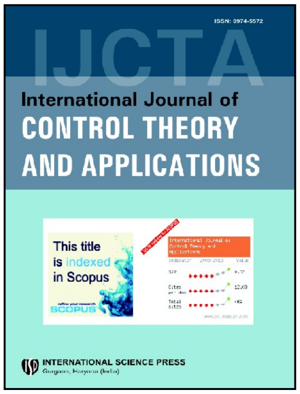

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Investigation of NARMA L-2 and Artificial Bee Colony Tuned PID Controllers for Bench Scaled Nonlinear Dynamical System

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Abstract: This paper presents performance analysis of a bench scaled nonlinear dynamical system (NLDS) with NARMA L-2 and Artificial Bee Colony (ABC) tuned linear and nonlinear PID controllers. The nonlinear dynamical system identification and design of NARMA L-2, linear and nonlinear PID controllers is demonstrated through simulation study in MATLAB/Simulink. A comparison of dynamic performance of NLDS in terms of settling time, rise time and dead zone is presented and analysed. Effectiveness of ABC tuned nonlinear PID controller to that of NARMA L-2 and ABC tuned linear PID is investigated by determining performance index in terms of effective tracking of a given reference trajectory.

Keywords: Nonlinear Autoregressive Moving Average;Linear PID; Non-linear PID; PID tuning; Swarm intelligence; Artificial Bee Colony algorithm; Nonlinear Dynamical System

I. INTRODUCTION

Most of the real time systems are nonlinear, complex, multidimensional, unstable, highly interconnectedand dynamical, and may exhibit unpredictable behaviour due to sluggish or sudden change of plant dynamic parameters. Analysis of these systems are oftenly complex when compared to the linear systems. Nonlinear system stabilization has been a major area of interest for control engineering research since a long time[1], [2]. The plant model is a mathematical representation of a system, and will always be an approximation to the real behaviour of the plant. If a linear plant model is used to design a controller, then the performance of the controller will be governed by mathematical accuracy of the plant model. Majority of the systems for which approximate model is sufficient for control. However there are many systems which are not linearizable or modelled by mathematical functions alone, for which conventional controller would be so inadequate and perform badly during dynamic regime.

Hence, in these situations the conventional controllers may be equipped with intelligent techniques to deal above mentioned complexities. Multi-layer neural networks based controllers have been used in the identification and control of nonlinear dynamical systems due to the universal approximation capability[3]. One of the major controller in this category is Nonlinear Auto Regressive Moving Average Level-2 (NARMA L-2) controller.It is simply a readjustment of the system dynamical behaviour and trained off-line by batch process. It requires the least computation of most neural architectures as the only computation is forward pass through the neural network controller. On the other hand, the NARMA L-2 controller[4] response is inspired from S-type curve, which is nonlinear.The only drawback of this controller is that the system being controlled in approximated companion form which creates the more chattering in real systems. The PID controllers are still extensively dominative and popular in control of dynamical systems due to their easy implementation and robustness. Moreover, the principle of PID controller is easier to understand than neuro inspired controllers. Many tuning approaches are proposed for PID and PI control[5] for systems with monotonic transient responses. Usually the PID controller dynamics can be employed by the linear control actions in the form tracking error with fixed gains called as linear PID(L-PID)[6]. As a result, it oftenly reduces the performance of bench-scaled plants if the controller operates over a wide range about the point of tuning and needs to compromise among the overshoot and fastness of the control response. In order to avoid this ambiguity and to improve the performance of plant, nonlinear PID was introduced with nonlinear characteristics called nonlinear PID(NL-PID)[7]. The nonlinear combination can offers further degree of freedom to attain enhanced dynamical system performance. However, this enhancement can only be achieved at the cost of higher complexity in controller. Artificial intelligence based bio-inspired algorithms can reduce some of the technical hitches such as tedious tuning by fusing priori knowledge into the controller. In recent past several artificial intelligence based Meta algorithms such as Genetic Algorithm (GA)[8]–[13], Particle Swarm Optimization (PSO)[14], [15], Ant Colony Optimization (ACO)[16], [17] etc. have been proposed to estimate the optimized tuning gains of the L-PID controllers and tested with linear systems. This has been the inspiration for some new tuning techniques that aim to compute L-PID and NL-PID gains according to the bench scaled nonlinear dynamical system, such that optimization of classical tuning techniques are diminished. Unlike existing literature, the work in this paper analyzes the design, modelling and implementation of Nonlinear Auto Regressive Moving Average Level-2 (NARMA L-2) controller, artificial bee colony algorithm (ABC) tuned L-PID and NL-PID controllers for nonlinear dynamical system.

This paper is organized in six sections commencing with introduction followed by section II, which analyzes the mathematical modelling and Lyapunov stability of bench scaled nonlinear dynamical system. Section III discusses the NARMA L-2 controllers followed by identification and design of the controller, which is applied to the test problem of bench scaled nonlinear dynamical system. In section IV the methodology of artificial bee colony (ABC) algorithm and ABC tuning of L-PID and NL-PID controllers for bench scaled nonlinear dynamical system is presented. Section V presents the simulation&discussion and section VI gives conclusion.

