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Research Article

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An adaptive neural network controller for chilled water temperature in HVAC systems

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ABSTRACT

This paper proposed an adaptive neural network controller to maintain the chilled water temperature in heating, ventilation and air conditioning(HVAC) systems. The heat transfer behavior between chilled water and refrigerant is highly nonlinear. It is significant to design a controller that can handle the nonlinearity of the process. Firstly,by analyzing the heat transfer process from mechanism perspective, factors which influence the process have been obtained. Then the frequency of the compressor is manipulated to control the chilled water temperature in the outlet of the evaporator and uncontrolled variables are taken into the neural network controller. With a novel adaptive law for the neural network controller, both the nonlinear phenomenon and disturbance of uncontrolled variables can be handled. To further illustrate the performance of the NN controller, experiment was conducted on a pilot HVAC system. Then the result was compared with that of conventional PID controller. Real time experiment result showed the effectiveness of the adaptive neural network controller.

Keywords: chilled water temperature, neural network controller, adaptive control

INTRODUCTION

Heating, ventilation and air conditioning system are now widely used in office buildings and other commercial facilities to provide comfort indoor air temperature and relative humidity. Being accused of consuming almost half of the energy related to buildings according to Romero*et al.* [8], HVAC system have attracted numerous attentions to improve their energy efficiency. Being responsible for generation of chilled water in HVAC system, the refrigeration loop plays an important role in HVAC system and forms roughly 50% of the power consumption of the whole system. Hence, a lot of research efforts have been devoted to improving the performance of the temperature controller in refrigeration loop.

To achieve better control performance, modeling techniques have been extensively investigated to describe the dynamic characteristics of the process. Zhang and Zhang [9] proposed a moving-boundary approach to model the transient behavior of evaporators. But such numerical integration methods will sometime fail to achieve adequate accuracy under various operating conditions and may even lead to unstable performance. Based on the mass, momentum and energy conservation principles, Ding *et al.*[2] proposed a hybrid method to build a semi-mathematic model of process in the evaporator. But this kind of model is established based on steady state values and can hardly be used for control purpose.

On the other hand, data driven models and black-box methods have attracted numerous research interests thanks to their accuracy and practicability. Russell *et al.* [7] proposed first and second order linear models to approximate the dynamic behavior of heat transfer in evaporator. But the linear models can hardly capture the characteristics of the heat transfer process of over whole operating range. Bechtler*et al.* [1] used neural network to model the vapor-compression process, only input and output data were used to train the neural network, so it could lead to unsatisfied result when the operating condition changes.

With effective online weight tuning algorithm, neural networks are integrated into adaptive controller directly. In direct neural network(NN) controller, no initial learning phase is required and the controller exhibits learning-while-functioning feature. So in this paper, a neural network controller is proposed to handle the nonlinear heat transfer between the chilled water and refrigerant. Uncontrolled variables are taken as input vector of NN and the nonlinear disturbance is rejected by the controller with an online weight tuning algorithm. The rest of this paper can be divided into 4 sections: problem formulation is given in section 2，controller design is described in section 3，to illustrate the performance of NN controller, experimental result is compared with that of conventional PID controller in section 4 and conclusion is made in section 5.

PROBLEM FORMULATION

System setup

System under investigation is shown in Fig.1. The refrigeration loop of our HVAC system is a typical vapor-compression one consisting of an evaporator, a condenser, an electronic expansion valve and a compressor. Connecting to the refrigeration loop is a chilled water loop. Both the compressor and chilled water pump are equipped with variable speed drivers so that the flow rate variables in either loop can be adjusted continuously to satisfy the demand of varying working condition. To complete a closed control loop, resistance temperature detectors(RTD) are installed in the inlet and outlet of the evaporator to measure the temperature of chilled water and refrigerant. Both speed signals and temperature signals are transmitted to a computer via RS232 protocol.

Problem formulation

The heat transfer behavior under investigation involves two loops: the chilled water loop and the refrigerant loop.

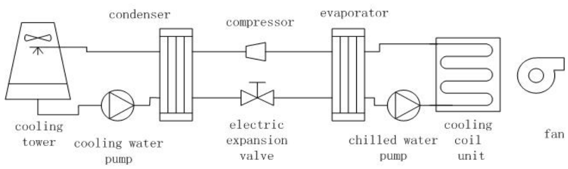

Fig.1: System diagram

In the refrigerant loop, after passing the electronic expansion valve, the refrigerant enters into the evaporator with reduced pressure causing it to boil and flash into vapor. Heat is transferred from the chilled water to the refrigerant through the metal wall. By the time the vapor refrigerant reaches the outlet of the evaporator, it is superheated to several degrees higher than its saturated temperature.

