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ACCURACY COMPARISON OF ARX AND ANFIS MODEL OF AN ELECTRO-HYDRAULIC ACTUATOR SYSTEM

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Abstract – Precise control of electro-hydraulic actuator (EHA) system has been an interesting subject due to its nonlinearities and uncertainties characteristics. Good control can be designed when precise model of the system is available. Linear ARX modelling has widely been applied and satisfying result has been obtained, through linearization process. The objective of this paper is to compare ARX model with nonlinear ANFIS (Adaptive Neuro-Fuzzy Inference System) model, which can represent the real EHA system more precisely using same linearized data. Results show that ANFIS model is more accurate in approximation estimation of EHA system than ARX model on linearized data.

Index terms: ARX, ANFIS, electro-hydraulic, linearization, nonlinear.

I. INTRODUCTION

Electro-hydraulic actuator (EHA) system is one of the fundamental drive systems in industrial sector and engineering practice. EHA system is more preferred over electric drive in certain applications because of its high power to weight ratio, fast and smooth response, high stiffness and good positioning capability [1]. Examples of applications of EHA systems are electro-hydraulic positioning systems [2-3], active suspension control [4], and industrial hydraulic machines [5]. EHA system has the ability to generate high forces in conjunction with fast response time and have good durability. This ability puts the system in high interest among heavy engineering [6].

Due to the merit in positioning, EHA system's position tracking accuracy has been one of the most interesting researches in last decades. EHA system's nature behaviour of highly nonlinearities, uncertainties [7] and time varying characteristics [8] make the research challenging. Most of the electro-hydraulic applications require precise and accurate control. The nonlinear dynamics of EHA system make the controlling process a tough task [9]. In order to design a good controller for the system, system model which can accurately represent the real system have to be obtained first.

Process to obtain model is the first step of any system analysis [10]. Modelling can be done either by physical law based modelling or system identification. Physical law based modelling method such as performed in [1, 11-15] is hard to perform as it requires expert knowledge and thorough understanding about the system. System identification, also well known as "black box" identification, requires only set of stimulus-response data and no prior knowledge about the system in order to construct the model.

There is a number of researches apply system identification technique to construct linear model for EHA system. A linear model is popular as it is the simplest, discrete time model which can represent the relationship between input and output. Among the linear model used, ARX (autoregressive with exogenous) model is widely used to represent EHA system [16-20]. Research has show that ARX model can approximate the EHA system with high precision using linearized data set.

Fuzzy modelling is another alternative to construct a model for the system under test. ANFIS (Adaptive Neuro-Fuzzy Inference System) which is the major training routine of Takagi-Sugeno fuzzy model, has shows the ability to estimate nonlinear systems for different applications [21-25]. However, despite the ability of the technique in modelling, it is not being used on an EHA system, except fuzzy model which have been applied once [26-27]. The research by [26-27] applies Mamdani model to an EHA system, and the results is satisfactory.

The objective of this paper is to compare a linear ARX model with a nonlinear ANFIS model for the electro-hydraulic actuator system, which can more precisely approximate the response of EHA system. Both models are trained by same set of linearized data.

II. MODELLING PROCESS

Modelling process is performed on MATLAB platform, which requires System Identification Toolbox installed. To perform system identification on the EHA system, a set of stimulus-response signal has to be obtained. Stimulus signal is used to excite the system and produce response signal. When the stimulus signal excite more operating region of the system, stimulus-response data set obtained will contain more system characteristics. A good stimulus signal often consists of different amplitudes and frequencies. Stimulus signal used to excite the EHA system under test is a multisine signal, given in following equation.

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

By looking at equation (1), one can visualize that the stimulus signal comprises of three different frequencies, which are 0.05Hz, 0.2Hz and 1Hz. Take note that the highest frequency of stimulus signal is limited to 1Hz, as the EHA system performs like a low pass filter, which only response to low frequencies. Combination of different frequencies and amplitudes, the stimulus signal is believed can excite most of the operating region of EHA system. Figure 1 shows the stimulus signal used and Figure 2 reflects the response signal of EHA system.

