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Modelling and Identification of Electrohydraulic System and Its Application

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Abstract: In general, the first and the most important step in system analysis, prediction and control is the proper model of the system. In order to design the controller of nonlinear electrohydraulic system, several modeling techniques are proposed: the transfer function of the electrohydraulic system is identified using first-principle method, and the intelligent models are built by fuzzy modeling and neural networks. First, the Automatic Depth Control Electrohydraulic System (ADCES) of a certain type of weapon is introduced, and how to obtain the input-output data is proposed. Then, three modeling algorithms are detailed, including transfer function, fuzzy system and neural networks. Finally, five models are identified based on the ADCES; and the analysis of the obtained models lays the foundation of the controller design.

1. INTRODUCTION

The electrohydraulic system has many advantages of fast response, wide adjustable speed range, high power to weight ratio and high durability, so it has been widely used in industrial manufacture, agricultural machinery and weapon system (Merritt, 1967, Younkin, 2003). In order to analyze and control electrohydraulic system, a proper model is needed; however it is difficult to obtain an accurate model of electrohydraulic system due to its nonlinear characteristics, including saturation, nonlinear gain, fraction, fluid compressibility and nonlinear flow/pressure relation.

Traditionally, the first principle method is the mostly used technique in electrohydraulic system modelling, which develops a group of linear mathematical equations based on physical principle, such as the continuity equation and the Newton second law. Ziaei (2000) established a fourth-order transfer function and a linear difference equation for an experimental hydraulic test station. Guanglin (2006) constructed a third-order transfer function for a pump-cylinder velocity control system, and researched its dynamic characteristics. Qing-Hua (2006), Kemmetmuller (2007) and Garett (1999) built the mathematical models of the electrohydraulic systems, and designed nonlinear controllers based on the obtained models. However, these imprecise linear models can not fit the essential nonlinear characteristics of the electrohydraulic system, and are limited in practice.

The nonlinear characteristics of the electrohydraulic system can not be presented directly by the above mentioned linear model, but the input-output data, which contain all the nonlinear information about the electrohydraulic system, can be gathered easily. So some researchers pay attention to data-based intelligent modelling methods. Costa (2000) built Mamdani fuzzy model using grid partition for an electrohydraulic system, and the obtained model is much interpretable while inaccurate. He (1999) employed neural network to model the electrohydraulic system, and concluded that the neural network is more precise than linear models. Kang (2005) established the equivalent neural network for an electrohydraulic system and proposed its learning algorithm, and the obtained neural network was employed as emulator in the designed adaptive controller.

This paper studies several modelling techniques, including first principle method and intelligent modelling method, based on the Automatic Depth Control Electrohydraulic System (ADCES) of a certain type of weapon. Firstly, the ADCES is introduced, and the technique to generate input signals is proposed. Then, the transfer function of the ADCES is built using first principle method; and the intelligent modelling approaches, including fuzzy modelling and neural network, are detailed. Finally, the above mentioned models of the ADCES are identified, and the results are analyzed.

2. THE AUTOMATIC CONTROL DEPTH ELECTROHYDRAULIC SYSTEM

The Automatic Depth Control Electrohydraulic System (ADCES) of a certain type of weapon is composed of servo valve, hydraulic cylinder, copying shoe, shaft position encoder, and plough, as illustrated in Fig.1. In the process of forward-marching, the copying shoe inducts the shape of ground surface, and the shaft position encoder measures the angle between the plough arm and level plane, thus the actual embedded depth of plough can be calculated. The automatic depth control is accomplished by the telescopic movement of hydraulic cylinder, which is operated by the servo valve according to error between actual embedded depth and the set value of embedded depth. In ADCES, there are fixed specific single-input single-output mapping functions among the displacement of piston, the angle of shaft position encoder, and the actual embedded depth. So, without loss of generality, the input signal of the ADCES is the control voltage of servo valve, and the output of the ADCES is the displacement of piston.

