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Design OFPI Controllers for Unstablemimo System Using Firefly Algorithm

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Abstract: ***In this paper, Proportional Integral (PI) controller is designed for unstable MIMO (Multi-Input Multi-Output) systems using Firefly Algorithm (FA). PI controllers are designed for the diagonal elements of transfer function for unstable first order plus time delay (FOPTD) systems. The main work of this paper is to design the PI controller with simplified decoupler for unstable TITO systems using firefly algorithm. The decoupler eliminates the interaction effects between the loops and thus gives two non-interacting independent loops. The performance assessment of the proposed controller design procedure is carried out using the heuristic methods, such as Firefly Algorithm, Particle Swarm Optimization (PSO) and also using ETF's model and Direct Synthesis. The Proportional Integral controller with decouplers is designed for an example of TITO (Two-Input Two-Output) unstable systems which is considered to demonstrate the feasibility and effectiveness of the proposed method.***

Keyword: Decoupler, Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Direct Synthesis, Multi-Input Multi-Output (MIMO),Equivalent Transfer Function (ETF).

1. Introduction

Controlling of the unstable systems with time delays are more difficult, when compared to stable systems[21]-[23]. The most of the industrial processes are multivariable and nonlinear systems. The interactions between the control and measurement signals are always complicated. It is difficult to design an appropriate controller for Multivariable systems, due to the interactions between numerous input and output variables. There are several control methods available, to handle MIMO systems [1].In this paper, we have design proportional Integral (PI) controller because, proportional Integral Derivative (PID) controller [2]-[5],[17]-[20], [26] have high difficulty in designing than PI. Integral part in the Proportional Integral controller is to eliminate the steady state error.PI controller is mostly used in areas where speed of the system is not an issue [1], [25], [27], [28]. Multivariable control problems are usually solved by centralized PI controllers to obtain the desired overall control function. The problems due to centralized controller design for MIMO systems are complex computations, maintenance due to the size and a high risk of failure even though it provides a better performance. Whereas, decentralized strategies based on mathematical analysis, provide scalable and flexible solutions with simple SISO controllers. There will be more interactions in MIMO processes. The decoupler is introduced to eliminate the interaction between the loops and stabilizing values of PI controller is obtained in the parameter plane (K_P, K_I).There are three types of decoupler [6]-[8]: ideal, simplified, and inverted decouplers. The ideal and inverted decouplers are sensitive to modelling errors. The simplified decoupler has a simple decoupler form.This paper presents a design methodology for decentralized PI controller using decoupling and Firefly Algorithm to solve the problem of interactions, which is a multivariable process. The results are compared withheuristic methods, like Particle Swarm Optimization (PSO) [10]-[13]and also using ETF's model [1] and Direct Synthesis [9]. In this paper, a controller design technique is proposed for the multivariable process where in the control system is designed in three steps: Initially, a decoupler is designedto eliminate the interactions; Then, a decentralized control structure is configured using Relative Gain Array (RGA) concept; Finally, thePI controller parameters are tuned by optimization using FA [14]-[15],[24] and the results are compared.

2. Decoupler Design

When the system is provoked with two strongly interacting loops, they introduces new elements called decouplerto eliminate the interaction between the loops and thus gives two non-interacting control loops. [1], [6]-[8]

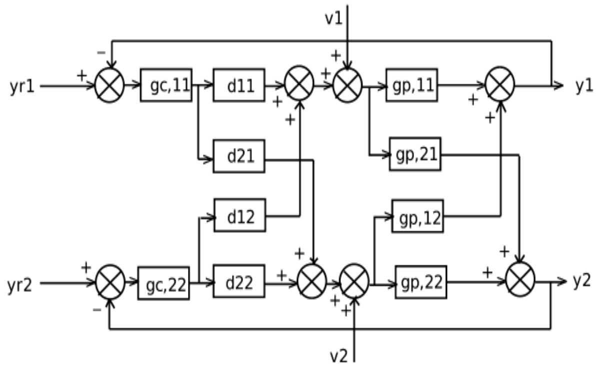


Figure 1: Block diagram for decoupler

Consider the TITO systems with the decoupled control which is shown in Figure 1. The input-output relationship is given by,

