Multi-step ahead prediction of vapor compression air conditioning system behaviour using neural networks

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Abstract. Cooling capacity and super heat temperature control for air conditioning (AC) system operation is necessary to ensure that the system operates efficiently. In this paper, multi-step-ahead prediction of AC system behaviour is presented using backpropagation neural network model as the first effort to develop the effective control strategy. Several step-ahead cooling capacity and superheat temperature performance are predicted under modulation of compressor speed and expansion valve opening. The prediction is proposed to capture the dynamic behaviour of system that can be applied in predictive control purpose. The configuration of ANN model is developed based on nonlinear autoregressive network with exogenous input (NARX) structure. Input and output data for training and validation of ANN model are generated by AC simulator. The ANN model is optimized by investigating the effect of number of neuron and time delay input on prediction accuracy. The results show that the ANN model developed in present study has good accuracy in predicting several step-ahead of cooling capacity and superheat temperature. Accordingly, this ANN model is applicable for predictive control in future study.

1. Introduction
In recent years, the increase of population and economic growth lead energy consumption increases especially in building sector. In daily life, it can be estimated that people may spend around 80% of their time inside the building. It forces the heating ventilating and air conditioning (HVAC) system to work every time to provide the thermal comfort for occupants. Accordingly, this system takes a large portion among the total energy consumption in building. Many researchers have paid much attention on building energy research especially on HVAC system. Developing a proper control strategy for cooling capacity and superheat temperature is one of the solutions to increase the efficiency of AC system operation. Since the system operates frequently, it can contribute in reducing building energy consumption significantly.

Several classical control strategy including ON/OFF and PI have been developed for AC system for residential building application. However they have limited operational condition and high energy consumption [1]. Additionally, it is hard to tune the proper gain for PI control that can cover wide operation condition. Alternatively, intelligent control strategy can be considered to improve the system efficiency.

Modelling dynamic behaviour is the important step to develop control strategy. Before being applied in actual system, the control performance should be tested and evaluated in the model that represents real system. It is not easy and very complex. The complexity comes from the nonlinear correlation between input and output of the system [2]. In the other hand, multi-input multi output (MIMO) characteristic of the system makes the system more difficult to model.

The modelling of AC system behaviour have been introduced using physical model which is established based on energy and mass balance, and thermodynamic and heat transfer theory [3]. Even though this method is believed to have high accuracy, however it requires many detail parameters in regard to the system characteristic. Even in some cases, they should be extracted from system’s manufacturer. As the alternative solution, the dynamic behaviour of the system can be modelled using
artificial neural network (ANN) approach. The system identification using ANN is simple and faster compared to physical model if input-output data is available.

Several ANN models have been successfully applied in AC system to model temperature and humidity [4]; building heating load [5]; chilled water temperature and superheat temperature [6]. In this paper, ANN model with Bayesian regularization is developed to predict superheat temperature and cooling capacity under modulation of expansion valve and compressor speed in unsteady condition. The motivation of present study is to develop ANN model that can capture dynamic response of superheat temperature and cooling capacity with different compressor speed and valve opening that can be applied for predictive control.

2. Methodology

2.1. System description

The schematic diagram of general vapour compression AC system used in present study is shown in Fig. 1. The system consists of several subsystems i.e. compressor, condenser, expansion valve, and evaporator which are connected to each other. The work of vapour compression cycle (VCC) can be briefly explained through the diagram shown in Fig. 1. The heat $Q_E$ comes from conditioned space at room temperature $T_R$ is absorbed by evaporator via refrigerant and released to the environment at ambient temperature $T_A$ through condenser in amount of $Q_C$. The refrigerant R410A is selected as the working fluid to transfer the heat from low to high temperature condition. The notation $T_{SH}$ represents the temperature difference between refrigerant at evaporator outlet with its saturation vapour at the same pressure. Number 1-4 indicates the refrigerant state in the cycle.

![Schematic diagram of vapour compression cycle](image)

**Figure 1.** Schematic diagram of vapour compression cycle

2.2. Data sets fabrication

The feature of data sets has a significant influence on the performance of ANN model. The system behaviour that can be identified by ANN highly depends on the trend of data used in the training. It is important to note that when preparing data sets for identification in nonlinear system, the signal excitation scenario should cover all amplitudes. So the data feature that will be applied for learning can represent the dynamic of system. In this paper, N-samples-constant is proposed to meet the various amplitude signals [7]. To provide training data for dynamic system, the system is simulated by
randomly varying compressor speed $N$ and valve opening $V$ to produce dynamic response of cooling capacity $Q_E$ and superheat temperature $T_{SH}$ with the condition provided in Table 1. The simulation is conducted using AC system simulator developed using physical-mathematical model and has been validated with actual system [8]. The input and output signal for identification is presented in Fig. 2.

Table 1. Simulation condition

| Simulation condition                  | Setting | Unit |
|--------------------------------------|---------|------|
| Condenser air inlet temperature      | 35      | °C   |
| Condenser air velocity               | 0.28    | m/s  |
| Evaporator air velocity              | 0.1     | m/s  |
| Cooling load sensible                | 1.89    | kW   |
| Volume                               | 167.75  | m$^3$|
| SHR                                  | 1       | -    |
| Initial room temperature             | 19.36   | °C   |

2.3 Dynamic neural network
Multilayer perceptron (MLP) ANN model has been applied in many applications to solve the approximation problem. In the simple form, the structure of MLP network is depicted in Fig. 3. This
network is arranged by input layer, hidden layer and output layer. The relation between input and output is connected by some mathematical function via hidden neuron.

