Real-Time Fuzzy Identification of Twin Rotor MIMO System

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Abstract

This paper presents identification of laboratory Twin Rotor MIMO System (TRMS) using fuzzy logic. The TRMS is a challenging system to control since it is a non-minimum phase system and is a laboratory bench mark system for air vehicles like helicopters. This system has two degrees of freedom with strong cross-coupling between the vertical and horizontal axes. For optimal tuning of the fuzzy system parameters, the gradient descent algorithm is employed in this paper. In order to reduce the computation complexity and at the same time to increase robustness of the fuzzy model, the online learning method is used here. Experimental results show effectiveness of the proposed approach.

Keywords: Twin rotor MIMO system, Fuzzy system, Gradient descent algorithm, Online learning.

1. INTRODUCTION

Soft computing refers to a consortium of computational methodologies. Some of its principal components include fuzzy logic, neural network and genetic algorithm, all having their roots in artificial intelligence. In today's highly integrated world, when solutions to problems are cross-disciplinary in nature, soft computing promises to become a powerful means for obtaining solutions to problems quickly, yet accurately and acceptably. In the triumvirate of soft computing, fuzzy logic is concerned with adaptive learning, non-linear function approximation, and universal generalization.

System identification is a process, which determines the proper model for the system based on data and measured parameters. This process is very important because the effectiveness of many controlling approaches is related to the model accuracy. Fuzzy systems are universal approximators. On the other hand, the results of experiments, which have been performed by experts, can be used as the empirical and applied approach in order to form a fuzzy rule bases which leads to design proper fuzzy system. Hence, the application of the fuzzy system as the identifier is logical for nonlinear system.

Some researchers have addressed the modeling and control of a TRMS using various model based and artificial intelligence based approaches [1] to [12]. Darus et al. have proposed a system identification using parametric linear approaches for a TRMS using GA [4] and [5]. In their approach the global search technique of GA has been used to identify the parameters of the TRMS based on one-step-ahead prediction. In [7], performance analysis of 4 types of conjugates gradient algorithms in the nonlinear dynamic black box modeling of a TRMS using feedforward neural networks has been reported.

The remainder of the paper is organized as follows: a description of the system is presented in Section 2. Section 3 discusses the process of designing the fuzzy identifier. Experimental results to demonstrate the effectiveness of the identifier are presented in Section 4. Concluding remarks are provided in Section 5.

2. SYSTEM DESCRIPTION

The TRMS, as shown in Fig. 1, is a laboratory set-up developed by Feedback Instruments Ltd. [13]. It is a highly nonlinear system with cross-coupling influences between its axes. The TRMS is driven by two DC motors. Its two propellers are perpendicular to each other and joined by a beam pivoted on its base that can rotate freely in the horizontal and vertical plane. The joined beam can be moved by changing the input voltage in order to control the rotational speed of the propellers. The system is equipped with a Pendulum Counter-Weight hanging from the beam and is used for balancing the angular momentum in steady state or with load.

In certain aspects, its behavior 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 lists the main differences between a helicopter and a TRMS.

