Identification of Thrust Response of a Multi-Nozzle Block System By an Optimized ANFIS Technique

Nayyer Nayab Malik and M. Javed Hyder

***Abstract*—This paper presents the Black Box System Identification (BBSI) for estimation of thrust response of Multi-Nozzle Block using optimized Adaptive Neuro Fuzzy Inference System (ANFIS) technique. Complex systems are highly nonlinear and uncertain in nature. For such reasons, it is difficult to elaborate the dynamic equations for accurate model abstraction. BBSI is a signal processing method that could be employed for representing the system from input/output data without knowing the internal dynamics. An experimental prototype has been setup that accepts the input in the form of valve position to generate output thrust at Multi-Nozzle Block exit. A novel algorithm has been introduced to optimize ANFIS parameters for robust and precise prediction of the signals against data obtained from the real time system. The approximation of system is carried out in LabVIEW software environment using testing and validation data. The current research would contribute in developing and understanding the prognostic capability of ANFIS structure utilizing simplistic approach to model valid physical phenomenon. The simulation reveals high performance against 75% datasets with model using 7 membership functions. The proposed technique shows good forecasting capability even with limited 25% of training data showing remarkable performance for the reliable evaluation of output thrust.**

***Index Terms*—Nozzle Thrust Estimation, Black Box System Identification, Optimized ANFIS, LabVIEW, Signal Processing.**

I. Introduction

THE jet propulsion technological research is one of the attractive fields that has gained significant importance in the academic investigations during past few years. The performance of the aerodynamic systems is dependent on the geometrical and dynamic framework. Thrust is one of the crucial parameters that determine the launching capability of airborne vehicles. The thrust calculations and estimation has an important role to play in designing, prototyping and testing of nozzles for jet propulsion applications. Aerodynamic systems have complex nonlinear characteristics and it not possible to precisely model the working operation using the governing mathematical expressions [5], [8].

The procedures involving the theoretical calculations are based on assumptions and leaves some degree of uncertainty that causes inability to define complicated processes. For this reason, real time data driven observer is required to approximate the system behavior that needs no prior information regarding its internal dynamics. This is achieved through utilization of identification techniques that could predict the system with reasonable accuracy having capability to handle the rapid varying nonlinear transient characteristics. The correlated data of the applied input and the output thrust response yielded at the nozzle exit is to be recorded. Furthermore the correlated data sets are employed for training, testing and validation of the identification structure by comparison with the experimental data to check the degree of conformity between data sets (based on acceptance criterion) for the true representation of the system [1], [6]. The appropriate estimation of generated thrust assists in accomplishing better model based controller design.

BBSI is standard traditional approach that is established in early 60s and substantial research is carried out regarding its utilization in different engineering fields including automotive, electronics, process estimation, actuation systems, aerodynamics etc [2], [33], [35], [36], [37]. Various algorithms have been formulated for the linear and nonlinear systems estimation depending on input/output data. Euler et al. [31] applied the linearnonlinear identification technique using DSRe and Bouc-Wen model to examine the dynamics of movable nozzle. The review of a unified network for takling the estimation problem is presented by Jose et al. [**?**] utilizing Support Vector Machines (SVM) methodology. A Support Vector Regression (SVR) approach is proposed in [5] and its performance is compared with ARX/NARX models. Comprehensive investigations have been carried out in [3], [4] to briefly analyze ARX, ARMAX, NARX and NAR-MAX models. The study of the Hammerstein-Wiener (HW) theory and application of the adopted technique is described in [3], [4]. The fuzzy based approximation theory and its effectiveness has been explored by [12], [13].The survey of Artificial Neural Network (ANN) based black box modeling is conducted in [14] and is performance is evaluated by comparison with other modeling schemes. In [6], [8] the different neuro-fuzzy identifiers are discussed in detail. The literature survey from previous research reveals that neuro-fuzzy strategy is robust self-learning scheme that could be employed in identification of complex highly nonlinear processes such as nozzle thrust response.

