



MODEL IDENTIFICATION AND EXPERIMENTAL VERIFICATION OF MRAC ON 1DOF TRMS PROCESS

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ABSTRACT

Twin rotor MIMO system abbreviated as TRMS has high degree of non-linearity and cross-coupling between its inputs and outputs. Control of the TRMS is a challenging task unless its appropriate model is available. Here, to obtain a model of 1DOF pitch of TRMS we have used a black box system identification technique using input and output data sets. Appropriateness of the identified model is further validated with the aim of fulfilling the design requirement for the controller. Usually conventional feedback controllers fail to perform satisfactorily for TRMS due to variation in process dynamics and uncertainty in the nature of disturbances. To overcome the limitation of conventional fixed gain controllers Model Reference Adaptive Control (MRAC) scheme is reported here using modified MIT rule. Superiority of MRAC in comparison to PID controller has been verified for TRMS through simulation results as well as real time experimental verification.

Keywords: ARMAX Model, MIT rule, MRAC, System Identification, TRMS.

I. INTRODUCTION

Research on improved controlling of aircraft has gained importance in recent years. The twin rotor MIMO system (TRMS) resembles the laboratory prototype of helicopter dynamics with significant cross coupling between the longitudinal and lateral axes. Finding out an appropriate model of TRMS is essential to accomplish a better control policy for it. Lagrangian approach to derive a mathematical model of TRMS is utilized in [1]. In [2] analytical approaches in conjunction with neural networks based empirical approaches are used to derive dynamic models for 1DOF TRMS. But, the flight mechanics are not always easy to establish from first principles for aircraft modeling. However, these equations are imperative for designing and studying flight control systems. A large number of works [3, 4] are reported in literature addressing parameter estimation techniques for conventional aircraft.

We know that to design an effective controller, ideally a true model of the plant is needed. Hence, model identification is an integral part of controller designing for TRMS. But, finding out the appropriate model of a TRMS is a difficult task due to its non-linear behaviour and cross coupling effects. We know that first principle based modeling approach requires considerable knowledge about plant dynamics which is not straight forward in case of TRMS. Hence, black box based system identification technique is a good alternative for modeling of TRMS [5] where both model structure and model parameters are unknown. Here, we perform the model identification and validation of main rotor or pitch dynamics of a 1DOF TRMS. Then, based on the identified model we attempt to control that 1DOF TRMS by using MRAC scheme.



A widevariant of control strategies [6-9]for controlling the TRMS towards achieving improved performances are reported by researchers. A hybrid fuzzy PID controller is developed in[10]. The result obtained from this hybrid fuzzy PID controller seems to outperform a fixed gain conventional PID controller. The common objective of all the researchers towards designing a controller for TRMS is to overcome its nonlinearity issues. The nonlinearity occurs because of the variation in process dynamics due to nonlinear actuators, changes in environmental conditions and variation in the character of the disturbances and the controller ought to be adaptive and robust to accommodate these changes.

To overcome the limitations of conventional fixed gain controllers, researchers deal with the designing of adaptive controllers for a TRMS. Among the various adaptive mechanisms MRAC scheme using the MIT rule [11-13] is an effective technique. The designed MRAC controller gives satisfactory results, but is very sensitive to the changes in the amplitude of the command signal. So, here we employ the MRAC scheme that uses MIT rule along with the normalized algorithm to handle the variations in the reference signal amplitude and this adaptation law is referred as modified MIT rule. Performance based comparative analysis is made between MRAC and conventional fixed gain PID controller for controlling the TRMS in Matlab/Simulink environment. Simulation results illustrate that our proposed MRAC shows better tracking as well as improved disturbance rejection performance with lesser control effort compared to PID controllers. In addition to simulation results real time experimental study further substantiates the superiority of MRAC scheme.

