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APPLICATION OF MULTI-OBJECTIVE CONTROLLER TO OPTIMAL TUNING OF PID PARAMETERS FOR DIFFERENT PROCESS SYSTEMS USING CUCKOO SEARCH ALGORITHM

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ABSTRACT

A time domain performance criterion based on the multi-objective Pareto front solutions is proposed to tune the Proportional-Integral-Derivative (PID) controller parameters with the Cuckoo Search (CS) algorithm for different process systems: first order plus dead time (FOPDT) and high order dynamics. The proposed multi-objective cost function consists of conflicting objective functions including the overshoot, rise time, settling time and steady state error. In this paper, multi-objective genetic algorithm (MOGA) is used for obtaining the Pareto optimal solutions of the conflicting objective functions. The weights in the proposed multi-objective cost function are calculated by way of nondominated solutions of the obtained Pareto fronts based on the four conflicting objective functions. Also, the optimal tuning parameters of the PID controller are obtained by minimizing the integral based objective functions commonly introduced in the literature using the CS algorithm. The obtained results show that the CS optimized approach based on the proposed objective cost function outperforms than that of the integral based objective functions with higher efficiency and better quality no matter whether the process systems are employed under unload or load conditions.

Keywords: Multi-objective optimization; Pareto Front; GA; CS; PID control

1. INTRODUCTION

The development of algorithms for optimizing PID controllers have arisen in the last decade and their application in industry. The reasons for the PID controllers dominating the industrial world are their simplicity, applicability and acceptance by the industry based on minimum knowledge of the process to be controlled. By now, despite the fact that there are several advanced control structures for industrial control applications, the PID controllers are still the most used in industries. This is because the implementation and operation of the PID controllers are easy [1]. Another reason is that the controllers are reliability and robustness in performance [2]. In case of changing parameters based on a set point, the PID controller can exhibit better performance and adapt to the changes in demand. Accordingly, the performance of the system mainly depends on the determination of three parameters of the PID controller.

In recent years, various tuning methods have been proposed to optimize the parameters of the PID controller. The classical tuning methods comprise the Ziegler-Nichols (ZN) method and the phase-margin methods, etc [3-5]. On the other hand, when coping with the complex problems, the tuning parameters of the PID controller are often hard to determine in these methods. In order to overcome this challenge, it is a good way to tune the PID controller parameters by many artificial intelligent algorithms for satisfactory performance. In recent years, various soft computing approaches including the genetic algorithm (GA), the particle swarm optimization (PSO), the artificial bee colony (ABC), the differential evolution (DE), the ant colony optimization (ACO) and the cuckoo search (CS) algorithms have been proposed to tune the parameters of the PID controller for different performance criteria and plant models by researchers.

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Mousakazemi et al. [6] employed real-coded GA for the design and performance of the PID controller for non-linear PWR power control system. A certain objective function concerning peak overshoot, settling time and stabilization time with the same weighting coefficients was used to determine the optimum controller parameters. The simulation results demonstrated that the optimized PID has excellent and smoothed output tracking performance. Gaing [7] proposed an optimal PID controller tuned by PSO with a time domain performance criterion for the AVR system. In that paper, the comparison of the results between PSO and GA algorithms has been given. The comparative results demonstrated that the proposed method has better tuning capability compared to GA and is more efficient and robust in improving the performance of the system in terms of time domain specifications. Kao et al. [8] presented a novel design approach for the self-tuning PID control using PSO in a slider-crank mechanism system. In that paper, they used the time domain performance criterion including the maximum overshoot M_p, rise time t_r, settling time t_s and steady-state error. Also, the responses obtained from the proposed PSO self-tuning PID controller were compared with that of GA. The results showed the potential of the proposed controller. Gozde et al. [9] implemented ABC based optimization approach to tune the PID parameters of the automatic generation control (AGC) system. Also, the robustness of the power system was investigated using well-known integral performance indices including the integral time-weighted absolute error (ITAE), integral absolute error (IAE), integral time-square error (ITSE) and integral square error (ISE). Finally, it was seen from that study, the ABC algorithm can be applied to the AGC system successfully and its tuning capability is composed. Gozde and Taplamacioglu [10] studied comparative performance analysis of ABC algorithm for obtaining optimal control using the performance criterion ITSE. Also, for the purpose of comparison, PSO and DE algorithms were used in terms of their tuning performances and contributions to the robustness of the control system. From the results, it was observed that the ABC based PID controller gives a good control of the AVR system robustly and optimally. Blondin et al. [11] presented an optimal tuning approach for the PID parameters using a novel combination of the ACO algorithm and Nelder-Mead method for the AVR system. In that paper, the objective function consisting of overshoot, rise time, settling time, steady-state error was chosen for the PID tuning with the proposed algorithm. The results showed that the proposed approach could achieve better or equivalent PID solutions according to the overall transient response compared to other AVR tuning approaches. Dash et al. [12] proposed a two degree of freedom (2DOF) controller - integral plus double derivative (2DOF-IDD) for first time in AGC system as secondary controller. The gains and parameters of secondary controller were tuned with the CS algorithm using minimization of the cost function given by ISE. The simulation results revealed that the proposed 2DOF-IDD controller provides much better dynamic response compared to 2DOF- PI and 2DOF-PID controllers.