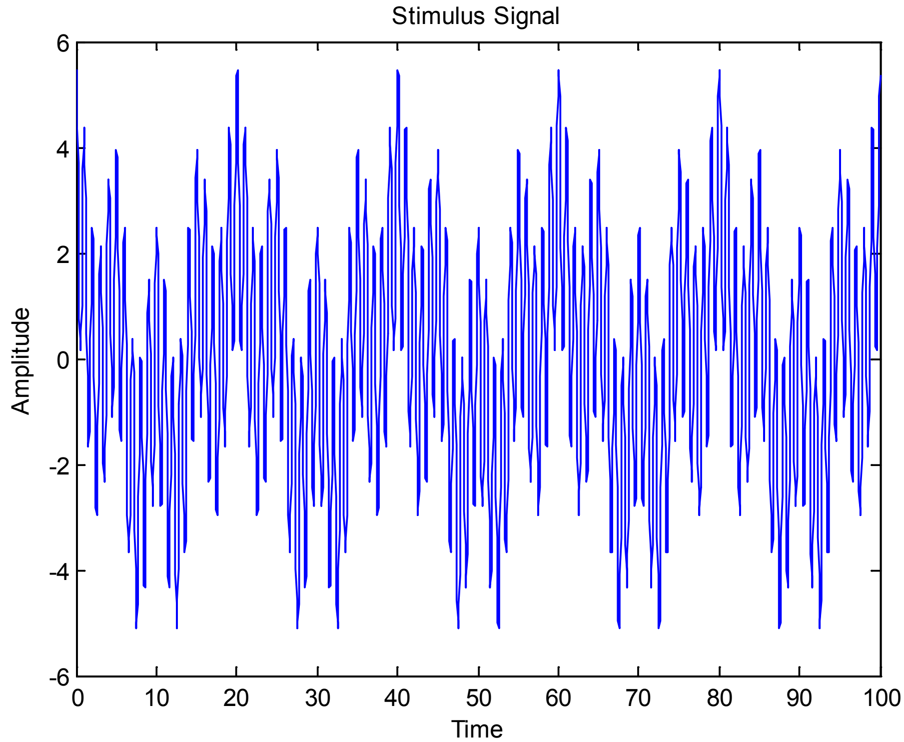

Figure 1: Stimulus Signal

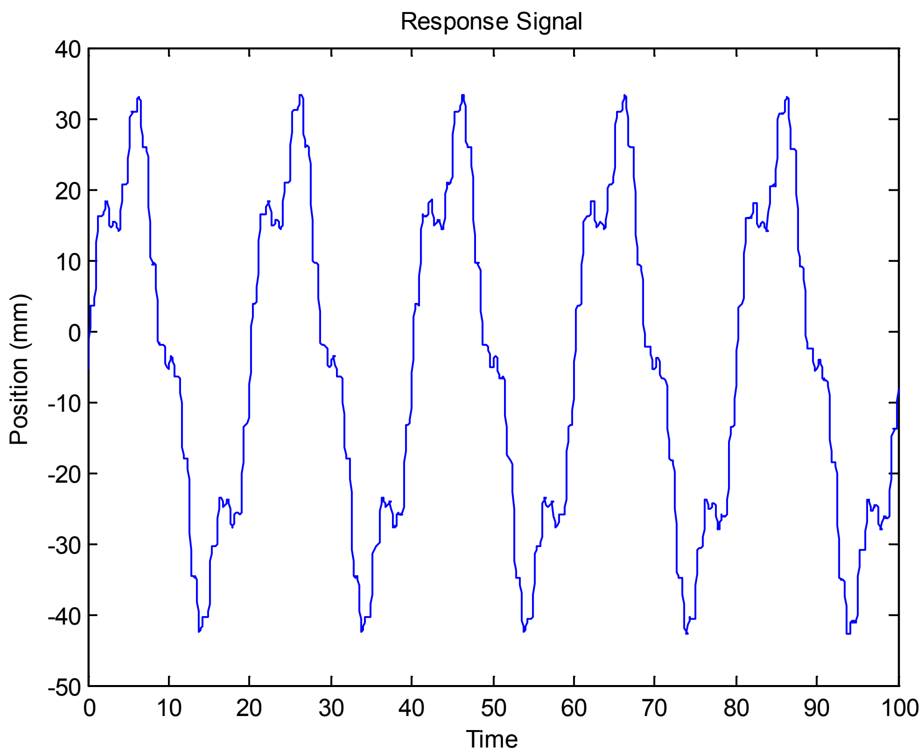

Figure 2: Response Signal (Linearized)

In this paper, an ARX model and an ANFIS model is obtained from data set above and later the accuracy of both model is compared. Note that ARX model is a linear model while ANFIS model is nonlinear model. Figure 3 shows the general ARX model, where *u* and *y* represent input and output, *e* indicates error signal, *A* and *B* are parameters to be estimated. Takagi-Sugeno fuzzy model is chosen as ANFIS model. General form of Takagi-Sugeno fuzzy model is showed in Figure 4. Three fuzzy inputs and one functional output is determined. Each input contains two generalized bell (gbell) membership functions. Functional output of Takagi-Sugeno model is a linear model.