II. EXPERIMENTAL SETUP

TRMS plant consists of a tower with a beam attached by two bearings. These two bearings allow the beam to move freely in the horizontal and vertical planes within some limits. At the two ends of the beam, rotors are attached which are physically 90° shifted from each other allowing them to generate horizontal and vertical thrusts. A beam with a counterweight is attached to the housing of the bearings. This counter weight is used to change the equilibrium position of the TRMS, and it also dampens the dynamics of the system. The main beam is locked so it cannot roll. The rotor generating vertical thrust is called the main rotor. This enables the pitch motion in the vertical plane. The rotor generating the horizontal thrust is called the tail rotor. This enables the plant yaw motion which is the rotation in the horizontal plane. Locking screws are provided to prevent the motion either in vertical or horizontal planes and then it is known as 1DOF TRMS. To interface the TRMS plant with PC, a PCL-812 I/O board is used. The interfaced PC is equipped with Matlab/Simulink software. Control algorithms are implemented through Simulink for real time experimentation [14]. The laboratory set-up of TRMS is shown in Fig. 1.



Fig.1: Laboratory set-up of TRMS.

III. SYSTEM IDENTIFICATION

System identification is an integral part of control system engineering that determines physical characteristics of a plant and represents them in the form of mathematical expression by using real time experimental data. Usually statistical methods are used to build mathematical models of dynamical systems from the measured data. Due to the complexity and diversity of the real system, the actual modelling problem from data acquisition stage to model establishment is a difficult task to complete by manual labour. The system identification toolbox of Matlab can simplify the calculation process and improve the efficiency of identification. So the system identification toolbox of Matlab is an effective way of estimating the models for systems that are difficult to handle manually. System identification toolbox constructs mathematical models of dynamic systems from measured input-output data and it is based on black-box approach which doesn't assume anything about the actual plant and thus gives a good estimate of the plant's characteristics.

The models developed from statistical methods provide an approximate behaviour of the real plant but it is good enough for control purposes. Flowchart of system identification process is shown in Fig.2. After collecting an experimental data set, most essential stages of model identification process involves (i) selection of parametric or non-parametric modelling technique and choice of the model structure, (ii) model estimation and finally (iii) model validation [20].

The model structure options provided for parametric identification are auto-regressive exogenous (ARX), auto-regressive moving average exogenous (ARMAX), Box-Jenkins (BJ) and state space model [15]. After choosing ARMAX technique with appropriate model structure, estimation of plant is carried out using plant input-output data. The objective of model estimation is to minimize the error function between measured and predicted output. Model validation is vital to find out the model credibility whether the model is capable to produce measured data or not. It can be achieved by examining the model fitting and auto-correlation analysis of residual function between input and output.

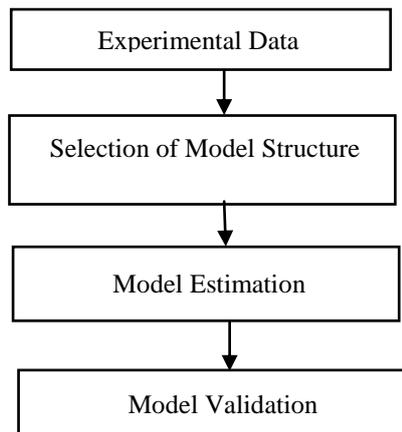


Fig. 2: Flowchart of system identification.

IV. IDENTIFICATION RESULTS

To find out a model of the TRMS plant a mixed sinusoidal signal of varying frequencies are used to produce a desired excitation signal [14]. After providing excitation to the plant both the input and output experimental data sets are collected which are exploited through system identification toolbox [16] to estimate a model for TRMS.

4.1 Experimental data

In this work real time experimental data sets are collected through the interfaced PC from the TRMS according to the guideline given in [14]. 1000 input-output data points are used for estimation of parameters for the pitch input u_1 (volt) and the output pitch angle y_1 (rad). First we load the pitch measurement data such as input voltage, sampling time, and output angle in toolbox and then initialize input and output as vectors in MATLAB work space. Initial values are considered as zero for both input and output data array.

