iteration.

Table 4: Results comparison of the proposed method, Grid search and the original study

Method	Best RMSE		Complexity	
	Heating	Cooling	No. of Iterations	Tuning time (h)
Moo	12.72	9.4	7,000	349
Grid Search [6]	12.56	9.28	1,500	79
Original Study [57]	25.05	12.84	Using 4,000 random samples and Gaussian Process Regression	

To illustrate the effect of data size on the accuracy of supervised models, RMSE is plotted versus the number of training and test records forecasting heating and cooling loads of EnergyPlus data which is depicted in Figure 7. To evaluate the accuracy and generalisation of RF model in predicting energy loads, 10-fold cross-validation is utilised. The prediction confidence intervals, which are maximum and minimum values of all folds along with the mean value, are illustrated in Figure 7. Figure 8 shows the average training and testing times versus the number of records.

From two figures, it can be seen that there is a trade-off between accuracy and time complexity of the model. However, the results indicate that the sample size of 45,000 is sufficient for training a dependable model. With that record size, the model which is trained and tested at an average of 64.14 and 0.51 seconds achieves the RMSE of 6.97 and 4.61 kWh/m^2 for heating and cooling loads, respectively. It should be noted that this testing time relates to the forecasting of 4,500 samples. This figure denotes that the model has the capability of processing 8,8000 building records in one second.

The calculated confidence intervals at that point assure building a reliable model not only because the narrow band but also due to the fact that the data covers the space of possible values of the selected features for building design. Moreover, the use of 10-fold cross-validation and a random selection of records grants a fair test procedure. Therefore, the upper bound of the RMSE in the presented graph can be considered as models' worst performance.

To show the model performance using the full capacity of generated data,

(a)

(b)

Figure 7: RMSE of predicting (a) heating and (b) cooling loads by varying the number of total number of samples used for training

Figure 8: Average training and testing time of energy loads models the versus number of records.

339 400,000 records are fitted into a model in 6672 seconds achieving the accuracy
 340 of 2.78 and 2.12 kWh/m^2 for heating and cooling loads (4% of mean energy
 341 load values). Figure 9 shows the predicted (model estimation) vs actual
 342 (simulated) values of energy loads testing over 30,000 buildings along with
 343 the error distributions.

344 Due to the nature of RF models in training independent trees in which
 345 different feature set is selected, they are able to determine input variables im-
 346 portance in target estimation. This competency which is known as sensitivity
 347 analysis provides useful information in the analysis of the studied system. In
 348 this study, we fitted 30 RF model over 100,000 random building samples to
 349 generate a better empirical distribution of feature importance. Figure 10
 350 illustrated the results of the sensitivity analysis of these RF models, which
 351 are configured based on the MOO algorithm outputs (best hyper-parameters
 352 set).

353 In comparison with the results from training two different models for

Figure 9: Actual and predicted (a) heating and (b) cooling and (c) and (d) their error

Figure 10: Importance of features for energy loads prediction using RF model.

each of heating and cooling loads [6], it can be seen the important features in our model is a combination of those in two separate models. Moreover, the results indicate that prediction of heating loads mostly rely on building characteristics while cooling load forecasting depends on weather features. Here, the unimportant variables are ‘avrh’, ‘avdni’, ‘iqrdni’, ‘iqrgi’, ‘medrh’, ‘sumdni’, however, ‘avghi’ and ‘sumghi’, which had an insignificant impact on modelling cooling loads still play a considerable role in this model. Although the advanced machine learning can ignore unimportant features despite the traditional statistical modelling, removing those from the data can reduce the model time complexity and slightly increase the accuracy. Table 5 presents the results of testing the model by removing the identified features. It can be seen that the RMSE fluctuations of the folds are also reduced compared to the original model.

5. Conclusion

This research addresses the issues regarding inaccurate modelling of building energy loads using ML techniques. As mentioned in the reviewed litera-

Table 5: Performance comparison of ML models including all features and removing unimportant ones.

