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Prediction of Lift Response of Single/Multi-Nozzle Thruster Blocks by Concurrent SISO ANFIS Technique

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***Abstract* - This paper presents the Black Box System Identification (BBSI) for prediction of Lift response of Multi-Nozzle thruster Block based on Concurrent SISO Adaptive Neuro-Fuzzy 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 physical phenomenon from input/output data without knowing the internal dynamics of the system. An experimental prototype has been setup that is driven by source pressure supplied by the compressor and is regulated by the precise angular movement of servo ball valve actuator to produce a lift force accordingly at the thruster(s) exit. The output response of thruster block is monitored and data is collected at a fixed interval of time. The approximation of system is carried out in LabVIEW software environment by novel ANFIS technique utilizing data obtained in real time process. The proposed technique with seven membership functions provided reasonably accurate forecasting capability even with limited training data showing remarkable performance in reliable evaluation of the generated lift force.**

Index Terms – Aerodynamics, Artificial Intelligence, Lift Prediction, Thruster.

INTRODUCTION

The research based on the enhancing the hovering and VTOL (Vertical Takeoff & Landing) capability of airborne vehicles is one of the attractive fields that have 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. Lift is one of the crucial parameters that determine the launching capability of airborne vehicles. The lift force calculations and estimation has an important role to play in designing, prototyping and testing of these aerial vehicles. Aerodynamic systems have complex nonlinear characteristics and it is almost impossible to precisely model the working operation using the governing mathematical expressions [1-2] derived from first principles. To handle this multiplex problem, black box or grey box models are usually employed for approximating the system's response.

The procedures involving the theoretical calculations are based on assumptions and leave 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 [3-4]. The appropriate estimation of generated thrust assists in accomplishing better model based controller design.

BBSI is standard traditional approach that is established in early 60's and substantial research is carried out regarding its utilization in different engineering fields including automotive, electronics, process estimation, actuation systems, aerodynamics etc. [5-9]. Various algorithms have been formulated for systems estimation depending on input/output data. Euler et al. [10] applied the linear and nonlinear identification technique using DSRe and Bouc-Wen model to examine the dynamics of movable nozzle. The review of a unified network for tackling the estimation problem is presented by Jose et al. [11] utilizing Support Vector Machines (SVM) methodology. A Support Vector Regression (SVR) approach is proposed in [1] by Robert et.al and its performance is compared with ARX/NARX models. Comprehensive investigations have been carried out in [12-13] 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 [14-16]. The fuzzy based approximation theory and its effectiveness has been explored by [17-18].The survey of Artificial Neural Network (ANN) based black box modeling is conducted in [19] and is performance is evaluated by comparison with other modeling schemes. The authors in [2], [4] have discussed briefly on different neuro-fuzzy identification procedures. The literature survey from the past research reveal that neuro-fuzzy strategies are robust self-learning schemes that could be employed in accurate prediction of complex and highly nonlinear processes.

ANFIS is an appealing intelligent strategy can be used for modeling variety of engineering processes. The technique has been proposed in early 90's by Roger Jang [20] 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. [21-27]. Fuzzy logic does not have the intuitive learning capacity while the neural network based black box approach has no means 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.

The main contribution of the current research includes the estimation of dynamic lift response of a single block of multi-nozzles that was not previously studied and investigated for the model identification. Apart from that, intuitive Concurrent SISO ANFIS based strategy has been implemented to get reasonably accurate approximation model.

In this paper Black Box System Identification (BBSI) technique has been presented to predict the lift response of Single/Multiple Nozzle based Thruster Blocks utilizing Concurrent SISO ANFIS strategy (optimized by hybrid learning algorithm). The proposed strategy has been implemented on the small scale experimental setup that consists of Single/Multi Nozzle Thruster Blocks (mounted on the test stand) and load cell is fixed just below it to measure the lift force in response to the applied inputs. This data is then used for training the identification model. A hybrid algorithm consisting of combination of Gradient decent (GD) and Least Square Estimation (LSE) is employed to optimize ANFIS parameters relying on the deviation in outputs of the measured and predicted data. The software development is carried out in LabVIEW environment. The proposed strategy is compared with the conventional ANFIS technique to check its efficacy in forecasting the missing data. The accuracy of the suggested method is observed and analyzed by assigning different number of Membership Functions (MF) to determine its effectiveness in abstracting complex nonlinear dynamic process.

THE METHODOLOGY

In this section simplified Concurrent SISO-ANFIS architecture with conventional hybrid learning approach has been introduced. The strategy involves the reduction of number of rules (with less parametric variables) to lower down the computational time for estimating the system and to analyze the accuracy of the proposed model. In this scheme each of the inputs are individually processed using separate SISO ANFIS architectures and then their results are combined to give the final output. The inputs to the model are in the form of parametric values and their variation. Gaussian membership functions are employed for the identification procedure for smooth transition between different operating levels while utilizing the minimum set of parameters for the proposed identifier. The number of rules for each input is defined by "No. of Rules = 2M-3" where M is the number of membership functions. The structure of Concurrent SISO ANFIS structure is given in Fig 1.

