Prediction of Residential Building Energy Efficiency Performance using Deep Neural Network

Muhammad Irfan, Faizir Ramlie, Widianto, Merinda Lestandy, Amrul Faruq

***Abstract*— One of the important discussions currently in building energy use is the prediction of energy consumption. To achieve energy savings and reduce environmental impact, the prediction of energy consumption in buildings is crucial to improve energy performance. In this paper, an improved prediction of energy efficiency performance for the heating load (HL) and cooling load (CL) of residential buildings is demonstrated. A deep learning method using a deep neural network (DNN) based on a multilayer feed-forward artificial neural network (ANN) trained with stochastic gradient descent using back-propagation was examined. The proposed DNN method was also compared with a simple multilayer perceptron (MLP) ANN method. The error performances of both DNN and ANN methods were also analyzed against various machine learning algorithms used in previous studies. The results showed that the proposed DNN method performed better in terms of error performance for the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) values compared with the other methods. Adequate values of coefficient of determination (R2) were also obtained for both HL and CL predictions of the proposed DNN method, an indication of good prediction performance. Overall, the proposed ANN and DNN methods proved to outperform the other methods reviewed in this study. Based on these findings, it was concluded that the proposed DNN method was statistically a significant approach within the related research area.**

***Index Terms*— Energy Efficiency, Machine Learning, Deep Learning, Prediction.**

I. INTRODUCTION

THIS recent years energy consumption has increased worldwide [1] and can be attributed to heating, ventilation, and air conditioning (HVAC). These factors have a catalytic role in the discussion of indoor climate and play an important role in most of the energy use in buildings [2]. Energy consumption is a demand that is used to show the amount of energy that must supply a building at a certain time. HVAC usually contributes to 50% of various sources of energy use globally [3], [4]. Smart occupancy detection sensor technology, visible light communication for high-throughput communication and indoor positioning, and machine learning algorithms are applied to HVAC by providing several solutions to make buildings more energy-efficient. These solutions also include favourable features of user transparency, low cost, good privacy, and high precision of occupancy count [4]. As people become more concerned about energy efficiency, research on building energy use is becoming more common. In addition, there is also increasing concern about energy wastage and its negative impacts on the environment. Therefore, the prediction of building energy consumption plays an important approach in energy management, for both individuals and society to design a new building more wisely.

Further, buildings' orientation and layout are proved to be crucial in reducing their energy consumption in cold and hot climates. Nevertheless, the design is limited by the specific characteristics of a building's plan and size, and the shape and orientation of the building plots. In general, climatic conditions in residential buildings can be determined using technologies such as air conditioning and heating. For efficient building design, the calculation of HL and CL is needed to determine the specifications of heating and cooling equipment needed for maintaining comfortable indoor air conditions [5]. Nevertheless, the continuous use of such equipment can result in high energy consumption. As HL and CL contribute to 30-40% of a building's energy consumption, minimising them is critical for reducing overall energy consumption in buildings [6]. Moreover, architects and building designers need information about the building and space it is conditioned to, climate, and uses for the necessary heating and cooling. As a result, energy-efficient buildings with special designs such as orientation, insulation, and windows can be properly adapted to withstand adverse weather conditions [7].

Various methods have been used by researchers to predict building energy consumption and efficiency including through computer experiments, simulation tools, and machine learnings. Computer experiments have been conducted in building energy studies to optimise residential

Manuscript received Jan 11, 2021; revised June 26, 2021. This work is carried out under the basic scientific research scheme, as known as Penelitian Dasar Keilmuan (PDK), Universitas Muhammadiyah Malang, year 2020.

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and industrial structure parameters for energy efficiency improvement. Prior research in this area has indicated that CL and HL effects greatly impact the energy needs of buildings [5]. In addition, many building energy simulation tools are currently widely used to analyse or predict the energy consumption of buildings, and also to facilitate the design and operation of buildings. Nevertheless, the accuracy of the estimation results can vary and can be costly depending on the software used. Therefore, in practice, many researchers rely on machine learning to study the effects of various building parameters on energy variables [8].