ANFIS is an appealing intelligent strategy can be used for modeling variety of engineering processes. The technique has been proposed in early 90s by Roger Jang [15] and has been successfully implemented in areas of application including control systems, fault diagnosis, medical diagnosis, signal processing, weather forecasting, pattern recognition, system identification etc. [16], [17], [18], [20], [21], [27], [32]. Fuzzy logic does not have the intuitive learning capacity while the neural based black box approach has no means

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of distinctive knowledge representation. ANFIS combines the superior characteristics of both Fuzzy Inference System (FIS) and neural network, having enhanced capability of robust identification of system dynamics with limited data recorded from the output response. The recursive learning ability and adaptability to the complex nonlinear behavior of system makes the ANFIS an effective high performance predictor for modeling the dynamic processes.

In this paper Black Box System Identification (BBSI) of multi-nozzle block output thrust employing ANFIS technique (optimized by hybrid learning algorithm) is presented. The proposed strategy has been implemented on the small scale experimental setup consisting of four convergent nozzles in a single block mounted on the test stand and load cell is fixed just below it to precisely predict the thrust in response to the applied inputs. A novel algorithm is utilized to optimize ANFIS parameters. The software development is carried out in LabVIEW environment. Step by step procedure of system identification has been discussed in detail. The performance and efficiency of the suggested method is observed and analyzed to determine its effectiveness in modeling complex nonlinear dynamic processes.

II. ANFIS Black Box Identification

The use of black- box model has been consistently used for modeling complex systems. This procedure can be applied on both linear and nonlinear systems. ANFIS based black-box model is an effective intelligent scheme that is stable and has robust capability of approximating the system response precisely with limited provision of data. The execution of estimation process involves signal acquisition, data logging, training of the ANFIS structure and data validation. The data is divided into three subcategories including training data, testing data and checking data. Training data tunes the ANFIS parameters by an iterative approach for reasonably accurate model abstraction while the testing and checking data are utilized to validate the methodology. The performance of the applied procedure is dependent on the Root Mean Square Error (RMSE) value and the number of epochs required to achieve reliable identification structure [25], [26], [28], [29], [34].

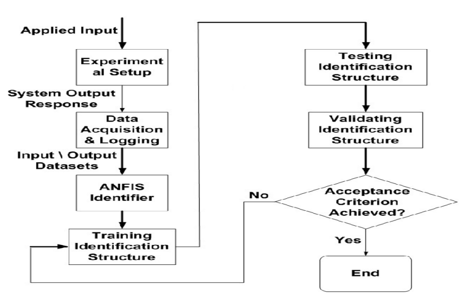


Fig. 1. ANFIS Black- Box Identification Process

A. ANFIS Architecture

ANFIS is one of the viable techniques that incorporates the characteristics of both fuzzy inference system (FIS) and artificial neural networks (ANN), capable of handling complex nonlinear systems. The approach that is adopted for ANFIS identification and control problems is based on T-S fuzzy rules [15][30].For two given variables x_1 and x_2, the rules can be defined as:

if x_1 $is\ A_1\ and\ x_2\ is\ B_1\ then\ f_1 = p_1 x_1 + q\ {}_1 x_2 + r_1$

if x_1 $is\ A_2\ and\ x_2\ is\ B_2\ then\ f_2 = p_2 x_1 + q_2 x_2 + r_2$

On the basis of the variable parameters it can be divided into two separate portions i.e. antecedent part and consequent part. The antecedent part modifies the membership functions while the consequent part defines the output as a linear combination of results.Let us consider the ANFIS method with two inputs x_1, x_2 and the output y.

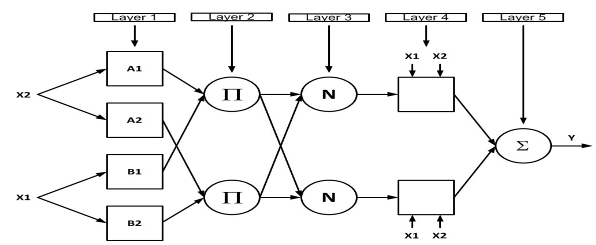


Fig. 2. ANFIS Architecture

The ANFIS structure can be divided into five stages represented by number of nodes that can be described as:

Layer1: In this layer each node corresponds to the degree of membership mu that is calculated from the pre-defined membership function for a given set of input values. The membership functions of different graphical shapes can be utilized like triangular, trapezoidal, Gaussian etc. Usually bell shaped membership functions are used in solving identification and control problems for smooth output transition and are mathematically expressed as:

$$\mu_i(x) = \frac{1}{1 + (\frac{x - c_i}{a_i})^{2b_i}}$$

Layer2: It evaluates the firing strength of each rule by taking the product of degree of membership functions resulting from the given input values (or any other T-norm).

