HVAC's Chilled Water Flow and Temperature Prediction for Buildings in Tropical Zones

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Abstract

The weather in a tropical region, which mainly consists of high temperature and humidity, is clearly different from those in cold and desert climate regions. These factors strongly affect the cooling load demand of heating, ventilating, and air conditioning (HVAC) systems in order to provide required thermal comfort in buildings. Thus, they should be taken into consideration together for determining cooling load demand. Traditional approaches such as physically based models and statistically based methods are extremely difficult to derive and time consuming to develop. Artificial neural networks (ANNs), which are a powerful modeling technique with robust, fast, and nonlinear modeling advantages, can flexibly and simply capture ambient conditions and cooling demand. In this study, the main objective is to investigate the performance of ANNs' predictive ability for HVAC systems. The ANNs are applied to predict flow and temperatures of chilled water in HVAC systems of a multifunctional building in Thailand. The obtained model can be used to effectively plan the energy use of such systems. In addition, thermal energy storage can be properly managed, including its capacity and size. The main features representing temperature and humidity are ambient temperature and relative humidity of indoor and outdoor conditions. The characteristics of cooling load demand are flow rate and temperatures of chilled water. The obtained prediction results show that a properly designed ANN model outperforms multiple linear regression (MLR). Moreover, they can easily be extended to predict multiple factors(such as temperatures) with satisfactory results.

Keywords: Artificial neural networks, Building, Cooling load, Temperature and humidity, Tropical zone

1. Introduction

World energy demand has considerably increased over the past decades. Due to the concern of energy shortage in the near future, the use of renewable energy has gained a wide acceptance as an alternative solution. Energy conservation and management are a tangibly strategic approach to better energy consumption and utilization. For buildings, energy efficiency in subsystems such as in

HVAC and lighting systems is a key to reduce the cost in building operations. In Thailand, HVAC systems take the highest share of energy consumption in buildings at approximately 50-70% [1-3], which is a direct consequence of cooling load demand. Its energy use and utility cost can be reduced significantly by using Thermal Energy Storage (TES) systems [4]. TES is as an integrated system for optimal operation of a chiller plant to efficiently store the thermal load and control the distribution system. Peak load reduction can be managed by producing chilled water or ice during times of lower electricity rate, at night time. However, thermal storage systems are often found not to operate as efficiently as estimated during its design stage [5]. An equilibrium condition is necessarys in which the required amount of thermal energy storage is equal to the available produced amount of energy storage. Operational management and energy use optimization are required to overcome this problem. The pattern of cooling load demand in buildings should be specifically identified to increase the efficiency of TES during the design stage and actual operation. Therefore, a proper predictive model pattern of cooling load demand is necessary for the accomplishment of an energy conservation goal. Based on these reasons, this research was conducted to study a predictive model of cooling load demand by using artificial neural networks (ANNs). ANNs are attractive because they can capture patterns of input factors regardless of their statistical distribution assumption. This assumption must be verified to validate the results obtained by traditional statistical methods. Furthermore, multiple output prediction can be simply developed by using ANNs if outputs are correlated. This is rather difficult and time consuming for other methods.

Cooling load is a requirement by HVAC systems to provide a thermal comfort condition for occupancy. Heat is removed from the conditioned space to maintain a thermal comfort condition. Several parameters such as, outdoor air temperature, relative humidity, solar radiation and wind speed are outdoor environmental factors that affect the amount of cooling load requirement. Moreover, the number and activity of occupants in buildings also influence the amount of cooling load demand. Outdoor temperature is a key environment factor that has been selected as neural networks input to accurately predict cooling load for desert and subtropical regions in Kuwait and Japan, respectively [6-7].

For a tropical climate, as in Thailand, temperature and relative humidity ratios are high and different from those in other geographic zones. These two factors directly affect human comfort, resulting in increasing amounts of cooling load demand in buildings. In this paper, these two factors of outdoor and indoor conditions are selected as inputs for Cooling load prediction. Supply and Return Chilled Water Temperatures (SCWT and RCWT) and Chilled Water Flow (CWF) of air conditioning system are used as outputs. Cooling load demand could mainly be computed by the chilled water flow and the difference of chilled water temperatures.