Table 1. The main differences between a helicopter and a TRMS

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

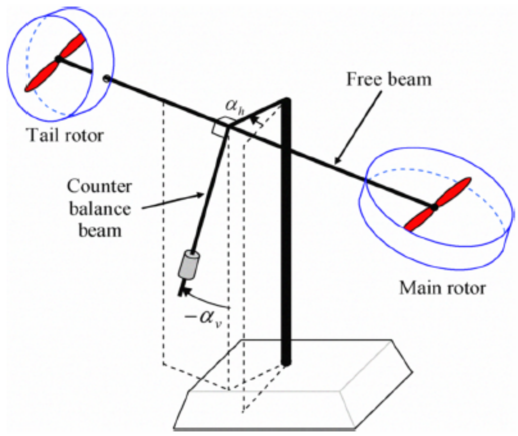

Fig. 1. The twin rotor MIMO system

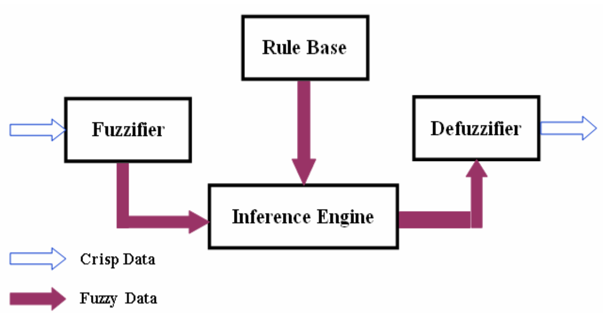

Fig. 2. Basic component of fuzzy system

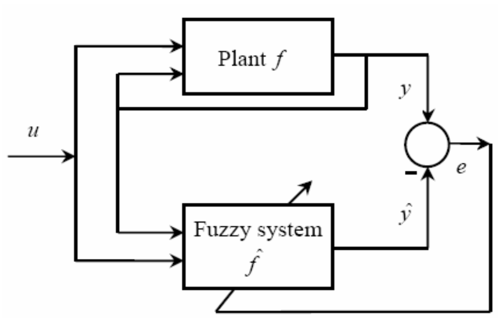

Fig. 3. Block diagram identification with fuzzy system

3. FUZZY IDENTIFICATION

The fuzzy system is built based on human expertise and is composed of four main parts: fuzzy rule bases, fuzzy inference engine, fuzzifier and defuzzifier. The block diagram of a fuzzy system is shown in Fig. 2.

Designing fuzzy system according to input-output data can be classified in two categories. In the first one, the fuzzy rule bases is first created according to the input-output data and then the fuzzy system is constructed by proper selection of the fuzzy inference engine, the fuzzifier and the defuzzifier. In this method, the parameters of the fuzzy system are fixed. In the second approach, on the other hand, the fuzzy system structure is first determined, and then, some parameters of the fuzzy system can be varied based on the input-output data and some criteria. In this paper, the gradient descent algorithm is used to obtain optimal parameters for the fuzzy system [14].

It is well known that in order to increase the performance accuracy of the fuzzy systems, there must be more fuzzy membership functions for each input variable of the system, which in turn yields more fuzzy rules. This unwanted phenomenon, known as the curse of dimensionality, incurs a lot of computational burdens and many researchers try to avoid that. In this paper, in order to reduce the number of rules substantially, online learning approach is adapted for tuning the parameters of the fuzzy identifier [14]. The other advantage of the on-line learning method is that the model will be robust against changes in the TRMS, since the adaptive fuzzy model can cope with such variations in the plant.

In this section, summary of gradient descent algorithm is represented initially and then, the process of designing the fuzzy identifier is discussed.

3.1. GRADIENT DESCENT ALGORITHM

Consider the following nonlinear and discrete system:

$$y(k+1)=f(y(k),\dots,y(k-n+1); u(k),\dots,u(k-m+1)) \qquad (1)$$

where f is an unknown function, which will be identified based on fuzzy logic, u and y are the input and the output of the system, respectively, and m and n are positive scalars.

Assume the nonlinear function $f(x)$ is approximated by a fuzzy system and is shown by $\hat{f}(x)$. Substituting $f(x)$ with $\hat{f}(x)$ in (2) yields

$$\hat{y}(k+1)=\hat{f}(y(k),\dots,y(k-n+1); u(k),\dots,u(k-m+1)) \qquad (2)$$

The objective is to adjust the parameters of $\hat{f}(x)$ in a way that the model output is converged to actual system output while k approaches infinity (Fig.3).

