The Optimum Start-up of Central Air-conditioning Based on Neural Network

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***Abstract*—The preheat time of central air-conditioning system preheating space is not only affect the comfort of environment, but also affect energy consumption. A preheat time model is established based on the thermodynamics principle, and an optimum stat-up algorithm of central air-conditioning system is proposed based on the NN(neural network), the simulation result shows that this method can predict the preheat time accurately which make central air-conditioning system save energy.**

Keywords-central air-conditioning system; preheat time; neural network; Optimum Start-up; energy saving

I. INTRODUCTION

Construction of the total energy consumption accounts for nearly 30% of China's energy consumption today, and the energy cost of air-conditioning takes 50% of the whole and maintains a steady growth in a building with central air-conditioning. Therefore, energy saving modification of central air-conditioning will lead to good economic and social benefits.

In fact, because many shopping malls and comprehensive buildings are used in daytime, so central air-conditioning runs by the intermittent operation mode (Fig.1)

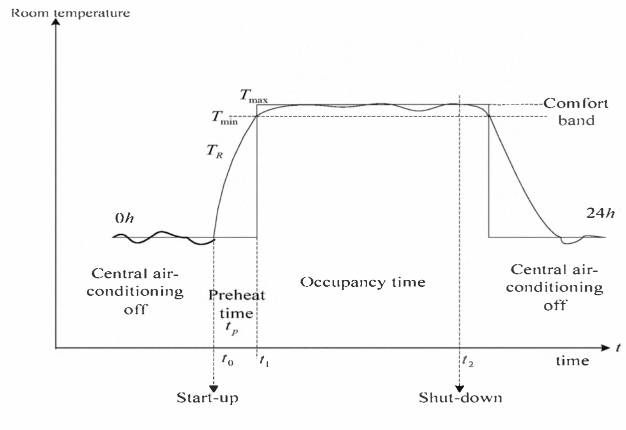

Figure 1. Intermittent operation of the central air-conditioning

Owe to the thermal inertia of the central air-conditioning and that of the buildings, a preheat time t_p is necessary, so that the required temperature is reached at the moment of occupation. The performance of any start-up controller will depend on the accurate estimation of the preheat time. Overestimation will cause unnecessary energy wastage, while underestimation will lead to loss of comfort conditions at the start of occupancy. Similarly, if a certain permitted temperature drop at the end of the occupancy period can be allowed to occur, the central air-conditioning can be switched off earlier, producing further energy saving. Therefore, the main goal of the optimum shut-down time controller is to find the correct time, t_s, when the central air-conditioning can be switched off without allowing the room temperature to drop below minimum comfort conditions, T_{min}.

The first law of thermodynamics and the compatibility of temperature measurements when written in conjunction with the constitutive and dynamic relations enable the time variations in thermal systems to be determined. Hence, it is easy to obtain the preheat time model, based on which the NN(neural network) control algorithm is simulated in this paper. The simulation result shows this method has better energy saving effects.

II. PREHEAT TIME PREDICTION MODEL

According to the first law of thermodynamics and the compatibility of temperature measurements, it is simple get the preheat time prediction model [1],[2]:

$$t_p(0) = \{\frac{T_d - Q_h / Hi - T_b(0)}{Q_h \sqrt{4R_e / \Pi C_e}}\}^2$$

or $$t_p(0) = k_1 + k_2 T_b(0) + k_3 T_b^2(0) \qquad (1)$$

Where t_p is the preheat time, T_d is the desired room temperature at occupancy start time, Q_k is the power of central air-conditioning, T_b is the bulk temperature, C_e is the thermal flow store of bulk. And the equation (1) is a linear model as a special case.

So far, the derivations have ignored the possibility of heat flows to or from the structure which are not taken into account in the calculation of bulk temperature by a single point measurement of the external air temperature, for example, solar heat gain, wind losses or heat flows to or from adjoining rooms. Since these unmeasured disturbances might be expected to show degree of correlation from day to day, a simple first-order moving-average noise process with non-zero mean can be included in equation (1) to describe their influence on preheat time. Thus, rewriting equation (1)

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in discrete time form, the preheat time at the nth sampling instant is given by the difference equation [3],

$$t_p(n) = k_4 + k_4 T_b(n) + k_6 T_b(n)^2 + e(n) + k_7 e(n-1) \qquad (2)$$

Where *e(n)* is taken from a zero mean independent noise sequence.

