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System Identification of Electro-Hydraulic Actuator System using ANFIS Approach

T. G. Ling, M. F. Rahmat*, A. R. Husain

Department of Control and Mechatronic Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

*Corresponding author: fuaad@fke.utm.my

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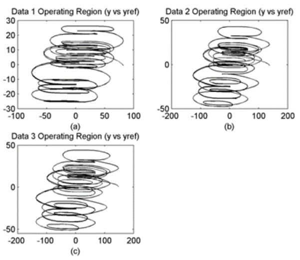
Graphical abstract



Abstract

Precise control of an electro-hydraulic actuator (EHA) system has been an interesting subject due to its nonlinearities and uncertainties characteristics. Suitable controller can be designed when the precise model of the system is available. Adaptive Neuro-Fuzzy Inference System (ANFIS) modeling technique has proven can model various nonlinear systems at high accuracy. The objective of this paper is to obtain an ANFIS model from EHA system stimulus-response data with less complicated model structure and fewer system parameters. The validation of ANFIS model is done using various data sets which contain different operating region and limited data set, where data set is reduced to small operating region. Results show that ANFIS model can estimate the response nonlinear EHA system with more than 97% high best-fitting accuracy, with simple structure, under different operating region condition.

Keywords: EHA; ANFIS; precise model; simple structure; operating region

Abstrak

Kawalan tepat penggerak sistem elektro-hidraulik (EHA) telah menjadi subjek yang menarik kerana ciri-ciri tak lelurus dan tidak menentu. Pengawal yang sesuai boleh direka apabila model sistem yang tepat disediakan. Teknik pemodelan Adaptive Neuro-Fuzzy Inference System (ANFIS) telah terbukti dapat memodelkan pelbagai sistem tak-linear pada ketepatan yang tinggi. Objektif kertas ini adalah untuk mendapatkan model ANFIS daripada data rangsangan-tindak balas EHA sistem dengan struktur model yang kurang rumit dan kurang parameter sistem. Pengesahan model ANFIS dilakukan dengan menggunakan pelbagai set data yang mengandungi kawasan operasi yang berbeza dan set data yang terhad, di mana set data dikurangkan ke kawasan operasi yang kecil. Hasil kajian menunjukkan model ANFIS boleh menganggarkan tindak balas sistem EHA tak-linear dengan ketepatan terbaik sesuai yang melebihi 97% dengan struktur yang ringkas, di bawah keadaan kawasan operasi yang berbeza.

Kata kunci: EHA; ANFIS; model yang tepat; struktur ringkas; kawasan operasi

■1.0 INTRODUCTION

Electro-hydraulic actuator (EHA) system is one of the most important drive systems in industrial sector and engineering practice due to its high power to weight ratio, fast and smooth response, high stiffness and good positioning capability [1]. EHA system's ability to generate high forces in conjunction with fast response time and have good durability puts the system in high interest among heavy engineering, such as active suspension control and industrial hydraulic machine [2]. EHA system's position tracking accuracy has been one of the most interesting researches in last decades due to the merit in positioning. Most of the electro-hydraulic applications require precise and accurate control, however the system's nature behavior of highly nonlinearities, uncertainties [3] and time varying characteristics [4] make the research challenging and the controlling process a tough task [5]. In order to design a precise controller for the system, accurate model representing the real system have to be obtained at the first place.

Modeling is the process to obtain the model of a system, which is the first step of any system analysis [6]. Modeling can be done either by physical law based modeling or system identification. Physical law based modeling method such as performed in [1, 7-11] is hard to perform as it requires knowledge and understanding of the system. System identification, on the other hand, is the process of formulating the mathematical model of system using measurement data without need of prior knowledge about the system [12]. The term identification was introduced by Zadeh [13], referring to the problem of determining the input-output relationships of a black box based on experimental data sets.

There are a number of researches apply system identification technique to construct a linear model for EHA system. A linear model is popular as it is the simplest approach and discrete time model which can represent the relationship between input and output of the system. Among the linear model used, ARX (autoregressive with exogenous) model is widely used to represent EHA system [14-18]. Research has shown that ARX model can approximate the EHA system with high precision.

