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The Predictive Control Method of VAV Air Conditioning System

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Abstract

Aiming at the characteristics which variable air volume air conditioning system is multi-variable, nonlinear and uncertain system, normal fuzzy neural network is hard to meet the requirements which dynamic control of multi-variable. In this paper, we put forward a recursive neural network predictive control strategy based on wavelet neural network model. Through recursive wavelet neural network predictor on line established controlled object's mathematical model, and using Elman neural network controller on line corrected information we get, thus to improve control effect. The simulation results show that recursive wavelet neural network predictive control has stronger robustness and adaptive ability, high control precision, better and reliable control effect and other advantages.

Keywords: *variable air volume aie conditioning (VAV), recursive wavelet neural network (RWNN), elman neural network, predictive control.*

1. Introduction

Variable air volume (VAV) air conditioning system is a full air system of multi-variable and nonlinear. In VAV air conditioning system, when the air conditioning load changes or indoor air parameters' set value changes, it will adjust air flow into the room automatically, and adjust the air conditioning parameters to set value, to meet comfort and energy-saving requirements [1]. Therefore, this paper puts forward a kind of recursive neural network predictive control method based on T-S fuzzy model, to establish reference model online, to complete the identification of system's dynamic characteristics, and using neural network control method to improve control effect.

2. The Working Principle of VAV Air Conditioning System

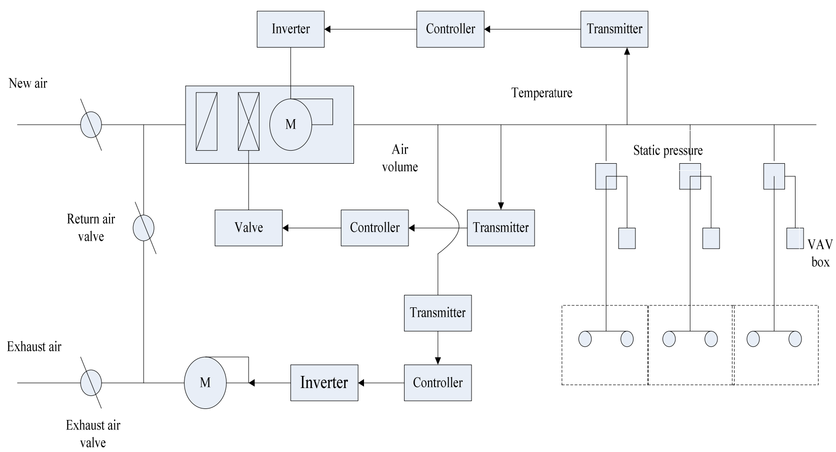

Figure 1. Typical VAV System Working Principle Diagram

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VAV air conditioning system is mainly composed of VAV air conditioning units and VAV Box. The typical VAV system is shown in Figure 1. Its working principle is: According to control requirements, it regulate new air volume, put air volume into VAV box, and then adjust VAV box to complete control function. So, in order to achieve temperature control requirements, to improve the comfort and energy saving effect, we need good control strategy to meet the needs of people [2].

3. Application of Recursive Neural Network based on Wavelet Neural Network Model in Predictive Control of VAV System

The VAV air conditioning control system structure is shown in Figure 2. In this paper mainly completes temperature control of system. The controllers are composed of recursive wavelet neural network predictor and RBF neural network controller [3]. The predictor uses the characteristics which recursive neural network based on wavelet neural network model can effective control non-linear, time-varying and uncertainty system, and predict object's future output, and then according to the future output to adjust control strategy online, to achieve optimal control of air conditioning [4].

