Multi-Objective Optimisation for Tuning Building Heating and Cooling Loads Forecasting Models

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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 much dependant on the selection of the right hyper-parameters for specific building dataset. This paper proposes a method for optimising ML model 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 tune one model to precisely predict building energy loads but also accelerates the process of model optimisation. The study utilises a simulated building energy data generated in EnergyPlus to demonstrate the efficiency of 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

1. Introduction

There have been several approaches proposed to enhance the energy efficiency of buildings in many countries during the last couple of 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 (X. Li, Bowers, & Schnier, 2010).

Every attempt to optimise buildings' energy performance involves series of calculations to estimate the energy consumption and create an index such as Energy Performance Indicator (EPI) or Energy Use Intensity (EUI) from the measured data (T. Hong, Koo, Kim, Lee, & Jeong, 2015; Nikolaou, Kolokotsa, Stavrakakis, Apostolou, & Munteanu, 2015). Most prevailing optimisation methods are simulation-based where the energy-related objectives (i.e. energy consumption or gas emission) are calculated by a Building Performance Simulation (BPS) tool such as EnergyPlus, TRNSYS or ESP-r. This approach limits the computation complexity of the algorithms to BPSs' calculation time. As such, when a large number of solutions are defined, the calculation and optimisation process may become extremely costly to handle. For this reason, most of the studies which focused on decision making for energy performance improvement of buildings either investigated basic or simple optimisation models or targeted retrofitting only one or two parts of envelopes to pare-down total calculation time and cost. It is also noted that the majority of studies targeted residential buildings, and there are only a few examples of research related to non-domestic buildings. A key component of achieving global development and meeting climate change mitigation targets is the optimisation of the building stock. This process requires significant testing and planning to deliver.

With the tremendous growth in the amount of valid and attainable datasets of structures 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) (Seyedzadeh, Rahimian, Glesk, & Roper, 2018).

The use of ML models needs particular consideration of the accuracy and suitability of the data and relationships inferred from the data. It has been demonstrated that the process of tuning a model not only increases the predictive accuracy but also reduces model complexity, ease of use, and consistency of predictions (Seyedzadeh, Rahimian, Rastogi, & Glesk, 2019).

ML techniques have been widely used for modelling building energy loads and performance. Traditionally, the defaults 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 (Ahmad, Mourshed, & Rezgui, 2017; Jain, Smith, Culligan, & Taylor, 2014; C. Li, Ding, Zhao, Yi, & Zhang, 2017; Massana, Pous, Burgas, Melendez, & Colomer, 2015). Tuning ML model hyper-parameters using grid search could be very time-consuming when a complex one is chosen such as Artificial Neural Networks or models based on decision trees.

When MLs are utilised to forecasting multiple measures such as heating and cooling loads, it is required to optimise models for both the targets (Papadopoulos, Azar, Woon, & Kontokosta, 2018; Seyedzadeh et al., 2019). This procedure, in turn, increases the time required and exacerbates the usability of MLs. To address the issues mentioned above, this paper proposes a method based on an evolutionary algorithm for optimisation of ML models for accurate prediction of both heating and cooling loads. The proposed approach uses a multi-objective optimisation (MOO) to find the most appropriate hyper-parameters for Random-Forest (RF) model. The selection of RF method is due to the high precision of in prediction and the ability to simultaneously forecast multiple targets.

The next section presents a review of previous studies and issues with tuning ML models in predicting building energy consumption. That is followed by a description of the RF method, the case study, and results from our tuning approach. The final section contains recommendations and discusses future work.

2. Background and Motivation

Machine Learning refers to a set of algorithms that can learn from existing data (features and targets) to predict outputs on new, unseen inputs. The learning algorithms are divided into two categories: supervised learning, in which the target is known, and unsupervised learning, where there is no "output" to learn and predict. Supervised learning is either one of regression or classification, in which input

features (X) are mapped to one or more targets variables (Y). Unsupervised learning includes techniques such as clustering, which organises data into groups based on similarities among the samples in a dataset. Unsupervised learning is applied to an unlabeled dataset, i.e., where the there are no labels to test against, while a supervised learning algorithm detects the relation between inputs and output and used this function to predict new records.

