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A Hyper Parametrized Deep Learning Model for Analyzing Heating and Cooling Loads in Energy Efficient Buildings

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ABSTRACT: The huge increase in energy consumption in recent decades, has made it cumbersome to anticipate energy usage in the residential sector. However, despite substantial advancements in computation and simulation, the modelling of residential building energy use is still in need of improvement for efficient and reliable solutions. To this end, the overarching objective of this research study is to construct a self-adaptive model (HBO-DL) for predicting the amounts of heating and cooling loads in residential buildings. The developed HBO-DL model is envisioned on coupling Bayesian optimization with deep learning neural network. Five statistical metrics of mean absolute percentage error (MAPE), root mean squared error (RMSE), root mean squared logarithmic error (RMSLE), mean absolute error (MAE) and normalized root mean squared error (NRMSE), are leveraged to measure and test the accuracies of the developed HBO-DL. Analytical results explicated that the developed HBO-DL model can endorse informed decision-making and foster energy conservation in built environment.

Key words: Energy consumption, heating and cooling loads, residential buildings, Bayesian optimization, deep learning neural, network

INTRODUCTION

The economic growth of any country is highly influenced by the amount of reduced energy consumption in its buildings (Liu et al., 2021). The buildings are responsible for 46%, 40%, and 27% of the total carbon dioxide emissions in the United Kingdom, United States and Australia, respectively (Kelly et al., 2012; Filippín, 2020.) The energy demand of both residential and commercial buildings accounts for 40% of the total energy demand in the United States and the European Union. However, this percentage is only 30% in China, with 63% of it consumed in heating and cooling purposes (Huebner et al., 2015). It is estimated that a 20% improvement of the buildings' energy performance in the European Union will lead to an annual saving of 60 billion Euros (Li et al., 2010). Mitigating the buildings' emissions and energy consumption requires an alteration in human behavior, application of environmentally friendly products, and controlling the root causes of these emissions. Therefore, construction of energy-efficient buildings and improvement of energy usage in existing buildings act as great moves to reduce global warming (Seyedzadeh et al., 2018). Accordingly, several efforts have been exerted by researchers to predict the building energy consumption (Cuce et al., 2015). The energy performance indicator or energy use intensity of any building is measured by kWh/m^2/time period (Hong et al., 2015; Nikolaou et al., 2015). The obstacles in predicting the building energy consumption are listed as follows: a) determining the most accurate and convenient approach, and b) recommending the most suitable model in different cases. It shall be noted that it is crucial to compromise between the accuracy and computational time of the prediction approaches (Liu et al., 2019). Hence, the ultimate objective of this study is to create a self-tuning deep learning-based model for accurate forecasting of heating and cooling loads in residential buildings.

LITERATURE REVIEW

The assessment of building energy could be categorized into four classes namely, engineering methods, simulation models, statistical models, and machine learning models [6]. Most of the research efforts utilized statistical methods while only rare studies applied machine learning in the performance evaluation (Liu et al., 2019). The engineering methods comprise applying mathematics or dynamics for deriving the energy usage of building components. The simulation models involve the application of computer software models for simulating the performance of buildings. The statistical methods aim at finding a relationship between the output (i.e. energy consumption) and the influencing input parameters using historical data. However, the main drawbacks of these approaches are reliance on high-quality historical data and large computer memory as well as consuming a long time and producing inaccurate and insignificant results. The machine learning method was developed to overcome the limitations of the statistical methods (Liu et al., 2019; Seyedzadeh et al., 2018). The objective of machine learning is forecasting the output(s) without evolving strict or complex conditions (Samuel, 1967). The machine learning models have been applied in wide research areas. However, their utilization in the energy consumption field is still in an infancy stage (Liu et al., 2019)

