Neuro-Predictive Control for Automotive Air Conditioning System

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***Abstract*- This paper presents a neuro-predictive controller for temperature control of automotive air conditioning system. A numerical model for the automotive refrigeration cycle, which includes transient operating conditions, has been employed in simulations. In this model, which has been created from numerous laboratory tests on a typical passenger car, the vehicle is divided into two linked modules representing the air conditioning (A/C) system as well as the passenger compartment climate. Moreover, the thermal loads have been considered. This system demonstrates variable and large time delays, which is the case in reality. The simulation results show good performance of the proposed controller.**

Keywords: Model predictive control, Neural network, Automotive air conditioning system

I. INTRODUCTION

The refrigeration systems are used in many Applications. The goal of controlling a refrigeration system is to track that a desired temperature; and in some applications to track the relative humidity as well. As a result, one would expect considerable energy savings and cost reductions.

Various conventional and intelligent strategies have been used for refrigeration system control in literatures. Some examples of conventional methods are: on/off control [1], feedback control [2], proportional-integral (PI) control with pre compensator [3], optimal control for saving energy [4], and multivariable adaptive control [5]. Some intelligent methods also have been proposed, such as fuzzy control [6], [7], neural networks [8], [9], and neuro-fuzzy controllers [10], [11].

The concept of model predictive control has been employed for many years by researchers. Since the early 1970's numerous algorithms have been put forward to achieve improved process regulation. Model predictive control algorithms have many applications. For example, a multiple objective model predictive control method allows definition of different control goals at different operating points for a solar refrigeration plant [12].

The climate control of a passenger vehicle is an important and complex problem. In this paper a neuro-predictive control algorithm is proposed for temperature control of an automotive air conditioning system model that is near the actual system. The thermal loads, such as solar loads, human heat loads, and vehicle thermal loads have been taken into account in this model. This model has variable time delays, related to the compressor speed.

The rest of this paper is organized as follows. Section II presents the automotive air conditioning system model. Section III describes the proposed neuro-predictive control algorithm, and finally section IV draws some conclusions about this paper.

II. AUTOMOTIVE AIR CONDITIONING SYSTEM MODEL

In this section a numerical model for automotive air conditioning system is presented. This model consists of major components such as evaporator, compressor, condenser, orifice, and air handling. Pressure drop and thermal capacity for the evaporator, condenser, and connecting ducts/hoses are accounted. Model outputs are temperature and mass flow rate of air to the passenger compartment. The refrigerant is of R-134a type [13]. The schematic diagram of refrigeration cycle is shown in Fig. 1. In the initial step, the fluid enters the evaporator at low pressure and continuously evaporates until it becomes a slightly superheated gas. Subsequently, compression of the fluid increases in pressure and temperature. In order to remove the heat absorbed by the evaporator (and compressor), a condenser is necessary. Since the fluid entering the condenser has a temperature above ambient, air can be used to extract the heat from the fluid, thereby condensing and slightly sub cooling the refrigerant. To close the cycle, a throttling device is provided to reduce the pressure and temperature in the refrigerant, thereby transferring it from the slightly sub cooled liquid state to the two phase, low quality state; a point at which it enters the evaporator and the cycle is closed [9]. The airflow to the evaporator absorbs heat from the passenger compartment.

A. Compressor Model

The goal of compressor model is to calculate the actual enthalpy. Compressor model algorithm is shown in Fig. 2. Volumetric efficiency can be described by [13]

$$\dot{m} = V \,.\, eff_{Vol} \,.\, RPM \,.\, d \tag{1}$$

where $\dot{m}$ is the mass flow rate (kg/s), V is the volume of the refrigerant (m^3), eff_{Vol} is the compressor volumetric efficiency, *RPM* is the compressor shaft speed, and d is the density of the refrigerant (kg/m^3).The actual enthalpy is calculated by the following equation:

$$eff_{\text{isen}} = \frac{i_{o,\text{ideal}} - i_i}{i_{o,\text{actual}} - i_i} \tag{2}$$

where eff_{isen} is the compressor isentropic efficiency, $i_{o,\text{actual}}$ is the actual outlet, $i_{o,\text{ideal}}$ is the ideal outlet, and i_i is the inlet current of the refrigerant.

