PREDICTING COOLING ENERGY DEMANDS OF ADAPTIVE FACADES USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Adaptive Façades (AFs) have proven to be effective as a building envelope that can enhance energy efficiency and thermal comfort. However, evaluating the performance of these AFs using the current building performance simulation (BPS) tools is complex, time-consuming, and computationally intensive. These limitations can be overcome by using a machine learning (ML) model as a method to assess the AF system efficiently during the early design stage. This study presents an alternative approach using an Artificial Neural Network (ANN) model that can predict the hourly cooling loads of AF in significantly less time compared to BPS. To construct the model, a generative parametric simulation of office tower spaces with an AF shading system were simulated in terms of energy consumption using Honeybee add-on in Grasshopper which are linked to EnergyPlus for training the ANN model. The prediction results showed a highly accurate model that can estimate cooling loads within seconds.

Keywords: Adaptive Façade, Automatic Control, Cooling Energy Demand, Machine Learning, Artificial Neural Network.

1 INTRODUCTION

According to the International Energy Agency (IEA), energy consumption by buildings is increasing significantly; currently, buildings account for 40% of the global energy use. Furthermore, the IEA reported that energy demand is estimated to increase by 30% by 2035 (Building and Codes 2013). Therefore, different countries have formed new regulations to achieve net zero buildings (NZB) and reduce CO2 emissions. To meet the current targets of designing high performance buildings with the future of nearly zero energy buildings (NZEB), there is a need to continue the advances made in the design, technology, and materials of buildings. The building envelope plays an important role in achieving this target; it acts as a separator element between the indoor and outdoor environments of a building and is a crucial factor that determines the quality of indoor conditions (Sadineni et al. 2011). Since despite the extreme temperatures in hot climates, highly curtain wall glazing systems are the dominant type of building envelopes found in most high-rise and mid-rise buildings, it is vital to install shading systems on such buildings to control the penetration of solar radiation into the internal spaces. The intense solar radiation can have an impact on increasing the cooling energy loads required to achieve human comfort in these offices.

Because buildings are exposed to dynamic environmental factors, where outdoor conditions change continuously throughout the day and the year, numerous studies have been conducted regarding substituting the static envelope with an adaptive one (Choi et al. 2017a; Elzeyadi 2017; Hosseini et al. 2019a; Samadi et al. 2020; Shi et al. 2020; Tabadkani et al. 2021a). Researchers and designers around the world have developed adaptive façades (AF) to achieve greater efficiency and performance by exploiting the dynamic environment. These AFs have unique features or behaviours that repeatedly and reversibly change over time according to variable boundary conditions and respond to changing requirements, aiming to improve the overall building performance (Loonen et al. 2017). Due to the multi-functionality and complexity of predicting the performance of AF systems, this study proposes a framework to predict AF energy performance early in the design process using supervised machine learning (ML) methods. The ML approach promises greater efficiency in the evaluation of building performance than does conventional simulation (Chakraborty and Elzarka 2019). Artificial neural networks (ANN) have been successfully used to predict buildings' energy performance in most studies because of their ability to address non-linear problems. Thus, ANN could be applicable to predict the performance of a building with an AF once the system is trained with a sufficient set of data.

2 RESEARCH BACKGROUND

2.1 Adaptive Façade Overview

The advances in architectural envelopes have changed the design approach from static and conventional envelopes to adaptive and responsive ones that aim to improve the performance of the whole building. Nguyen and Aiello (2013) promoted the application of adaptable buildings to optimise energy consumption, while Ghaffarianhoseini et al. (2016) concluded that intelligent façades can contribute to reducing energy and responding to indoor and outdoor environments. Giovannini et al. (2015) developed the Shape Variable Mashrabiya (SVM) shading system for an office building in Abu Dhabi. The authors applied the shading in two different orientations – the east and west façades – to analyse the effect of the SVM shading system on reducing the global energy demand and annual lighting demand. The results revealed the immense potential of an adaptive façade shading system on both daylighting and energy saving. Overheating problems were minimized, and "consequently the EPc values (-17.2% and -9.9% compared to SG41 and to venetian blinds (VB), respectively)" Page (6).