$$w_i = \mu_i(x_1).\mu_j(x_2) \tag{1}$$

Layer3: This layer determines the ratio of individual firing strength of each rule to the sum of strengths of all firing rules. the output of this layer is called the normalized firing strength.

$$\bar{w_i} = \frac{w_i}{w_1 + w_2 + w_3 + ... + w_n} \tag{2}$$

Layer4: The product of each of the normalized firing strengths and the resulting output function is obtained. The functions are selected from the rules that are triggered for the given set of input values. the node functions contain the consequent parameters which affects (by scaling) the output response.

$$\bar{w_i} f_i = \bar{w_i}(p_i x_1 \ + q_i x_2 + \ r_i) \tag{3}$$

Layer5: It gives the overall control output after summing up the each of the values obtained from the previous layer.

$$y = \sum_i \bar{w_i} f_i \tag{4}$$

The premise parameters and the consequent parameters are optimized to get the best result. The tuning of parameters produces the variation in the geometry of membership functions and scales the output response to get best possible results. Various optimization techniques have been adopted in previous research including deterministic, probabilistic, stochastic evolutionary and combined hybrid algorithms. These techniques are comprehensively discussed in [15], [23]

B. Conventional Method for Optimizing ANFIS Parameters

ANFIS parameters are optimized to reconfigure the identification structure, giving robust optimal performance in modeling the system input/output response. There are various mechanisms that could be employed for selecting viable ANFIS parameters. Three of the commonly used methods are Least Square Error (LSE), Back Propagation(BP) and Hybrid technique. In the hybrid approach, the premise parameters are updated using BP while the consequent parameters are revised by LSE algorithm to provide optimal solution.

C. Proposed ANFIS Strategy

In this section SISO based ANFIS architecture with simplified learning approach has been discussed. The strategy involves the reduction of number of rules and skipping layer2 of ANFIS which reduces the computational time for estimating the model. Bypassing layer2 means that the membership value is considered equivalent to the weight factor i.e.$\mu_i \approx w_i$. Furthermore updating parameters based on the target ratio has been introduced. The considered SISO ANFIS architecture comprises of number of rules established on splitting of universe of discourse. In the identification process three different rules set are utilized and their performance is evaluated.

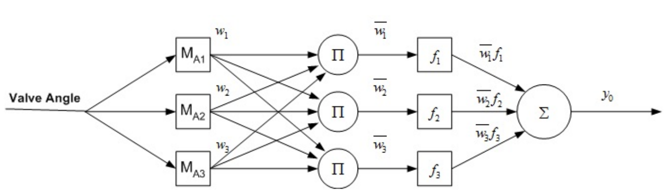


Fig. 3. ANFIS SISO Architecture

The output and function defining each set of rule is defined by the fowing expressions:

$$f_i = \xi_i \cdot A \tag{5}$$

$$O_i = w_i \cdot \xi_i \cdot A \tag{6}$$

The training of ANFIS parameters require a robust approach to reliably approximate data in shortest possible time. To achieve this goal a new strategy is proposed that is simple yet giving reasonable results. The parameters are updated in accordance to the target ratio (ζ) which is the defined as ratio of the predicted value to the actual process. The equation for updating the ANFIS parameters are given as under:

$$a_{i+1} = (1 - \zeta)\alpha + a_i \tag{7}$$

$$c_{i+1} = (1 + \zeta)\alpha + c_i \tag{8}$$

$$\xi_{i+1} = (1 - \zeta)\beta + \xi_i \tag{9}$$

III. Experimental Setup & Procedure

The experimental setup consists of block of multi nozzles vertically fixed on a test stand.The details of the geometrical structure of the nozzle block is given in figure 4.

Fig. 4. Multi-Nozzle Block

The multi nozzle block is connected to a secondary servo actuator through soft tube, which is again joined to primary servo actuator attached to compressor, supplying the air with adjustable pressure ranging from 1 Bar to 3 Bar. The primary servo actuator regulates the input pressure while the secondary actuator controls the mass flow rate by changing valve angle using the feedback mechanism. Just below the nozzle block, load cell (with holding capacity of 10kg) is fixed at a distance of 4mm. The thrust response signals coming from the load cell against the inputs (inlet pressure valve angle) are amplified by 24bit Hx711 amplifier board. The data obtained is filtered by signal conditioning circuits to obtain reliable real-time data with less noise disturbance. The refined filtered signal is then sent to arduino mega based data acquisition and control unit. Shielded wires are used for signal propagation and communication purpose to nullify the electromagnetic effect and other distortions. The digitized signal coming from the sensors after refinement are then sent to the computer where it is interpreted, processed, monitored and recorded.