In [9], the support vector machine (SVM) model was applied to predict the hourly cooling load in the building. The simulation results demonstrated that the SVM model was effective and achieved better accuracy and generalisation compared with the back-propagation neural network (BPNN) model. Further, an SVM model was presented in [10] to forecast building energy consumption utilising a neural network algorithm. Apart from SVM, another form of machine learning that has been applied for building energy prediction is the ANN model. In [11], the effectiveness of the ANN model was investigated to forecast the seasonal hourly electricity consumption. The obtained results demonstrated the capability of the ANN model with improved performance including adequate error and coefficient of determination value. Furthermore, neural networks and genetic algorithms were applied in [12] to predict building energy.

Recent studies in computer simulation of energy consumption have been conducted using data-driven algorithms including random forest (RF), gradient boosting, multilayer neural network SVM [13], polynomial regression, decision trees, ANN [14], genetic programming (GP) [15], and support vector regression (SVR) with ANN [16]. Through a major study in energy building efficiency in [5], it was identified that RF hugely outperformed other compared models in finding an accurate functional relationship between the input and output variables. Further, the study in [17] significantly improved the work in [5] in terms of assessment accuracies by predicting both the HL and CL for residential buildings using evolutionary multivariate adaptive regression splines (EMARS). In other words, the HL and CL predictions were improved using a genetic approach. Despite the extensive studies conducted in this area, there is always room for improvement in predicting building energy consumption as it is a never-ending process.

Although various techniques have been introduced to address the performance issue of CL and HL in energy consumption estimation, to date the use of an advanced machine learning approach has not been piloted as suggested in [18], [13]. Despite the abundance of literature available in the field, the utilisation of deep learning as part of the machine learning technique to predict CL and HL is still lacking [8]. The performance of deep learning as data mining technique utilizing a limited data has been successfully presented in [19]. Therefore, the usefulness and application of deep learning and neural network approach for improving CL and HL predictions as energy consumption in buildings is investigated in this study.

In this study, the DNN method employed for predicting CL and HL was based on a multilayer feed-forward ANN. The dataset obtained from the University of California, Irvine (UCI) Machine Learning Repository was used for data training and testing. This study also calculated feature importance for the dataset to consider features based on how important the technique was in predicting targets (output variables or parameters). In addition, the performance of the ANN and DNN prediction models were compared using several evaluation criteria: RMSE, MAE, and MAPE. Furthermore, the deep learning and ANN techniques examined in this study were also compared with previous research works in particular problems. The significance of this study can help reveal the potential mechanisms for an advanced data-driven model for predicting energy consumption. With the development of artificial intelligence (AI) techniques (ANN and DNN) that can predict CL and HL with better accuracy in predicting energy consumption, the initial design of buildings for energy conservation can be facilitated.

The following is the remaining structure of this paper: Section II presents the approach by describing the dataset characteristics and the data processing framework; Section III discusses the results, and Section IV concludes the study results.

II. Materials and Methods

A. Description of the Dataset

Previous studies have designed a group of buildings to predict HL and CL in buildings by taking into account certain variables: relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing distribution area [5], [20]. From the collected data, as many as 12 types of buildings were simulated using software called Ecotect [5]. As established in [5], each type consisted of various blocks with the same volume (771.75 m^3) and material but with different surface areas and dimensions. The dataset was obtained from the UCI Machine Learning Repository with eight input parameters: relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution, and two outputs: HL and CL. The dataset was then normalized to develop a new range from the existing range.

TABLE I
Representation of the Dataset Input and Output Parameters

Rep.	Name	I/O Type	Min.	Max.	Mean.	Values
X1	Relative Compactness	set	0.62	0.98	0.76	12
X2	Surface Area	set	514.5	808.5	671.71	12
X3	Wall Area	set	245	416.5	318.50	7
X4	Roof Area	set	110.25	220.5	176.60	4
X5	Overall Height	set	3.5	7	5.25	2
X6	Orientation	set	2	5	3.50	4
X7	Glazing Area	set	0	0.4	0.23	4
X8	Glazing Area Distribution	set	0	5	2.81	6
Y1	Heating Load	range	6.01	43.1	22.31	586
Y2	Cooling Load	range	10.9	48.03	24.59	636

In this study, the dataset used was the efficiency energy of residential buildings as used in [5]. The dataset consisted of 768 data (types of buildings) with eight parameters as inputs and two parameters as outputs as mentioned earlier. The mathematical representation of the inputs and outputs of the dataset is shown in Table I including each parameter's range of values.