Assessing the applicability of AFs during the early stages of design is extremely significant, but it is mostly restricted to the existing simulation tools for faster quantification (Tabadkani et al. 2021b). Loonen et al. (2017) stated that predicting the performance of buildings with AFs is a challenging task that is mostly determined by the local boundary conditions, interactions with the building's users, and other building systems. The authors also examined the methods of simulation in both conventional static building envelopes and adaptive envelopes. In traditional static envelopes, the simulation process is less complex and requires certain factors, such as the U-value and g-value, in order for predictions to be made. On the other hand, an AF is more complex and has a variety of factors, which makes accurately predicting the building performance of an AF more challenging. Some of these factors are: (1) the time variation behaviour, (2) modelling the dynamic operation of the façade adaptation, and (3) the multiple physical domains. Therefore, some of the existing simulation tools were not developed for predicting performance with an AF specifically. Moreover, these tools are limited and provide misleading information for adaptive systems (Loonen et al. 2017).

According to the literature, most designers evaluate AF using their own simulation strategy because there is no straightforward approach to assess the performance of AF for energy performance or for human comfort (Attia 2019; Tabadkani et al. 2020c, 2021b). Therefore, inaccurate results might be obtained when assessing their performance and applicability in the long term (Tabadkani et al. 2020c). Since the development of AF by many researchers has increased significantly in recent years (Elzeyadi 2017; Hosseini et al. 2019b; Böke et al. 2020; Bui et al. 2020; Panya et al. 2020; Shi et al. 2020), it is essential to find an alternative approach that requires less computation knowledge and that is less time consuming to predict their performance efficiently during the early design stages.

2.2 Artificial Neural Network for Predicting the Performance of AFs

In recent years, several studies have been conducted on integrating the ML approach for the prediction of building performance, which includes building-energy performance, estimating heating and cooling loads, daylighting, human comfort, and indoor temperatures. Zhao and Magoulès (2012) agreed that the ML approach has proven to be efficient in the prediction of building performance. Unlike conventional modelling methods, supervised ML has major benefits in terms of requiring less computation time and less effort and of being computationally inexpensive (Huang et al. 2015). Regarding a simulation-based model approach, Keshtkarbanaeemoghadam et al. (2018) developed a neural network (NN) model, trained by a back-propagation algorithm (BP), to estimate the total heating energy demand of a shelter located in Iran. The study obtained its data by conducting 328 computer simulations using a Grasshopper plugin linked to the EnergyPlus engine. Nine inputs were selected to train and test the NN: "wall thickness, wall U-value, wall R-value, window U-value, window R-value, number of occupants, equipment load, and infiltration rate" Page (734). According to the results, the best ANN model had an MSE of 0.73, which indicates that the ANN model is a promising approach and can serve as a substitute for other methods to predict the heating energy demand in buildings.

In another similar approach, Wong et al. (2010) conducted a simulation using EnergyPlus to generate a database of daily energy consumption for office buildings with daylighting. Then, these generated data were used to train and test the developed ANN model to predict daily building energy usage in fully air-conditioned office buildings in the early design stages. The results for "cooling, heating, electric lighting and total building electricity were 0.994, 0.940, 0.993, and 0.996, respectively" Page (551), which represents a highly predictive model. To date, no studies have explored the integration of ANN into predicting the energy performance of AFs. In addition to the abovementioned studies related to the existing performance simulation tools, these tools are not developed specifically for AFs but provide limited and misleading information for adaptive systems (Loonen et al. 2017). Therefore, this shortfall emphasizes the need to examine different approaches for the performance of AFs in the initial design stage to speed up the prediction process of AFs.

3 RESEARCH METHODOLOGY

The methodological framework of this research is divided into three main stages. In the first stage, a generative parametric simulation of office spaces with an AF shading system was modelled and simulated in terms of energy consumption using EnergyPlus. In the second stage, an automatic (closed loop) shading control was employed to actuate the behaviour changes of the AF system on an hourly basis based on two predefined environmental sensors. The aim of these two stages was to assess the impact of AFs on the energy performance of a shared office room and to create a large synthetic database of hourly cooling energy demand (Wh/m^2) for training data. These datasets were synthetically produced through an iterative loop. In the third stage, an ANN surrogate model was developed and evaluated in terms of its ability to predict the hourly cooling demand of an AF system for a closed office space. In order to achieve a high accuracy model, a hyper-parameter tuning analysis was performed by evaluating and training several ANN models using K-fold cross validation method. In this research, the Honeybee and Ladybug Grasshopper plugins in conjunction with EnergyPlus were used to generate and simulate the model in terms of energy consumption.