Fuzzy modeling is another alternative to model a system. ANFIS (Adaptive Neuro-Fuzzy Inference System) is the major training routine of Takagi-Sugeno fuzzy model. ANFIS has shown the ability to estimate various nonlinear systems of different applications [19-23]. However, despite the ability of the technique in modeling; it is not being widely used on an EHA system. Research in [24, 25] applies Mamdani fuzzy model to an EHA system, and the result is satisfactory. However, data captured from the system is only used to generate the rules for fuzzy model instead of parameters training purpose.

The first objective of this paper is to obtain an accurate EHA system model with less complicated model structure, rules and fewer parameters using ANFIS training approach. Simpler model which contains fewer numbers of rules and number of parameters is more preferred than a more complex model when the accuracies of both models are similar based on Parsinomy Principle [26, 27]. The second objective is to investigate the estimation ability of ANFIS model in different condition, which is at different amplitude of input, different operating region from different data set and limited training data set.

2.0 EXPERIMENTAL SETUP

The experiment setup of the EHA system consists of a few main parts: hydraulic pump, piston, position sensor, servo valve, and hydraulic motor, as depicted in Figure 1.

Stimulus signal is generated using MATLAB platform, and sent to the servo valve through NI-PCI-6221 card. The servo valve controls the flow of hydraulic fluid and moves the piston accordingly. The position of the piston, which is connected to a load, is measured by wire sensor, WDS 300 p60. The wire sensor can measure up to 300 mm, corresponding to the piston length, which is 300mm as well. Experiment is started by setting the piston to the middle position to perform response when stimulus signal is provided.

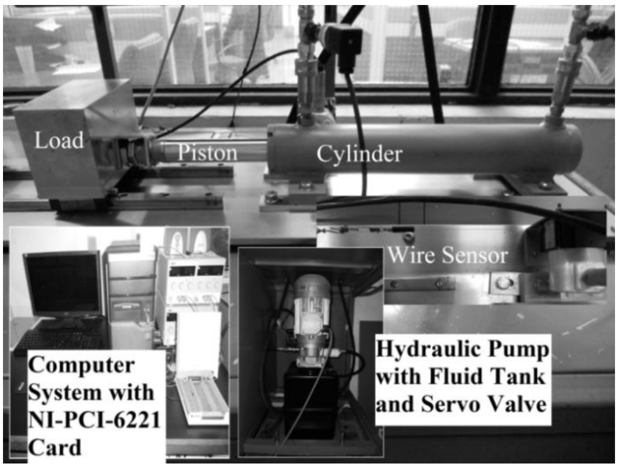


Figure 1 Experiment setup

3.0 ANFIS MODEL GENERATION

The first step in system identification of an ANFIS model for EHA system is to obtain a set of stimulus response data from the system. Stimulus signal is used to excite the system, and the characteristic of the system is captured. Stimulus signal which is rich in amplitude and frequency can excite more operating region of the system and realize its characteristic. The signal expressed in (1) is used as the stimulus signal to EHA system. Figure 2 shows the stimulus and response signal of EHA system being excited by signal in equation (1).

$$u(t) = 15(1.5cos(2\pi 0.05t) + 1.5cos(2\pi 0.2t) + 2.5cos(2\pi t)) \tag{1}$$

As shown in Figure 2, the stimulus signal's (reference position) limit is ranging from -72.9 mm to 82.5 mm, while the EHA system has the operating range limit of -150 mm to 150 mm. Thus, another two sets of data with different limit range are obtained, which is from -126 mm to 137 mm and -136 mm to 148 mm. The purpose of these data sets taking is to test the ability of the model to estimate the response of EHA system when the system is operating near its limit. The operating region of the data set is a plot by stimulus signal versus response signal. The operating region of each data set is shown in Figure 3.