II. MODELLING OF BENCH SCALED NONLINEAR DYNAMICAL SYSTEM

The nonlinear dynamical system (NLDS) is represented using state equations, differential equations or difference equations. The reference nonlinear dynamical system[3] considered in this paper is represented by the equation (1), where *y(t)* is output and *u(t)* is input of the system. This system is a nonlinear, non-homogeneous and it does not produce a bounded solution which can imitates the exact solution. If some initial solution to the dependent variables are known then only the solution could be determine, otherwise if the equilibrium point is calculated and the phase plane analysis of the system is performed with zero input, *u (t)* to graphically analyze the system behaviour.

$$\frac{d^2y}{dt^2} + 0.7\frac{dy}{dt} + 0.2y + 0.3y^3 = u \tag{1}$$

It is not possible to find the analytical solution for NLDS and the system equation can be solved numerically with help of classical fourth order Runge-Kutta method, which achieves the accuracy of Taylor's series expansion without requiring the calculations of higher derivative. The equation (1) rewritten as (2) and shown in Figure.1 (a)

$$y'' + 0.7y' + 0.2y + 0.3y^3 - u = 0 \tag{2}$$

The initial conditions assumed as $y(0) = 0.1, y'(0) = 1 and\, u(t) = t$ then $y(0.2)$ are to be determined by correcting four decimal places can be solved as $y = 0.2872$ and $y' = 0.8773$. The specific state can be described in state-space representation by two state variables x_1 and x_2 such that $\dot{x}_1 = x_2$ and $\dot{x}_2 = -0.7x_2 - 0.2x_1 - 0.3{x_1}^3 - x_1$. The Lyapunov stability analysis is performed for NLDS through generalized Krasovskii theorem by assuming continuouscontrollaw $u = -ky$. Therefore, the system condition when k=1 is determined and compactly written as equations (3), (4), (5) and (6)

$$f_1(x) = x_2 \tag{3}$$

$$f_2(x) = -0.7x_2 - 0.2x_1 - 0.3{x_1}^3 - x_1 \tag{4}$$

$$V = f^T(J^TP + PJ)f \tag{5}$$

$$Q = J^TP + PJ \tag{6}$$

Where P and Q are symmetric matrices and J is Jacobian matrix of the system.

$$J = \begin{bmatrix} 0 & 1 \\ -0.2 - 0.9x_1^2 & -0.7 \end{bmatrix} \tag{7}$$

$$Q = \begin{bmatrix} 0 & -0.2 - 0.9x_1^2 \\ -0.2 - 0.9x_1^2 & -1.4 \end{bmatrix} \tag{8}$$

$$det|Q| = -(0.2 + 0.9x_1^2)^2 \tag{9}$$

Since Q is negative definite then $\dot{V}$ must be negative

$$\dot{V}(x) = -0.33x_1^2 - 0.42x_2^2 - 0.58x_1^4 - 0.06x_1^6 + 1.10x_1x_2 + 1.26x_1^2x_2^2 + 1.54x_1^3x_2 + 0.54x_1^5x_2 \tag{10}$$

Here P and Q are the two symmetric positive definite matrices, such that $\forall x \neq 0$ the matrix is negative semi –definite in some neighborhood region of the origin. If the region is whole state space and if in addition $V \to \infty$ as $\| x \| \to \infty$ then the nonlinear dynamical system is asymptotically stable at equilibrium points (-0.816, 0) and (0.816, 0). The NLDS transient and steady state responses without any controller is shown in Figure.1 (b). The actual response is compared with a reference, which represents the actual desired response of the controlled variable. This graph shows the tracking performance of underdamped system and also find the value of the adaptive parameters which are not exactly the same as that of the desired parameters, the tracking is achieved by using of controller.

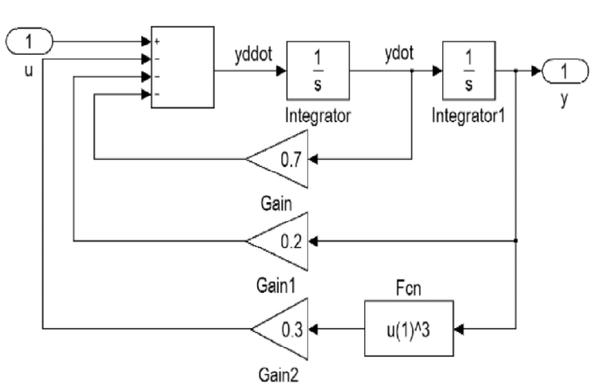

Figure 1(a): Model of the bench scaled nonlinear dynamical system

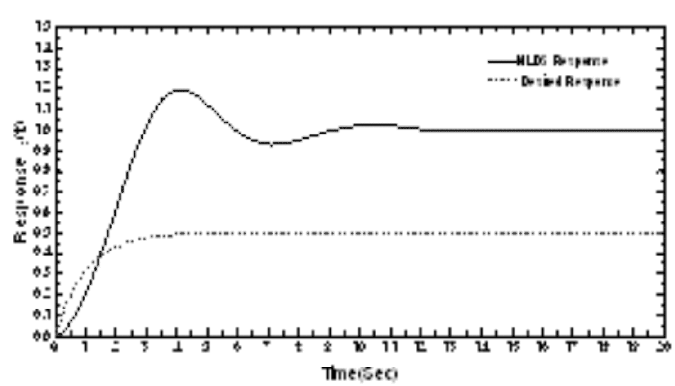

Figure 1(b): Bench scaled NLDS response

III. IMPLEMENTATION OF NARMA L-2 CONTROLLER

Now a days neural networks have been widely applied in nonlinear dynamic systems which are involved with lagged variables and requires more appropriate system identification. System identification is a mathematical technique to measure observed input-output description of a system. Multilayer neural networks have the universal approximation capability which makes it a popular selection for modelling systems and used asa general purpose controller.Two stages are involved in neural network implementation such as system identification and controller design. In the first stage, an identical neural network model of the system has to be mimicked. Subsequently, the developed neural model is then used to train the controller. Nonlinear autoregressive-moving average level-2 (NARMA L-2) controller[4][15][18] is simply a readjustment of the plant model that is trained off-line in batch process. It requires the least computation of most neural architectures as the only computation is forward pass through the neural network controller. The only drawback of this form of controller design is that the system being controlled should be in companion form or must be capable of being approximated by a companion form model. This type of control is also known as feedback linearization control.