3.1 Simulation Settings

A hypothetical high-rise office building in the downtown of Riyadh, Saudi Arabia, was generated as a case study. The office building has 30 floors with a building height of 120 m, which is the common height situation found in the centre of the King Abdullah Financial District. The dimensions of the layout and core area were fixed in all floors of the building as follows: (35 m * 35 m), with a total area of 1225 m^2 (see Figure 1). In this study, only shared side-lit office zones with an adaptive shading system were examined on each floor of the proposed office building, which faced the main orientations (north, south, east, west) to quantify the impact of an AF on building energy performance. The variable input parameters for this research were selected considering the building envelope properties and the dynamic behaviour changes of the AF shading system, namely hour, date, month, orientation, building context, external wall U-value, glazing type U-value, solar radiation setpoint, operative temperature setpoint, shade factor (SF), and opening ratio. Tables 1 and 2 lists the fixed and dynamic input parameters used in this research to conduct the energy analysis using the EnergyPlus engine.

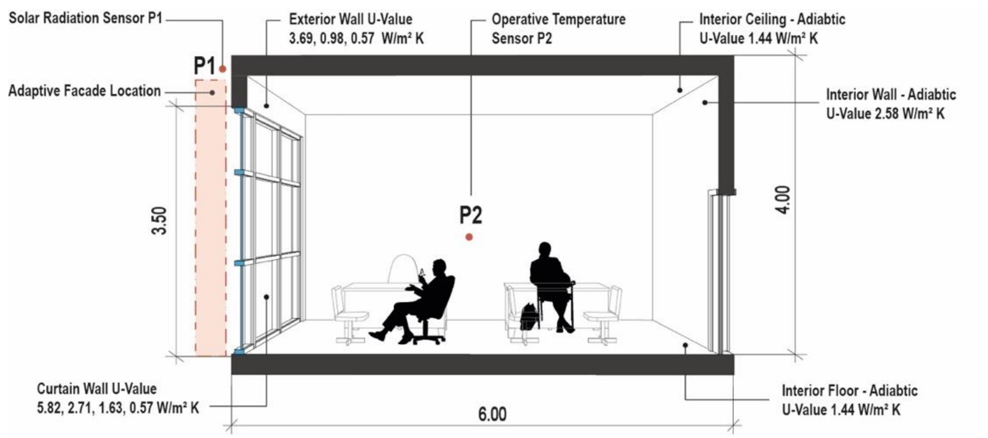

Figure 1. Closed office room with detailed constructions and sensor location.

Table 1. Dynamic simulation parameters

Dynamic Input Parameter	**Assigned Value(s)**	**No. of Iterations**
Orientation	*South, West, North, East*	4
Building Context 00	*Low, Medium, High*	3
Building Context 01	*Low, Medium, High*	3
Façade Level Hight	*lower than average, Average, and Higher than average*	3
Exterior wall – U-value	*0, 1, 3 W/m2 K*	3
Glazing type – U-value	*0, 1, 2, 3 W/m2 K*	4

Total No. of iterations		1296
Month	*March, June, September, December*	-
Day	*01 – 31*	-
Hour	*1:00 - 24:00*	-
Shading States	*A, B, C, D, E, F*	-
Total No. of hourly cooling data		3,794,688

Table 2. Fixed simulation parameters

Parameter	**Assigned Value(s)**
Location	Riyadh, Saudi Arabia
Space type	Shared Office Room
Glazing ratio	80 %
Room width, height, and length	4.00 m - 4.00 m - 6.00 m
Cooling/ Heating set points	C: 24 C / H: 22 C
HVAC system	ideal air load system
Number of people	2 people
Lighting density	3 W/m2
Number of occupants	0.5 ppl/m2
Equipment load (W/m2)	2 W/m2
Infiltration rate	0.0001 (m3/s m2)

The material parameters of the office were defined based on ASHRAE 90.1-2010 climate region number 1, a database provided by EnergyPlus (ASHRAE materials databases) as the recommended materials for the climate zone of the study, which were assigned for a hot-dry climate region. Different types of external walls for the office room were considered with distinct U-values. Partitions/interior walls were assumed to be adiabatic and to be gypsum board with a U-value of 2.58 (ASHRAE 90.1-2010), which means that there was no heat transfer across the interior walls. In addition, glazing was considered as one of the main variables in the energy simulation of the model. Therefore, different types of glazing system (single U-value 5.82, double clear U-value 2.71, double Low-e coating U-value 1.63, and triple glazing- Krypton Filled U-value 0.57) were investigated for the studied model, which had different solar heat coefficient values and thermal transmittance U-values (Gadelhak and Lang 2016). Table 3 lists the specifications for the construction material parameters that were implemented in this study.

