Development of ANN-based models to predict the static response and dynamic response of a heat exchanger in a real MVAC system

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Abstract. This paper presents a systematic approach to develop artificial neural network (ANN) models to predict the performance of a heat exchanger operating in real mechanical ventilation and air-conditioning (MVAC) system. Two approaches were attempted and presented. Every detailed components of the MVAC system have been considered and we attempt to model each of them by one ANN. This study used the neural network technique to obtain a static and a dynamic model for a heat exchanger mounted in an air handler unit (AHU), which is the key component of the MVAC system. It has been verified that almost all of the predicted values of the ANN model were within 95% - 105% of the measured values, with a consistent mean relative error (MRE) smaller than 2.5%. The paper details our experiences in using ANNs, especially those with back-propagation (BP) structures. Also, the weights and biases of our trained-up ANN models are listed out, which serve as good reference for readers to deal with their own situations.

Nomenclature

\[ c \] specific heat capacity (kJ/kg K)
\[ p \] density (kg/m³)
\[ V \] velocity (m/s)
\[ S \] area (m²)
\[ Q \] heat transfer rate (kW)
\[ T \] temperature (°C)
\[ M \] mass flow rate (kg/s)
\[ MRE \] mean relative error
\[ iw \] weight of the neural network
\[ b \] bias of the neural network

Subscripts

\[ h \] heat exchanger
\[ a \] air
\[ chw \] chilled water
\[ s \] supply side
\[ r \] return side
\[ in \] inlet
\[ out \] outlet
1. Introduction
The current interest in artificial neural networks (ANNs) is mainly due to their ability to mimic the nature through learning. They learn from examples by constructing an input-output mapping without explicit derivation of the model equations. They find applications in fields like pattern classification, function approximation, optimization, prediction, automatic control, adaptation, fast information processing and many others.

Heat exchangers are key devices used in a wide variety of thermal applications such as refrigeration and air-conditioning systems. It is extremely complicated and non-linear that the prediction of their operation from first principles is virtually impossible. Different models of heat exchangers with neural networks were developed in the past few years. Yasar Islamoglu [1] developed a steady-state model to predict the heat transfer rate of the wire-on-tube type heat exchanger with ANNs. Arturo Pacheco-Vega et al [2] considered the problem of accuracy in heat transfer rate estimations from ANN based models of heat exchangers. Bechtler et al [3] modeled the steady-state performance of a vapor-compression liquid heat pump with the use of ANNs, and Gerardo et al [4] proposed a scheme for dynamic prediction and control of heat exchangers using ANNs. Numerous applications of ANNs for HVAC systems were listed in the open literature and accurate prediction of these ANNs was recognized by several research works [3, 5, 6]. From the literature survey, it was found that most of the applications of ANNs to heat exchangers were related to the refrigeration process. An ANN was applied for prediction of the steady state [7] and the dynamic behavior [8, 9, 10] of heat exchangers. However, the heat exchanger was tested as a standalone component in these studies. Without the external factors introduced from other thermal components in an air-conditioning system, the behavior of these exchangers would deviate too much from those in real operation. There is a great interest to develop mathematical models to predict the behaviors of a heat exchanger operating in a real air-conditioning system.

Apart from ANN-based models, there exists another kind of mathematical models that can predict the behaviors of a heat exchanger. They are incorporated in commercial software packages and are very complicated. Users require inputting detailed technical information of an exchanger to manipulate them. However, such information is not usually disclosed to users such as geometrical parameters. They cannot be used to solve practical engineering problems that frequently occur. Imagine that an engineer needs to estimate the heat transfer rate of an exchanger for an emergency fault repair under site conditions. This kind of models cannot help. To cater for this issue, models utilizing black-box approach should be employed. An ANN-based model is the best candidate that does not require users to possess specific knowledge of a physical system. Together with the fact that ANNs of the multilayer perceptron (MLP) type were proved to successfully model the chiller system satisfactorily [11-15], we decided to employ this type of ANNs to model the behaviors of a heat exchanger under real operation. In this study, the two ANN-based models of a heat exchanger were developed. One of them was used to predict the steady-state performance of a heat exchanger that can be used in practical situations. Another one was used to predict its dynamic performance that can be used in air-conditioning control. Their details will be mentioned in next sections so that readers can employ the information in this paper for their own use.

