Differential Evolution Algorithm for System Identification and Tuning of a Fuzzy Modified Model Reference Adaptive Controller for a Coupled Tank Level Process

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Abstract— **Improving the transient performance of the MRAC has been a point of research for a long time. The main objective of the paper is to design an MRAC with improved transient and steady state performance. This paper proposes a Fuzzy modified MRAC (FMRAC) to control a coupled tank level process. The FMRAC uses a proportional control based Mamdani-type Fuzzy inference system (MFIS) to improve the transient performance of a direct MRAC. In addition, it proposes the application of Differential Evolution (DE) algorithm to tune the membership function parameters off-line of the FMRAC to improve its performance further. The proposed controller is called DE based Fuzzy Modified Model Reference Adaptive Controller (DEFMRAC). In this study, an MRAC, an FMRAC and the proposed DEFMRAC are designed for a coupled tank level process and their performances are compared. The coupled tank level process is modeled by using system identification procedure and the accuracy of the resultant model is further improved by parameter tuning using DE. The simulation results show that the FMRAC gives better transient performance than the direct MRAC. The results also show that the proposed DEFMRAC gives better transient performance than the direct MRAC or the FMRAC. It is concluded that the proposed controller can be used to obtain very good transient and steady state performance in the control of nonlinear processes.**

Keywords- Model Reference Adaptive Controller; Coupled tank process; System identification; Fuzzy modified Model Reference Adaptive Controller; Differential Evolution Algorithm; Differential Evolution based Fuzzy modified Model Reference Adaptive Controller

I. INTRODUCTION

Industrial applications of liquid level control are found in food processing, beverage, dairy, filtration, effluent treatment, nuclear power generation plants, Pharmaceutical industries, water purification systems, industrial chemical processing and boilers [1]. Traditionally, PID controllers are used for level control [2, 3]. The controller performance is sub-optimal whenever the operating point is shifted out of the linearized region or when the plant parameters change due to environment and ageing [4]. Therefore, the PID controller parameters need to be re-tuned. Designing a more effective controller needs identification of the process as accurately as possible [4].

Conventional identification methods such as least squares [5] and maximum likelihood method [6] hold good only when the process is operated at about the selected operating point [4]. They do not provide globally optimum solution for nonlinear systems [7]. Further, they require vast amount of input-output data from the system to be identified [4]. The coupled tank process considered in this paper is a classic example of a nonlinear system [4]. Soft computing approaches like Neural Network (NN), Fuzzy Logic (FL) [8] and Differential Evolution (DE) can be used to identify nonlinear processes. Storn and Price [9, 10] introduced DE, a heuristic approach for minimizing nonlinear and non-differentiable continuous space functions. Babu and Sastry [11] used DE for the estimation of effective heat transfer parameters of trickle bed reactors. Babu and Rakesh Angira [12] applied a modified DE to non-linear chemical engineering problems. Babu and Munawar [13] used DE to estimate the minimum heat transfer area required for a given heat duty in shell-and-tube heat exchangers. This paper proposes the use of Differential Evolution (DE) for the parameter tuning of the identified model of a coupled tank level process to improve the model accuracy as much as possible.

As the level process is nonlinear [4, 14] adaptive controllers are more appropriate than fixed parameter controllers [15]. Gain Scheduling, Dual Control, Self-Tuning Regulation (STR), and Model Reference Adaptive Control are the approaches used in adaptive control [15]. The Gain Scheduling, STR and Dual Control have some

shortcomings when compared with the MRAC [15]. Model reference adaptive control (MRAC) is an important adaptive control approach that provides feedback controller structures and adaptive laws for control of systems with parameter uncertainties to ensure closed-loop signals boundedness and asymptotic tracking of independent reference signals despite uncertainties in the system parameters [16]. MRAC has been used in the control of nonlinear processes [4, 17-20].

A few proposals to improve the transient performance of the MRAC are reported in the literature. A modified traditional MRAC proposed by [21] has shown improved transient and steady state performance. However, the improvement in performance is limited by the size of the unmodeled dynamics. Hosseini-Suny et al. [22] proposed a new adaptive controller to ensure the stability and good performance of a teleoperation system while a wide range of time delays is considered. Miller and Davison [23] proposed a controller, which can provide arbitrarily good transient and steady state performance for a single-input single-output linear time-invariant plant [4]. Miller and Mansouri [19] proposed a scheme for better noise performance in MRAC. It used linear predictive control in an MRAC set up. A rapidly varying control signal is used in order to achieve the desirable features. The rapidly varying control signal requires fast actuators, which may not be practical. The authors in their recent paper [4] have used a PID controller along with an MRAC to improve the transient performance of the MRAC in controlling the level of a hybrid tank process. However, the PID controller parameters are tuned for a given operating condition. Hence, when the operating conditions change considerably the modified MRAC needs to be tuned again to get the same level of optimal performance. If a nonlinear fuzzy logic controller replaces the PID controller in the modified MRAC [4], it can overcome the above said shortcoming. The authors [24] have recently proposed a modification to the standard direct MRAC, which employs a proportional-control based Mamdani-type Fuzzy Inference System (MFIS) along with the MRAC to improve its transient performance. The resultant controller is termed as Fuzzy modified MRAC (FMRAC). The fuzzy if-then rules are designed in such a way that the controller mimics the control action of an experienced operator. The shape and the parameters of the fuzzy membership functions are designed by using the knowledge of the operator of the plant. The transient and steady state performance of the FMRAC can be further improved by optimizing the membership function parameters. Hu and Mann [25] used GA to optimize a fuzzy PID controller. Chang [26], Valarmathi et al. [27] and Asan Mohideen et al. [4] applied Real-coded GA (RGA) for system identification and controller tuning. Although many versions of genetic algorithm have been developed, they are still time consuming [28]. DE overcomes this disadvantage [9]. It has been applied to several engineering problems in different areas [28-31]. The method requires few control variables, is robust, easy to use, and suitable for parallel computation [9, 32, 33]. It gives better search-space exploration characteristics with similar or even better results than previously employed optimization routines [31]. This paper proposes the application of DE to fine-tune the parameters of the fuzzy membership functions off-line and the resultant proposed controller is referred to as DE based Fuzzy modified MRAC (DEFMRAC) in the paper. This improves the transient and steady state performance of the FMRAC further. A direct MRAC, an FMRAC and the proposed DEFMRAC are designed and implemented to control liquid level in a coupled tank level process in this study.

II. EXPERIMENTAL SETUP

The coupled tank setup used by Asan Mohideen et al. [4] is used in this study. Fig. 1 shows the coupled tank setup. The influent rate F1 to tank1 and the liquid level L2 of tank2 are the manipulated variable and the controlled variable respectively.

III. SYSTEM IDENTIFICATION

System identification is the process of constructing mathematical model of dynamic systems from the observed input-output data [6]. Continuous-time process models, denoted by PnDIZU, with identifiable coefficients describe a system transfer function in terms of zeros, poles, integration and delay [4]. This study uses the above-mentioned process models [4]. The parameters of the best model in terms of fit are further fine-tuned using DE to increase the accuracy of the identified model.
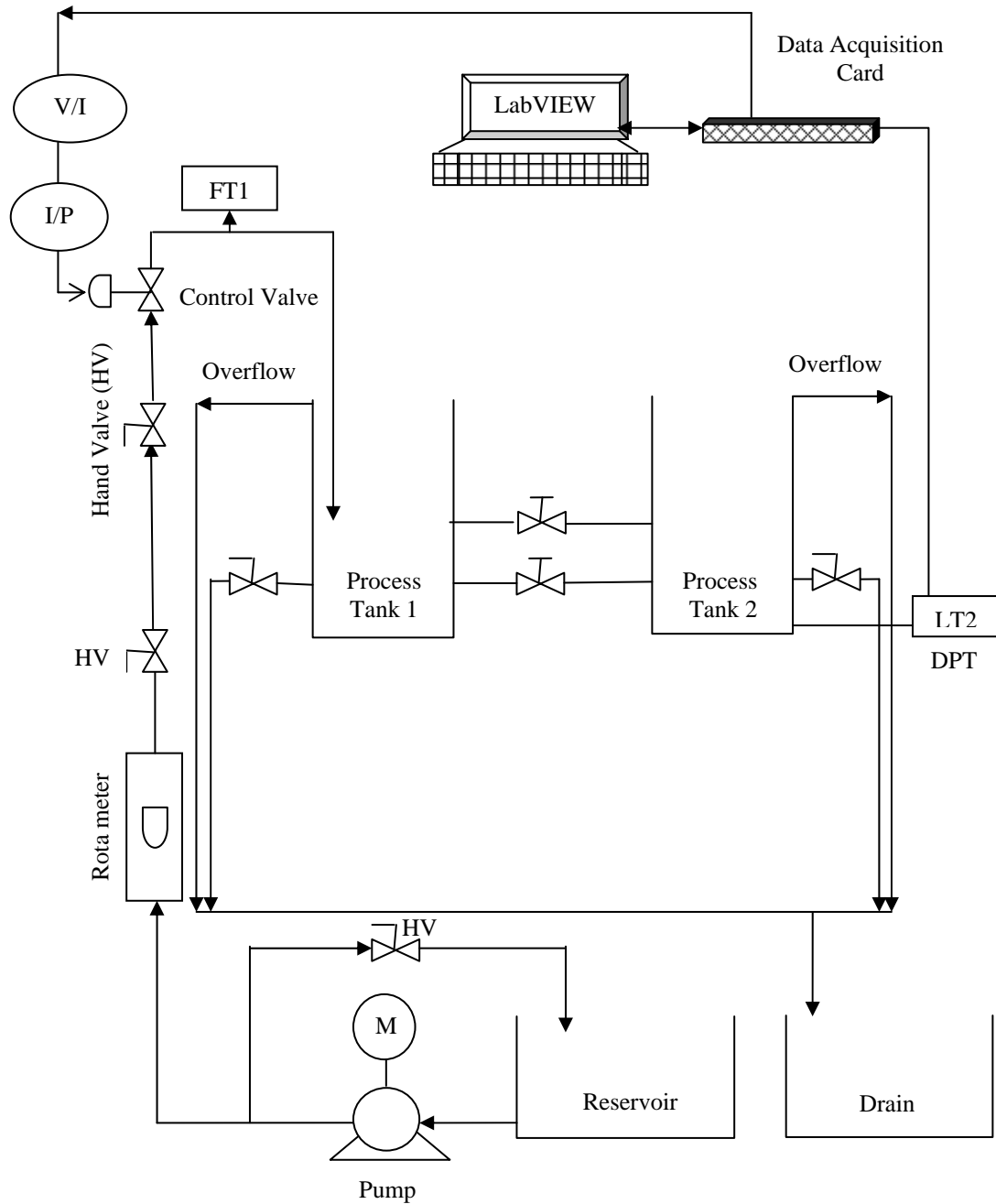
Fig. 1. Coupled tank setup