$$Y(s) = G(s)D(s)U(s) \tag{1}$$

For the Two-Input Two-Output (TITO) system,

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} 1 & d_{12} \\ d_{21} & 1 \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} \tag{2}$$

$$G(s)D(s) = \begin{bmatrix} g_{11}^* & 0 \\ 0 & g_{22}^* \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} 1 & d_{12} \\ d_{21} & 1 \end{bmatrix} = \begin{bmatrix} g_{11}^* & 0 \\ 0 & g_{22}^* \end{bmatrix} \tag{4}$$

The Realizable decoupleris designed as,

$$d_{12}(s) = -\frac{g_{p,12}(s)}{g_{p,11}(s)} \qquad d_{21}(s) = -\frac{g_{p,21}(s)}{g_{p,22}(s)} \tag{5}$$

3. Controller Design

A. ETF Method

Here we combine the simplified decoupler approach with the ETF model in order to get the benefits of both the methods. [1] The EOTF (derived from DRGA) is equivalent to the ETF (derived from RNGA and RARTA). The expression for ETF is derived for higher dimension systems using relative average residence time array (RARTA), relative gain array (RGA), and relative normalized gain array (RNGA). It has the same structure as the corresponding open-loop transfer function. In the TITO system, if the second feedback controller is in the automatic mode, with $y_{r2} = 0$, then the overall closed-loop transfer function between y_1 and u_1 is given by

$$g^{eff}_{p,11} = \frac{y_1}{u_1} = g_{p,11} - \frac{g_{p,12}\, g_{p,21}}{g_{p,22}} \tag{6}$$

$$g^{eff}_{p,22} = \frac{y_2}{u_2} = g_{p,22} - \frac{g_{p,12}\, g_{p,21}}{g_{p,11}} \tag{7}$$

For an unstable system, ETF can be expressed as,

$$\hat{g}_{p,ij}(s) = \frac{k_{p,ij}}{\wedge_{ij}} \frac{e^{-\gamma_{ij}\theta_{ij}s}}{\gamma_{ij}\tau_{ij}s - 1} \tag{8}$$

The PI controllers are designed based on the unstable ETFs for diagonal matrix,

$$g_{c,ii}(s) = k_{c,ii}\left(1 + \frac{1}{\tau_{1,ii(s)}}\right) \tag{9}$$

$$k_{c,ii}k_{p,ii} = 0.8668\varepsilon_{ii}^{-0.8288} \text{ for } 0.1 \le \varepsilon_{ii} \le 0.7 \tag{10}$$

$$\frac{\tau_{1,ii}}{\tau_{ii}} = 0.1523e^{7.9425\varepsilon_{ii}} \text{ for } 0 \le \varepsilon_{ii} \le 0.7 \tag{11}$$

Where $\varepsilon_{ii} = \dfrac{\theta_{ii}}{\tau_{ii}}$

B. Direct Synthesis Method

The Analytical expressions for PI controllers are derived through the Direct Synthesis method [9]. The PI controllers are designed for a first-order plus time delay model.

$$G_p(s) = \frac{Ke^{-\theta s}}{\tau s + 1} \tag{12}$$

The transfer functionis expressed as,

$$\frac{y}{d} = \frac{G_p(s)}{1 + G_p(s)G_c(s)} \tag{13}$$

The PI controller parameters are,

$$K_C = \frac{1}{K}\frac{\tau\theta + 2\tau\tau_C - \tau_C^2}{(\tau_C + \theta)^2} \tag{14}$$

$$\tau_I = \frac{\tau\theta + 2\tau\tau_C - \tau_C^2}{\tau + \theta} \tag{15}$$

$$\tau_C = \lambda\theta \tag{16}$$

Where $\lambda = 1,2,3.....$

For large values of τ_C, abnormal results can occur because K and K_C can have opposite signs and τ_I can become negative.As τ_C decreases, the closed-loop response becomes faster.