2. Literature Review

ANNs are widely used in various areas of energy management, such as overall thermal transfer value, cooling load, air ventilation and thermal comfort in buildings. Demonstrated by several articles, ANNs have a better capability over traditional methods, such as time series and regression. Their advantages are non-linear modeling capability and faster development time.

Focusing on the predictive capabilities of ANNs, Kreider and Wang [8] studied the application of expert systems to

HVAC diagnostics in commercial buildings by using ANNs for determining the energy use of chillers based on hourly averaged data collected from the system. Karatasou et al. [9] implemented modeling and predicting a building's energy use with neural networks. The statistical procedures such as hypothesis testing, information criteria and cross validation were advantageously used in term of guidance to improve the performance of ANN for modeling and predicting a building's energy use. Kajl et al [10] proposed a fuzzy-neural assistant as a comparable method to the DOE-2 building analysis program for the simplified and detail estimation methods of a building's energy consumption. Three beneficial input parameters including orientation, insulation thickness, and transparency ratio were developed for the prediction of building energy consumptions by Ekici and Aksoy[11]. ANNs prediction for the energy consumption of passive solar, with faster development time than the dynamic simulation programs, has been studied by Kalogirou and Bojic[12]. Olofsson and Andersson have also developed ANNs to perform long-term energy demand prediction based on short-term measured data. The model parameters were indoor and outdoor temperature difference and energy for heating and internal use [13]. Moreover, prediction of a building's temperature using neural networks models for predictive control of air conditioning system has been proposed by Ruano et al. [14]. A neural network was also applied to the thermal load prediction case. Investigation of four predictive methods, namely Autoregressive Integrated Moving Average (ARIMA), Exponentially Weighted Moving Average (EWMA), Linear Regression (LR), and ANNs, was comparatively conducted for the use of hourly thermal load prediction by Kawashima et al. [15]. ANNs gave the highest thermal load prediction accuracy and clearly outperformed other methods. This resulted in a decrease of operating cost without thermal energy shortage. Optimizations based on neural networks modeling have also been implemented to the energy management field. Curtiss et al. reported [16] ANNs could be used to optimize the energy consumption in a commercial scale HVAC system. Information from an actual system was used for training a network to optimize the energy consumption without sacrificing comfort by considering all the physical limitations of the system. On-line set-point resets in an actual HVAC control system were successfully performed by ANN based energy management. A variant of ANNs has been applied to energy management as well [7]. General regression neural networks (GRNN) are a powerful instrument for optimizing thermal energy storage in buildings based only on the use of external temperature. External hourly temperature readings for a 24-hour period were used as network inputs to predict an hourly cooling load for the next day.

The application of ANNs was introduced to the system identification and the intelligent control of an air handling unit by Albert and Wai [17]. ANN traced the online parameters relative to the air handling unit as an identifier and then controlled the system. Atthajariyakul and Leephakpreeda [18] studied a practical approach to determine human thermal comfort quantitatively via neural computing. The feedforward neural network model allowed a real time determination of a thermal comfort index, the predicted mean vote (PMV) index. In contrast, a major obstacle of the conventional method for PMV calculation is its long computational time and hence it cannot be calculated in real time.

The literature above has confirmed the performance of neural networks in prediction. However, there is still no study about the performance of neural networks in cooling load prediction for tropical regions by using both temperature and humidity of indoor and outdoor conditions as inputs. Therefore, this study is focused on the feasibility of using ANNs for tropical cooling load prediction.

3. Methodology

Section 3.1 and 3.2 discuss the fundamentals of a machine learning technique, ANNs, and widely used traditional method, multiple linear regression (MLR).

3.1 Multiple outputs artificial neural networks regression

Artificial Neural Networks (ANNs) imitate the learning process of human brain. They eliminate the need of using complex mathematically explicit formulas, computer models, and impractical and costly physical models. ANNs can capture relationships between input and output by adjusting weights on each link while learning from data. Their advantages are robustness, speed, and nonlinear modeling. Furthermore, they can perform both single and multiple output predictions. In this study, a feedforward backpropagation neural network was attempted to predict flow and temperatures of chilled water of an air conditioning system. A neural network normally has two elementary components, processing elements and connection weights. A feedforward network has no loops as opposed to a feedback type. A classic learning algorithm, backpropagation, was used by propagating errors backward to train and update the weights on each link of a neural network with training examples. These weights capture the pattern of multivariable functions through learning. In other words, they were used to capture the relationship between temperature and humidity of indoor and outdoor conditions, and flow and temperatures of chilled water of air conditioning systems. Weight adjustment between processing nodes in backpropagation is carried out according to the difference between the target and the output values of the neural network. This difference is measured by mean squared error shown below [19]:

$$E = \frac{\sum_{p=1}^{P}\sum_{k=1}^{K}(d_{pk} - o_{pk})^2}{pk} \qquad (1)$$

where d_{pk} is the k^{th} desired value of the p^{th} data and o_{pk} is the actual output.