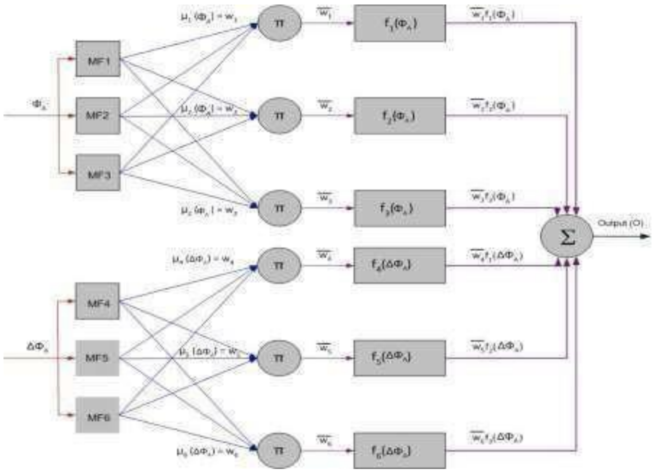


Fig. 1: Concurrent SISO-ANFIS Structure

The uniform distribution scheme of mapping the membership function over the universe of discourse (inputs range) is adopted. The approximation process is based on the error dynamics of the output(s) in response to the input variable(s), implemented with two sets of Concurrent SISO-ANFIS frameworks. The error and change in error (obtained by calculating the error(s) in output and change in output) are the means of formulating the cost function that helps in improving accuracy and interpolation capability of model response. The iterative methodology is executed on the basis of termination criteria of minimization of the cost function. The overall proposed estimation process is demonstrated in Fig 2

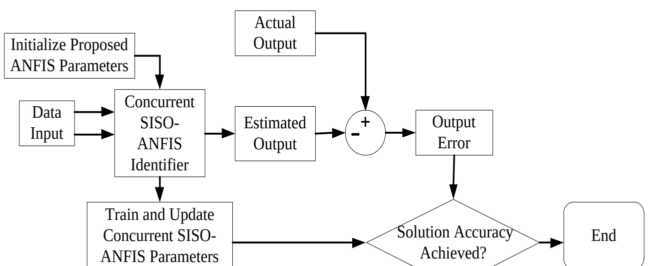


Fig. 2 : Block Diagram of Overall SISO ANFIS Based Estimation Process

The real- time response data obtained from the experiment is used. The input from the measured data is applied to proposed model and its output is compared with the actual output response. If the output error does not lie within the desired limits then the Concurrent ANFIS parameters are trained and updated using conventional hybrid technique comprising of Back-Propagation (BP) and Least Square Estimation (LSE) methods. The identification procedure continues till the desired accuracy of output is achieved.

EXPERIMMENTAL SETUP AND OPERATIONAL PROCEDURES

The experimental setup consists of Cylindrical Thruster Block (with different number of Convergent Nozzles) vertically fixed on a test stand that is designed to generate the specific amount of thrust in response to the regulated mass flow rate. Each nozzle in the thruster block is a conical convergent type having length of 40mm. The details of the geometrical structure of the different blocks are given in Fig.3 to Fig.5.

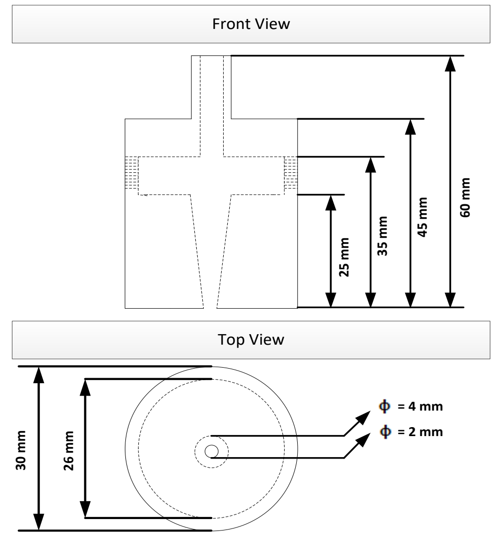


Fig. 3: Thruster Block with Single Nozzle

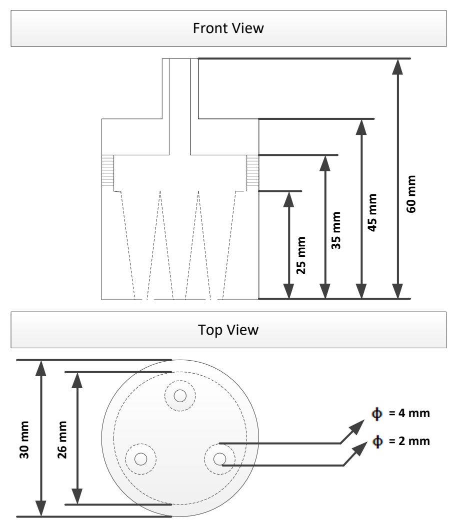


Fig.4: Thruster Block with Three Nozzles

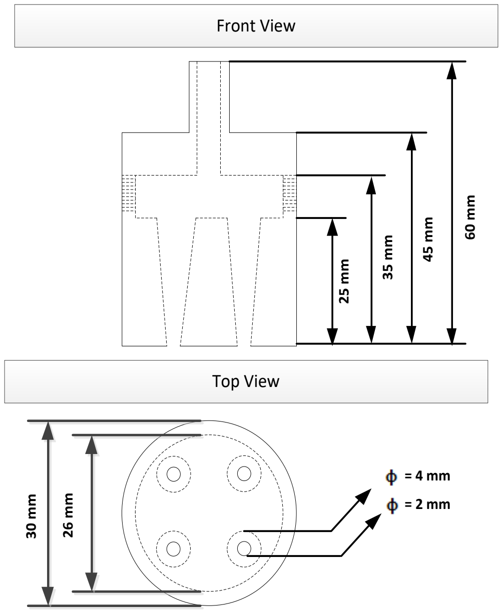


Fig.5: Thruster Block with Four Nozzles

The thrust producing block is connected to a electromechanical servo actuator through soft tube, which is joined to the compressor (with the capacity of air mass flow at 1.33kg/s), supplying the continuous air flow with adjustable pressure ranging from 0.5 x 10^5 Pa to 3.0 x 10^5 Pa. The pressure Transducer (SKU237545 having range 0-1.2Mpa) is attached to compressor to monitor the change in pressure. ATMEGA 6250 controller module is employed for acquiring data and to send control signals to servo ball valve actuators. The servo actuator controls the mass flow rate by changing valve angle (over a span of 0° to 90°) 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 (supply pressure & valve angle) are amplified by 24bit Hx711 amplifier board having built-in signal conditioning circuit that filters the measured signal to obtain reliable real-time data with less noise disturbance. 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 via controller where it is interpreted, processed, monitored and recorded. The experimental setup for nozzle thrust analysis is shown in Fig.6.