3.1. Identification of NARMA L-2 controller

The first step is feedback linearization to identify the system to be controlled. For training of a neural network to represent the forward dynamics of the system, the second step is to choose a model structure. One standard model to represent general discrete-time nth order nonlinear systems has relative degree, the companion form of NARMA expressed by equation (11).

$$y(k+d) = F[\,y(k), y(k-1), \dots, y(k-n+1), u(k), u(k-1), \dots, u(k-n+1)] \tag{11}$$

Where $u(k) \in R$ the sequence of control is input, and $(k) \in R$ is the sequence of system output and is the system delay taken as 1. To train the neural network in identification phase, the nonlinear function is approximated as $F: R^{2n} \rightarrow R$ and $F \in C^{\infty}$. The nonlinear controller equation is developed, for the system output $y(k+d)$ followed reference trajectory $y_r(k+d)$ given in equation (12).

$$u(k) = g[\,y(k), y(k-1), \dots, y(k-n+1), yr(k+d), u(k-1), \dots, u(k-m+1)] \tag{12}$$

The difficulty to exploit NARMA L-2 Controller is relatively sluggish due to dynamic back-propagation training and it will create a function G to minimize the mean square error. The solution is to approximate model by equation (13).

$$\hat{y}\,(k+d) = f[\,y\,(k), y(\,k-1) \dots .\, y\,(k-n+1), u(\,k-1), \dots ., u(\,k-\,m+1)] + g[\,y(k), y(k-1) \dots \dots, y(k-n+1), u(k-1), \dots ., u(k-m+1).\, u(k) \tag{13}$$

Where

$$f = F[y(k), \dots, y(k-n+1), \dots, u(k) = 0, u(k-1), \dots, u(k-n+1)] \tag{14}$$

$$g = \frac{\partial F}{\partial u(k)}\Big|_{(y(k),\dots,y(k-n+1),\dots,u(k)=0,u(k-1),\dots,u(k-n+1))} \tag{15}$$

In this companion model the f and g are functions of the former values of both the output y and controller input u and hence, the relation among the subsequent value of output $y(k+d)$ and controller input at the recent step $u(k)$ seems linearly without inside nonlinearities. The advantage of this form is the control input causes the system output to follow the reference $y(k+d)$ and is equal to the $y_r(k+d)$. This means that the system seamlessly tracks a reference trajectory. The control law for NARMA L-2 controller is derived as equation (16).

$$u(k) = \frac{y_r(k+d) - f[y, y(k-1), \dots, y(k-n+1), u(k-1), \dots, u(k-n+1)}{g[y(k), y(k-1), \dots, y(k-n+1), u(k-1), \dots, u(k-n+1)]} \tag{16}$$

Using this control law the controller input u(k) directly determined based on the output $y(k)$ at the same time. So, instead of companion model an approximate model is used and shown in equation (17) for $d \geq 2$. The structure for NARMA L-2 controlled NLDS plant model is shown in the Figure 2.

$$\begin{aligned} y(k+d) = {} & f[y(k), y(k-1), \dots, y(k-n+1), u(k), u(k-1), \dots, u(k-n+1)] \\ & + g[y(k), \dots, y(k-n+1), u(k), \dots, u(k-n+1)].u(k+1) \end{aligned} \tag{17}$$

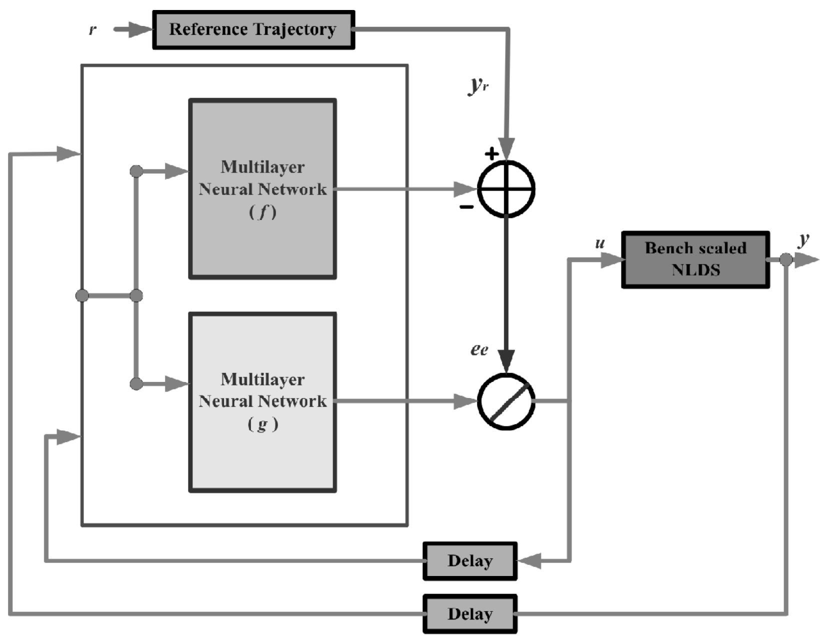

Figure 2: Structure design of NARMA L-2 with bench scaled NLDS plant

3.2. Design of NARMA L-2 controller

The first stage in controller design is to identify bench scaled nonlinear dynamical system through NARMA L-2 neuro controller by feedback linearization. Initially the whole system is modelled with help of Simulink, with NARMA L-2 neuro controller. The bench scaled nonlinear dynamical system is identified with the following multi-layer neural network architecture parameters by choosing number of delayed plant inputs as 4, delayed plant outputs as 3, 6 hidden layers, and sampling interval of 0.1 (sec). The second stage is to obtain a neural network model of bench scaled nonlinear dynamical system, which is used to train the controller. The gradient descent back propagation with adaptive learning rate used as training algorithm[4][15]. The training data parameters selecting with10000 training samples, 2 maximum plant inputs, -2 minimum plant input, 0.1(sec) maximum time interval, (sec) as minimum time interval, 1000 training epochs and trainlm employed as a training function to get good results. The model of NARMA L-2 controlled bench scaled nonlinear dynamical system is shown in Figure 3 and the control signal from NARMA L-2 controller is also shown in Figure 4.