The weights (W) are adjusted toward the gradient direction that produces a smaller approximation error as follows:

$$\mathbf{W}(\mathrm{t}+1) \Leftarrow \mathbf{W}(\mathrm{t}) + \eta\boldsymbol{\delta}(\mathrm{t})\mathbf{y}(\mathrm{t}) \qquad (2)$$

where η is a positive constant called learning rate, δ is the gradient of the difference between the desired and actual neuron's responses, and $\mathbf{y}$ is the input vector. The weight matrix adapted at time t becomes equation (2) at the next instant.

In regression problems, the following set of data $\{(\mathbf{x}_1, \mathbf{y}_1), \ldots, (\mathbf{x}_p, \mathbf{y}_p)\} \subset \Re^m \times \Re^n$ can be approximated by using ANNs. The $\mathbf{x}_i$ is the vector set of temperature and humidity of indoor and outdoor conditions and $\mathbf{y}_j$ is the output vector which consists of service and return chilled water temperatures and chilled water flow conditions. ANNs prediction model was first implemented with a single output to investigate its effectiveness as compared with a traditional method like the MLR. Theoretically, the advantages of ANNs are robustness, nonlinear modeling ability and nonparametric concept. However, ANNs have a major disadvantage as the physical relationship among input and output cannot be explained. A proper architecture of ANNs must be chosen from the split data sets among training and validation sets to avoid overfit problems. In addition, care must be taken while selecting a proper architecture of ANNs to avoid overfit problems. Data must be split into three sets, training, validation, and test sets, to help select such architecture.

3.2 Multiple linear regression

Multiple linear regression analysis is a statistical technique which is very useful for exploring the relationships between two or more variables ($\mathbf{x}_i, y_i$). $\mathbf{x}_i$ represents the independent variables which contain a set of temperature and humidity variables of indoor and outdoor conditions. y_i is an interesting dependent variable consisting of the set of chilled water flow of an air conditioning system. Chilled water flow output was chosen for this pilot experiment due to its variation in operation. Normally, a chiller system is operated in accordance with the cooling load demand by varying the amount of chilled water flow and fixing the value of chilled water temperatures at some level ranges. That means the amount of chilled water flow can consistently reflect the characteristic of cooling load demand.

Suppose that there are m independent variables and p observations (x_{i1}, x_{i2}, x_{i3},…, x_{im}, y_i); i = 1, 2,…, p. The fitted regression model can be described as:

$$y_i = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij} \qquad i = 1, 2, \ldots, p \;; \quad (3)$$

and j = 1, 2, …, m.

The parameters β_0 and β_j, j = 1, 2,…, m are called the regression coefficients which will be determined by the method of least squares.

The difference between the observation {y_i} and the fitted value $\hat{y}_i$ is a residual, $e_i = y_i - \hat{y}_i$. $\hat{y}_i = \hat{\beta}_0 + \sum_{j=1}^{m} \hat{\beta}_j x_{ij}$

and $\hat{\beta}_0$ and $\hat{\beta}_j$ are the estimators of the regression coefficients. The criterion used is the sum of squared error:

$$S_r = \sum_{i=1}^{p} e_i^2 = \sum_{i=1}^{p} (y_i - \hat{y}_i)^2 \qquad (4)$$

The quality of the models is estimated by considering the correlation coefficient R between the actual and predicted outputs. It can be described as:

$$R = \frac{p\sum y_{ij}\hat{y}_i - (\sum y_{ij})(\sum \hat{y}_i)}{\sqrt{p\sum y_{ij}^2 - (\sum y_{ij})^2}\sqrt{p\sum \hat{y}_i^2 - (\sum \hat{y}_i)^2}} \qquad (5)$$

MLR is the most widely used regression method because it can describe the relationship between input and output. Moreover, it is quite fast and simple due to the use of a closed form solution for the determination of regression coefficients.