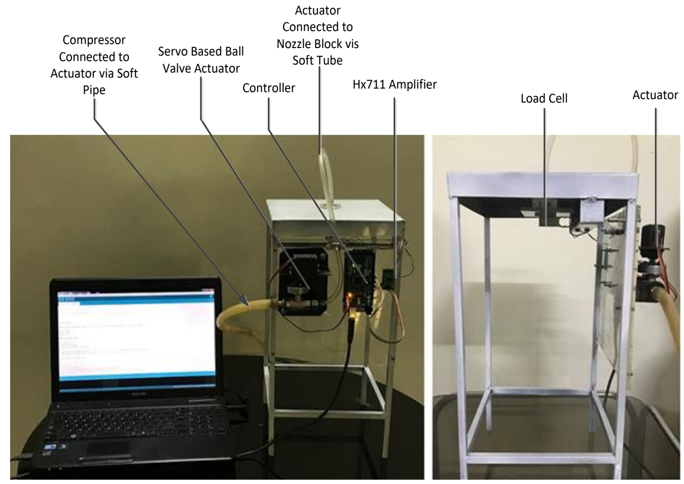


Fig. 6: Experimental Setup for Thrust Estimation of Propulsion System

The LabVIEW platform is used to implement ANFIS algorithms to estimate and analyze the system response based on dynamically changes occurring in 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 thruster block (for each nozzle) generates the lift force (F_l) expressed by the equation given by:

$$F_l = \dot{m}v_e + (p_e - p_o)A_e \quad (1)$$

Where, ṁ is the Air Mass Flow Rate, v_e is the Air Velocity at Nozzle Exit, p_e is the Air Pressure at Nozzle Exit, p_o is the Ambient Air Pressure and A_e is the Area of the Nozzle Exit

Above equations show that thrust generated is highly dependent on momentum (product of velocity and mass flow rate of air) at nozzle exit. The control of servo valve angle causes the dynamic variations in air mass flow rate and the velocity will also change accordingly. Since the pressure at nozzle outlet is very low, it has little role to play in producing the resultant reaction force. The thrust produced by the cylindrical block 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. The data is collected (at a sampling rate of 80 Hz) from the load cell when the excitation signal with periodic staircase pattern is applied to trigger the servo ball valve actuator. The valve angle of servo actuator is varied in a periodic stair case pattern at specific interval of time (5 ms). The data acquisition and logging process is carried out in LabVIEW environment. The overall Prediction process can be represented by the Fig. 7 and Fig. 8.

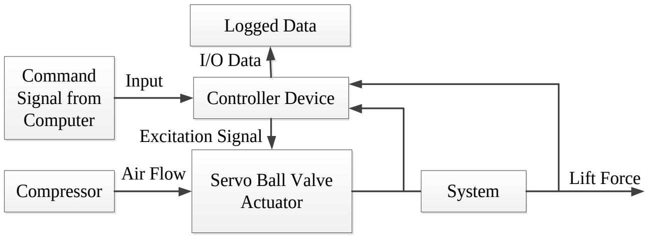


Fig. 7: Data Acquisition Procedure

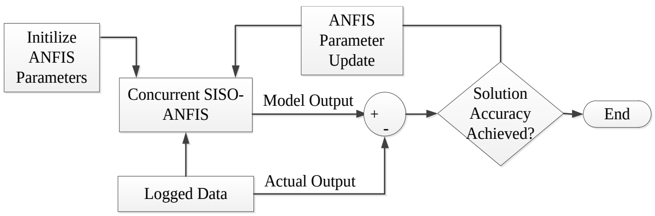


Fig. 8: Prediction of Thrust Response of Different Thruster Blocks

SIMULATION AND RESULTS

The main purpose of carrying out the simulations is to predict the behavior of uplift force generated by the thruster blocks with different number of nozzles by varying the air mass flow rate. Initially the periodic stair case lift response is observed by applying different step excitation signals (PWM) to the system at specific interval of time (15s) for obtaining consistent data. The sequence of input signals, formulated in LabVIEW software environment, is sent to the system via Arduino MEGA 2560 controller. These stimuli signals tend to rotate the stem of the servo ball valve actuator for varying the air mass flow rate accordingly. The process data (associated with dynamic thrust) is sampled at 67Hz that is sufficient for representing the physical process mechanism. The data obtained is then logged in a storage file that can be further utilized for carrying out the analysis. The overall data acquisition process formulated in LabVIEW is shown in Fig.9.

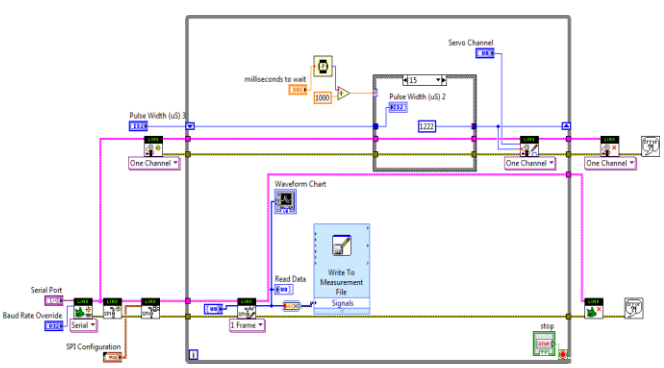


Fig. 9: Data Acquisition and Logging Process in LabVIEW

For a single set of trial operation, the multi stair case lift response curve representing the particular sequence of sampled data (given in Table 1) is shown in Fig.10.