Table 3. Characteristic of materials used in the simulation

Material Name	Layers	U-value	R-value
ASHRAE90.1-2010 EXTWALLMASS CLIMATEZONE 1	1IN Stucco 8IN CONCRETE HW RefBldg 1/2IN Gypsum	3.690821	0.270942
ASHRAE 90.1-2010 EXTWALL MASS CLIMATEZONE ALT-RES 1	1IN Stucco 8IN CONCRETE HW RefBldg Mass Wall Insulation R-4.23 IP 1/2IN Gypsum	0.983672	1.016599
ASHRAE 90.1-2010 EXTWALL METAL CLIMATEZONE 1-2	Metal Siding Metal Building Wall Insulation R-9.45 IP, 1/2IN Gypsum	0.573406	1.743964

3.2 Automatic Control System

The study implemented the following steps to control the changing behaviour of the AF: (1) controlling the opening size of the external AF shading system based on two outdoor and indoor sensors; (2) calculating the annual SF per hour of each shading state to be translated as a transmittance schedule; (3) calculating the annual incident SR on the exterior surface hourly; and (4) establishing a control scheme through Energy Management System (EMS), which is an embedded function in EnergyPlus, to define sensors, control, and actuators on hourly time steps (Hong and Lin 2013) (see Figure 2). According to the literature, an AF system is triggered automatically by environmental stimuli, such as SR, relative humidity, surface temperature, etc. The combination of both Solar radiation (SR) as a sensor at the exterior surface and operative temperature (OT) in the interior space provided the best system in terms of energy performance and human comfort (Tabadkani et al. 2020a; van Moeseke et al. 2007; Evola et al. 2017). Thus, an automatic shading control based on two predefined sensors, specifically SR and OT, was employed as environmental sensors to adjust the opening ratio of the AF system in an automatic way with the integration of a closed (feedback) loop control system. For the purpose of this study, a simple parametric unit shaped in a kinetic prismatic modular element was implemented with a scaling and translating movements. The aim of this pattern is to provide hierarchical configurations and self-shading geometry for the envelope. Thus, six different shading states that varied in terms of their opening ratio (State-A 100%, State-B 80%, State-C 60%, State-D 40%, State-E 20%, State-F 0%) were defined based on SR and OT thresholds see Figure (3). The shading system closed when the external total SR on the exterior surface and OT exceeded a chosen set point. The SR range varied between 0 and 450 W/m2 with a 50 W/m2 step, while the OT ranged from 21 ^{o}C to 24 ^{o}C. These thresholds were determined based on some of the previous studies that recommended an appropriate activation threshold for each climate zone (Al Touma and Ouahrani 2017; Yun et al. 2017; Tabadkani et al. 2020b). To this end, a conditional statement was coded within the EMS interface an embedded function in EnergyPlus to adjust the desired opening ratio based on the defined program logic. The shading (state A) is fully open when the SR is equal to or below 50 W/m2 and the OT is equal to or below 21 ^{o}C. On the other hand, shading (state F) is fully closed when the SR is equal to or above 450 W, and the OT is higher than 24 ^{o}C. Other intermediate shading states were considered in between these thresholds.

Figure 2. Energy management system (EMS) principles.

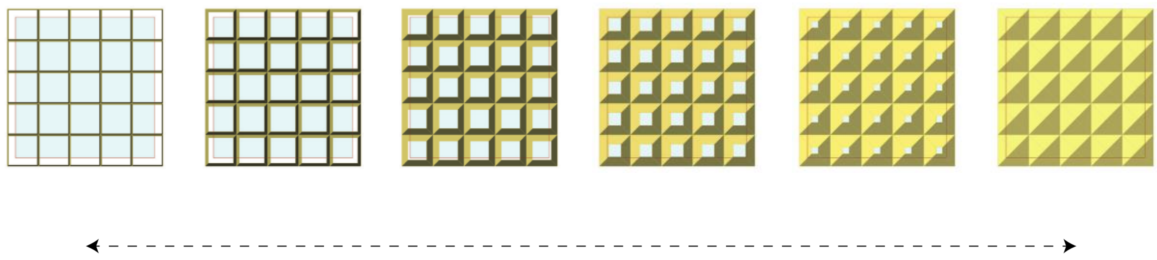

Figure 3. Modelling process of the AF geometry with scaling movements.