![Multilayer perceptron network](image)

Figure 3. Multilayer perceptron network

The predicted output resulted from MLP network can be described through the following equation:

\[
y(k) = f_2(w_2n(k) + b_2) \\
n(k) = f_1(w_1u(k) + b_1)
\]

(1)

(2)

The network is trained to adjust the weight and bias coefficients to minimize the prediction error and weight coefficient. Weight coefficient minimization is intended to improve the generalization of the network. In this case, the network is trained to achieve high prediction accuracy with high generalization capability. Hence the Bayesian’s theorem combined with Levenberg-Marquardt algorithm is employed to minimize objective function which can be written as follows:

\[
J = \beta E_D + \alpha E_W
\]

(3)

where \(E_D\) and \(E_W\) represents prediction error and total weight coefficients respectively. Notation \(\beta\) and \(\alpha\) shows the regularization parameters determined by Bayesian’s theorem. The ratio \((\alpha/\beta)\) controls the network performance.

\[
RMSE = \left(\frac{1}{N}\sum_{j=1}^{N}(y_j - t_j)^2\right)^{1/2}
\]

(4)

\[
CV = \frac{RMSE}{\frac{1}{N}\sum_{j=1}^{N}y_j} \times 100
\]

(5)

Generally there are two ANN model type namely static and dynamic networks. Static networks calculate the output directly using input without feedback element and input delays. While dynamic networks include the previous inputs or outputs to predict the next step output. In this paper the dynamic ANN model is considered to predict several step ahead dynamic system behaviour.

Fig. 4 shows dynamic ANN structure where the previous compressor speed \(N\) and valve opening \(V\) are used to predict the next cooling capacity \(Q_e\) and superheat temperature \(T_{S_H}\). The number of time delay for input and output is indicated by \(du\) and \(dy\) respectively. The dynamic network can be used to predict one-step or multi-step ahead output prediction. The multi-step-ahead prediction is performed by feeding back the ANN output as the input for the next prediction; whereas one-step-ahead prediction takes the true output obtain from simulation as the input for the next prediction.
3. Results and discussion
In this work, the ANN model is developed by investigating number of tapped delay lines (TDL) and neuron in hidden layer. The proper number of TDL is first analyzed by testing the performance of ANN using various number of TDL from 2 to 10 TDL. It should be noted that the initial weight and bias coefficients are randomly set for training, the prediction accuracy obtained from the same structure can be slightly different due to different convergence point at training process. To ensure that the network has a good performance at every structure, the network was trained 10 times with 20000 maximum iterations, learning rate of 0.01, and 10 neurons. The lowest error is then selected to be the best network. The prediction results for cooling capacity and superheat temperature under different number of TDLs is demonstrated in Fig. 5. It can be observed that the prediction error tends to decrease as number of TDL increases. This is due to the effect of the history of input sequence, the more input are used, the network has more information to fit the data with high accuracy. The minimum error for cooling capacity is shown at 5 TDLs and superheat temperature at 7 TDLs. In this case, there are two options for the optimum number of TDL that can be considered for the prediction. Since the gap of accuracy between 5 and 7 TDL in cooling capacity prediction results is not significant, we select 7 TDLs as the optimum number of TDLs in present study.
Figure 5. Prediction results under different number of TDL (a) cooling capacity (b) superheat temperature

Furthermore, to improve the prediction accuracy, the effect of neuron is also investigated using optimized input delay (7 TDLs). Number of neuron is varied from 2 to 20 neurons with the increment of 2 neurons. The ANN performance with various number neurons is shown in Fig. 6. As number of neuron increases the prediction accuracy for either cooling capacity or superheat temperature is getting better. The significant difference is shown by 2 and 4 neurons where the RMSE value goes down drastically. When only few neurons were applied, the network doesn’t have sufficient weight coefficient to fit the data, therefore it has no capacity to perform accurate prediction. Otherwise, if too many neurons are used in the training, the network complexity increases and produces over fitting. Based on the results shown in Fig. 6, the optimum configuration for the dynamic ANN in present study can be proposed with 7 TDLs and 4 neurons.

Figure 6. Performance of ANN under different number of neurons

The prediction output generated by optimized ANN configuration is shown in Fig. 7. The network was tested using constant input signal with the compressor speed and valve opening is 53.25 rps and 14.09 % respectively. The results show a good agreement between the predicted and corresponding values for both cooling capacity and superheat temperature with CV for superheat temperature is 0.066% and cooling capacity is 0.2%.
Figure 7. Prediction result (a) cooling capacity and (b) superheat temperature for 20 step ahead prediction

4. Conclusion
Dynamic ANN model has been developed to predict behavior of AC system with two inputs and two outputs in unsteady condition. The optimized network with 7 TDLs and 4 neurons shows satisfied accuracy for 20 steps-ahead prediction. Accordingly, the developed ANN model in present study can be implemented for predictive control in vapor compression AC system application to control cooling capacity and superheat temperature to achieve better efficiency compared to classical control.

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