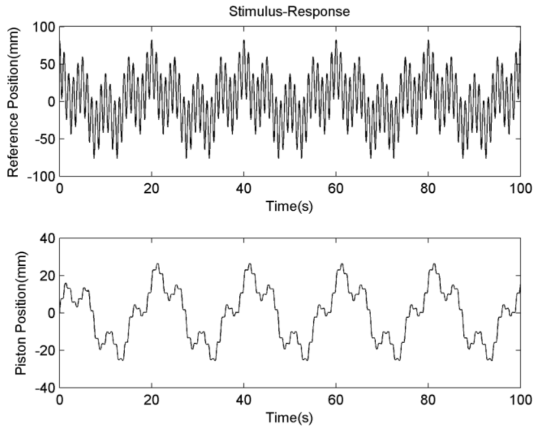


Figure 2 Stimulus-response of EHA system

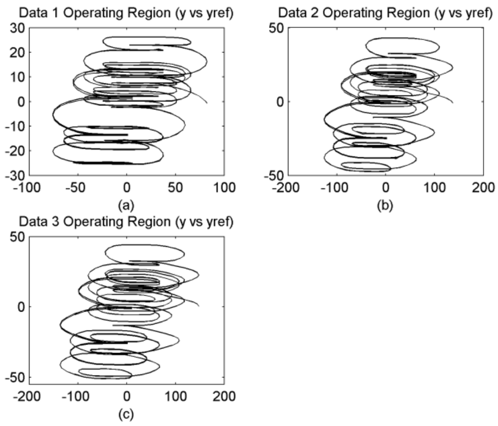


Figure 3 Operating region of different data set

Figure 3 shows the different operating region of each data set. Figure 3(a) is the EHA system's response when excited using stimulus data 1 which is limited from -72.9 mm to 82.5 mm. Figures 3(b) and 3(c) are the system's response excited by stimulus data 2 and 3 and the limits are from -126 mm to 137 mm and -136 mm to 148 mm. Even though all three sets of data having a different operating region, the patterns of the responses are similar. For system identification process, the total data set is divided into two parts, one is for the parameter estimation and another is for model validation. The data set used for parameter estimation is known as training data. Training data covers all the operating region of the system and can ensure a better model with higher accuracy. Normally, training data contains 50% of total data set. Limited training data set is provided to test the ability of modeling.

Figure 4 shows the operating region of data 1 with 50%, 30% and 10% training data. As shown in Figures 4(a) and 4(b), the operating region of data sets are approximately the same. Thus, both data sets contain similar information regarding the characteristic of the system. Training data with 10% data as shown in Figure 4(c) shows a smaller operating region, indicates loss in system information comparing to Figures 4(a) and 4(b).

Second step is the generation of the ANFIS model structure. ANFIS modeling technique was first developed by Jang [28]. ANFIS is the integration of the interpretability of a fuzzy inference system with adaptability of a neural network. ANFIS architecture as shown in Figure 5 contains five layers in the inference system. Each layer involves several nodes, which is described by node functions. Nodes are having similar function among layers and different function between layers. Output of the nodes of present layers will be served as input for the next layers. Details of the nodes' function can be found in [28].