The use of machine learning models in the analysis of buildings was first used by Kalogirou et al. (1997) to estimate building heating loads considering envelope characteristic along with the desired temperature. The work (S. A. Kalogirou, 2000) was completed in 2000 by using ANNs to predict the hourly energy demand of holiday dwellings, calculated using ZID software. Kalogirou et al. (S. Kalogirou, Florides, Neocleous, & Schizas, 2001) also used ANN to estimate the daily heat loads of model house buildings with different combinations of the wall and roof types (i.e. single vs cavity walls and roofs with different insulation applied) using a typical meteorological data for Cyprus. In that study, TRNSYS software acted as an energy evaluation engine for all cases and the data validated by the comparison of one building energy consumption with the actual measurement. Since then, ANN has been widely used for estimating building heating and cooling loads (C. Deb, Eang, Yang, & Santamouris, 2016; S. M. Hong, Paterson, Mumovic, & Steadman, 2014; Paudel, Elmtiri, Kling, Corre, & Lacarrière, 2014; Yokoyama, Wakui, & Satake, 2009), Electricity demand (Mena, Rodríguez, Castilla, & Arahal, 2014; Platon, Dehkordi, & Martel, 2015), energy demand (Dombayci, 2010; Kialashaki & Reisel, 2013; Neto & Fiorelli, 2008) and overall energy performance (Khayatian, Sarto, & Dall'O', 2016; Wong, Wan, & Lam, 2010; Yalcintas, 2006).

Support Vector Machine (SVM) for building energy forecasting was introduced by Dong et al. (2005) and adopted by several studies for prediction of cooling and heading loads (Hou & Lian, 2009; Q. Li, Meng, Cai, Yoshino, & Mochida, 2009; Xuemei, Jin-hu, Lixing, Gang, & Jibin, 2009) electricity consumption (Massana et al., 2015; Xing-ping & Rui, 2007), and energy consumption (Chen & Tan, 2017; Jain et al., 2014; H. Zhao & Magoulès, 2010).

Ensemble ML models such as RF and gradient boosted regression trees have been introduced for decades, but their use in building energy domain is recent (Deng, Fannon, & Eckelman, 2018; Papadopoulos, Azar, Woon, & Kontokosta, 2017; Tsanas & Xifara, 2012; Wang, Wang, Zeng, Srinivasan, & Ahrentzen, 2018).

Simple models with few parameters like SVM are easy to optimise, but when the number of hyper-parameters is increased the search space becomes huge. 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 precise tuning in comparison with SVM or Gaussian process regression (Seyedzadeh et al., 2019). Forecasting two or more building energy measures such as heating and cooling loads at one time 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 time as well as selection of the ideal model.

This study proposes a framework for optimising models with several hyper-parameters and ability to predict multiple targets from the same set of features concurrently.

3. Methodology

Figure 1 demonstrates the proposed optimisation procedure for selecting the best hyper-parameters. ML models operate as a black box, so further information about the building is not required. As is clear, the first step is to select a set of features for representing the building energy system. Although data-driven methods build models with fewer variables than engineering techniques, it is crucial to generate a logical input set for ML models. These features are not necessarily raw building characteristics or weather data; instead, they could be complex variables calculated from basic ones, e.g. mean daily global radiation (H.-X. Zhao & Magoulès, 2012). The next step is to optimise the model itself.

In this study, the use of an evolutionary optimisation algorithm for selecting the best parameter of an RF model in forecasting heating and cooling loads of buildings is proposed. The proposed optimisation algorithm and machine learning model are implemented using Python programming language, and tests have been carried out on a PC with Intel Core i7-6700 3.4GHz CPU, 32GB RAM. An RF model for prediction of heating and cooling loads is also tuned using a grid search method. All models are trained

and tested using 10-fold cross-validation and five thousand randomly selected building records.