In order to motivate the ADCES sufficiently and obtain complete data containing all the dynamic characteristics of the ADCES, it is important to select an appropriate input signal. In the field of linear system identification, the Pseudo-Random Binary Signal (PRBS) that only contains two amplitude levels is widely used. However, the identifiability will be lost for the nonlinear ADCES using PRBS. So an input signal that contains all interesting amplitudes and frequencies and all their combinations should be employed, such as Pseudo-Random Multi-Level Signals (PRMS), chirp signals, and independent sequences with a Gaussian or uniform distribution. Experience shows that the PRMS is the most suitable choice of input signal for identification of hydraulic system (Jelali, 2003, Senger, 1996). So in this paper the PRMS is selected as the input signal for the ADCES.

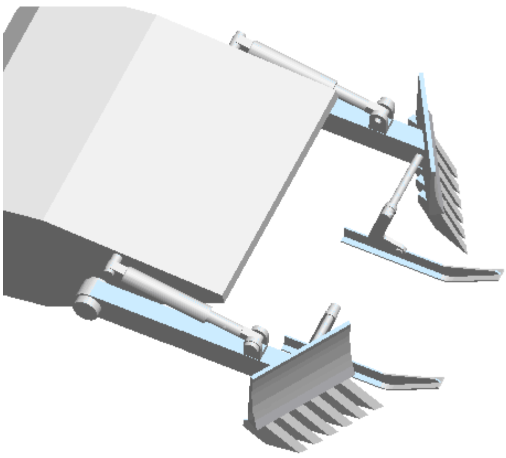

Fig.1. The automatic depth electrohydraulic control system

3. MODELLING AND IDENTIFICTION OF THE ADCES

This section details three modelling algorithms, including transfer function based on first principle method, fuzzy system and neural network based on intelligent technique.

3.1 Transfer function

In order to establish transfer function (TF) of the ADCES, the functions of servo valve and hydraulic cylinder should be identified primarily according to several physical laws, including the dynamic equation of servo valve, the flow equation, the continuity equation and the force balance equation(Merritt, 1967, Martin, 1976,Younkin, 2003, Zeb, 2003).

The ADCES can be described by a third-order system:

$$\frac{x_p}{u}=\frac{K_q K_v}{\frac{V_t M_t}{4\beta_e A_p}s^3+\left(\frac{K_{ce}M_t}{A_p}+\frac{V_t B_p}{4\beta e A_p}\right)s^2+\left(A_p+\frac{K_{ce}B_p}{A_p}+\frac{KV_t}{4\beta_e A_p}\right)s+\frac{K_{ce}K}{A_p}},$$

where x_p is displacement of piston, u is input voltage signal, K_q is valve flow gain, K_v is the gain of servo valve, K_{ce} is the total coefficient of flow/pressure, K is the equivalent spring gradient of soil, V_t is the sum of two volume, M_t is total mass of piston and load referred to piston, A_p is the area of piston, β_e is the effective bulk modulus, B_p is viscous damping coefficient of piston and soil.

The parameters of the transfer function can be calculated according to the manuals provided by the manufacturers, however it is difficult to obtain the leakage coefficient, and it is impossible to determine the equivalent spring gradient of soil. So, in this paper, the parameters of the transfer function are identified based on the input-output data using MATLAB software.

3.2 Fuzzy system

Fuzzy sets theory, introduced by professor Zadeh thirty years ago (Zadeh, 1965), has been applied in a wide range of areas (Babuska, 1998). Fuzzy modelling is one of the most successful disciplines that are used in simulation and control. There are two types of fuzzy systems: the Mamdani fuzzy model with high interpretability and the TS fuzzy model with high accuracy (Takagi, 1985). In order to simulate dynamic characteristics of the ADCES precisely, the TS fuzzy system is used in this paper. There are several approaches which have been proposed to build fuzzy system from numerical data, including fuzzy clustering-based algorithms (Gomez-Skarmeta, 1999), neuro-fuzzy systems (Jang, 1996) and genetic fuzzy systems (Cordon, 2000). This paper employs GK fuzzy clustering algorithm (Gustafson, 1979) to identify the antecedents of TS fuzzy system, and employs the least square method to identify the consequence of TS system; thus the TS fuzzy system of the ADCES can be obtained.

In order to improve interpretability of TS fuzzy system of the ADCES, the membership functions of the fuzzy system is simplified. The detail simplification techniques can be found in the reference (Setnes, 1998).