C. Particle Swarm Optimization

PSO is a stochastic, global, optimization technique which applies swarming behavior's observed in flock of birds, school of fish or a swarm of bees, from which the intelligence has emerged [10]-[13]. It was developed in 1995, by James Kennedy and Russell Eberhart. This technique makes use of a number of particles that constitute a swarm moving around in an N- dimensional search space looking for the best solution. Each particle keeps track of its coordinates in the solution space associated with the best solution achieved so far by that particle. This is called as personal best position (p_{best}). The other best value obtained so far by any particle in the neighbourhood of that particle is called as global best position (g_{best}).

Each particle tries to modify its position using the following information.

- Current positions
- Current velocities
- Distance between the p_{best} and current position
- Distance between the g_{best} and current position

Advantages of PSO

- Implementation of PSO is easy and only few parameters need to be altered.
- Only global best particle (g_{best}) gives out information to the others.
- It is more robust than GAs.
- PSO can be more capable than gas. (i.e.) PSO often finds the solution with fewer objective function evaluations than that required by GAs.
- Comparing to other heuristic algorithms, PSO has the flexibility to control the balance between global and local exploration of the Search Space.

PSO Algorithm

Let X and V denote the particle'svelocity and its corresponding position in search space respectively. At iteration K, each particle 'i' has its position defined by $X_i^K = [X_{i,1}, X_{i,2} \ldots X_{i,N}]$ and a velocity is defined as $V_i^K = [V_{i,1}, V_{i,2} \ldots V_{i,N}]$ in search space N. Velocity and position of each particle in the next iteration can be calculated as

$$V_{i,n}^{k+1} = W \times V_{i,n}^{k} + C_1 \times rand_1 \times (pbest_{i,n} - X_{i,n}^{k}) + C2 \times rand_2 \times (gbest_n - X_{i,n}^{k}) \tag{17}$$

where $i = 1, 2 \ldots\ldots\ldots p$

$$n = 1, 2 \ldots\ldots\ldots m$$

$$X_{i,n}^{k+1} = \begin{cases} X_{i,n}^{k}+V_{i,n}^{k+1} & \text{if } X_{min,i,n} \leq X_{i}^{k+1} X_{maxi,n} \\ X_{min\ i,n} & \text{if } X_{i,n}^{k+1} < X_{min\ i,n} \\ X_{max\ i,n} & \text{if } X_{i,n}^{k+1} > X_{max\ i,n} \end{cases} \quad (18)$$

An important factor for the PSO's convergence is the inertia weight W. The usage of Wis to control the impact of past history of velocities on the current velocity. A large inertia weight factor enables global exploration (i.e., searching of new area) while small weight factor enables local exploration. Therefore, it is better to select large weight factor for initial iterations and gradually decrease weight factor in successive iterations. This can be done by using

$$W=W_{max}-(W_{max}-W_{min}) \times Iter/Iter_{max} \quad (19)$$

Where W_{max} and W_{min} are initial and final weight respectively, $Iter_{max}$ is maximum iteration number and Iter is current iteration number. Acceleration constant C_1 called cognitive parameter pulls each particle towards local best position while constant C_2 called social parameter pulls the particle towards global best position. Until stopping criterion is reached the process is repeated.