The machine learning models can also act as alternatives for traditional building energy rating schemes because they extract the underlying patterns in various features of building data sets, which can be used for classifying the buildings and estimating their ratings (Deb et al., 2016). A significant amount of energy data has been produced recently due to a rise in interest in building energy use, claimed by Wei et al. (2018), which strengthens the data-driven algorithms for widespread use in the construction industry. This article examines the prevalent data-driven techniques used in building energy analysis across a range of archetypes and granularities. These techniques include prediction techniques like artificial neural networks and support vector machines as well as classification techniques like K-mean clustering, self-organizing maps, and hierarchy clustering. The review's findings show that data-driven approaches have successfully addressed a wide range of applications related to building energy, including load forecasting and prediction, energy pattern profiling, mapping regional energy consumption, benchmarking for building stocks, global retrofit strategies, and developing guidelines, among others. Importantly, this review clarifies a few crucial responsibilities for changing data-driven methodologies when used to building energy analysis. Through the proper refit and the addition of renewable energy technology, the findings of this review may help future micro-scale changes in the energy use of a specific building. Additionally, it opens up a path for investigating the potential of large-scale energy reduction while taking customer demands into account. All of these will be helpful in developing a more effective long-term plan for urban sustainability.

For example, Alawadi et al. (2022) examined and compared the application of 36 different machine learning models to forecast the hourly indoor temperature of a smart building. The data was acquired from sensors linked to the HVAC system (i.e. underfloor heating status, underfloor heating temperature, air condition status, air conditioning temperature, air conditioning humidity, indoor temperature, and previous indoor temperature) and the nearest weather station (i.e. humidity, temperature, and solar radiation). Results showed that the Extra Trees algorithm performed better in terms of the correlation coefficient and root mean square error. Besides, it ranked first according to Friedman's statistical test. Besides, this algorithm was proved to be less sensitive to outliers and noise data. Its performance was also not affected by increasing the forecasting period. Therefore, the application of a standard machine learning algorithm was found to be successful in forecasting the indoor temperature of smart buildings. Moayedi et al. (2020) proposed a hybrid artificial intelligence model to predict the cooling loads in residential buildings. The input parameters comprised the relative compactness, surface area, roof area, wall area, glazing area, glazing area distribution, orientation, and overall height. The model optimized the multi-Layer Perceptron (MLP) using three metaheuristic algorithms namely; Elephant Herding Optimization (EHO), Ant Colony Optimization (ACO), and Harris Hawks Optimization (HHO). The results revealed that the EHO-MLP model yielded the highest accuracy and required the least computational time, followed by the HHO-MLP and ACO-MLP.

Liu et al. (2020) forecasted the energy consumption in an office building using three Deep Reinforcement Learning (DRL) techniques which are; Asynchronous Advantage Actor-Critic (A3C), Deep Deterministic Policy Gradient (DDPG), and Recurrent Deterministic Policy Gradient (RDPG). These DRL techniques were compared against three common supervised machine learning models (i.e. multiple linear regression, backpropagation neural networks, and random forest) in terms of the convergence speed, computation time, and prediction accuracy. The model accounted for the historical energy consumption data, system status, and meteorological data including wind speed, outdoor temperature, and wind speed. It was found that the DDPG and RDPG techniques improved the prediction accuracy while requiring more computation time. On the other side, the A3C technique was proved to be the most efficient technique despite reducing the prediction accuracy.

Zekić-Sušac et al. (2021) incorporated the concepts of big data and machine learning for managing the energy efficiency of public buildings. The prediction models were developed using deep neural networks, RPART regression tree, and random forest algorithms. The random forest algorithm was found to be the most accurate model.

Moon et al. (2020) forecasted the building electricity consumption in a typical office building using a stacking ensemble approach. The model accounted for the weather factors including the wind speed, temperature, and humidity as well as the time series data and historical electric load data. Various deep neural networks with different numbers of hidden layers and sliding window-based principal component regression were constructed to forecast the building's electric energy consumption. The proposed model was verified against actual electric energy consumption data using the mean absolute percentage error and mean absolute error. Results yielded that the proposed model boosted the prediction performance of building electric energy consumption. Zeng et al. (2020) predicted the electricity usage of six different commercial buildings using a Gaussian process regression method. The model accounted for the occupancy schedule and weather conditions (i.e. enthalpy, dry-bulb temperature, and wet-bulb temperature). The significance of these input parameters was affirmed by conducting a correlation analysis with the building's energy use. The prediction results were compared against the real electricity consumption in these buildings using RMSE and Normalized Mean Bias Error (NMBE). It was observed that the proposed model improved the prediction accuracy and reduced the computational time for forecasting building electricity use.