IV. MODEL REFERENCE ADAPTIVE CONTROLLER

Nonlinear nature of a system merits the use of adaptive controllers such as MRAC and STR [3]. The Model Reference Adaptive System (MRAS) is an adaptive servo system in which a reference model gives the desired closed loop performance [15]. Fig. 2 shows the block diagram representation of an MRAC [4]. The transfer functions, $G(s)$ and $G_M(s)$, represent the process and the reference model respectively. The controller has to make the process output y follow the model output y_m as closely as possible by adjusting the process input u.
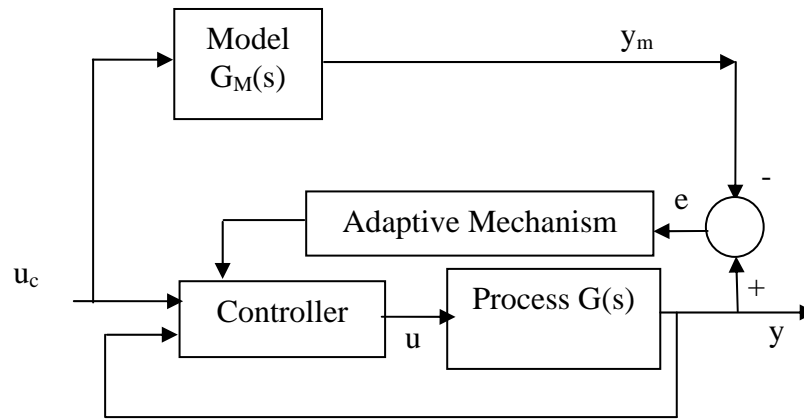
Fig. 2. Model Reference Adaptive Controller

The adaptive mechanism either changes the parameters of the controller or modifies the controller output [4] based on the error e, as shown in (1)

$$e = y - y_m \tag{1}$$

The adaptation of controller parameters can be obtained by using either gradient method or stability theory [15]. This paper uses gradient method. An MRAC is designed using the MIT rule as shown below. The process input u is modified by adaptively changing the controller parameters θ_1 and θ_2. The controller output is

$$u = \theta_1 u_c - \theta_2 y \tag{2}$$

If the cost function $J(\theta)$ is taken as $e^2/2$ [15], the controller parameters change with respect to time as given in (3)

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma \frac{\partial e}{\partial \theta} \tag{3}$$

where $\partial e / \partial \theta$ is the sensitivity derivative of the system, γ is the adaptation gain and e is the tracking error.

The adaptation gain determines the speed of convergence. If the adaptation gains are too small it takes a long time for the output y to converge with y_m. On the other hand, if they are too large, the output y will oscillate. Hence, a trade-off is always required between the stability and the speed of convergence while selecting the value of γ [4]. γ_1 and γ_2 are the adaptation gains that are used in updating the values of θ_1 and θ_2 respectively. The systems obtained with the MIT rule work as expected for small adaptation gains [15]. Very small values are assigned for γ_1 and γ_2 initially and then they are gradually increased so that y asymptotically converges with y_m in the shortest possible time [4]. In order to improve the transient performance, a modification to the MRAC scheme is used in this paper.

V. FUZZY MODIFIED MODEL REFERENCE ADAPTIVE CONTROLLER

Fig. 3 shows the fuzzy modified MRAC (FMRAC) [24]. It employs a Mamdani-type fuzzy inference system (MFIS) along with the MRAC to improve the transient performance of the MRAC. The MFIS has the tracking error e of the MRAC as its input and the defuzzified output of the MFIS is added with the MRAC output to generate the process input u. The output of the MFIS represents volumetric flow rate in liters per hour (lph).
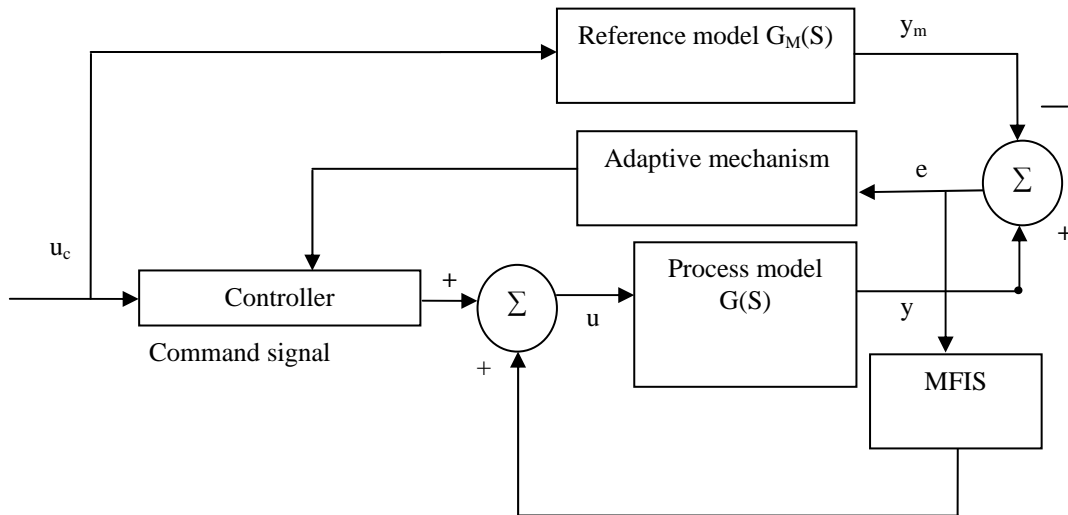
Fig. 3. Fuzzy modified MRAC

VI. Differential Evolution Algorithm Implementation

A. System Identification using DE

The DE fine-tunes the parameters of the model that is obtained by applying the standard system identification procedure. As shown in Fig. 4, the output $\hat{y}(k)$ of the model and the actual output $y(k)$ of the process are compared and the difference is given to the DE algorithm in the form of mean square error (MSE) as given in (4).

$$MSE = \left(\frac{1}{N}\right)\sum_{k=0}^{N}\left(y(k) - \hat{y}(k)\right)^2 \tag{4}$$

where k is the time instant. The DE optimizes the model parameters so that the MSE is minimized. It maximizes a fitness function F [4]
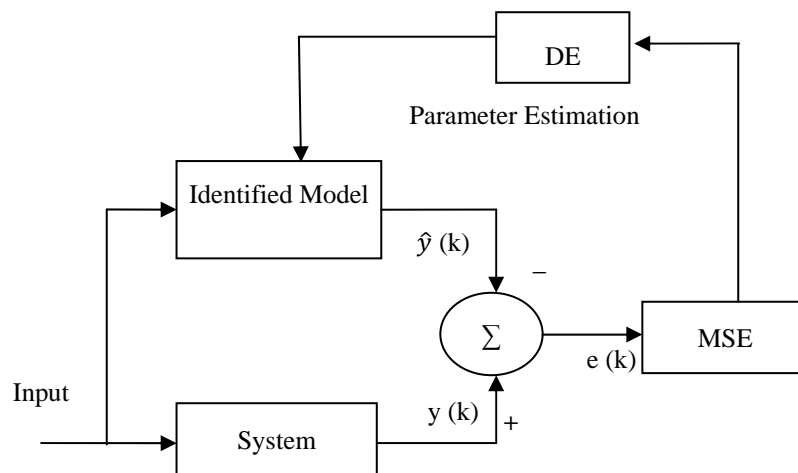
$$F = \frac{1}{(1 + MSE)} \tag{5}$$

Fig. 4. Parameter estimation using DE

B. Controller Tuning using DE

The DE optimizes the fuzzy membership function parameters of the MFIS based on the error e and the plant output as shown in Fig. 5. It updates the membership function parameters in each generation until the stopping criterion is met. It minimizes the objective function (6) and maximizes the fitness function (5).