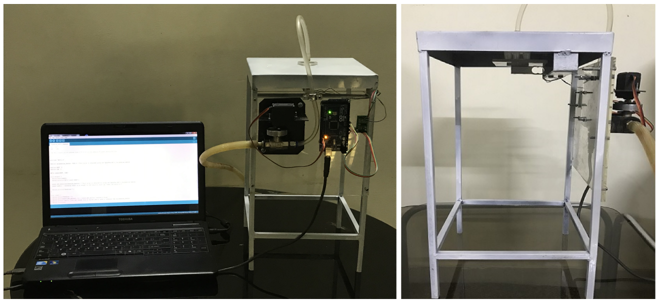


Fig. 5. The Experimental Setup

The LabVIEW platform is used to implement ANFIS algorithm to estimate and analyze the system response on changing the input variables. The analysis procedure has been executed in various steps. The primary requirement involves the collection of data in response to the input signals generated by the computer. The PWM signal is sent from the computer to the servo based electromechanical actuators for modifying the inputs. The multi nozzle block generates the output thrust expressed by the equation:

$$F_{th} = \dot{m}(v_e) + (P_e - P_a)A_e \tag{10}$$

$$T = F_{th1} + F_{th2} + F_{th3} + F_{th4} \tag{11}$$

Where F_{th}=Thrust Generated at Nozzle exit,
$\dot{m}$=Mass flow rate of Air coming out of compressor,
v_e= Velocity of Air at Nozzle Exit,
P_e=Pressure at Nozzle Exit,
P_a=Ambient Pressure,
A_e=Nozzle Exit Area,
T=Overall Thrust Generated by Nozzle Block

The thrust generated is directly measured by the load cell and corresponding signals are sent to computer through the data acquisition process where it is interpreted, processed and stored in a data-logging file.

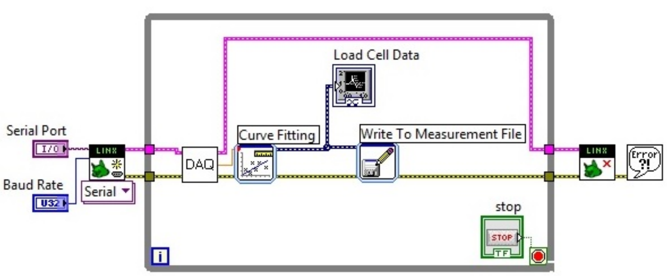


Fig. 6. System Response Data Logging

In ANFIS structure different the input range, number and type of Membership Functions (MF's) are defined. The Gaussian membership functions are utilized due to its smooth and rapid learning response with accurate prediction capability. Greater number of MF's increases the precision on the expense of complexity in the identification structure. On the other hand less number of MF's increases the learning rate but would not be able to estimate the model correctly. About 441 data samples are selected for the analysis generated by variable input signals. To carry out identification, these samples are then divided into (different proportions of) training and checking data. These are used to evaluate the performance of the ANFIS identifier. The training data updates the ANFIS parameters by a novel learning process while the checking data is used to validate the model.

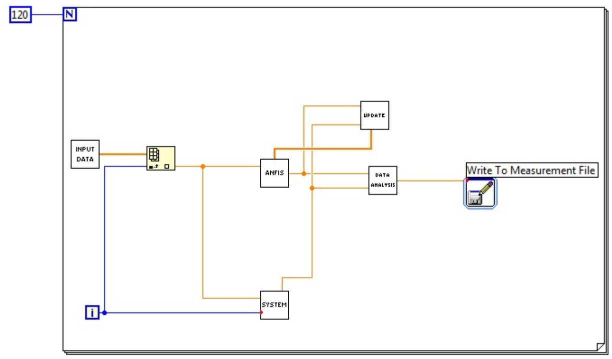
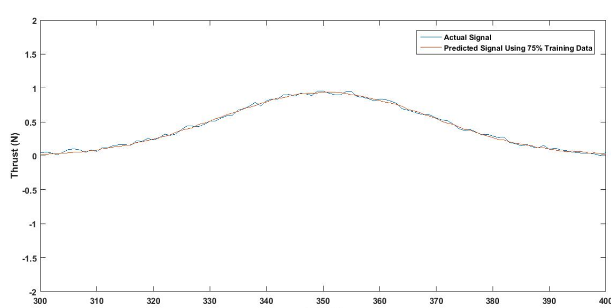