B. Data Normalization

Normalisation is a mapping technique for finding a new range from an existing range which is very helpful for prediction or forecasting purposes [21], [22]. The technique used in this study was the Z-score normalisation as follows:

$$v_i' = \frac{v_i \bar{E}}{std(E)} \tag{1}$$

where v_i' is the Z-score normalisation value, while v_i is the $\bar{E}$ rows value from i^{th} columns. While $std(E)$ can be defined by (2):

$$std(E) = \sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(v_i - \bar{E})^2} \tag{2}$$

In this study, normalised input data was passed to the training step. The composition of the training and testing data in this study was 80% and 20% of the dataset, respectively.

C. Artificial Neural Network (ANN)

ANN is a mathematical model inspired by the human nervous system. The initial neural network model was the MLP [23], which included an input layer, hidden layer, and output. Each layer corresponds to the next and previous layer neurons, which are similar in MLP with multiple inputs and outputs. The values obtained from the previous layer are summed by the multiple weights for each neuron and bias b. Finally, the activation function (f) is used to change the number, which may be different for each neuron, as shown in Fig. 1. In this study, the design of the proposed-ANN is set using sigmoid activation function, with training cycles 200, learning rate is 0.01, and number of hidden layer is set to 25.

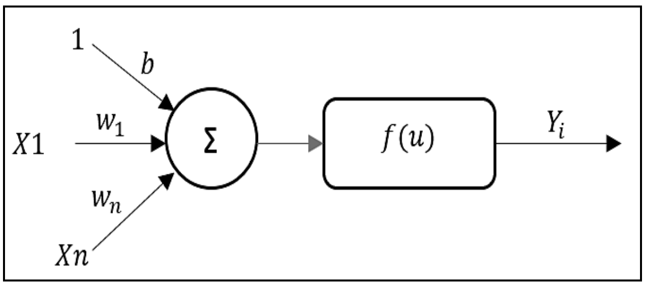

Fig. 1. Artificial neural network with its operation

D. Deep Neural Network (DNN)

In this study, the deep learning technique used was based on a multilayer feed-forward ANN trained with stochastic gradient descent using back-propagation and neural network model for predicting the CL and HL. A two-step process was followed as illustrated in Fig. 3 including data gathering and normalisation and then fitting the data into the deep learning model. This process was performed using `RapidMiner Studio` (version 9.0), a comprehensive data science software platform with visual workflow design and full automation.

The MLP DNN architecture is illustrated in Fig. 2, where the network can contain multiple hidden layers between the input and output layers [24]. These hidden layers consist of neurons with `tanh`, `rectifier` and `maxout` activation functions. The DNN parameters setting were set up with two hidden layers, defined as H1 and H2, which consisted of 50 and 150 nodes, respectively. The `rectifier` activation function was used with a maximum of 200 epochs and 2 training sample iterations.

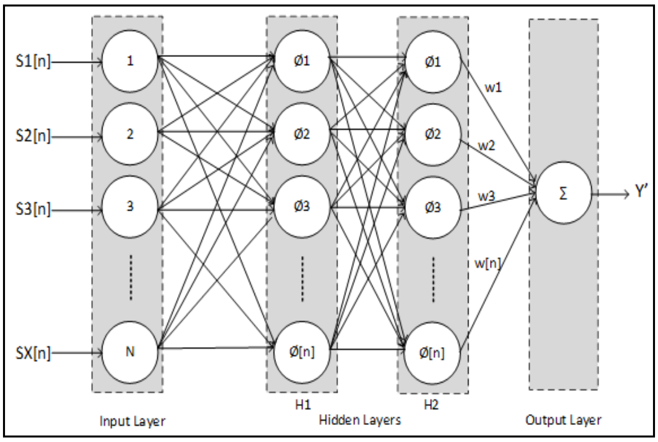

Fig. 2. MLP Deep Neural Network Architecture

E. Feature Importance

In this study, a significant machine learning feature investigated is the feature importance, which represents the probability ratio value of a parameter reaching a node. It can be further defined as the probability that a node is the ratio of each sample that can reach the node compared to the number of instances in the dataset. The higher the feature importance value, the more important the parameters are regarded [25]. As seen in (3), ni_i represents the importance value of node j, w_j is the weight of the target node, C_j is the impurity value of node j , `left (j)` and `right` (j) represents the child vertices of the left and right vertices j respectively.