D. Firefly Algorithm

The Firefly Algorithm (FA)is a metaheuristic, optimization and evolutionary algorithm based on the social (flashing) behaviour of fireflies or illuminating bugs, in the tropical temperature regionsin the summer Sky [14],[15], [24]. It was established by Dr.Xin-She Yang at Cambridge University in 2007 and is based on the swarming behaviour of fish, insects or bird schooling in nature. Its main advantage is the fact that it uses mainly real random numbers and is based on the global communication among the swarming particles (i.e., the fireflies), as a result of which, it seems more effective in multi-objective optimization such as the Economic Emission Load Dispatch problem (EELD) in our case. It is known that the light intensity at a particular distance r from the light source obeys the Inverse Square law. Then, the light intensity I decrease as the distance r increases. Iα 1/r2. Furthermore, the air absorbs light which fades as the distance rises. These two combined features make most fireflies visible only to a limited distance, usually several hundred meters at night, which is adequate for fireflies to communicate. The firefly algorithm has three notable idealized rules based on some of the major flashing characteristics of real fireflies. These rules are enlisted as follows;

(1) All fireflies are unisex and they will move towards more attractive and brighter ones regardless their sex.
(2) The degree of attractiveness of a firefly is proportional to its brightness which decreases as the distance from the other firefly increases as that the air absorbs light. If there is not a brighter or more attractive firefly than a particular one, it will then move randomly.
(3) The brightness or light intensity of a firefly is determined by the value of the objective function of a given problem. For maximization problems, thevalue of the objective function is proportional to the light intensity.

Attractiveness

In the firefly algorithm, the form of attractiveness function of a firefly is the following monotonically decreasing function

$$\beta(r) = \beta_0^* \exp(-\gamma r^m), \text{ with } m \geq 1, \quad (20)$$

Here, r is the distance between any two fireflies, β_0 is the initial attractiveness at $r = 0$, and γ is an absorption coefficient that controls the reduction of the light intensity.

Distance

The distance between the two fireflies i and j, at positions $x_i$and$x_j$respectively, and is defined as a Cartesian or Euclidean distance as follows

$$rij = \sqrt{(xi - xj)^2 + (yi - yj)^2} \quad (21)$$

The calculation of distance r can also be defined using other distance metrics, based on the nature of the problem, such as Mahalanobis distance or Manhattan distance.

4. Results and Discussion

Consider an example given by Flesch et al., [16] which has diagonal elements of unstable and unequal poles:

$$G_p(S) = \begin{bmatrix} \dfrac{1.6e^{-s}}{(-2.6s+1)} & \dfrac{0.6e^{-1.5s}}{(2.5s+1)} \\ \dfrac{0.7e^{-1.5s}}{(3s+1)} & \dfrac{1.7e^{-s}}{(-2.2s+1)} \end{bmatrix} \quad (22)$$

A. ETF Method

The dynamic elements such as normalized gain matrix (K_N), RNGA (φ), average residence time (T_{ar}), and RARTA (Γ) to obtain ETF matrix are calculated by using Eqn. [1],[7]:

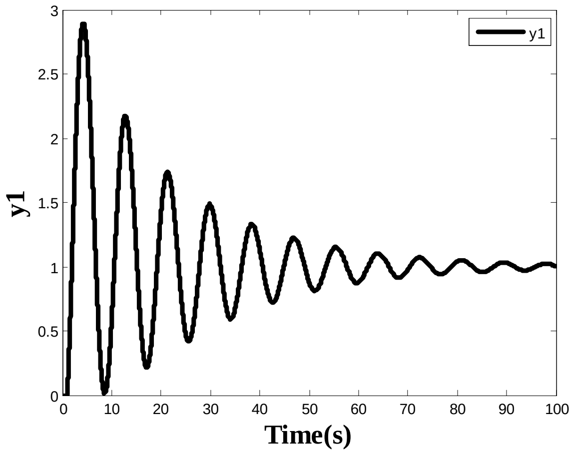
$$T_{ar} = \begin{bmatrix} 3.6 & 4 \\ 4.5 & 3.2 \end{bmatrix}; \quad K_N = \begin{bmatrix} 0.444 & 0.1500 \\ 0.1556 & 0.5313 \end{bmatrix}$$

$$\wedge = \begin{bmatrix} 1.1826 & -0.1826 \\ -0.1826 & 1.1826 \end{bmatrix}; \quad \phi = \begin{bmatrix} 1.1097 & -01097 \\ -0.1097 & 1.1097 \end{bmatrix};$$