Since there is phase change in refrigerant loop, the energy change can be expressed by Larsen (2006)

$$\dot{Q} = \dot{m}(h_i - h_o) \tag{1}$$

where $\dot{m}$ is the mass flow rate of the refrigerant, h_i is the enthalpy of refrigerant in the inlet of evaporator and h_o is the enthalpy of refrigerant in the outlet of evaporator.

In the chilled water loop, the heat transfer is a single-phase forced convection process, the energy change in chilled water passing the evaporator can be expressed as

$$\dot{Q}_w = c_w \dot{m}_w (T_{wi} - T_{wo}) \tag{2}$$

where $\dot{m}_w$ is the mass flow rate of chilled water, c_w is the specific heat of chilled water, T_{wi} and T_{wo} are temperature of chilled water in the inlet and outlet of evaporator, respectively.

By taking the related variables in (1) and (2), the chilled water temperature in the outlet of evaporator can be expressed as:

$$T_{wo} = H(T_{wi}, \dot{m}_w, h_o, h_i, \dot{m}) \tag{3}$$

where H is a nonlinear function.

According to Koury *et al.* (2001), values of enthalpy and mass flow rate of refrigerant are determined by the speed of compressor F_{cp} and opening degree of electronic expansion valve D_v. And $\dot{m}_w$ is solely determined by the speed of chilled water pump F_p. So (3) can be rewritten

$$T_{wo} = K(T_{wi}, F_p, F_{cp}, D_v) \tag{4}$$

where K is a nonlinear function.
Next, for simplicity, define $y = T_{wo}$ as the system output and $u = F_{cp}$ as the control input. Thereafter, for control purpose, a general dynamic model of the process can be presented in discrete-time[3]

$$\begin{aligned} y(k+1) &= f(y(k),...,y(k-na),u(k-1),...,u(k-nb),d(k)) \\ &+g(d(k))u(k) \end{aligned} \tag{5}$$

where na and nb are output order and input order respectively, $d = [T_{wi}, F_p, D_v]$ denotes the measurable disturbance and $f(\cdot)$ is an unknown nonlinear function, $g(\cdot)$ is an unknown by always positive nonlinear function of d.

CONTROLLER DESIGN
Rewrite the system dynamic as below

$$y(k+1) = f(Y(k)) + g(d(k))u(k) \tag{6}$$

$$Y(k) = [y(k),...,y(k-na),u(k-1),...,u(k-nb),d(k)] \tag{7}$$

Assume the desired chilled water temperature as $y_d = T_{wod}$, define the tracking error

$$e(k) = y(k) - y_d(k) \tag{8}$$

Thus the dynamic of tracking error can be obtain

$$e(k+1) = f(Y(k)) - y_d(k+1) + g(d(k))u(k) \tag{9}$$

If function and are known, a desired controller can be designed as

$$u_d(k) = g(d(k))^{-1}(y_d(K+1) - f(Y(k)) + k_c e(k)) \tag{10}$$

where k_c is a constant parameter such that $|k_c| < 1$. Therefore, (10) generates

$$e(k+1) = k_c e(k) \tag{11}$$

which is asymptotic stable[10]. However, since $f(\cdot)$ and $g(\cdot)$ are unknown, the desired controller cannot be implemented directly.

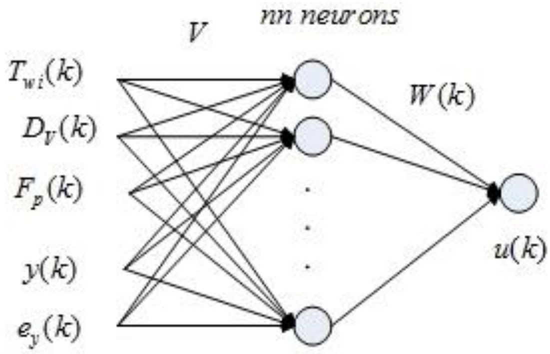

Fig.2: Neural network structure

In the meantime, due to its universal approximation ability, two-layer neural network can approximate any smooth nonlinear functions[4]. With an effective online weight tuning algorithm, disturbance caused by uncontrolled variables can be rejected. So this paper employs an adaptive neural network controller with following form to approximate the desired controller of (10)