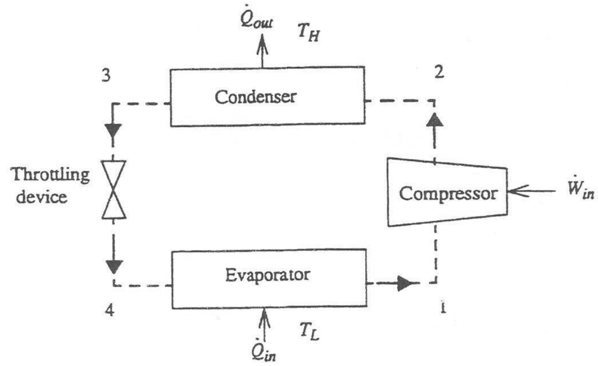

Fig. 1. Schematic diagram of various components in refrigeration cycle.

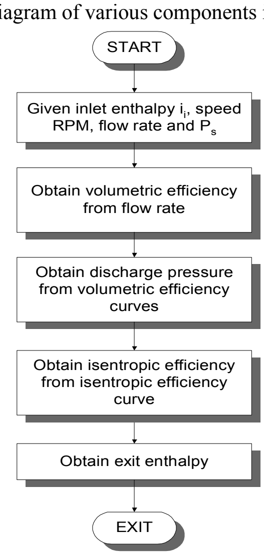

Fig. 2. General flow chart for compressor model.

B. Orifice Tube Model

The mass flow rate in the orifice can be calculated as

$$\dot{m}_O = C_d A_O \sqrt{2d_{in}(P_{in} - P_{out})} \tag{3}$$

where C_d is the discharge coefficient, P is the pressure (Pa), d_{in} is the density of the input refrigerant, and A_o is the area of orifice (m^2). Since the change in potential and kinetic energies between the input and output is negligible and heat transfer is insignificant, it is reasonable to consider constant flow enthalpy.

C. Evaporator Model

Simulation of evaporator behavior under all conditions requires study of heat transfer, pressure drop in the single- phase and two-phase regions, the evaporator geometry factor and the thermal inertia changes in the materials. To take into account the local influence on the heat transfer, pressure drop, temperature, and phase change at the refrigerant side, a control volume approach is employed [13]. In this method, along with the direction of refrigerant flow, the evaporator is divided into a number of small control volumes or elements to evaluate the local heat transfer and pressure drop variations within a segment under transient operations. Evaporator model algorithm is shown in Fig. 3. The energy balance for an element is given by

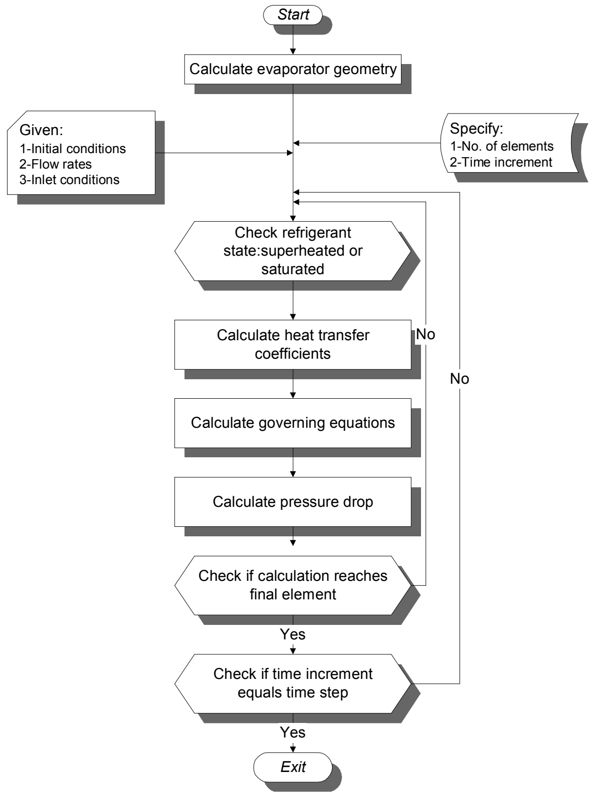

Fig. 3. General flow chart for evaporator model.