$$MSE = \left(\frac{1}{N}\right) \sum_{k=0}^{N} \left(y(k) - y_m(k)\right)^2 \qquad (6)$$

where $y(k)$ is the output of the model at the instant k and $y_m(k)$ is the output of the reference model at the instant k [4].
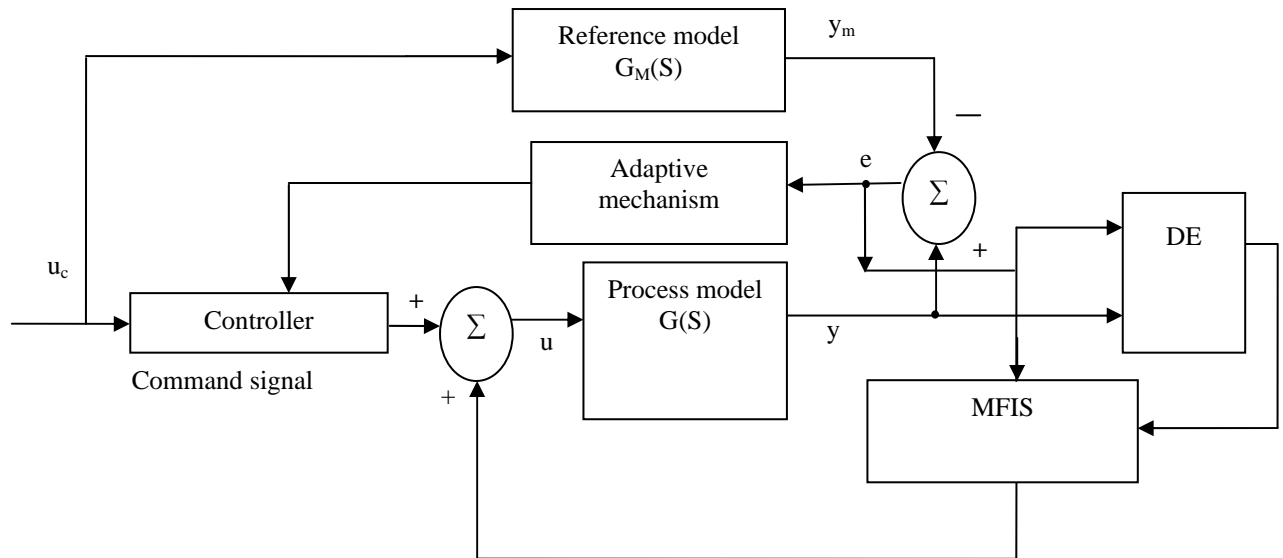

Fig. 5. Controller tuning using DE

VII. RESULT AND DISCUSSION

A Experiment and Data Acquisition

Fig. 6 shows the photograph of a laboratory-scale coupled tank setup. Its constructional details can be found in [4].

B. Step Response Analysis

First, flow F1 is set at 205 lph and level L2 reaches a steady state of 3 cm. Then, a step change is applied to F1 to increase it to 615 lph and L2 is measured. Fig. 7 shows the step response. The new steady-state value of L2 is 18.5 cm.

The process response looks like the response of a second order system [4] given in (7)

$$G(s) = \frac{K_p}{(\tau^2 s^2 + 2\zeta\tau s + 1)} e^{-T_d s} \qquad (7)$$

where K_p, τ, ζ and T_d are the gain of the process, the time constant, the damping factor and the time delay respectively. System identification toolbox is used to get the initial estimate of the process parameters that are shown below.

K_p: 0.036 cm/lph

τ: 154.46 s

ζ: 1.4654

T_d: 0 s

Process settling time is approximately 1600 s.

Fig. 6. Photograph of the experimental setup of Hybrid Tank Process
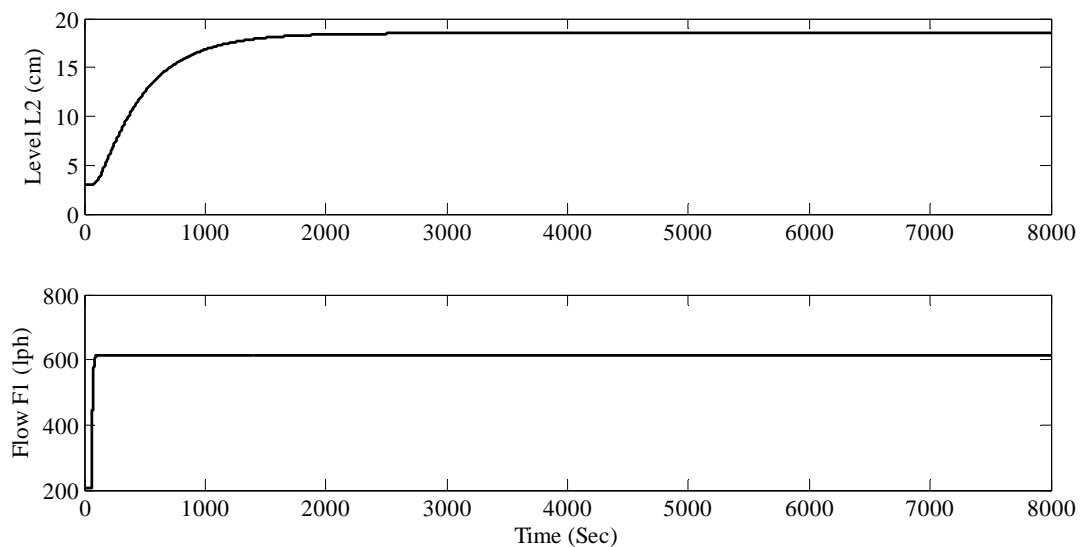

Fig. 7. Step response of the coupled tank level process

C. Binary Input Experiment

In this experiment, a persistently exciting signal such as pseudo-random binary signal (PRBS) is used to excite the process [6, 34]. The sampling time is selected so that it is neither too short nor too long [35]. This study uses a PRBS signal whose range is in 205 to 615 lph with a sampling time of 50 s [4]. The nominal operating values of F1 and L2 are 405 lph and 10 cm respectively and they will represent zero flow and zero level henceforth. Fig. 8 shows the input-output data of the experiment, which has 780 samples in 39000 seconds. Data from 50 to 20000 seconds are used for estimation and the rest for validation. Pre-processing of the data is carried out [4].
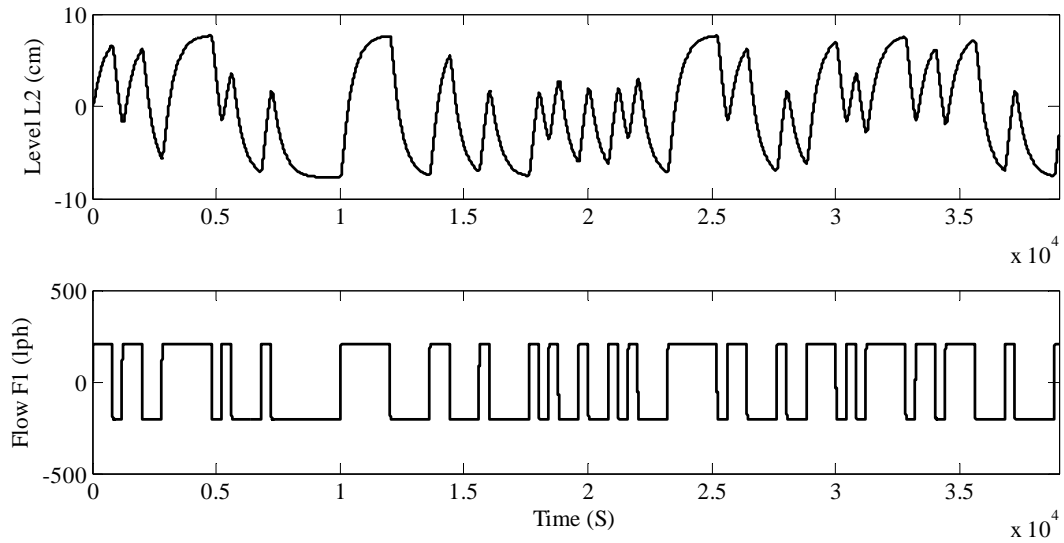
Fig. 8. Input-output data of binary input experiment

D. Model Estimation

System identification toolbox in MATLAB is used to estimate the model. Prediction error method (PEM) is used here. Fig. 9 shows the outputs of the P2D and P2DU models and the estimation data. As the coupled tank process has two tanks the first order model is not considered here. The model outputs and estimation data are close to each other.
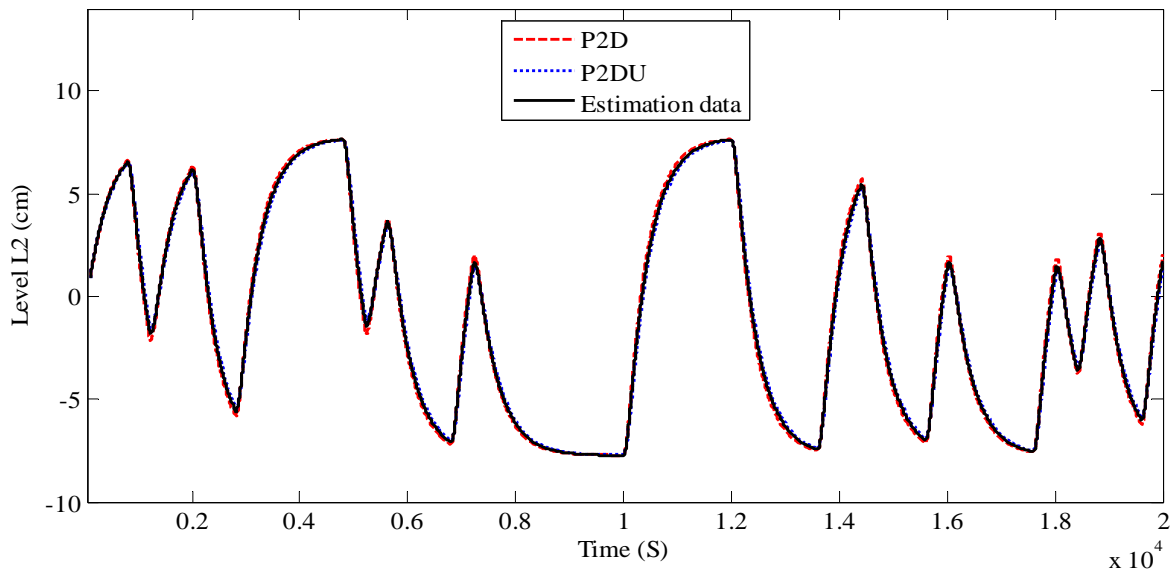

Fig. 9. Comparison of estimation data and model outputs

As the two tanks interact, the P2DU model is preferred to P2D model. The above procedure results in the following transfer function (8) model of the process.