In order to apply the gradient descent method to the fuzzy system, first the structure of the fuzzy system one must be determined. Primary structure of the fuzzy system is made up of Mamdany multiplication inference engine, singleton fuzzifier, center average defuzzifier and Gaussian membership [14]

$$f(x)=\frac{\sum_{l=1}^{M}\bar{y}^{l}\left[\prod_{i=1}^{n}\exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right)\right]}{\sum_{l=1}^{M}\left[\prod_{i=1}^{n}\exp\left(-\left(\frac{x_i-\bar{x}_i^{l}}{\sigma_i^{l}}\right)^2\right)\right]} \qquad (3)$$

where M and n are positive scalars which refer to the number of rules and the number of fuzzy system inputs, respectively, $\bar{x}_i^l$ and σ_i^l are the center and the width of fuzzy membership functions of the i^{th} input and the l^{th} rule, respectively, $\bar{y}_l$ is center of output membership function corresponding to l^{th} rule.

The objective of the gradient descent algorithm is find the optimal values for the parameters of the fuzzy system ($\bar{x}_i^l$, σ_i^l and $\bar{y}_l$ in (3)), to minimize the following performance index:

$$E(k) = \frac{1}{2}\left(\hat{f}(x(k)) - y(k)\right)^2 \tag{4}$$

where $\hat{f}(x(k))$ is the output of the fuzzy system and $y(k)$ is the actual system's output (see Fig. 3).

The adaptation laws for determination of the optimal parameters by the use of the gradient descent algorithm are

$$\bar{y}^l(k+1) = \bar{y}^l(k) - \alpha \frac{\partial E(k)}{\partial \bar{y}^l(k)} \tag{5}$$

$$\bar{x}_i^l(k+1) = \bar{x}_i^l(k) - \alpha \frac{\partial E(k)}{\partial \bar{x}_i^l(k)} \tag{6}$$

$$\sigma_i^l(k+1) = \sigma_i^l(k) - \alpha \frac{\partial E(k)}{\partial \sigma_i^l(k)} \tag{7}$$

where $0 < \alpha < 1$ is called the learning rate.

3.2 DESIGNING FUZZY IDENTIFIER

In order to identify the TRMS with two degrees of freedom, two fuzzy identifiers must be developed; one for the horizontal axis and the other one for the vertical axis.

The horizontal fuzzy identifier has three inputs, which are the actual yaw angle of the TRMS ($y_h(k)$), the input voltage of the tail rotor ($U_h(k)$) and input voltage of the main rotor ($U_v(k)$), all at instant k. The output of the identifier is the estimated yaw angle ($\hat{y}_h(k+1)$) at instant $k+1$. The vertical fuzzy identifier has two inputs, which are the actual pitch angle of the TRMS ($y_v(k)$) and the input voltage of the main rotor ($U_v(k)$) both at instant k. Its output is the estimated pitch angle ($\hat{y}_v(k+1)$) at instant $k+1$ (Fig. 4).

Because the movement of TRMS is physically limited in both vertical and horizontal axes, the range of changes in the yaw and pitch angles are $\left[-170^0 \quad 170^0\right]$ and $\left[-58^0 \quad 58^0\right]$, respectively. Thus, the range of changes of inputs and the output of the fuzzy system for the vertical and the horizontal subsystems are considered as follows:

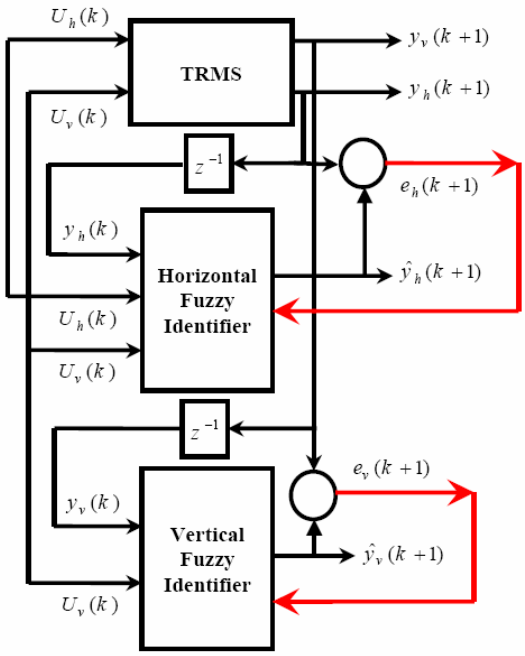

Fig. 4. Block diagram of TRMS with Fuzzy system identifier

$$\begin{aligned} & y_h(k) \in [-3 \quad 3] \quad \text{rad} \\ & U_h(k) \in [-2.5 \quad 2.5] \quad \text{V} \\ & U_v(k) \in [-2.5 \quad 2.5] \quad \text{V} \\ & \hat{y}_h(k+1) \in [-3 \quad 3] \quad \text{rad} \end{aligned} \tag{8}$$

$$\begin{aligned} & y_v(k) \in [-1 \quad 1] \quad \text{rad} \\ & U_v(k) \in [-2.5 \quad 2.5] \quad \text{V} \\ & \hat{y}_v(k+1) \in [-1 \quad 1] \quad \text{V} \end{aligned} \tag{9}$$

Three Gaussian membership functions have been selected for every input and the output of the fuzzy system.

The most important part of a fuzzy system is the fuzzy rule base. These rules have are determined in accordance with the system response to different types of reference signals. The fuzzy rule bases have been shown for vertical axis in Table. 1. The horizontal fuzzy rule bases are shown in three tables due to three inputs for this identifier (Tables 2, 3, and 4).

Table. 1. Fuzzy rules of vertical fuzzy identifier

		$U_v(k)$		
		N	**Z**	**P**
$y_v(k)$	**N**	**N**	**N**	**N**
	Z	**Z**	**Z**	**Z**
	P	**P**	**P**	**P**

Table. 2. Fuzzy rules of horizontal fuzzy identifier ($y_h(k)$ is N)

		$U_v(k)$		
		N	**Z**	**P**
$U_h(k)$	**N**	N	N	N
	Z	N	N	N
	P	N	N	N

Table. 3. Fuzzy rules of horizontal fuzzy identifier ($y_h(k)$ is Z)

		$U_v(k)$		
		N	**Z**	**P**
$U_h(k)$	**N**	Z	Z	Z
	Z	Z	Z	Z
	P	Z	Z	Z

Table. 4. Fuzzy rules of horizontal fuzzy identifier ($y_h(k)$ is P)

		$U_v(k)$		
		N	**Z**	**P**
$U_h(k)$	**N**	P	P	P
	Z	P	P	P
	P	P	P	P

Based on (3), the fuzzy identifier for each axis has the following form:

$$\hat{y}_h(k+1)=\frac{\sum_{l=1}^{27}\bar{y}_h^l\left[\prod_{i=1}^{3}\exp\left(-\left(\frac{x_{h_i}-\bar{x}_{h_i}^l}{\sigma_{h_i}^l}\right)^2\right)\right]}{\sum_{l=1}^{27}\left[\prod_{i=1}^{3}\exp\left(-\left(\frac{x_{h_i}-\bar{x}_{h_i}^l}{\sigma_{h_i}^l}\right)^2\right)\right]} \qquad (10)$$

$$\hat{y}_v(k+1)=\frac{\sum_{l=1}^{9}\bar{y}_v^l\left[\prod_{i=1}^{2}\exp\left(-\left(\frac{x_{v_i}-\bar{x}_{v_i}^l}{\sigma_i^l}\right)^2\right)\right]}{\sum_{l=1}^{9}\left[\prod_{i=1}^{2}\exp\left(-\left(\frac{x_{v_i}-\bar{x}_{v_i}^l}{\sigma_{v_i}^l}\right)^2\right)\right]} \qquad (11)$$

where $x_{h_i}(k)$, $\bar{y}_h^l(k)$, $\bar{x}_{h_i}^l(k)$ and $\sigma_{h_i}^l(k)$ are i^{th} input of the fuzzy system, the center of the output membership functions in l^{th} rule, the center and width of i^{th} input membership functions in l^{th} rule, all for the horizontal identifier, respectively. Moreover, $x_{v_i}(k)$, $\bar{y}_v^l(k)$, $\bar{x}_{v_i}^l(k)$ and $\sigma_{v_i}^l(k)$ are the same but for the vertical identifier, respectively.