In this section, first, the RF model is introduced, followed by an explanation of MOO. Then the evaluation criteria, along with the optimisation parameters, are elaborated. Finally, the description of the building dataset, which is used as the case study for the evaluation of the proposed approach will be presented.
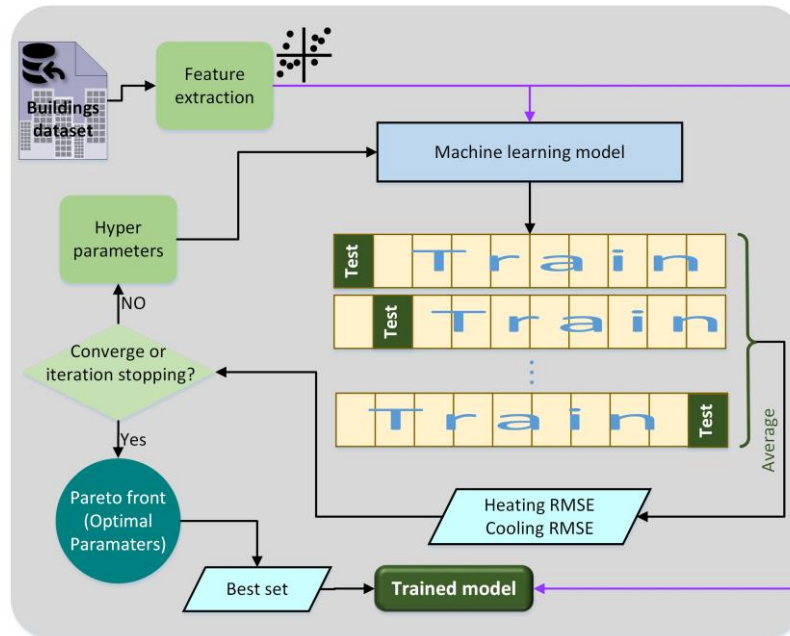

Figure 1: Schematic diagram of the proposed MOO-ML method.

3.4.   Random Forest

Random forest is a collection (ensemble) of randomised decision trees (DTs). A DT is a non-parametric ML algorithm that establishes a model in the form of a tree structure. DT repeatedly divides the given records into smaller and smaller subsets until only one record remains in the subgroup. The inner and final sets are known as nodes and leaf nodes. As the precision of DT is substantially subject to the distribution of records on in the learning dataset, it is considered as an unstable method (i.e. tiny alteration in the observations will change the entire structure). To overcome this issue, a set of DTs is used and the average predicted values of all independent trees is selected as the final target. In general, RF applies bagging and boosting to combine separate models with similar information to generate a linear combination from many independent trees.

RF requires several hyperparameters to be set. The main parameter is the number of independent trees in the forest. There is a trade-off between the accuracy of model and training and predicting computational cost. Thereby, this parameter should be tuned to choose the optimal value. Other parameters include the number of features to consider when seeking for the best split, whether bootstrap (generating multiple different models from a singular training dataset) samples are used when creating trees and a minimum number of a data sample to split on nodes.

3.4.   Multi-objective optimisation approach

There are several tuning methods for optimising the MLs for accurate predictions. These approaches include grid and random search techniques, evolutionary algorithms or Bayesian optimisation. Generally, these methods are applied to optimise a single objective criterion. However, in applications where two or more objective functions (i.e. heating and cooling loads) are optimised, those approaches are not adequate to designate the behaviour of the ML, and the Pareto front of multiple criteria has to be considered. 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:

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

Subject to

$$g(\vec{x}) \le 0$$
$$h(\vec{x}) = 0$$

where

$$x_i^{min} \le x_i \le x_i^{max} \ (i = 1,2,\dots,n)$$
$$x = [x_1, x_2, \dots, x_n]^T \in \Theta$$
$$y = [y_1, y_2, \dots, y_m]^T \in \psi$$

Here m is the number of objective functions which is three in our problem. Φ is the search space with n dimensions and identified by upper and low 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 $f(x)$. $g_j(\vec{x}) \le 0 (j = 1,2,\dots,p)$ 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.

Our tuning method involves an improved multi-objective genetic algorithm (NSGA-II) (K. Deb, 2014). Genetic algorithm is initiated by randomly generated solutions as a population and sorts them into fronts based on non-domination criteria. These solutions are evolved from one generation to another based on the objective evaluation, selection, crossover and mutation operators.