The experimental data used for training the neural network is shown in figure 5. The testing and validation data sets for NARMA L-2 controller are shown in figure 6 and 7, respectively. After the validation of the training and testing data, the best validation performance is obtained 3.0604 e^{-12} at 1000 epoch, and the response of the NARMA L-2 controlled NLDS is shown in figure 8. It is observed from the results that the bench scaled NLDS system is stabilized from an unstable state.

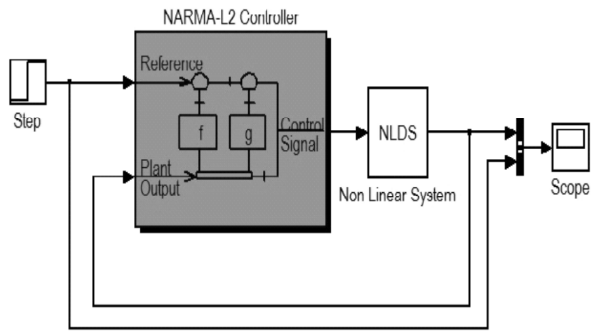

Figure 3: NARMA L-2 controlled bench scaled NLDS

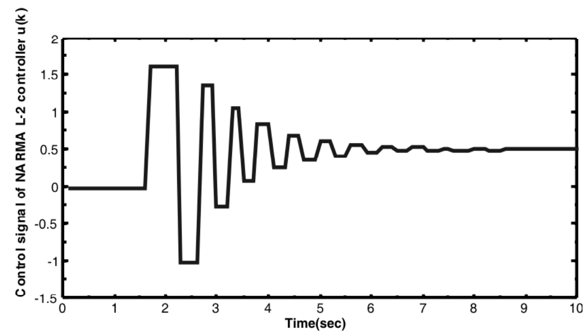

Figure 4: Control signal of NARMA L-2 controller

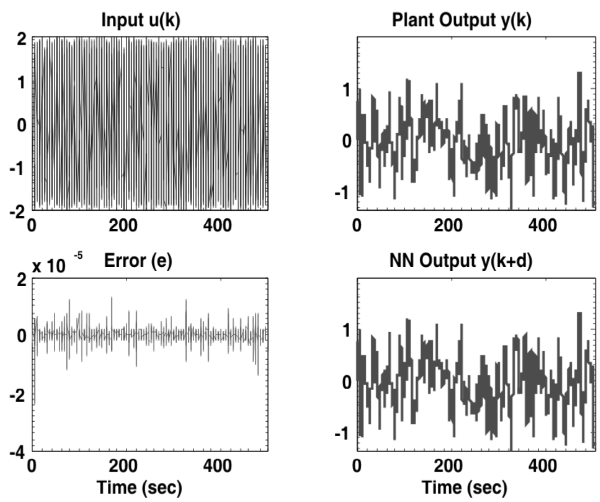

Figure 5: Experimental training data of neural model

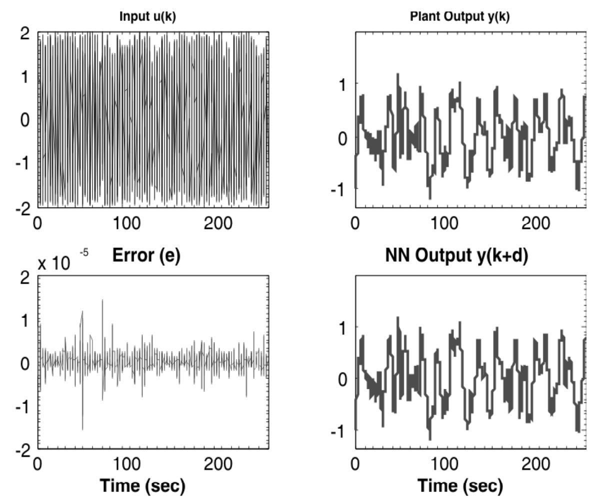

Figure 6: Testing data of neural model

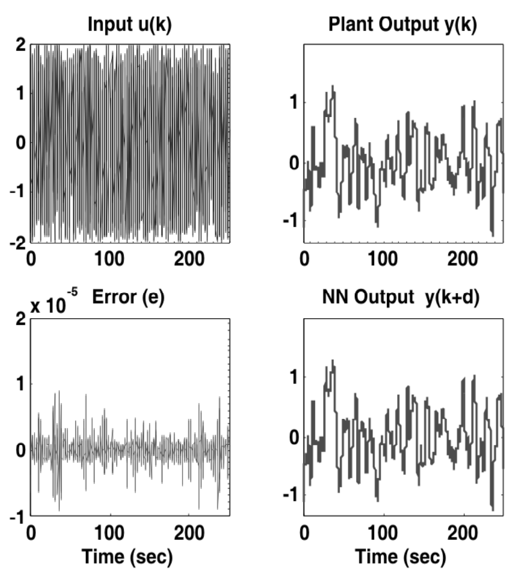

Figure 7: Validation data of neural model

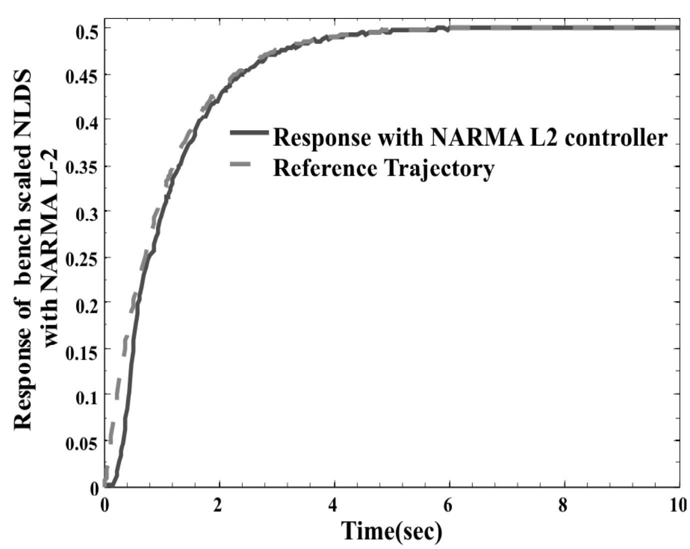

Figure 8: Response of bench scaled NLDS with NARMA L-2 controller

IV. IMPLEMENTATION OF ABC TUNED LINEAR AND NONLINEAR PID CONTROLLERS

The controllers for bench scaled nonlinear dynamical systems are designed and tuned by bio-inspired intelligent tuning technique such as artificial bee colony(ABC) algorithm to achieve the optimal gains for the entire operating envelop.Currently the ABC optimized adaptive critic design for PID controllers is inviting much renewed interest among the researchers to automate the design and tuning process to a useful degree. Artificial bee colony algorithm is one of the latest swarm intelligence algorithm having limited control parameters as compare to other population based algorithms such as genetic, PSO and ACO algorithms. The ABC algorithm was methodically studied by Karaboga and Basturk in unconstrained optimization problems[19][20][21]. According to colony of artificial bees consist of three stages such as forager bees, observer bees and scout bees. Number of forager bees are equal to the number of food sources. The forager bee of a discarded food site is forced to become scout bee for finding new food site randomly. Forager bee memorizes the quality and quantity of food source and shares this information with observer bees at hives, so that the observer bees can choose a food source to forage. In ABC, the food sources are modeled and mutated with their neighbors to develop new solution based on objective function. The mathematical segments involved in ABC algorithm are as follows.