$$G_p(s) = \frac{0.0377}{(19600s^2 + 421.48s + 1)} \qquad (8)$$

E. Model Validation

Model validation can be done using residual analysis, correlation analysis and cross-validation [4, 6, 34]. Fig. 10 shows the residual analysis of the P2DU model. The autocorrlation of the output residuals and the cross-correlation between the process input and the output residuals lie in between the 99% confidence intervals. Hence the model is considered valid.
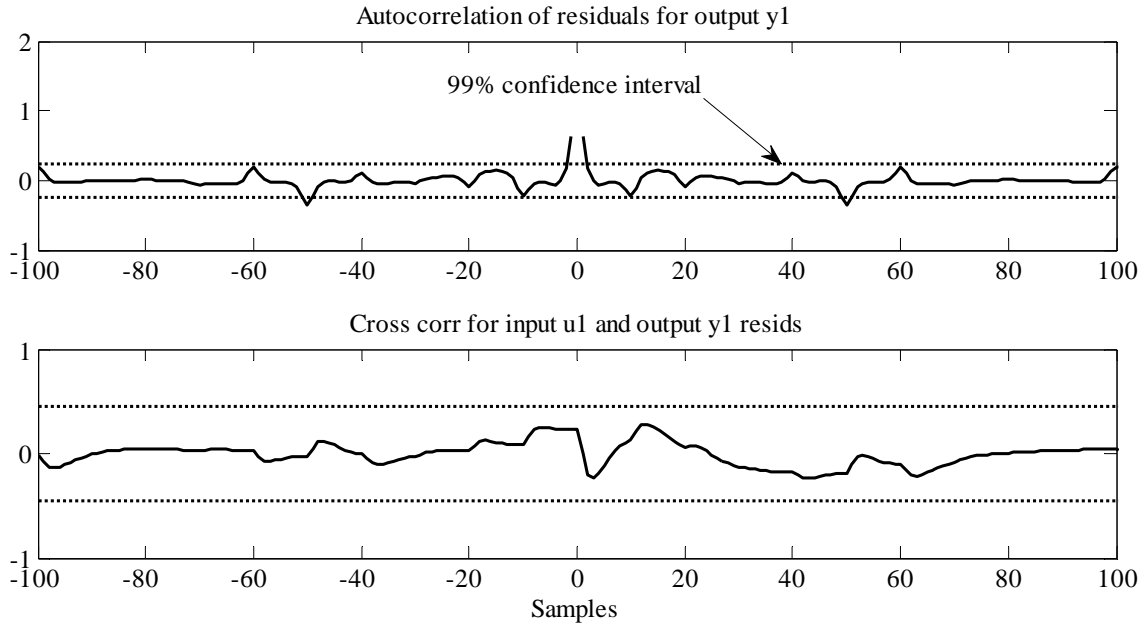
Fig. 10. Residual analysis of the P2DU model

The impulse and step responses are obtained in correlation analysis. Fig. 11 shows the impulse response. The response shows that the process is over-damped without any delay. Fig. 12 shows the step response with zero delay and a steady-state gain of 0.03752. It resembles the step response of a high order process. All these results confirm those obtained through the previous tests.
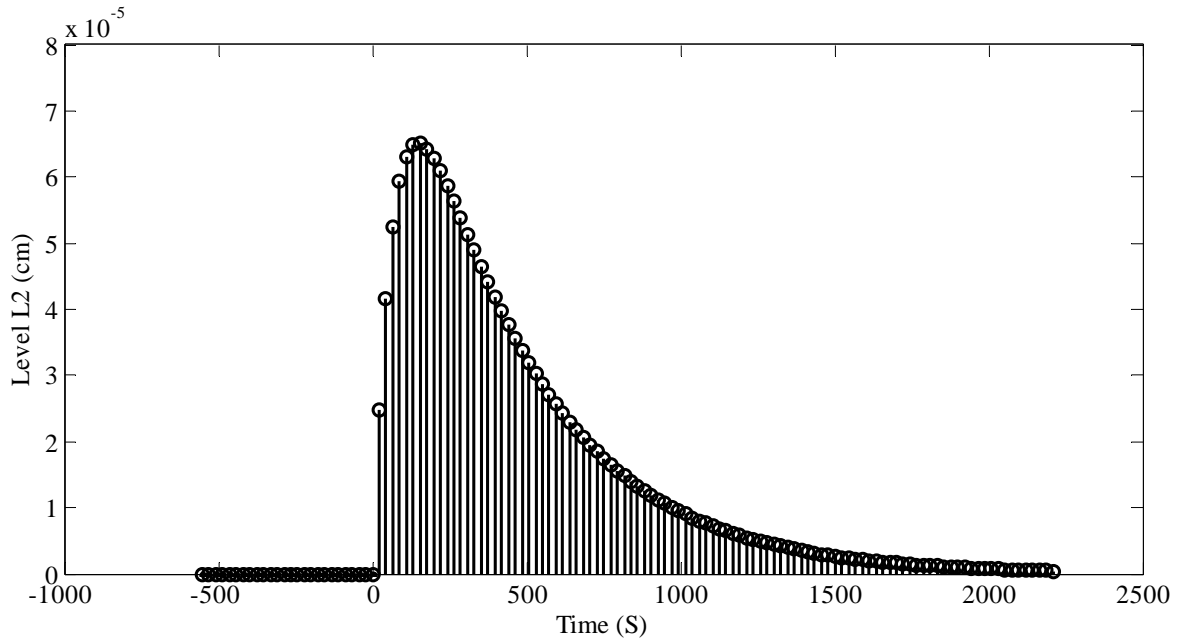

Fig. 11. Impulse response estimated by using correlation analysis

Fig. 13 shows the comparison between the output of the P2DU model and the validation data set. The fit percentage between the two is 95.7. These results validate the estimated P2DU model of the coupled tank process.
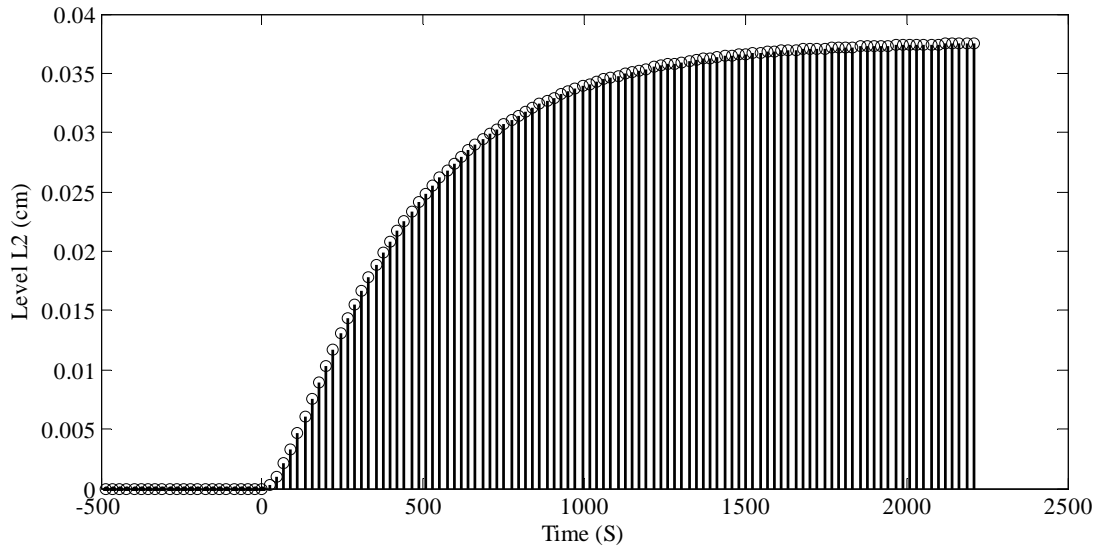
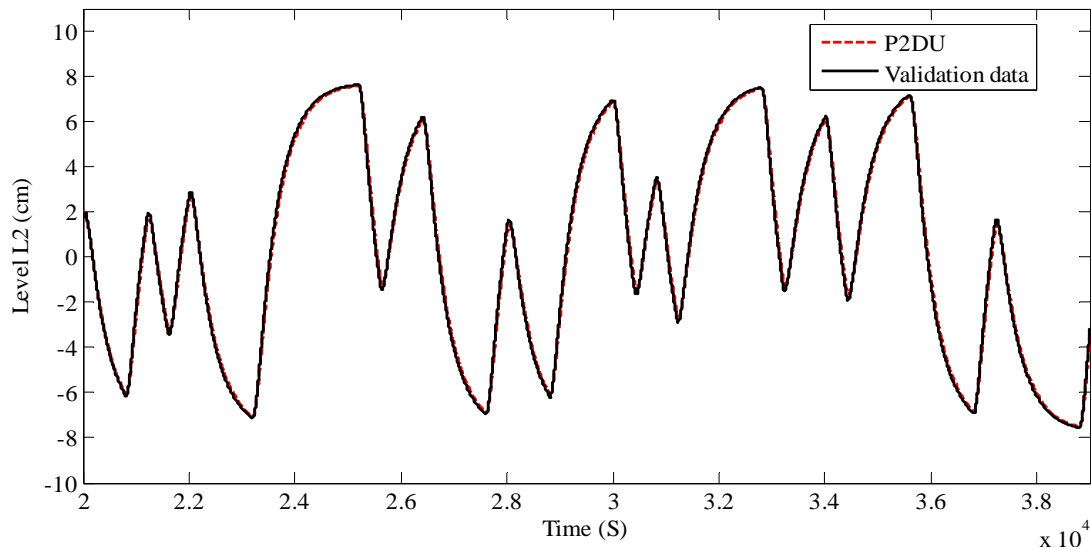Fig. 12. Step response estimated by using correlation analysis]

Fig. 13. Comparison of validation data and model output

F. Application of DE in System Identification

DE is used to fine-tune the parameters of the P2DU model further. This study uses the strategy "DE/rand/1/bin" [9, 33] for identification and controller tuning. This strategy is fast, robust and one of the most widely used [33]. The software code for the algorithm is written in MATLAB. Population size *NP* should be larger than 4 for DE/rand/1/bin [33].

The terms K_p, τ^2 and $2\tau\zeta$ of the second order transfer function (7) are represented by the variables p, q and r respectively in the optimization experiment. A six-digit floating-point number represents each variable and the number of generations is the stopping criterion used.