3.5. Evaluation criteria and optimisation variables

The objective functions for our optimisation problem are the accuracy of a model in the prediction of heating and cooling loads. This measure is calculated as the average root mean square (RMSE) for both heating and cooling estimations. When the MOO algorithm generates a population, each solution contains a set of RF parameters. Table 1 summarises these variables.

Table 1RF model hyper-parameters for tuning.

Parameter	Description	Type	Values
n_estimator	The number of trees in the forest.	integer	200 – 1200
max_features	The number of features to consider when looking for the best split:	category	26, 5
max_depth	The maximum depth of the tree	integer	10 – 100
min_samples_split	The minimum number of samples required to split an internal node	integer	2 – 10
min_samples_leaf	The minimum number of samples required to be at a leaf node	integer	1 – 10
bootstrap	Whether bootstrap samples are used when building trees	boolean	True, False

In every generation, solutions are evaluated by training and testing a model over 5000 building records. The train and test procedure is performed using k-fold cross-validation. In this procedure, the data is divided into k exclusive subsets, and each combination of model parameters and architecture is fitted to each distinct group of $k-1$ subsets and tested on the remaining subset. This process provides a distribution of errors for a given model choice on different parts of the dataset, i.e., an estimate of the general applicability of the model to represent the variation in the dataset. The average amount of RMSE

of *k* folds is then considered as the evaluation measure for each solution.

Table 2 List of input variables for model training of buildings heating and cooling loads

Group	QTY	Stats	Description	Range	Code	Unit
Building	U-value	Average	Average U-value of envelope	0.14–6.06	*uval*	W/m² K
	Thermal Mass	Sum	Sum of thermal storage capacity	1e-4–7.61	*tmass*	MWh/K
	Envelope Ratios	Ratio	Ratio of window area to wall area	0.58–85.00	*wwr*	-
			Ratio of window area to floor area	0.01–0.42	*wfr*	-
	Massing	Ratio	Form Factor (Volume / Wall Area)	2.47–17.14	*ff*	-
			Roof Ratio (Roof / Wall Area)	0.31–2.73	*rr*	-
Mixed	Shading	Average	Average sunlit percentage of envelope	0.35–100	*avgsunperc*	%
	Infiltration	Sum	Annual sum of energy gained due to infiltration	0–0.74	*suminfgain*	GWh
			Annual sum of energy lost due to infiltration	−2.7– -1e-4	*suminfloss*	
Other		Sum	Annual sum of Internal Heat Gain	0.03–5.24	*sumIHG*	GWh
Climate	Degree Days	Sum	Annual sum of cooling degree days	(9.6–160)e4	*cdd*	C-day
			Annual sum of heating degree days	424–64878	*hdd*	
	Dry BulbTemp (Hourly)	Avg.	Annual average of dry bulb temperature	−3.11–28.39	*avgtdb*	C
		Median	Median dry bulb temperature	−7.20–30	*medtdb*	
		IQR	Inter-quartile range of dry bulb Temp	3.6–34	*iqrtdb*	
	Dry Point Temp (Hourly)	Avg.	Annual average of dry point temperature	−7.41–21.43	*avgtdp*	C
		Median	Median dew point temperature	−6.4–24.2	*medtdp*	
		IQR	Inter-quartile range of dew point temperature	0–26.8	*iqrtdp*	
	Global Horizontal Irradiation (Hourly)	Avg.	Annual average of global horizontal irradiation	190–509	*avghi*	MWh/m2
		Sum	Annual sum of global horizontal irradiation	0.40–2.23	*sumghi*	
		IQR	Inter-quartile range of global horizontal irradiation	(0.84–5.2)e-3	*iqrghi*	
	Direct Normal Irradiation (Hourly)	Avg.	Annual average of direct normal irradiation	57–676	*avgdni*	MWh/m2
		Sum	Annual sum of direct normal irradiation	−10.34–3.15	*sumdni*	
		IQR	Inter-quartile range of direct normal irradiation	(0.38–26.3)e-4	*iqrdni*	
	Humidity(Hourly)	Avg.	Annual average of relative humidity	22–98	*avrh*	%
		Median	Median relative humidity	18–99.6	*medrh*	

3.6. Description of the datasets

A building datasets simulated using BPS tools is utilised. This data includes 460,000 domestic and non-domestic buildings simulations characterised by 7 structural, 16 climate and 3 mixed features as presented in Table 2. The characteristics of building cases are selected from different sources including, United States Department of Energy commercial building reference database and residential houses in Geneva, Switzerland and north of Germany.