$$d_W V_W C_W \frac{dT_W}{dt} = h_r A_r (T_r - T_W) + h_a A_a e' (T_a - T_W) \tag{4}$$

$$d_r V_r \frac{di_r}{dt} = \dot{m}_r (i_{r,i} - i_{r,o}) + h_r A_r (T_W - T_r) \tag{5}$$

$$d_a V_a C_a \frac{dT_a}{dt} = d_a A_a U_a C_a (T_{a,i} - T_{a,o}) + h_a A_a e' (T_W - T_a) \tag{6}$$

where T is the temperature (K), h is the convective heat transfer coefficient (W/m^2.K), and A, C, V, i, and d are the same as defined before. Indices W, a, and r stand for wall, ambient, and refrigerant, respectively.

D. Condenser Model

The equations and the algorithm used to model condenser are the same as for the evaporator, with minor differences. The condenser is considered to have three characteristic zones, which are superheated, two-phase, and sub cooled; and the elements are not the same because of the unequal number of flow channels in each row [13].

E. Air Handling System Model

The heat from the engine and the solar radiation make the instrument panel and the space beneath to become hot. The hot air flowing in the gap between instrument panel and air ducts brings extra heat to the cooling air flow before it enters the passenger compartment. The control volume method is used to model air ducts.

Based on the first law of thermodynamics, three governing equations are derived for each control volume as follows:

$$d_W V_W C_W \frac{dT_W}{dt} = h_f A_f (T_f - T_W) + h_a A_a (T_a - T_W) \tag{7}$$

$$d_f V_f C_f \frac{dT_f}{dt} = d_f A_f U_f C_f (T_{f,i} - T_{f,o}) + h_f A_f (T_W - T_f) \tag{8}$$

$$d_a V_a C_a \frac{dT_a}{dt} = d_a A_a U_a C_a (T_{a,i} - T_{a,o}) + h_a A_a (T_W - T_a)\,. \tag{9}$$

F. Air Conditioning System Integration Model

From the mathematical point of view, there are three parameters needed to describe a refrigerating loop. They are the discharge pressure, the suction pressure, and the refrigerant flow rate. The general flow chart in Fig. 4 shows the principal steps used to integrate a complete air conditioning system. After simulation of refrigeration cycle in a time instant, the temperature in outlet channel is calculated. Then the thermal loads including solar, human, glasses and the vehicle wall are evaluated. The passenger compartment temperature is calculated using the lamp capacitance method [13].

G. Model Validation

The simulation results are compared to the experimental data to show the validity of the model. Average air temperature at vent outlet is shown in Fig. 5 and the condenser average outlet air temperature is shown in Fig. 6 [13]. As these Figs. show, the results obtained from the simulation model are in good agreement with the experimental data.