The optimality of the estimate is ensured by following the guidelines given below with regard to the design parameters.

• The number of generation *G* can be increased as long as there is improvement in the fitness of the solution. If the best fitness does not improve considerably with more generations, it indicates optimal or near-optimal solution.

• For the scale factor *F*, *F*=0.5 is a good initial choice [9]. If the solution is trapped in a local minimum, then the values of *F* and/or *NP* can be increased so that it will move towards the global minimum.

• Large values of crossover rate CR speeds convergence [9, 33].

Table 1 shows the parameter estimates at various stages. It gives the average of thirty individual runs. The best estimates of the variables are obtained with the following design parameters.

Number of generations (N_g): 300

Population size (NP): 5

Crossover rate (CR): 0.8

Scale factor (F): 1.1

Fig. 14 shows the convergence of the best fitness. The convergence is slow and moves towards the global optimum due to the large value of F. After 150 generations, the best fitness does not change considerably with more generations indicating optimal or near optimal solution for the parameter values. The resultant model is called P2DUDE. Simulated output of the P2DUDE model is obtained and compared with the experimental data. Its fit percentage with the estimation data and validation data are determined.

Table I
Parameter Estimates by using DE in Different Iterations

N_g	NP	CR	F	Range			Fitness	Estimate		
				p	q	R		p	q	R
100	5	0.5	0.5	[0.02 0.05]	[0 30000]	[0 700]	32550	0.03777	7733	454.8
100	5	0.8	0.8	[0.02 0.05]	[0 30000]	[0 700]	56203.1	0.0378	11623	440.05
200	4	0.8	0.9	[0.02 0.05]	[0 30000]	[100 600]	64679	0.0378	22405	453.54
200	5	0.8	1.1	[0.03 0.04]	[10000 30000]	[300 600]	235533	0.0378	22229	450.52
300	5	0.8	1.1	[0.03 0.04]	[10000 30000]	[400 500]	239517	0.0378	22305	449.54

Fig. 15 shows the comparison among the simulated outputs of P2DU and P2DUDE, and the estimation data. Fig. 16 shows the comparison among the simulated outputs of the two afore-mentioned models and the validation data and Table 2 compares the parameters and fit percentages of the models P2DU and P2DUDE. These results establish the effectiveness of the application of DE in the system identification procedure.

Table II
Comparison of Models Before and After DE Tuning

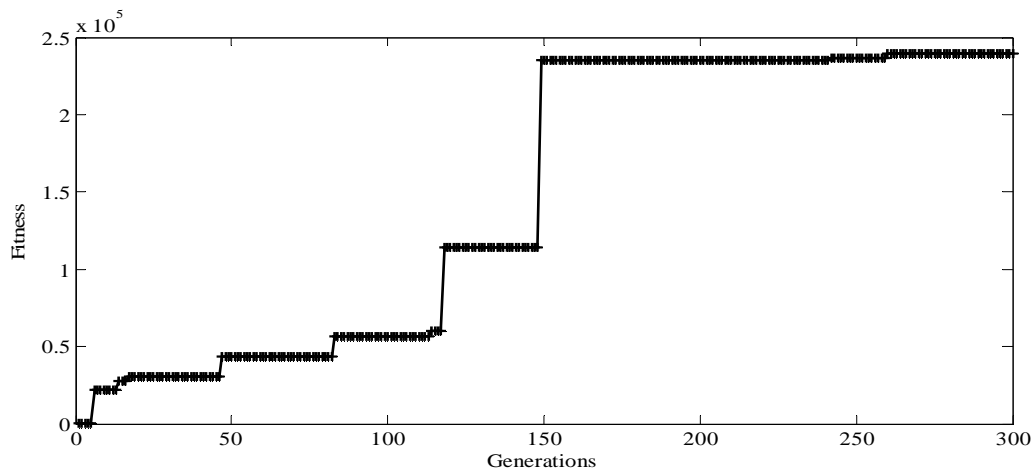| Model	Parameters			Fit (%)	
	p	q	r	Estimation data	Validation data
P2DU	0.0377	19600	421.48	96.04	95.7
P2DUDE	0.0378	22305	449.54	99.96	99.94

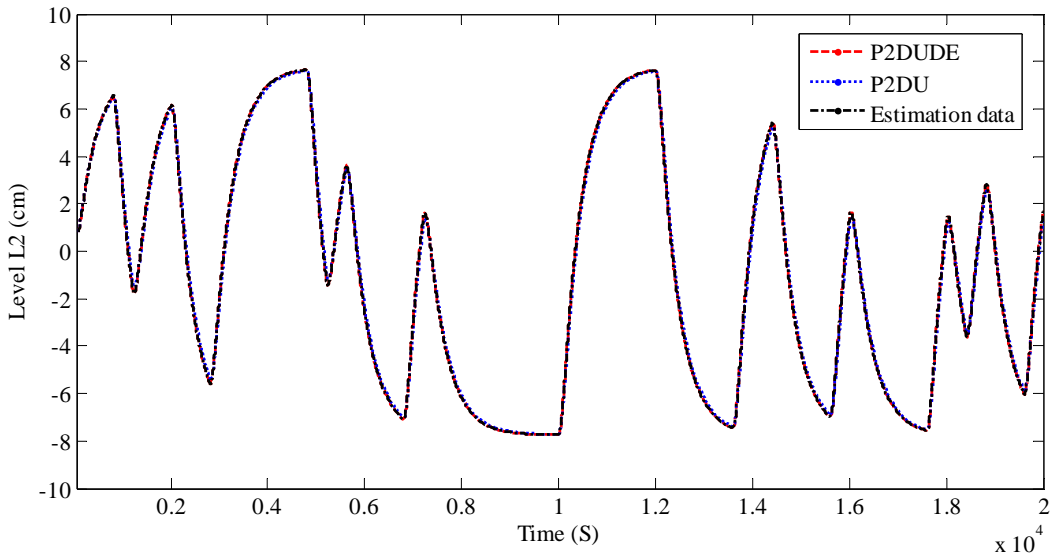Fig. 14. Convergence of fitness in identification

Fig. 15. Comparison of estimation data and model output before and after DE tuning
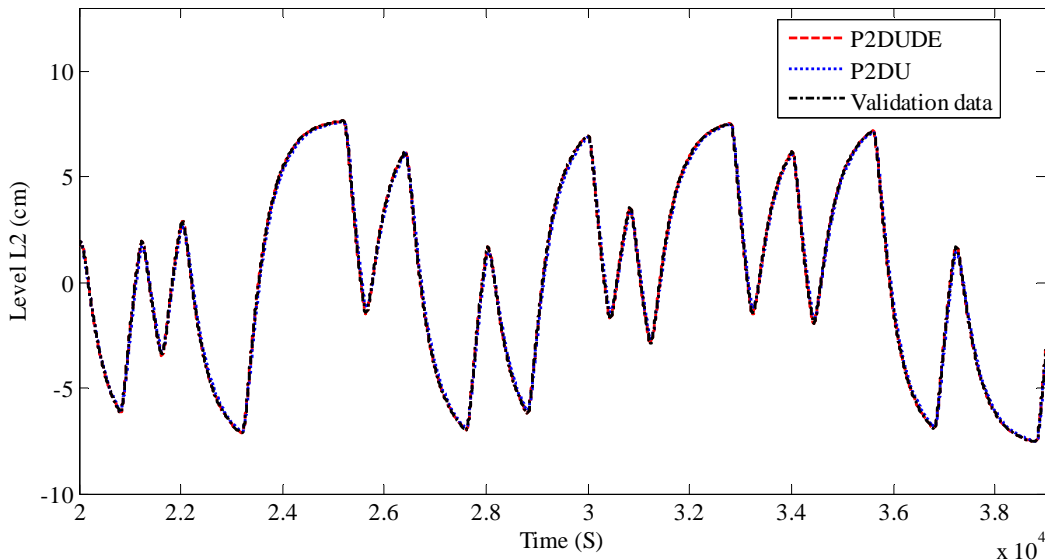

Fig. 16. Comparison of validation data and model output before and after DE tuning

The transfer function of the identified P2DUDE model of the coupled tank system is given by

$$G_{de}(s) = \frac{0.0378}{22305s^2 + 449.54s + 1} \tag{9}$$

The coupled tank setup in the hybrid tank process is identified as an over-damped second order system with zero delay. The steady-state gain is 0.0378, the damping factor is 1.5049 and the time constant of the process is 149.3485 seconds.

G. Controller Tuning

In this section an MRAC, an FMRAC and a DEFMRAC are designed for the coupled tank system. A reference model is expected to have a faster response when compared with the open loop response of the process. Faster response can be ensured by having smaller time constants than the time constants of the process or by moving the zero, if present, in the transfer function of the process towards the origin in the S-plane. The first method is used in the selection of the reference model given in the paper.

For the real physical system, the reference model is selected subject to the following constraints

a)   The dead time of the reference model should not be less than that of the process.

b) The time constant of the reference model is less than that of the plant in order to increase the speed of response as increasing the speed of response is one of the main objectives of using a controller.

c) The output y $_m$ of the reference model should lie within the dynamic range of the output y of the process. If not, y would never be able to follow y $_m$ for all time. If y $_m$ is greater than the maximum allowable value of y, the manipulated variable u of the process would have to go beyond its maximum value which is physically impossible as the final control element has its own limits.

A reference model is selected as per the above said guidelines and the transfer function of the reference model is

$$G_{M1}(s) = \frac{0.1}{40000s^2 + 400s + 1} \tag{10}$$

The adaptation rules for the MRAC parameters θ_1 and θ_2 are

$$\frac{d\theta_1}{dt} = -\gamma_1 e\left(\frac{400s + 1}{40000s^2 + 400s + 1}\right)u_c \tag{11}$$

$$\frac{d\theta_2}{dt} = -\gamma_2 e\left(\frac{400s + 1}{40000s^2 + 400s + 1}\right)y \tag{12}$$

where γ_1 and γ_2 are the adaptation gains for θ_1 and θ_2 respectively. Some other reference models are also tried to show that the proposed controllers are robust.

