Identification of pressure control model in a solenoid valve based on GA-BP neural network

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Abstract. A pressure control solenoid valve (PCSV), which is a sophisticated combination with mechanical characteristics, hydraulic characteristics and electromagnetic characteristics, is studied in this paper. An identifier is developed for identifying its pressure control model. For obtaining the input and output data of valve, its model is established by AMESIM. MATLAB is utilized to develop the identifier with genetic algorithm-back propagation (GA-BP) neural network to process the data from AMESIM. Simulation is implemented to verify the effect of the designed identifier by choosing proper parameters. In the end, results demonstrate that the identifier designed here can identify pressure control model of the PCSV with high speed and accuracy.

1. Introduction

The solenoid valve has already been widely used in aerospace, industry and agriculture because of its advantages like long service life, high reliability and compact design, etc. [1]. The pressure control solenoid valve (PCSV) studied in this paper plays an important role in automatic transmission (AT) of mobiles. The work performance of valve is affected by factors like oil temperature, viscosity oil and hysteresis, etc. [2]. Due to the multi-system coupling and complexity of the PCSV, it is difficult to obtain its accurate pressure control model by traditional mathematical modelling methods. Many researchers used different modelling methods or control algorithms to reduce the control inaccuracy caused by model errors [3-5]. However, the establishments of model and algorithm are both complicated, and the final control effect is usually not optimal. In recent years, system identification method has gradually become one of the most important systems modelling method. This method is very suitable for nonlinear systems with unclear or complicated mechanism. And it is a method of experimental modelling, which records the input and output data during normal work process, and then estimates the system model by some algorithm [6-8].

A model of the PCSV is established by AMESIM in this paper, and the input and output data of valve are obtained by simulation in it. Because it is difficult to figure out the specific control characteristics with this model, the error back propagation (BP) neural network and genetic algorithm (GA) are combined to develop an identifier of PCSV’s pressure control model with these data. This method is an effective, quicker and more convenient modelling method.
2. Problem description
The diagram of the PCSV studied in this paper is shown in Figure 1. And its pressure control principle is force balance with hydraulic force, electromagnetic force, spring force and friction force. For the valve, the input parameters are supply voltage $V_s$ and supply pressure $P_s$, and the output parameter is the control pressure $P_c$.

![Figure 1 diagram of the PCSV](image1)

![Figure 2 The model of PCSV in AMESIM](image2)

As shown in Figure 2, the model of the PCSV is established by AMESIM. The volume 1, volume 2 and orifice in Figure 2 stand for the $V_1$, $V_2$ and the damping orifice in Figure 1. A fixed displacement pump motived by an electric motor is used to supply oil flow to the valve. And instead of voltage signal, the current input signal is adopt here to simplify the valve model. In addition, the mass component is used to represent the mass of spool in the valve and the friction between the spool and the sleeve. The viscous frictions and leakages inside the valve are also considered. The input and output data of the PCSV can be obtained by the simulation in AMESIM.

3. Identification method based on GA-BP neural network

3.1. BP neural network
The BP neural network is a multilayer feedforward neural network, and the network structure for model identification used in this paper is shown in Figure 3. It includes the input layer, the hidden layer and the output layer. And there are 5 nerve cells in the hidden layer. Such a structure has been proved to approximate any nonlinear system before $[9]$. Input variables of the input layer is $x_1$ and $x_2$, which are just the input current and supply pressure of the PCSV. The input and output of each nerve cell in the hidden layer are:

$$\sigma_j = \sum_{i=1}^{m} \omega_{ij}x_i - \rho_j, \quad \tau_j = f(\sigma_j) = f \left( \sum_{i=1}^{m} \omega_{ij}x_i - \rho_j \right), \quad (j \in [1,5])$$

(1)

where $m = 2$ is the number of the input variables in the network, $\omega_{ij}$ and $\rho_j$ are the weight and threshold of the hidden layer. $f(\sigma_j)$ is the transfer function of the hidden layer, and $\text{tansig}()$ is used here. The output variable is $y$, which is just the control pressure of the PCSV. In the network, the input and output of the output layer are:

$$u = \sum_{j=1}^{n} \omega_j' \tau_j - \rho', \quad y = f(u) = f \left( \sum_{j=1}^{n} \omega_j' \tau_j - \rho' \right)$$