4. Results

The results from the grid search require further investigation to select the best model. Besides, it is not possible to search every potential value for the parameters in the grid due to the size of the huge search space. Therefore, as the hyper-parameters are discretely introduced to the grid, the chance of the optimisation algorithm, which smartly selects the values is higher to reach a model with better accuracy. As expected, the best models from MOO and grid search achieves mean RMSE of 12.56 and 13.68 KW/m2 for heating and 9.28 and 9.43 for cooling predictions, respectively.

Regardless of the obtained accuracy, MOO converged on the selection of the best hyper-parameters 4.5 times faster than the time required for the grid to search the whole space. Considering the average time of 18 seconds for training and test of each fold and the size of possible combinations of the hyper-parameters as almost seven thousand, the grid is completed in 14 days whereas MOO evaluates around 1,500 solutions in 3 days.

The best hyper-parameters providing the most accurate predictions for both heating and cooling loads are as follow: *n_estimators = 337, bootstrap = False, max_depth = 30, max_features = 'sqrt', min_samples_split = 3, min_samples_leaf = 1.*
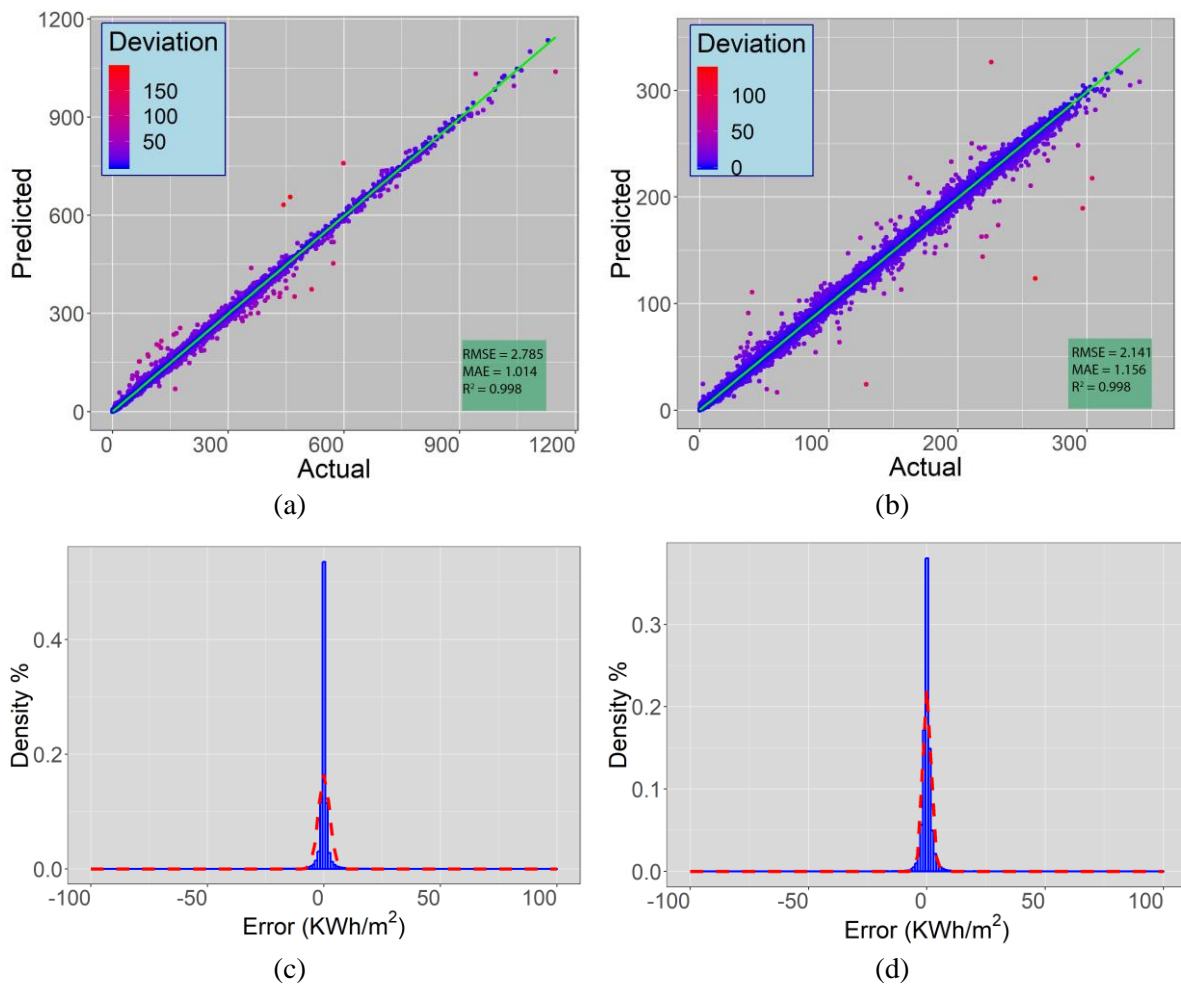