4. Results and discussions

The objective of this study is to investigate the feasibility of using neural networks to predict the cooling load demand. The causal method was used for such a task. The data collection was performed between November 2008 and January 2009 at the main campus of Shinawatra University in Pathum Thani. The input parameters are temperature and relative humidity of indoor and outdoor conditions. The outputs are service and return chilled water temperatures and chilled water flow data. Temperature and relative humidity of indoor and outdoor conditions were recorded by temperature and humidity measuring devices and a weather station at the main campus. The Building Automation System (BAS) monitoring program was used to collect data of supply and return chilled water temperatures and chilled water flow. Those data of chilled water temperatures are in Celsius with the magnitudes of ones and tens. The data of chilled water flow are in gallons per minute (GPM) with the magnitude of hundreds. All data were recorded every fifteen minutes. ANNs and

MLR predictions were implemented in MATLAB 7 with neural networks and multiple linear regression toolboxes to develop the cooling load demand model.

4.1 Chilled water flow (CWF) prediction

A pilot experiment for MLR's prediction has been implemented to compare its predictive ability with that of ANNs. The prediction was performed only with CWF as single output because, as mentioned earlier, CWF is a major factor of cooling load determination. The experiment was set up by using large and small sizes of data sets with 3520 and 200 selected data points in order to see the characteristic of MLR prediction on different sizes of data sets. These selected data were randomly divided into training and test subsets for building and verifying the MLR predictive model. The training and test sets contained 75% and 25% of data sets. The selected data of ANNs were randomly divided into three subsets for training 50%, validation 25%, and testing 25%, as demonstrated in Figure 1.

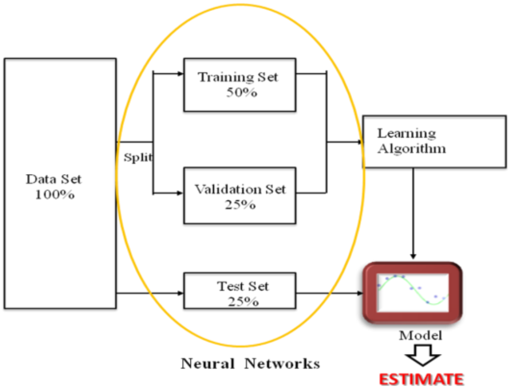

Figure 1. Model selection method diagram.

Details for the procedures of ANNs single output prediction are discussed in section 4.2. The performance of each technique was evaluated by using the average R-value. Comparative accuracy results between the average R-values of MLR's and ANNs' predictions are presented in Table 1. In comparison between these two regression methods, ANNs show an excellent prediction performance due to the high level of R-values for both small and large size data sets. Furthermore, when applied to a much larger data set, ANNs produce a slight decrease of performance, although they have to deal with higher variation. By increasing the data size from 200 to 3520 data sets, the R-value results drop from 0.930 to 0.908 for training set and 0.899 to 0.892 for test set. For MLR prediction, it performs fairly well for a small size data set. Conversely, it makes a poor prediction for a large size of data sets. By increasing the data size from 200 to 3520 data sets, the R-value results decrease from 0.807 to 0.645 for training sets and 0.797 to 0.641 for test sets.

Table 1. Comparative accuracy results between the average R-values of MLR and ANNs for CWF.

Predictive Model	Average R-value			
	200 data sets		3520 data sets	
	Training Set	Test Set	Training Set	Test Set
ANNs	0.930	0.899	0.908	0.892
MLR	0.807	0.797	0.645	0.641

The predicted outputs by ANNs and MLR regression are plotted against the actual outputs as shown in Figures 2 and 3. The predicted outputs from ANNs regression are quite close to the actual outputs, whereas the predicted outputs from MLR vary widely from the actual outputs. These obviously illustrate the superiority of ANNs over MLR, numerically and graphically.