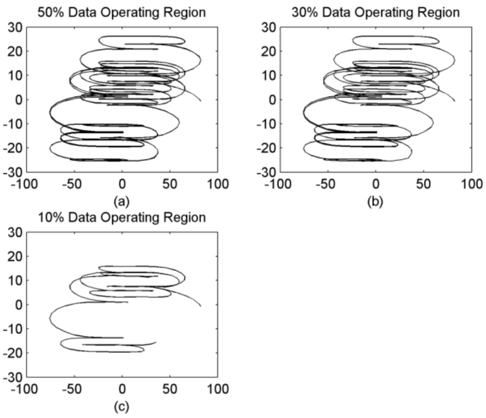


Figure 4 Operating region with different training data

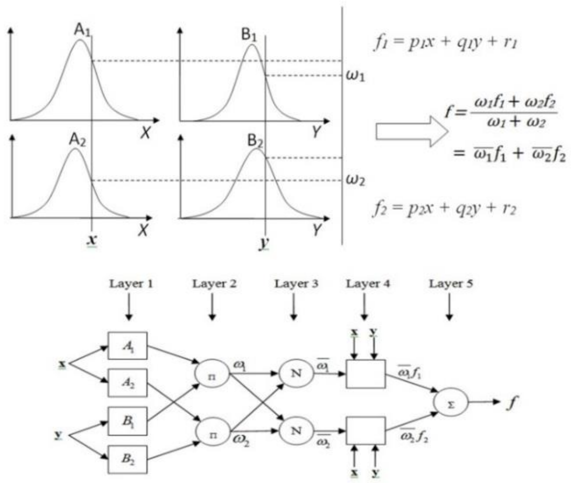


Figure 5 ANFIS architecture [28]

To perform ANFIS modeling, preliminary system model such as the choice of inputs, number of inputs, number of membership function (MF) has to be provided. The structure can be determined using Parsinomy Principle [26, 27]. Parsinomy Principle states that, out of two identifiable model structure that fit certain data, the model with simpler form will be chosen. Thus, model with simpler structure and less parameters, while accuracy is similar to a more complex model, is selected as the model of the system. The accuracy of the model is validated by the best fitting percentage and Root Means Squared Error (RMSE) between model simulated and actual response of the response. Higher best fitting percentage and lower RMSE indicate better and more accurate system model. The preliminary model obtained is then trained with the training data using ANFIS algorithm.

4.0 RESULTS AND DISCUSSIONS

The first objective of this paper is to obtain a system model of EHA system, which is accurate with less complicated model structure, fewer rules and model parameters. Model identification process to achieve first objective is discussed in part 1 and part 2, which the model input selection and number of Membership Function (MF) decision. Second objective is to investigate the ability of ANFIS modeling in different conditions, such as in different operating region as in part 3 and limited training data set in part 4. All the tests are conducted using three different sets of data as discussed in previous section.

4.1 Selecting the Inputs for ANFIS Model

Firstly, number of input arguments to the ANFIS model is determined. Number of input variables is directly related to the structure of the system model. Larger number of inputs will result in more complicated structure. In this case, ANFIS model of two inputs and three inputs structure are obtained using following training criteria:

a. 50 % of data set 1 is used for model's parameter training
b. The number of MF for each input is 2, with type of generalized bell shape MF
c. Initial inference system is generated using grid partitioning on given data set
d. Number of rules is the product of the total number of MF in each input
e. ANFIS training option of parameters is set to 1 epoch of training, 0.01 initial step size, 0.5 step decreasing rate and 1.5 step increasing rate. These values are the default parameters for ANFIS training algorithm.

The input is selected throughout several candidates: u(k) which is input and also stimulus signal to the system and delayed sample output y(k-1), y(k-2), y(k-3), and y(k-4). The output of the system model is always y(k), which is the response of the system. For selecting two inputs, first input is u(k) and another one selected from delayed output. For three inputs structure, first input is u(k) and another two inputs is selected from delayed output. Both models are run through the variable selection process by obtaining a model for each possible combination of all the input candidates, and the model which has the highest best fitting accuracy and lowest Root Means Squared Error (RMSE) is selected as the model. Best fitting accuracy and RMSE are obtained by comparing the simulated response and actual response of the system. The models of two inputs structure and three input structure are compared.