1) Design of Fuzzy Modified MRAC: An FMRAC is designed as shown in Fig. 3. The inference used in this work is 'max min' method, where 'min' operation is used for 'and' conjunction and 'max' is used for 'or' conjunction. Implication and aggregation are 'min' and 'max' methods respectively. The centroid method is the most physically appealing of all the defuzzification methods [36]. This paper uses centroid method of defuzzification.

Table 3 shows the design parameters of the MFIS used in the study. Input and output variables are assigned ranges of [-10 10] and [-400 400] respectively. The membership functions that are most commonly used in practice are the triangular and the trapezoidal membership functions [36]. The mathematical representation of a triangular membership function denoted by [a b c] is

$$Triangle\ (X: a, b, c) = \begin{cases} 0 & X < a \\ (X - a)/(b - a) & a \le X < b \\ (c - X)/(c - b) & b \le X \le c \\ 0 & X > c \end{cases} \tag{13}$$

The mathematical representation of a trapezoidal membership function denoted by [a b c d] is

$$Trapezoid\ (X: a, b, c) = \begin{cases} 0 & X < a \\ (X - a)/(b - a) & a \le X < b \\ 1 & b \le X < c \\ (d - X)/(d - c) & c \le X \le d \\ 0 & X \ge d \end{cases} \tag{14}$$

where the variable, a, b, c and d are the parameters of the membership functions.

Each variable range is divided into five fuzzy subsets as shown in Table 3. The fuzzy subsets of the input variable *e* are: large negative [a1 b1 c1 d1]; small negative [a2 b2 c2]; zero [a3 b3 c3]; small positive [a4 b4 c4] and large positive [a5 b5 c5 d5]. The fuzzy subsets of the output variable flow rate are: negative high [a6 b6 c6 d6]; negative medium [a7 b7 c7 d7]; zero [a8 b8 c8]; positive medium [a9 b9 c9 d9] and positive high [a10 b10 c10 d10]. Triangular and trapezoidal membership functions are used as shown in the Table. The total number of parameters is 36. The values of the adaptation gains γ_1 and γ_2 used are 0.0000015 and 0.000005 respectively. Increasing the values of the adaptation gains have resulted in oscillation.

Table III
Design parameters of the MFIS

Variable	Range	Fuzzy subset	Membership function (MF)	Parameters of MF
Input	[-10 10]	Large negative	Trapezoidal	[-15 -10 -1.5 -0.005]
		Small negative	Triangular	[-1.5 -0.005 0]
		Zero	Triangular	[-0.005 0 0.005]
		Small positive	Triangular	[0 0.005 1.5]
		Large positive	Trapezoidal	[0.005 1.5 10 15]
Output	[-400 400]	Negative high	Trapezoidal	[-600 -400 -300 -240]
		Negative medium	Trapezoidal	[-300 -240 -40 0]
		Zero	Triangular	[-40 0 40]
		Positive medium	Trapezoidal	[0 40 240 300]
		Positive high	Trapezoidal	[240 300 400 600]

2) Performance Analysis of the MRAC and the FMRAC: An MRAC as per Eqns. (2), (9), (10), (11) and (12), and an FMRAC as shown in Fig. 3 are designed, and their step responses are obtained. The size of the step input applied to u_c is 60. Fig. 17 shows the responses of the reference model, MRAC and FMRAC. The output of MRAC takes a long time to reach the steady state when compared with the time taken by the FMRAC. The output of the FMRAC closely follows the output of the reference model. In this context, rise time T_r is taken as the time it takes for the plant output y to reach 90% of the final value from 10% of the same. The rise times of the outputs of the reference model, MRAC and FMRAC are 671.5823, 9.5498e3 and 698.3699 seconds respectively. The values of MSE in the cases of MRAC and FMRAC are 2.3535 and 8.0721e-4 respectively. Although, it is a huge improvement as far as the FMRAC is concerned, the value of T_r is still greater than that of the reference model. In order to improve the performance of FMRAC further, DE is applied to find the optimal values of the membership function parameters. Fig. 18 shows the process inputs during the above experiment. The process inputs remain well within the bounds. It shows that the controllers can be implemented to control the hybrid tank process.

3) DE based Fuzzy Modified MRAC: The design parameters are selected as explained in section *VII-F* to ensure the optimality of the solution. Since there are 36 parameters, each solution has 36 dimensions. A six-digit floating-point number represents each membership function parameter. Different combinations of DE parameters are tried and random restart is carried out twenty times. The average of the individual runs represents the solution. Maximum fitness is obtained with the assignment of the values 100, 5, 0.8 and 1.6 to number of generations (N_g), population size (NP), crossover rate (CR) and scale factor (F) respectively. The stopping criterion used here is the number of generations.
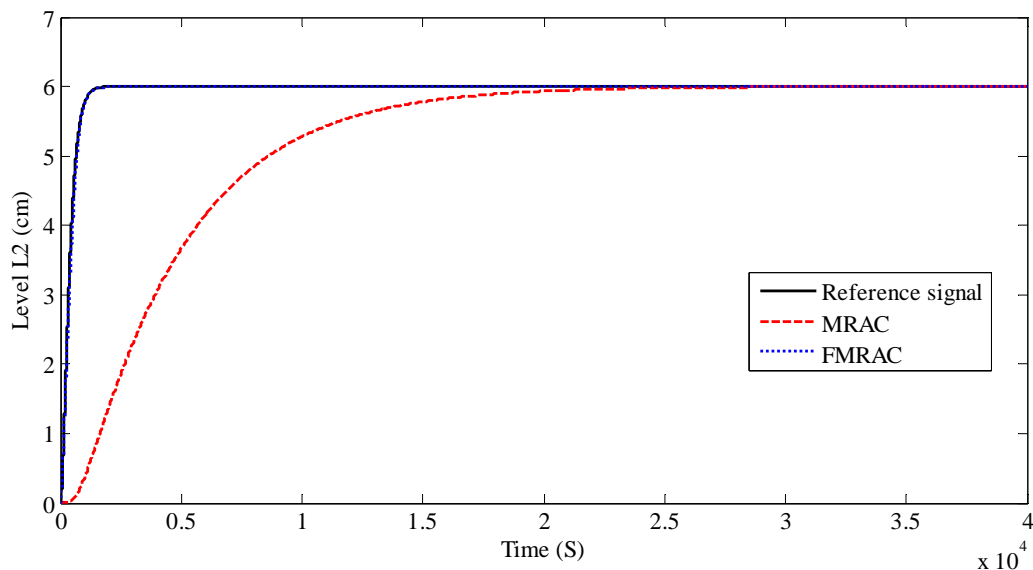

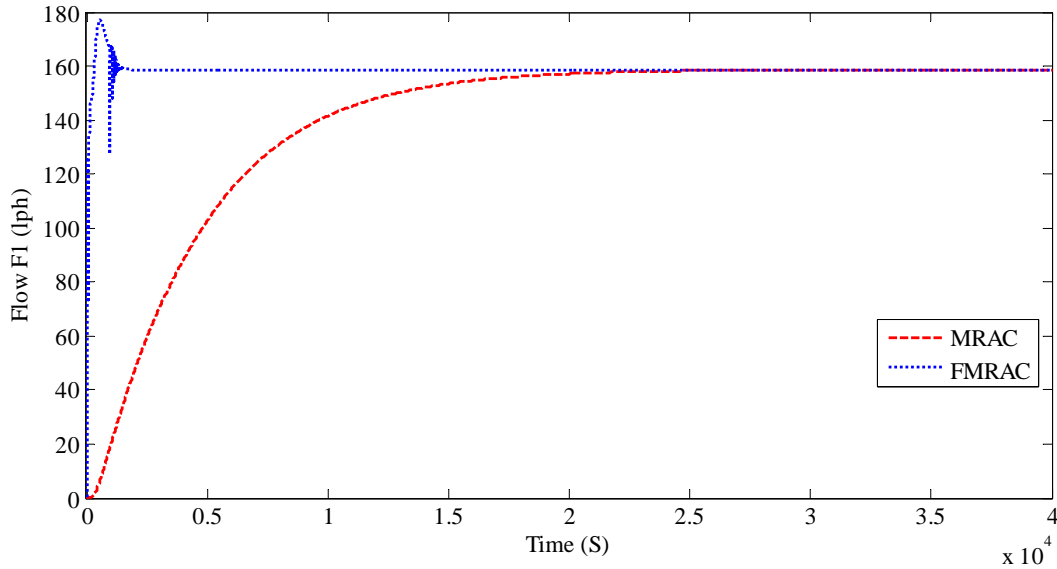Fig. 17. Response of MRAC and FMRAC for a step change in level