$$ni_i = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \tag{3}$$

Once the importance nodes are obtained, the importance of each feature is calculated using (4), where $f(i)_i$ represents the value of the feature i, and ni is the node importance of the node j.

$$fi_i = \frac{\sum j : node\ j\ split\ on\ feature\ ni_j}{\sum k\ \in all\ nodes\ ni_k} \tag{4}$$

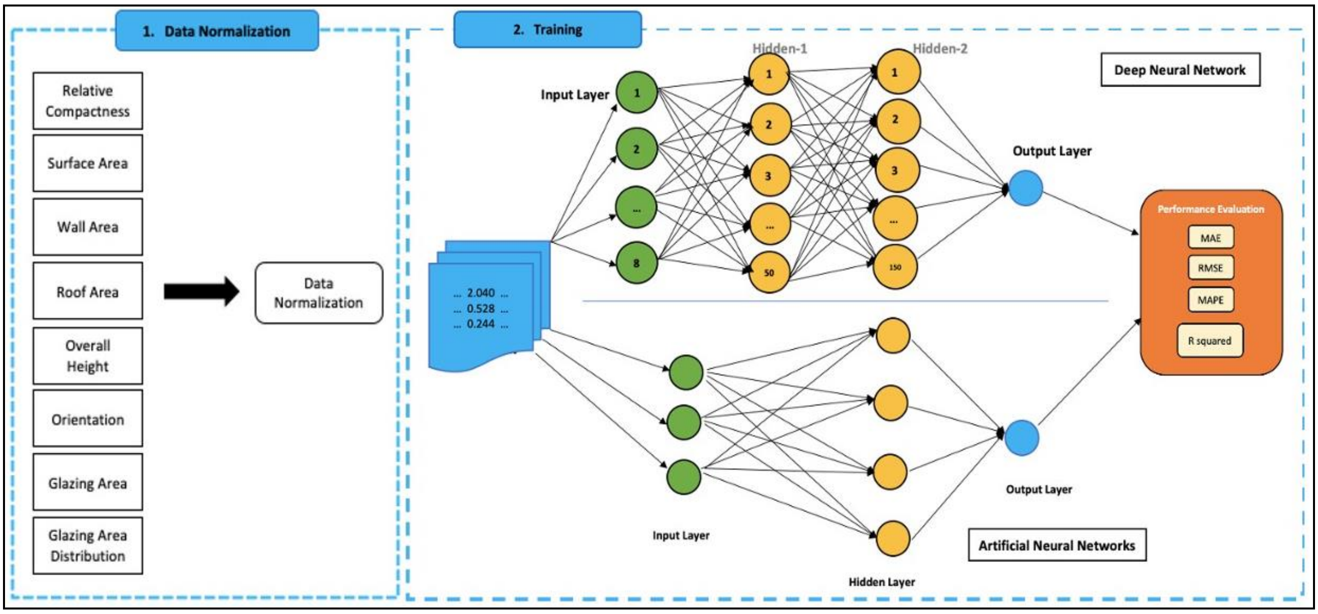

Fig. 3. HL and CL energy estimation using Deep NN and ANN

F. *Evaluation of Performance*

The standard of evaluation metrics used in this study, as suggested in [16], were MAE, RMSE, MAPE, and the coefficient of determination (R^2). These metrics math formulas are respectively stated in (5)–(8). MAE indicates the overall agreement in actual units; RMSE indicates the overall agreement in actual units with the deviations squared; MAPE is the percentage difference between the predicted variables, and R^2 represents the proportion of variance in the observed dataset that can be explained by the model.

$$MAE = \frac{1}{S}\sum_{i \in \varrho} |y_i - \hat{y}_i| \tag{5}$$

$$RMSE = \frac{1}{S}\sum_{i \in \varrho} |y_i - \hat{y}_i|^2 \tag{6}$$

$$MAPE = 100.\frac{1}{S}\sum_{i \in \varrho} \frac{|y_i - \hat{y}_i|}{y_i} \tag{7}$$

$$R^2 = \frac{\sum_{i=1}^{n}(\,y' - \bar{y})^2}{\sum_{i=1}^{n}(\,y - \bar{y})^2} \tag{8}$$

