APPLICATION OF AN IDENTIFICATION METHOD OF BP NEURAL NETWORKS IN THE SPEED CONTROL SYSTEM OF HYDRAULIC ELEVATOR

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ABSTRACT

The complexity and undecidability are analyzed in the modeling of speed control system of hydraulic elevator. The back-propagation neural networks model is used and formed by the system identification. The test result of system is given in this paper.

KEYWORDS: hydraulic elevator, back-propagation neural networks, Identification

INTRODUCTION

The hydraulic elevator with the feedback of car speed is a type of creative control system (Fig. 1). Normally the flow rate feedback is widely used, by which the constant and steady elevator characteristics can not be obtained due to the friction between car and guide rails, and the temperature changing of hydraulic oil. So the car speed feedback control is a solution to avoid the problems. However it causes the difficulties in the system modeling and the complexity in dynamics of mech-electro-hydraulics. It is very difficult to obtain the precise mathematic model (transfer functions or state equations) of the system. These can be solved through the system identification. In recent years, the neural network theory is widely applied in control system. More and more engineering examples have proven its availability as a better solution.

The paper presents a method of using the back-propagation neural network model with the feature of self-learning on the identification of the hydraulic elevator control system with car speed feedback.

THE BACK-PROPAGATION NEURAL NETWORK MODEL (BP MODEL)

In 1986 Mr. Rumelhart presented the back-propagation neural networks model [1],[2], which is applicable for the multi-layer neural network for it considers weight parameters in all layers. The multi-layer network is shown as Fig.2. There are one or more layers of neural cells between input layer and output layer. These cells have no direct communications to the external, but the change of their states can influence the relations between input and output.

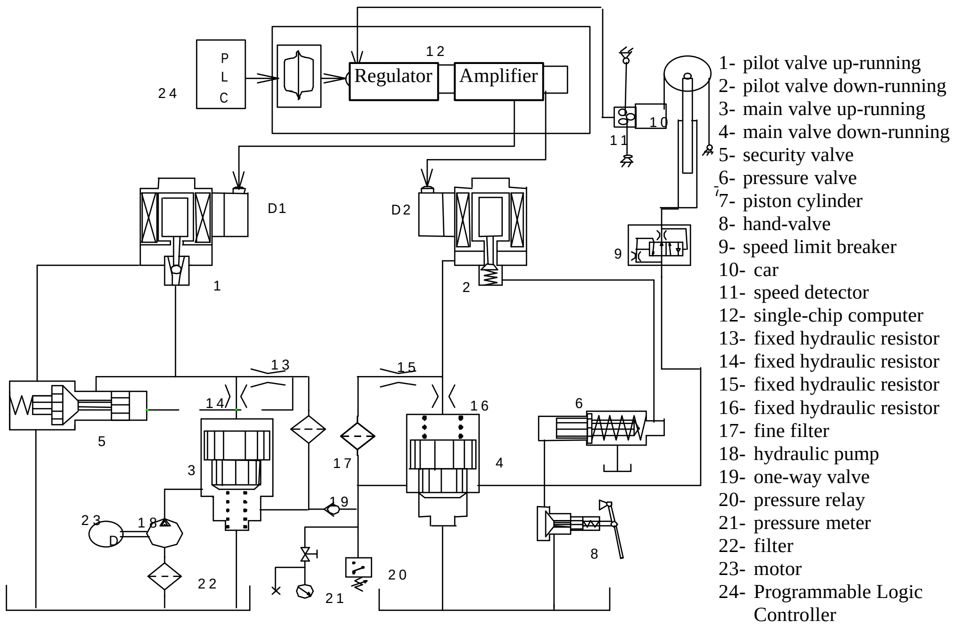

Fig. 1 Schematic drawing of Hydraulic Elevator with Car Speed Feedback

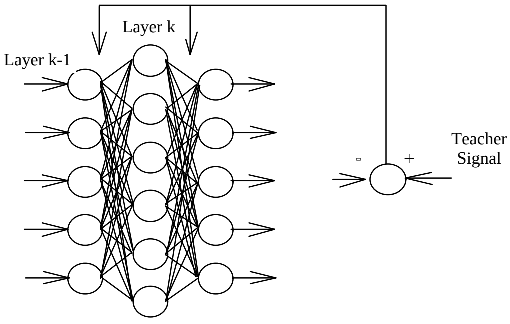

Fig.2 Multi-layer Network

Set a neural network with m layers, add input mode on the input layer, and assume the sum of input on cell i of layer k is U_i^k, its output is V_i^k, the weighting value from cell i of layer k-1 to cell i of layer k is w_{ij}, $f()$ is a relation function between input and output. So we get:

$$V_i^k = f(U_i^k) \qquad (1)$$

$$U_i^k = \sum_j w_{ij} V_j^{k-1} \qquad (2)$$

(1) and (2) are the propagation in one direction, from input to output with layer by layer. The state of cell in one layer has influences only on next layer. To improve the precision the back propagation is introduced. That is the weighting value w_{ij} could be changed according to the error between actual output and expected output, so as to minimize the error. Define the error function:

$$r = \frac{1}{2}\sum_j (V_j^m - y_j)^2 \qquad (3)$$

here,

y_j --- expected output;

V_i^m --- actual output, the function of input mode and weighting value w_{ij};

the modification of w_{ij}:

$$Dw_{ij} \propto -\frac{¶ r}{¶ w_{ij}}$$

$$\because \quad \frac{¶ r}{¶ w_{ij}} = \frac{¶ r}{¶ U_j^k} \cdot \frac{¶ U_j^k}{¶ w_{ij}}$$

$$= \frac{¶ r}{¶ U_j^k} \cdot \frac{¶}{¶ w_{ij}} (\sum w_{ij} V_j^{k-1}) = \frac{¶ r}{¶ U_j^k} V_j^{k-1}$$

$$Dw_{ij} = -e \frac{¶ r}{¶ U_j^k} V_j^{k-1} \qquad (4)$$

here, $e > 0$ --- step length

To improve the astringency, the formula below could be adopted:

$$Dw_{ij}(t+1) = -e \frac{¶ r}{¶ U_j^k} V_j^{k-1} + aDw_{ij}(t) \qquad (5)$$

here, a --- coefficient

THE ANALYSIS OF HYDRAULIC ELEVATOR SYSTEM

The speed control system of a hydraulic elevator is shown as Fig.3, which consists of controller, proportional valve, hydraulic driving and car load. Fig.4 is equivalent structure schematics of the hydraulic elevator control system.

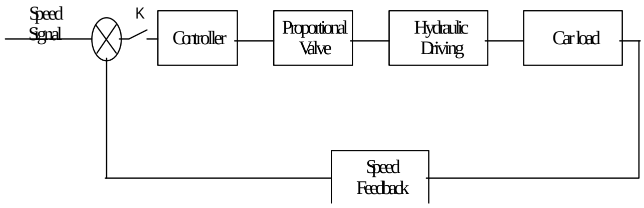

Fig.3 The simplified drawing of the hydraulic elevator control system

The controller can be regarded as proportional gain for its time constant is very small. The proportional valve is a 1st-order component for its higher frequency response:

$$G_V = \frac{K_{PV}}{1 + \frac{s}{w_V}}$$

here,

$w_V = R/L$ --- kink frequency of coil of proportional valve

K_{PV} --- gain of proportional valve

From Fig. 4 it can be seen there are two 2nd-order resonant components. One is composed by car, spring

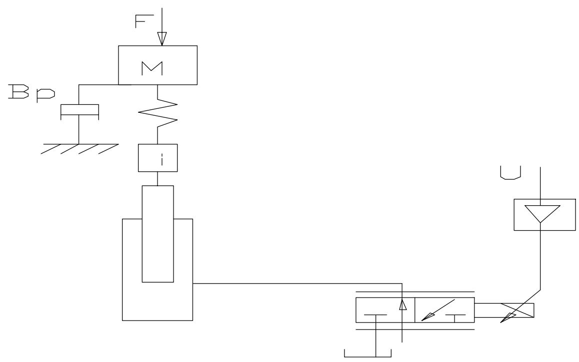

Fig.4 The equivalent structure schematic of the hydraulic elevator control system

(cascade of hydraulic spring and rope) and damp. Another by piston and its equivalent spring. The dynamics model is shown in Fig.5.