Fig. 7. ANFIS Editor

The trained ANFIS structure is then validated by checking and testing data operation. The data set is divided into various percentage of training and checking data. The outcome of these procedures gives the comparison between the trained estimator against the system input/output data to evaluate its efficiency and performance of identification process providing the true representation of dynamic process.

IV. Performance Evaluation & Discussion

The data obtained from the real time experimental setup giving the thrust response against periodic input signals utilized for the model abstraction. ANFIS based model estimation is carried out in LabVIEW environment. The prediction of data is done by employing variations in ANFIS structure including the modification in training testing data samples. Furthermore the number of Membership functions are altered to check the integrity of the data approximation method. The comparison of the actual signal with the predicted signal gives the overview of the authenticity of the estimation model.



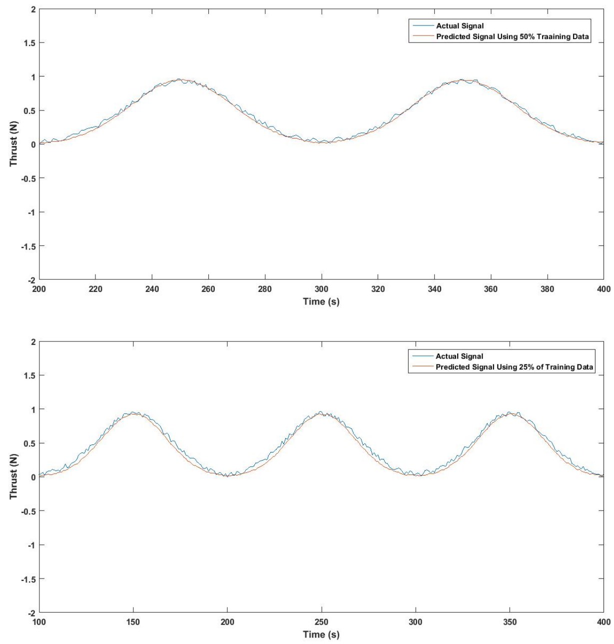
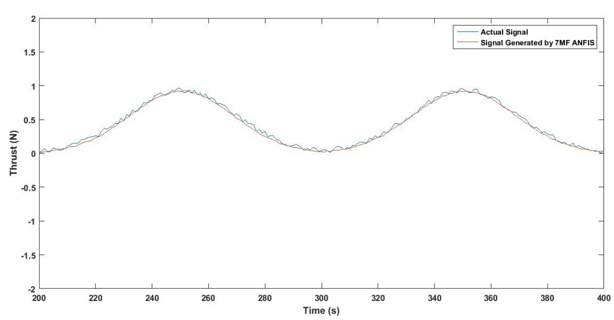
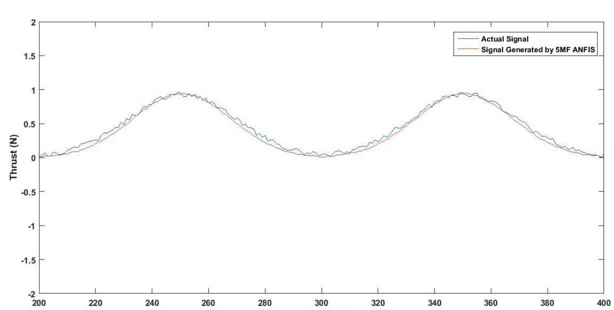


Fig. 8. Comparison of Actual Signal with ANFIS Predicted Signals Utilizing Different Datasets

In Fig 8 it is observed that variation in datasets marginally effects the simulated signals. By increasing the training dataset, optimal results can be achieved. This shows that for more training data the identifier gets more information about the behavior of actual system dynamics which enhances the forecasting capability of ANFIS structure.