III. Result and Discussions

Useful reviews of the existing approaches, including the most commonly used methods have been given in [26], [25]. Based on these reviews, Table II highlights the performance of machine learning algorithms in numerous studies: iteratively reweighted least squares (IRLS), RF, classification and regression tree (CART), SVM, multivariate adaptive regression splines (MARS), BPNN, RBFNN, general linear regression (GLR), chi-squared automatic interaction detector (CHAID), decision tree (DT), geometric semantic genetic programming (GSGP), GSGP with local search (GSGP-LS), GGSP with local search linear scaling (GGSP-LS-LIN), adaptive neuro-fuzzy inference system (ANFIS), and fuzzy inductive reasoning (FIR). The results obtained using the methods proposed in this study were also compared with these studies in terms of the error performances for HL and CL. For detailed analysis, the results were analysed using `RapidMiner Studio` (version 9.0) software.

The proposed-ANN and DNN workflow are illustrated in Fig. 4 and Fig. 5, respectively. Import Efficiency Energy data obtained from UCI Machine Learning with 8 parameters and 2 outputs, namely Relative Compactness, Surface Area, Wall Area, Roof Area, Overall Height, Orientation, Glazing Area, Glazing Area Distribution, Heating Load and Cooling Load. To locate new ranges from existing ranges, data normalisation using Z-score normalisation is used. Based on the overall data, 768 data points were split into 80 percent training data and 20 percent testing data. The proposed ANN and DNN model then computed the data to produce the predicted result.

It is found that in terms of error performance, the proposed DNN method performed better than the rest with the lowest error values of MAE (0.204), RMSE (0.542), and MAPE (0.461) for CL prediction. While for HL performance, the proposed DNN method provides the lowest error of MAE (0.181) and the second-lowest error for RMSE (0.425) and MAPE (0.472) values. Furthermore, for HL results, the proposed ANN and DNN methods provides lower values for MAE and MAPE compared with the other sixteen methods. Nevertheless, the DT method demonstrated in [27] provided the lowest RMSE value for HL with a value of 0.267. Compared with the proposed DNN method, the proposed ANN method only achieved better performance for MAPE in HL with a value of 0.461, which is the lowest among the methods. In addition, comparing the RMSE performance between the proposed ANN and proposed DNN for CL, an improvement of 70.58% was achieved. Nevertheless, the improvements achieved by the proposed DNN against the proposed ANN varied between the error metrics for HL and CL, except for MAPE in HL.