This paper will complete the design of predictor and controller.Among them: $r(k)$ is temperature setting ; $e(k)$ is temperature deviation between room temperature and temperature setting; $u(k)$ is control output; $y(k)$ is output temperature; $y^*(k)$ is predictive temperature; Δe_1 is the difference of control output. Δe_2 is the error of output and predictive value;

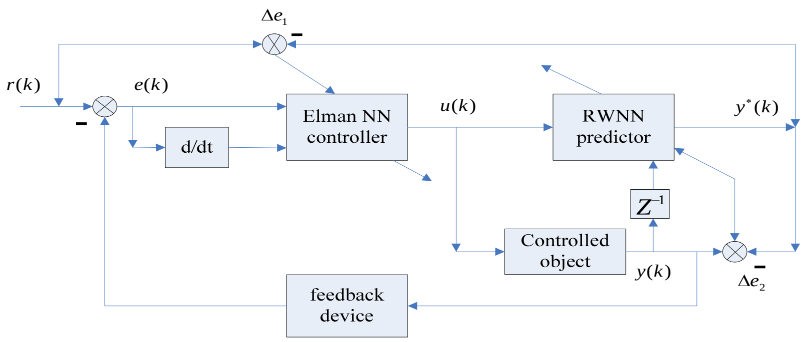

Figure 2. Structure Diagram of Control System

3.1. Recursive Neural Network based on Wavelet Neural Network Model Predictor Design

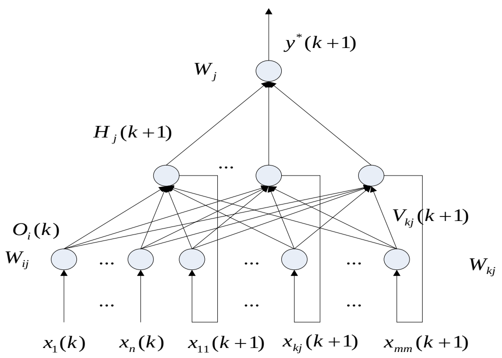

Figure 3. Structure Diagram of Multi-input, Single Output Recursive Wavelet Neural Network

In this paper the design of predictor adopts recursive wavelet neural network. The structure diagram is shown in Figure 3. In this network structure, the input of hidden layer is composed of output of input layer and output of associated layer, [5] so recursive network structure has good dynamic characteristics, for VAV air conditioning system which has dynamic, time-varying, non-linear, uncertain system, it has good control effect.

The input layer of network has n neurons, this paper takes n=3, neurons of input layer are $x_1(k)$, $x_2(k)$, $x_3(k)$, on behalf of output $u(k)$ of neural network controller, actual output delay $y(k-1)$ of controller object and the error $y(k)-y^*(k)$ of object's actual output and predicted output. $O_i(k)$ is input layer's output, $i=1,2...n$. Hidden layer and associated layer both have m neurons. At k moment, output of hidden layer is $H_j(k+1)$, so input of associated layer is expressed as $x_{kj}(k+1)=\alpha H_j(k)$, α is feedback gain [5]. Associated layer's output is $V_{kj}(k+1)$. So, recursive wavelet neural network's output is:

$$y^*(k+1)=\sum_{j=1}^{m}\omega_j\varphi(\sum_{i=1}^{n}\omega_{ij}O_i(k)+\sum_{k=1}^{m}\omega_{kj}V_{kj}(k+1)-\theta_j) \quad (1)$$

θ_j is wavelet function's translation coefficient, $\varphi(\bullet)$ is wavelet function. ω_j is the weight between hidden layer and output layer, ω_{ij} is the weight between input layer andhidden layer, ω_{kj} is the weight between associated layer and hidden layer.

Take wavelet function:

$$\varphi(x)=(1-x^2)e^{-\frac{x^2}{2}} \quad (2)$$

Define the error performance index function of this network:

$$E=\frac{1}{2}[y(k+1)-y^*(k+1)]^2 \quad (3)$$

Among them, $y(k+1)$ and $y^*(k+1)$ represent actual output and reference model output of predictor, at $k+1$ moment.

The learning of parameters takes adapt gradient descent method, we can get:

$$\omega_j(k+1)=\omega_j(k)+\eta\Delta\omega_j(k)+\alpha[\omega_j(k)-\omega_j(k-1)] \quad (4)$$

$$\omega_{ij}(k+1)=\omega_{ij}(k)+\eta\Delta\omega_{ij}(k)+\alpha[\omega_{ij}(k)-\omega_{ij}(k-1)] \quad (5)$$

$$\omega_{kj}(k+1)=\omega_{kj}(k)+\eta\Delta\omega_{kj}(k)+\alpha[\omega_{kj}(k)-\omega_{kj}(k-1)] \quad (6)$$

$$\theta_j(k+1)=\theta_j(k)+\eta\Delta\theta_j(k)+\alpha[\theta_j(k)-\theta_j(k-1)] \quad (7)$$