4 ANN'S SURROGATE MODEL DEVELOPMENT

Employing sufficient data is essential to have a satisfactorily accurate ANN model that can predict the hourly cooling energy demand. For this purpose, 1,296 simulation iterations of an office room with AF were performed by the Honeybee plugin with various inputs to train the model. A total of 1,581,120 (1296 * 4 months (122 days) *10 hours) hourly cooling energy data was recorded, corresponding mainly to the variation of the AF system per hour together with other input parameters. Cooling loads in kWh/m2 were generated as an output of the ANN model and a total of thirteen variables were used as inputs as follows: month, hour, day, orientation, building 00, building 01, façade level height, glazing type U-value W/m^{2}K, exterior wall U-value W/m^{2}K, AF opening ratio, AF-SF, SR W/m^2, and OT. The generated energy results database was uploaded to the Design Explorer webpage, which is a web-based tool allowing comparison analysis between the studied input parameters (http://tt-acm.github.io/DesignExplorer/?ID=BL_3fQFpeE). Based on all studied cases, the total annual energy consumption of the office room with AF shading system ranges from 142 kWh/m2 to 82 kWh/m2. The simulation results were compared with the CIBSE energy consumption benchmark for existing office buildings (CIBSE Guide F 2012). According to CIBSE Guide F, energy benchmarks for good practice of air-conditioned standard offices in the UK count approximately 128 kWh/m2 per year of treated floor area for HVAC, whereas for typical practice count for 226 kWh/m2 per year (CIBSE Guide F 2012). Most models in the current study achieved below the CIBSE practice recommendations except some models that has a higher U-value. To construct the ANN model, three main steps needed to be considered: (1) Data pre-processing, (2) Model training and hyper-parameter optimisation, and (3) Model validation (Westermann and Evins 2019). Regrding the machine learning modelling, we used ANN in the form of a regression learning using Pytorch. ANN is considered as a surrogate method to approximate any continuous function by virtue of the universal approximation theorem.

The ANN network is constructed of basic units named neurons, and it is assumed that these neurons are arranged in different layers. Each neuron takes the input from the previous layer where the inputs are multiplied with weights. The output of a neuron is a non-linear function of the linear combination of weighted inputs, described by the following equation.

$$y = \sigma\,(x_1 w_1 + x_2 w_2 + x_3 w_3)$$

The non-linear function σ is called the activation function. In the experiments, the activation used was the Rectified Linear Unit (ReLU), which is defined as follows:

$$\sigma(x) = \max(0, x).$$

For the experiments, the network architectures used were one-, two-, three-, and four-layer networks with 64, 128, 256, and 512 neurons: that is, for an *n*-layer network, all the *n*-layers had 64, 128, 256, or 512 neurons. In total, the model selection was done from a total of 16 network configurations. The details are explained in Section 6. So, the function, *y*, approximated by the neural network of *n* layers, is as follows:

$$y = \sigma \ldots \sigma\big(\sigma\,(X_1 W_1)\big) W_2 \ldots) W_n$$

Here X_1 is the input matrix of dimensions N x d, where N is the number of data points, d is the dimension of the data, and W_1 is the weight matrix in the first layer of dimensions d x d_1. Similarly, $\sigma\ (X_1W_1)$ forms the input for the second layer, and W_2 is the weight matrix for the second layer and has the dimensions d_1x d_2. The datasets may have complex patterns that may not have linear dependencies. In other words, to detect these patterns, it is necessary to analyse the non-linear interactions in the input data space. The non-linear function σ was used in this regard. The objective was to find a function in terms of the inputs that gives the cooling load as an output. A NN was used to approximate this function. For this purpose, the NN was used in a regression setting using the selected inputs. Then, the discrete inputs were one-hot encoded. The network was then trained to predict the cooling loads as an output. The data flow overview of the modelling process is described in Figure 4.

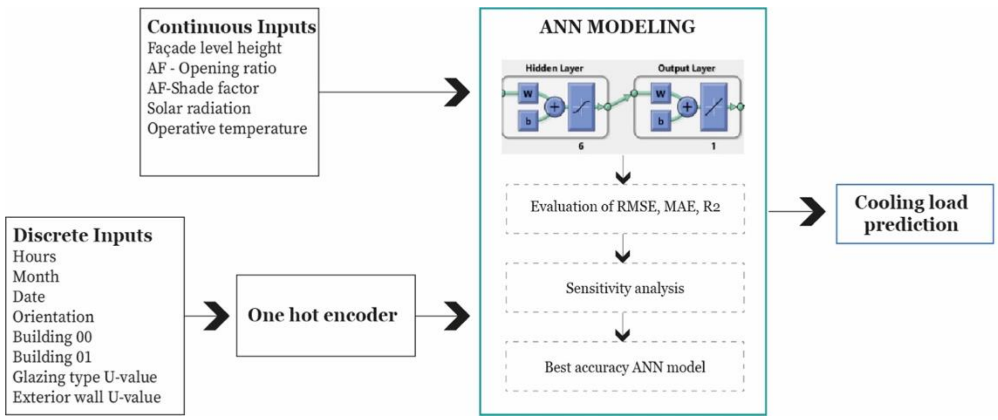

Figure 4. Data flow overview.