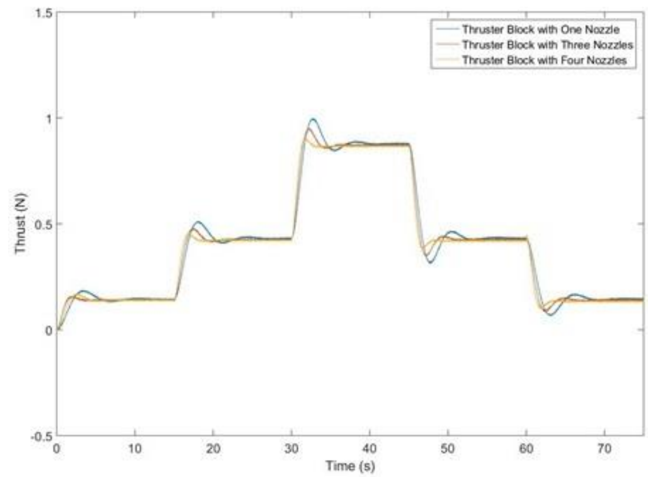
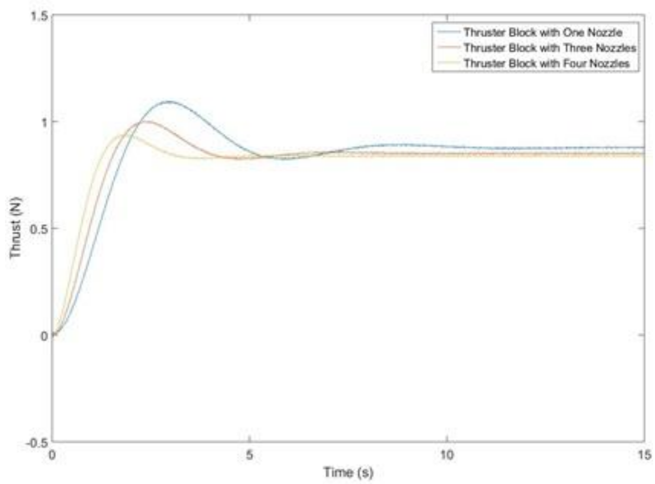


Fig.10: Multi Staircase Lift Response of Different Nozzle Blocks

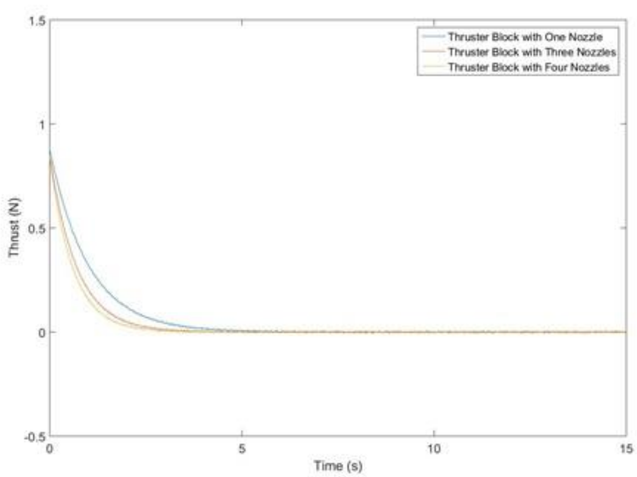
Table 1: Sample Representative Data for the Lift Response of Thruster Blocks

Time (s)	Lift Force Generated by Thruster Block with a Single Nozzle (N)	Lift Force Generated by Thruster Block with Three Nozzles (N)	Lift Force Generated by Thruster Block with Four Nozzles (N)
0	-0.00126	-0.0016321	-0.0025975
0.05	0.000453	0.00131840	-0.0009388
0.1	-0.00266	6.72E-05	5.52E-05
0.15	-0.00214	-0.0016723	3.37E-05
0.2	0.000657	-0.0013299	-4.28E-05
0.25	-0.000982	0.00107439	-0.00122762
0.3	-0.00233	0.003883185	-0.00176847
0.35	0.000934	0.003815026	-0.00115574
0.4	0.000591	0.002164217	-0.00091847
0.45	-0.00109	0.00287384	0.000109945
0.5	0.000457	0.005077522	0.002014017
0.55	0.00301	0.008846083	0.003880156
0.6	9.91E-05	0.009267108	0.005341034
0.65	0.00045	0.008524355	0.006231803
0.7	0.00374	0.009378448	0.006395938
.	.	.	.
.	.	.	.

To observe the characteristic behavior of thruster blocks, the servo ball valve actuator angle is changed from the closed to the fully opened position and then back to the closed position upon receiving the precise PWM input. The output response for the three different thruster blocks is given in Fig.11.



