ANFIS Modelling of a Twin Rotor System

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Abstract: Interest in system identification especially for nonlinear systems has significantly increased in the past few decades. Soft-computing methods which concern computation in an imprecise environment have gained significant attention amid widening studies of explicit mathematical modelling. In this research, an adaptive neuro-fuzzy inference system (ANFIS) network design is deployed and used for modelling a twin rotor multi-input multi-output system (TRMS). The system is perceived as a challenging engineering problem due to its high nonlinearity, cross coupling between horizontal and vertical axes and inaccessibility of some of its states and outputs for measurements. Accurate modelling of the system is thus required so as to achieve satisfactory control objectives. It is demonstrated experimentally that ANFIS can be effectively used for modelling the system with highly accurate results. The accuracy of the modelling results is demonstrated through validation tests including training and test validation and correlation tests.

Keywords: Adaptive neuro-fuzzy inference system, Dynamic modelling, Soft-computing, Twin rotor multi-input multi-output systems

1. INTRODUCTION

Vibration suppression using soft computing methods is an active area of research with potential applications in the aerospace sector, where airplane wings and helicopter blades are examples of engineering structures that are prone to vibration due to high-speed manoeuvres, wind gust, and other environmental disturbances. Such disturbances can lead to high amplitude structural vibrations, which may cause degradation or catastrophic failure of the structural components. Therefore, the task of reducing these undesirable vibrations is of prime importance for engineering systems.

In a model-based control framework, a pre-requisite to developing an effective control mechanism for a system is to model and predict the behaviours of the system based on given input-output data (Åström and Eykhoff, 1971). A high-fidelity system model is an important first step in control system design and analysis. A number of techniques have been devised by researchers to determine models that best describe input-output behaviour of a system. In many cases when it is difficult to obtain a model structure for a system with traditional system identification techniques, intelligent techniques are desired that can describe the system in the best possible way (Elanayar, 1994).

Soft computing is a practical alternative for solving computationally complex and mathematically intractable problems. The main components of soft computing namely fuzzy logic and neural network have shown great ability in solving complex nonlinear system identification problems (Aldebrez, *et al.*, 2004; Nariman-Zadeh, *et al.*, 2003; Rahideh, *et al.*, 2008). Additionally, vast applications have been devised using the fusion of artificial neural network and fuzzy logic through adaptive neuro-fuzzy inference system (ANFIS) (Jin, *et al.*, 1995; Juang and Lin, 1998; Lin and Xu, 2006; Mat Darus and Tokhi, 2003; Mat Darus and Tokhi, 2004).

Neural networks possess a variety of alternative features such as massive parallelism, distributed representation and computation, generalization ability, adaptability and inherent contextual information processing. On the other hand, fuzzy sets constitute the oldest and most reported soft computing paradigm. They are well suited to modelling different forms of uncertainties and ambiguities, often encountered in real life. The objective of the synergy or hybridization (using neural networks and fuzzy logic) through ANFIS has been to overcome the weaknesses in one technology during its application, with the strengths of the other by appropriately integrating them. More often, the complexity surrounding a problem has called for a judicious combination of the technologies, when a technology individually applied has failed to obtain an efficient solution.

An ANFIS is proposed as a core neuro-fuzzy model that can incorporate human expertise as well as adapt itself through repeated learning. An adaptive network is a multi-layer feed-forward network in which each node (neuron) performs a particular function on incoming signals. The form of the node functions may vary from node to node. In an adaptive network, there are two types of nodes: adaptive and fixed. The function and the grouping of the neurons are dependent on the overall function of the network. Based on the ability of an ANFIS to learn from training data, it is possible to create an ANFIS structure from extremely limited or no mathematical representation of the system. In sequel, the ANFIS architecture can identify near-optimal membership functions of fuzzy logic for achieving desired input-output mappings. The network applies a combination of the least square method and the back propagation gradient descent method for training fuzzy inference system (FIS) membership function parameters to emulate a given training data set. The system converges when the training and checking errors are within the acceptable bound. This architecture has demonstrated high performance in many applications. The ANFIS system generated in the MATLAB allows for generation of a standard Sugeno style fuzzy inference system or a fuzzy inference system based on sub-clustering of the data (MathWorks, 1995).