The performance of the network was evaluated with the root mean square error (RMSE) value, mean absolute error (MAE), and R^2 score. The RMSE value describes the square of the difference between the actual cooling load values and the predicted ones. On the other hand, the MAE value describes the absolute value of the difference between the two. The difference is also known as the residual. Both the values can take any value greater than zero, and a model is said to be performing well when both values are as low as possible. The R^2-value evaluates the scatter of the predicted values around the regression line. In statistics, it is also called the coefficient of determination. It is defined as the ratio of variance explained by the model to the total variance. The performance metrics were calculated using the following formulae.

$$\text{RMSE} = \sqrt[2]{\frac{1}{|y|}\sum_{i=1}^{n} (y_i - \hat{y}(i))^2}$$

$$\text{MAE}\ (\text{y}, \hat{y}) = \frac{1}{|y|}\sum_{i=1}^{|y|} |y(i) - \hat{y}(i)|$$

$$R^2\ (\text{y}, \hat{y}) = 1 - \frac{\sum_{i=1}^{|y|}(y(i) - \hat{y}(i))^2}{\sum_{i=1}^{|y|}(y(i) - \bar{y})^2}$$

4.1 Experiments Settings

In this section, we describe the details of the NN modelling procedures for predicting the cooling loads. The objectives of the modelling are as follows: (1) choosing the optimal architecture: in our experiments, one-, two-, three- and four-layer architectures were considered. Each of these architectures was tested with 64, 128, 256 and 512 neurons. Hence, the first step was to choose the optimal architecture from these options. The k-fold cross validation methodology was adopted for this, and the process is explained in detailed in Section 5. (2) analyzing the performance of the optimal architecture: once the right architecture had been chosen, a machine learning model had to be built such that it could be used as a surrogate mechanism to predict the cooling loads from the inputs described in Table 1 without performing the actual simulations.

Apart from choosing the right architecture, the other parameters were fixed as follows. The dropout rate was chosen as 0.5, batch size as 20000, number of epochs as 100 and the early stopping criteria as 10 epochs. The hardware used was Intel Xeon E5-2630 CPU, 80 GB RAM, and Nvidia GeForce GTX 1080-Ti GPU. For learning, the Backpropagation (BP) algorithm [9] was used. The weights of the layers were initialized using the Kaiming initialization method (Kaiming et al. 2015).

4.2 Data Pre-Processing

Data pre-processing refers to the processing steps that the categorical data inputs must undergo. The categorical inputs must be given an appropriate mathematical representation to improve the performance of the network rather than using them as such. The discrete inputs used for the modelling were hour, month, date, orientation, building 00, building 01, glazing type U-value, and exterior wall U-value. One-hot encoding (Seger 2018) is the data pre-processing that is applied to the categorical inputs. One-hot encoding is a mechanism to represent categorical variables as a mathematical vector that contains zeros and ones. The vector will have a dimension equal to the number of possible values it can take. A value of one is given to the coordinate corresponding to the value taken by the variable, and the remaining coordinates will be zero. For better representation, the one-hot encoded categorical features were fed into an embedding layer. In this layer, the one-hot encoded vector already created was again changed to another meaning vector rather than being used in their original form of just ones and zeros. The continuous inputs used for the modelling were level height, AF (opening percentage), AF-SF, SR, and OT. These inputs were fed into the batch normalizing layer (Ioffe and Szegedy 2016). Then, the data were fed into the ANN in batches. Since the network was not fed with the entire data, the data distribution tended to vary as each batch was processed. This caused some instability with the learning process. To rectify this effect, batch normalization was introduced. This standardized the input in the form of batches that were fed to the ANN layers. It helped to stabilize the learning process and reduced the number of epochs required to train the networks.