Parameters in ARX model are optimized using least-squared method. ANFIS constructs the model by performing Fuzzy C-Means clustering algorithm and the parameters are estimated by hybrid learning algorithm (least-squared and back propagation gradient descent method). When the models are obtained, validation of the models is done on the checking data set, which will be discussed later. Accuracy of the models is compared. In this paper, RMSE (Root Mean Squared Error) and Best Fitting Percentage are used as standard to indicate the precision of either ARX or Fuzzy model. Error plot is also shown for further visualization.

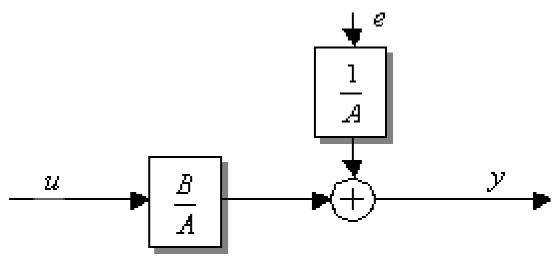

Figure 3: General ARX model

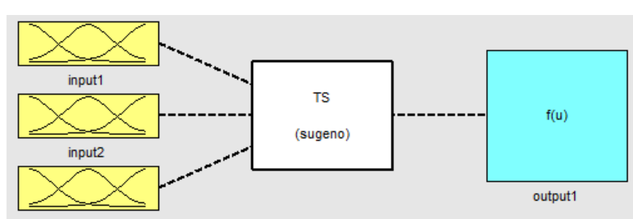

Figure 4: Takagi-Sugeno Fuzzy Model

As the present of nonlinearities properties in EHA system, the data taken have to be linearized before performing linear ARX model identification. Linearization process is done by adding an additional offset value to stimulus signal before send to EHA system. Adding such offset value eliminates some nonlinearity which appears in the system. In order to have better comparison, ANFIS modelling is also performed on same set of linearized data.

The data set is captured by sampling time 50ms, which is the best sampling interval [20]. The best ARX model structure for EHA system is ARX 331 [16, 20], which also is the structure of ARX model in this paper. The data recorded for 100 seconds, which equivalent to 2000 sample data. Modelling is performed by firstly divide the sample data into training data and checking data. Training data is used to train the parameters of the model, while checking data is used to validate the model. In this paper, different model is obtained for different training and checking data portion. First model is obtained by 50 percent training data and 50 percent checking data. Second model is produced by training 30 percent of total data and remaining 70 percent data used for checking. Following model is acquired by performing 10 percent data training and 90 percent data checking. Lastly, first 400 samples of data is used for system identification, with 100 data for training and another 300 data for checking. Accuracy of both ARX and ANFIS model is later compared in term of best fitting percentage and RMSE (Root Mean Squared Error).

III. RESULTS AND DISCUSSION

ARX model and ANFIS model obtained by different training data sets are validated with the checking data set each. The accuracy of each model is presented and compared.

a. 50 percent training data 50 percent checking data

When total sampled data is divided into 50 percent data for training and 50 percent data for testing, ARX 331 model have the ability to estimate the response of system with 95.27 percent fit to measured data as shown in Figure 5. ANFIS on the other hand have better approximation ability, which is 99.61 percent similarity to the measured data, which is indicated in Figure 6. RMSE of ARX model estimation and ANFIS model estimation mark at 1.05 and 0.09, where ANFIS model produces far less error than ARX model. Error plot shows that ARX model's error ranging from -2 to 2 while for ANFIS, ranging from -0.5 to 0.5. The model validation shows that ANFIS model does perform better than ARX model with higher approximation accuracy and less RMSE. Error plot shows that ANFIS model is more stable with consistent error value. The reason

ANFIS model performs better because it is a nonlinear model, comparing to linear ARX model which fail to model all the nonlinearities of the system.