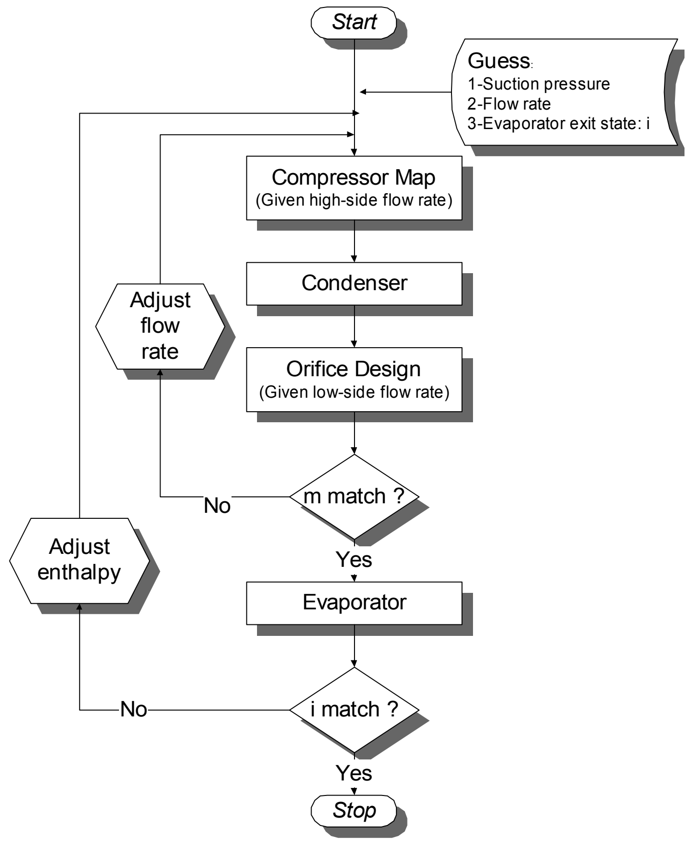

Fig. 4. General flow chart for air conditioning system integration

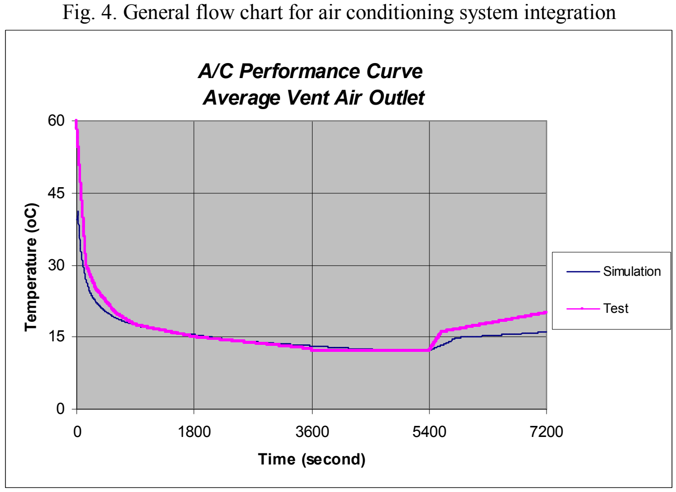

Fig. 5. Average air temperature at vent outlet

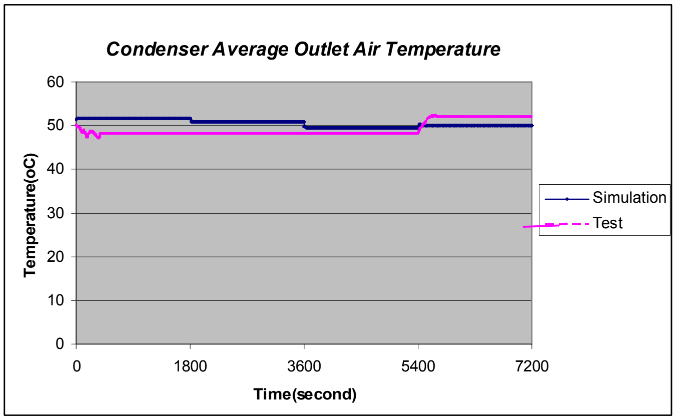

Fig. 6. Condenser average outlet air temperature

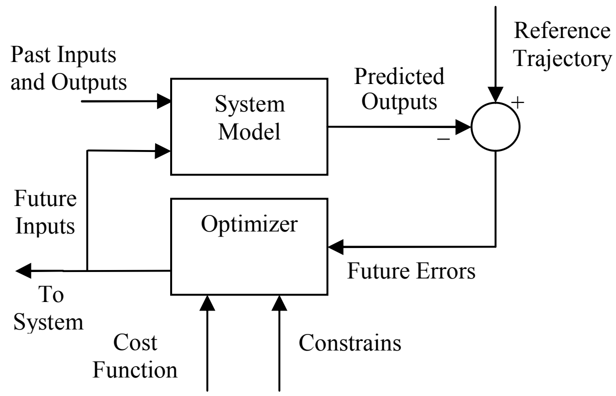

Fig. 7. Basic structure of model predictive control

III. NEURO PREDICTIVE CONTROL

The term Model Predictive Control (MPC) does not designate a specific control strategy but a very wide range of control methods, which make an explicit use of a model of the process to obtain the control signal by minimizing a cost function. The basic idea of model predictive control can be explained generally as

- Explicit use of a model to predict the process output at future time instants (horizon).
- Calculation of a control sequence in order to minimize an objective function.
- Employing a receding strategy, so that at each instant the horizon is shifted towards the future. Then, applying the first control signal from the sequence calculated at each step.