4.3 Operations Inside the Layers

(1) Linear layer + ReLU: The input to the network was given to a dense or linear layer. For the non-linear activation of the inputs in the neurons in the linear layer, the ReLU function defined as $f(x) = \max(0, x)$ was used. **(2) Batch normalization:** The output of ReLU was batch normalized. Batch normalization concepts were discussed in the previous section. **(3) Dropout regularization:** Dropout is a mechanism to ensure the generalization capability of the network by avoiding over-fitting. It is the process of disabling certain neurons randomly so that the learning process becomes robust, and dependency on specific neurons is decreased. The percentage of neurons to be disabled is treated as a hyper-parameter, and it was taken as 0.5 out of 1 in these experiments. **(4) Output of the network:** The output of the network is a neuron without any activation function: that is, the input of the neuron is multiplied by the weight, and no further processing is done.

5 K-FOLD CROSS VALIDATION

A neural network can have a different number of layers where each layer can have a different number of neurons. To address this, a k-fold cross validation experiment was conducted. Choosing an appropriate network is important to avoid the under-fitting and over-fitting of the data and to achieve better generalization of the network to be used in the unseen future data. Therefore, we started with a one-layer network, and added numbers of neurons to it in steps. Firstly, 32 neurons were given, then 64, and then 128. The experiment was repeated for two-layer, three-layer, and four-layer networks. For this experiment, the data was split into training, validation, and test sets. The models were trialled using the training and validation data splits, and the model that was finally chosen was tested with the test data.

5.1 Data Split

Initially, the whole data set was split into training, validation, and testing sets: 80% of the data was assigned to the training set, 6.67% to the validation set, and the remaining 13.37% was assigned to the testing se. The k-fold cross validation was then done on the training fold and the chosen value of k was 5. For the k-fold cross validation procedure, one of the folds became the testing set, and the remaining folds became the training set. In this case, one-third of the testing case data was reserved as the validation set for that particular instance of the validation procedure. Table 4 reports a summary of the average across five folds while doing the k-fold cross validation. To provide fuller representation of the chosen architecture, the results are graphically visualized in Figure 5. Moreover, the performance metrics of the best performing model from the one-, two-, three-, and four-layer networks are given in Figure 6.

No. of layers	No. of neurons in each layer	RMSE	MAE	R2- score
1	**128**	**0.000478**	**0.0383**	**0.862678**
2	128	0.000547	0.04106	0.75022
3	128	0.000703	0.04616	0.620949
4	128	0.00074	0.0492	0.690268

Table 4. Sensitivity analysis results for ANN architecture.

The results are graphically represented as shown in Figure 5 and 6.

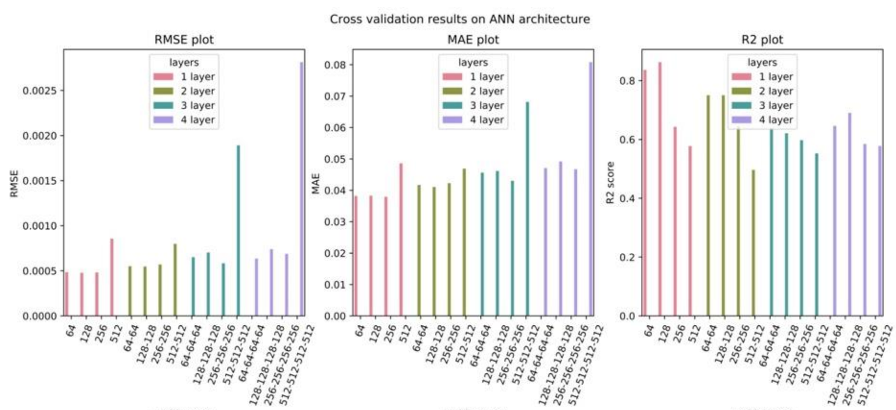

Figure 5. K-fold cross validation results on choosing ANN architecture.

From these figures, we can note the following.

i) As we increase the number of layers, the RMSE increases. The best results are for networks with only one layer.
ii) The performance score drops for deeper networks compared to shallow networks.
iii) This indicates that having deeper networks with a large number of neurons results in over-fitting or poor generalization to the data.
iv) On the other hand, the performance of deeper networks with a lower number of neurons (64 and 128) is comparatively better than that of those with a larger number of neurons.
v) The performance decreased when more layers were added.

vi) The trend discussed in the previous point was followed by all three performance metrics, namely RMSE, MAE and R2 score.

vii) Based on the experiments, the architecture chosen was a 1-layer neural network with 128 neurons. For all these experiments, the train/test ratio of the data used was 80%/20%, the learning rate was 0.01, the number of epochs was 100, and the batch size was 20,000