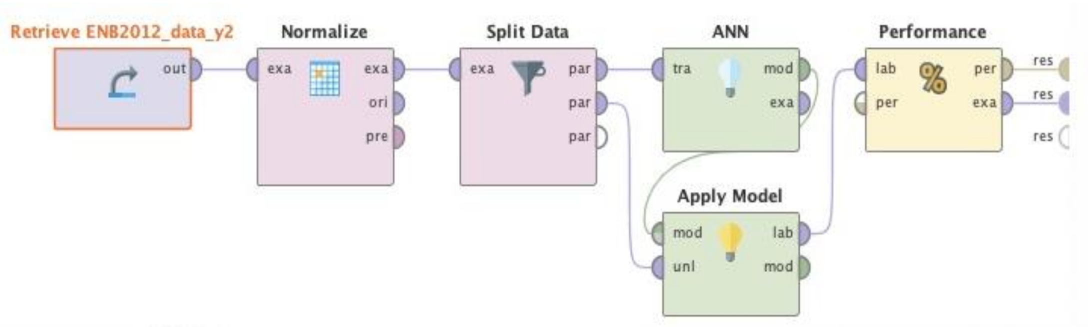

Fig. 4. Proposed ANN schematic workflow in RapidMiner

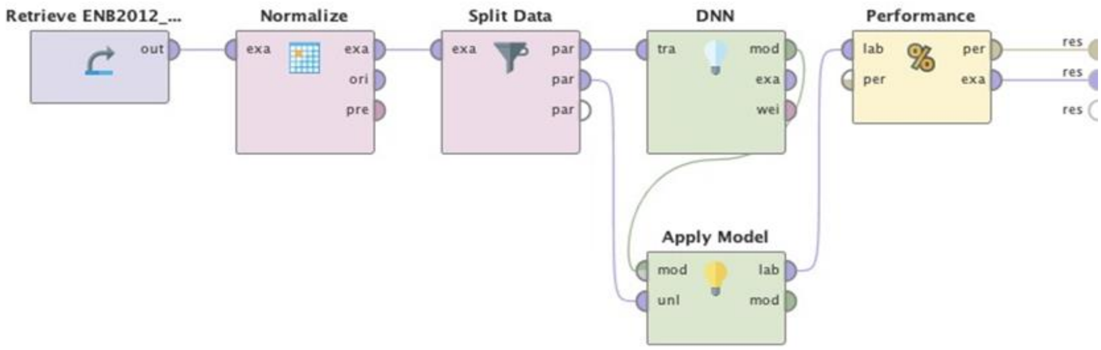

Fig. 5. Proposed DNN schematic workflow in RapidMiner

TABLE II
COMPARISON OF ERROR PERFORMANCE FOR HL AND CL (THE LOWEST VALUE FOR EACH ERROR PERFORMANCE IS IN BOLD)

Method	HL			CL		
	MAE	***RMSE***	***MAPE***	***MAE***	***RMSE***	***MAPE***
IRLS [5]	2.14	3.14	10.09	2.21	3.38	9.41
RF [5]	0.51	1.01	2.18	1.42	2.57	4.62
CART [17]	0.73	1.11	3.29	1.31	1.94	4.72
SVM [17]	2.19	2.49	10.87	2.1	2.49	9.01
MARS [17]	0.53	0.68	2.93	1.12	1.65	4.09
BPNN [17]	1.61	2.25	8.05	1.92	2.63	8.04
RBFNN [17]	0.51	0.67	2.76	1.3	1.69	5.4
SVR [16]	0.89	1.647	2.985	0.89	1.647	2.985
GLR [16]	1.292	1.74	4.966	1.174	1.74	4.02
CHAID [16]	1.174	1.859	4.104	1.292	1.859	4.104
DT [27]	0.347	**0.267**	1.497	1.175	3.693	4.055
GSGP [15]	1.31	1.06	1.13	1.47	2.36	5.55
GSGP-LS [15]	1.26	1.04	1.09	1.37	2.36	5.58
GSGP-LS-LIN [15]	0.51	0.79	0.62	1.18	2.04	4.15
ANFIS [20]	0.37	0.52	-	1.03	1.76	-
FIR [20]	0.35	0.49	-	1.09	1.72	-
Proposed ANN	0.27	0.519	**0.461**	3.393	1.842	6.31
Proposed DNN	**0.181**	0.425	0.472	**0.294**	**0.542**	**0.461**

In Fig. 6, the feature importance or parameter that significantly affected the dataset energy consumption was found to be X2 (surface area), with weight values of 88.086 and 87.696 for HL and CL, respectively. Then followed by X4 (roof area) with weight values of 73.632 and 45.155 for CL and HL. While the least feature was X1 (relative compactness) with weight values of 0.106 and 0.112 for HL and CL. Furthermore, as shown in Fig. 7 and Fig. 8, the obtained coefficient of determination (R^2) values for HL and CL were the same (0.997) for DNN. These values indicated that the DNN method was good in terms of the performance of the prediction.