a) Thruster Lift Response for Increasing Valve Angle

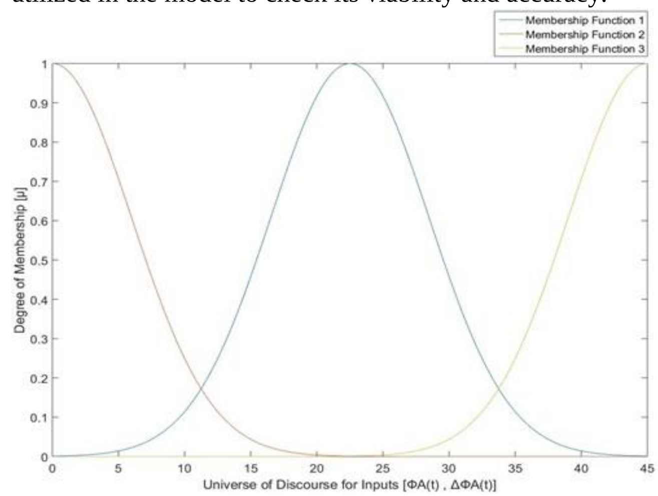


b) Thruster Lift Response for Decreasing Valve Angle

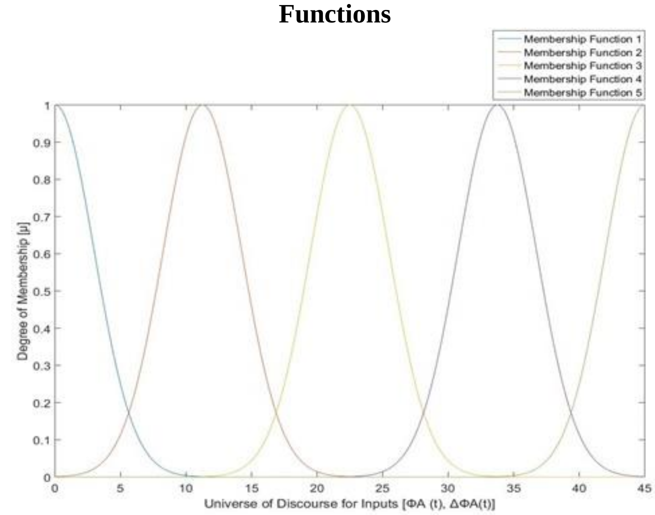
Fig.11: Lift Response of Thruster Blocks with Different Number of Nozzles

In Fig.4.14, the lift force produced by thrusters with distinct number of nozzles has been examined to determine its performance for the upper and lower set-points. It is observed that the increases in number of nozzles significantly reduces the overshoot, gives smooth operational response and improves the quality of thrust generating process. The main reason behind it is that when more number of nozzles is used the flow of air through the thruster blocks is steady and less turbulent. This results in improving the systems reaction time and stable output response.

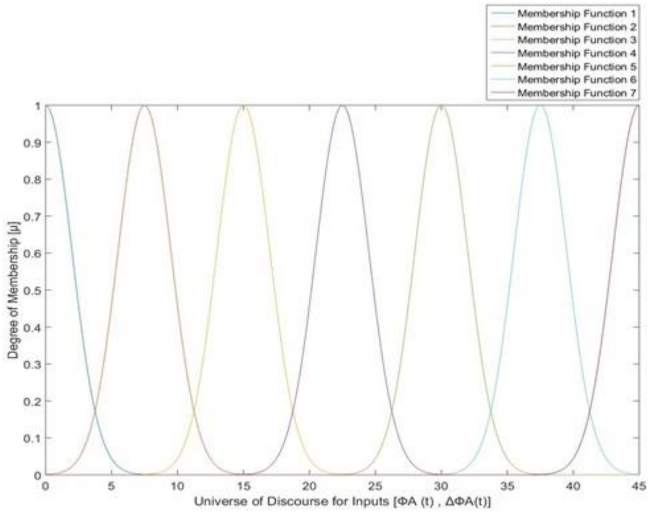
To predict the dynamic response of thruster block other than the sampled data, Concurrent SISO ANFIS model has been proposed. The presented model consists of the inputs in the form of valve angle (ϕ_A) and change in valve angle ($\Delta\phi_A$) with respect to time while the output is represented by the lift force. The range of the valve angle and change in valve angle is set to 0-90^o (from closing to opening position) to formulate the universe of discourse. Each input variable within the universe of discourse is mapped on the Gaussian membership functions to give values between (0 to 1). For nonlinear response usually Gaussian or Bell shaped membership functions are used [28-31]. Since the Gaussian membership functions have less variable parameters, these are selected for the proposed model as shown in Fig.12. Different number of membership functions (3, 5, and 7) is utilized in the model to check its viability and accuracy.



a) Universe of Discourse with Three Membership Functions



b) Universe of Discourse with Five Membership Functions



c) Universe of Discourse with Seven Membership Functions

Fig. 12: Universe of Discourse with Different Number of Membership Functions

The number of rules is defined based on Takagi-Sugeno (T-S) criterion. These rules are established to develop a relationship between the inputs and output. For three membership functions the rule base formed for predicting the lift response of thruster blocks are given as following:

R1: If $\phi_A \geq 0$ **and** $\phi_A < 22.5$ **then** $f_1(\phi_A) = p_1 \phi_A + c_1$
R2: If $\phi_A = 22.5$ **then** $f_1(\phi_A) = p_2 \phi_A + c_2$
R3: If $\phi_A > 22.5$ **and** $\phi_A \leq 45.0$ **then** $f_1(\phi_A) = p_3 \phi_A + c_3$
R4: If $\Delta\phi_A \geq 0$ **and** $\Delta\phi_A < 22.5$ **then** $f_1(\Delta\phi_A) = p_4 \Delta \phi_A + c_4$
R5: If $\Delta \phi_A = 22.5$ **then** $f_1(\Delta \phi_A) = p_5 \Delta \phi_A + c_5$
R6: If $\Delta \phi_A \geq 22.5$ **and** $\Delta \phi_A < 45.0$ **then** $f_1(\Delta \phi_A) = p_6 \Delta \phi_A + c_6$

Similarly, the rules for five and seven membership functions are defined.

From the experimental data, 25000 samples are selected for the analysis. These datasets are then divided into 70% training and 30% checking datasets for the proposed prediction model. The proportion of these datasets are selected based on the research articles presented in [32-35]. For the same input data, the real-time outputs and the model outputs are compared to estimate the error. The parameters of the proposed ANFIS predictor are tuned by the training data utilizing Back Propagation (BP) and Least Square Estimation (LSE) methods to minimize the resulting error [36]. The training has been carried out for fixed number of iterations (epochs) i.e. for 1000 iterations. The model is the validated by checking data to evaluate its accuracy. The proposed model has been programed in LabVIEW as shown in Fig.13.