2. Neural networks
Artificial neural networks (ANNs) are systems of weighted vectors, whose component values are established through various machine-learning algorithms. An ANN takes a set of known patterns as inputs and produces output which closely matches with the actual output of the input patterns.

Among the various types of ANNs employed by previous researchers including Hopfield networks and Kohonen networks, multilayer feed-forward ANNs are perhaps the most popular. In the early 1990s, conclusive proofs were obtained by numerous researchers that multi-layer feedforward networks are capable of approximating any continuous functions on a compact set in a very precise and satisfactory sense. As a result, such networks find applications in many fields, such as function approximation and pattern recognition. An ANN operates like a ‘black box’ model and does not
require detailed information about the system. Instead, they learn the relationship among the input parameters, the controlled variables and the uncontrolled variables by studying previously recorded data, similar to the approach used in a non-linear regression model. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They can ignore the data of minimal significance, which often occur frequently in such complicated system. By concentrating on learning the characteristics from important data, they can effectively predict the performance of these systems.

In this study, the multilayer feed-forward network (i.e. BP network), was chosen due to several advantages [16]:

i) free of linear assumptions,
ii) possessing large degree of freedom,
iii) and more effectively dealing with nonlinear functional forms.

There are three kinds of layers of neurons. The input layer receives input from the outside world and passes the input signals to the ANN. The signals are then processed in hidden layers which are situated between input and output. The output layer is the last layer from the feed-forward point of views. It is responsible to generate the output back to the outside world based on the information from the hidden layers. The strength of the network depends on the interconnections between the neurons, which are modified during training. Training is done by exposing the network to a specific data set of information and by applying a training algorithm to enable the network to produce the desired output. Although there are various training methods, the back-propagation algorithm [17] is one of the most common learning methods to train ANNs. The training style used in our study was batch training, in which weights and biases were only updated after all of the inputs and targets were presented to an ANN. Mean square error (MSE) was adopted as the index to evaluate the performance of a multilayer feed-forward network. It is defined in equation (1).

\[
MSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (o_i - d_i)^2}
\]

\(o_i\) is the output calculated from an ANN, \(d_i\) is the desired output in the training set and \(N\) is the total number of data in the training set.

3. Description of the system and the experimental data

The heat exchanger used in our study has a surface area of 0.3068 m² (0.82 m * 0.44 m), which is mounted in the AHU of a real MVAC system in the laboratory at the City University of Hong Kong. Figures 1 and 2 show the structural diagram and the real photograph of the AHU system respectively. The experimental system consists of two parts. One is the air handler unit with supply air duct and return air duct, and the other part is the refrigeration system with evaporator, compressor, condenser and thermal expansion valve. Air ducts, heat exchanger and the variable speed fan are the main components of the AHU.

The heat exchanger is the water-to-air type. We can change the mass flow rate of hot air through the exchanger by changing the speed of the supply air fan which is in turn controlled by a variable frequency motor drive. We can also change the mass flow rate of chilled water by varying the signal applied to the three-way valve. During the experiments, we operated the devices manually via the buttons on the control panel or automatically through a personal computer. During March-July 2003, a series of experiments was conducted. The experimental data was taken from the heat exchanger at 1-minute sampling interval via the ADLINK data acquisition board which was installed at the personal computer. Chilled water temperature (\(T_{chw}\)), supply air temperature and return air temperature were measured by electronic temperature sensors with accuracy of ±0.2K. For each parameter, both inlet and outlet conditions were recorded simultaneously and hence two temperature sensors were required. The mass flow rate of the chilled water was measured by a flow meter with an accuracy of ±1% of full
scale reading. We also employed an air speed transducer to obtain the velocity ($V_a$) of the air through the heat exchanger with an accuracy of ±5% of full range.