The above mentioned literatures carry out optimization of the PID parameters considering only a single objective function including the time or frequency domain and the integral performance indices. But the problem in a practical control system design includes many conflicting design objectives. For example, Zamani et al. [13] presented a performance criterion in both the time and frequency domain specifications for making the control strategy easier. The objective function in that paper consists of the terms including the rise time, settling time, overshoot, steady state error, the IAE, integral of squared input, phase and gain margins. The weight factors used in the function determines the significance of each term. Accordingly, depending on the different weight factors assigned to the conflicting objective functions by the designer, the designed controller can give better performance. However, adjusting these factors in the conflicting objective function is not an easy task [13].

Recently, a PID control survey has suggested the need for an optimal tuning approach for multiple design objectives in the time domain, frequency domain and robust performance criterion. Consequently, multiple design objectives which are conflicting each other in most cases are required in tuning the PID controller parameters. In this context, the use of multi-objective optimization techniques can help in finding suitable values of the tunable PID parameters for a given process, by considering the multiple design objectives. As a result, in the multi-objective optimization, the time domain, frequency domain or robustness performance specifications can be directly formulated as a multiple objective function in the tuning process. Accordingly, the tuning objectives and parameter variations can be directly combined to determine the most suitable PID controller parameters [14].

A recently popular technique comprises using evolutionary multi-objective optimization algorithms for determining the optimal parameters of the PID controllers since these optimization algorithms have capability to successfully solve multi-objective design optimization problems. The multi-objective problem occurs when multiple objectives and necessities must be carried out by the designer. Due to conflicting objectives, the best trade-off solution must be computed and chosen for implementation. Generally, the solution is Pareto optimal solution. In the case of multi-objective optimization, various algorithms have been designed and used in a wide variety of applications [15-17]. Such algorithms mostly find a representative set of Pareto optimal solutions as a Pareto front. Consequently, multi-objective optimization algorithms have capability to optimize multiple objectives simultaneously and obtain both of a single optimal solution and a set of Pareto optimal solutions achieved between conflicting objectives.

This work proposes a time domain performance criterion that includes maximum overshoot, rise time, settling time and steady state error. First, a multi-objective optimization approach based on GA for producing the multi-objective Pareto solutions is applied to a family of first order plus dead time (FOPDT) process models. Secondly, the Pareto solution is computed for each case and the optimal design of PID controller is achieved by minimizing the proposed conflicting objective function using the CS algorithm.

The remaining part of this paper is organized as follows. In Section 2, the introductions of the PID controller, objective functions and CS algorithm is described in detail. The multi-objective optimization approach is given in Section 3. Simulation results and comparative study are presented in Section 4. Finally, the conclusions are given.

2. PROBLEM FORMULATION

Two different types of process model have been considered to evaluate the tuning performance of the PID controller based on the proposed multi-objective cost function. One of them is First Order Plus Dead Time (FOPDT) systems and the other one is high order dynamic systems.

The most commonly used model to describe the dynamics of many industrial processes is the First Order Plus Dead Time model. Any delay that is called dead time in control loops always reduces the stability of a system and causes to make satisfactory control more difficult to achieve. The transfer function of the FOPDT systems can be characterized as:

$$P_1(s) = \frac{K}{1 + Ts} e^{-Ls} \tag{1}$$

where K is the gain of the system, T is the time constant, and L is the time delay. The system dynamics can be fully characterized in terms of the normalized dead-time, defined as $\tau = L/T$, which can be associated to a measure of the difficulty in controlling the system.

The tuning method used in this study is also performed for high order dynamic systems. Therefore, the transfer function of the high order dynamic systems can be characterized as:

$$P_2(s) = \frac{K}{(1+Ts)^n} \tag{2}$$

where *K* is the gain of the system, *T* is the time constant, and *n* is the degree of the system.

2.1. PID Controller

A PID controller has three basic coefficients: proportional (K_p), integral (K_i) and derivative (K_d) which are varied to get optimal response. The transfer function of the PID controller is given as:

$$C(s) = K_p + K_i\frac{1}{s} + K_d s \tag{3}$$

In literature, many methods have been proposed for tuning these PID parameters effectively. In recent years, for the purpose of overcoming the limitation of traditional methods, many optimization algorithms are preferred in order to optimize the PID controller for various systems. One such optimization algorithm is a nature inspired technique developed based on reproduction of cuckoo birds called Cuckoo Search (CS) Algorithm. In this study, the optimal design of PID controller is achieved by using the CS algorithm with integral based performance index and a multi-objective cost function proposed in this study.

2.2. Objective Functions

During the controller design by using an optimization algorithm, the most crucial step is to select the most appropriate objective function. Time domain objective functions can be divided into two categories: Integral based objective functions and dynamic performance indices based objective functions.

Integral based objective functions commonly used in literature are: IAE (Integral of Absolute Error), ITAE (Integral of Time Absolute Error), ISE (Integral of Squared Error) and ITSE (Integral of Time Squared Error). The formulas of these objective functions are described as:

$$IAE = \int_0^t |e(t)|dt \tag{4}$$

$$ITAE = \int_0^t t|e(t)|dt \tag{5}$$

$$ISE = \int_0^t e^2(t)dt \tag{6}$$

$$ITSE = \int_0^t te^2(t)dt \tag{7}$$

where $e(t)$ is the error signal which represents the difference between the system output and reference signal ($e(t) = r(t) - y(t)$). Each one of them has advantages and disadvantages. For example, since IAE and ISE criteria are independent of time, the obtained results have relatively small overshoot but a long settling time. On the other hand, ITAE and ITSE can overcome this disadvantage; but, they cannot provide a desirable stability margin.