The first stage of the algorithm generates $\overrightarrow{x_i} = (i = 1,...,SN)$ solutions randomly by equation (18) where *SN* distributed population solution $\overrightarrow{x_i}$, represents i^{th} solution in population with dimensional vector of the problem D.

The second stage, for each forager bee produces a new source by equation (19) where $\emptyset_{ij}$ is uniformly distributed real random number within -1 to 1, and *k* is the index of the solution picked randomly from the colony ($k = int(r$ and $* SN) + 1$)

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \tag{19}$$

The third stage of the algorithm, each observer bee picks a food source site with the probability anticipated by equation (20), where fit_i is fitness of $\overrightarrow{x_i}$.

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{20}$$

If the number of sequences through which a source cannot be improved by more than the predetermined value, the source will be exhausted. The forger bee associated with this exhausted source become scout bee and starts random search in problem domain to find a new solution by equation (18) until the termination criterion met.

4.1. ABC tuned linear PID controller

An overall ABC tuned L-PID configuration with NLDS is shown in Figure.9 which feeds the desired output signal to the NLDS, the error between the actual output and the desired output signal along with a controller proportional (K_P) integral (K_i) and differential gains (K_d) generate the output control signal u(t) as given by equations(21) and (22)

$$e(t) = y_d(t) - y(t) \tag{21}$$

$$u(t) = K_P e(t) + K_i \int e(t)dt + K_d \dot{e}(t) \tag{22}$$

Where u(t) is L-PID control output feed to the bench scaled NLDS, e(t) is error or set point, y(t) is bench scaled NLDS output, y_d (t) is desired output.The internal systematic structure design of L-PID and output control signal are shown in Fig. 10 and 11 respectively.