![Diagram](image1)

**Figure 1.** Structural Block Diagram of the real MVAC system.

![Photograph](image2)

**Figure 2.** Photograph of our real MVAC system.
With these measurement parameters, we can deduce the mass flow of the air and the heat transfer occurring in the heat exchanger by equations (2) and (3) respectively.

\[ m_a = V_a * S_b * p_a \]  

\[ Q = m_{c_{ch}} * c_{ch} * (T_{ch\text{in}} - T_{ch\text{out}}) = m_a * c_a * (T_a - T_{air}) \]

where \( c_{ch} \) and \( c_a \) are the specific heat capacity of chilled water and air respectively. For heat transfer calculation, the average value of heat transfer in air side and water side was used. The solution of the heat transfer was found automatically by a tailor-made computer program developed in Visual Basic.

4. ANN models of heat exchanger

The ANN models of the heat exchanger inside the real MVAC system were implemented under MATLAB. It was because MATLAB provides a very convenient computing environment to handle calculation for derivation of the ANNs. Firstly, substantial experiments were conducted and data was captured from the real MVAC system. This data serve as a training set which we employed to train our ANN in MATLAB. Training was stopped until the MSE reached a certain low limit. In this way, the ANN behaved closely with the real heat exchanger under the conditions used in the experiments which were useful for later processing.

In order to allow readers to follow our work in their own situations, the method to train our ANN was clearly presented. In this study, the training scheme employed is the back-propagation that combines adaptive learning and momentum training. This algorithm uses heuristic techniques, which is developed from researchers carrying out analysis on the performance of the standard steepest descent algorithm. With the standard steepest descent algorithm, the learning rate is held constant during training. Its performance is too sensitive to the setting of the learning rate. If the rate is set too high, the algorithm oscillates and becomes unstable. If the rate is too small, the convergence time will be very long. It is not practical to determine the optimal setting of the learning rate before training. In fact, the optimal learning rate changes throughout training as the algorithm moves across the performance surface. The performance of the steepest descent algorithm can be improved if we allow the learning rate to change during training. An adaptive learning rate will attempt to keep the learning step size as large as possible while still maintaining the learning process stable.

4.1. Steady-state performance prediction

The objective of the static ANN model is to predict the heat transfer rate of a heat exchanger under steady-state conditions. Its input parameters are easily accessible by site engineers. In this way, they can use it to accurately predict the heat transfer rate to facilitate their daily operation. The input parameters include inlet chilled water temperature (\( T_{ch\text{in}} \)), outlet chilled water temperature (\( T_{ch\text{out}} \)), the inlet temperature of hot air (\( T_{air} \)), the mass flow rate of chilled water (\( m_{ch} \)) and the mass flow rate of air (\( m_a \)). The output is obviously the heat transfer rate. All inputs and the output are restricted to the range specified in table 1. Any value beyond the range cannot be modeled accurately using BP network. Thus, cautions were taken for this during the experiments in which training set was generated. All raw data in the training set were normalized to [0, 1] range before inputting to the ANN for processing. There were 445 sets of data patterns recorded in the experiments. 345 sets were chosen randomly to serve as the training data set and the remaining sets were used for validation.

| Parameters                     | Max  | Min  |
|--------------------------------|------|------|
| Air inlet temperature(°C)     | 29   | 22   |
| Air outlet temperature(°C)    | 19   | 14   |
| Chilled water inlet temperature(°C) | 15 | 8    |
| Chilled water outlet temperature(°C) | 19 | 12   |
| Mass flow rate of the air(Kg/s)| 1.5  | 0.2  |
| Mass flow rate of the chilled water(Kg/s)| 1.0 | 0.4  |
With the training data set, an ANN with 5 input nodes, one output node and \( n \) hidden nodes in between was trained in MATLAB environment. To determine the final structure of the ANN, the rate of error convergence was checked by changing \( n \). It was observed that the ANN with 10 hidden nodes could achieve convergence. Figure 3 showed this ANN with a 5-10-1 configuration. After 137187 epochs with the initial learning rate of 0.01 and the momentum rate of 0.9, MSE reached 0.0000999998 which was smaller than the criterion (ie. 0.0001). The training process was stopped and the validation process then proceeded with the remaining 100 data sets. Figure 4 showed the comparison between the measured \( Q \) value and the predicted \( Q \) value of the ANN. Relative errors were evaluated and were shown graphically in figure 5. From this figure, it was found that most of the predicted values were within 95-105% of the measured values. The mean relative error (MRE) was 1.38% and the maximum relative error was 4.87% caused by the sixty-eighth sample number. The accuracy of this ANN is acceptable in site conditions and can be employed by site engineers for checking purposes. The weights and biases of the static ANN model for the heat exchanger were listed out in Appendix I for later reference.