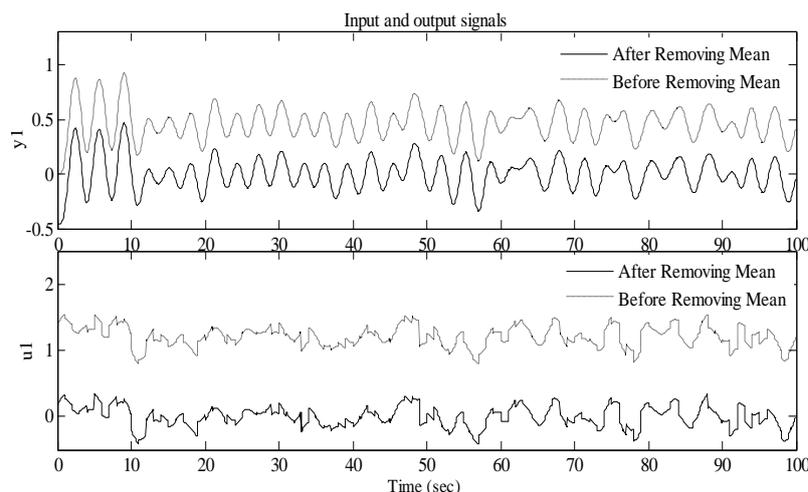


Fig. 3: Real time measured input-output data before and after removing mean.

The choice of sampling time is very crucial both for identification and control. Since the TRMS plant dynamic response is relatively slow, for this reason, the identification of the discrete model is carried out with the sampling time of $T_s = 0.1s$ [14]. Fig. 3 shows the time domain representation of observed data; both pitch angle



y_1 and input voltage to the rotor u_1 is plotted during entire identification period 0 to 100s resulting 1000 samples. Thereafter the mean value is subtracted from the measurement data to remove offset.

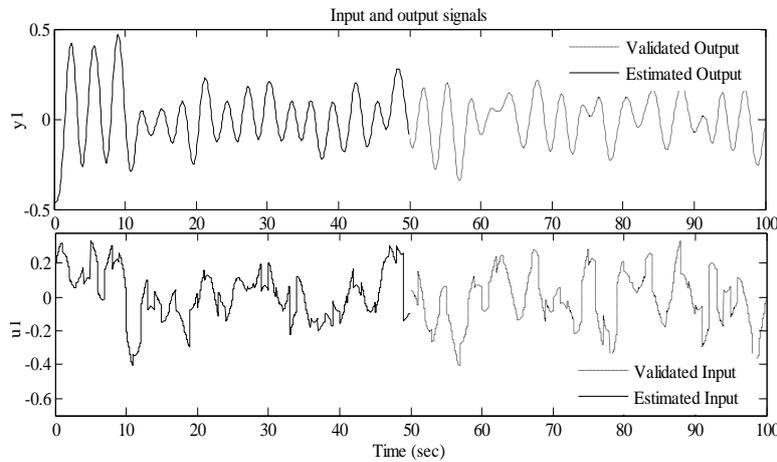


Fig. 4: Estimation and validation data set.

Finally, the entire measurement data is divided in two parts, keeping the first part reserved for estimation and other for validation. Half of data set i.e. first 500 samples is selected for estimation and the rest 500samples is reserved for validation. Fig. 4 shows the estimation and validation data sets for both input and output. The estimation data is used as an input, and these data sets are input to the model estimator to predict the model as reported in [15].

4.2 Selection of model structure

We choose parametric model identification technique which usually provides complete model description that truly describes the actual dynamics of the plant. The basic disadvantage with the simple model structure like ARX has the limitation in describing the effects of the disturbance term. To accommodate the contribution of noise term ARMAX model structure is selected [15]. This structure is used to get an initial estimate of 1DOF pitch model of TRMS plant [16-18]. In this model structure the current plant output is a function of previous outputs (auto regressive part, $A(q)y(t)$), previous inputs (exogenous part, $B(q)u(t)$) and current and previous noise terms (moving average part, $C(q)e(t)$) [15, 20]. ARMAX models can be described by the form as given in Eq. (1).

$$y(t) + a_1y(t - 1) + \dots + a_{n_a}y(t - n_a) = b_1u(t - 1) + \dots + b_{n_b}y(t - n_b) + e(t) + c_1e(t - 1) + \dots + c_{n_c}e(t - n_c) \quad (1)$$

Eq. (1) can be rewritten,

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \quad (2)$$

where q is the shift operator.

