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LINEAR MODELLING OF MAGNETO-RHEOLOGICAL DAMPERS USING HYBRID INTELLIGENCE TECHNIQUE

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Abstract

In this paper, the local linear models of a magneto-rheological (MR) damper are obtained based on the Takagi-Sugeno (T-S) fuzzy modelling approach. In these local linear models, the output force of the MR damper is expressed as the linear summation of the state variables (relative displacement and relative velocity) and input voltage. To obtain these local linear models with high accuracy, the genetic algorithm (GA) with a new encoding method is applied to search for the optimal model parameters. The proposed hybrid intelligence technique can evolve the fuzzy rule structure (number of rules and selection of rules) and the input structure (number of premise inputs and selection of premise inputs) simultaneously so that the obtained linear models have the simplest structures without decreasing the modelling accuracy. To validate the proposed approach, the modelling errors between the MR damper output and the corresponding linear model output are compared for the given number of rules case and for the automatically selected rules case with using three different selection approaches for the premise input variables. It is confirmed by the validation results that the proposed hybrid intelligence technique can find the optimal linear model for the MR damper.

1. INTRODUCTION

Magneto-rheological (MR) dampers have recently attracted significant research and application interests in vibration reduction of buildings, bridges, and vehicle suspensions etc. The MR damper is a semiactive control device that employs a special type of controllable fluids, the magneto-rheological fluids, which typically consist of micron-sized, magnetically polarisable particles dispersed in a carrier medium such as mineral or silicone oil. When a magnetic field is applied to the fluid, the particles are lined up in chains so that the fluid becomes semisolid within a few milliseconds, exhibiting a plastic behaviour. However, the practical use of MR dampers for control is still hindered by their inherently hysteretic and highly nonlinear dynamics. This makes the modelling of MR dampers more important for their applications. In order to characterise the performance of MR dampers, several models, which include the phenomenological model, neural network model, nonlinear black-box model, and viscoelastic-plastic model etc., have been proposed. Although these models have shown different advantages in describing the dynamic behaviours of MR dampers, they are all described as nonlinear models. Thus, linear control theory cannot be directly applied to design the optimal controllers for the real-world applications of MR dampers. To deal with this problem, in this paper, the local linear models of an MR damper are obtained based on the Takagi-Sugeno (T-S) fuzzy modelling approach.

Nowadays, the T-S fuzzy modeling technique is becoming powerful engineering tools for modelling and control of complex dynamic systems. The T-S fuzzy model is a system described by fuzzy if-then rules which can give local linear representation of the nonlinear system. For the reason that it employs linear model in the consequent part, conventional linear system theory can be applied for the system analysis and synthesis easily. The methods for learning T-S fuzzy models from data are based on the idea of consecutive structure and parameter identification [1]. To accommodate new input data, adaptive online learning of T-S fuzzy model has been developed [2]. On the other hand, design of a fuzzy model can be formulated as a search problem in multidimensional space where each point represents a possible fuzzy model with different rule structure, membership functions (MFs), and related parameters. Due to the search capability, evolutionary algorithms (EAs), such as genetic algorithms (GAs) and evolution strategies (ESs), have been utilised greatly in evolutionary fuzzy modelling. In some of EA-based fuzzy models, only parameters of fuzzy models are optimised using EAs while the structure itself is fixed [3]. Since parameters and rule structure of fuzzy models are codependent, they should be designed or evolved simultaneously. Thus, methodologies that try to change the rule structure by encoding all the information into the chromosome have been developed [4]. In this paper, the GA-based fuzzy modelling algorithm is developed. Especially, an encoding scheme that consists of three kinds of genes in one chromosome, which allows simultaneous optimisation of parameters of antecedent MFs, rule structure (number of rules and selection of rules), and input structure (number of premise inputs and selection of premise inputs) is proposed. For simplicity in the specified application, the fitness function only considers one evaluation criterion (accuracy) in terms of the sum of squared error (SSE), and the other aspect, compactness (number of rules) is constrained with the maximal number.

To demonstrate the effectiveness of the developed evolving T-S model, the presented model is applied to approximate the dynamic behaviour of an MR damper in the form of the linear T-S fuzzy model. The use of the T-S model to emulate the dynamic behaviour of the MR damper is validated by numerical values.