In this paper, the ANFIS structure is considered for dynamic modelling of TRMS in vertical plane motion (one degree of freedom). The objective of the identification experiments is to estimate a model of the TRMS in hovering mode without any prior system knowledge pertaining to the exact mathematical model structure. The rig configuration is such that it permits open-loop system identification, unlike a helicopter which is open-loop unstable in hovering mode.

2. EXPERIMENTAL SET-UP

The twin-rotor multiple-input multiple-output (MIMO) system (TRMS) is a laboratory set-up developed by Feedback Instruments Limited (Feedback Instruments Ltd., 1996) for control experiments. Its behaviour in certain aspects resembles that of a helicopter. For example, it possesses a strong cross-coupling between the collective (main rotor) and the tail rotor, like a helicopter. However, the TRMS is different from a helicopter in many ways. Table 1 list the main differences between a helicopter and a TRMS (Rahideh *et. al*, 2008).

Table 1: Main differences between a helicopter and a TRMS

	TRMS	Helicopter
Location of pivot point	Midway between two rotors	Main rotor head
Lift generation of vertical axis	Speed control of main rotor	Collective pitch control*
Yaw is controlled by	Tail rotor speed	Pitch angle of tail rotor blades
Cyclical control	No	Yes *for directional control*

* The pitch angles of all the blades of the main rotor are changed but at constant rotor speed.

The system is balanced in such a way that when the motors are switched off, the main rotor end of the beam is lowered. The controls of the system are the motors' supply voltages. It is important to note that the geometrical shapes of the propellers are not symmetric. Accordingly, the system behaviour in one direction is different from that in the other direction. Rotation of a propeller produces an angular momentum which, according to the law of conservation of angular momentum, is compensated for by the remaining body of the TRMS beam. This results in interaction between the moment of inertia of the motors with propellers. This interaction directly influences the velocities of the beam in both planes. The measured signals are: position of the beam, namely two position angles, and the angular velocities of the rotors. A schematic diagram of the TRMS is shown in Fig. 1.

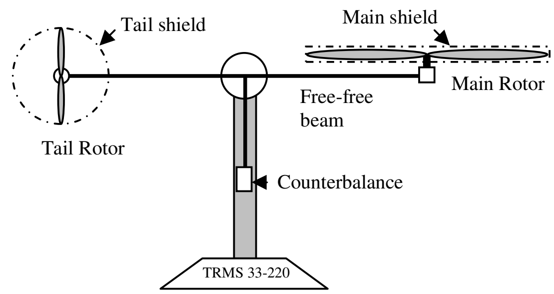


Fig. 1: Schematic diagram of the TRMS

3. MODELLING USING ANFIS

An ANFIS consisting of a set of TSK-type fuzzy IF-THEN rules is used to map the system inputs to outputs. This hybrid combination enables to deal with both the verbal and the numeric power of intelligent systems. As is known from the theory of fuzzy systems, different fuzzification and defuzzification mechanisms with different rule base structures can lead to various solutions to a given task.

The fuzzy regions are parameterized and each region is associated with a linear subsystem. Owing to the fuzzily defined antecedents, the nonlinear system forms a collection of loosely coupled multiple linear models. The degree of firing of each rule is proportional to the level of contribution of the corresponding linear model to the overall output of the model. For simplicity, the fuzzy inference system under consideration is assumed to have two inputs x and y and one output z. The membership function for both the inputs is set to be six. The ANFIS structure with first-order Sugeno model containing 36 rules is shown in Fig. 2.