Walker et al. (2020) evaluated the hourly electricity demand in commercial buildings at an individual level and an aggregated level by applying many machine learning models. These models include the boosted-tree, random forest, SVM-linear, quadratic, cubic, fine-Gaussian, and ANN models. The models accounted for weather-related factors (i.e. outdoor temperature, dry bulb temperature, and relative humidity), categorical factors (i.e. day of the week, hour of the day, month of the year, and seasons), intervention event (i.e. working day), energy consumption related autoregressive parameters (i.e. energy consumption of the previous day and energy consumption of the previous week). Results revealed that the ANN, boosted-tree, and random forest provided the best results when compared to other models in terms of computational time and error accuracy. Marzouk and Mohammed Abdelkader (2020) introduced a fuzzy-based model for optimizing sustainability related impacts of construction operations. In their model, a multi-objective optimization model was formulated based on minimizing project time, cost, environmental impact and energy consumption. A multi-criteria decision making model was then created to reap the best design alternative among the Pareto optimal solutions.

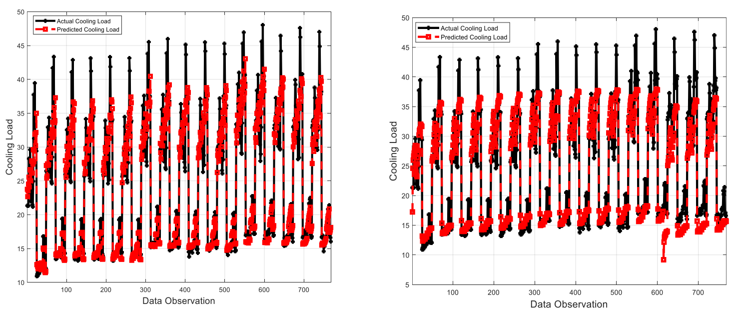
MODEL DEVELOPMENT

The primary objective of this study is to construct an efficient hybrid Bayesian optimization-based deep learning model for projecting heating and cooling loads in residential buildings. The dataset used herein, relies on the published work by Tsanas and Xifara (2012). In their dataset, 768 simulation records were produced based on spatial varying characteristics of the buildings. Ecotect energy analysis software was then harnessed in their study to compute heating and cooling loads for each combination of building characteristics. In their energy efficiency dataset, the amounts of heating and cooling loads were determined based on the input features of glazing area distribution, glazing area, overall height, orientation, surface area, wall area, roof area and relative compactness. The possible scenarios of glazing area distribution, glazing area, overall height, orientation, surface area, wall area, roof area and relative compactness are 4, 6, 2, 4, 12, 7, 4 and 12, respectively. The developed hybrid model capitalizes on the amalgamation of Bayesian optimization (BO) and deep learning neural network (DL) for predicting the amounts of heating and cooling loads in residential buildings. In the recent few years, optimization algorithms evinced their effectiveness in amplifying the training mechanism of machine learning models (Dong et al., 2022; Ly et al., 2022; Mohammed Abdelkader et al., 2020). In this respect, Bayesian optimization is leveraged for two vital reasons: 1) automated optimization of hyper parameters of deep learning neural network, and 2) autonomous identification of the influential input features. It is noteworthy pointing out that the developed model is characterized by its self-adaptive nature. Hence, different optimum architectures are triggered by the inputs and outputs present in the dataset. Thus, an optimum architecture of deep learning neural network is appended for each type of load prediction. The developed HBO-DL model is tested against the classical data-driven models of support vector machines (SVM), generalized regression neural network (GRNN), cascade forward neural network (CFNN), back-propagation artificial neural network (BPANN), long short-term memory network (LSTM) and regression tree (RTREE). The performance evaluation is measured stepping on the renowned statistical metrics of mean absolute percentage error, root mean squared error, root mean squared logarithmic error, mean absolute error and normalized root mean squared error (Alshami et al., 2023; Elshaboury et al., 2021; Saleh et al., 2017).