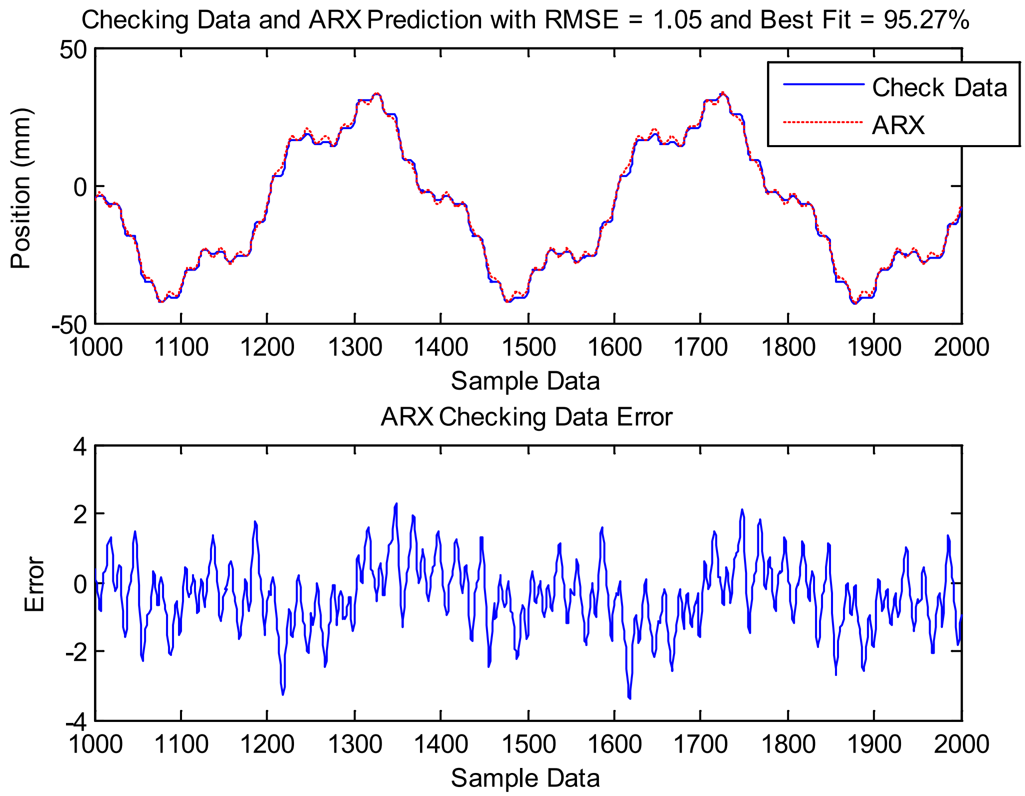

Figure 5: ARX 331 50 percent training model validation.

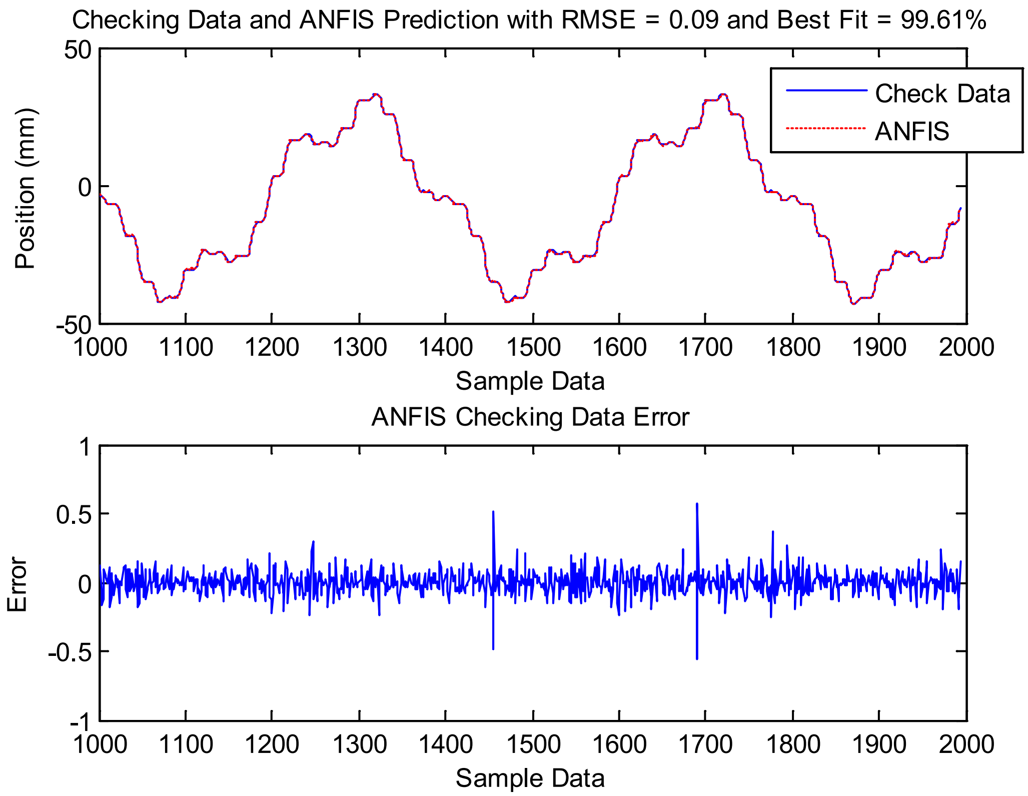

Figure 6: ANFIS 50 percent training model validation.

b. 30 percent training data 70 percent checking data.