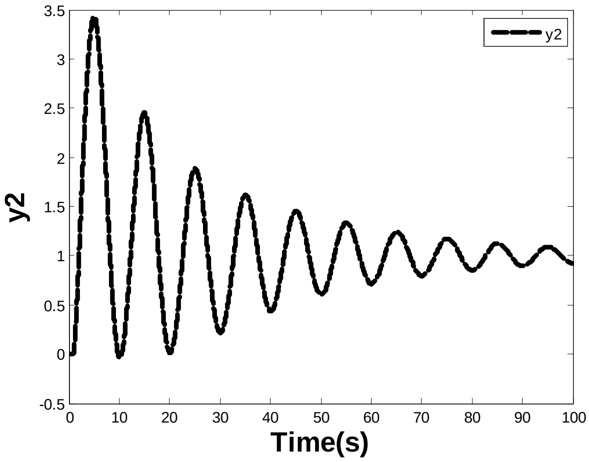
$$\Gamma = \begin{bmatrix} 0.9383 & 0.6005 \\ 0.6005 & 0.9383 \end{bmatrix} \quad (23)$$

By using the preceding concepts, the ETF matrix is obtained as

$$\hat{G}_p(s) = \begin{bmatrix} \dfrac{1.3529e^{-0.9383s}}{(-2.4396s+1)} & \dfrac{-3.2857e^{-0.9008s}}{(1.5013s+1)} \\ \dfrac{-3.8333e^{0.9008s}}{(1.8016s+1)} & \dfrac{1.4375e^{-0.9383s}}{(-2.0643s+1)} \end{bmatrix} \quad (24)$$



(a)



(b)

Figure 2 (a) & (b): Response of PI controllers with decouplers using ETF method for a step input in y1 and y2 separately**.**

According to eqn. (5), Decoupler is given by

$$D(s)=\begin{bmatrix} 1 & \dfrac{(7.8s-3)e^{0.5s}}{(20s+8)} \\ \dfrac{(15.4s-7)e^{-0.5s}}{(51s+17)} & 1 \end{bmatrix} \quad (25)$$

The PI controllers for the diagonal elements of ETF are calculated by eqns. (9),(10),(11) as

$$G_c(s)=\begin{bmatrix} -1.3797\left(1+\dfrac{1}{8.4s}\right) & 0 \\ 0 & -0.98\left(1+\dfrac{1}{11.62s}\right) \end{bmatrix} \quad (26)$$

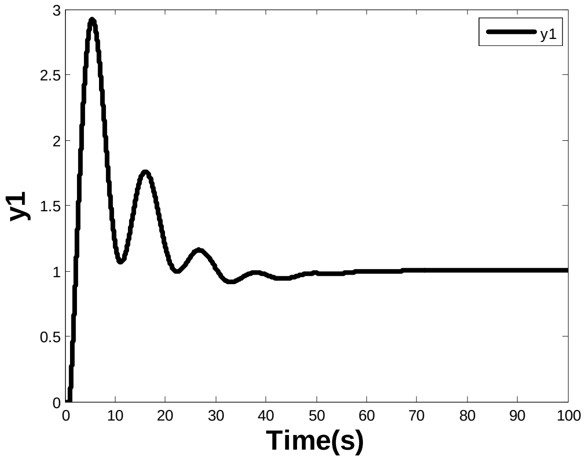
B. Direct Synthesis Method

By considering the same process we have designed PI controllers using Direct Synthesis method [9]. The following are the formulae to calculate K_C and τ_I value.