III. THE PREHEAT TIME BASED ON BP NEURAL NETWORK PREDICTOR

Neural network prediction can identify system model using the current input and output information of system, and predict the future output value. The procedure of neural network prediction is divided into two steps, the first step is model identification, and the second is prediction and model assessment. The BP (Back Propagation) neural network is adopted to identify the parameters in this paper. Considering the problems of local optimal and the training time of neural network, the momentum BP-NN that can avoid local optimal problem and the fast BP-NN that can short training time are used to identify system model. System model identification is divided into three steps: determining neural network model structure, processing input and output data and network training.

A. Determining Neural Network Model Structure

A three-layer neural network that includes input layer, hidden layer and output layer is determined to calculate the preheat time. Considering the main factors that effect preheat time and time series, the three-layer neural network has four input nodes T_b, T_b^2, $t_p(n-1)$, $t_p(n-2)$, and one output node $t_p(n)$, and nine neural cells that is designed in the light of the rule of 2n+1[4]. The activation function of hidden layer is hyperbolic tangent function, and from the hidden layer to output layer the transfer function is linear. Therefore, the proportion of number of nodes in the three-layer neural network model structure is 4:9:1(Fig.2)

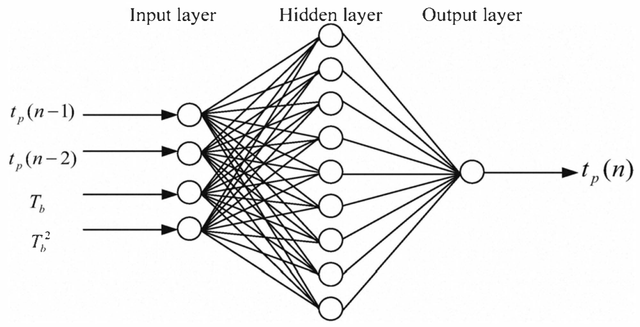

Figure 2. Three-layer neural network model structure

B. Processing Input and Output Data

In order to avoid the impact of data on neural network, the history data must be processed before training sample data and prediction. The data processing algorithm of normalization is used to process input and output data of neural network. The input data is processed by eqn.3 and the output data is processed by eqn.4.

$$y = \frac{x - \frac{1}{2}(\overline{x} + \underline{x})}{\frac{1}{2}(\overline{x} - \underline{x})} \qquad (3)$$

$$x = \frac{1}{2}(\overline{x} - \underline{x})y + \frac{1}{2}(\overline{x} + \underline{x}) \qquad (4)$$

Where x is original data, $\overline{x}$ is the maximum value of original data, $\underline{x}$ is the minimum value of original data, y is the value after normalization.

The T_b is calculated by eqn.5

$$T_b(k) = aT_b(k-1) + bT_o(k) + cT_R(k) \qquad (5)$$

Where a=0.8, is the time constant of bulk temperature, $b=(1-a)f$, $c=(1-a)(1-f)$, f=0.63. $T_o(k)$ is the outdoor temperature, $T_R(k)$ is the room temperature before preheat, $T_b(k-1)$ is the last bulk temperature, $T_b(k)$ is the current bulk temperature[5],[6].

C. Network Training

Training samples of BP neural network are divided into two parts: training set and testing set.

And the training samples consist of 151 sets of data that were record from November 2008 to March 2009. After they are normalized, the first 120 sets of data forms training set that is used to train network and the remaining 31 sets of data forms testing set.

Before network training, the other parameters of network are set. The maximum cycle number is 10000, target error is 0.001, original learning rate is 0.03, its increasing ratio is 1.04, the momentum factor is 0.95, and the initial weight value and the threshold value are got automatically by Initff function. And the improved BP network is trained by Trainbpx function. The formation of Initff and Trainbpx function is showed as follow:

[w1, b1, w2, b2]=initff(X, 9, 'tansig', 1, 'purelin') ;

[w1, b1, w2, b2, te, tr]=trainbpx(w1, b1, 'tansig', w2, b2, 'purelin', X, Y, tp) ;

Where w1 and b1 are the weight value and the threshold value between the input layer and the hidden layer, w2 and b2 are the weight value and the threshold value between the hidden layer and the output layer, te is the actual training times of network, tr is the column vector of error square sum of network training, X is the input vector, Y is the Aim Vector, tp is the optional training parameter that decides how to train network.