The second category of the time domain objective functions is based on the performance indices of the system dynamic output. These functions usually involve the maximum overshoot (M_p), rising time (t_r), settling time (t_s), and steady-state error (E_{ss}). For example, the objective function given in below is proposed in [18]:

$$W(\beta) = \left(1 - e^{-\beta}\right)\left(M_p + E_{ss}\right) + e^{-\beta}(t_s - t_r) \tag{8}$$

where β is weighting factor to allow the designer to determine the significance of performance criteria to others.

2.3. CS Optimization Algorithm

Cuckoo Search (CS) is an optimization algorithm developed by Xin-she Yang and Suash Deb in [19]. This algorithm is inspired from the brood parasitic breeding strategy of certain species of cuckoos by laying their eggs in the nests of other host birds. The algorithm imitates the cuckoo's behaviour of finding the nest of other bird species for development and care of young ones.

According to the CS algorithm, generating the new nest for cuckoos, the global random walk is performed by using a law named Lévy flights which is given below:

$$X_i(n+1) = X_i(n) + \alpha \otimes levy(\lambda) \tag{9}$$

where $n = 1, 2, 3, \ldots, N$ indicates the current iterations in which N denotes the predetermined maximum iteration number. $\alpha > 0$ is the step size regarding the scales of the problem of interest. $levy(\lambda)$ represents Lévy flight for both local and global searching. Lévy flight process is basically a random walk which is derived from the Lévy distribution with an infinite variance and infinite mean, given below [19]:

$$levy(\lambda) = t^{-\lambda}, \qquad (1 < \lambda \leq 3) \tag{10}$$

where t is the current iteration. The algorithm can also be extended to more complicated cases where each nest contains multiple eggs (a set of solutions) [19]. In that case, the new nest is randomly generated by using the following equation:

$$X_i^{new} = \begin{cases} X_i + stepsize \cdot randn, & randn_i > p_a \\ X_i, & else \end{cases} \tag{11}$$

where

$$stepsize = 0.01 \cdot \left(\frac{\sigma(\zeta) \cdot randn}{randn}\right)^{\frac{1}{\beta}} \cdot (X_i - X_{best}) \tag{12}$$

and $randn$ is a random value between $[0,\ 1]$, ζ is a constant between $1 \leq \zeta \leq 3$, and the standard deviation function $\sigma(\zeta)$ is:

$$\sigma(\zeta) = \left(\frac{\Gamma(1+\zeta) \cdot \sin(\pi \cdot \zeta/2)}{\Gamma\left(\left(\frac{1+\zeta}{2}\right) \cdot \zeta \cdot 2^{\left(\frac{\zeta-1}{2}\right)}\right)} \right)^{\frac{1}{\zeta}} \tag{13}$$

The Cuckoo Search Optimization Algorithm generally involves the following steps:
Step 1: Introduce a random population of n host nests, namely X_i.
Step 2: Generate a new solution $X_i new$ using by Lévy flights (Equation 9).
Step 3: Calculate its cost function, $J(X_i new)$.
Step 4: Select a nest randomly among the host nests say X_j and calculate its cost function value, $J(X_j)$.
Step 5: If $J(X_i new) < J(X_j)$, then replace X_j by new solution $X_i new$, else let X_j be the new solution.
Step 6: Leave a fraction of P_a of the worst nest by building new ones at new locations using Lévy flights.
Step 7: Keep the current optimum nest, go to *Step 2* if maximum iteration number is not reached.
Step 8: Find the optimum solution.

3. MULTI-OBJECTIVE OPTIMIZATION

3.1. Generalities

Multi-objective optimization comprises multiple optimization problems including more than one objective function that are to be minimized or maximized simultaneously. As opposite to single-objective optimization problems which accept one single optimum solution, multi-objective optimization problems propose a set of alternative optimum solutions. Each member of the alternative solution set represents the best possible trade-off among the objective functions. The set of all alternative solutions is called Pareto optimal set (PO) and the graph of the PO set is called Pareto front [20].

3.2. Multi-objective Problem Definition

In the multi-objective optimization problem, the main objective is:

$$\text{minimize:} \quad \vec{f}(\vec{k}) = [f_1(\vec{k}), f_2(\vec{k}), \quad \dots, \quad f_m(\vec{k})] \tag{14}$$

where $f_i(\vec{k}) \colon \mathbb{R}^n \to \mathbb{R}, i = 1, \dots, m$ are the objective functions, and $\vec{k} = [k_1, \dots, k_n]$ is the parameter vector for these objective functions.