MPC presents a series of advantages over other methods, amongst which stand out:

- MPC is suitable to control multivariable systems.
- It intrinsically has compensation for dead times.
- It can be used to control a wide range of processes, such as those with relatively simple dynamics to more complex ones, including systems with long and varying delay times or non-minimum phase or unstable systems.
- It is very useful when future references are known.

The basic structure of model predictive control is shown in Fig. 7. A model is used to predict the future plant outputs, based on the past and the current values of the control actions. These actions are calculated by an optimizer, in which the cost function (where the future tracking error is considered) and the constraints have been taken into account. The model of process plays a decisive role in the performance of the controller [14]. It is well known by researchers that neural networks and fuzzy systems can approximate nonlinear systems with good accuracy. The various model predictive control algorithms propose different cost functions to obtain the control law. The general form of a suitable objective function can be expressed as

$$J(N_1, N_2, N_u) = \sum_{j=N_1}^{N_2} a_1(j)[\hat{y}(t+j\mid t) - ref(t+j)]^2 + \sum_{j=1}^{N_u} a_2(j)[\Delta u(t+j-1)]^2 \tag{10}$$

where $\hat{y}(t+j\mid t)$ is the value of output at the instant $t+j$ calculated at instant t and $ref(t+j)$ is the reference signal. N_1 and N_2 are the minimum and maximum cost horizons, respectively. They mark the limits of the instants in which it is desirable for the output to follow the reference. N_u is the control horizon. The coefficients $a_1(j)$ and $a_2(j)$ are sequences that consider the future behavior, usually constant values or exponential sequences are considered. In some methods, the second term in (10), which considers the control effort, is not taken into account.

In practice, all processes are subject to constraints. Therefore, the required constraints must be introduced to the cost function. Normally, bounds in the amplitude and in the slew rate of the control signals and limits on the output signals are typical [14]:

$$u_{\min} \le u(t) \le u_{\max} \quad \forall t \tag{11}$$

$$du_{\min} \le u(t) - u(t-1) \le du_{\max} \quad \forall t \tag{12}$$

$$y_{\min} \le y(t) \le y_{\max} \quad \forall t. \tag{13}$$

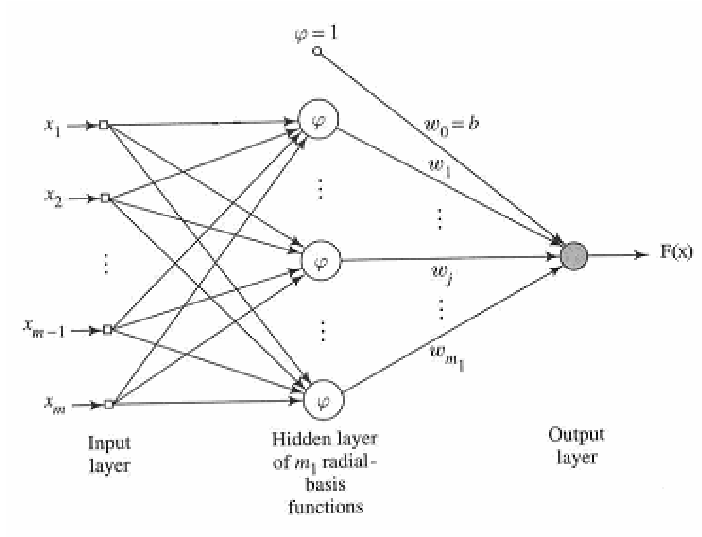

Fig. 9. Structure of RBF network

In this paper, a neuro-predictive controller is designed for automotive air conditioning system. The block diagram of the closed-loop control system has been shown in Fig. 8. The control signal is the compressor speed (in RPM) and the system output is the air temperature at air conditioning system outlet (T_{air}). T_{ref} is the reference temperature and Δ is the backward shift operator ($\Delta T_{\text{air}}(k) = T_{\text{air}}(k) - T_{\text{air}}(k-1)$). The air conditioning system is modeled with a radial basis function (RBF) network. RBF networks have three layers: input layer, hidden layer and output layer. An RBF network is shown in Fig. 9. The RBF network output is described by the following equation:

$$F(x) = \sum_{i=1}^{m1} w_i \varphi_i(x) = \sum_{i=1}^{m1} w_i \exp\left(-\frac{\|x - t_i\|^2}{2b_1^2} \right) + b \tag{14}$$

where w_i is ith neuron output weight, t_i is the ith neuron Gaussian function center, b_l is the corresponding Gaussian function width, and b is the bias [15]. The neural network used to model the air conditioning system, has 5 inputs, 1 output and 18 neurons in the hidden layer. The inputs and output are normalized to [0,1].

In order to train the RBF network, 1500 random inputs and respected outputs are used. The RBF network is trained off-line and the output layer's weights are obtained by least mean square method. Gaussian function centers are chosen from the training data set. In order to have better results, the neural network is trained on-line in closed loop system and weights of the output layer are adapted by the gradient-descent algorithm [15]. The training error at the end of the off-line training phase has been shown in Fig. 10. As this Fig. shows, the neural network has modeled the system with good accuracy.

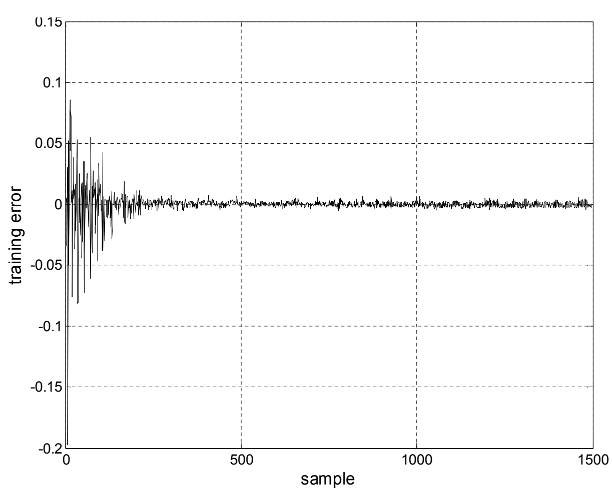

Fig. 10. The training error at the end of off-line training

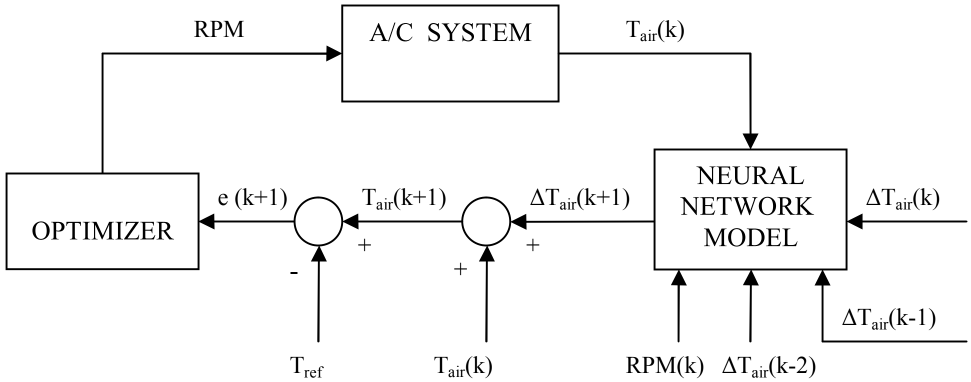

Fig. 8. Diagram of neuro-predictive controller for air conditioning system.