(2)
where $n = 5$ is the number of the nerve cell in the hidden layer, $\omega_j'$ and $\rho'$ are the weight and threshold of the output layer, respectively. $f(u)$ is the transfer function of the output layer, and $\text{purelin}(\cdot)$ is adopted here.

$$e = y_o - y$$

where $y_o$ is actual output of the valve. And the weights and thresholds can be updated based the error by using following equations:

$$\omega_{ij} = \omega_{ij} + \beta \tau_j (1 - t_j) x_i \omega_j' e,$$

$$\omega_j' = \omega_{ij} + \beta \tau_j e,$$

$$\rho_j = \rho_j + \beta \tau_j (1 - t_j) \omega_j' e,$$

$$\rho' = \rho' + e$$

where $i \in [1, 2]$ and $j \in [1, 5]$ as mentioned above. $\beta$ is the learning rate of neural network. The weights and thresholds are continuously updated to make the error between the actual output and the expected output gradually approach to the descriptive minimum value. The training process will end when global error of the network reaches this minimum value, and the global error here can be expressed as $E_g = \frac{1}{2} e^2$.

### 3.2 Optimization method by GA

For improving the accuracy of model identification, a genetic algorithm is used to optimize weights and thresholds in the BP neural network to find their optimal value. Figure 4 shows the step block diagram of GA. The first step is to establish the initial population by considering these weights and thresholds as individuals of the population, the purpose is to generate a string population of a specific length and perform a chromosome-like encoding for each individual [10]:

$$M: m_l m_{l-1} m_{l-2} \cdots m_2 m_1 \quad m_k \in [a_k, b_k]$$

where $l$ is the length of the individual and its value is 21 in this paper, which is the sum of weighs and thresholds. $a_k$ and $b_k$ are the upper and lower bounds of $m_k$. The fitness value is the evaluation criterion of the individual’s quality. In order to minimize the error value during learning process, the global error $E_g$ can be considered as the fitness value and the individual’s survivability is stronger with smaller fitness value.

Genetic optimization mainly includes three operations: select operation, cross operation and mutation operation. The select operation refers to selecting individuals from the old group to the new group with a certain probability. The selection probability $s_k$

$$s_k = \frac{1}{F_k} / \sum_{k=1}^{P} \frac{1}{F_k}$$

where $P$ is the population size.
where $P$ is the population size. The cross operation is to produce new excellent individuals with the exchange and combination of chromosomes in two old individuals according to the cross probability $p_c$. The cross operation between two individuals can be expressed as:

$$
M_1: m_1^1m_{l-1}^1m_{l-2}^1 \cdots m_2^1m_1^1 \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad \ quad}
Table 1 Parameters specification of the identifier

| Parameter | Value | Description       |
|-----------|-------|-------------------|
| $\beta$   | 0.1   | Learning rate     |
| $P$       | 30    | Population size   |
| $p_c$     | 0.2   | Cross probability |
| $p_m$     | 0.1   | Mutation probability |
| $T$       | 15    | Maximum evolution generation |

Figure 6 Variation of the average fitness

Figure 7 is a comparison of the identification output and the actual output, and Figure 8 shows the identification error. It can be seen that the identification output is basically consistent with the actual output, and the identification accuracy is high except some peak or inflection points.

5. Discussion

From the simulation result, it can be concluded that the identifier developed in this paper can used to identify pressure control model of the PCSV with high accuracy and speed. However, the output error is still relatively large, especially at the peak or inflection points. There are two possible reasons. One is that the model of the PCSV is not very accurate, and the relationship between the input and output data is not unique. The other is improper selection of the maximum evolutionary generation, population size, cross probability and mutation probability in the GA, which will affect the accuracy and speed of identification. Therefore, in the further study, we will develop more accurate model of valve, or directly
obtain the input and output data in the actual work by setting up a test platform. And the optimal parameters of identifier will be also determined through experiments.

6. Conclusions
This study has introduced an identifier based on GA-BP neural network for pressure control model of the PCSV. The control model of valve is established in AMESIM, and the input and output data is obtained by simulation in it. The GA-BP neural network is developed by MATLAB, which can combine with AMESIM to receive the data. The results of simulation demonstrate that the identifier designed in this paper can be used to identify pressure control model of the PCSV with high identification speed and accuracy.

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