The set of all Pareto optimal solutions is called Pareto optimal set and denoted by $\mathcal{P} = \{\vec{k}_{p1}, \vec{k}_{p2}, \dots, \vec{k}_{pl}\}$. Given $\mathcal{P}$ for a MO optimization problem defined by $\vec{f}(\vec{k})$, the Pareto Front is given by [21]:

$$\mathcal{PF} = \left\{ \begin{matrix} f_1(\vec{k}_{p1}) & f_2(\vec{k}_{p1}) & \cdots & f_m(\vec{k}_{p1}) \\ f_1(\vec{k}_{p2}) & f_2(\vec{k}_{p2}) & \cdots & f_m(\vec{k}_{p2}) \\ \vdots & \vdots & & \vdots \\ f_1(\vec{k}_{pl}) & f_2(\vec{k}_{pl}) & \cdots & f_m(\vec{k}_{pl}) \end{matrix} \right\} \tag{15}$$

The method of converting MO problem to a single weighted objective function is commonly used approach. In that situation, the main objective function is defined as a single weighted sum objective function [21]:

$$J(\vec{k}) = \sum_{i=1}^{m} \omega_i f_i(\vec{k}) \tag{16}$$

where $\omega_i, i = 1, \ldots, m$ are the weights with $\sum_{i=1}^{m} \omega_i = 1$. These weights are real values used to express the relative importance of the objectives in the overall objective function. However, the choice of the weighting factors is not an easy task. Since the variation range of each objective function is unknown, its percentage of contribution in the overall objective function is also unknown. In order to overcome this problem, an approach is proposed in [21]. The weights are selected according to the design specifications indicated by an importance value by taking account their different standard deviations.

For a given term in an objective function, $f_i(\vec{k})$, with a standard deviation σ_i, the corresponding contribution percentage $CP[f_i(\vec{k})]$ can be calculated using:

$$CP[f_i(\vec{k})] = \frac{\mu_i}{\sum_{j=1}^{m} \mu_j} \times 100\% \tag{17}$$

where μ_i is the mean value of all of the Pareto solutions corresponding to $f_i(\vec{k}_{pj})$ for $j = 1,2, \ldots, l$:

$$\mu_i = \frac{1}{l} \sum_{j=1}^{l} f_i(\vec{k}_{pj}) \tag{18}$$

The weight factors are inversely proportional to the contribution percentage:

$$\omega_i = \frac{1}{CP[f_i(\vec{k})] \times \sum_{j=1}^{l} \frac{1}{CP[f_j(\vec{k})]}} \tag{19}$$

By substituting Equation 17 into Equation 19, weight factors' formula is obtained as [21]:

$$\omega_i = \frac{1}{\mu_i \times \sum_{j=1}^{l} \frac{1}{\mu_j}} \tag{20}$$

3.3. Proposed Approach

In this paper, a multi-objective cost function in the time domain is proposed for evaluating the optimal PID controller parameters. This multi-objective cost function combines individual time domain objective functions including overshoot (M_p), rise time (t_r), settling time (t_s), and steady-state error (E_{ss}), into a single function. In order to optimize these four objective functions simultaneously, it is needed to utilize multi-objective optimization method.

The multi-objective optimization problem is defined as in Equation (14), where $n = 4$ and:

$$\begin{aligned} f_1(\vec{k}) &= J_{Mp} = M_p \\ f_2(\vec{k}) &= J_{Tr} = t_r \\ f_3(\vec{k}) &= J_{Ts} = t_s \\ f_4(\vec{k}) &= J_{Ess} = E_{ss} \end{aligned} \tag{21}$$

As mentioned in previous section, the main objective function is defined as a single weighted sum objective function:

$$J(\vec{k}) = \omega_{mp} J_{Mp} + \omega_{tr} J_{Tr} + \omega_{ts} J_{Ts} + \omega_{Ess} J_{Ess} \tag{22}$$

Here, ω_{mp}, ω_{tr}, ω_{ts}, ω_{Ess} are the weights for overshoot, rise time, settling time, and steady-state error, respectively. These weights are real values and express the relative importance of the objectives in $J(\vec{k})$.

The terms of the objective function given in Equation 22 usually have different standard deviations. For example, the standard deviation of E_{ss} is much less than that of t_r or t_s. Thus, in order to compensate for this difference, the weight factor selected for the E_{ss} should be greater than that selected for the t_r or t_s. In this paper, the proposed objective function evaluates the weighting factors according to their percentage of contribution in the objective function. The method of evaluating the weighting factors is based on the multi-objective Pareto front solutions.

4. RESULTS AND DISCUSSIONS

In this section, in order to evaluate the tuning performance of the PID controller based on the proposed multi-objective cost function and seven performance criteria defined by Equations 4-8, two simulation experiments have been conducted by using the CS algorithm. In each experiment, the weights in the proposed multi-objective cost function formulated in Equation 22 are calculated using Pareto front. The settling time, rise time, overshoot and steady state error given in the proposed multi-objective cost function are contradictory in nature so the best results can be found by the Pareto front of GA. Moreover, Pareto front and Pareto optimal solution sets are given as a table for each system in the simulation experiments. In the PID tuning strategy for each system, the CS algorithm employs both of the proposed objective function and the other performance criteria aforementioned. Also, several robustness tests are carried out to illustrate the robustness of the proposed tuning method.

As given in Table 1, the simulation parameters of the CS and multi-objective GA (MO-GA) algorithms and the computational efforts are considered for determining the optimal parameters of PID and Pareto optimal solutions. The multi-objective genetic algorithm tool by using the MATLAB® engine library is used for obtaining the different values of the PID controller parameters from the Pareto optimal solutions. Also, during optimization, the search space for the controller parameters is given in Table 1 for less overshoot, fast rise time, low settling time and zero steady state error.

Table 1. Parameters used for all the algorithms.