3.3 Neural network

Neural network is a type of highly nonlinear dynamic system imitating neuron of human brain, and it also owns learning capability (Jinkun, 2005). The Radial Basis Function (RBF) and the multilayer forward neural network (NN) are the most used neural networks in modelling physical system. In general, the RBF can approximate system more accurately. However, when input space is large, the RBF becomes computationally intensive (He, 1999). So in this paper, a three-layer forward NN is chosen to model the ADCES.

In the three-layer forward NN, the function of the hidden layer is tan-sigmoid function, and the output layer adopts linear function. The number of node in input layer equals to the number of inputs, and the number of node in hidden layer is twice as the number of node in input layer. The Levenberg-Marquardt algorithm (Priddy, 2005) is employed to train the neural network:

$$\Delta\Theta = (J^T J + \lambda I)^{-1} J^T E \, , \tag{32}$$

where Θ is matrix of weights and bias of NN, E is error matrix, J is the Jacobian matrix, λ is the control parameter to adjust convergence speed.

4. EXPERIMENTS

In the ADCES, the input signal is the control voltage of servo valve in the range of [-8 8] volt, and the output signal is the displacement of the piston in the range of [0 0.45] meter. Although the ADCES is a high-order nonlinear system, it will not be vibrated within the normal input allowed. So the experiment to gather data is conducted without any closed loop controller. With 100ms sampling time, 10000 data are collected. The first 600 data are used to train the model, while the other 400 data are employed to validate the obtained model. As illustrated in Fig.2: (a) presents the input data, and (b) shows the output data.

In order to weigh the performance of different models of the ADCES, the Root Mean Square error (*RMS*) is applied to measure the precision of model:

$$RMS(y, y_m) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y(i) - y_m(i))^2} \, ,$$

where y is the actual output of displacement, y_m is the output of the obtained model, N is the number of data.

With small value of displacement, the *RMS* of the model is so small that it is difficult to indicate the similarity between the obtained model and the ADCES distinctly. So the Variance Accounted For (*VAF*) is adopted to assess the quality of the model by comparing the measured output and the output of the model:

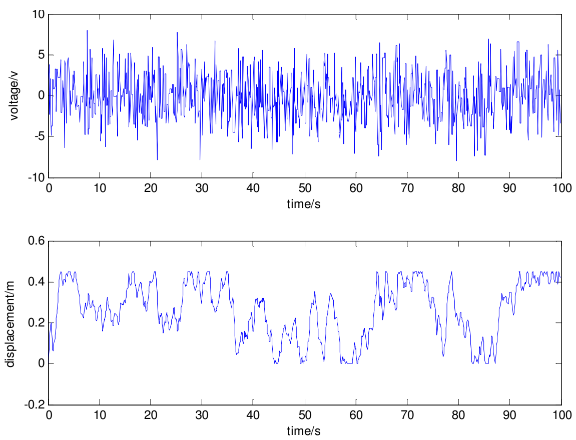

Fig.2. Input-output data of the ADCES: (a) input voltage of valve, (b) output displacement of piston

$$VAF(y, y_m) = \left[1 - \frac{\mathrm{var}(y - y_m)}{\mathrm{var}(y)}\right] \times 100\% \, ,$$

where var () is the variance operation. A higher *VAF* means that the obtained model is more similar to the ADCES.

4.1 Transfer function of the ADCES

After identification, the transfer function (TF) of the ADCES is obtained as:

$$\frac{x_p}{u} = \frac{4.01}{8.46s^3 + 863.91s^2 + 1802.17s + 1} \, .$$

The outputs of the ADCES and outputs of the transfer function are depicted in Fig.3: (a) shows the training data and (b) shows the validation data. The *RMS* and the *VAF* of the obtained transfer function are 0.093, 48.514%, 0.150 and 14.30% for training data and validation data, respectively. It is clearly that the identified transfer function can only describe the ADCES roughly, and the generalization of the model is poor.