Among them:

$$\Delta\omega_j=-\frac{\partial E}{\partial\omega_j}=-\frac{\partial E}{\partial y^*(k+1)}\bullet\frac{\partial y^*(k+1)}{\partial\omega_j}=[y(k+1)-y^*(k+1)]\sum_{j=1}^{m}\varphi(\sum_{i=1}^{6}\omega_{ij}O_i(k)+\sum_{k=1}^{m}\omega_{kj}V_{kj}(k+1)-\theta_j) \quad (8)$$

$$\Delta\omega_{ij}=-\frac{\partial E}{\partial\omega_{ij}}=-\frac{\partial E}{\partial y^*(k+1)}\bullet\frac{\partial y^*(k+1)}{\partial\omega_{ij}}=[y(k+1)-y^*(k+1)]\sum_{j=1}^{m}\omega_j\varphi'(\sum_{i=1}^{n}\omega_{ij}O_i(k)+\sum_{k=1}^{m}\omega_{kj}V_{kj}(k+1)-\theta_j)O_i(k) \quad (9)$$

$$\Delta\omega_{kj}=-\frac{\partial E}{\partial\omega_{kj}}=-\frac{\partial E}{\partial y^*(k+1)}\bullet\frac{\partial y^*(k+1)}{\partial\omega_{kj}}=[y(k+1)-y^*(k+1)]\sum_{j=1}^{m}\omega_j\phi(\sum_{i=1}^{n}\omega_{ij}O_i(k)+\sum_{k=1}^{m}\omega_{kj}V_{kj}(k+1)-\theta_j)V_{kj}(k+1) \tag{10}$$

$$\Delta\theta_j=-\frac{\partial E}{\partial\theta_j}=-\frac{\partial E}{\partial y^*(k+1)}\bullet\frac{\partial y^*(k+1)}{\partial\theta_j}=-[y(k+1)-y^*(k+1)]\sum_{j=1}^{m}\omega_j\phi(\sum_{i=1}^{n}\omega_{ij}O_i(k)+\sum_{k=1}^{m}\omega_{kj}V_{kj}(k+1)-\theta_j) \tag{11}$$

η is leaning rate, α is inertial parameter, and η,α both in the range of $(0,1)$.

3.2. Elman Neural Network Controller Design

At present, Bp neural network is widely used in the VAV air conditioning control field, but Bp neural network has the drawbacks of the slow convergence speed and easily getting into local minimum. Elman neural network could not only have fast learning speed but also not easily get into local minimum [6].

In addition to the input layer, hidden layer and output layer, Elman network has also a unique structural unit which is used for memory of hidden-layer output at previous time, and it can be thought as a step time-delay matrix. And the basic Elman network can be improved by adding a self-feedback connection of a fixed-gain (α) [7]. As shown in Figure 4.

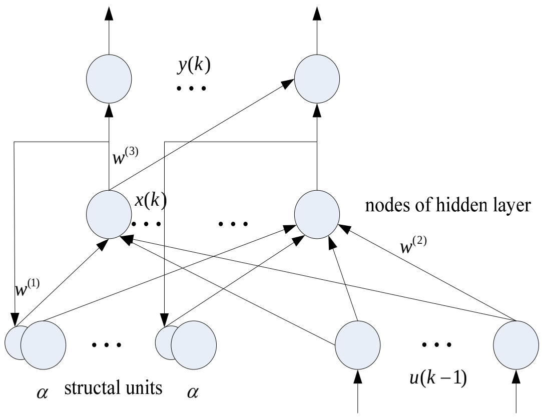

Figure 4. Structure of Modified Elman Neural Network

$$x_{cl}(k)=\alpha x_{cl}(k-1)+x_l(k-1) \tag{12}$$

Where $x_{cl}(k)$ is the output of structural unit and $x_l(k)$ is the output of hidden layer, and α is a self-feedback gain factor. It can simulate the high order system [8].