MO-GA	CS	Common Boundary Settings
Population Size $= 50$ CrossoverProbability= 0.8 MigrationFraction=0.2 MigrationInterval=20 SelectionFunction=Tournament MutationFunction= Constraint-dependent ParetoFraction= 0.5 MaxStallGenerations=150	Number of Nests $n = 10$ Abandon Probability $p_a = 0.25$ Constant ζ in (12) is set to 1.5	Number of Iterations $Max\_Iter = 150$ Simulation Time t in (22) is set to 100s Sampling Time $t_i = 0.01$s $0 < K_p,\ K_i,\ K_d < 6$

In this paper, a first-order-plus-dead-time (FOPDT) process and a process with high-order dynamics are considered to evaluate and illustrate the performances of the proposed multi-objective cost function and PID tuning method.

4.1. Optimization of Set Point Tracking and Disturbance Rejection For FOPDT Process

In this experiment, a FOPDT process with $\tau = 4$ is considered [22]:

$$P_1(s) = \frac{1}{10s+1} e^{-4s} \tag{23}$$

The Pareto front for the multi-objective problem defined in the proposed multi-objective cost function can be found by considering all the combinations of the controller parameters using the MO-GA algorithm. From this point of view, the Pareto front values of the four objective functions and their corresponding nondominated Pareto optimal solutions are obtained as given in Table 2.

By combining the four objective functions ($J_{Mp}, J_{Tr}, J_{Ts}, J_{Ess}$) in a single weighted sum function, the contribution of these conflicting objective functions to the value of the proposed multi-objective cost function is releated to their mean values as given in Table 3. As can be observed in the table, these values points out that the contribution of J_{Ts} is much greater as compared with that of others. As a result, by using the weight values given in Table 3, the proposed multi-objective cost function used in tuning the PID control of FOPDT process with CS is:

$$J(k) = 0.0148\, M_p + 0.0001\, t_r + 0.00001\, t_s + 0.9851\, E_{ss} \tag{24}$$

In optimizing the PID controller parameters, the CS algorithm employs the proposed cost function defined in Equation 4 and other performance criteria. All the relevant results by using these objective functions are compared in Table 4. Also, the set-point tracking for the representative solutions as given in Table 4 is showed in Figure 1.

Table 2. Pareto front values and set of Pareto optimal solutions based on the MO-GA for the FOPDT process.

Pareto Front Sets				Pareto Optimal Solutions		
J_{Mp}	J_{Tr}	J_{Ts}	J_{Ess}	K_p	K_i	K_d
0.0005	3.4600	11.9900	0.000005	2.0245	0.1717	3.0696
0.0002	3.4700	11.9900	0	2.0280	0.1727	3.0138
3.8396	3.4000	8.2300	0.000547	2.0734	0.196	2.8261
2.5829	3.3000	8.2400	0.000635	2.0742	0.1953	3.0811
0.4462	3.7400	8.9400	0	1.9864	0.1733	2.5288
0.0001	3.6900	8.9500	0.000001	1.9914	0.1729	2.6251
0.0012	3.5500	8.8100	0.000012	2.0234	0.1738	2.8421
1.8032	3.6200	8.6400	0.000004	2.0326	0.1774	2.5832
0.4626	3.4900	8.5800	0.000023	2.0515	0.1772	2.8344
0.0270	3.5100	8.6900	0.000056	2.0371	0.1760	2.8537
4.2923	3.4700	8.2900	0.000516	2.0631	0.1948	2.7073
2.0474	3.3300	8.3400	0.000665	2.0556	0.195	3.0807
0.0011	3.5700	8.7600	0.000011	2.0246	0.1746	2.7671
0.4462	3.7400	8.9400	0	1.9864	0.1733	2.5288
3.4165	3.4400	8.3200	0.000557	2.0573	0.1944	2.7986
3.9691	3.5800	8.4300	0.000242	2.0562	0.1853	2.5337
0.0001	3.6900	8.9500	0.000001	1.9914	0.1729	2.6251
2.8804	3.4400	8.3500	0.000521	2.0599	0.1912	2.8152
3.4869	3.6400	8.5300	0.000089	2.0429	0.1812	2.4704
1.3206	3.3600	8.4000	0.000441	2.0683	0.1849	3.0295
1.9838	3.3400	8.3300	0.000654	2.0576	0.1948	3.0622
2.5829	3.3000	8.2400	0.000635	2.0742	0.1953	3.0811
0	3.6000	8.9900	0	2.0016	0.1720	2.8219
0.0002	3.4700	11.9900	0	2.0280	0.1727	3.0138
4.9869	3.5000	8.3000	0.000489	2.0631	0.1950	2.6196

From the Pareto front sets given in Table 2, the mean values of J_{Mp}, J_{Tr}, J_{Ts} and J_{Ess} and the weights ω_{M_p}, ω_{t_r}, ω_{t_s}, $\omega_{E_{ss}}$ are computed using Equation 18 and 20, respectively as given in Table 3.

Table 3. The weights in the proposed multi-objective cost function for PID controller tuning for FOPDT process.

	The Weights			
	ω_{Mp}	ω_{Tr}	ω_{Ts}	ω_{Ess}
Mean Value	0.0162	3.5080	8.9688	0.0002
Contribution Percentage	% 0.1299	% 28.0791	% 71.7890	% 0.0020
Weight Value	0.0148	0.0001	0.00001	0.9851

Table 4. Comparative controller parameters and dynamic performance for the FOPDT process.

