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## Article

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## Heat load estimation using Artificial Neural Network

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### Abstract

Electricity demand from air conditioners are increasing every year due to increasing ambient air temperature. Several air-conditioned rooms in Thailand currently use low-efficient fixed-speed air conditioners. Prediction of heat load entering air-conditioned rooms may lead to better control of these air conditioners. In this paper, the Artificial Neural Network (ANN) model was developed, trained, and verified. Data from experiments were collected and used in the model. Sensitivity analysis showed that Tamb, Troom, and Gsolar are the major factors affecting heat load. The 3 factors were identified as the main input to the ANN model. There are 17 different model settings used in the study. The settings covered different model configurations such as the transfer function of the output layer, the transfer function of the hidden layer, the number of hidden layers and the number of neurons. It was found that an increasing number of neurons can increase the performance of the ANN model. Nonetheless, it is not conclusive that the increasing number of hidden layers can increase the performance of the model. Finally, it was found that choosing “tansig” as the transfer function of the output layer and “tansig” and “logsig” as transfer function of hidden layers offers the best model performance.

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*Keywords:* ANN model; Heat load calculation

### 1. Introduction

In recent years, electricity peak demand in Thailand increases due to economic growth and high environment temperature. However, it is well-known that the peak is the majority caused by the high ambient temperature. High ambient temperature in summertime leads to the increasing use of air conditioners. Thus, it is general that electricity peak demand in Thailand mostly occurs in the summer period (March to May), as shown in [Fig. 1](#).

There are two main types of air conditioners used in Thailand. In large buildings, the central cooling system is popular. Water chiller is mostly used to produce cold water. Then, cold water is distributed to parts of the building. Heat from rooms are transferred to the cold water and the cold water is returned to the water chiller for heat

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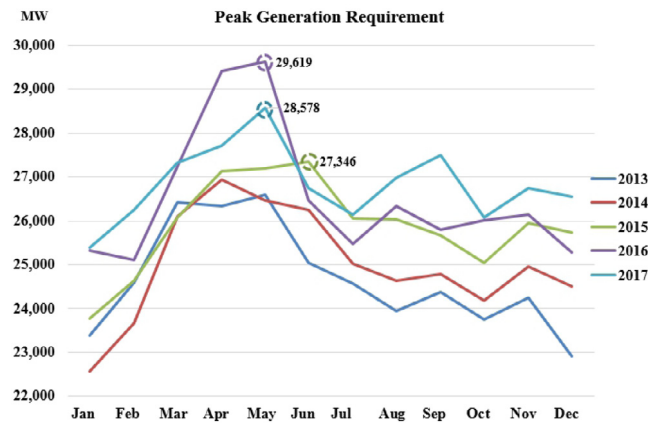


Fig. 1. Historical monthly electricity peak demand of Thailand by EPPO [1].

removal. Air temperature and humidity of each room are adjusted or set from a single control location. On the other hand, the split-type air conditioner is common in small buildings. Some large buildings with several tenants also use split-type air conditioners. The split-type air conditioner provides total control on how to condition the air inside each room.

The energy statistics of Thailand 2018 by EPPO [1] reported that the electricity consumption of the residential sector was accounted for 24% of Thailand's national electricity consumption. The energy consumption of the air conditioner was accounted for 60% of the total electricity consumption of the residential section. The electricity is used to operate the vapor-compression cycle, which removes heat load from the air-conditioned room. Therefore, the heat load becomes the key factor of air conditioner operation.

In order to reduce the electricity consumption and peak demand, quick and accurate heat load forecast is needed. The trend of upcoming heat load can be used for air conditioner operation management. If expected increasing of room air temperature is accurately predicted, sequencing or queuing of air conditioner operation can be optimized for minimizing the peak demand.

Theoretically, the heat load can be calculated using the thermal resistance network approach. However, this approach requires many inputs and takes a long time. Sensitivity analysis can be used for reducing this complexity. Correlation between independent and dependent variables can be constructed. Then, regression analysis can review the strength of each variable by Hamby [2]. Although, the number of variables can be reduced, finding the right correlations is not easy work. In recent years, Artificial Neural Network (ANN) becomes in focus for many researchers for modeling complex systems by Abhishek et al. [3], Zhang et al. [4], Hecht-nielsen [5] and Kwok et al. [6]. In energy management, demand and supply matching of electricity is important. Recent work provides examples of using ANN for forecasting short-term electricity load by using historical hourly load data by Elgarhy et al. [7]. This short term prediction can be used for supply management. Also, shorter time forecasting (15-min ahead) of electricity consumption in commercial buildings using ANN with adaptive training by Chae et al. [8]. Similar work on heat load prediction was performed on a district cooling and heating system by Sakawa et al. [9]. A recurrent neural network (RNN) was recommended instead of a Three-Layered Neural Network (TLNN) due to its superior prediction performance. A more comprehensive ANN model was also developed to estimate convective heat transfer in the evaporator of air conditioners by Ricardo et al. [10]. A maximum error of not more than 10% was achieved.