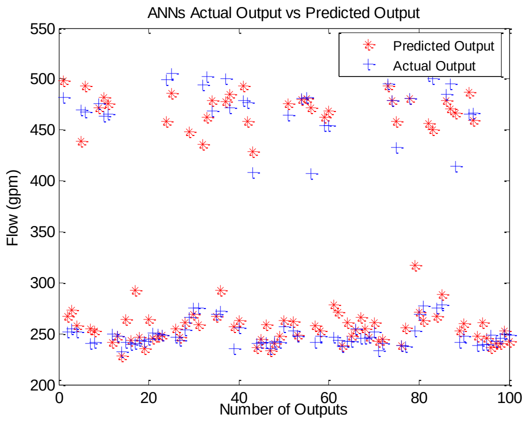

Figure 2. ANNs actual output vs predicted output.

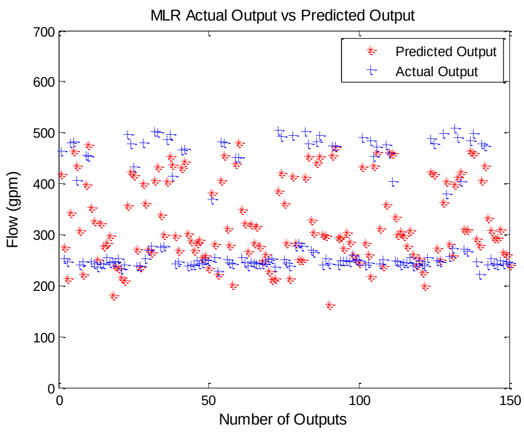

Figure 3. MLR actual output vs predicted output.

In summary, the MLR technique was outperformed by ANNs. Higher prediction accuracy for large size and high variation data could be expected from ANNs. As addressed before, there are more than one output parameter to be used for cooling load calculation. This prediction requirement of multiple outputs, chilled water flow (CWF), return chilled water temperature (RCWT), and service chilled water temperature (SCWT) can easily be handled by ANNs. Section 4.2 initially describes single output ANNs and subsequently generalizes to multiple outputs.

4.2 ANNs' prediction for CWF, RCWT and SCWT

In this section, the procedures of ANNs' prediction for CWF, RCWT, and SCWT are described for each and every cooling load parameter and all of them simultaneously.

Generally, input parameters of the target function are composed of various magnitudes. The one with higher magnitude may dominate others with lower magnitudes. Therefore, preprocessing should be applied to raw data before training. Thus, the raw data were normalized to [-1,1] for every factor: temperature of indoor (T_i), temperature of outdoor (T_o), relative humidity indoor (RH_i), and relative humidity outdoor (RH_o)

In this study, 3520 data were randomly selected from 8832 for developing the cooling load model. Due to the large selected data set, the holdout method was chosen as a validation technique for model selection and performance estimation of the constructed model. The data were randomly divided into three subsets for training, validation, and testing subsets as illustrated in Figure 1.

Training neural networks with training set is done to determine optimal weights. Then, a validation set is used for tuning the parameters and estimating the optimal number of hidden units or a stopping point of the training algorithm. The testing set is used to assess the performance of properly trained and validated model. The procedure and randomization eliminates bias of ANNs, while increasing their generalization ability.

For single output prediction, ANNs were designed with 4 inputs and 1 output. There are three single output models for the predictions of CWF, RCWT, and SCWT. Each predictive model was separately developed for each output. Temperature and relative humidity of indoor and outdoor conditions were used as inputs. The proper architecture, the number of hidden layers, the number of hidden nodes in each layer, and the number of iterations was selected based on generalization performance indicators by using trial and error approach. The combination of these ANNs parameters that provided the lowest training error, and shared the same trend as validation error, was experimentally found. The experiment was conducted for 10 runs for each structure from 5 to 50 nodes in the first hidden layer. Five nodes were increased each time. The second hidden layer was also attempted in the same fashion. The final architectures with minimum error are 4-25-20-1, 4-25-15-1 and 4-25-20-1 for chilled water flow prediction, return and service chilled water temperature predictions, respectively, as shown in Figures 4- 6.

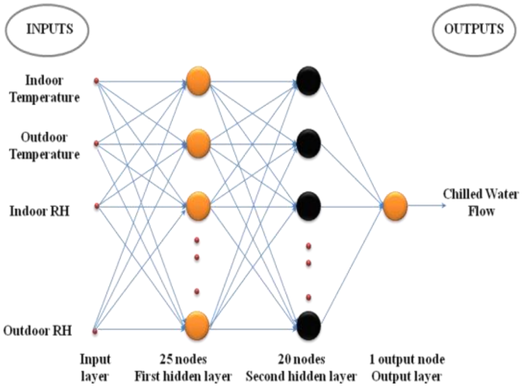

Figure 4. Final architecture, 4-25-20-1, of ANNs for CWF prediction.