Figure 2: Actual and predicted (a) heating and (b) cooling and (c) and (d) their error

distributions, respectively.

After determining RF parameters, a model is then trained and tested with 400,000 building records. The model was fit using 300,000 samples and tested over the rest. Figure 2 illustrates the results as predicted (estimated) loads against loads from the simulator (actual values), and the distribution of errors between simulated-predicted pairs. To investigate the effect of data size on the accuracy of supervised models, mean RMSE of heating and cooling is plotted against the number of train and test records which is depicted in Figure 3. Here, a 10 fold cross- validation is used in the RF model and worst, best and mean RMSE of all folds are presented. Mean training time is also displayed as the top axis for evaluating computational overhead.
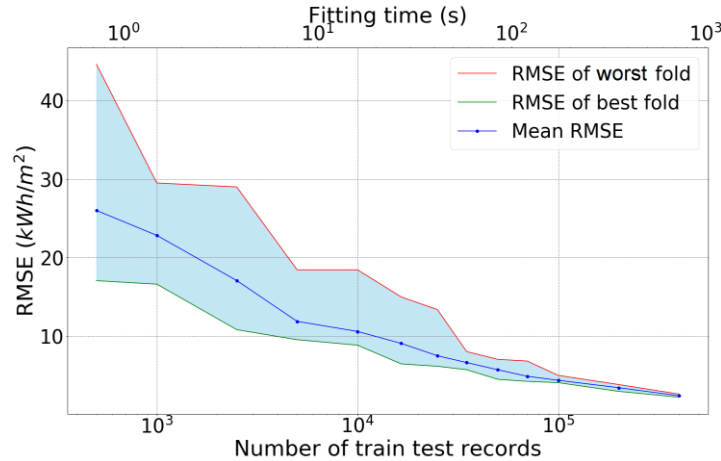

Figure 3: RMSE for heating load against the total number of samples used for training

5. Conclusion

This research addresses the gap in using ML models which require precise tuning to accurately predict building energy loads. As mentioned in the reviewed literature, most research reviewed used MLs without model optimisations, and they proposed to separately model the heating and cooling loads. This paper has proposed a method based on MOO to facilitate the process of selecting hyper-parameters, and simultaneously to optimise the model for both forecasting heating and cooling loads. 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 our proposed approach was demonstrated through comparison with traditional grid search methods. Generating an accurate model for calculation of the energy loads with fast and robust method paves the way for more informed and productive design decisions for built environments. Furthermore, along with the optimisation algorithms, ML also offers a promising solution for efficient retrofit planning of complex buildings, where engineers are not able to carry out massive calculations readily.

Acknowledgements

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