It is clear that ANN can be used for a number of applications, especially in the heat transfer area with a number of dynamic independent variables. Prediction of heat load entering the air-conditioned room is one of those applications. So this research will develop an ANN model that can provide high accuracy of heat load prediction.

## 2. Methodology

In this study, experiments had been carried out in an air-conditioned room. In the meantime, the ANN model was also developed using MATLAB. The first set of collected data was used to train the developed model. Another

set of collected data was used to verify the trained model. Details of the experiment and model development can be found in this section.

### 2.1. Experimental set up and data collection

An air-conditioned room was used for heat load data collection. The room is on the 8th floor of the Faculty of Engineering, Chiang Mai University, Thailand. The room was situated on the west side of the building. The floor area of this room is 65.7 m<sup>2</sup>. Measurement devices such as thermocouples, Pyranometer, and Power meter were used to measure important data every minute as shown in the following schematic (Fig. 2). There are 4 conditions for data collection, which are AC-off, AC-on with 25 °C  $T_{room}$ , AC-on with 26 °C  $T_{room}$ , AC-on with 27 °C  $T_{room}$ . The duration for data collection was 4 weeks for each condition. During the experiment, there is no latent heat load and human activity inside the room.

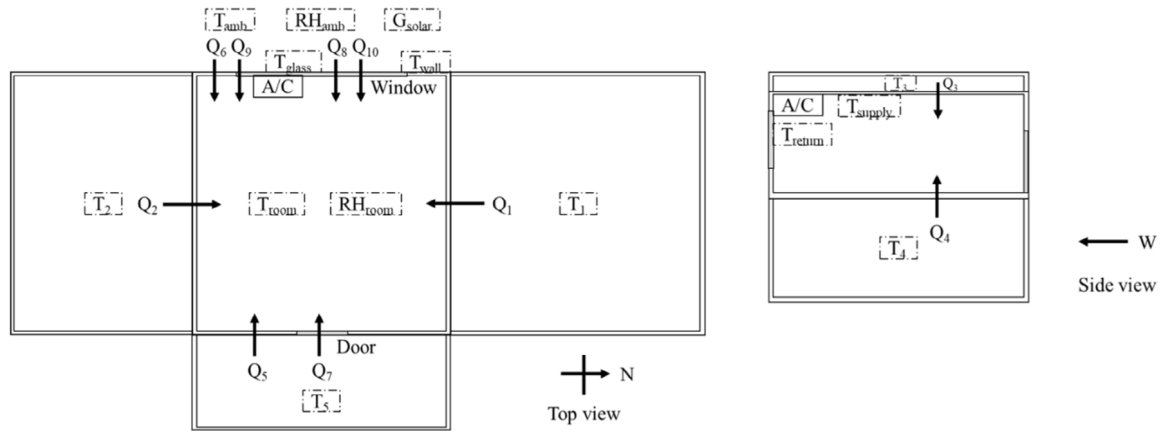


Fig. 2. Schematic of the experimental room.

Since the ambient conditions for each day were different, it is important to select daily data from different days which the different of  $T_{amb}$  is less than 10% for the whole day. The selected data will be used for calculating heat load using traditional method and training and verification of the ANN model.

The calculation of heat load with traditional method involves heat transfer from every direction to the experimental room. Equations used for calculation of the heat load are as shown in (1)–(11).

$$Q_{total} = Q_1 + Q_2 + Q_3 + Q_4 + Q_5 + Q_6 + Q_7 + Q_8 + Q_9 + Q_{10} \quad (1)$$

$$Q_1 = A_{northwall} \times U_{northwall} \times (T_1 - T_{room}) \quad (2)$$

$$Q_2 = A_{southwall} \times U_{southwall} \times (T_2 - T_{room}) \quad (3)$$

$$Q_3 = A_{ceiling} \times U_{ceiling} \times (T_3 - T_{room}) \quad (4)$$

$$Q_4 = A_{floor} \times U_{floor} \times (T_4 - T_{room}) \quad (5)$$

$$Q_5 = A_{eastwall} \times U_{eastwall} \times (T_5 - T_{room}) \quad (6)$$

$$Q_6 = A_{westwall} \times U_{westwall} \times (T_6 - T_{room}) \quad (7)$$

$$Q_7 = A_{door} \times U_{door} \times (T_5 - T_{room}) \quad (8)$$

$$Q_8 = A_{window} \times U_{glass} \times (T_{amb} - T_{room}) \quad (9)$$

$$Q_9 = A_{westwall}(\alpha G) + \varepsilon_{westwall} \sigma A_{westwall} (T_{westwall}^4 - T_{surround}^4) \quad (10)$$

$$Q_{10} = A_{window}(\tau G) + \varepsilon_{window} A_{window} (T_{window}^4 - T_{surround}^4) \quad (11)$$