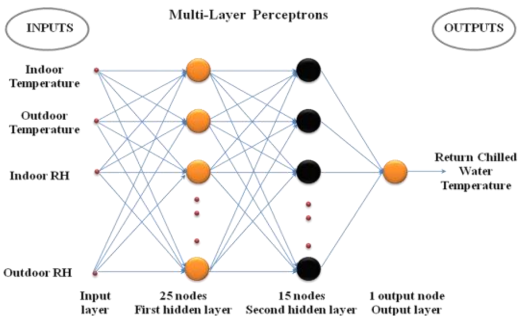

Figure 5. Final architecture, 4-25-15-1, of ANNs for RCWT prediction.

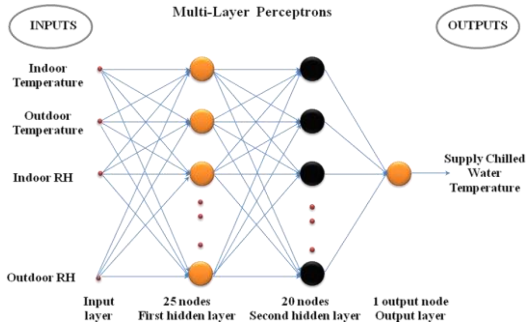

Figure 6. Final architecture, 4-25-20-1, of ANNs for SCWT prediction.

For multiple outputs prediction, a neural network was created with 4 inputs and 3 outputs. These four inputs and three outputs were the same as those in the previous single output case but they would be used together to develop a prediction model. The selection for the best architecture was also the same. The final architecture with minimum error is 4-30-15-3 as shown in Figure 7.

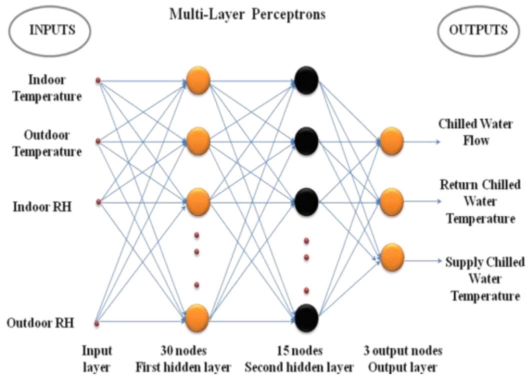

Figure 7. Final architecture, 4-30-15-3, of ANNs for multiple outputs prediction.

The activation functions used were the hyperbolic tangent sigmoid transfer functions or "tansig" for all hidden nodes. Because it is differentiable and covers the bipolar continuous range (-1,1), it is commonly used in backpropagation networks. The linear transfer function or "purelin" was used for the output node(s) in the last layer since the network output(s) could take on any value. The speed-up optimizer, Levenberg and Marquardt backpropagation, was used to train neural networks by minimizing mean squared error.

Five measures of accuracy were chosen to evaluate the performance of ANNs. They are coefficient correlation (R), the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), and the Mean Bias Error (MBE).

R-value can be determined by using linear regression analysis between the predicted outputs and the desired corresponding targets. MSE and RMSE are commonly used to evaluate models based on two reasons. Firstly, they penalize large forecasting errors proportionately. Most users of forecasts prefer a model that produces consistently moderate errors to one that produces some small errors and some very large errors. Secondly, the mean squared error can be used to estimate the variance of the random error component. MSE and RMSE can be described as:

$$MSE = \frac{\sum_{i=1}^{p} (y_i - \hat{y}_i)^2}{p} \qquad (6)$$

and

$$RMSE = \sqrt{\frac{\sum_{i=1}^{p} (y_i - \hat{y}_i)^2}{p}} \qquad (7)$$

where $\hat{y}_i$ is the predicted value, y_i the measured value.