2. PHENOMENOLOGICAL MODEL OF MR DAMPER

A phenomenological model has been proposed by Spencer et al [5] to portray the behaviour of a prototype MR damper. This model is governed by the following seven simultaneous equations:

$$
\begin{aligned}
&F = c_1\dot{y} + k_1(x - x_0),\\
&\dot{y} = \frac{1}{(c_0 + c_1)}[\alpha z + c_0\dot{x} + k_0(x - y)],\\
&\dot{z} = -\gamma\,|\,\dot{x} - \dot{y}\,|\,z\,|\,z\,|^{n-1} - \beta(\dot{x} - \dot{y})\,|\,z\,|^{n} + A(\dot{x} - \dot{y}),\\
&\alpha = \alpha_a + \alpha_b u,\\
&c_1 = c_{1a} + c_{1b}u,\\
&c_0 = c_{0a} + c_{0b}u,\\
&\dot{u} = -\eta(u - v),
\end{aligned}
\tag{1}
$$

where F is the force generated by the MR damper; x is the displacement of the damper; y is an internal pseudo-displacement of the MR damper; u is the output of a first-order filter; v is the command voltage sent to the current driver. z is the evolutionary variable. In this model, k_1 is the accumulator stiffness; c_0 and c_1 are the viscous damping coefficients observed at large and low velocities, respectively; k_0 is the gain to control the stiffness at large velocities, and x_0 is the initial displacement of spring k_1 associated with the nominal damper force due to the accumulator; γ, β, A are hysteresis parameters for the yield element, and α is the evolutionary coefficient. c_{0a}, c_{0b}, c_{1a}, c_{1b}, α_a, α_b, and η are coefficients. In this model, there are a total of 14 model parameters to characterise the MR damper. The obtained values for the 14 parameters can be determined by fitting the model to the experimental data obtained in the experiments. As an example, a set of parameter values which was obtained by Spencer at al was given in paper [5]. And, it was also used in this paper for the numerical simulation.

3. LINEAR MODELLING OF MR DAMPER

3.1 Linear Model Represented by Takagi-Sugeno Fuzzy Model

In this paper, the output force of MR damper is ideally expressed by the following linear model:

$$F = \sum_{i=1}^{r} \xi_i f^i = \sum_{i=1}^{r} \xi_i (p_1^i x + p_2^i \dot{x} + p_3^i v), \tag{2}$$

$$\xi_i = \frac{\mu^i}{\sum_{i=1}^{r} \mu^i}, \tag{3}$$

$$\mu^i = \prod_{j=1}^{n} A_j^i = \prod_{j=1}^{n} e^{-\frac{(x_j - c_j^i)^2}{(b_j^i)^2}}, \tag{4}$$

where F, x, v are same with the variables explained in Section 2. $\dot{x}$ is the derivative of x and represents the velocity of the damper. A_j^i is a fuzzy set on the jth premise defined by the MF , $x_j = \{x_1, x_2, \ldots, x_n\}$ is the premise variable. c_j^i and b_j^i are centres and widths of membership function, respectively. p_1^i, p_2^i, p_3^i are linear parameters. r is number of rules, n is number of premise variables. r and n are determined by genetic algorithms.

The T-S fuzzy model is a system described by fuzzy IF-THEN rules which can give local linear representation of the nonlinear system by decomposing the whole input space into several partial fuzzy spaces and representing each output space with a linear equation. Such a model is capable of approximating a wide class of nonlinear systems. For the reason that it employs linear model in the consequent part, conventional linear system theory can be applied for the system analysis and synthesis accordingly. And hence, the T-S fuzzy models are becoming powerful engineering tools for modelling and control of complex dynamic systems. To obtain the linear expression (2) for an MR damper, we need using the fuzzy modelling technique as following:

$$
\begin{aligned}
&\text{IF } x_1 \text{ is } A_1^1 \text{ and } x_2 \text{ is } A_2^1 \text{ and} \ldots \text{and } x_n \text{ is } A_n^1, \text{THEN } f^1 = p_1^1 x + p_2^1 \dot{x} + p_3^1 v, \\
&\ldots \\
&\text{IF } x_1 \text{ is } A_1^r \text{ and } x_2 \text{ is } A_2^r \text{ and} \ldots \text{and } x_n \text{ is } A_n^r, \text{THEN } f^r = p_1^r x + p_2^r \dot{x} + p_3^r v,
\end{aligned}
\tag{5}
$$

Most of the studies on T-S fuzzy models consider that all inputs used in the premises are used in the consequents. However, in general, the premises of the rules describe different operating regions which depend on some antecedent inputs, while the consequents are linear (or affine) descriptions of the behaviour of the system in each of the operating regions that do not necessarily depend on the same inputs. So, in many applications, the approximation of a nonlinear system by local linear models requires many antecedent inputs to characterise the regions where the dynamics of the system can be considered as linear. On the contrary, inside each operating region, a simple linear autoregressive with exogenous input (ARX) model can approximate very well the local dynamical behaviour of the system. Hence, we consider that the antecedent vector $x_j = \{x_1, x_2, \ldots, x_n\}$ is not necessary the same as the vector $\{x, \dot{x}, v\}$ which was used in the consequent affine models. .