According to above set parameters, after the neural network is trained 4893, the error square sum is less than target error 0.001, which achieves the requirement of experiment. And parameters of w1, b1, w2 and b2 are calculated:

w1= [0.6777 -0.3090 0.9346 0.5062 -2.2203 -0.4026 -0.4915 0.0809 0.6388 1.1369 1.1070 -1.4036 2.2493 1.4762 -0.3597 -0.2740 1.2739 0.1119 -0.9371 -0.8897 1.2722 0.8855 -1.4316 -0.8403 -2.4009 -0.8872 1.1046 -2.1108 -

0.3210 -0.6760 1.2560 1.3418 -0.4039 1.7833 -0.1666 -0.8519];

w2= [0.4944 1.2063 1.2104 -1.3660 0.3607 0.9697 -1.4029 -0.3070 -1.0489];

b1= [-0.8950 -0.2413 -0.7859 -1.9907 -0.9480 -1.3495 0.2891 0.4320 -0.6209]^T;

b2= [0.1997];

D. Calculating the Preheat Time Using Prediction Model

The prediction simulation of preheat time is done using the prediction time based on the actual recorded data and the above parameters of w1, b1, w2 and b2. The program flow chart is showed (Fig.3)

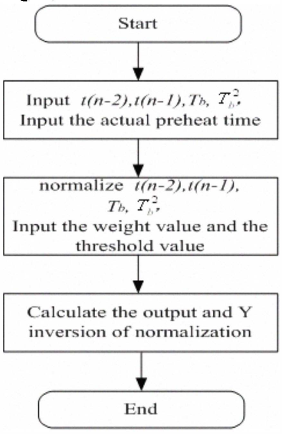

Figure 3. The program flow chart

Usually, the preheat time is a constant in a certain shopping mall or comprehensive building, it is designed to fully meet the demand of making the room comfort at the beginning of occupancy time in the coldest days. However, the preheat time in any shopping malls or comprehensive buildings varies with weather conditions. For example, the preheat time of the shopping mall that provides the data is 60 minutes, which far more than the true preheat and leads to energy waste. Therefore, the preheat time should be predicted accurately to saving energy.

After the prediction simulation using the neural networks in this paper, the predictive preheat time of 30 days is showed (Fig.4).

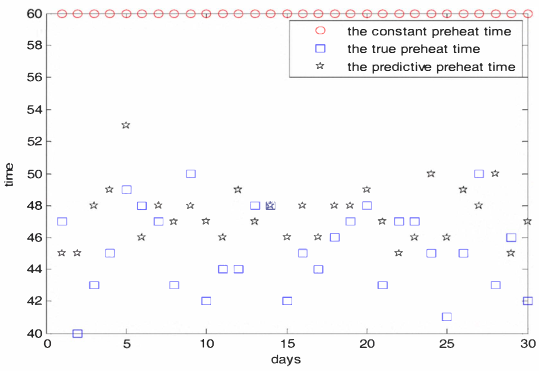

Figure 4. The comparison of three preheat time

In thirty days, there are seven days in which the predictive preheat time is shorter than the true preheat time and the biggest error is two minutes. And there are twenty three days in which the predictive preheat time is longer than the true preheat time and the biggest error is seven minutes, but the predictive preheat time is much shorter than the constant preheat time. After the calculations, the prediction using the neural network has a good effect with 20.89% energy saved.

IV. CONCLUSIONS

The experiment in the shopping mall shows neural network results in a good effect on energy saving of starting the central air-condition without accurate initialization parameters and the thermal characteristics of a central air-conditioning, therefore, there is a good prospect in designing the optimum start-up controller of central air-conditioning using the neural network.

ACKNOWLEDGMENT

This study was partially funded by the Youth Foundation of Xi'an university of architecture and technology (QN0823). The shopping mall of MinShen is thankfully acknowledged for their data. The professors of Ren and Yu are thankfully acknowledged for their support in research method.

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