The nonlinear state space expression described by the modified Elman neural network is:

$$x(k)=f\left(W^1x_c(k)+W^2u(k-1)\right) \tag{13}$$

$$x_c(k)=x(k-1)+\alpha x_c(k-1) \tag{14}$$

$$y(k)=g\left(W^3x(k)\right) \tag{15}$$

For this paper, there are two input values, x_1 is error value e, and x_2 is error variation Δe. The output value is control value $u(k)$ [9].

Define the performance index function:

$$E_p = \frac{1}{2}[r(k+1) - y(k+1)]^2 \tag{16}$$

In formula, $r(k+1)$ is desired output, $y(k+1)$ is system's actual output. Where define $y(k+1)$ and $r(k+1)$ as actual output and expected output respectively.

Hence:

$$\frac{\partial E_P}{\partial \omega_{ij}^3} = -\left(r_i(k+1) - y_i(k+1)\right)\frac{\partial y_i\left(k+1\right)}{\partial \omega_{ij}^3} = -\left(r_d\left(k+1\right) - y_i\left(k+1\right)\right)g_i^{'}(\cdot)x_j\left(k\right) \tag{17}$$

Where ω_{ij}^3 is the weight linking hidden neurons and output neurons.

Let,

$$\delta_i^0 = \left(r_d\left(k+1\right) - y_i\left(k+1\right)\right)g_i^{'}(\cdot), \tag{18}$$

Then,

$$\frac{\partial E_P}{\partial \omega_{ij}^3} = -\delta_i^0 x_j\left(k\right) \qquad i = 1, 2, \ldots, m; \qquad j = 1, 2, \ldots, n \tag{19}$$

$$\frac{\partial E_P}{\partial \omega_{jq}^2} = \frac{\partial E_p}{\partial x_j\left(k\right)}\frac{\partial x_j\left(k\right)}{\partial \omega_{jq}^2} = \sum_{i=1}^{m}\left(-\delta_i^0\omega_{ij}^3\right)f_j^{'}\left(\cdot\right)u_q\left(k-1\right) \tag{20}$$

Let,

$$\delta_j^h = \sum_{i=1}^{m}\left(-\delta_i^0\omega_{ij}^3\right)f_j^{'}\left(\cdot\right), \tag{21}$$

Then,

$$\frac{\partial E_P}{\partial \omega_{jq}^2} = -\,\delta_j^h\,u_q\left(k-1\right) \qquad j = 1, 2, \ldots, n; \quad q = 1, 2, \ldots, r \tag{22}$$

$$\frac{\partial E_P}{\partial \omega_{jl}^1} = \sum_{i=1}^{m}\left(-\delta_i^0\omega_{ij}^3\right)\frac{\partial x_j\left(k\right)}{\partial \omega_{jl}^1} \qquad j = 1, 2, \ldots, n; \quad l = 1, 2, \ldots, n \tag{23}$$

Because $x_c\left(k\right)$ depends on ω_{il}^1,

Hence,

$$\begin{aligned}\frac{\partial x_j\left(k\right)}{\partial \omega_{jl}^1} &= \frac{\partial}{\partial \omega_{jl}^1}\left(f_j\left(\sum_{i=1}^{n}\omega_{ji}^1 x_{ci}\left(k\right) + \sum_{i=1}^{r}\omega_{ji}^2 u_i\left(k-1\right)\right)\right) \\ &= f_j^{'}\left(\cdot\right)\left\{x_{cl}\left(k\right) + \sum_{i=1}^{n}\omega_{ji}^1\frac{\partial x_{ci}\left(k\right)}{\partial \omega_{jl}^1}\right\} \\ &= f_j^{'}\left(\cdot\right)\left\{x_l\left(k-1\right) + \sum_{i=1}^{n}\omega_{ji}^1\frac{\partial x_i\left(k-1\right)}{\partial \omega_{jl}^1}\right\}\end{aligned} \tag{24}$$

Also,

$$\Delta\omega_{ij} = -\eta \frac{\partial E_p}{\partial \omega_{ij}} \quad (25)$$

But the dependence of $x_l(k-1)$ and ω_{jl}^1 can be ignored in the modified Elman neural network [10].