**Figure 3.** Configuration of the static ANN for heat transfer rate prediction.

**Figure 4.** Comparison of predicted and measured \( Q \) (*: measured, o: ANN predicted).
4.2. Dynamic prediction of heat exchanger

The objective of the dynamic ANN model is to predict the dynamic response of a heat exchanger for air-conditioning control. As mentioned before, a heat exchanger is the key component that links the air side and the water side of a whole air-conditioning system. A good air-conditioning control usually requires the knowledge of dynamic behaviors of a heat exchanger to issue suitable control actions. Taking a VAV system as an example, the chilled water mass flow rate is adjusted to maintain the supply air temperature and the supply air mass flow rate is varied for different thermal loadings. Both mass flow rates are the inputs of a heat exchanger. In order to implement energy-saving feature, the dynamic behaviors of the heat exchanger must be taken into account in air-conditioning control algorithms. An ANN is the obvious candidates to perform this role. In fact, there was some previous research to employ ANN to model and control a plant. Narendra and Parthasarathy [18] proposed the four different identification models of discrete-time plants for control purposes. All these identification models contained ANNs as their sub-models with their structures different among each other to cater for their generality of dynamic systems. Back-propagation algorithms were applied to train the ANN. In the next stage of our study, we developed an ANN to prediction the dynamic response of a heat exchanger for control purposes.

For the dynamic ANN, its inputs include supply air mass flow rate ($m_a$), the mass flow rate of chilled water ($m_{chw}$), the inlet temperature of hot air ($T_{a,in}$) and the inlet chilled water temperature ($T_{chw,in}$). The outputs are the outlet temperature of hot air ($T_{a,out}$) and the outlet chilled water temperature ($T_{chw,out}$). One important aspect of this ANN is its order. We need to introduce the previous values of input parameters to the ANN’s input as well as their present values. It is similar to the situation of solving a differential equation of unknown order numerically. The high the order, the larger the number of previous states for which information must be provided as inputs. Gerardo indicated that the order of the system, if one has to chose an integer, is probably two and it is not necessary to assume a higher value [4]. In this study, there are two loops in the system – air loop and the chilled water loop. The order of both loops is the order of one which can be verified by their step responses. Thus, we introduce one previous value for each input parameter as an additional input parameter to the dynamic ANN. The configuration of the dynamic ANN model is shown in figure 6.

Figure 5. The relative errors between measured Q and predicted Q.
The training for the dynamic ANN model was performed using 410 data patterns out of a total of 502 measured data patterns. After 484240 epochs, the training was completed and the MSE was converged to 0.001, exactly same as our goal. The remaining data patterns were used for validation of the trained ANN. Figure 7 showed the comparison between the measured temperature of the outlet chilled water and its predicted value of the ANN. Figure 9 showed the comparison for the temperature of the outlet air. Figures 8 and 10 showed the relative error for the case of the outlet chiller water and that for the case of the outlet air respectively. It was seen that 90% of the predicted outlet chilled water temperature and more than 98% of the predicted outlet air temperature are within 95-105% of the measured values. For the chilled water outlet temperature, MRE is 2.45%, and the maximum relative error is 11.42% caused by the sixty-sixth sample number. MRE and the maximum relative error of the predicted outlet air temperature are 0.89% and 6.94% respectively. The weights and biases of the dynamic ANN model for the heat exchanger were listed out in Appendix II for later reference.

Figure 6. Configuration on a 10-20-2 ANN for dynamic prediction.