Modelling is done also with 30 percent data for training and remaining 70 percent data for testing. Result in Figure 7 shows that ARX model which is trained with 30 percent data still have the similar estimation ability as previous model (50 percent training data). However, the accuracy of best fitting decreases from 95.27 percent to 95.19 percent. ANFIS approximation result as shown in Figure 8, is identical to previous training, which is 99.61 percent. However, the error plot indicate that current ANFIS model approvimation result in slightly higher error than previous model. RMSE results in 1.08 for ARX model and 0.09 for ANFIS model, which is still far smaller. Error plot is identical to previous model; with ARX ranging from -2 to 2 while ANFIS from -0.5 to 0.5. Both models indicate that nearly identical result as previous model (50 percent training 50 percent checking) can be obtain even though less training data is provided for training.However, all the operating regions have to be included in the training data. The condition where not all the operating region is trained will be shown in next section.

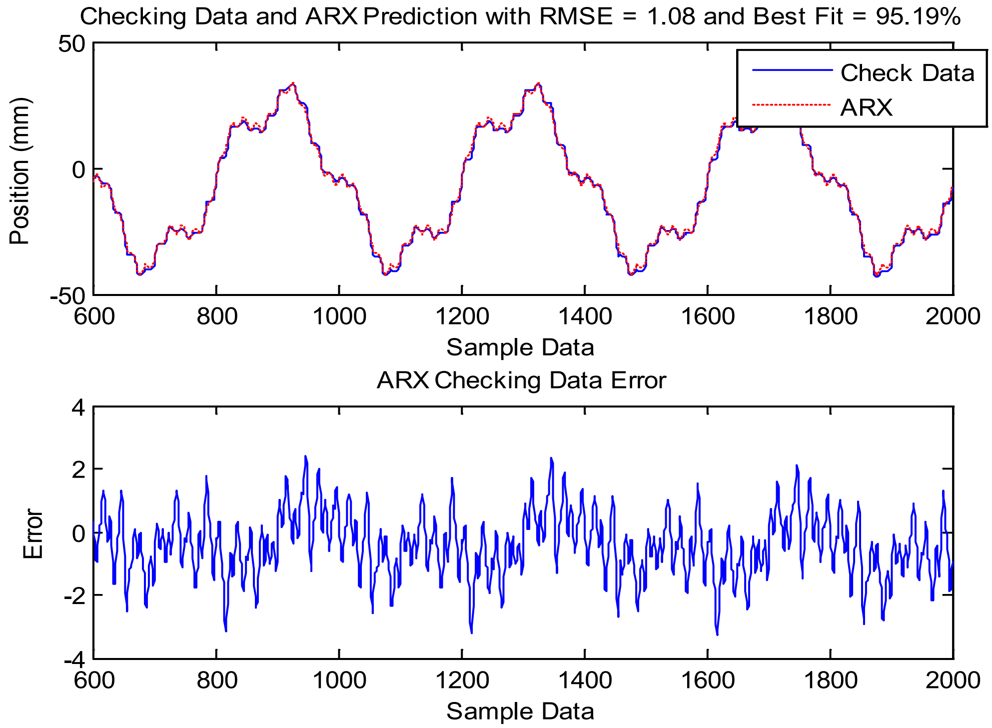

Figure 7: ARX 331 30 percent training model validation

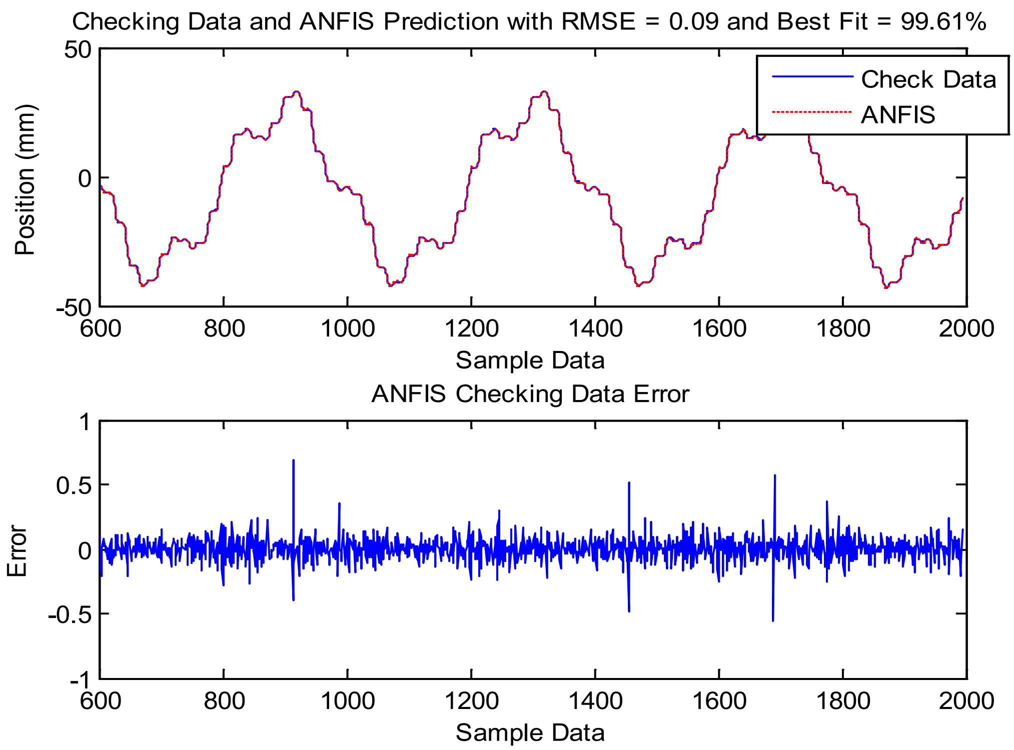

Figure 8: ANFIS 30 percent training model validation

c. 10 percent training data 90 percent checking data.

The ability of modelling using both methods is extended to condition where only 10 percent of the total data set is provided for training while remaining 90 percent data used for validation purpose. Note that at this condition, only parts of operating region of EHA system is provided for training. Estimation process shows that best fitting for ARX model is 92.42 percent with RMSE 1.70, as in Figure 9. As shown in Figure 10, ANFIS results in lower performance compared to previous training, with 97.94 percent best fitting and higher RMSE, which is 0.46. Error plot of ARX model indicates higher errorthan previous model. Interesting part in ANFIS modeling is that high error only appear at the region where no training data available. However, eventhough no data provided for training, ANFIS model still able to estimate the system with very high accuracy.