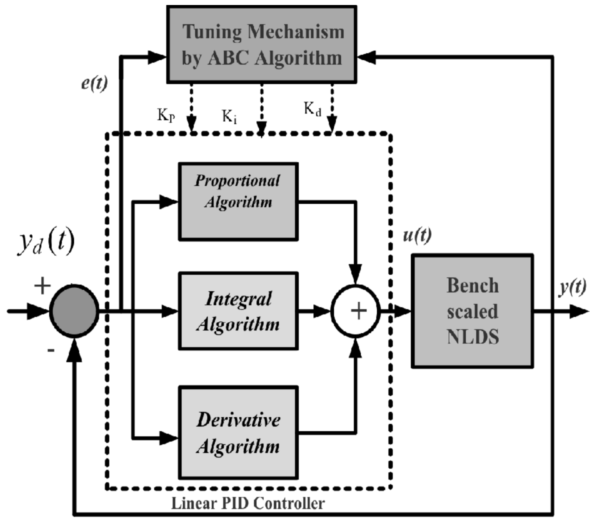

Figure 9: ABC tuned L-PID controller with bench scaled NLDS

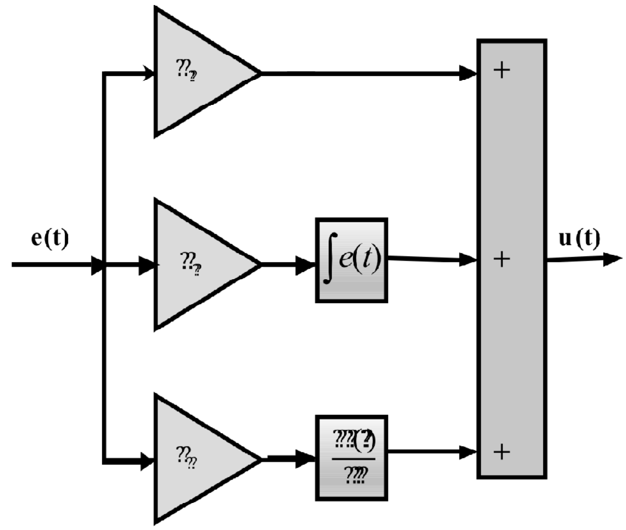

Figure 10: Systematic structure design of L-PID controller

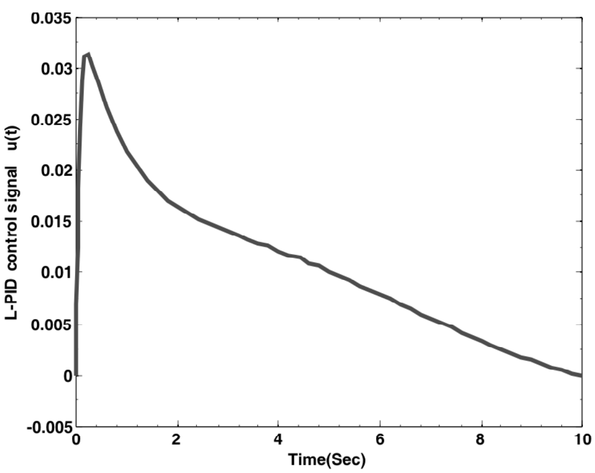

Figure 11: L-PID control signal

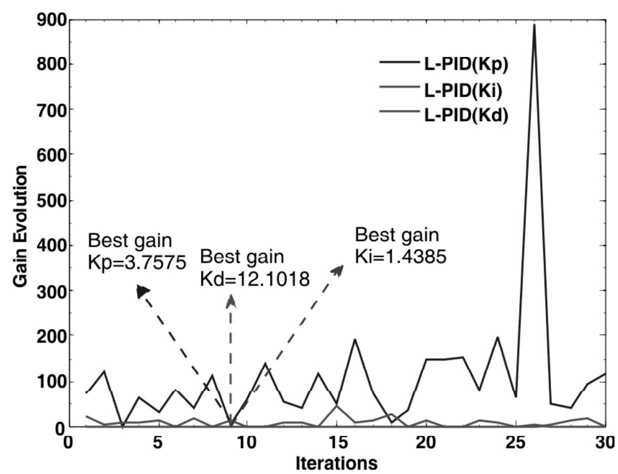

Figure 12(a): Best gain evolution by ABC for L-PID

The goal is to optimize the K_P, Ki and K_d parameters to control bench scaled NLDS, which minimizes the error, hence the performance objective function J(θ) can be considered as an integral square error given in equation (23)

$$J(\theta) = \int t[e(\theta, t)]^2 \, dt \tag{23}$$

Where $\theta = [K_p, K_i, K_d]$

The ABC algorithm implemented to tune L-PID of NLDS and the L-PID can transmit the current best valueswith quicker convergence during optimal tracking of model reference desired signal. Here the bee size, dimension of the problem, the maximum number of iterations, cognitive and acceleration factors are taken as 30, 3, 10, $c_1 = 0.8$, $c_2 = 0.3$, and $\omega = 1$ respectively. The ABC algorithm estimates the best K_P, Ki and K_d parameters at ninth iteration based on the error signal e (t) as K_p = 3.75755241063570, K_i = 1.43854203931719, K_d = 12.1018550978301 shown in Fig. 12 (a). The response of NLDS with L-PID is tuned by an ABC algorithm is shown in Fig.12(b)and the absolute error e(t)between system response and desired is shown in Fig.12(c).The minimum cost function, overshoot and error of ABC tuned L-PID controlled bench scaled NLDS with reference to iterations are shown in Fig. 12 (d).