MODEL IMPLEMENTATION

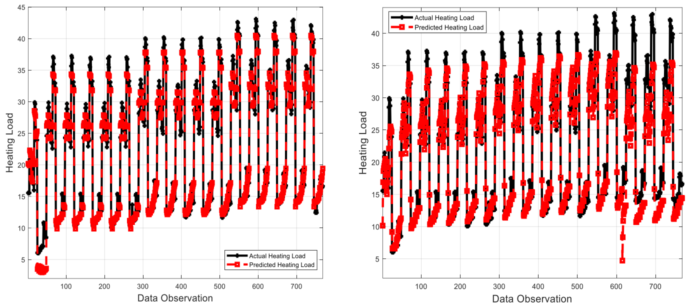
The energy efficiency dataset comprises 768 records such that 80 % (614) and 20% (154) are used for training and testing purposes, respectively. In predicting heating loads, the optimum architecture of the developed HBO-DL model is composed of five convolutional blocks with two, one, four, three and four fully connected layers. Each one of them is composed of five hidden neurons, and Swish is deemed as the optimum transfer function. The optimum epoch number, initial learning rate, momentum coefficient, L2 Regularization and minimum batch size are equal to 141, 6.1×10-4, 0.8423, 1.51×10-4 and 134, respectively. The most influential factors affecting heating loads are relative compactness, surface area, wall area, overall height, orientation and glazing area. As for predicting cooling loads, the optimum structure of the developed HBO-DL model encompasses five convolutional blocks. Each of which involves two, one, four, four and three fully connected layers. These layers contain seven hidden neurons and rectified linear unit is the optimum activation function. Additionally, the optimum values of epoch number, initial learning rate, momentum coefficient, L2 Regularization and minimum batch size are 247, 5.66×10-3, 0.80252, 4×10-4 and 248, respectively. The most implicating building characteristics on cooling loads are surface area, overall height, orientation, glazing area and glazing area distribution.

Figures 1 and 2 display the simulated and actual heating and cooling loads using the models of HBO-DL and LSTM. It can be noticed that the developed HBO-DL model was able to accurately the simulated heating and cooling loads. On the other hand, LSTM failed to emulate the heating and cooling loads. Figures 3 and 4 depict the error histograms of the developed HBO-DL and LSTM in forecasting heating and cooling loads. In heating loads, most of the error values achieved by the developed HBO-DL model ranged between 0.19 and 3.32 kW. As for LSTM, most of the error values were between 0.31 and 4.09 kW. In cooling loads, most of the error values of the developed model lied between 0.23 and 2.07 kW. With regards to LSTM, the largest portion of error values existed between 0.33 and 3.67 kW.



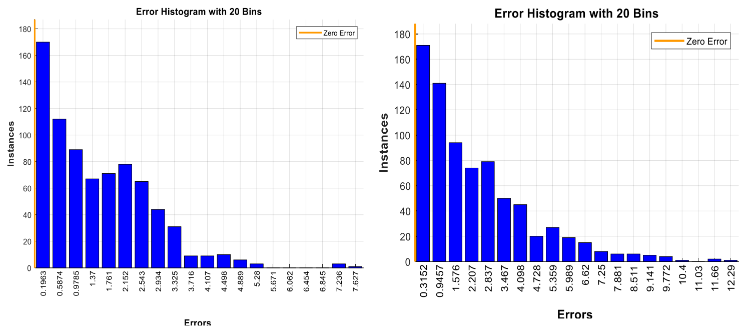
(b) LSTM

Figure 1. Visual representation of the simulated and observed heating loads using the developed HBO-DL model and LSTM