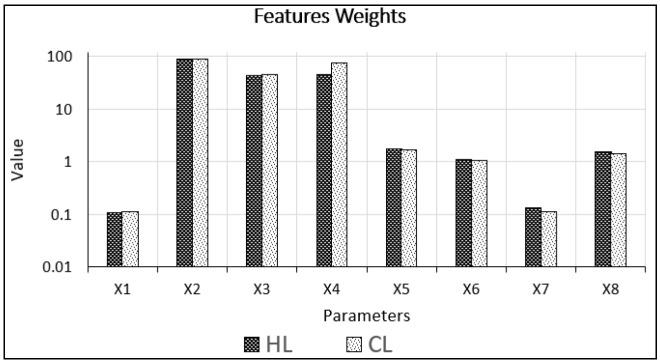

Fig. 6. Feature importance weights calculation

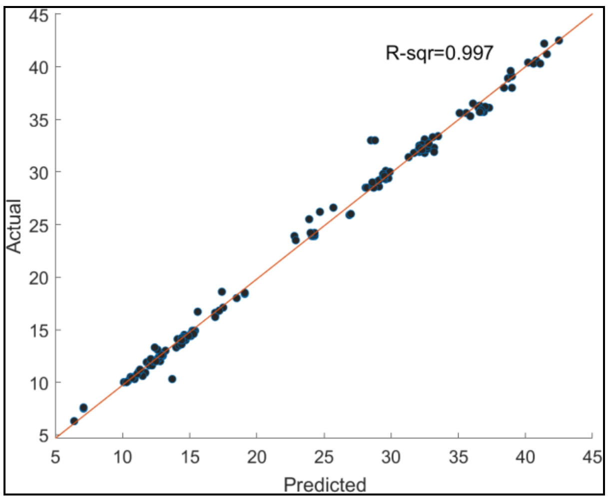

Fig. 7. Scatter plot R^2 of HL prediction and actual value using DNN

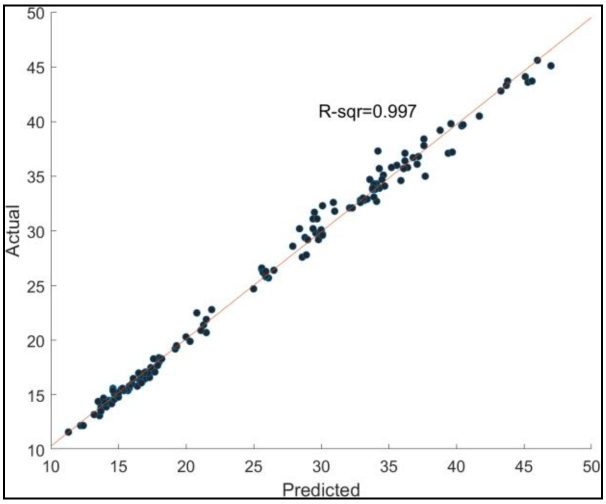

Fig. 8. Scatter plot R^2 of CL prediction and actual value using DNN

The obtained results demonstrated the adequacy of the proposed DNN method for predicting CL and HL in buildings. DNN also proved to be the best alternative to estimate the energy performance of buildings based on building design parameters (feature importance). In addition, the proposed DNN method showed better results than the other machine learning approaches for HL and CL prediction problems reviewed in this study. Despites, the RMSE performance shows that DT algorithm produce lower value compared with all mentioned and proposed methods. As such, this can pave the way for a possible work for improvement in the future including developing a hybrid algorithm for predicting CL and HL in buildings instead of using the standalone DNN method.

Although the proposed methods and the others reviewed in this study provided an adequacy results, some experiment by adjusting the input output as training and testing scheme is needed for further investigation. As the dataset used was only applicable to the twelve specified building types, more comprehensive tests on more real data are necessary to appropriately satisfy real-world situations where there can be more parameters involved including external factors.

IV. CONCLUSION

This study demonstrated the DNN technique to predict the energy performance of buildings. The characteristics of a building are an important factor in determining the HL and CL requirements. Therefore, the relevant building characteristics related to heating and cooling are needed to maintain comfortable indoor conditions for designing and constructing energy-efficient buildings. The two methods used in this study were ANN and DNN. The results achieved by the two methods were then compared with 16 other machine learning approaches presented by previous studies. Based on the analysis conducted, overall the ANN and DNN methods proved to be much better than the other methods. The DNN method particularly produced the best result in predicting CL based on the MAE, RMSE, and MAPE performance metrics. In addition, these fast and accurate prediction models can be very useful for building design and decision making as the energy performance of buildings has been recognised as a crucial aspect in the energy industry. For future work, there is a possibility to improve the HL prediction performance of the DNN method in terms of RMSE and MAPE to develop a superior prediction model.

ACKNOWLEDGMENT

The authors would like to acknowledge the Directorate Research and Community Services, Direktorat Penelitian dan Pengabdian Masyarakat (DPPM), Universitas Muhammadiyah Malang for giving the opportunity to undertake this research.

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