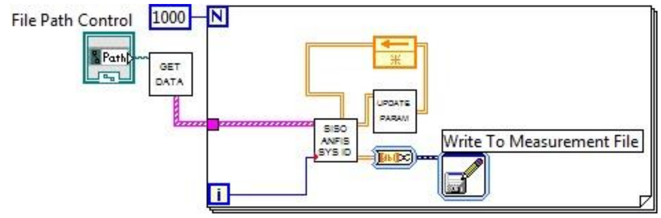
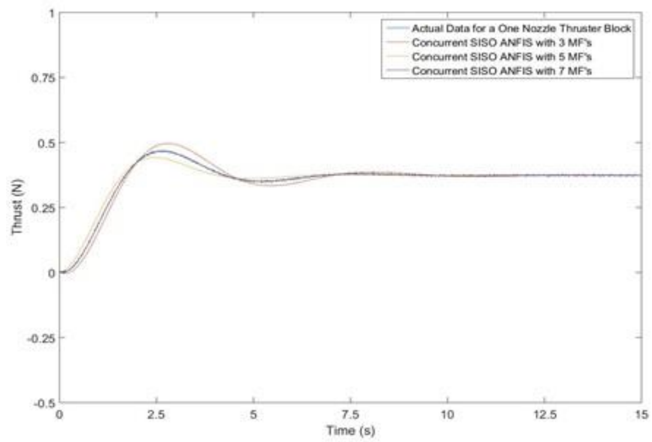
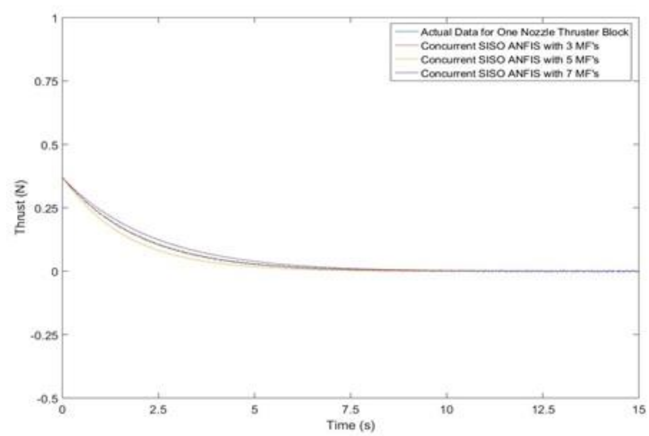


Fig.13: Prediction model Programmed in LabVIEW

The proposed estimator has an important role to play in obtaining the necessary information about the dynamics of operational process. For illustrating the forecasting capability of the presented model, let us consider the lift response of the thruster block for which the valve angle is changed from 0º (closed position) to 45º and then back to 0º. The predictive response of resulting output is shown in Fig.14 to Fig.16.

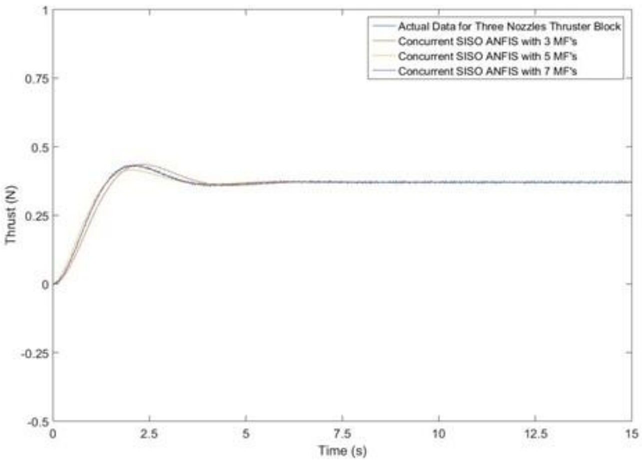


a) Thruster Lift Response for Increasing Valve Angle

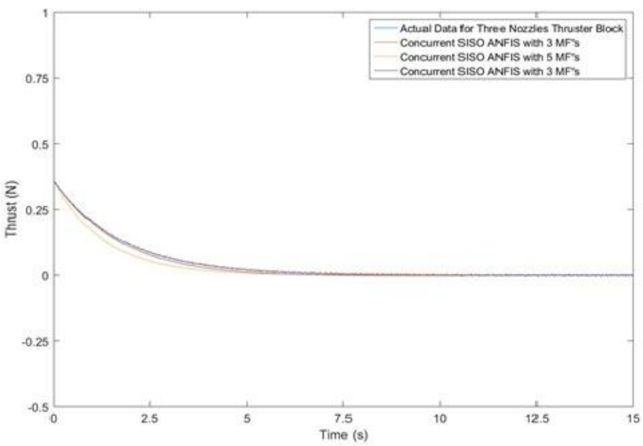


b) Thruster Lift Response for Decreasing Valve Angle

Fig.14: Prediction of Lift Response of a Single Nozzle Thruster Block with Concurrent SISO ANFIS Model

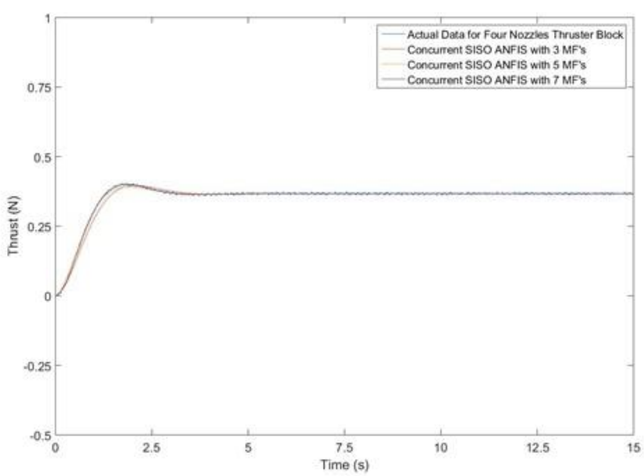


a) Thruster Lift Response for Increasing Valve Angle

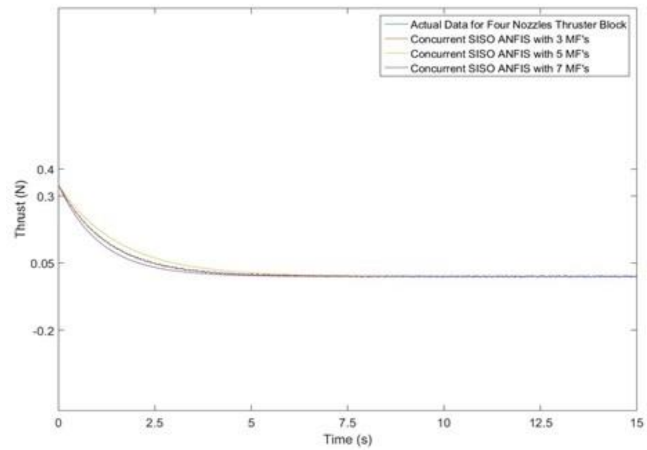


b) Thruster Lift Response for Decreasing Valve Angle

Fig.15: Prediction of Lift Response of Three Nozzles Thruster Block with Concurrent SISO ANFIS Model