	PID Tuning Parameters			Performance Parameters			
Objective Function	K_p	K_i	K_d	M_p	t_r $0.1 \rightarrow 0.9$	t_s $\pm 5\%$	E_{ss}
IAE	2.2535	0.1928	3.6697	12.2626	2.8200	14.6600	0.000001
ISE	2.3556	0.2413	5.0260	28.1132	2.0900	19.1900	0.000001
ITAE	2.1549	0.1863	2.9733	3.8904	3.2500	7.5100	0
ITSE	2.3748	0.2202	4.3824	22.9509	2.3500	14.3800	0
$W(0.7)$	2.1353	0.1918	3.0442	4.1058	3.2400	7.4900	0.000001
$W(1.0)$	1.5562	0.0570	3.5238	-	46.0000	75.7700	0.026057
$W(1.5)$	2.1753	0.1742	2.9310	3.4283	3.2700	7.5300	0.000016
$J(k)$	2.0431	0.1751	2.9268	0.0001	3.4700	8.6900	0

The observation of Table 4 and Figure 1 reveals that the objective function ISE gives an improved rise time of 2.0900 as compared to the other objective functions; whereas, the proposed multi-objective cost function provides a better controller design with smaller overshoot of 0.0001 and an improved steady state error and settling time in comparison with others. The performances of the responses do not have much difference in terms of rise time, settling time and steady state error for *ITAE*, $W(0.7)$, $W(1.5)$ and $J(k)$, however, the minimum overshoot of the responses is obtained with the proposed objective cost function.

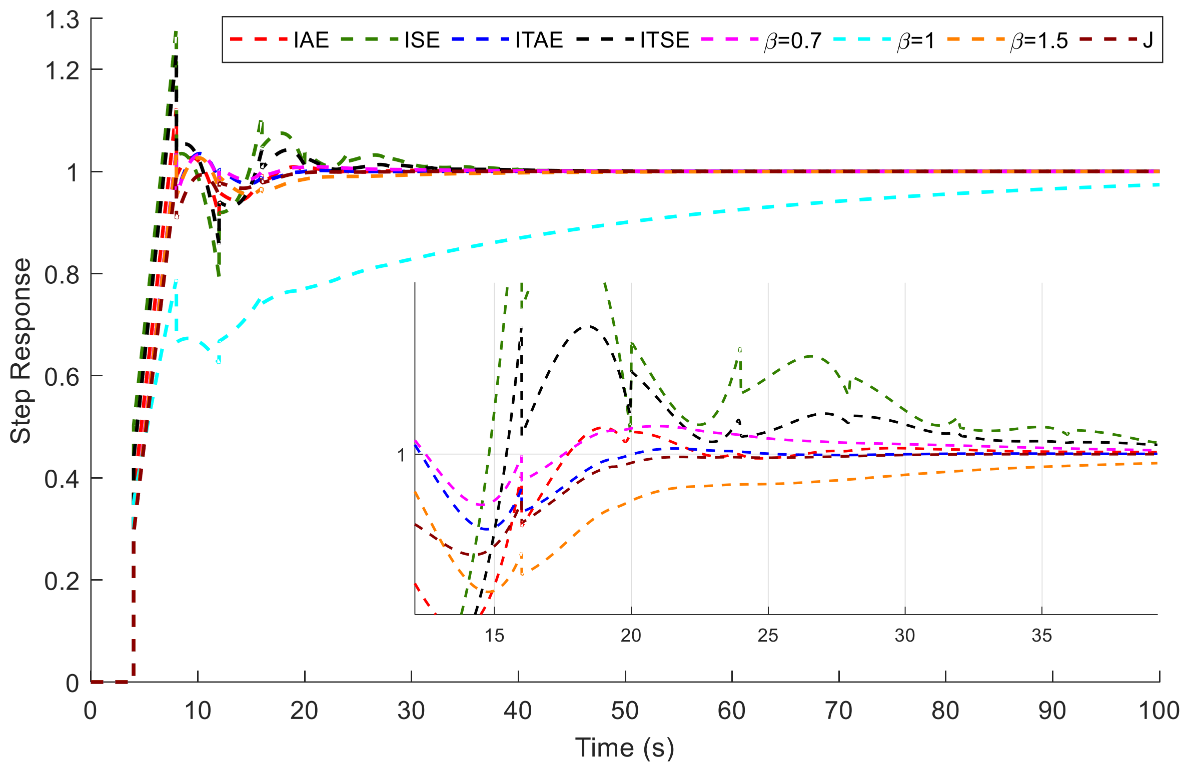

Figure 1. Step responses of the FOPDT process with the PID controller tuned based on different objective functions.

Load disturbance rejection is an important detail that requires to be considered in practice. Therefore, the strength of the tuned PID controller based on the proposed multi-objective cost function is tested in the presence of a disturbance. The values of the disturbance signals are equal to +100% and −100% of the set point at times 20 s and 50 s, respectively. Set point response due to step input at t=0 s and the response occurred in reaction to the disturbance at t=20 s and 50 s are depicted in Figure 2.

