DETERMINING OF THE DELAY TIME FOR A HEATING VENTILATING AND AIR-CONDITIONING PLANT USING MULTI-WEIGHTS NEURONS APPROACH

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Abstract: This paper presents an Multi Weights Neurons approach to determine the delay time for a heating, ventilating and air-conditioning (HVAC) plan to respond to control actions. The Multi Weights Neurons is a fully connected four-layer network. An acceleration technique was used to improve the General Delta Rule for the learning process. Experimental data for heating and cooling modes were used with both the Multi Weights Neurons and a traditional mathematical method to determine the delay time. The results show that Multi Weights Neurons can be used effectively determining the delay time for HVAC systems.

Key words: Multi Weights Neurons, HVAC, Delay time

1. INTRODUCTION

Since Wang shoujue proposed Multi Weights Neurons[1,2,3,4,5,6], it have widely applied pattern recognition[7,8,9,10,11,12,13,14]、control theory[15,16,24] and approximation theory[17]. In my paper, we will apply Multi Weights Neurons approach to determine the delay time for a heating, ventilating and air-conditioning (HVAC)[25,26,27,28] plan to respond to control actions.

Figure 1 denotes the control system of a general heating, ventilating and air-conditioning. $u(t)$, $y(t)$, $r(t)$, $e(t)$ denote the controlling parameter, controlled parameter, defining parameter and error. Given a signal (as figure 2), the system will responds as figure 2. In this figure, the interval BC at which $y(t)$ ascending from 5% to 95% is defined as ascending time (T_s). And the interval AB at which system does not respond is defined as delay time (T_d). The interval AC is defined as responding time (Tr). Ascending time is relevant with system and controller, but delay time is only relevant with system.

Fig.1. Multi-weighted neural networks feedback control system.

Delay time can also be defined by Dirac pulse. In theory, a Dirac pulse would respond at Y when a Dirac pulse happened at U (as figure 3b). But, in fact, the system responds as figure 3c. The interval of the pulse is defined as delay time. In general, the output of a controller can be parsed as a serial of Dirac pulse (as figure 4a). The system will produce a responding curve $y(t)$, which looks like $u(t)$ (as figure 4b). Every response has its own delay time. The comprehensive response of linear system to continuous control signal has the same delay time. Then, we can determine the delay time by comparing $u(t)$ and $y(t)$.

In this paper, we use neural network to determine the delay time of system. At first, get some control signal:

$u(0), u(Tc), u(2Tc), \dots, u(nTc), \dots$, and the corresponding responses:
 $y(0), y(Tc), y(2Tc), \dots, y(nTc), y[(n+1)Tc], y[(n+2)Tc], \dots, y[(n+k)Tc], \dots$,
 (Tc is the sample interval). If the response of control signal $u(nTc)$ is $y[(n+k)Tc]$, then the delay time T_d is the product of sample times and sample interval Tc :

Fig. 2. The response of system

Fig. 3. The response of Dirac pulse. Dirac pulse (b) Ideal response (c) Practical response

$$T_d = K \bullet T_C$$

(1)

The array $u(Tc), u(2Tc), \dots, u(nTc), \dots$ is much is the array $y([k+1]Tc), y([k+2]Tc), \dots, y([k+n]Tc), \dots$. We can determine the delay time by check whether $u(iTc)$ resemble $y([k+i]Tc)$ ($i=1,2,\dots,n$). Shown as Figure 5, when $u(iTc) = y([k+i]Tc)$, the output of z is 1, else the output of z is less than 1.0. The more $u(iTc)$ resembles $y([k+i]Tc)$, the more the value of z approaches 1.0. Here, we define z as resemble coefficient. In the paper, Multi Weights Neurons has two inputs, the one is $u(iTc)$, and the other is $y([k+i]Tc)$. The time corresponding to k which make the largest output of Multi Weights Neurons is delay time (as formula (1)).

2. THE THEORY OF MULTI WEIGHTS NEURONS

The present neurons are based on single-weight vector which can only reach the simple and regular shapes. In fact, the real shapes of some a pattern in the feature space, such as a given person’s face images, are irregular and

complicated, so we developed a novel theory of multi-weight vector neurons .