Based on (4), the adaptation error for every axis can be written as

$$E_h(k+1)=\frac{1}{2}(\hat{y}_h(k+1)-y_h(k+1))^2 \qquad (12)$$

$$E_v(k+1)=\frac{1}{2}(\hat{y}_v(k+1)-y_v(k+1))^2 \qquad (13)$$

where $y_h(k+1)$ and $y_v(k+1)$ are the actual yaw and pitch angles of TRMS at instant $k+1$, respectively. Based on (5), (6), and (7), the adaptation laws must be defined for the horizontal axes as well as the vertical axes.

4. EXPERIMENTAL RESULTS

In this section, the designed fuzzy identifiers are applied to the TRMS for two degrees of freedom simultaneously and in real time. The results of modeling presented in this section are in real time. The characteristics of reference signals are presented in Table. 5. The experimental results are shown in Figs. 5--16. As these figures show, the adaptive fuzzy systems demonstrate very good performance in identification of the highly nonlinear TRMS in real time.

Table. 5. Characteristics of the set of reference inputs

		Type	Amplitude (volt)	Frequency (Hz)
Mode 1	**Vertical**	**Sine**	**0.5**	**0.2**
	Horizontal	**Sine**	**0.6**	**0.05**
Mode 2	**Vertical**	**Sine**	**1**	**0.3**
	Horizontal	**Sine**	**0.05**	**0.2**