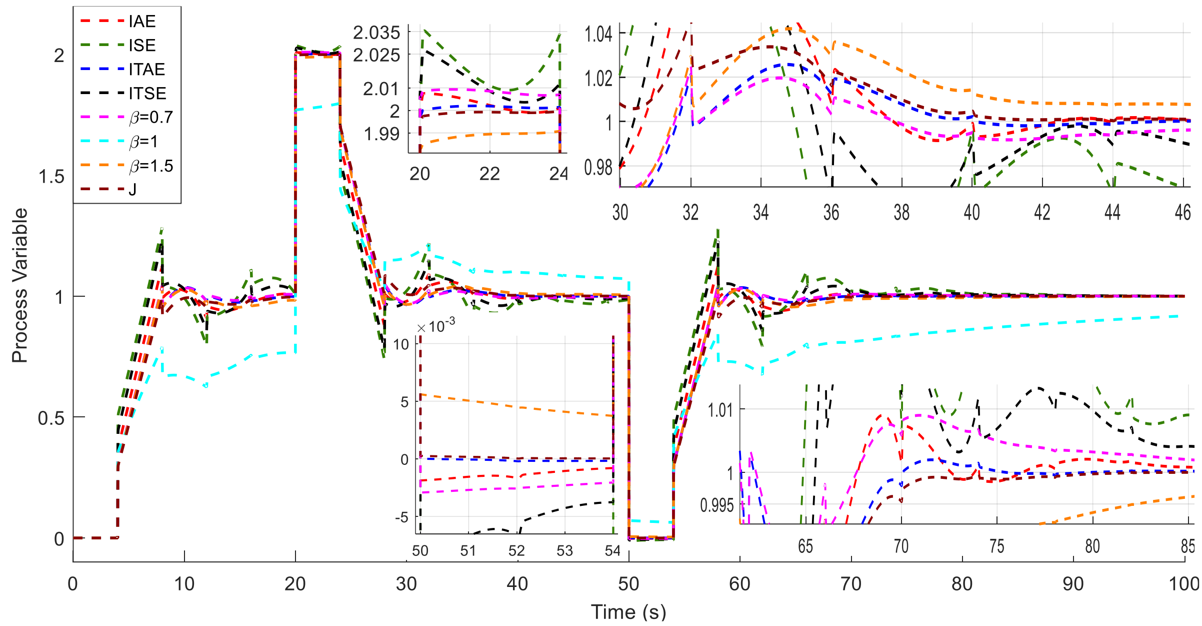

Figure 2. Reference tracking and disturbance rejection for the FOPDT system.

From Figure 2, it is clear that the PID controller optimized based on the proposed objective function has better capability to suppress the load disturbance as compared to the tuned PID controllers based on the other objective functions. Also, it can be seen from the figure, the minimum overshoot and undershoot with the proposed PID controller are provided. Consequently, the best system response is obtained with the PID controller tuned with CS based on the proposed objective function.

4.2. Optimization of Set Point Tracking and Disturbance Rejection for High Order Process

In this experiment, a process with high order dynamics has been is considered [22]:

$$P_2(s) = \frac{1}{(s+1)^4} \tag{25}$$

For this process, optimization is performed using multi-objective GA algorithm considering the multi-objective problem defined in the proposed cost function. The Pareto front set for four objective functions formulated in Equation 21 and their Pareto optimal solutions are obtained as given in Table 5.

The multi-objective problem defined by the four conflicting objective functions (J_{Mp}, J_{Tr}, J_{Ts}, J_{Ess}) is incorporated in the proposed multi-objective cost function using the weights as in Equation 4. As can be seen from Table 6, the contribution of J_{Ts} is much greater than that of the other conflicting objective functions in terms of the mean values. Therefore, during the optimization of the PID controller parameters for the high order process with CS, the proposed multi-objective cost function given below is used.

$$J(k) = 0.1097\, M_p + 0.0101\, t_r + 0.0008\, t_s + 0.8794\, E_{ss} \tag{26}$$

Table 5. Pareto front values and set of Pareto optimal solutions based on the MO-GA for the high order process.

Pareto Front Sets				Pareto Optimal Solutions		
J_{Mp}	J_{Tr}	J_{Ts}	J_{Ess}	K_p	K_i	K_d
4.8324	1.8800	2.8500	0	1.8666	0.5947	2.3084
0	2.3000	8.2000	0	1.6602	0.4323	1.7939
48.4498	1.0500	24.6600	0.001279	4.9866	0.6524	3.7036
0.0749	2.7400	7.7900	0	1.454	0.4125	1.6788
6.7183	2.3500	5.8500	0	1.5143	0.5250	1.4538
40.2473	1.1000	29.5000	0.010525	4.7837	0.2871	3.5094
3.2426	2.4600	3.6700	0	1.4704	0.4933	1.4862
19.6761	1.2500	36.3400	0.029062	3.5486	0.1699	3.5027
6.0644	1.4000	50.0000	0.168120	2.8703	0.0326	3.4905
10.0094	1.8200	4.8100	0	1.9779	0.6270	2.1466
32.1681	1.1400	25.7000	0.015064	4.2856	0.2431	3.5461
-	1.9100	39.0600	0.029833	2.1854	0.1364	2.5422
14.7335	1.2900	47.7100	0.046472	3.2873	0.1295	3.5828
3.8709	1.5800	31.4700	0.018290	2.5939	0.1758	2.8607
48.9100	1.0500	24.9300	0.000282	4.9868	0.6524	3.6148
0.0405	3.2100	8.1600	0	1.3587	0.3815	1.5828
16.9682	1.3500	20.8600	0.005181	3.2062	0.2797	3.0760
24.5998	1.1900	45.9000	0.044259	3.9089	0.1404	3.6124
4.8110	1.4300	50.0000	0.102615	2.7569	0.0690	3.4876
21.9867	1.2700	10.6400	0.000001	3.1119	0.6506	3.5529
10.6357	1.3500	24.5700	0.009144	2.9228	0.2290	3.5802
4.6905	1.4800	16.9000	0.001590	2.5024	0.2924	3.4052
1.4812	2.9500	6.2300	0	1.3353	0.4398	1.6994
38.6189	1.1100	19.8900	0.000683	4.4731	0.4931	3.7336
24.3904	1.2300	15.7100	0.000793	3.5486	0.4199	3.5027