Fig. 18. Process input for a step input of 60 to the command signal

Fig. 19 shows the pattern of convergence of the best fitness value. After 73 generations, the best fitness does not change for many more generations. Hence, the estimate can be said to be optimal or near optimal. The membership function parameters of the FMRAC are substituted by the optimal values found by the application of DE, and the resultant controller is called DE based Fuzzy modified MRAC (DEFMRAC). The optimal values of the membership function parameters are shown in Table 4.
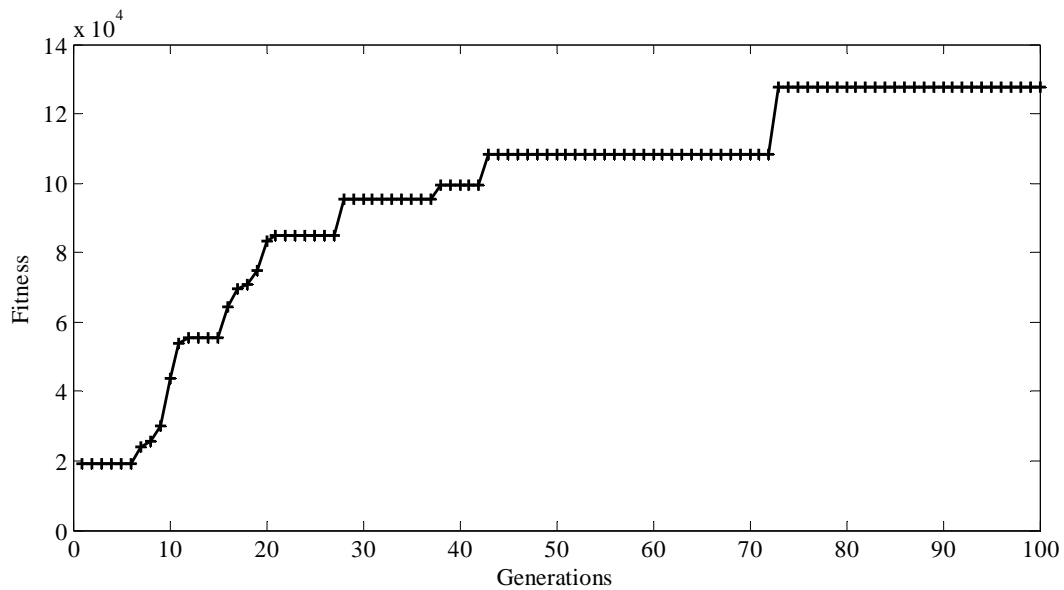

Fig. 19. Convergence of fitness in fuzzy membership function tuning

4) Performance Analysis of the Proposed Controllers: In order to carry out performance analysis of different controllers, a step input of size 50 is applied to the command signal u_c and the responses are shown in Fig. 20. The figure consists of the responses of the reference model, MRAC, FMRAC and DEFMRAC. The FMRAC performs better than the MRAC. But, the proposed controller of DEFMRAC performs the best as far as the performance criteria are concerned. The performance criteria are calculated for all the three controllers and shown in Table 5. Rise time T_r, settling time T_s and mean square error (*MSE*) are the three performance indices considered in the paper. In this context, T_s is the time it takes the process output y to reach within ± 5% of its final value and stay there. The objective is to make the process follow the reference model as closely as possible.

Table IV
Optimal Parameters of the MFIS by using DE

Variable	Range	Fuzzy subset	Membership function (MF)	Optimal parameters of MF
Input	[-10 10]	Large negative	Trapezoidal	[-15 -9.9759 -1.0177 -0041]
		Small negative	Triangular	[-1.009 -0.0670 0]
		Zero	Triangular	[-0.003 0 0.1]
		Small positive	Triangular	[0 0.0841 1.3829]
		Large positive	Trapezoidal	[0.0113 1.0344 9.9066 15]
Output	[-400 400]	Negative high	Trapezoidal	[-600 -404.5974 -322.3088 -269.481]
		Negative medium	Trapezoidal	[-300.5742 -200.9937 -15.6214]
		Zero	Triangular	[-10.1142 0 30.5443]
		Positive medium	Trapezoidal	[0 45.8633 260.9207 349.7023]
		Positive high	Trapezoidal	[262.5346 339.0674 400.7568 600]

The FMRAC has resulted in reduced values of all the three performance indices when compared with that of MRAC. However, the proposed strategy of using DE to fine tune the membership function parameters of the FMRAC has resulted in even further reduction of the values of rise time, settling time and MSE. The shorter rise times in the case of FMRAC and DEFMRAC enable the proposed controllers to adapt immediately to any change in the reference level of the process. Usually, the shorter rise time would result in larger overshoot and accompanying oscillations. However, the outputs of the proposed controllers have no overshoot at all and they have very low values of MSE when compared with the MRAC. During the step response analysis the process inputs in the cases of all the three controllers remain well within the bounds and are shown in Fig. 21. It shows that the proposed controller can be implemented to control the hybrid tank process.
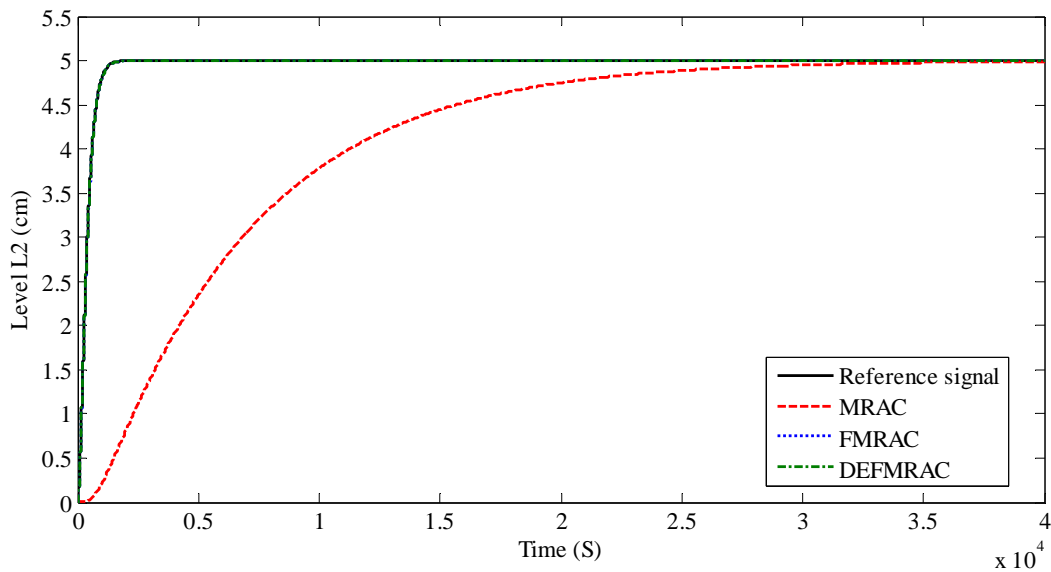

Fig. 20. Response of the three controllers for a step change in command signal
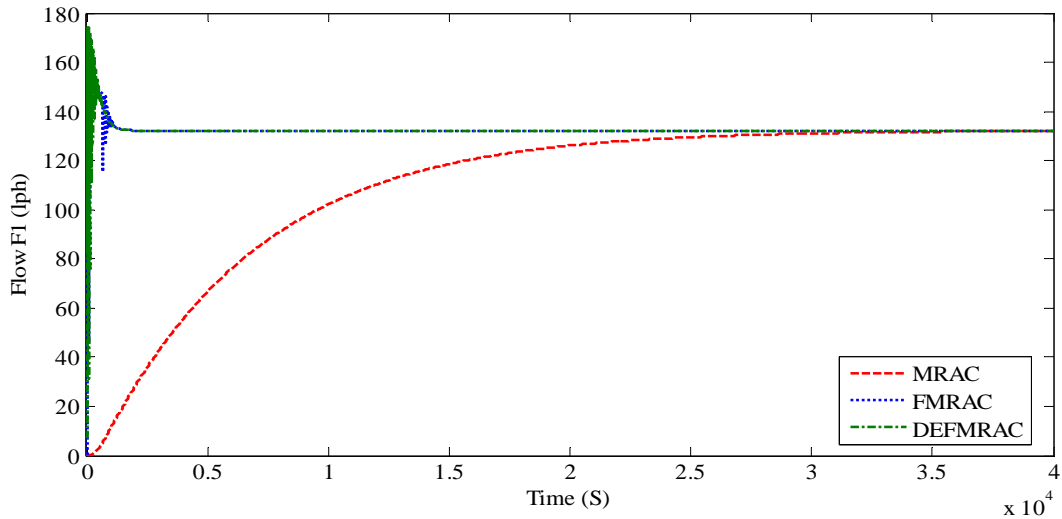
Fig. 21. Process input for a step input of 50 to the command signal

Table V
Comparison of Step Responses of Different Controllers

Performance index	Reference model	MRAC	FMRAC	DEFMRAC
T_r (s)	671.5823	1.4058e4	671.8692	671.5826
T_s (s)	1.1668e3	2.5160e4	1.1689e3	1.1673e3
MSE	-	2.2061	1.2961e-5	6.4153e-6

In order to check the robustness of the proposed controller, different types of command signals and different reference models are applied and the results are discussed below. Fig. 22 shows the responses of the three controllers to a sinusoidal command signal when G_{M1} (s) is used as the reference model. The output of the MRAC converges with the reference model output after eight cycles. However, the outputs of FMRAC and the proposed DEFMRAC follow the reference model output right from the beginning. The values of MSE for the MRAC, FMRAC and DEFMRAC are 0.8904, 2.3825e-5 and 6.0794e-7 respectively. Fig. 23 shows the responses of the three controllers to a step input followed by a sinusoidal signal. The output of the MRAC converges with the reference model output 4.041e4 seconds after the step input is applied and remains converged thereafter even when the sinusoidal input is applied to the command signal. The outputs of FMRAC and the DEFMRAC follow y_m very closely from the beginning itself. The values of MSE for the MRAC, FMRAC and DEFMRAC are 0.8837, 9.5625e-5 and 5.8256e-6 respectively.
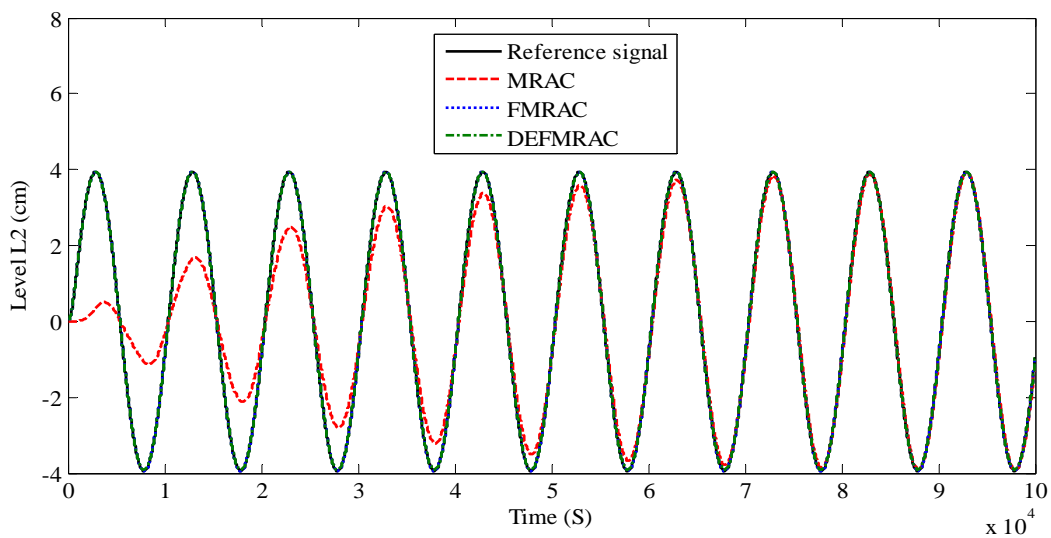