$$u(k) = -k_t(k)e(k) - k_v e(k)^2 \operatorname{sgn}(e(k)) \\ +\hat{W}(k)^T \phi(x(k)) \qquad (12)$$

where $k_t(k) = \xi[1 + \frac{\left|\hat{W}(k)^T \phi(x(k))\right|^2}{16} + \frac{\left|\bar{f}\right|^2}{16}]$, k_v and ξ are constant parameters, $\hat{W}^T \phi(x)$ is the output of neural network show in Fig.2. $\left|\bar{f}\right|$ is the upper boundary of $\left|f(\cdot)\right|$.

With the adaptive law:

$$\Delta\hat{W}(k) = -\Gamma\phi(x(k))e(k) - \gamma\Gamma\left|e(k)\right|\hat{W}(k) \qquad (13)$$

where Γ and γ are constant parameters. It can be proven that the error signal is asymptotic stable. See the proof, please refer to Sunan *et al*, [3] for more details.

To test the performance of adaptive NN controller, experiment will be conducted on a HVAC system. Result will be compared with that of conventional PID controller in the next section.

REAL-TIME EXPERIMENT

Experiment setup

To illustrate the performance of proposed NN controller, experiment is conducted on a pilot HVAC system and the result is compared with that of conventional PID controller. Since the cooling load on the chilled water side is the main factor causes nonlinear phenomenon, this paper takes T_{wi} and $\dot{m}_w$ to test the system. Command following test and disturbance rejection test are carried out:

(1) command following test: the desired chilled water temperature in the outlet of evaporator is changed and the controller was expected to respond so that the chilled water temperature can be maintained to its new set-point.

(2) disturbance rejection test: keep the set-point unchanged and vary the variables of F_p and T_{wi}, then employ the controllers to reject the disturbance.

Before real-time experiment, controller parameters should be set. Since the NN controller require the upper boundary of $\left|f(\cdot)\right|$, step response test is used to estimate $\left|\bar{f}\right|$. Finally, control interval is 10 seconds, system order is chosen as 1, ξ , k_v $\left|\bar{f}\right|$,number of neurons, Γ and γ are chosen as 0.08, 8, 5, 30, 0.002 and 0.001, respectively.Sigmoid function was used as activation function in NN.For PID controller, the parameters of k_p, k_i and k_d are chosen as 0.8, 0.8 and 3.

RESULTS

The experiments were conducted as follows:

(1) Command following test: T_{wo} was initially maintained at 8℃, at 200s, the desired chilled water temperature y_d changed to 7℃, both controllers were implemented to maintain the output to the new set-point.

(2) Disturbance rejection test: at 800s, the value of chilled water pump F_p increased from 25Hz to 35Hz to simulate a sudden disturbance of chilled water mass flow rate and the desired output was still 7℃. And at 1300s, the air flow rate in the CCU increased from 35Hz to 50Hz to simulate a disturbance of T_{wi}, both controllers were employed to reject the disturbance.

The experiment result is shown in Fig.3, due to the lack of system learning, the NN controller gave a sudden change in chilled water temperature. With the online learning algorithm, the NN controller still took shorter time to maintain the output to its new set-point than PID controller. In disturbance rejection experiment, the NN controller exhibited smaller overshot and quicker convergence than PID controller.

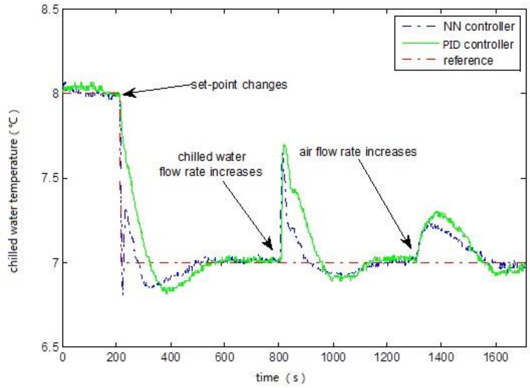

Fig.3:Real-time experiment result

CONCLUSION

An adaptive neural network controller for chilled water temperature was developed to address the unknown dynamic of heat transfer between chilled water and refrigerant in evaporator. Real-time experimental result shows the NN controller gives better performance than conventional PID controller to maintain the desired chilled water temperature in the outlet of evaporator.

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