Hence,

$$\frac{\partial x_j(k)}{\partial \omega_{jl}^1} = f_j^{'}(\cdot)\, x_{cl}(k) = x_l(k-1)\, f_j^{'}(\cdot) \quad (26)$$

Then the learning algorithm will degenerate into the following standard BP learning algorithm:

$$\Delta\omega_{ij}^3 = \eta\delta_i^0 x_j(k) \qquad i = 1,2,\dots,m; \quad j = 1,2,\dots,n \quad (27)$$

$$\Delta\omega_{jq}^2 = \eta\delta_j^h u_q(k-1) \qquad j = 1,2,\dots,n; \quad q = 1,2,\dots,r \quad (28)$$

$$\Delta\omega_{jl}^1 = \eta\sum_{i=1}^{m}\left(\delta_i^0\omega_{ij}^3\right)\frac{\partial x_j(k)}{\partial \omega_{jl}^1} \qquad j = 1,2,\dots,n; \quad l = 1,2,\dots,n \quad (29)$$

Where,

$$\delta_i^0 = \left(y_{di}(k) - y_i(k)\right) g_i^{'}(\cdot) \quad (30)$$

$$\delta_{jh}^h = \sum_{i=1}^{m}\left(\delta_i^0\omega_{ij}^3\right) f_j^{'}(\cdot) \quad (31)$$

According to the above, the dependence of $x_l(k-1)$ and ω_{jl}^1 can be ignored.

Hence,

$$\frac{\partial x_j(k)}{\partial \omega_{jl}^1} = f_j^{'}(\cdot)\, x_{cl}(k) \quad (32)$$

$$f_j^{'}(\cdot)x_{cl}(k) = f_j^{'}(\cdot)x_l(k-1) + \alpha f_j^{'}(\cdot)x_{cl}(k-1) \quad (33)$$

Then,

$$\frac{\partial x_j(k)}{\partial w_{jl}^{(1)}} = f_j^{'} x_l(k-1) + \alpha\frac{\partial x_j(k-1)}{\partial w_{jl}^{(1)}} \quad (34)$$

According to gradient descent method, we get iterative algorithm of output’s weight, radial basis function’s center and radial basis function’s width.

4. Simulation and Conclusion

In order to verity the reasonableness of the control scheme. We made a simulation experiment. In this paper, control object is second-order lag model, its transfer function is:

$G(s) = \dfrac{ke^{-\tau s}}{(T_1 s + 1)(T_2 s + 1)}$. Take $T_1 = 14, T_2 = 6, k = 11, \tau = 10$, set desired temperature is $24C^{\circ}$.The simulation comparison diagram of recursive wavelet neural network predictive control and common neural network control is shown in Figure 5.

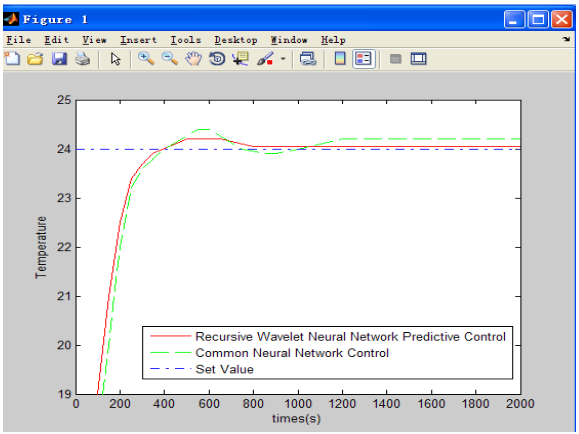

Figure 5. Comparison Diagram of Recursive Wavelet Neural Network Predictive Control and Common Neural Network Control

Figure 5 shows that: When the input temperature changes from $19^{\circ}C$ to $25^{\circ}C$, the adjusting time of common neural network control is at about $1250s$, and its overshoot is large. But recursive wavelet neural network predictive control has quick response speed and small overshoot, and its adjusting time is about $800s$. Therefore, recursive wavelet neural network predictive control has better dynamic performance. So, recursive wavelet neural network predictive control has small overshoot, short adjusting time, high control precision, strong robustness and good control performance.

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