MAE is an average of the absolute errors. It is one of the most popular and simplest for measuring the forecast errors. This measure provides a better intuitive feel for how much error is likely to occur when using a forecast from the model. Its measure is:

$$MAE = \frac{\sum_{i=1}^{p} \left| y_i - \hat{y}_i \right|}{p} \qquad (8)$$

MBE provides information on the long term performance of the correlations by allowing a comparison of the actual deviation between actual and predicted outputs term by term. The ideal value of MBE is zero which implies a lack of bias. A positive result or low bias indicates the condition that predicted outputs are consistently lower than the actual outputs. Whereas, a negative result or high bias demonstrates the condition that predicted outputs are consistently higher than the actual outputs. MBE can be described as:

$$MBE = \frac{1}{p} \sum_{i=1}^{p} (y_i - \hat{y}_i) \qquad (9)$$

From 10 replications of the best architectures of the single and multiple outputs, the results from each measures of accuracy are presented in Tables 2-6. After Training, the validation set was grouped with the training set to determine the performance of the developed predictive model for training. The actual assessment was also done with the unseen test set.

Table 2. Accuracy of average R-values.

		Average R-value					
		Training Set			Test Set		
		Output No.			Output No.		
ANNs Predictive Models	**Final Architecture**	**1**	**2**	**3**	**1**	**2**	**3**
		CWF	**RCWT**	**SCWT**	**CWF**	**RCWT**	**SCWT**
Single Output (CWF)	[4-25-20-1]	0.908	-	-	0.892	-	-
Single Output (RCWT)	[4-25-15-1]	-	0.901	-	-	0.879	-
Single Output (SCWT)	[4-25-20-1]	-	-	0.762	-	-	0.724
Multiple Outputs	[4-30-15-3]	0.904	0.876	0.726	0.890	0.860	0.704

Table 2 demonstrates the comparative accuracy results between average R-values of ANNs predictive models. The average R-values of training and test sets of all models are in the range of 0.70- 0.91 which can reflect the high performance of neural networks in cooling load prediction. The average R-values of training sets of all models are slightly higher than the average R-values of test sets of all models by about 2-3%. In comparison between ANNs predictive models for single and multiple outputs, ANNs predictive models for single output perform a better prediction as they produce the higher results of R-values. For a training set, the average R-value of each single output prediction is slightly greater than the average R-value of multiple outputs prediction, 0.908 and 0.904 for CWF, 0.901 and 0.876 for RCWT and 0.762 and 0.726 for SCWT. For a test set, the average R-value of each single output prediction is slightly higher than the average R-value of multiple outputs prediction with 0.892 and 0.890 for CWF, 0.879 and 0.860 for RCWT and 0.724 and 0.704 for SCWT. Notably, the average R-values of the training and test sets of SCWT are markedly lower than the average R-values of the other two outputs.

The slight differences between average R-values of training and unseen test sets show that ANNs can predict key parameters of cooling load with high generalization. With large size and high variation of data tested, ANNs are quite robust for cooling load prediction.

Table 3. Accuracy of average MSE values.

ANNs Predictive Models	Final Architecture	Average MSE					
		Training Set			Test Set		
		Output No.			Output No.		
		1	2	3	1	2	3
		CWF	RCWT	SCWT	CWF	RCWT	SCWT
Single Output (CWF)	[4-25-20-1]	1720.247	-	-	1993.042	-	-
Single Output (RCWT)	[4-25-15-1]	-	0.281	-	-	0.345	-
Single Output (SCWT)	[4-25-20-1]	-	-	0.319	-	-	0.365
Multiple Outputs	[4-30-15-3]	1787.338	0.348	0.361	2004.598	0.393	0.384

Table 4. Accuracy of average RMSE values.

ANNs Predictive Models	Final Architecture	Average RMSE					
		Training Set			Test Set		
		Output No.			Output No.		
		1	2	3	1	2	3
		CWF	RCWT	SCWT	CWF	RCWT	SCWT
Single Output (CWF)	[4-25-20-1]	41.476	-	-	44.643	-	-
Single Output (RCWT)	[4-25-15-1]	-	0.530	-	-	0.587	-
Single Output (SCWT)	[4-25-20-1]	-	-	0.565	-	-	0.604
Multiple Outputs	[4-30-15-3]	42.277	0.590	0.601	44.773	0.627	0.620

Table 5. Accuracy of average MAE values.