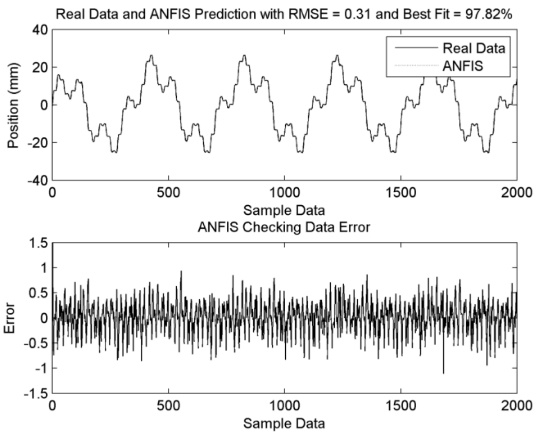


Figure 6 2 Inputs model simulation

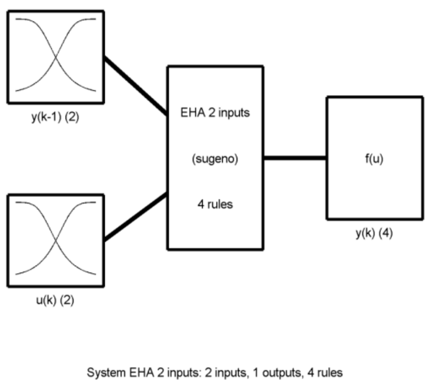


Figure 7 2 Inputs model structure

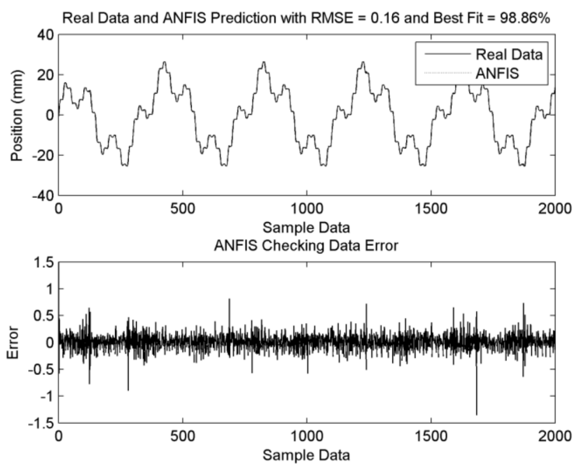


Figure 8 3 Inputs model simulation

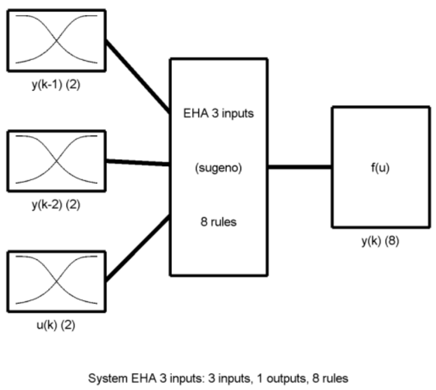


Figure 9 3 Inputs model structure

From Figure 6, it is shown that the estimation result of the model fits the real response of the EHA system by 97.82% with RMSE 0.31. This indicates the model is very accurate in simulating the response of the system being modeled. Error plot in Figure 6 shows that the estimation error is in between ±0.5mm. Figure 7 displays the structure of the model, with two inputs, y(k-1) and u(k) which has two MFs respectively, and total of four rules. Every rule is corresponding to one rule output. The final output, y(k) is the weighted average of all rule outputs.

Figure 8 shows the best fitting and RMSE result of the system model with three input structure. The best fitting accuracy is higher than two input model structure, which is 98.86%. The RMSE is also smaller, which is 0.16. Figure 9 shows the structure of the model. The model has three inputs, which are y(k-1), y(k-2) and u(k) with eight rules. Error plot also shows that the estimation error is smaller, less than ±0.5mm.

Increase in the number of inputs will results in more rules. Having more rules will cover more operating region of the system, thus will result in higher accuracy. This is shown by comparing Figure 6 and Figure 8. However, the increase in the number of inputs also means that the number of system parameters is increasing, and the structure of the system becomes more complex. From Figure 7 and Figure 9, it is shown that model with two inputs having four rules and four rule outputs, while the model with three inputs doubles in the number of rules and rule outputs. Three input structure model also has more parameters. Even though the model with three inputs is more accurate than the model with two inputs, the increase in accuracy is not significant, which is approximately one percent. According to Parsinomy principle, the model with two inputs which contains four rules is chosen as model rather than model with three inputs.