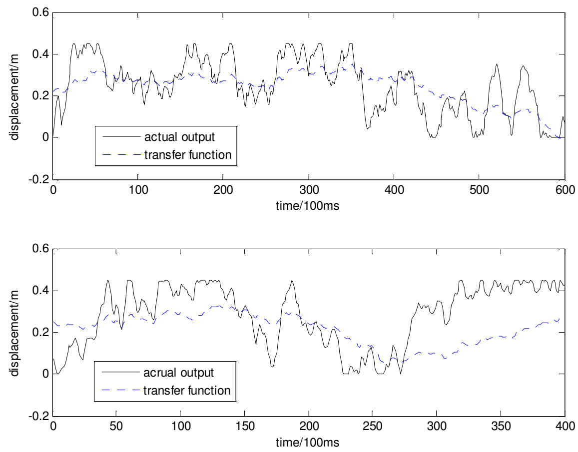

Fig.3. Actual output and transfer function output: (a) training data, (b) validation data

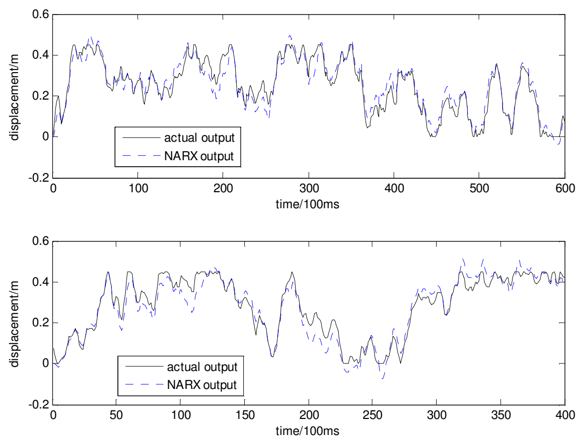

Fig.4. Actual output and NARX output: (a) training data, (b) validation data

4.2 Nonlinear Auto-Regressive model of the ADCES

To determine the nonlinearity of the ADCES, the second-order Nonlinear Auto-Regressive with eXtra inputs (NARX) is also employed to model the ADCES. The comparison of outputs is illustrated in Fig.4, and the performance indices are listed in Table 1 which shows that the *RMS* and the *VAF* of the obtained NARX are 0.040, 90.847%, 0.043 and 91.654% for training data and validation data. The obtained results indicate that the ADCES is a typical nonlinear system which can be modelled using NARX quite well.

4.3 TS fuzzy model of the ADCES

The TS fuzzy model is build for the ADCES employing GK fuzzy clustering algorithm and the least square method. The number of clusters is determined according to cluster validity measures (Zong-yi, 2005). With the algorithm proposed in section 3.2, we have

$$\begin{aligned}
&\text{IF } u(t) \text{ is } A_{11} \; and vu(t-1) \text{ is } A_{21} \; and \; y(t) \text{ is } A_3 \; and \; y(t-1) \text{ is } A_4 \\
&\quad \text{THEN } y(t+1) = 0.0036u(t) + 0.0034u(t-1) + 1.3013y(t) - 0.3359y(t-1) + 0.0101 \\
&\text{IF } u(t) \text{ is } A_{12} \; and vu(t-1) \text{ is } A_{22} \; and \; y(t) \text{ is } A_3 \; and \; y(t-1) \text{ is } A_4 \\
&\quad \text{THEN } y(t+1) = 0.0038u(t) + 0.0034u(t-1) + 1.3051y(t) - 0.3379y(t-1) + 0.0093
\end{aligned}$$

where A_{11}, A_{12}, A_{21}, A_{22}, A_3, A_4 are membership functions illustrated in Fig.5, which can be assigned the linguistic labels of “middle-small”, ”middle-large”, ”middle-small”, ”middle-large”, ”middle”, "middle” which can be interpreted easily.

Fig.6 diagrams the outputs of the ADCES and the outputs of the TS model, and Table 1 shows the performance indices of the TS model. The *RMS* and the *VAF* of the obtained TS model are 0.0095, 99.572%, 0.0115 and 98.484% for training data and validation data, respectively. These obtained results prove that the TS model can fit the dynamics of the ADCES preferably, and that the obtained model has high generalization capacity. However, the TS model is built by fuzzy clustering algorithm, which can not express sparse data accurately, so the obtained TS model presents large errors near the limit range of the displacement values.