a) Thruster Lift Response for Increasing Valve Angle

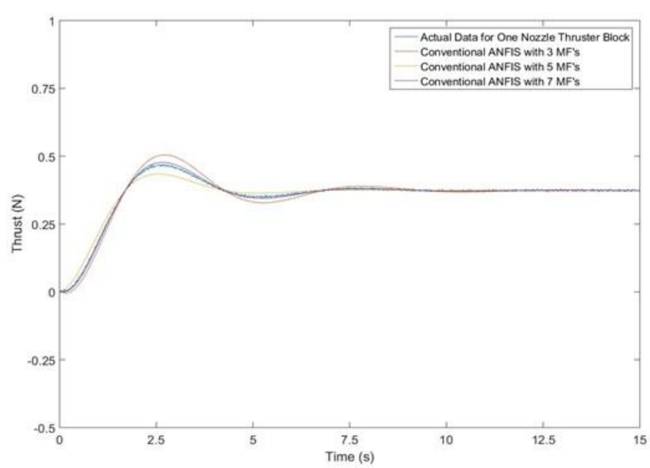


b) Thruster Lift Response for Decreasing Valve Angle

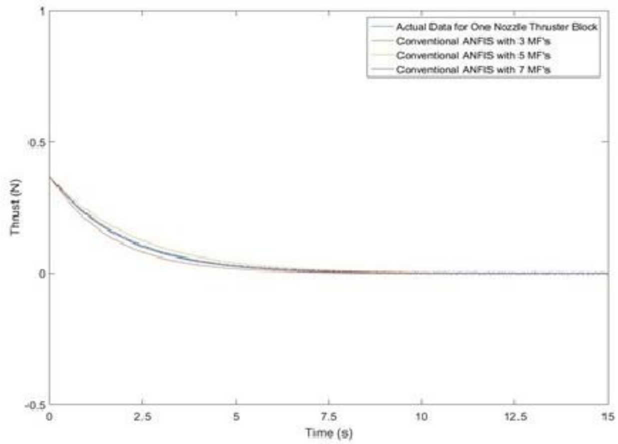
Fig.16: Prediction of Lift Response of Four Nozzles Thruster Blocks with Concurrent SISO ANFIS Model

It is seen that observed that increase in the number of membership functions finely discretizes the datasets over the universe of discourse which enables both the ANFIS frameworks to closely correlate with the system. By utilizing few membership functions the datasets are coarsely aggregated and results in loss of the valuable data required for the system identification. Thus the ability of the model to interpolate and the estimate the system response is significantly enhanced by employing more membership functions.

For the same case as above, prediction of lift response of thruster blocks has been carried out using conventional ANFIS model. The output response of the Conventional ANFIS model is given in Fig.17 to Fig.19.

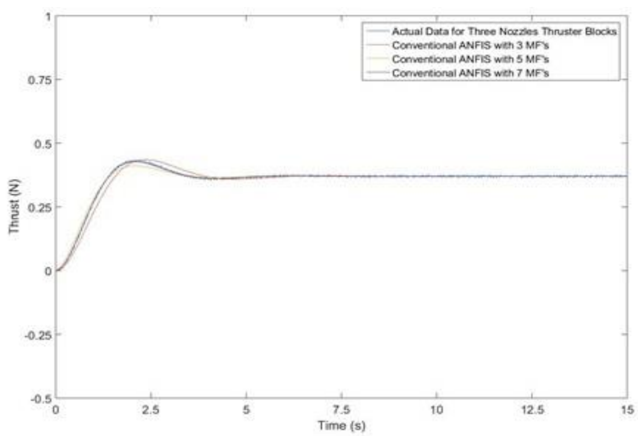


a) Thruster Lift Response for Increasing Valve Angle

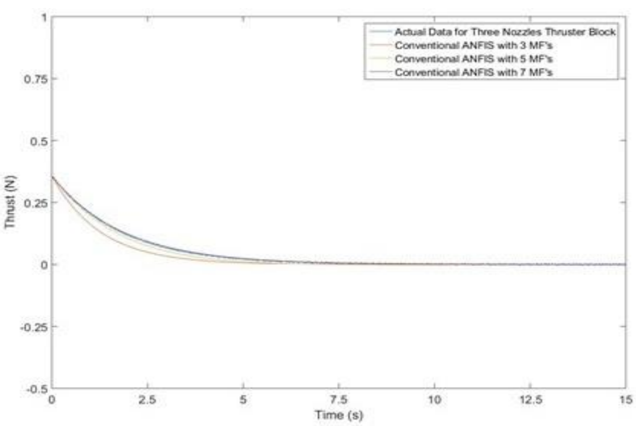


b) Thruster Lift Response for Increasing Valve Angle

Fig.17: Prediction of Lift Response of Single Nozzle Thruster Blocks with Conventional ANFIS Model