$$qu(t) = u(t + 1) \text{ and } q^{-1}u(t) = u(t - 1) \quad (3)$$



4.3 Model estimation

The best fit estimated model equation of the ARMAX along with the $A(q)$ and $B(q)$ polynomials are given by

$$A(q) = 1 - 2.796q^{-1} + 2.64q^{-2} - 0.8377q^{-3} \tag{4}$$

$$B(q) = 0.01508q^{-1} - 0.0237q^{-2} + 0.0124q^{-3} \tag{5}$$

$$C(q) = 1 - 1.237q^{-1} + 0.4473q^{-2} \tag{6}$$

Here we transform the discrete model into their continuous equivalent form is given below:

$$G_{11}(s) = \frac{0.1436s^2 + 0.2876s + 4.14}{s^3 + 1.771s^2 + 4.258s + 6.841} \tag{7}$$

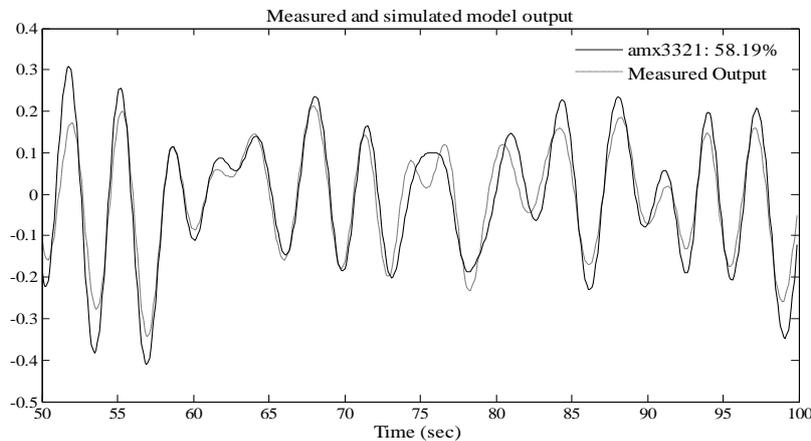


Fig. 5: Pitch model validation.

4.4 Model validation

Once a model of the system is obtained, it is required to verify whether the model is good enough to represent the systemdynamic behaviour or not. If not, the model structure should be changed and the parameters need to be re-estimated. In this context a number of validation tests are available in the literature [6, 21]. Here we apply model estimation and validation techniques by evaluating model performance based upon the following performance criteria: (i) minimizing final prediction error (FPE) and loss function (LF), (ii) choosing modelstructure which provide highest percentage of model fit, (iii) auto-correlation analysis of residual for output should be inside the confident region [21].

Data set not used in estimation (501 to 1000 samples) is selected for validation in order to ensure that there is norisk of over-fitting, this is called cross-validation. Henceforth, validation is performed for linear parametric models by checking how well the simulated or predicted output of the model matches the measured output. A plot is shown in Fig. 5 which shows the validation data (usually the working data) and the predicted values on the same plot each as a time series with the list of active models.



It is required to choose the best mathematical model for 1DOF pitch of TRMS by analysing all performance parameters. It can be observed that amx3321 model provide best fit up to 58.19 % with low FPE and LF compared to other ARMAX models. It is to mention that amx3321 model structures passed other validation tests. Fig. 5 shows best fit between measured and estimated output at different polynomial orders. Best result is achieved, when order is selected 3, 3, 2 for $A(q)$, $B(q)$ and $C(q)$ polynomials respectively. Table I shows the different percentage fit of the estimated models.

Table I

Model	Loss function	FPE	Best fit
amx3321	0.0070338	0.007260	58.19 %
amx4321	0.0169295	0.017539	51.11 %
amx5541	0.0095624	0.009600	56.82 %
amx6621	0.0079233	0.007955	55.29 %

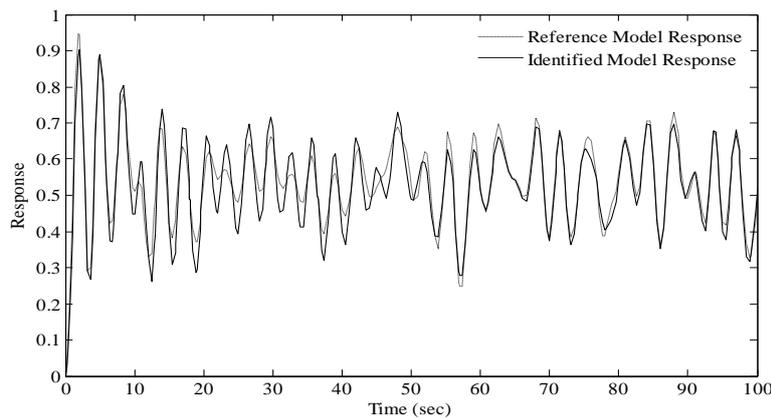


Fig. 6: Performance comparison with a reference model.