4.2 Number of Membership Functions

In part 1, the effect of the number of inputs to system model has been explored. Model structure identified is having two inputs. In this section, the influence of the number of membership function to model's accuracy is investigated. According to [29], when the number of MF increases, the accuracy of the model increases as well. This test is conducted by generating different model which contains a different number of MF for the input. The data partitioning method in this paper is grid partitioning, where the membership function is distributed equally throughout the input limit. The training criterion is remain the same with part 1, only the number of membership functions now varies from two MFs to four MFs.

The performance and structure of the model with two inputs and has two MF for each of the inputs is shown in Figure 6 and Figure 7. The accuracy of the model is 97.82% best fitting and low RMSE of 0.31. The accuracy of this model is being compared to other models which have three MF and four MF structure.

Figure 10 and Figure 11 display the model response accuracy and structure of the model with three MF in each input. Comparing to model with two inputs, the accuracy of the new model has increased from 97.82% to 97.91%. This indicates that the new model is better than first model in terms of best fitting accuracy. However, the increase of accuracy is not significant, and the structure is more complex with a total of nine rules, which is shown in Figure 11. Thus, the model with two MF per input is a better model according to Parsinomy principle in terms of simplicity of the model

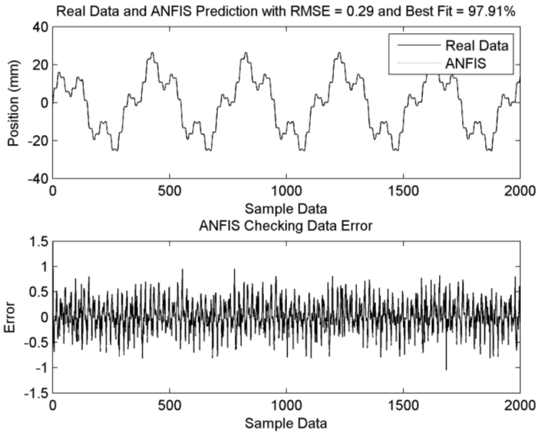


Figure 10 2 Inputs 3 membership function model simulation

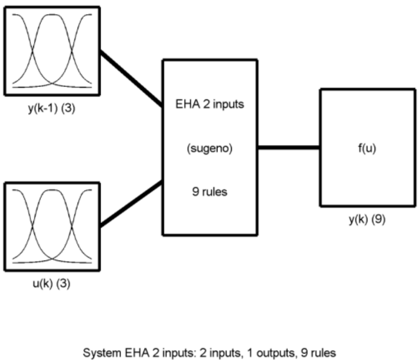


Figure 11 2 Inputs 3 membership function model structure

Figure 12 and Figure 13 have proven the theory in [29] that increasing the number of MF will have a better accuracy model. Four MF model structure has better accuracy of 97.98% comparing to previous two models, and have a total of 16 rules. However, the improvement of model accuracy is still not significant with slightly 0.16% increase, thus the model structure determined for EHA system is having two inputs with two membership functions per input.