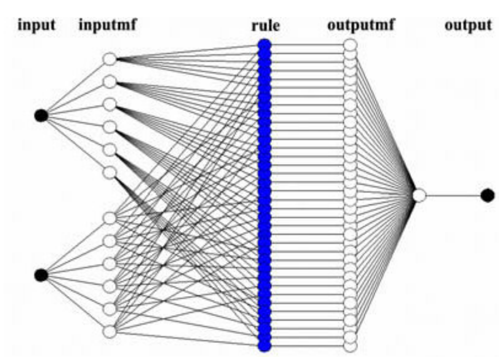
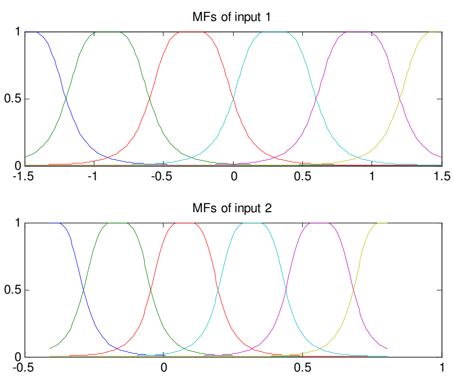


Fig. 2: ANFIS structure for modelling the TRMS

Gaussian membership functions with product inference rule were used at the fuzzification level. The ANFIS Gaussian function used for both input as well as the 36 rules is shown in Fig. 3. The fuzzifier outputs the firing strengths for each rule. The vector of firing strengths is normalized. The resulting vector is defuzzified by utilizing the first-order Sugeno model.



a) ANFIS membership function

Rules:

1. if (input1 is in1mf1) and (input2 is in2mf1) then (output is out1mf1)
2. if (input1 is in1mf1) and (input2 is in2mf2) then (output is out1mf2)
3. if (input1 is in1mf1) and (input2 is in2mf3) then (output is out1mf3)
4. if (input1 is in1mf1) and (input2 is in2mf4) then (output is out1mf4)
5. if (input1 is in1mf1) and (input2 is in2mf5) then (output is out1mf5)
6. if (input1 is in1mf1) and (input2 is in2mf6) then (output is out1mf6)
7. if (input1 is in1mf2) and (input2 is in2mf1) then (output is out1mf7)

36. if (input1 is in1mf6) and (input2 is in2mf1) then (output is out1mf36)

b) ANFIS rules

Fig. 3: ANFIS membership function and rules for modelling the TRMS

4. IMPLEMENTATION AND RESULTS

Results of modelling the TRMS in vertical plane motion with ANFIS are presented in this section. Model validation is varied out in time and frequency domains through comparative assessment of the system and model responses and correlation tests.

The TRMS set-up is very sensitive to the atmospheric disturbances; hence it was ensured that the identification experiments are conducted in calm air. The body resonance modes of the TRMS lies in a low frequency range of 0 to 3 Hz, while the main rotor dynamics are at significantly higher frequencies (Ahmad, et al., 2003). The excitation signal represents voltage input to the main rotor and the output signal represents the elevation angle (pitch angle) in radians. During experimentation, the yaw plane is physically locked, allowing only vertical plane motion. To investigate variations in the resonance modes, the system was excited with a pseudorandom binary sequence (PRBS) of different bandwidths (2 to 20 Hz). A PRBS of 5Hz bandwidth and 100s duration was finally chosen for this analysis. The PRBS magnitude was selected so that it does not drive the TRMS out of its linear operating range. Good excitation was achieved from 0 to 5 Hz, which includes all the important rigid body and flexible modes of the system.

At the identification of the TRMS, the fuzzifier possessed two inputs x and y where the rule base contained 36 rules and the defuzzifier had one output z. The data set, comprising 1000 data points, was divided into two sets of 300 and 700 data points respectively. The first set was used to train the network and the model was validated with the whole 1000 points including the 700 points that had not been used in the training process. Fig. 4 shows the prediction of the pitch angle of TRMS using ANFIS modelling with PRBS excitation input. The model reached a mean-squared error level of 0.0004218 in 100 training passes. It is noted from Figs. 4 and 5 that the ANFIS model performed well and it is obvious that the error between the actual and the predicted output of the model is very insignificant.