The variables in the above equations can be categorized into 2 groups. The first group of variables is related to materials properties, which are not sensitive to the environment. This group of variables can be treated as parameters. Another group of variables are those sensitive with the environment. There are 8 variables in this group. Sensitivity analysis had been carried out in order to identify sensitive parameters. It was found that only  $T_{amb}$ ,  $T_{room}$ , and  $G_{solar}$  that are strongly sensitive to the heat load entering the experimental room.

### 2.2. Model development

ANN model was developed under MATLAB using a feed-forward scheme with backpropagation. In this model, there are two main layers, i.e. hidden layer and output layer (as shown in 3). Information from one layer is forwarded to the next one, so-called feed-forward. The model was trained to know relationship among data by comparing output from the ANN model and the traditional heat load calculation. Backpropagation via adjust weights is used to ensure continuously adapting of neural network weighting.

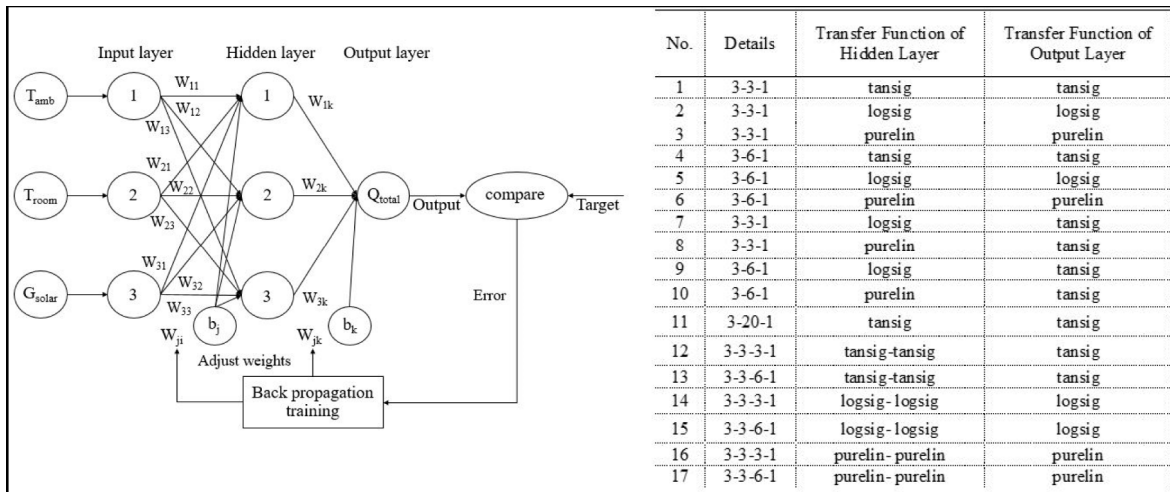


Fig. 3. Developed model on MATLAB platform (Sample of no.1 3-3-1 simulation setting).

The main components of the models consist of Input layer, Output layer, and Hidden layer which relationship between the input layer and output layer is constructed. The hidden layer composes of hidden nodes and transfer functions. The input for the model are  $T_{amb}$ ,  $T_{room}$ , and  $G_{solar}$ . The output is  $Q_{total}$ . The number of hidden layers and types of transfer functions used in the model can also be shown in Fig. 3.

There are 17 conditions of neural network for simulation in this study as shown in Fig. 3. The sample of 3-3-1 simulation setting is also described. In this simulation setting, there are 3 inputs, 3 neural networks, and 1 output. The transfer functions of hidden layers and output layers used in this study are tansig, logsig, purelin and their combinations.

Data from the experiment was divided into 2 groups. The first group of data (11,520 data set) was used as input to the model. The model would perform operations forwarded until it reached the output. Then, the output was compared with the target. Mean Squared Error (MSE) of the target and trained output was subsequently computed. The second group of data (5760 data set) was used to verify the accuracy of the model.

### 3. Results

Results from the training and verification of all experiments against all ANN setting is shown in Table 1. The performance of each ANN setting can be observed by the MSE and R.