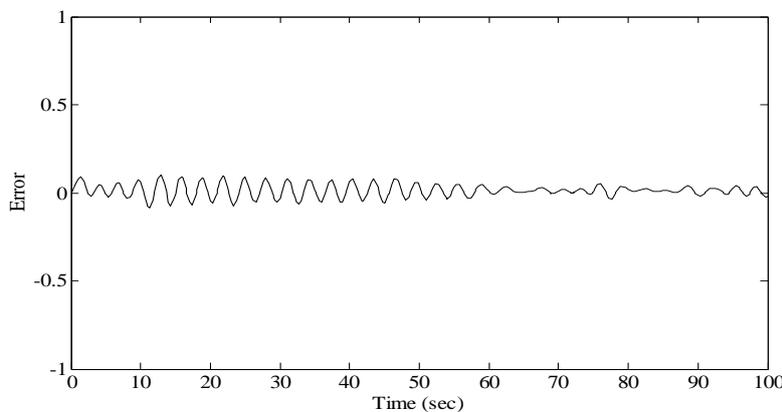


Fig.7: Error between two responses.

Furthermore, model validation is done in comparison with a reference model considering as standard. Here we take reference model provided in [14] and compare its responses with our identified model by examining the

error that should be as small as possible. Fig.6 shows responses of the reference model and identified model and the related error between two response shows in Fig.7. Results indicate that the proposed identification model can closely follow the dynamic behaviour of the 1DOF pitch motion of TRMS.

Another useful validation test is the residual analysis, which generates an autocorrelation plot. Here, the goal is not to have any significant autocorrelation remaining in residuals. Fig. 8 illustrates the auto-correlation of residual for the identified ARMAX model.

It can be found that the residual is within the confident range (-0.1 to 0.1) for those ARMAX models that fit up to 58.19%, ensuring that residuals are not correlated and independent from past input for the desired polynomial order.

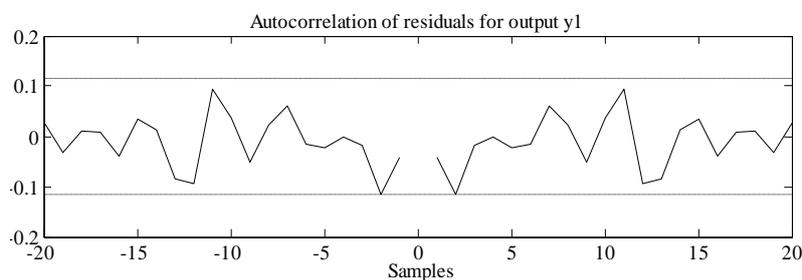


FIG.8: AUTOCORRELATION ANALYSIS OF ARMAX MODEL.

V. MODEL REFERENCE ADAPTIVE CONTROL (MRAC)

5.1 Principle of MRAC

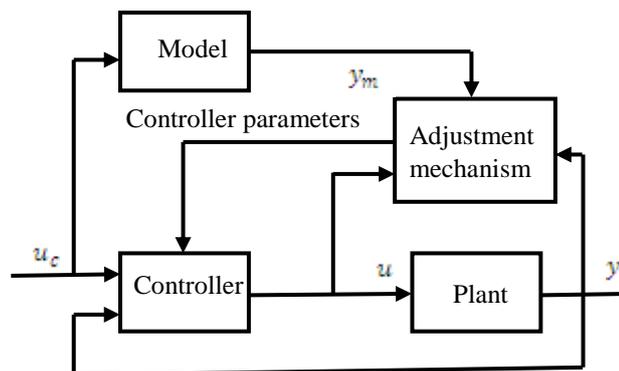


Fig. 9: Block diagram of MRAC.