The cost horizon for the proposed model predictive controller has been chosen equal to 20 and the control horizon is 5. Also, the following cost function is used:

$$J = \frac{1}{2}\sum_{i=1}^{20}[\hat{y}(t+i \mid t) - ref\,(t+i)]^2. \tag{15}$$

The constraint for compressor shaft speed is ($750 \leq RPM \leq 4500$) that should be included in the cost function. For minimization of the cost function, a subspace trust region method based on the interior-reflective Newton method is used.

The simulation results of the proposed neuro-predictive controller and fuzzy proportional integral derivative (PID) controller are shown in Figs. 11-13. As a comparison, the same model has been controlled with an advanced control method, like fuzzy PID controller (Figs. 12-15). As it can be seen, the reference temperature is tracked better with neuro-predictive controller than fuzzy PID controller.

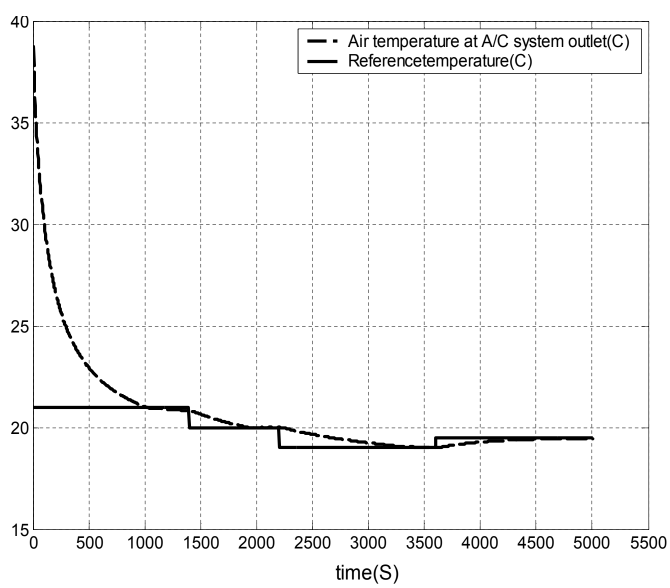

Fig. 11. Air temperature at air conditioning system outlet with neuro-predictive controller.