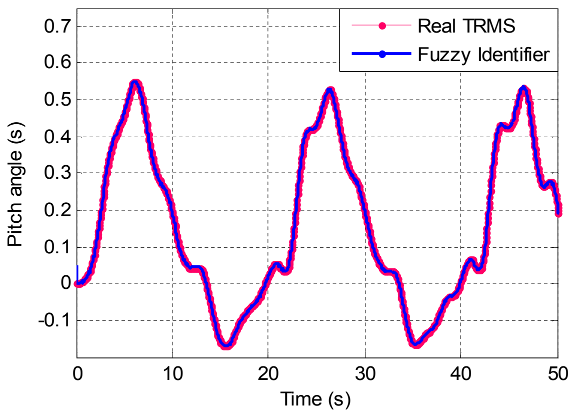

Fig. 5. Pitch angle of the TRMS in Mode 1

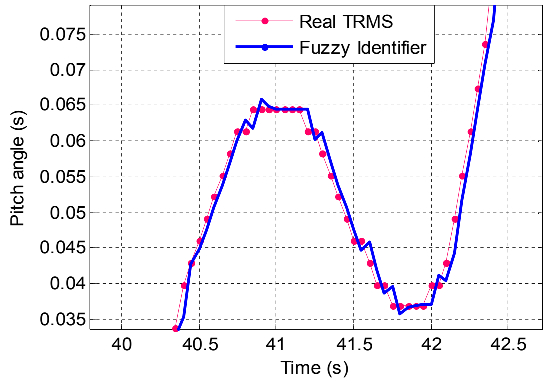

Fig. 6. Pitch angle of the TRMS in Mode 1

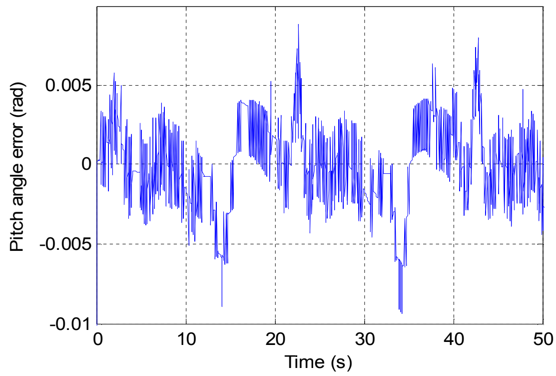

Fig. 7. Pitch angle error in Mode 1

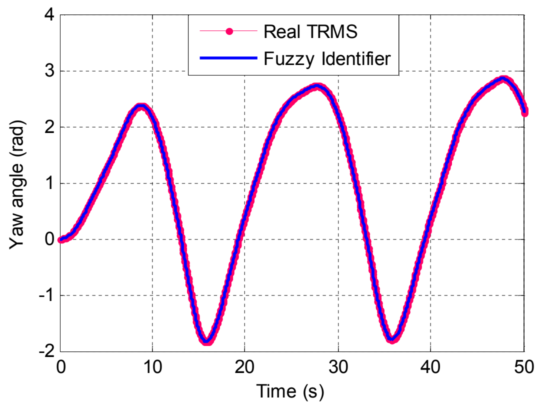

Fig. 8. Yaw angle of the TRMS in Mode 1

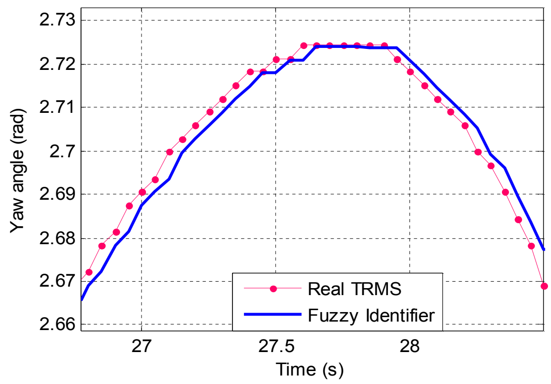

Fig. 9. Yaw angle of the TRMS in Mode 1

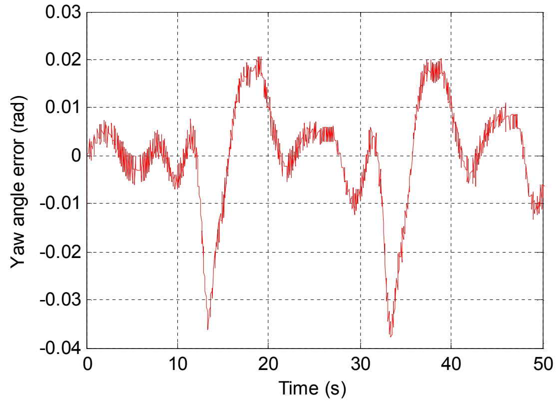

Fig. 10. Yaw angle error in Mode 1

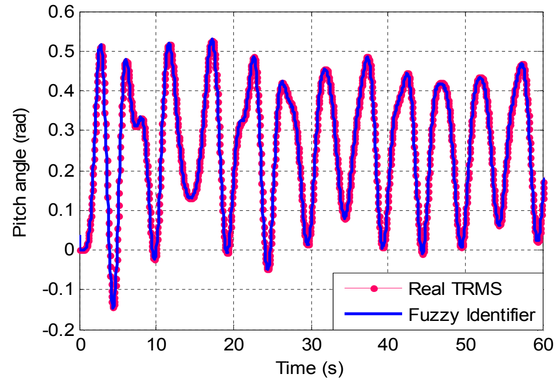

Fig. 11. Pitch angle of the TRMS in Mode 2

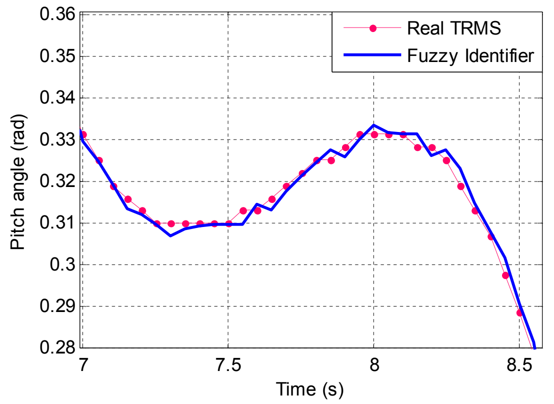

Fig. 12. Pitch angle error in Mode 2

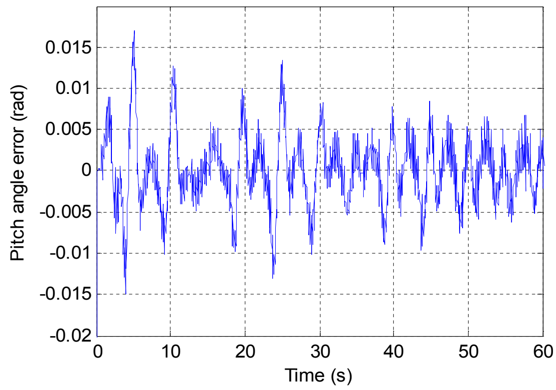

Fig. 13. Pitch angle error in Mode 2

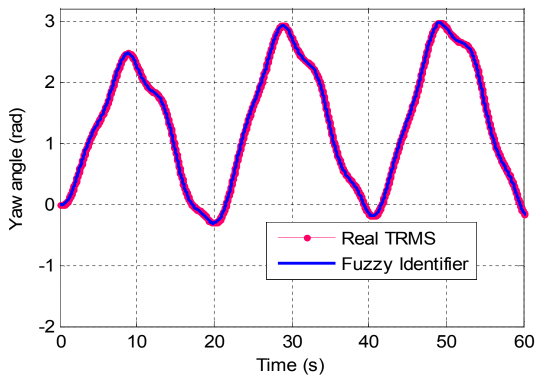

Fig. 14. Yaw angle of the TRMS in Mode 2

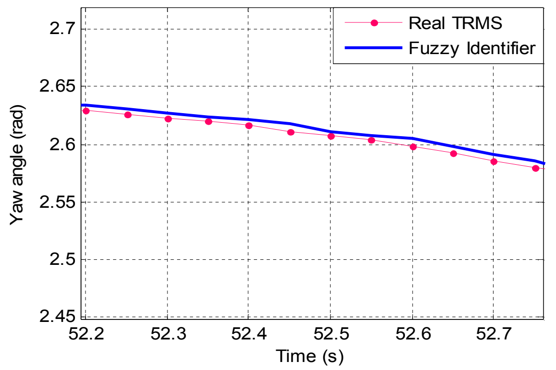