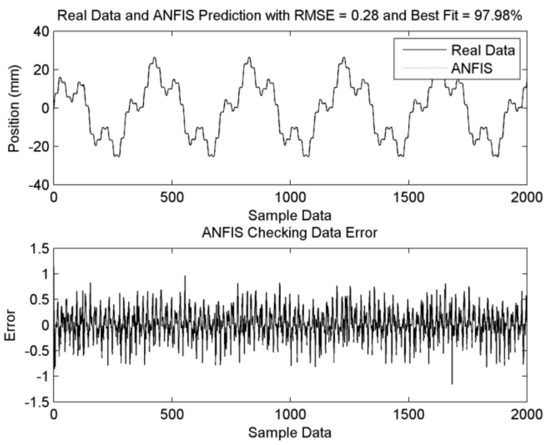


Figure 12 2 Inputs 4 membership function model simulation

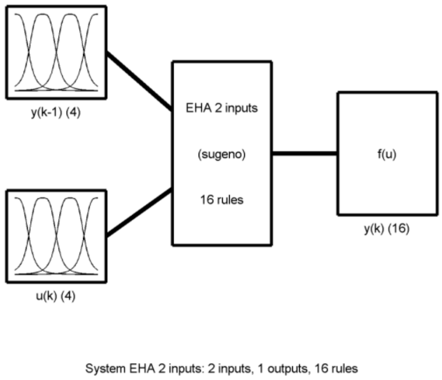


Figure 13 2 Inputs 4 membership function model structure

4.3 Different Stimulus Response Data Set

Part 3 and part 4 examine the estimation ability of the ANFIS model obtained. There are three sets of data from EHA system which have similar data response, but with different operating region, as shown in Figure 3. The investigation of the estimation ability is done by obtaining model using one of the data set and test on the other two sets of data. In this part, training criterion is same as in part 1, with structure of two inputs and two membership functions each. The accuracy of the model in estimating each pair of data set is shown in Table 1.

Table 1 System model best fitting percentage

System Model	Data Set		
	1	2	3
Model from data 1	97.82%	97.09%	96.78%
Model from data 2	97.43%	97.84%	97.88%
Model from data 3	97.35%	97.83%	97.89%

From Table 1, it is shown that at most conditions, model estimation accuracy is the best during condition where the data set is used to train the model. For example, model which is trained using data set 1 is having best accuracy when simulating the response with data set 1, comparing to another two set of data. Same situation goes to model which is trained with data set 3. The model simulation response of data set 2 have a slightly better response when simulating the response of data set 3, but the difference is not significance and is approximately the same. From the table, even though the best fitting accuracy varies when the model is estimating the response at which it is not being trained with, the difference is very small, and can be assumed that the ability of modeling is approximately identical. The ANFIS modeling ability of EHA system for this part has shown that the model can estimate the response of the system at the different operating region with high precision.

4.4 Limitation of Training Data Set

In previous part, ANFIS modeling ability has been tested on similar data set but with a different operating region. In this part, testing of ANFIS modeling ability is extended to limited data set. In previous part, the model is obtained by using 50% of total data set for training purpose. In this part, the data set is limited to 30% and 10% of total data set. Data set 1 is used for this part. The best fitting percentage and RMSE are compared with model which is trained with 50% data, which has best fitting 97.82% and RMSE 0.31, as shown in Figure 5.

Training criterion is same with part 1, with structure of two inputs with two MF for each input.

As shown in operating region figure in Figure 4(a) and 4(b), both data sets' operating region are very similar. This means the 30% training data contains similar information as 50% training data. The simulation result shown in Figure 14 indicates very high similarity comparing to result of 50% training data. Both model having best fitting accuracy of 97.82% and 97.81%, with equal RMSE, 0.31. This states that even though less training data is provided in model generation process, ANFIS model still can produce a same high accuracy estimation result, given that the training data set covers all the operating region of the system.

Figure 15 shows simulation result at condition where not complete data set is provided for model generation. From Figure 4(c), 10% of total data shows empty region in some operating region when compared to 30% and 50% of data. Result from this is that the model will lose some system characteristic during the model identification process. The loss can be seen in Figure 15, which displayed the response of the model with 10% training data. The best fitting accuracy is decrease to 96.98% and higher RMSE, 0.42 compared to previous two models. From the error plot, it is observed that higher error occurred starting from sample data 200 until 500.

Figure 16 shows the operating region plot which combines the data operating region from data sample 1 until 200, and data sample 200 until 500. It is shown that the combined operating region of both data sets cover the total operating region for total data set, which is shown in Figure 4(a) and 4(b). High error occurs in model estimation at the region where no training data is provided.

The model validation tests in this section show the effects of the training data set in the accuracy of the system model. When system model is trained using less data set which does not covers all the system's operating region, the accuracy of the model is slightly lower than model which is trained with more training data. Even though the model which is trained with limited data set still can provide high accuracy in response estimation, a sufficient amount of training data which covers all the operating region of the system is recommended to ensure a more accurate system model.