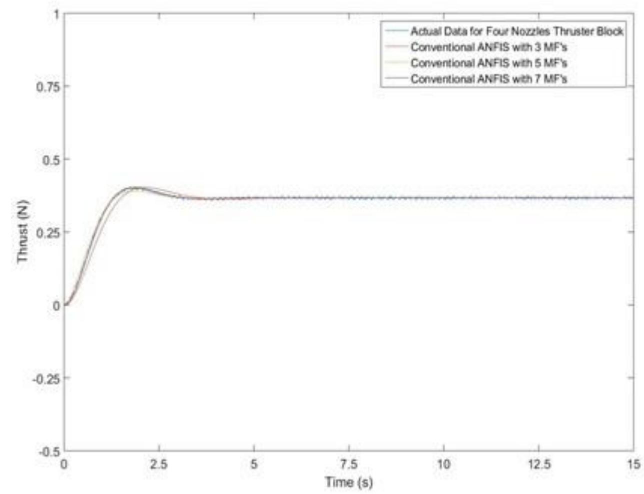


a) Thruster Lift Response for Increasing Valve Angle

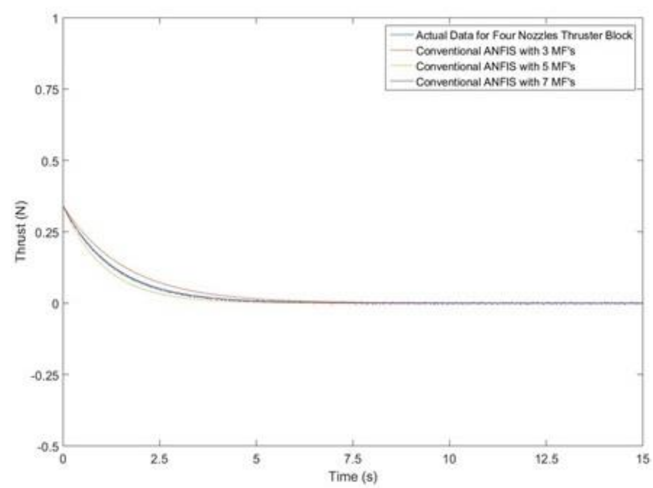


b) Thruster Lift Response for Decreasing Valve Angle

Fig.18: Prediction of Lift Response of Three Nozzles Thruster Blocks with Conventional ANFIS Model



a) Thruster Lift Response for Increasing Valve Angle



b) Thruster Lift Response for Decreasing Valve Angle

Fig.19: Prediction of Lift Response of Four Nozzles Thruster Blocks with Conventional ANFIS Model

The accuracy of proposed and conventional ANFIS models is compared by analyzing the statistical parameters. This comparison is made to determine the efficacy and feasibility of the models in predicting the lift response. The performance of the models is dependent on the tracking capability of the process behavior. The commonly used performance criterion may include determination of correlation coefficient (R), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) etc [37-39] that are dependent on the actual system output (y_i), model output ($\hat{y}_i$) and number of iterations (k).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.

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

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:

$$MAPE = \frac{1}{k}\sum_{i=0}^{k}\left(\frac{|y_i - \hat{y}_i|}{y_i}\right)\times 100 \tag{3}$$

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:

$$R = 1 - \frac{\sum_{i=0}^{k}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=0}^{k}\hat{y}_i^{\,2}} \tag{4}$$

For optimal solution, higher value of "R" with Lower values of "RMSE" and MAPE" are desirable. Each simulation is obtained for different data sets showing the performance of the identification model. The efficiency of the estimator is compared to select the best possible prediction method. The overall performance results for different strategies are shown in Table 2.

Table 2: Performance of the Proposed and Conventional ANFIS Models

For Proposed Predictor				
No. of Membership Functions	**Number of Nozzles in a Thruster Block**	**RMSE**	**MAPE (%)**	**R**
3	1	0.189	1.283	0.888
	3	0.157	1.248	0.899
	4	0.145	1.205	0.906
5	1	0.164	1.164	0.917
	3	0.139	1.127	0.323
	4	0.127	1.091	0.929
7	1	0.114	1.134	0.934
	3	0.109	1.119	0.948
	4	0.107	1.108	0.969
For Conventional ANFIS Predictor				
No. of Membership Functions	**Number of Nozzles in a Thruster Block**	**RMSE**	**MAPE (%)**	**R**
3	1	0.193	1.34	0.878
	3	0.163	1.306	0.891
	4	0.154	1.265	0.896
5	1	0.167	1.22	0.909
	3	0.145	1.185	0.915
	4	0.136	1.168	0.920
7	1	0.146	1.151	0.928
	3	0.141	1.136	0.941
	4	0.138	1.124	0.960

CONCLUSIONS

In this paper the Concurrent SISO ANFIS based black box identification technique has been presented for estimating the dynamic behavior of Single/Multi Nozzle Block designed for jet propulsion system. The experiment has been carried on the electromechanically actuated thruster blocks that receive the air supply from the air compressor to produce lift force. A small scale setup is developed to generate lift force from thruster blocks by applying different step signals to the ball-valve actuator (modulating the air flow of thruster blocks) and real-time data is recorded. The data is then utilized for training Concurrent SISO ANFIS and

Conventional ANFIS models to carry out the identification procedure in LabVIEW based software platform. To refine the applied methodology the accuracy of the applied technique is tested with different number of membership functions and prediction performance is evaluated for unknown inputs. The simulation results reveal that the thrusters with more number of nozzles produce stable lift force due to equal uniform displacement of air in the surrounding. For this reason, better quality of output signals are obtained with less intervention of noise and disturbance that plays a significant role in estimating the output response. The SISO ANFIS show improved accuracy and efficiency when compared with conventional ANFIS scheme. Furthermore the forecasting capability of the suggested predictor is slightly improved when increasing the number of membership functions. This is mainly due to fact that more number of membership functions enhances the predictability of real-time response for precise model abstraction. The overall results reveal that the model with 70% training data with Concurrent SISO ANFIS structure having 7 membership functions for each input, has the minimum MAPE, RMSE and max R values, demonstrating outstanding performance with the given amount of data. The precise abstraction of the simplistic model with limited number of rules would help in achieving the optimal predictor design for the jet based aerodynamic system.

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