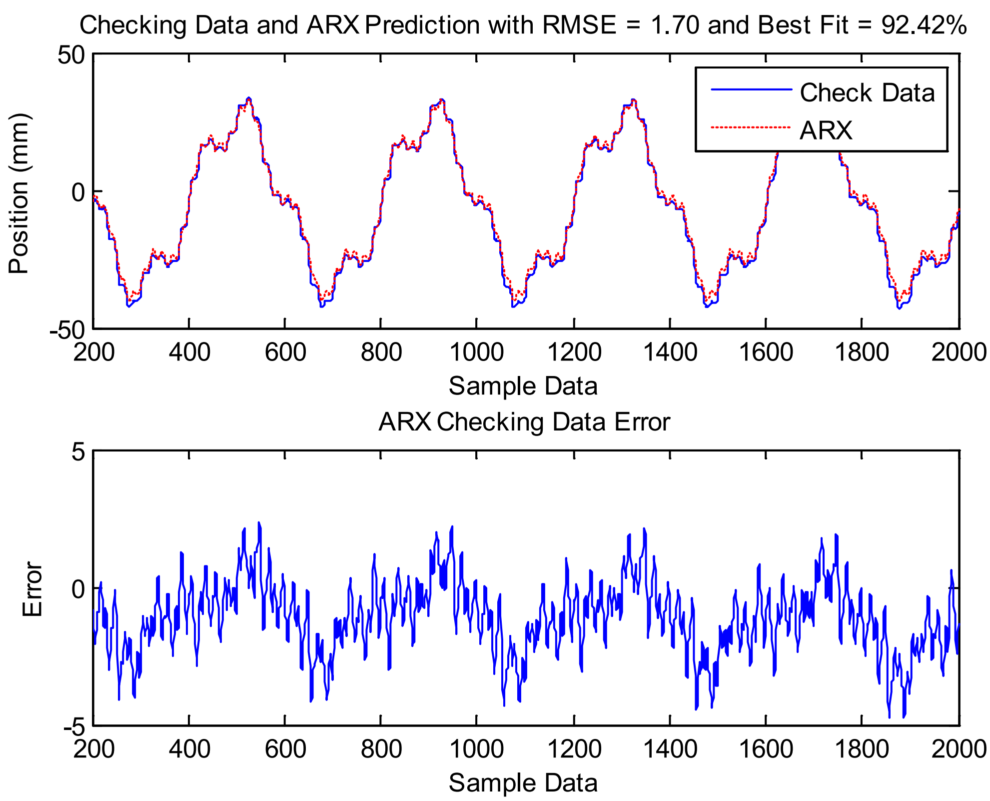

Figure 9: ARX 331 10 percent training model validation

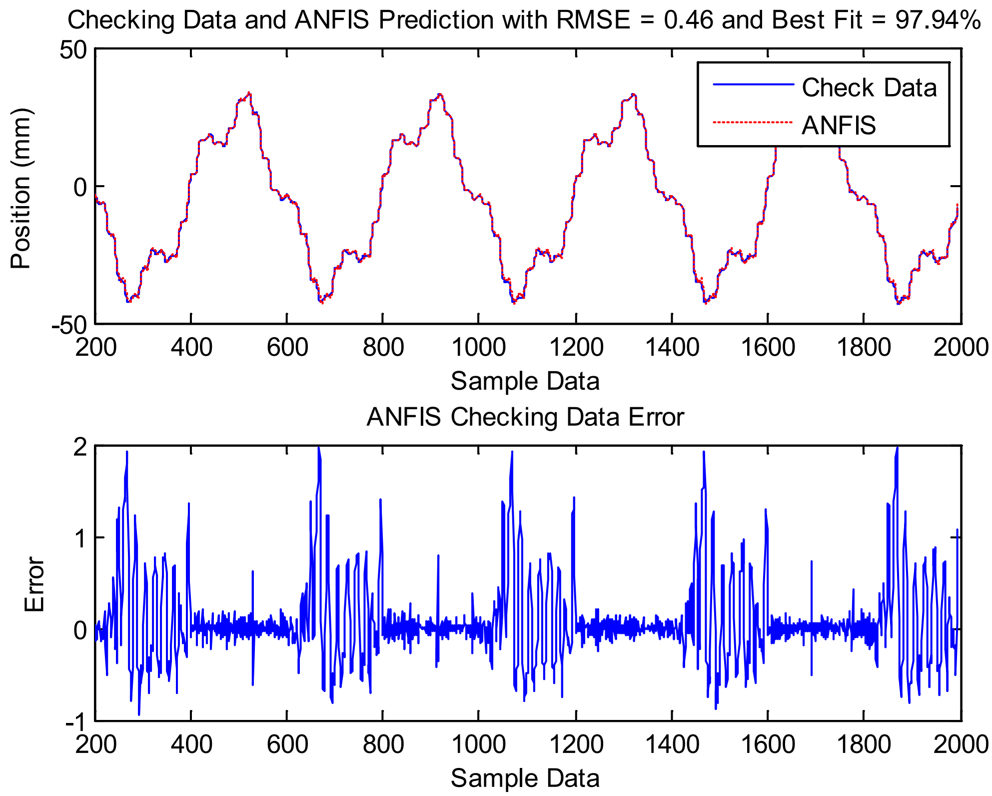

Figure 10: ANFIS 10 percent training model validation

d. 5 percent training data 15 percent checking data.

The ability of ARX and ANFIS modelling is further extending to condition where very little data is available for training. From the validation result as shown in Figure 11 and Figure 12, both model failed to estimate the system. From this research, it is shown that in order to develop a convincing model that can precisely represent a system, a sufficient set of data which cover all the operating regions of the system have to obtain.