The general idea behind the model reference adaptive control (MRAC) [11, 22] is that to design a closed loop controller with parameters which can be updated to modify the response of the system in the desired manner. The output of the system is compared with the response of a reference model. It generates an error and the controller parameters are updated based on this error. The goal is for the parameters to converge to ideal values that cause the plant response to match the response of the reference model.



5.2 Components of MRAC

- Reference model: It is used to give an ideal response of the adaptive control system to the reference input.
- Controller: It is usually described by a set of adjustable parameters. In this paper two parameters θ_1 and θ_2 are used to describe the control law. The value of θ_1 and θ_2 are primarily dependent on adaption gain.
- Adjustment mechanism: This component is used to alter the parameters of the controller so that plant could track the reference model. Mathematical approaches based on MIT rule is employed to develop the adjustment mechanism. In this paper we are using MIT rule with normalized algorithm and the technique is then referred as modified MIT rule. The basic block diagram of MRAC system is shown in the Fig. 9.

5.3 MIT rule

The MRAC control strategy is obtained using negative gradient approach of MIT rule. According to gradient approach, a cost function $J(\theta)$ is decided in terms of tracking error (e) as shown below. The tracking error is defined as difference between output of reference model and plant output.

$$e = y - y_m \tag{8}$$

$$J(\theta) = \frac{1}{2} e^2 \tag{9}$$

According to the MIT rule, rate of change of θ is directly proportional to negative gradient of cost function, as shown in Eq. (10)

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma \cdot e \frac{\partial e}{\partial \theta} \tag{10}$$

where θ = controller parameter vector, e = tracking error, γ = adaptation gain and $\frac{\partial e}{\partial \theta}$ = sensitivity derivative.

Sensitivity derivative determines how the parameter θ will be updated. A controller may contain several parameters that require updating.

5.4 Normalized MIT algorithm

For large values of reference input, system may become unstable when the system is controlled by MRAC using MIT rule because it is very sensitive to the changes in the amplitude of the reference input. Hence to overcome this problem, normalized algorithm is used to the MIT rule to develop the control law.

Normalized algorithm modifies the adaptation law in the following manner

$$\frac{d\theta}{dt} = \frac{\gamma \varphi e}{\alpha + \varphi^T \varphi} \tag{11}$$

where $\varphi = \partial e / \partial \theta$ and α ($\alpha > 0$) is introduced to remove the difficulty of zero division when φ is small.

Eq. (11) is also applicable in the conditions when there is more than one adjustable parameter. With the above modifications using normalized algorithm, the adaptation law is referred as modified MIT rule [23].

Another important fact for designing MRAC is selection of an appropriate reference model. Normally, the reference model is so selected by the designer that it offers the desirable response from the system under all possible operating conditions.

VI. SIMULATION RESULTS

Simulation study is made with linearized plant model obtained from the model identification experiment and designing of MRAC controller is performed based on this model. Simulation experiment is realized in Matlab/Simulink environment using modified MIT rule and the resultant MRAC scheme is applied on identified model of 1DOF TRMS.

Here we use a mixed sinusoidal signal with different frequencies for the command signal of pitch position $\psi_{desired}(t)$. We have compared the performance of the designed MRAC with the conventional fixed gain PID controller. The results are obtained with and without of unknown disturbance to the system. The performance of the two controllers are evaluated and compared in terms of set point tracking and disturbance rejection. The performance indices IAE (Integral Absolute Error), ITAE (Integral Time Absolute Error) are computed to demonstrate the superiority of MRAC over conventional PID controller.

6.1 Tracking performance

The designed MRAC controller is now tested in terms of reference signal tracking performance. Performances obtained from MRAC and PID controllers during set point tracking for controlling only pitch motion of TRMS is shown Fig. 10 and Fig. 11 respectively.

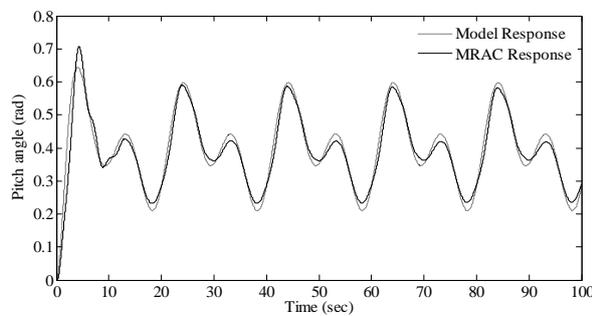


Fig. 10: MRAC response of 1DOF pitch.