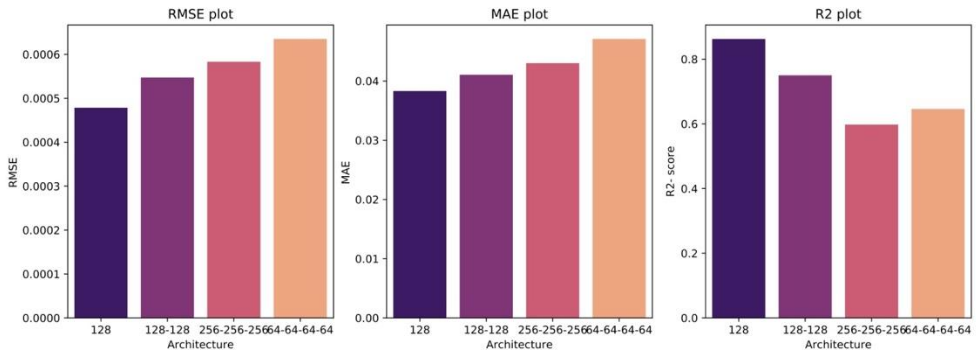

Figure 6. RMSE, MAE and R3 score of the best performing models among different layers.

6 TESTING THE SELECTED ARCHITECTURE

The one-layer network with 128 neurons was selected through the k-fold cross validation applied to the validation set and the test set. For this purpose, a new model was built using the entire training set. This model was tested with the test set. The results obtained are as follows: the RMSE value was 0.00008809, MAE was 0.00718157, and the R2-score was 0.8531965. The training loss and validation loss of this network are plotted in Figure 7. As we can see from the figure, the training loss starting from 0.20 decreased steeply to less than 0.01 in the first few iterations. This indicates that our neural network has learned in the desired way. We tested the model for some randomly cases of actual and predicted values on different days of the year (21st March, 21st June, 21st September, and 21st December), and building orientations (South, West, North, and East). we observed that the ANN model can accurately predict the cooling load in seconds compared to BPS tools.

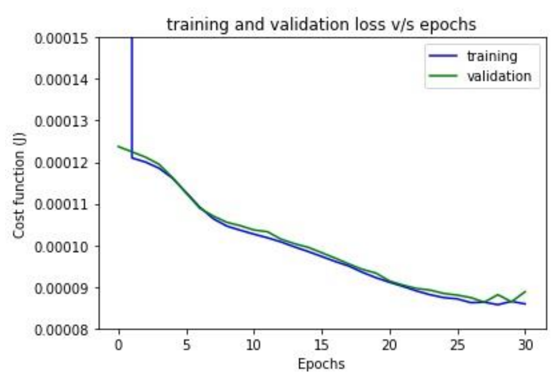

Figure 7. Training and validation loss against number of epochs.

7 CONCLUSION AND RECOMMENDATIONS

This paper aimed to find an alternative method to evaluate the performance of adaptive façade systems to avoid the difficulties that are faced while making predictions using the existing BPS tools. To achieve this, a supervised machine learning approach was employed, specifically an ANN model, to estimate the hourly cooling demand of AF in hot climates. Initially, the AF model was performed using the Honeybee and Ladybug add-ons in the Rhino/Grasshopper software to create a large synthetic datasets of cooling loads. After the simulation, the generated data were then used to train, validate, and test the proposed ANN model.

To discover the best prediction outcome of the ANN model, a hyper-parameter tuning analysis was performed to select the most suitable architecture. We tested the architecture with different numbers of hidden layers and neurons through a k-fold cross-validation technique. Based on our experiment, we noted the following observations: (1) at the conclusion of our experiment, we found that the one-hidden-layer network with 128 neurons performed better than other networks. Therefore, we fixed the model, choosing these parameters as follows: a one-layer neural network with 128 neurons, a train/test ratio of 80%/20%, a learning rate of 0.01, 100 epochs, and a batch size of 20,000. (2) The best results achieved were an RMSE value of 0.00008809, MAE pf 0.00718157, and an R2-score of 0.8531965. (3) We compared the results of the ANN model with the actual simulated output for random cases, and we observed that the ANN model shows a strong and promising approach to predict the cooling load with greater accuracy.

Due to the unavailability of a real dataset, we resorted to creating a synthetic one in a generative parametric system using a simulation-based approach. Furthermore, the case study focused only on a hot climate region and tall office towers within an urban context, so its applicability to other climates remains to be tested in future work. Planned future work will experiment with other machine learning techniques such as Decision Tree (DT), and Recurrent Neural Network (RNN) to compare our findings to these models in terms of model prediction accuracy. We are also planning to integrate other building performance metrics and develop a ML surrogate model to assess the overall performance of AF.

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