3.2 Encoding Scheme

Using GAs to design a T-S fuzzy model, one of the first important things is to encode the T-S fuzzy model into the chromosome with an efficient method. When the rule structure (number of rules and selection of rules), the input structure (number of inputs and selection of inputs), and the parameters of MFs associated are specified, the T-S fuzzy model will be specified. In order to realise the automatic selection of rules and inputs, a new encoding scheme is presented. The proposed encoding scheme uses a chromosome that consists three parts as shown in Figure 1. The first part deals with the rule selection and the optimisation of number of rules, the second part deals with the input selection and the optimisation of number of inputs, and the third part deals with the optimisation of parameters of MFs. Here, we adopt the binary-coded GAs and every gene in the chromosome is represented by a binary value `1' or `0'.

In the first and second parts, each gene represents one rule or one input. The position of one gene in the first part will denote the corresponding sequence of one rule in all the rule sets, and the position of one gene in the second part denotes the corresponding sequence of one input in all the input sets. The selection of rules or inputs is made by checking the binary value of the gene. If a specified gene in the first part is zero, then the corresponding rule is not valid and vice versa. If a specified gene in the second part is one, then the corresponding input is valid and vice versa. So, the information of genes in the first and second parts represents whether a certain rule or input is used or not for the current rule structure or input structure of an individual.

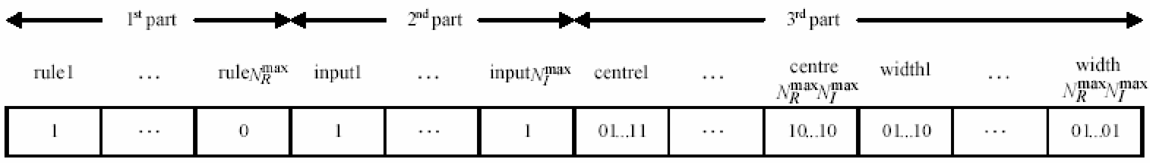

Figure 1. Encoding scheme for individual chromosome

3.3 Evolving T-S Fuzzy Model

Using the standard GAs together with the presented encoding scheme, the evolving T-S fuzzy model can be obtained by the following steps:
Step 1: Encode all the model parameters into chromosome using the presented encoding scheme.
Step 2: Generate initial population.
Step 3: Calculate objective functions. Firstly, after the centres, widths, and the numbers of rules and inputs are generated, the weights are calculated using the pseudo-inverse algorithm. Secondly, calculate the objective function. The SSE for the training data or the testing data is regarded as the objective function of each chromosome. If necessary, the evolved number of rules and number of inputs can be added into the objective function to obtain the reasonable sizes of the rules and inputs. Finally, record every objective function that corresponds to every set of parameters to a suitable fitness value according to the rank-based fitness assignment approach.
Step 4: Apply evolutionary operators: selection, crossover, and mutation.
Step 5: Use the elitist reinsertion approach.
Step 6: Evaluate the fitness of each individual.
Steps 3 to 6 correspond to one generation. The evolution process will repeat for a fixed number generations or will end when the search process converges with a given accuracy. The best chromosome will be used to determine the optimal numbers of rules and inputs, centres and widths.