Theoretically, the TRMS will have an infinite number of resonance modes with associated frequencies. However, it is intuitively assumed that the main dynamics (modes) of the TRMS lie in the 0 to 10 Hz range. It is further assumed that the rotor dynamics are at significantly higher frequencies than the rigid body dynamics. Hence, these can be neglected, and the rotor influence is lumped into the rigid body derivatives (Ahmad, et al., 2003). The power spectral density plot of the vertical plane motion in response to the PRBS input signal, as shown in Fig. 6, indicates closely spaced modes between 0 and 10 Hz as expected, with a main resonance mode at 0.37412 Hz which can be attributed to the main body dynamics.

Correlation validation of vertical plane motion model of TRMS in hovering position is shown in Figure 7. If the model error (residual) contains no information about past residuals or about the dynamics of the system, it is likely that all information has been extracted from the training set and the model approximates the system well. The correlations will never be exactly zero for all lags and the 95% confidence bands defined as $|r| < 1.96\sqrt{N}$ are used to indicate if the estimated correlations are significant or not, where N is the data length and r is the correlation function (Billings and Voon, 1986; Billings and Zhu, 1994). It is noted that all the five correlation functions; auto-correlation of residual (Fig. 7a), cross-correlation of input and residuals (Fig. 7b), cross-correlation of input square and residuals (Fig. 7c), cross-correlation of input square and residuals square (Fig. 7d) and cross-correlation of residuals and input multiplied by residuals (Fig 7e) are within the 95% confidence bands indicating that the model behaviour is close to that of the real system.

5. CONCLUSION

ANFIS architecture has demonstrated a good performance in modelling the TRMS in vertical plane motion. The best feature of ANFIS is that it pre-processes all the data into several membership functions before mapping the data into an adaptive neuro structure. This pre-processing feature allows ANFIS to converge faster and better. The results have been obtained in both time and frequency domains and the ANFIS modelling method has also been validated using input-output mapping and correlation tests. The resulting model will be used for further development of analysis and control strategies for twin rotor MIMO systems.