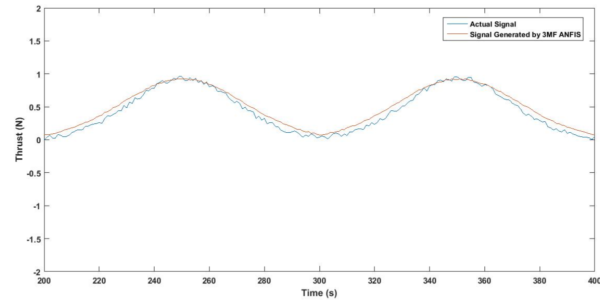


Fig. 9. Comparison of Actual Signal with ANFIS Predicted Signals Utilizing Different Number of MF's

Fig 9 shows the choosing different number of membership function on the predicted response. As greater number membership functions gives the best possible solution as the dataset is finely discretized over the universe of discourse which enables the ANFIS to closely correlated with the system. Utilizing less membership functions coursely aggregated the datasets missing the valuable data for the system identification.

The accuracy of the results can be evaluated by analyzing the statistical parameters. The commonly used performance criterion may include determination of correlation coefficient (R), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) etc [26], [34], [28].The entities that are utilized to examine the reliability of model structure is briefly explained below.

1) Root Mean Square Error (RMSE): It gives the standard deviation of the residuals and determines how far are the error points from the regression line. Hence determining the error persisting between actual and predicted data samples. This method is usually used for verifying the experimental results.

$$RMSE = \sqrt{\frac{1}{k}\sum_{i=0}^{k}(y_i - \bar{y_i})^2} \tag{12}$$

2) Mean Absolute Percentage Error (MAPE): It is one of the popular method for trending and forecasting errors that determines the prediction accuracy representing the percentage deviation of the estimated value and the actual value given by:

$$MAPE = \frac{1}{k}\sum_{i=0}^{k}(\frac{|y_i - \bar{y_i}|}{\bar{y_i}}) \times 100 \tag{13}$$

3) Correlation Coefficient (r): It shows the success factor in reducing the standard deviation and is widely used for measuring the linear dependence between the output of the model and the real time data ranging from [-1 1] showing positive or negative correlation of the actual and predicted values with exception of zero value where there is no association between data sets. Correlation coefficient can be expressed as:

$$r = 1 - \frac{\sum_{i=0}^{k}(y_i - \bar{y_i})^2}{\sum_{i=0}^{k}\bar{y_i}^2} \tag{14}$$

For optimal solution, higher value of r with Lower values of RMSE and MAPE are desirable. Each simulation is obtained for different data sets shows the performance of the identification model. The efficiency of the estimator is compared to select the best possible prediction method. The error trending plots for different PWM input values producing best results are shown in the following figures:

The overall results are given in table 1.1

Fig. 10. Table 1.1 :Overall Performance of ANFIS Identifier

%Training Data	%Checking Data	Membership Function (MF)	RMSE	MAPE	R
25	75	3	0.189	1.51	0.688
50	50	5	0.134	1.16	0.789
75	25	7	0.113	0.79	0.93
25	75	3	0.162	1.43	0.716
50	50	5	0.119	1.05	0.833
75	25	7	0.097	0.73	0.937
25	75	3	0.142	1.37	0.732
50	50	5	0.105	0.98	0.895
75	25	7	0.078	0.69	0.941

The simulation reveals slight decrease in error as more data is available for training the ANFIS structure making it familiar with the system working mechanism to precisely validate the its output response by utilizing checking data.
Furthermore the results demonstrate marginally low performance for the slow actuator operation. At low PWM input, frictional losses and vibration induced by the actuator results in noisy output response. On the contrary high PWM sooths out the system operation to give stable output thrust, improving the model abstraction process.

V. Conclusion

In this paper the ANFIS based black box identification technique has been presented for estimating the dynamic behavior of Multi Nozzle Block designed for jet propulsion system. The model is approximated by analyzing the output thrust response generated by the nozzle. The real-time data collected from the small scale experimental setup against periodic input signal. lt is further processed and utilized by T-S ANFIS intuitive structure to carry out the identification procedure in LabVIEW based ANFIS structure. The testing is carried out with different percentage of training and checking data sets. To cross validate the applied methodology the performance of the applied technique on different data sets and number of membership functions are evaluated. The results reveal that the model with 75

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