From Table 1, it was found that the “tansig” transfer function of the output layer offers the best performance during the training. The MSE of every case is lower than 1.0 as clearly observed in no. 1, 4, 7, 8, 9, 10, 11, 12, 13. The model was used further in the verification and found that the heat load obtained from the ANN model is similar to the heat load obtained from the traditional calculation in every case. The lowest MSE is obtained from 3-3-1 (no.1 — tansig–tansig) setting. The “logsig” transfer function of the output layer performs the worst. In the neural network setting no. 2, 5, 14, 15, the MSE is in the range of 27–40. The heat loads obtained via this ANN setting were not accurate. The “purelin” transfer function of the output layer can be very competitive with the “tansig” it offers high performance of heat load prediction.

**Table 1.** Result of ANN verification.

No.	Details	Transfer function of hidden layer	Transfer function of output layer	Training error (MSE)	R	A/C-off (MSE)	25 °C (MSE)	26 °C (MSE)	27 °C (MSE)
1	3-3-1	tansig	tansig	0.1164	0.99474	0.1754	0.0905	0.321	0.0905
2	3-3-1	logsig	logsig	40.4044	0.90336	40.7288	41.726	27.6426	49.9663
3	3-3-1	purelin	purelin	0.252	0.98857	0.157	0.2266	0.765	0.2684
4	3-6-1	tansig	tansig	0.0756	0.99658	0.1278	0.1138	0.2464	0.0934
5	3-6-1	logsig	logsig	40.402	0.90368	40.7175	41.7161	27.6522	49.9727
6	3-6-1	purelin	purelin	0.2519	0.98857	0.157	0.2266	0.765	0.2684
7	3-3-1	logsig	tansig	0.0989	0.99553	0.1486	0.0916	0.2666	0.0988
8	3-3-1	purelin	tansig	0.1901	0.99142	0.1394	0.2066	0.5515	0.2323
9	3-6-1	logsig	tansig	0.0905	0.99591	0.1177	0.0919	0.2701	0.1261
10	3-6-1	purelin	tansig	0.1917	0.9915	0.1501	0.2086	0.5145	0.245
11	3-20-1	tansig	tansig	0.0541	0.99756	0.1601	0.0995	0.2416	0.0751
12	3-3-3-1	tansig-tansig	tansig	0.0807	0.99636	0.1574	0.0932	0.2672	0.0928
13	3-3-6-1	tansig-tansig	tansig	0.1012	0.99542	0.1942	0.105	0.2939	0.1063
14	3-3-3-1	logsig-logsig	logsig	40.4023	0.90308	40.7219	41.7186	27.6604	49.9709
15	3-3-6-1	logsig-logsig	logsig	40.4024	0.90372	40.7171	41.7165	27.6531	49.9696
16	3-3-3-1	purelin-purelin	purelin	0.2519	0.98857	0.1546	0.2269	0.772	0.2683
17	3-3-6-1	purelin-purelin	purelin	0.2519	0.98857	0.1528	0.2267	0.7631	0.2663

For the transfer function of the hidden layer, it was found that both “tansig” and “logsig” perform better than other transfer functions. The MSE of the verification for both transfer functions are mostly lower than 0.1. It was also found that the “purelin” performs the worst among the transfer functions tested.

The effect of the increasing number of hidden layers can be observed via two pairs of setting no. 1–12 and 4–13. ANN setting no 1 (3-3-1) and 4 (3-6-1) are the base case with different numbers of neural network. One more hidden layer was added to both setting and become case no. 12 (3-3-3-1) and 13 (3-3-6-1). It was found most of these cases, the MSE increased with the increase of hidden layers in both cases. However, this observation is not conclusive since there are several cases that the MSE decreased with the increase of the hidden layer.

The number of neurons can affect the performance of the ANN model. This can be observed via case no. 1 (3-3-1), 4 (3-6-1), and 11 (3-20-1). In all 3 cases, the MSE decreased when the number of neurons increased during the training. The same observation can also be perceived during the verification in all 4 AC operation settings.

#### 4. Summary

This paper successfully developed ANN models for heat load calculation. The model was tested against the traditional calculation method. It was found that only 3 most sensitive inputs (Tamb, Troom, and Gsolar) are needed. Different model settings were investigated. Increasing number of neurons can increase the performance of the ANN model. Nonetheless, it is not conclusive that the increasing number of hidden layers can increase the performance of the model. Finally, it was found that choosing “tansig” as the transfer function of the output layer and “tansig” and “logsig” as transfer function of hidden layers offers the best model performance.

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