4. MODELLING OF MR DAMPER

4.1 Data Collection and Pre-processing

In this paper, data for training and testing of the T-S model are obtained from the phenomenological model of the MR damper proposed by Spencer et al in [5]. In order to obtain a high quality trained model, a high quality training and testing data must be obtained first. To make the identified model fully represent the underlying system, the training samples should cover all possible combinations and ranges of input variation in which the MR damper will operate. This is to ensure that the evolving T-S models trained using these samples can accurately represent the behaviour of the MR damper to be simulated. Normally, the limits of these input signals are dependent upon the characteristic and specific application of the MR damper. Advanced knowledge of the input signals enables the creation of more useful training data. Given this idea, note that the maximum operational voltage of the MR damper is 2.25 V, which is defined as the saturation voltage of the damper and is obtained experimentally, and the situation of zero voltage will also be common during operation of the MR damper. Therefore, ranges of the voltage signal and its frequency are set as 0-2.25 V and 0-1 Hz, respectively, in this study. Likewise, the displacement of the MR damper ranges from ± 2 cm and its frequency ranges from approximately 0-5 Hz in this study. Signals of displacement and voltage used for training are produced using band-limited Gaussian white noise and some specified filters are used to obtain such random signals in indicated frequency ranges. Velocity signal is obtained by differentiating the displacement signal. Figure 2 shows the histories of displacement, voltage, and damper force. Out of these data, the first half data sets are used as the training data while the remaining data sets are used as the testing data for the T-S model.

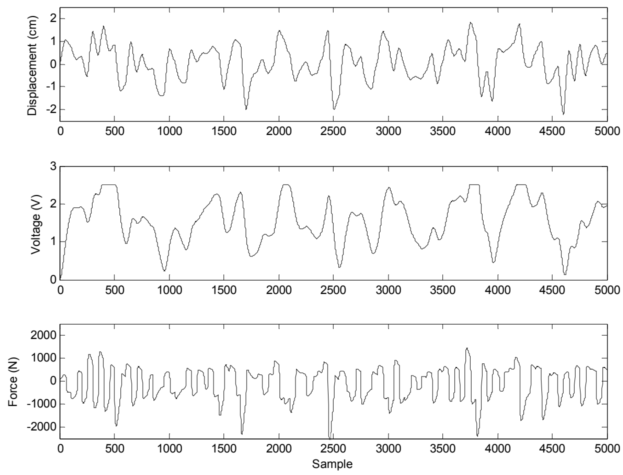

Figure 2. Training and testing data.

4.2 Forward Model

With the training and testing data established, the developed evolving T-S model is used to create a mapping model that emulates the "forward" dynamic behaviour of the MR damper. This model shows that the force generated by the MR damper depends on the command voltage, the displacement of the MR damper at the location where the damper is attached and its velocity. The SSE results between the true output and the model prediction and the obtained numbers of rules and inputs are calculated and listed in Tables 1 and 2 for 50 runs, where "Method 1" uses the same premise inputs as the consequent variables, and the premise inputs are given; "Method 2" uses the given premise inputs and given consequent variables but the premise inputs are different from the consequent variables; "Method 3" uses the given consequent variables and automatically selects the premise inputs using the presented algorithm. Table 1 shows the results for different methods with given number of rules, and Table 2 shows the results for different methods with automatically selected number of rules. It can be seen from Table 1 that for every given number of rules, "Method 3" can always give the best results among three different methods, and "Method 2" can give the results better than "Method 1". For three methods, when the number of rules is given as 30, the obtained results are relatively better than the other given numbers of rules for both the training and the testing data. It can be seen from Table 2 that with the automatically selected number of rules and premise inputs, "Method 3" can give reasonable good results compared to the other two methods. Figure 3 shows the predicted force of the MR damper using the well trained evolving T-S model for the data sets. It can be seen that predicted force matches with the target force.

Table 1. Modelling results in SSE using different methods with given number of rules

	Method 1				Method 2				Method 3			
	Training		Testing		Training		Testing		Training		Testing	
No	Min	Ave	Min	Ave	Min	Ave	Min	Ave	Min	Ave	Min	Ave
10	115	125	96	105	87	119	76	93	74	93	69	91
30	111	121	124	159	95	108	91	109	76	89	69	92
50	96	106	342	514	84	96	108	138	70	104	77	136
70	78	85	1713	2682	78	86	153	217	68	188	93	265

Table 2. Modelling results in SSE using different methods with automatically selected number of rules

	Method 1		Method 2		Method 3	
	Min/Max	Ave/Best	Min/Max	Ave/Best	Min/Max	Ave/Best
Training	113	138	89	127	79	109
Testing	102	122	80	110	79	109
Rule Number	9/19	13/18	12/25	18/20	4/33	17/32
Premise Number	3/3	3/3	6/6	6/6	1/8	4/7