Parameters	All inputs		Selected inputs	
	Heating	Cooling	Heating	Cooling
RMSE (kWh/m^2)	6.97 ± 3.29	4.61 ± 2.02	6.19 ± 1.55	4.48 ± 1.64
MAE (kWh/m^2)	2.54	2.36	2.44	2.22
R^2	0.992	0.993	0.993	0.993
Fit time (s)	64.16		64.16	
Test time (s)	0.51		64.16	

ture, most research studies used MLs without model optimisations, and they proposed to model each energy metric, such as heating and cooling loads separately. The latest attempt to enhance the performance of those data-driven models included exhaustive exploration of variable parameters to choose the best performing model. This paper has proposed a method based on MOO to expedite the process of selecting hyper-parameters, and simultaneously to optimise one single model for forecasting both heating and cooling loads. The main advantages of this method over traditional approaches include a reduction in the time complexity of creating reliable models and improvements in the accuracy of predictions by fine-tuning of the ML models. The proposed approach was evaluated by implementing the random forest decision tree algorithm and testing the accuracy over a building data which was simulated using EnergyPlus. The effectiveness of the proposed approach was demonstrated through comparisons with conventional grid search methods and traditional statistical modelling. Generating an accurate model for calculation of the energy loads with fast and robust process paves the way for more informed and productive design decisions for built environments. Furthermore, the use of ML in the complex buildings goes beyond mere optimisation support matters by offering efficient retrofitting plans, without which it would be a rather cumbersome task for the engineers to carry out complicated calculations readily and make informed decisions.

This study highlights the importance of features in predicting heating and cooling loads using the built-in mechanisms of RF models. The results showed how practically ML models can balance the influential variables on computing energy loads and ignore irrelevant ones without affecting the accu-

395 racy. The importance of using ML techniques and model optimisation is more
396 emphasised while complicated energy modelling (e.g. considering occupancy
397 in estimations) using deep learning. By adding layers of learning models to
398 extract complex relations in the data, the number of hyper-parameters and
399 model sensitivity is considerably increased.

400 The research highlights the potential of ML model-based techniques in
401 modelling building energy indicators, which are sometimes laborious to sim-
402 ulate or calculate using engineering methods. It has been approximated that
403 only three per cent of industrial data is currently being used in a meaningful
404 way. This is why Industry 4.0 has put more emphasis on the utilisation of
405 technologies that could take advantage of the ever-growing data.

406 As policy tightens on inefficient energy consumption and our understand-
407 ing of the limitations of BEM-led design decision-making, the necessity for
408 more efficient and flexible models increases. Research over the last few years
409 has been giving greater credence to designing buildings with consideration
410 for medium-term climate change and any number of occupant presence or
411 behaviour uncertainties. Every extension to the potential configurations ex-
412 ponentially inflates the problem space while likely reducing the conventional
413 options solution space. Furthermore, these climate and utilisation proper-
414 ties are internal to BEMs, however, design and retrofit analysis is increasingly
415 considering external and more challenging to integrate properties. The frame-
416 work shown in this paper demonstrates that algorithmic decision-making ca-
417 pabilities are not nearing their limit and lays a foundation for more complex
418 ML frameworks.

419 The work presented here makes a significant contribution to research and
420 practice of energy management in buildings. In particular, the prediction of
421 heating and cooling loads, which is mired with several challenges for practi-
422 tioners, is going to be easier and more accurate using the approach outlined
423 here. The application of ML techniques in the heating and cooling load fore-
424 cast is not widely used at the moment and the authors claim that this research
425 provides the practitioners with a novel approach to address the challenges
426 they encounter in this important and key area of their routine activities.
427 Although the potentials of ML techniques in predicting heating and cooling
428 loads have been reported by several researchers, the credibility of results may
429 be questionable without the tuning of ML models. Tuning of models not only
430 increases the predictive accuracy, but also reduces model complexity, ease of
431 use, and consistency of predictions. Particularly, when the solution space
432 grows exponentially due to the large number of hyper-parameters, searching

433 for the optimal solutions without tuning of models is a non-trivial task. This
434 research addresses these issues and validates them on a substantial volume
435 of realistic data drawn from both tertiary as well as residential buildings.

436 The authors believe that there are significant implications of this work
437 not only on the industry in terms of informing the design process and making
438 it more efficient but also for the energy modelling software industry in terms
439 of utilising the approaches demonstrated in this paper in the development of
440 their software solutions.

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