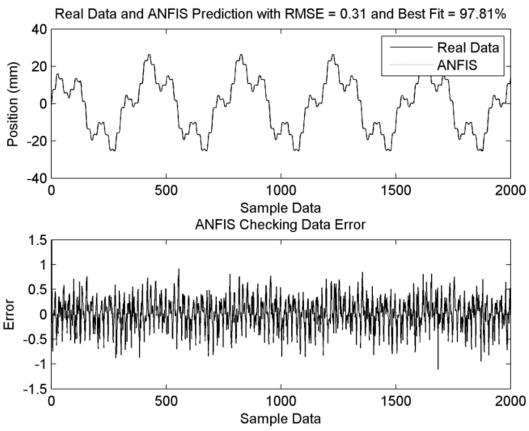


Figure 14 30% training model simulation

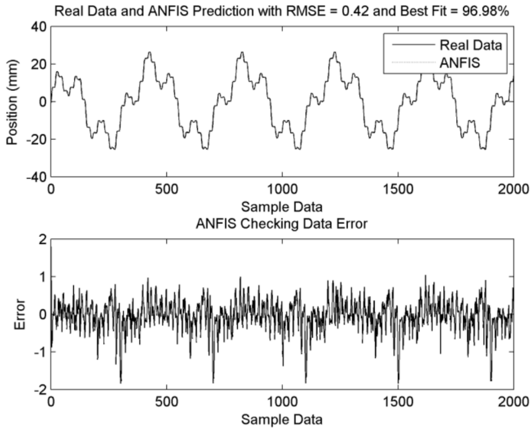


Figure 15 10% training model simulation

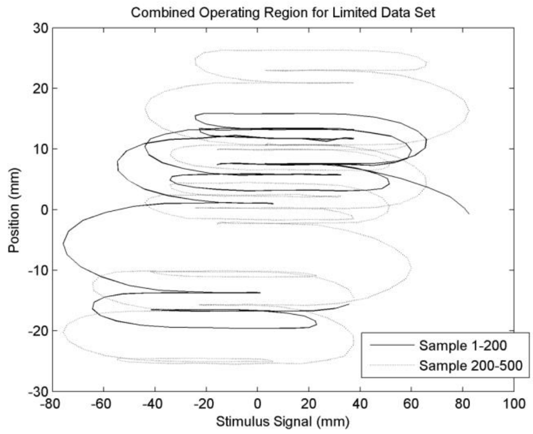


Figure 16 Combined operating region of limited data set with complete data set

5.0 CONCLUSIONS

The selection of inputs and number of membership functions are the two main keys in determining the structure of ANFIS model of a system. The increase of the number of inputs and membership functions will increase the accuracy of the model, but also result in more complicated model structure with more rules and parameters. The aim of the system identification process of the EHA system is to obtain a model which can represent the system at high accuracy, with less complicated structure and fewer system parameters. The ANFIS model obtained for EHA system is having two inputs, and each of the inputs have two membership functions. Total rules of the model is four, corresponding to four outputs. Final output is the average weight of the four outputs. The increase in the number of inputs and rules does not significantly increase the accuracy of the model.

ANFIS modeling has shown to have the ability to estimate the response of the system in different situations. Provided with three sets of data with different operating region, ANFIS model provides an estimation result with similar accuracy with model generated from either set of data. ANFIS modeling also showed the ability in estimation when provided with limited data set. Higher error occurs at the region where no training data is available. Although the error appears to be bigger, the model is able to estimate the overall system with high precision with 96.98% best fit accuracy. However, sufficient training data which covers the entire operating region is recommended to ensure a more accurate system model.

Due to capability of ANFIS model in precisely estimate the response of EHA system, there are some recommendations in obtaining model for EHA system using a more statistical approach for future study. Firstly, input selections of the model can be determined from mathematical modeling of the EHA system. Secondly, number of membership functions can be determined using statistical approach, such as gap statistic. Both of the recommendations can help in modeling by less heuristic approach.

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