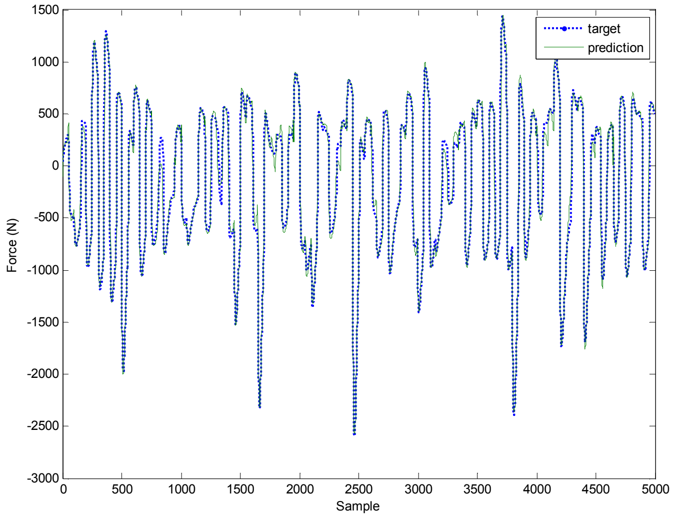

Figure 3. Training and testing result.

4.3 Model validation

To further validate the effectiveness the T-S fuzzy model in modelling the dynamic behaviour of an MR damper, two more sets of validation data, where validation data I uses random displacement and random voltage with different frequency characteristics, validation data II uses sinusoidal displacement and sinusoidal voltage, are generated. Figure 4 shows the predicted force of the MR damper for validation data I. Figure 5 shows the predicted force of the MR damper using the T-S fuzzy model for validation data II. It can be seen that the predicted forces match the targeted forces. It is noticed from the validation results that the T-S fuzzy model can emulate the dynamic behaviour of an MR damper with acceptance even when the input data are different from the training data in both frequency and amplitude.

5. CONCLUSIONS

In this paper, a local linear model based on T-S fuzzy model is developed to emulate the dynamic behaviour of an MR damper. The rule structure, input structure, and the MF parameters are simultaneously evolved by GA with the objective to reduce the SSE between the predicted out and the true output. It is certified by the testing and validation data that the presented evolutionary T-S fuzzy model can emulate the dynamic behaviour of the MR damper with simple linear representation.

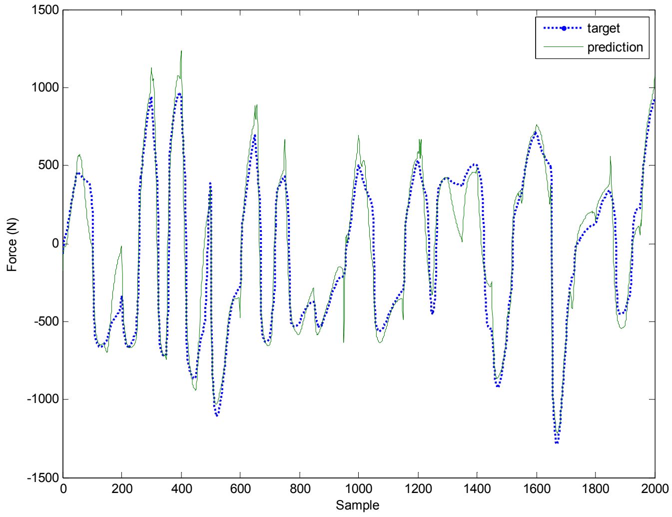

Figure 4. Validation result for validation data I.

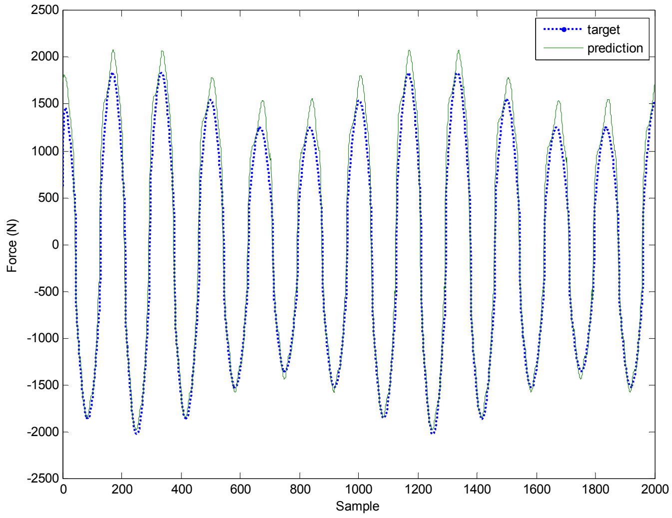

Figure 5. Validation result for validation data II.

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