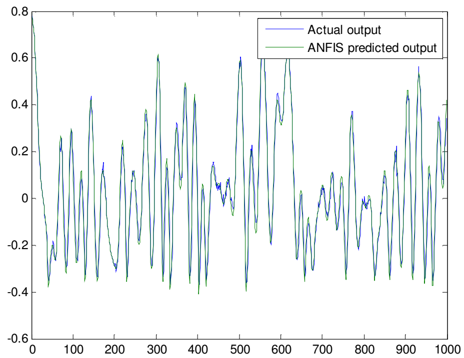


Fig. 4: Actual and predicted outputs

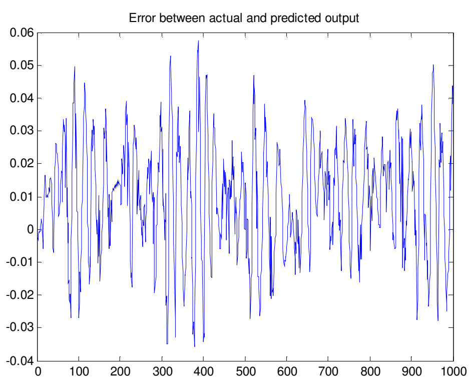


Fig. 5: Error between actual and predicted outputs

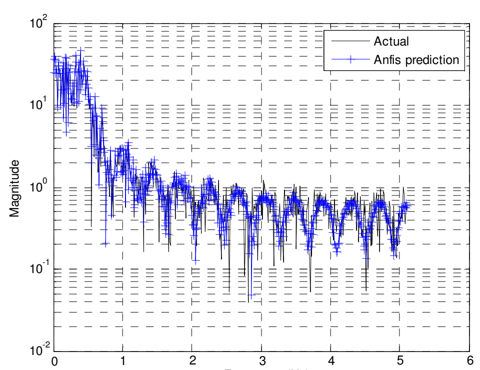


Fig. 6: Spectral densities of the outputs

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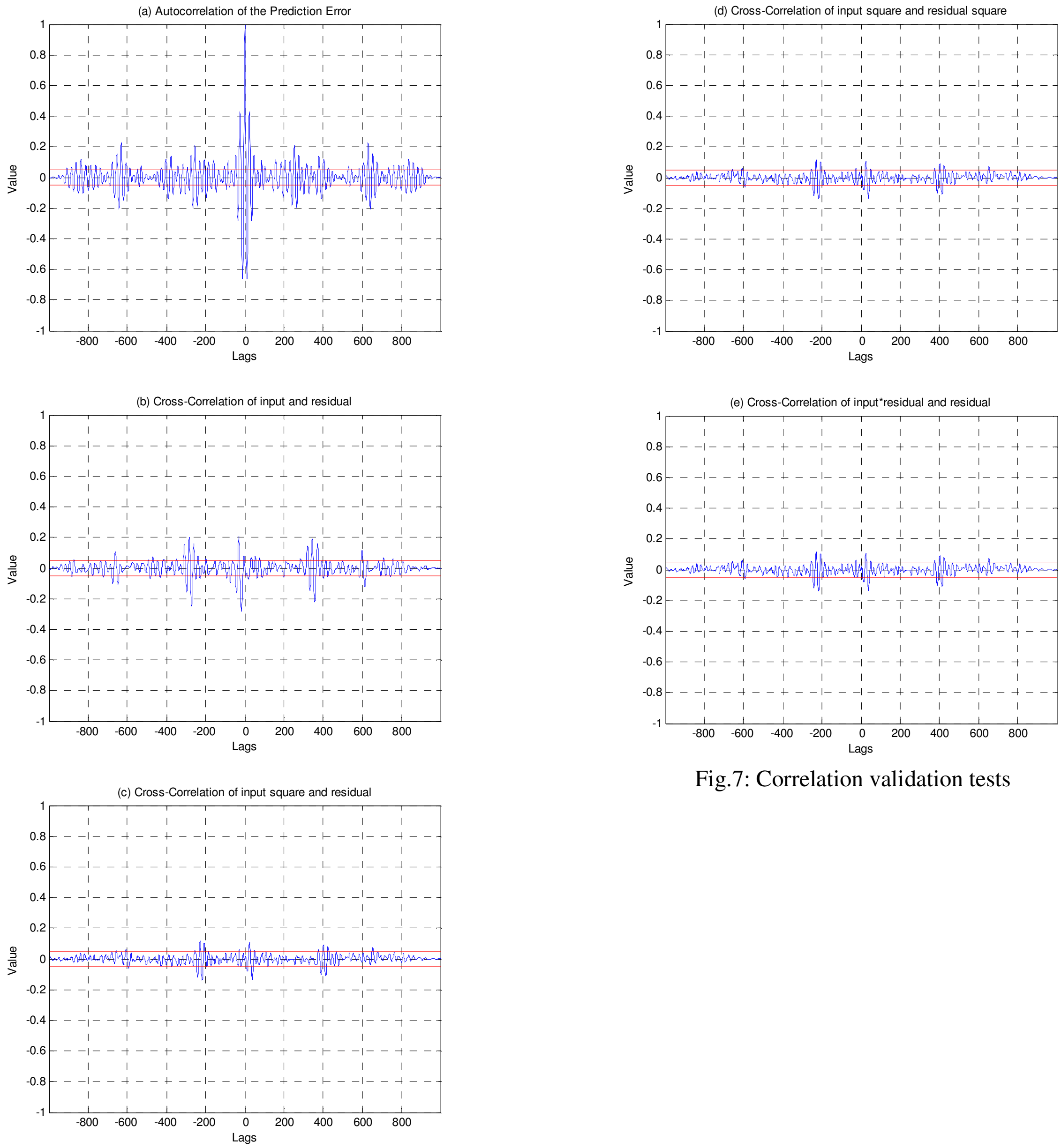

Fig.7: Correlation validation tests