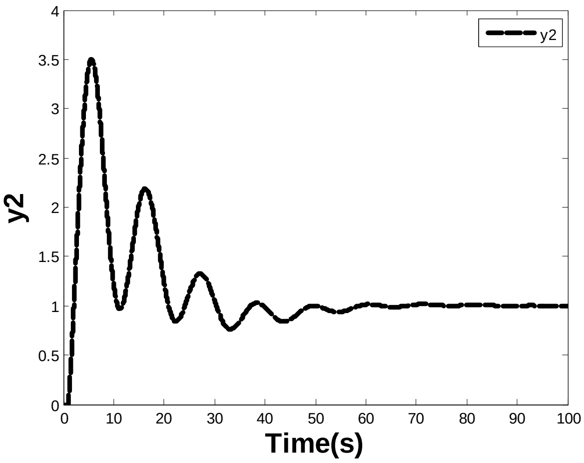
$$K_P=\frac{1}{K}\frac{\tau\theta+2\tau\tau_C-\tau_C^2}{(\tau_C+\theta)^2} \quad (27)$$

$$\tau_I=\frac{\tau\theta+2\tau\tau_C-\tau_C^2}{\tau+\theta} \quad (28)$$

where $\tau_C=\lambda\theta$. For Direct Synthesis method, the value of $\lambda=3$ was chosen. Using eqn (27) and (28), we get K_{P11}= -1.0625 $\tau_{I11}=17$ K_{P22}=-0.897 $\tau_{I22}=20.333$.The simulation results are shown in figure 3 (a) and (b). The IAE and ISE values are indicated in table 1.



(a)

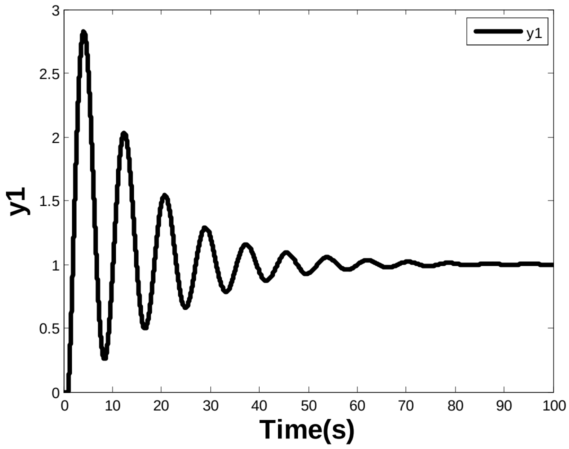


(b)

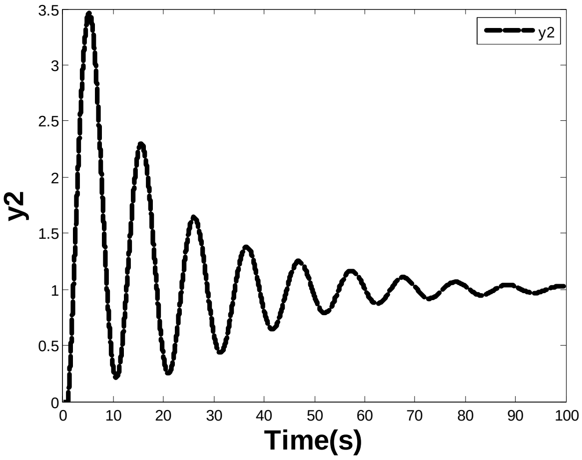
Figure 3 (a) & (b): Response of PI controllers with decouplers using Direct Synthesis method for a step input in y1 and y2 separately**.**

C. Particle Swarm Optimization

The performance of the proposed particle swarm optimization (PSO) algorithm [10], [11] is evaluated. For the controller values K_{P11}=-1.4251, K_{I11}=-0.1369, K_{P22}=-0.9440, K_{I22}= -0.0716, we obtain stable response along with the decoupler.