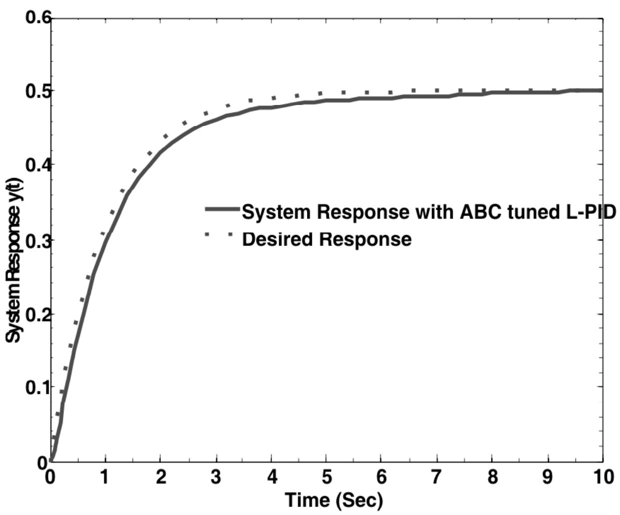

Figure 12(b): Trajectory bench scaled NLDS with ABC tuned L-PID

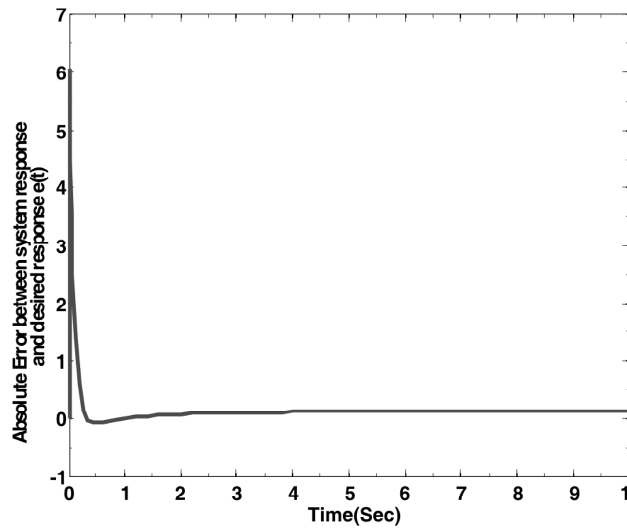

Figure 12 (c): Absolute error

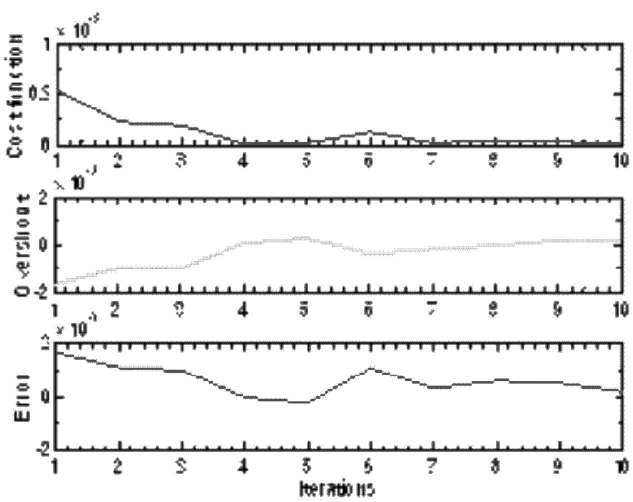

Figure 12 (d): cost function, overshoot and error with reference to iterations

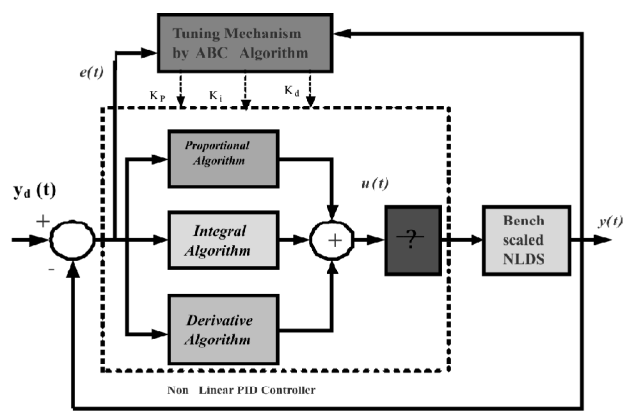

Figure 13: ABC tuned NL-PID controller with bench scaled NLDS

4.2. ABC tuned nonlinear PID controller

Mostly the L-PID controllers are the widely used controllers for control of systems due to simple structure, efficacy and easy tuning. While L-PID controllers are often insufficient for controlling systems which are nonlinear, long-time delaying and strong cross coupling. During high performance control, these controllers are also compromised with system response speed and stability. In order to improve the performance of L-PID controller a kind of complex Non-Linear PID controller is offer additional degree of freedom with much system performance. The general ABC tuned NL-PID configuration with NLDS is shown in Fig. 13. The NL-PID control structure can be represented by equation (24). Where is the error signal, δ describes the linear range of the function, here function can accommodate a greater range of nonlinear characteristics which is determined by.The control signal generated by the NL-PID is given in equation (25)

$$f(e,\alpha,\delta) = \begin{cases} |e|^{\alpha} sign(e) |\gamma| \geq \delta \\ \dfrac{e}{\delta^{1-\alpha}} |\gamma| < \delta \end{cases} \tag{24}$$

$$u(t) = K_p e f_p(e_p, \alpha_p, \delta_p) + K_i f_i(e_i, \alpha_i, \delta_i) \int edt + K_d f_d(e_d, \alpha_d, \delta_d) \frac{de}{dt} \tag{25}$$

The function $f(\alpha, \delta, e)$ denotes the rate of error feedback, to compensate the nonlinearity of the systems considered the value of α_p is taken in the range of $\alpha_p \in [0, 1]$ since the system need to have lower gain when the error is high and vice versa. The integral saturation problem of the integral term can be rectified by using α_i in the range of $\alpha_i \in [-1, 0]$. The value of differential term is chosen as $\alpha_d > 1$ so that when the steady state is reached then effect of the differential term is reduced. The systematic structure design and control signal of NL-PID are shown in Fig.14 and 15 respectively.

The ABC algorithm with the same settings was implemented for tuning of NL-PID configured with bench scaled NLDS in the presence of desired model reference trajectory. The ABC algorithm estimates the best $K_{P,}$ Ki, K_d gain parameters based on the error signal e (t) as K_P =52.5514210985258, Ki =1.15305861951294, Kd=39.6173913597581shown in Fig.16 (a) The response of NLDS with APSO algorithm tuned NL-PID is shown in Fig.16 (b) and the absolute error e(t) between system response and desired trajectory response is shown in Fig.16(c). The minimum cost function, response, error of ABC tuned NL-PID controlled NLDS with reference to iterations are shown in Fig. 16 (d)

V. SIMULATION&DISCUSSION

The simulation study of the bench scaled NLDS closed loop response using NARMA L-2controller, ABC tuned L-PID controller and ABC tuned NL-PID controllers are presented through a numerical simulation in MATLAB/ SIMULINK. The exponential reference trajectory considered is a model reference for bench scaled NLDS, together with the error elimination and the transient behaviour of the system has been taken into account. The system is originally unstable due to the existence of disturbances, unmodelled dynamics and parametric variations. Fig 9, Fig.13(b) and Fig 17(b) shows the system trajectory tracking responses with NARMA L-2,ABC tuned L-PID and ABC tuned NL-PID controllers in respect of various performance criteria like settling time, rise time, and dead zone, have been determined through the dynamic response analysis of bench scaled NLDS and summarized in Table 1.