Figure 7. Comparison of predicted and measured Tchout: * measured, o ANN predicted.
Figure 8. The relative errors between measured and predicted $T_{chwout}$.

Figure 9. Comparison of predicted and measured $Taout$: * measured, o ANN predicted.

Figure 10. The relative errors between measured and predicted $Taout$. 
5. Conclusions
In this paper, the artificial neural networks for static and dynamic modeling of the heat exchanger mounted in the air handler unit were successfully built. The static performance prediction of heat transfer rate $Q$ had a very high accuracy. Most of the predicted data fell within 95-105% of actual measured values. This technique was extended to the prediction of the dynamic behavior of the heat exchanger. Nearly all of the dynamic predicted values were within 95-105% of the measured values. These results showed that neural network models are good alternatives to models based on first principles. The weights and biases of the neural network models were listed out in this paper. Readers are welcome to use them as the starting points to model their own heat exchangers. Moreover, the methodology presented serves as good reference for others to follow to tackle their own specific problems. It is suggested that future studies should be concentrated on the neural network model of every component of the refrigerant system and the air-conditioning system. In this way, an actual ANN-based intelligent control will be made possible.

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Appendix A. The weights and biases of the static ANN model
The weights $iw\{1,1\}$ of the input layer to the hidden layer and the biases $b\{1\}$ of the hidden layer are given as following:

\[
iw\{1,1\} = \begin{bmatrix} -1.8238 & 0.23903 & -3.7437 & -2.3333 & 7.6793 \\ 1.0895 & 5.0046 & 2.3387 & 2.4777 & 6.4082 \\ -4.7603 & -4.128 & 4.1778 & 0.69466 & -3.0078 \\ -1.6213 & 4.3857 & -2.3719 & 1.2905 & -6.2273 \\ -2.4033 & 4.9215 & 0.8787 & 2.8981 & -6.276 \\ 0.93757 & -6.5539 & 1.4616 & -4.4043 & 0.18518 \\ -1.3678 & 4.8775 & -4.2193 & 1.124 & 2.3118 \\ 3.89 & 4.4202 & 3.3856 & -2.7854 & 3.0706 \\ -3.9293 & 4.5327 & 4.5957 & -1.4631 & 2.2357 \\ -0.088459 & 6.6874 & 2.3753 & -2.3389 & -4.3948 \\ b\{1\} = \begin{bmatrix} -0.0044227 \\ -10.9538 \\ 5.2333 \\ 5.168 \\ 2.1535 \\ 2.4854 \\ -1.0764 \\ -5.0495 \\ -4.8985 \\ -0.87511 \end{bmatrix}^T
\]

The weights $iw\{2,3\}$ of the hidden layer to the output layer and the biases $b\{2\}$ of the output layer are given as following:

\[
iw\{2,3\} = \begin{bmatrix} -0.055273 & 0.025317 & 0.048236 & -0.2129 & 0.0037788 & -0.044548 & -0.16468 & -0.010956 & 0.006001 & -0.034814 \end{bmatrix} \\
\]

\[
b\{2\} = \begin{bmatrix} 0.44031 \end{bmatrix}
\]

Appendix B. The weights and biases of the dynamic ANN model
The weights $iw\{1,1\}$ of the input layer to the hidden layer and the biases $b\{1\}$ of the hidden layer are given as following:

\[
iw\{1,1\} = \begin{bmatrix} 1.2227 & 2.159 & -0.24234 & 2.7042 & 2.593 & -1.2744 & 0.29241 & -2.3571 & -3.5642 & 0.35716 \\ -1.878 & 2.8427 & -1.8483 & 0.82631 & -2.6026 & 0.32495 & 0.78694 & -0.51321 & -1.2928 & 1.8051 \\ -3.1877 & 1.7423 & 1.8708 & 0.40873 & 1.5341 & 1.0247 & -0.41598 & 3.5062 & 1.6169 & -0.53716 \\ 0.76255 & -3.2006 & -2.0035 & -1.8677 & 0.84147 & -0.35738 & -2.5084 & -0.87851 & 3.1204 & -0.64938 \\ 1.6421 & 0.84689 & 0.67342 & -3.0667 & -4.9436 & 1.0865 & -0.75494 & 1.9098 & -5.1293 & 0.35316 \\ 3.6328 & 1.2625 & -0.85703 & 1.6564 & 0.27888 & -1.1537 & 0.036942 & 1.4462 & -0.61717 & 1.8955 \\ 1.3087 & 3.0329 & -3.3437 & 1.8725 & -0.13522 & -0.77356 & -0.15418 & 3.4181 & 4.0597 & -0.028022 \\ 2.7597 & 1.3675 & 1.5204 & 1.0733 & -2.6209 & -0.3354 & -0.8597 & 4.2673 & -3.0879 & 0.014794 \\ -2.8083 & -2.1848 & 2.2202 & 0.38389 & 0.30721 & -0.39373 & 3.0813 & -2.3811 & -1.6911 & 2.9524 \end{bmatrix}
\]

\[
b\{1\} = \begin{bmatrix} -5.9538 & 5.2333 & 5.168 & 2.1535 & 2.4854 & -1.0764 & -5.0495 & -4.8985 & -0.87511 \end{bmatrix}^T
\]

The weights $iw\{2,3\}$ of the hidden layer to the output layer and the biases $b\{2\}$ of the output layer are given as following:

\[
iw\{2,3\} = \begin{bmatrix} -0.055273 & 0.025317 & 0.048236 & -0.2129 & 0.0037788 & -0.044548 & -0.16468 & -0.010956 & 0.006001 & -0.034814 \end{bmatrix} \\
\]

\[
b\{2\} = \begin{bmatrix} 0.44031 \end{bmatrix}
\]
$\begin{align*}
2.3663 & 2.9621 -0.24359 -2.5128 0.16021 2.5756 0.20478 -0.23379 2.8334 0.2767; \\
1.8306 & -0.38956 2.7918 -0.31596 1.4272 0.12378 1.6943 -1.5901 0.62235 -2.6775; \\
0.7344 & -2.6954 0.49061 -0.94239 -1.9225 -0.59211 -0.95995 0.49811 -3.8635 -1.6684; \\
-2.5215 & -2.0585 0.93634 0.19321 0.95443 0.83395 -0.44365 -2.9004 -0.59461 -2.1191; \\
1.2039 & -0.23089 0.32491 0.75716 -0.43259 2.8799 -4.4877 5.6427 -1.0076 -1.6056; \\
0.86465 & -0.77438 -3.5115 -2.6824 2.3361 1.1558 -1.5113 -3.7463 -1.8182 1.5042; \\
1.1756 & 0.71485 -2.9008 2.0522 -1.8779 3.4041 -1.0658 -0.82193 2.3812 -0.61424; \\
-2.272 & -0.54662 3.4873 -0.90217 0.66656 0.92972 2.2935 2.162 -0.52904 -1.7684; \\
-0.63183 & -1.734 -0.53339 0.1495 -1.0506 4.4096 -2.2113 -1.1041 4.3692 -0.99105; \\
-0.04168 & 0.48585 3.0926 1.414 -2.1723 2.3274 1.3268 -2.2748 -2.5101 -0.47864; \\
2.1804 & -1.1548 2.3081 -1.4757 -1.3656 1.9614 -1.15 1.2472 -2.1055 1.6369].
\end{align*}$

The weights $iw_{2,3}$ of the hidden layer to the output layer and the biases $b_2$ of the output layer are given as following:

$iw_{2,3} = [-0.26307 0.56747 0.050325 -0.66722 0.091092 0.6113 0.28562 -0.29746 0.22478 0.10306$
$0.38168 0.24852 -0.41703 0.23193 -0.16467 0.03477 -0.15405 -0.066351 0.59836 0.043979 -0.14839$
$-0.31973 0.1191 -0.092308 0.11385 0.19194 0.28305 -0.29104 0.31398 0.19022 0.14416 0.22225 -0.19415 0.34237 -0.2436 -0.068907 -0.20503 -0.18364 0.31122 -0.49946].$

$b_2 = [-0.59372; 1.0329].$

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