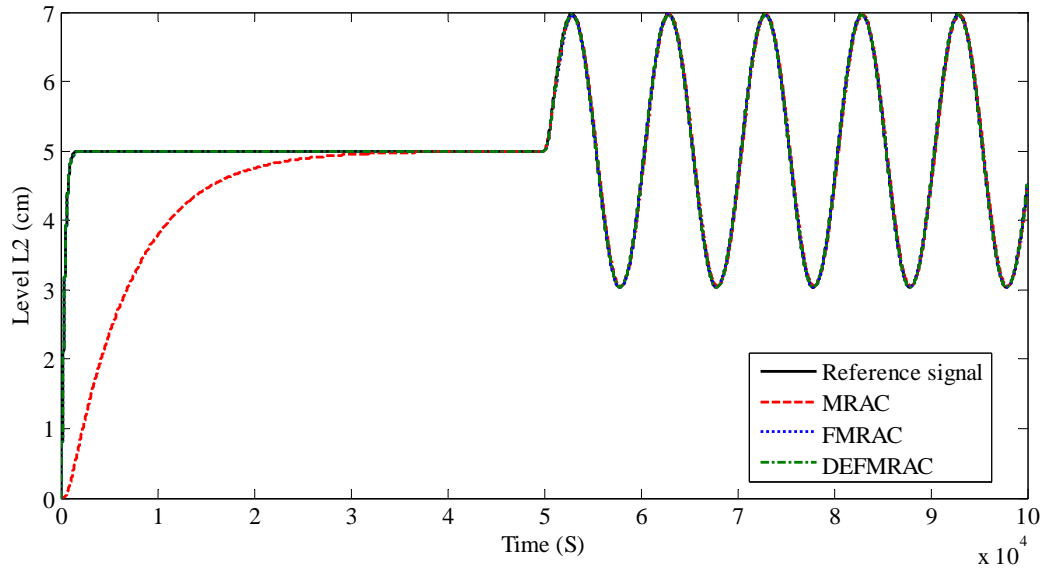Fig. 22. Response of the three controllers to a sinusoidal command signal

Fig. 23. Response of the three controllers to a step input followed by a sinusoidal input

Two different reference models whose parameters are very different from that of the process are used in order to test the robustness of the proposed controller. Fig. 24 shows the responses of the three controllers to a step command signal when a reference model whose transfer function is given in (15) is used. This model represents a coupled tank system without interaction where the time constant of a single tank is 148s. The output of MRAC takes 4.466e4 seconds to converge with y_m whereas the outputs of FMRAC and the proposed DEFMRAC closely follow y_m from the beginning itself. The values of MSE for MRAC, FMRAC and DEFMRAC are 1.4919, 4.0758e-4 and 1.4912e-5 respectively.

$$G_{M2}(S) = \frac{0.1}{21904\,S^2 + 296\,S + 1} \tag{15}$$

Fig. 25 shows the step responses of the three controllers when a first order transfer function given in (16) is used as the reference model. The reference model has larger steady-state gain and smaller time constant when compared to that of the process model. The outputs of FMRAC and the proposed DEFMRAC closely follow y_m from the beginning itself. The values of MSE for MRAC, FMRAC and DEFMRAC are 2.9348, 0.0039 and 0.0013 respectively.

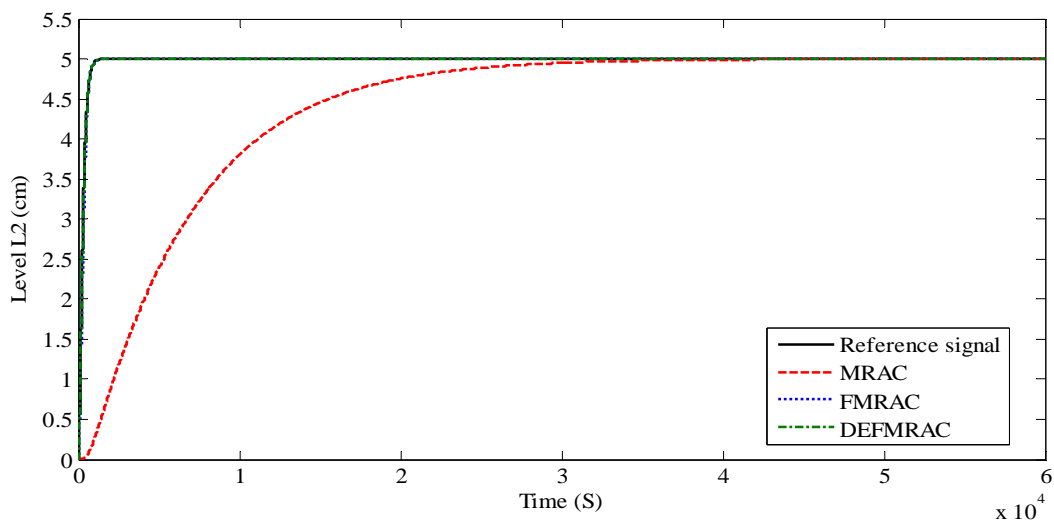$$G_{M3}(S) = \frac{0.15}{300\,S + 1} \tag{16}$$

Fig. 24. Response of the three controllers to a sinusoidal command signal when G_{M2} (S) is used as the reference model
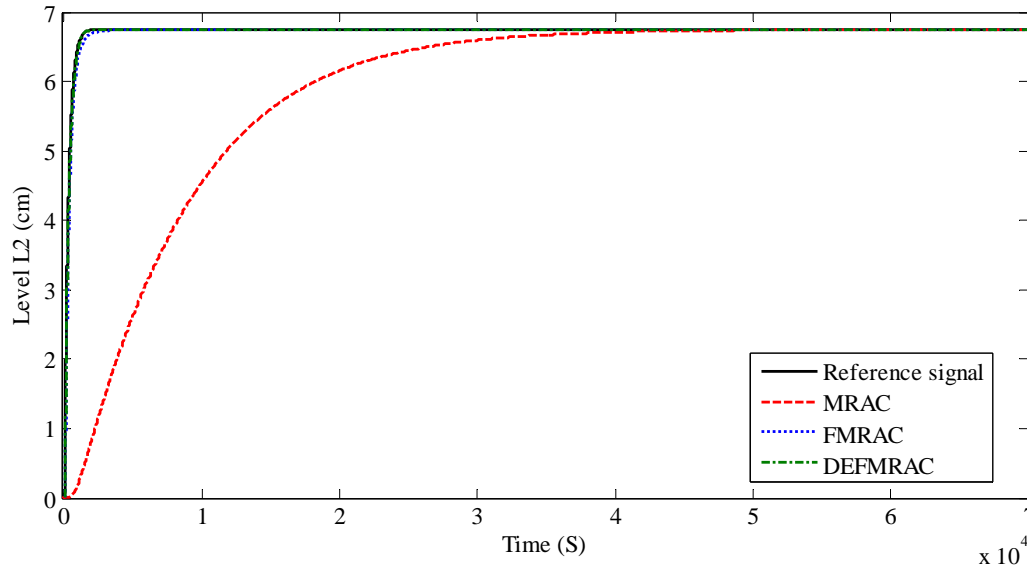
Fig. 25. Response of the three controllers for a step change in set point when G_{M3} (S) is used as the reference model

From the analysis of the results, it can be said that the proposed DEFMRAC gives very good transient and steady state performance for any type of command signal. It is also shown that even in the case of the reference model parameters being very different from the process model parameters; the proposed controller gives stable response and the process shows improved transient and steady state performance when compared to the performance of MRAC. The proposed application of DE to fine-tune the membership function parameters of FMRAC gives better performance than the FMRAC does. Even if the plant parameters change due to ageing and any other external disturbances, and consequently the process parameters and the reference model parameters become very different from each other the process will faithfully follow the reference model.

VIII. CONCLUSION

The coupled tank level process is identified as an over-damped second order process using standard system identification procedure. Then, the accuracy of the model is increased by using DE to fine-tune the parameters of the selected model. The validation results showed that the obtained model is quite capable of capturing the main dynamic characteristics of the coupled tank level process. The coupled tank process used in this study is a nonlinear process. Hence, an adaptive controller like MRAC is preferred to a PID controller in the study. For the coupled tank process, an MRAC and an FMRAC are designed and their performances are compared. The FMRAC gives better transient performance when compared to the performance of MRAC. The application of DE to fine-tune the membership function parameters of the FMRAC has given even better transient and steady state performance than that of the FMRAC. The simulation results establish that the proposed DEFMRAC performs better when compared to FMRAC and MRAC. It has also been shown that the proposed controller performs very well for different types of command signals like step, sinusoid, and step followed by a sinusoid. It has also performed very well even when the reference model parameters are very different from the process model parameters indicating the robustness of the proposed design. Process inputs remain well within the bounds in all the experiments. The designed FMRAC and DEFMRAC can be used for the control of other nonlinear processes as well. Future work aims to adapt the values of the adaptation gains γ_1 and γ_2 by using fuzzy logic in order to obtain improved transient performance.

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