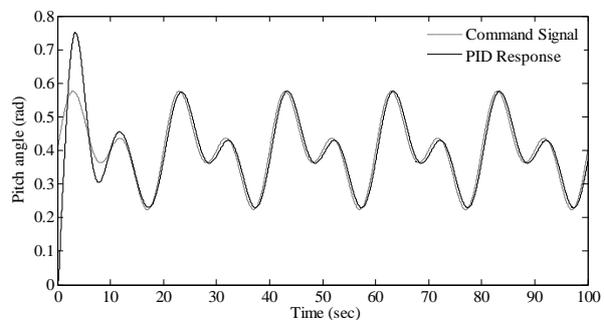


Fig. 11: PID response of 1DOF pitch.

6.2 Disturbance rejection performance

Performance of MRAC along with conventional PID controller is tested in presence of load disturbance. The load disturbance is introduced by adding a band limited white noise and pulse having magnitude 0.2 rad. Comparative results between MRAC and PID controllers during disturbance rejection performance for controlling 1DOF pitch motion of TRMS is shown Fig. 12 and Fig. 13 respectively. Performance indices for both the controller during tracking and load rejection phases are depicted in Table II.

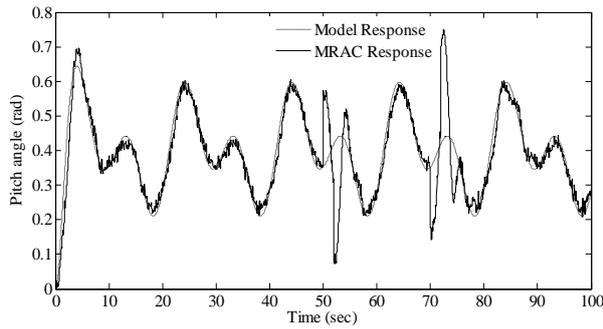


Fig.12: MRAC response of 1DOF pitch in presence of white noise and disturbance.

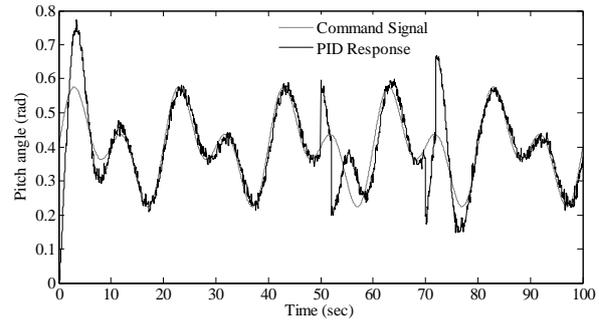


Fig.13: PID response of 1DOF pitch in presence of white noise and disturbance.

Table II

1DOF Pitch	IAE		ITAE		TV	
	PID	MRAC	PID	MRAC	PID	MRAC
Set point tracking	2.49	1.87	84.30	82.46	0.43	0.35
Disturbance Rejection	4.10	3.27	182.90	172.70	4.24	2.68

VII. Real time experimental results

The performance of MRAC is also tested on a hardware based TRMS platform. Performance of MRAC controller which is already reported in previous section is compared to PID controller used for controlling vertical motion (pitch) of TRMS. For this experimentation mechanical locking screw is used to prevent any horizontal motion and as a result 2DOF TRMS acts as a 1DOF system.

7.1 Real time tracking performance

The designed MRAC along with conventional PID controller is now tested during tracking of pitch motion and the corresponding responses are shown Fig. 14 and Fig. 15 respectively.

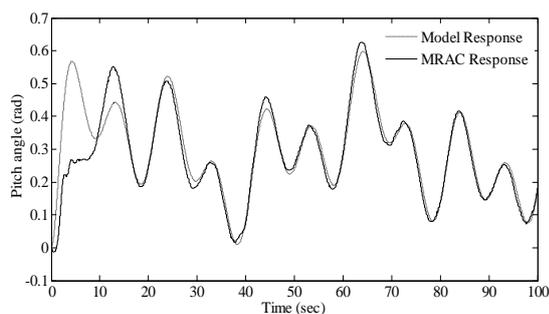


Fig. 14: MRAC response of 1DOF pitch.