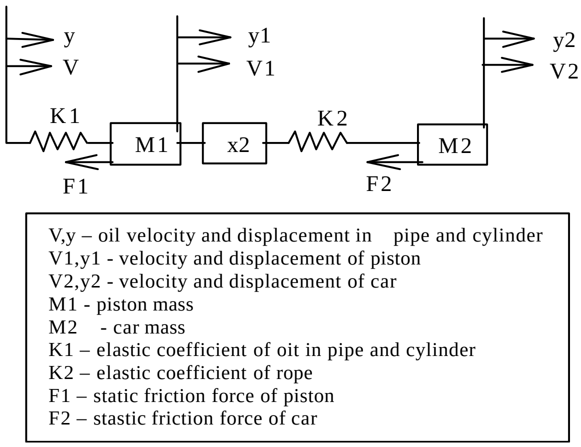

Fig.5 Dynamics of car, cylinder and pipe

From Fig.5, we can get Fig.6 and then Fig.7.

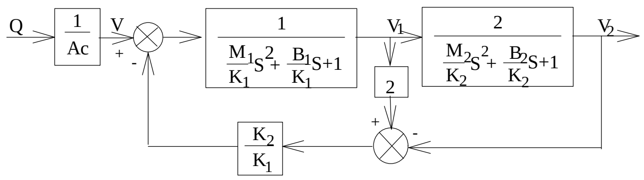

Fig. 6 Diagram of Transfer Function

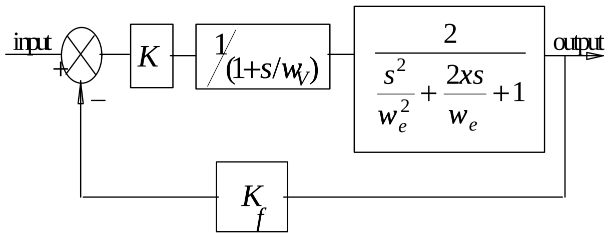

Fig. 7 Simplified Diagram of Transfer Function

At last the final and synthetic system transfer function is:

$$\frac{dY}{dt} = \frac{2K}{(1+\frac{S}{w_V})(\frac{S^2}{w_e^2} + \frac{2z_e}{w_e} S + 1)} \cdot U$$

here,

$\frac{dY}{dt}$ - car speed

U - input signal

ESTABLISH OF NEURAL NETWORK MODEL

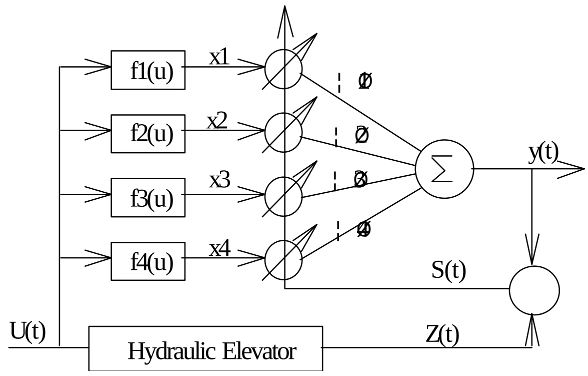

Fig.8 Structure of neural network model

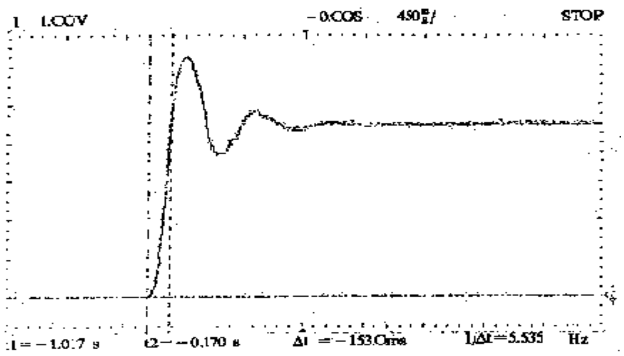

Fig.9 Step response curve of system by testing

Set the structure of neural network model as Fig. 8 due to real-time reason and testing curve shown in Fig.9. and choose non-linear functions as below:

$$x_1 = f_1 = a_1 u^2 + a_2 u + a_3$$
$$x_2 = f_2 = a_4 \sin(a_5 u + a_6) + a_7 \cos(a_8 u + a_9)$$
$$x_3 = f_3 = a_{10} e^{-a_{11} u}$$
$$x_4 = f_4 = a_{12} e^{-a_{13}(u+1)}$$