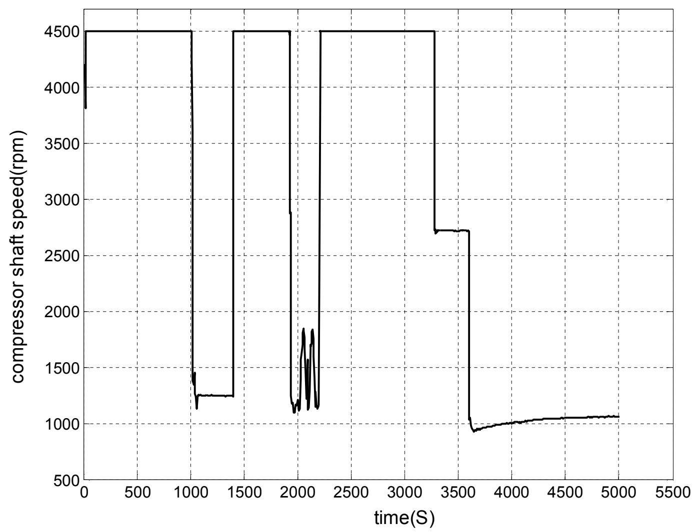

Fig. 12. Compressor shaft speed with neuro-predictive controller

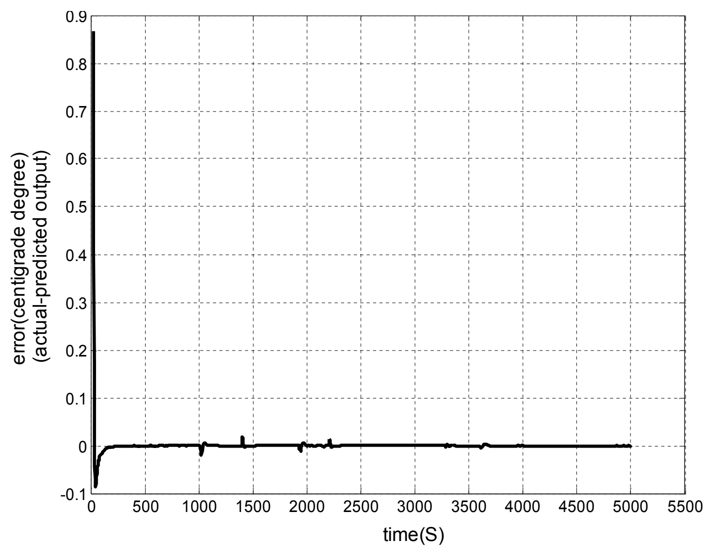

Fig. 13. Prediction error between the actual and the predicted output with neuro-predictive controller.

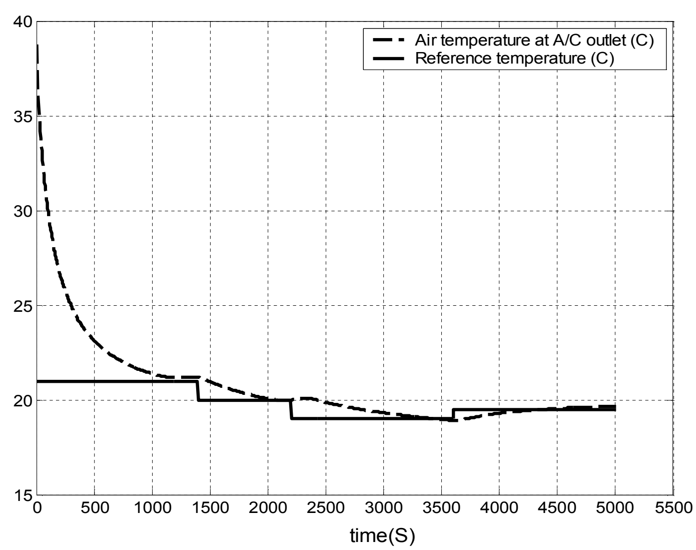

Fig. 14. Air temperature at air conditioning system outlet with fuzzy PID controller.

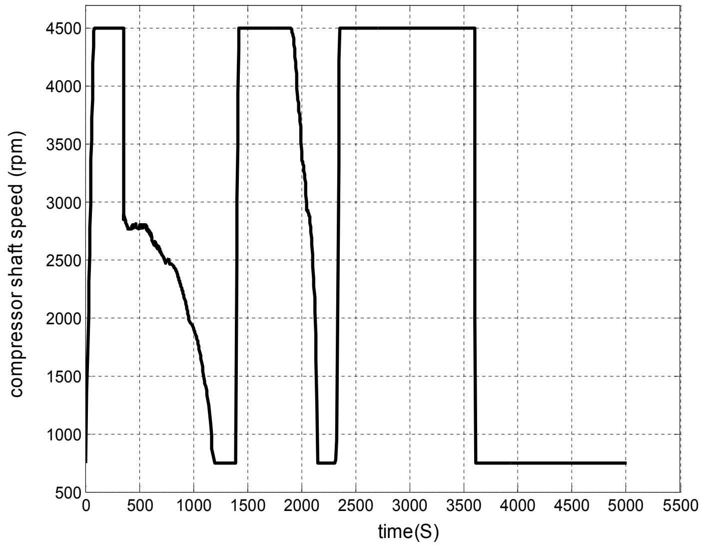

Fig. 15. Compressor shaft speed with fuzzy PID controller.

IV. CONCLUSION

In this paper, a neuro-predictive control algorithm was proposed and applied to an automotive air conditioning system. Since the air conditioning system had variable and large time delays, the predictive control algorithm was used to compensate the delays. The performance of the neuro-predictive control algorithm was compared with that of fuzzy PID controller. Simulation results showed that the predictive control performs better than the fuzzy PID control. But, it should be mentioned that the neuro-predictive control requires more calculation time than the fizzy PID controller.

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