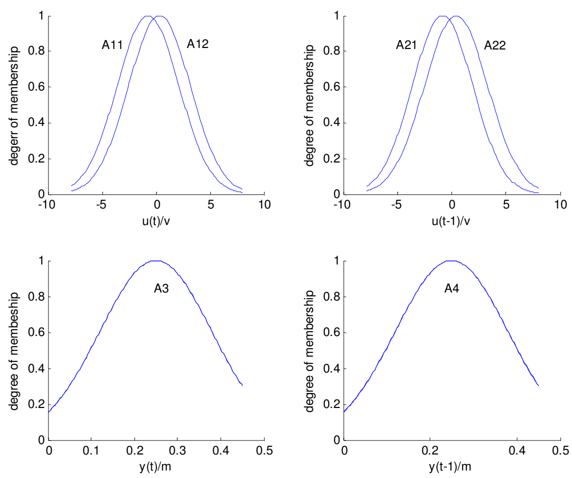

Fig.5. Membership of the obtained TS fuzzy model

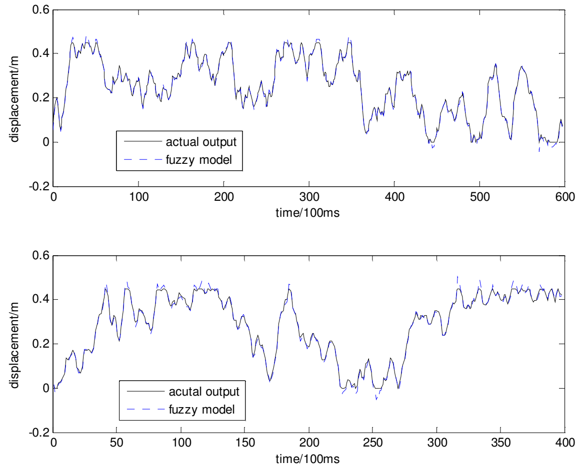

Fig.6. Actual output and TS fuzzy model output: (a) training data, (b) validation data

4.4 Adaptive Neuro Fuzzy Inference System of the ADCES

To overcome the shortcoming of the TS fuzzy model, the Adaptive Neuro Fuzzy Inference System (ANFIS) is employed to identify the ADCES. The fuzzy-clustering-based ANFIS adopted in this paper has learning ability, so it must have higher precision than TS fuzzy model, as illustrated in Fig.7. The *RMS* and the *VAF* of the obtained ANFIS are 0.0013, 99.990%, 0.0090 and 99.612% for training data and validation data, respectively. In order to show the performance visually, the training error and validation error of the ANFIS are diagrammed in Fig. 8. It is clearly that the training error is far less than validation error and that the higher validation errors also occur near the limit range of values as that of TS model.

4.5 Neural network of the ADCES

The three-layer feed forward neural network (NN) is established for the ADCES. The number of nodes in hidden layer is 8, and the training times are 1000. The NN is trained 10 times, and average values of outputs, *RMS* and *VAF* are calculated to against uncertainty of NN initialization. The outputs and the indices are given in Fig.9 and Table1. The *RMS* and the *VAF* of the obtained ANFIS are 0.0037, 99.920%, .0047 and 99.894% for training data and validation data, respectively. The results show that the NN can model the ADCES precisely with high generalization, and that the NN has smallest training and validation error and highest similarity, and that NN can describe the characteristics of the ADCES even near the limit range of values.

To conclude the obtain model of ADCES, Fig. 10 depicts the training error and validation error of the obtained five models. Combined with Table 1, we can conclude as follows: the ADCES is a typical nonlinear system; the transfer function built with first principle method can only describe the ADCES roughly, while the intelligent model, including TS model, ANFIS and NN, can approximate the nonlinearity of the ADCES preferably; in normal (not the limit range) working domain, the TS fuzzy model and the NN have nearly the same capacity to describe the ADCES; in the subsequent controller design, the intelligent model (TS model or NN) should be employed firstly.