Fig. 15. Yaw angle of the TRMS in Mode 2

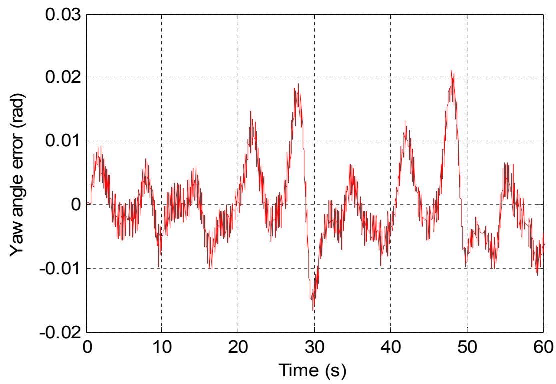

Fig. 16. Yaw angle error in Mode 2

5. CONCLUSION

In this paper, adaptive fuzzy systems have been employed to characterize the dynamic behavior of a TRMS in two degrees of freedom. Two fuzzy identifiers have been first designed for the vertical and horizontal axes based on the system in real time. The gradient descent algorithm with online learning capability has been used for obtaining optimal parameters of fuzzy systems, which lead to less computation time, more accuracy, and faster convergence. The performance of the designed identifiers has been evaluated by various reference inputs. Experimental results show effectiveness of the fuzzy identifiers in the prediction of system behavior in real time.

6. REFERENCES

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