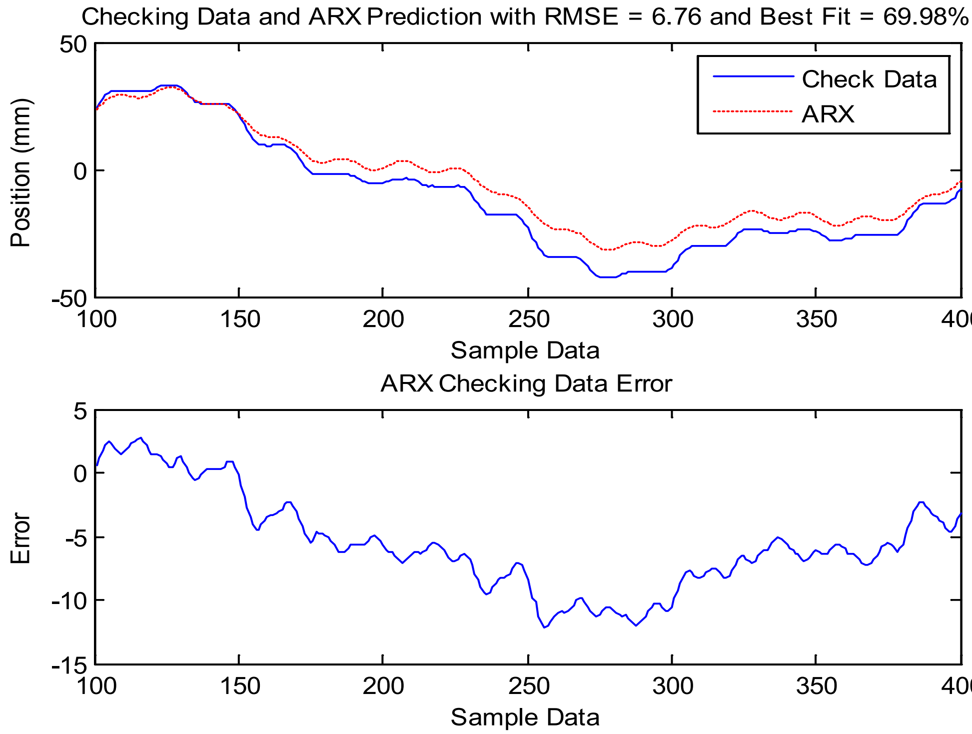

Figure 11: ARX 331 5 percent training data model validation

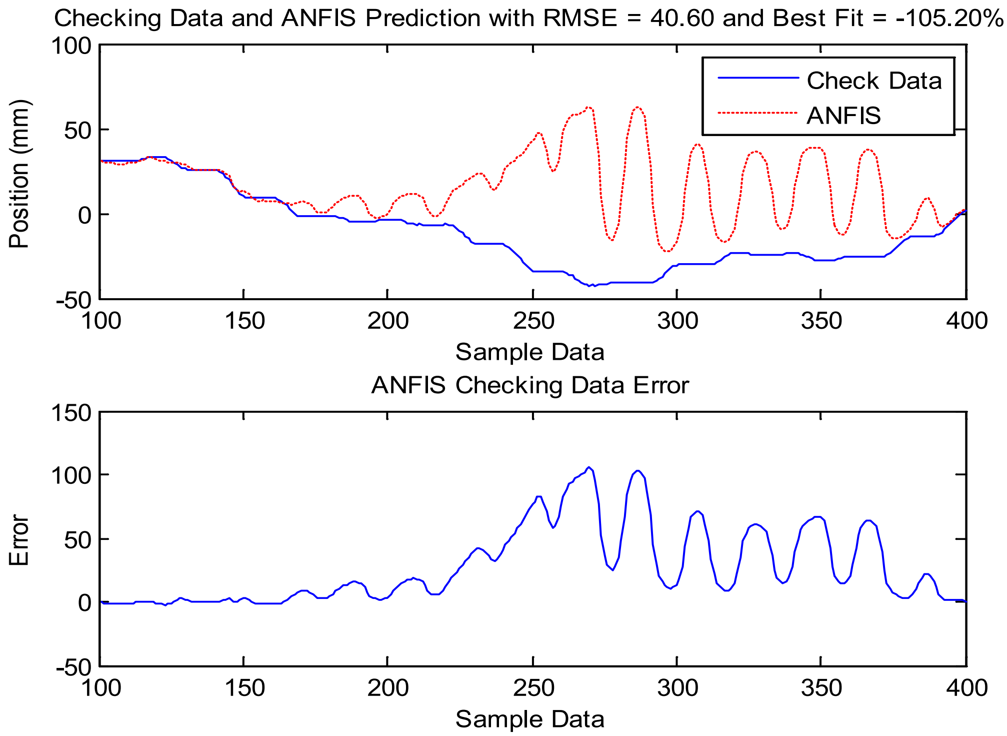

Figure 12: ANFIS 5 percent training data model validation

VI. CONCLUSIONS

ANFIS model has shown to be a better model than ARX model, either in condition where sufficient training data is available or less training data. Both models fail to produce a satisfactory approximation result under condition where very less data available. Thus, in order to obtain a good model, sufficient training data which include all operating region of system have to be included. ANFIS model has performed better with significantly higher accuracy than ARX model because of its nonlinear approximation capability. Future work is recommended to perform ARX modelling and ANFIS modelling with a set of nonlinear data. This will shows the ability of both techniques to produce a model which can approximate a nonlinear system.

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