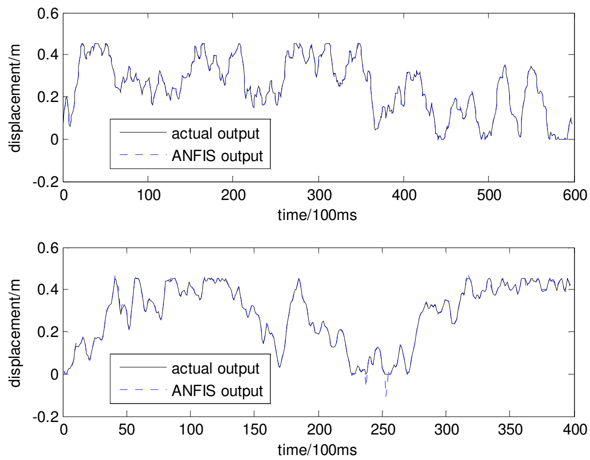

Fig.7. Actual output and ANFIS output: (a) training data, (b) validation data

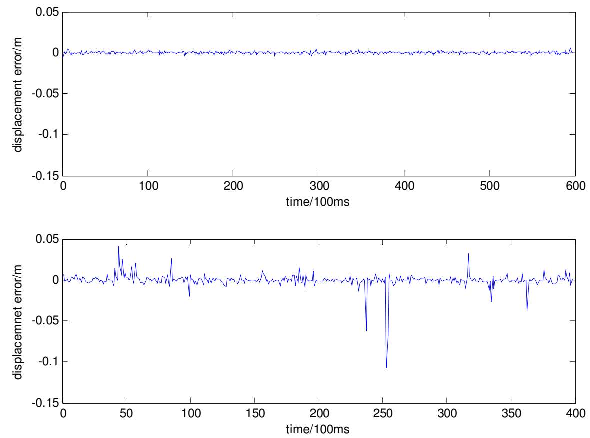

Fig.8. ANFIS output error: (a) training data, (b) validation data

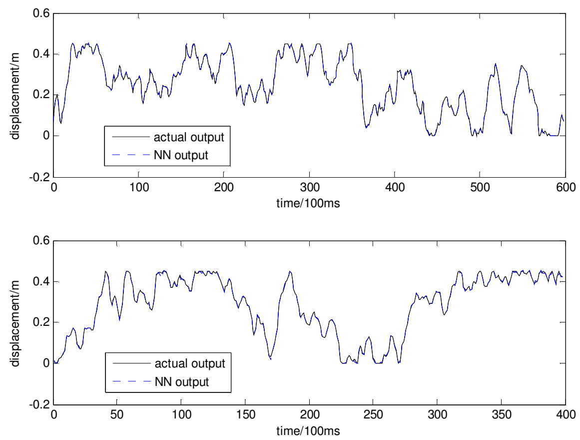

Fig.9. Actual output and NN output: (a) training data, (b) validation data

Table 1. Performance of five models for the ADCES

Models	Training *RMS*	Training *VAF*	Validation *RMS*	Validation *VAF*
TF	0.093	48.514%	0.150	14.30%
NARX	0.040	90.847%	0.043	91.654%
TS	0.0095	99.572%	0.0115	98.484%
ANFIS	0.0013	99.990%	0.0090	99.612%
NN	0.0037	99.920%	0.0047	99.894%

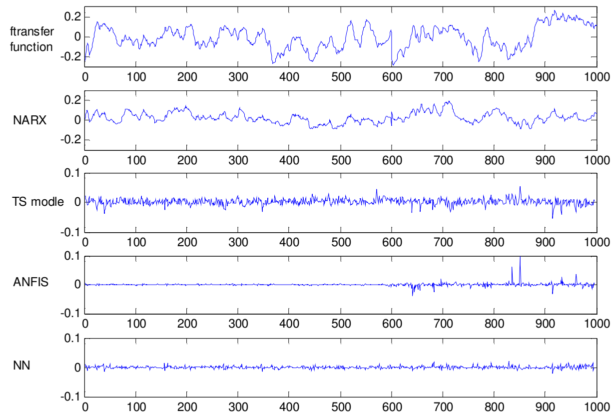

Fig.10. Training error and validation error of the obtained five models for the ADCES

5. CONCLUSION

Electrohydraulic system is a type of typical nonlinear system. Based on the ADCES, five models, including transfer function, NARX, TS fuzzy model, ANFIS, and neural network are identified. The analysis of the obtained models lays the foundation of the consequent controller design. The continued works of the paper is precision control of the ADCES based on fuzzy model or neural network.

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