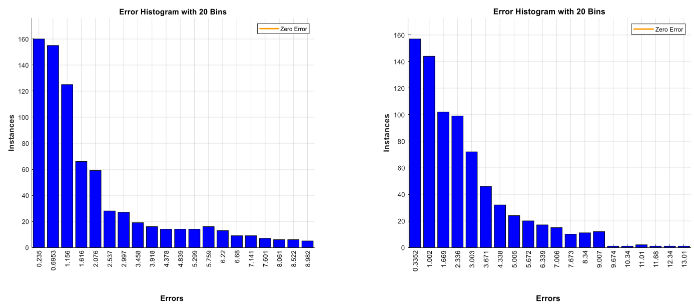
(a) Developed HBO-DL (b) LSTM

Figure 2. Visual representation of the simulated and observed cooling loads using the developed HBO-DL model and LSTM



(a) Developed HBO-DL (b) LSTM

Figure 3. Error histograms of the developed HBO-DL model and LSTM in predicting heating loads



(a) Developed HBO-DL (a) Developed HBO-DL (b) LSTM

Figure 4. Error histograms of the developed HBO-DL model and LSTM in predicting cooling loads

Tables 1 and 2 compile the test results of the investigated data-driven models in predicting heating and cooling loads. It can be inferred that the developed HBO-DL model outperformed the remainder of data-driven models accomplishing MAPE, RMSE, RMSLE, MAE and NRMSE of 5.73%, 1.39, 0.03, 1.35 and 0.05, respectively. On the contrary, LSTM obtained the highest MAPE (18.89%), RMSE (5.23), RMSLE (0.1) and MAE (4.59). In cooling loads, the developed HBO-DL model managed to notably perform better than other data-driven models yielding MAPE, RMSE, RMSLE, MAE and NRMSE of 6.81%, 2.79, 0.04, 1.95 and 0.09, respectively. The least prediction accuracies were associated with LSTM that sustained MAPE, RMSE, RMSLE, MAE and NRMSE of 15.73%, 4.88, 0.09, 4.06 and 0.17, respectively.

Table 1. Performance comparison between data-driven models in predicting heating loads

Performance metrics	HBO-DL	SVM	GRNN	CFNN	BPANN	LSTM	RTREE
MAPE	5.73%	11.38%	10.09%	11.13%	13.60%	18.89%	8.71%
RMSE	1.69	3.24	2.49	2.72	3.82	5.23	2.77
RMSLE	0.03	0.05	0.06	0.06	0.07	0.1	0.04
MAE	1.35	2.89	2.12	2.03	3.11	4.59	2.29
NRMSE	0.05	0.09	0.07	0.07	0.17	0.16	0.09

Table 2. Performance comparison between data-driven models in predicting cooling loads

Performance metrics	HBO-DL	SVM	GRNN	CFNN	BPANN	LSTM	RTREE
MAPE	6.81%	8.88%	10.25%	9.36%	12.00%	15.73%	9.85%
RMSE	2.79	3.18	4.65	3.17	4.82	4.88	3.17
RMSLE	0.04	0.05	0.06	0.05	0.07	0.09	0.05
MAE	1.95	2.28	3.14	2.34	3.31	4.06	2.62
NRMSE	0.09	0.12	0.28	0.09	0.20	0.17	0.12

CONCLUSION

Building energy consumption prediction plays a significant role in enhancing energy utilization rate by assisting building managers in making better decisions. Accordingly, this study introduced a hybrid HBO-DL model for simulating heating and cooling loads in residential buildings. Analytical comparisons expounded that the developed model outranks six of the widely acknowledged data-driven models in forecasting both heating and cooling loads. For instance, the developed model was able to perform better than the widely used BPANN by 60.7% and 46.2% in predicting heating and cooling loads, respectively. With that said, it can be argued that the developed model can furnish more sustainable building design designs and retrofitting

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