Fig 5. Multi Weight Neuron Model

Mathematic expression of the shape by this neuron is:

$$| \overrightarrow{X} - \overrightarrow{W} |^2 = k$$

hyper-sausage is the topologic product of a line segment(1-dimensional manifold) and a hypersphere, this line segment's endpoints are decided by study samples A and B, and it is actualized by a two weights neuron.(The two weights are decided by A and B). The shape by this neuron is made of three parts: S_1 is the set of points whose distances to the line segment equal a certain constant k ; S_2 is the set of points whose distances to a sample

point A equal k ; S_3 is the set of points whose distances to a sample point B equal k . the mathematic expressions of them are:

$$S_1: |\vec{X} - \vec{W}_1|^2 - \left[(\vec{X} - \vec{W}_1) \bullet \frac{\vec{W}_2 - \vec{W}_1}{|\vec{W}_2 - \vec{W}_1|} \right]^2 = k$$

$$S_2: |\vec{X} - \vec{W}_1|^2 = k$$

$$S_3: |\vec{X} - \vec{W}_2|^2 = k$$

According to the theory of high-dimension space geometry[4], the volume of a hypersphere in k dimensions is :

$$V_1 = \begin{cases} \frac{\pi^{\frac{k}{2}}}{(\frac{k}{2})!} r_1^k, k = 2m \\ \frac{2^{\frac{k+1}{2}} \pi^{\frac{k-1}{2}}}{k!!} r_1^k, k = 2m + 1 \end{cases} \quad r_1 \text{ is the radius of the circle.}$$

and the volume of a hypersausage(hyper cylinder) is

$$V_2 = \begin{cases} \frac{2^{\frac{k}{2}} \pi^{\frac{k-2}{2}}}{(k-1)!!} r_2^{(k-1) \times h}, k = 2m \\ \frac{\pi^{\frac{k-1}{2}}}{(\frac{k-1}{2})!} r_2^{(k-1)} \times h, k = 2m + 1 \end{cases} \quad r_2 \text{ is the radius of the cylinder's}$$

bottom, which is $(k-1)$ dimension hypersphere; h is the altitude of it.

3. TOPOLOGY STRUCTURE OF MULTI-WEIGHTED NEURAL NETWORK.

The multi-weighted neural network's topology is shown in figure 6. The first layer is input layer which has two input node. The forth layer is the output layer which only has one neuron. The second and third layer both has five neurons. The output of controller and the response (temperature) which is normalized is the input of the Multi Weights Neurons. Every neuron is a Sigmoid function. The output of Multi Weights Neurons is between 0 and 1. The weights of the multi-weighted neural network were adjusted by the multi-weighted neural networks algorithm[20].

Fig. 6. The topology of the multi-weighted neural network.

We adapt Multi Weights Neurons in our experiment, one of them has three layers, and the other has four layers. Every hide layer of the Multi Weights Neurons both has five neurons. The simulation was shown in figure 7 and figure 8. The two criterions, mean square error (E_a) and the largest error (E_m), are used to assess our Multi Weights Neurons. The criterions were defined as follows:

$$E_a = \frac{1}{N_b} \sum_{b=1}^{N_b} (D_b - Y_b)^2 \quad (2)$$

$$E_m = \max \{ \text{abs}(D_b - Y_b) \} \quad (3)$$

D_b is between 0 and 1 which is the expect output of input state b in one circle of study; Y_b is the actual output, which is between 0 and 1. N_b is the number of input state in one circle of study. The learning algorithm also has a powerful influence on the multi-weighted neural network.[4].

4. EXPERIMENT

The HVAC in our experiment was composed with 2000-cfm fan-winding-pipes, refrigeration, cold water, hot water and steam-winding-pipes, a controller used to control the temperature of return wind. When heating, air is heated by steam; when cooling, air is cooled by cooler. Different operation has different delay time.

Fig. 7. The mean resemble coefficient of heating.

Fig. 8. The mean resemble coefficient of cooling

We get signals (control signal and the temperature of return wind) from controller with data sample system. And then the signals were normalized between 0 and 1. The Multi Weights Neurons can get resemble coefficients with interval K. In figure 7, curve 1 depicts the result of heating. In figure 10 curve 1 depicts the result of cooling. In figure 7, the largest resemble coefficient is 0.5 at $k = 18$, the interval of sample is 2.12 minute, so, the delay time of heating is 86. 1 minute. In figure 8, the largest resemble coefficient is 0.84 at $k = 15$, so the delay time of cooling is 50 minute.

5. CONCLUSION

In this paper, a Multi Weights Neurons with four layers was used to determine the delay time of HVAC system. The simulation and experiment denote that Multi Weights Neurons is efficient in determining the delay time of HVAC system. Compared with conventional algorithm, Multi Weights Neurons can eliminate the interrupt of input noise by adopting the bias and coefficient of the neuron. Then, Multi Weights Neurons is more precise than conventional algorithm. It can be used on controller to predict system delay time. When learning, the acceleration algorithm can improve the conventional learning algorithm, it lower the output error and accelerate the convergence.

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