ANNs Predictive Models	Final Architecture	Average MAE					
		Training Set			Test Set		
		Output No.			Output No.		
		1	2	3	1	2	3
		CWF	RCWT	SCWT	CWF	RCWT	SCWT
Single Output (CWF)	[4-25-20-1]	26.494	-	-	28.653	-	-
Single Output (RCWT)	[4-25-15-1]	-	0.361	-	-	0.391	-
Single Output (SCWT)	[4-25-20-1]	-	-	0.374	-	-	0.396
Multiple Outputs	[4-30-15-3]	27.634	0.405	0.408	29.346	0.425	0.416

The accuracy results of the average MSE, RMSE and MAE values of ANNs predictive models are depicted in Tables 3, 4 and 5, respectively. The average MSE and RMSE values of all ANNs predictive models demonstrate a similar tendency to the average MAE values of all ANNs predictive models. Results of training sets for all outputs in every model are slightly better than those of unseen test sets for all outputs.

Table 6. Accuracy of average MBE values.

ANNs Predictive Models	Final Architecture	Average MBE					
		Training Set			Test Set		
		Output No.			Output No.		
		1	2	3	1	2	3
		CWF	RCWT	SCWT	CWF	RCWT	SCWT
Single Output (CWF)	[4-25-20-1]	0.398	-	-	-1.271	-	-
Single Output (RCWT)	[4-25-15-1]	-	-0.00027	-	-	0.0036	-
Single Output (SCWT)	[4-25-20-1]	-	-	-0.0021	-	-	0.0049
Multiple Outputs	[4-30-15-3]	0.470	-0.0025	0.0026	-1.690	-0.0065	0.0060

Table 6 demonstrates the comparative accuracy results by using average MBE of ANNs predictive models. The average MBE results indicate a good performance of ANNs' predictions as they are entirely close to zero. All results of average MBE are between -0.0025 and 1.69. The results of average MBE for training sets of both types of outputs are slightly better than those of the unseen test sets for all corresponding outputs. Results of average MBE of CWF are slightly higher than the results of average MBE of RCWT and SCWT due to the differences in magnitude between CWF and RCWT and SCWT.

In summary, accuracy evaluations of all measures are consistent as the average results of training set and are superior to those of test set. This illustrates the distinct strengths of ANNs with high robustness and good generalization capabilities.

Comparing ANNs predictive models for single and multiple outputs, better results of all measures, R, MSE, RMSE, MAE and MBE, imply better performance in prediction. The less error in ANNs' prediction could be expected from single output predictive model when compared with multiple outputs model.

All three separated single output models slightly outperform the multiple outputs model due to the less complicated calculation required during input-output mappings of ANNs. However, the development time of the former was much large than that of the latter. The times it took to develop each single output model and the combined outputs model were about the same but three different outputs models were needed for the former and only one model was enough for the latter. Consequently, the selections of ANNs' best architectures including training, validation, and testing processes need to be implemented separately three times. The models accuracy is not much different, but the development time becomes more critical. Therefore, ANNs' multiple outputs prediction is more appropriate to be applied for practical work in this study

5. Conclusions

This work demonstrated that ANNs can be effectively applied to predict cooling load demand. As a result from a pilot experiment, ANNs have outperformed MLR in prediction. In comparison of ANNs and MLR, ANNs have superior performance in prediction as they could handle huge different sizes of data sets with high accuracy, about 0.9 for R-values. MLR showed fair performance in prediction for small data sets and quite poor predictive performance for large data sets, about 0.8 and 0.65 for R-values, respectively.

ANNs show excellent performance in prediction of flow and temperatures of chilled water of air conditioning system by using ambient temperatures and humidity rates of indoor and outdoor conditions with both large and small sizes of data sets. Good generalization of ANNs for unseen test set can be obtained. ANNs also show robustness in prediction with large and high variation data sets for all measures. Clearly, ANNs can be applied to capture implicit relationships between input and output factors for cooling load demand calculations. The results from ANNs single output prediction are more accurate than those from ANNs multiple outputs prediction with a slight difference. Development time of ANNs multiple outputs prediction is much less as opposed to the combined development time of all three separated single output models. As a result, ANNs' multiple outputs prediction can be further applied to real-time energy planning. They can effectively be utilized for optimization and management of energy use in HVAC systems. In addition, thermal energy storage can suitably be properly managed, including its capacity and size, by using this intelligent technique.

6. References

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