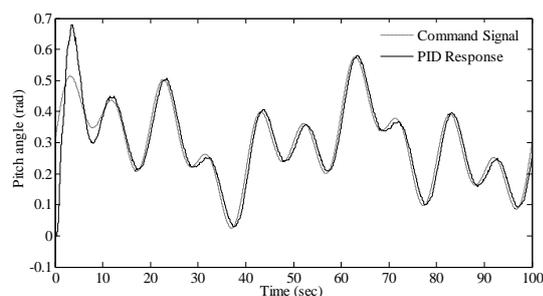


Fig. 15: PID response of 1DOF pitch.

7.2 Disturbance rejection performance

In addition to tracking performance MRAC controller is also tested with load disturbance. The load disturbance is introduced by adding a band limited white noise and pulse having magnitude 0.2 rad. Responses of MRAC and PID controller during disturbance rejection phases of 1DOF pitch motion of TRMS is shown Fig. 16 and Fig.17 respectively. Controller performance indices (IAE, ITAE and TV) are calculated during tracking and load rejection phases for both the MRAC and PID controllers as depicted in Table III. Lesser values of performance indices for MRAC establish the superior behaviour for MRAC compared to fixed gain PID controller.

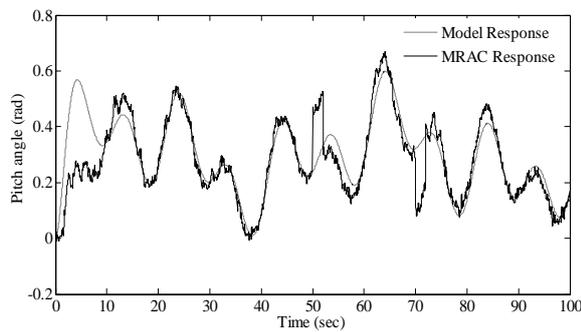


Fig.16: MRAC response of 1DOF pitch in presence of white noise and disturbance.

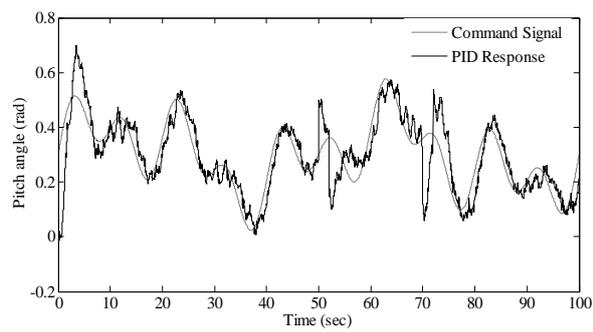


Fig.17: PID response of 1DOF pitch in presence of white noise and disturbance.

Table III

1DOF pitch	IAE		ITAE		TV	
	PID	MRAC	PID	MRAC	PID	MRAC
Set point Tracking	2.80	3.29	106.20	77.63	3.07	1.41
Disturbance Rejection	5.77	5.10	276.50	194.20	13.24	6.07

VIII. CONCLUSION

In this paper reported work concerns with system identification techniques to choose appropriate mathematical model that would be suitable to realize physical behaviour of a highly nonlinear system. A model for the 1DOF Pitch of twin rotor MIMO system is successfully identified. The extracted model is able to predict the system behaviour close to the actual one. Here we identified a low order linear ARMAX model which replicates higher order nonlinear model of 1DOF pitch motion. Clearly we can find the modelling limitation that the percentage of best fit is not more than 60 %. But, if we choose other model structures for better percentage fitness it results increased complexity and orders. Using the identified model performance of a MRAC scheme is verified and its performance is compared to a conventional fixed gain PID controller. During both the tracking and load rejection phases MRAC is found to provide improved performance during both the simulation and real time evaluation compared to conventional PID controller. Effectiveness of MRAC is also established in presence of



noisy measurement output. Performance of the designed MRAC can also be evaluated on a 2 DOF application of TRMS involving both the pitch and yaw motions simultaneously.

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