(a)



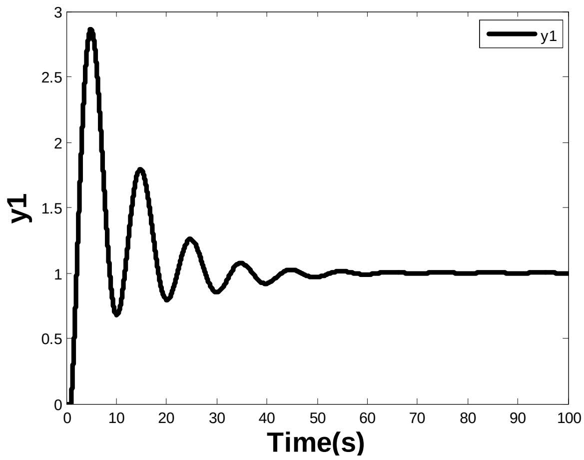
(b)

Figure 4 (a) & (b): Response of PI controllers with decouplers using Particle Swarm Optimization for a step input in y1 and y2 separately**.**

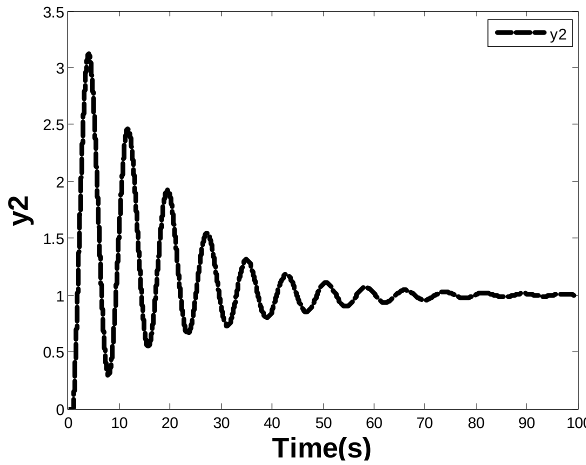
The Performance criteria like IAE and ISE values are tabulated in Table 1. And the response is showed in the figure 4 (a) and (b).

D. Firefly Algorithm

The convergence of the Firefly Algorithm (FA) towards finding the optimum controller parameters is presented [14]-[15], [24].



(a)



(b)

Figure 5 (a) & (b): Response of PI controllers with decouplers using Firefly Algorithm for a step input in y1 and y2 separately**.**

A stable response is obtained for the controller values K_{P11}=-1.1706, k_{I11}=-0.0897, k_{P22}=-1.2650, k_{I22}= -0.0650. And this heuristic algorithm produces less value of IAE and ISE when compared to above controller design methods. The outputs y_1 and y_2 response are shown separately in the figure 5 (a) and (b).

5. Performance Analysis

The Performance of the controller are evaluated using performance criteria like IAE, ISE. Integral Absolute Error (IAE) is a trade-off between both and generally gives better response and Integral Square Error (ISE) is used for suppressing large errors. The PI controller was designed for the given process and the controller design procedure is carried out using the heuristic methods, such as Particle Swarm Optimization (PSO), Firefly Algorithm and also using ETF's model and Direct Synthesis. By evaluating the values of IAE and ISE, Firefly Algorithm has lower value than other controller design used in this paper.

Table 1: Performance analysis for an example

Sl. No.	*Performance Criteria*		*ETF*	*DS*	*PSO*	*FA*
1	IAE	Y1	26.1	17.14	18.46	15.62
		Y2	39.08	24.05	31.24	23.38
2	ISE	Y1	19.74	17.71	14.44	14.65
		Y2	36.48	30.99	31.47	21.1
3	OVER	Y1	2.897	2.925	2.82	2.86
		Y2	3.428	3.5	3.46	3.12
4	SETTLING	Y1	130	70	80	60
		Y2	160	97	120	94

6. Conclusion

In this paper, PI controller with decoupler for Two-Input Two-Output system is designed using Firefly Algorithm. Better results were obtained using FA when compared to conventional methods such as ETF and Direct Synthesis method and heauristic method like PSO. Using Firefly Algorithm, the performance criteria such as IAE, ISE values are low when compared to other methods.

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