Theoretically the non-linear functions above can be discretional, so $a_1 \sim a_{13}$ in identification were chosen by random, and found no obvious differences by several testing but with much more different learning circles.

$w_1 \sim w_4$ in Fig.8 are weighting values. The output of neural network model:

$$y(t) = [w_1 \quad w_2 \quad w_3 \quad w_4] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \sum_{i=1}^{4} w_i x_i$$

learning function:

$$w(t_2) - w(t_1) = -t \; x(t_2)[z(t_2) - y(t_2)](t_2 - t_1)$$

discretely $t = k$,

$$w(k) - w(k-1) = -t\ \ x(k)[z(k) - y(k)]$$

here,

$$w = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix}, \qquad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

x - learning step-length coefficient

Use step signal as input for training, and get the response of the neural network model as Fig. 10, in which the dashed line is detected curve as teacher information and the solid line is the step response of the neural network model that was identified with computer.

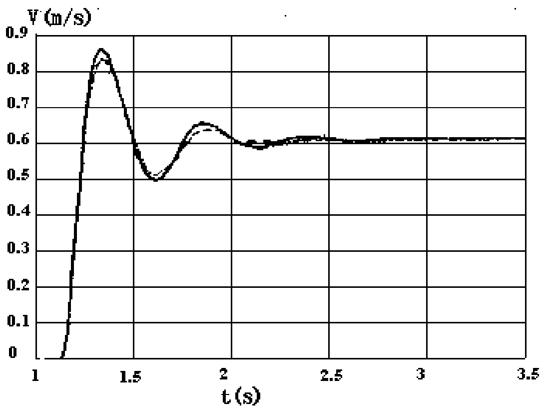

Fig.10 Step response by training

TESTING RESULTS AND CONCLUSION

The tests were done in a hydraulic elevator with 3 stops. Fig.11 is the initial running curve and Fig.12 is the curve after several running. In the figures curve 1 is actual running, curve 2 is setting curve and curve 3 is control output. From that we could see the control effect becoming better after several running. Theoretically the increasing of layers of neural network would be helpful for the increasing of identification precision. However it would spend much computing time. The suitable non-linear functions could be used for decreasing the layers.

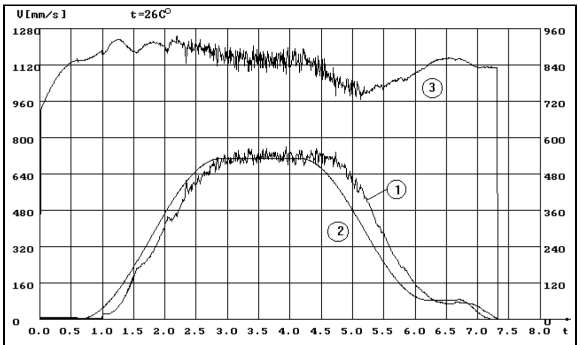

Fig. 11 Running curves of the elevator

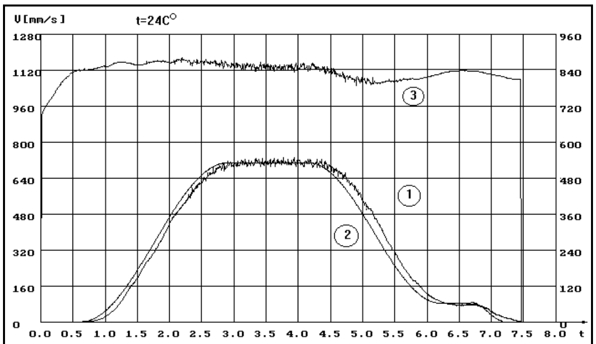

Fig. 12 Running curves of the elevator

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