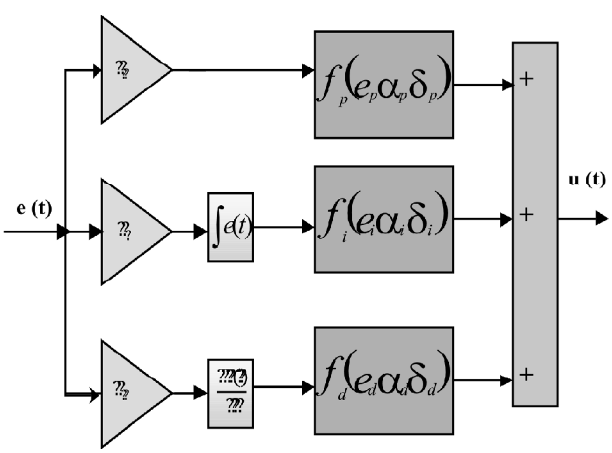

Figure 14: Systematic structure design of NL-PID controller

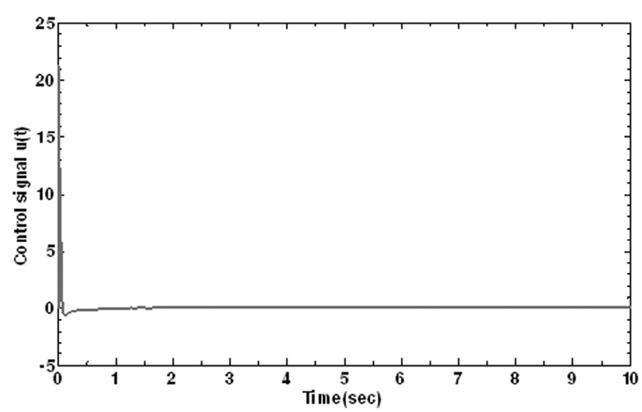

Figure 15: NL-PID control signal

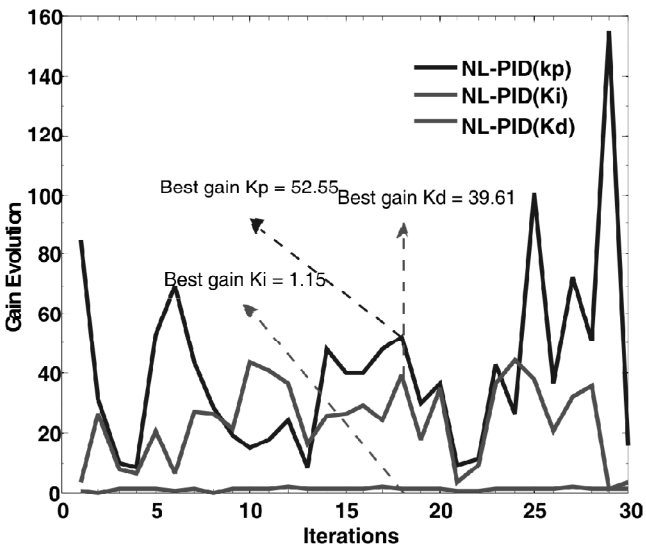

Figure 16(a): Best gain evolution by ABC for NL-PID controller

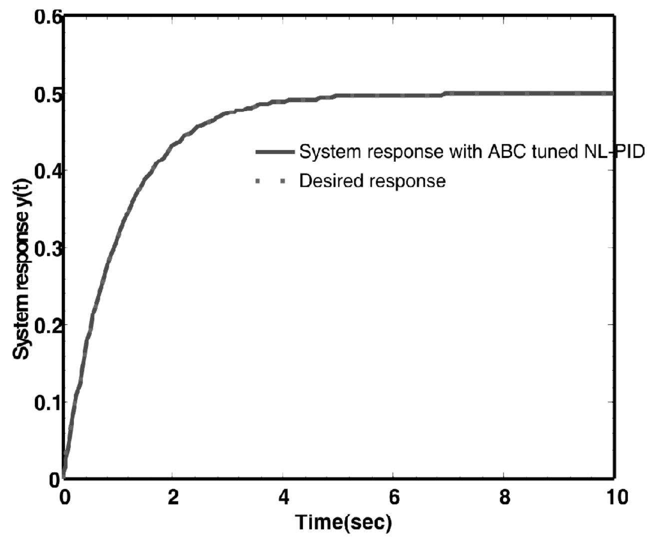

Figure 16(b): Response of bench scaled NLDS with ABC tuned NL-PID

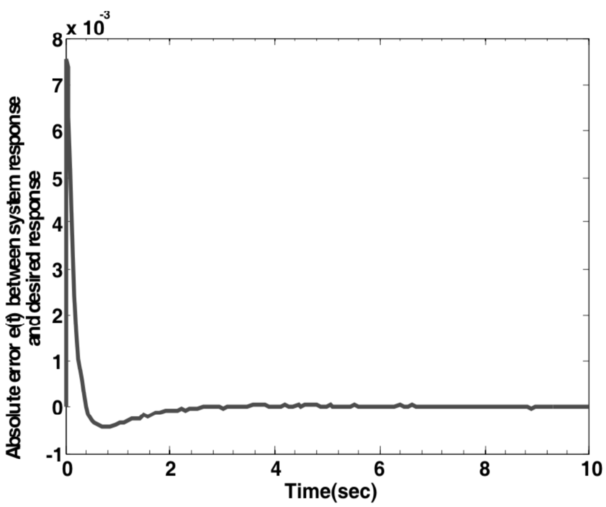

Figure 16(c): Absolute error

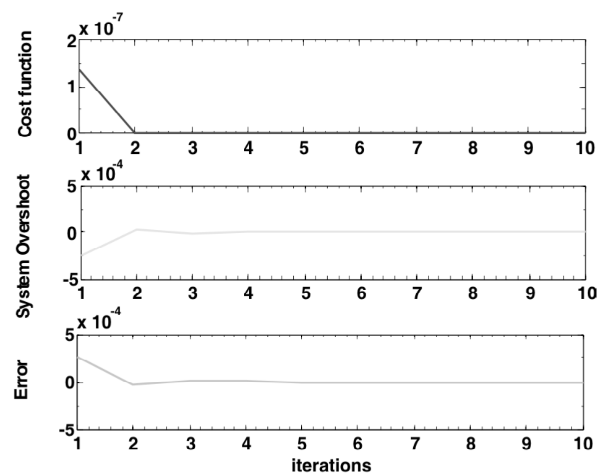

Figure 16(d): cost function, overshoot and error with reference to iterations

Table 1
Performance parameters of bench scaled NLDS with NARMA L-2, ABC tuned L-PID and NL-PID controllers

Controller	*Settling time (t_s) sec*	*Rise time (t_r)sec*	*Dead Zone sec*
NARMA-L2	10	2.2172	0.146
ABC tuned L-PID	10	2.6264	0
ABC tuned NL-PID	9.468	2.207	0

VI. CONCLUSION

The NARMA L-2 and optimally tuned linear and nonlinear PID controllers by ABC have been successfully developed and tested for their performance in terms of settling time, rise time, dead zone interval on a bench scaled NLDS. The numerical simulation results shows the effectiveness of these controllers for dealing with bench scaled NLDS for widely varying operating conditions. In comparison with the ABC tuned L-PID controller, the NARMA L-2 controller has the advantage of lesser rise time, but with the drawback of dead zone interval. On the other hand ABC tuned NL-PID controller yields better performance as compared to these two controllers.

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