Table 6 gives the mean values of J_{Mp}, J_{Tr}, J_{Ts} and J_{Ess} and the weights ω_{M_p}, ω_{t_r}, ω_{t_s}, $\omega_{E_{ss}}$ calculated by Equation 18 and 20 using the Pareto front sets given in Table 5.

Table 6. The weights in the proposed multi-objective cost function for PID controller tuning for the high order process.

	The Weights			
	ω_{Mp}	ω_{Tr}	ω_{Ts}	ω_{Ess}
Mean Value	0.1549	1.6756	22.4560	0.0193
Contribution Percentage	% 0.6372	% 6.8938	% 92.3894	% 0.0795
Weight Value	0.1097	0.0101	0.0008	0.8794

The proposed cost function defined above and the other objective functions are used in tuning the PID gains with the CS algorithm. The optimal controller parameter set and dynamic response characteristics for the PID controller based on the different objective functions are tabulated in Table 7. The graphical representations are also depicted in Figure 3.

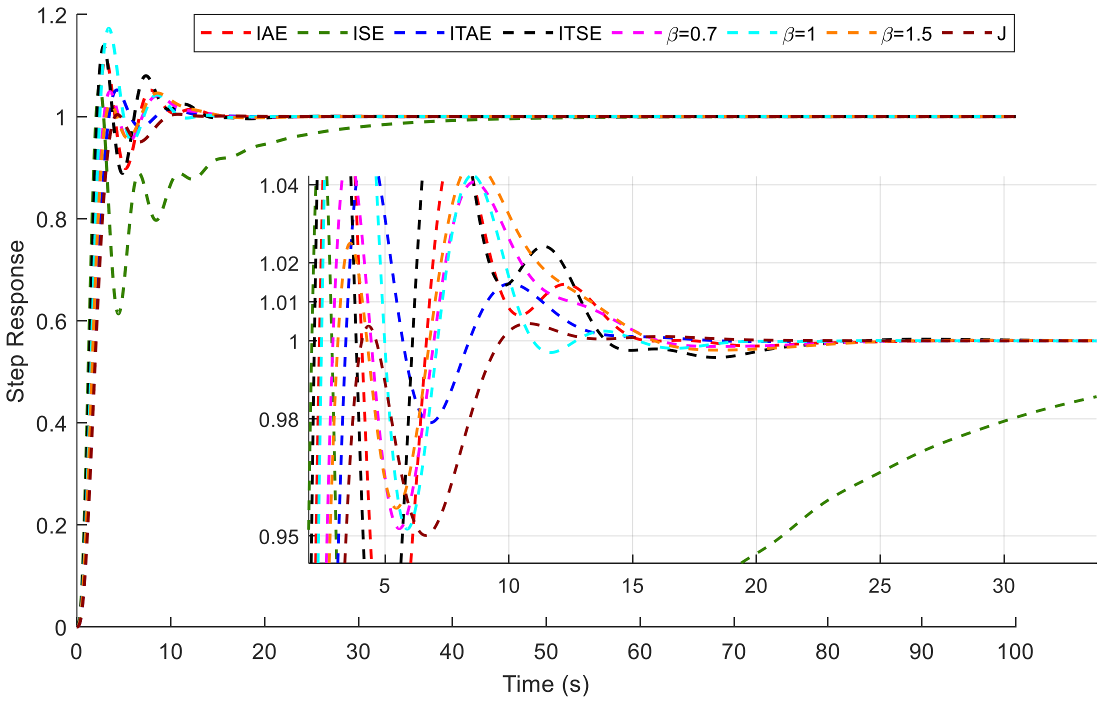

Figure 3. Step responses of the high order process with the PID controller tuned based on different objective functions.

Table 7. Comparative controller parameters and dynamic performance for the high order process.

	PID Tuning Parameters			Performance Parameters			
Objective Function	K_p	K_i	K_d	M_p	t_r $0.1 \rightarrow 0.9$	t_s $\pm 5\%$	E_{ss}
IAE	2.2814	0.7778	3.5119	11.2869	1.4300	8.1100	0
ISE	2.3488	0.2451	5.1412	5.9571	1.2200	21.0300	0.000022
ITAE	1.7179	0.5665	1.9123	5.1906	2.0800	4.4500	0
ITSE	2.3352	0.9213	4.1451	13.8081	1.3100	8.3400	0
$W(0.7)$	1.8886	0.6748	2.7384	4.8598	1.7500	2.6500	0
$W(1.0)$	2.3390	0.8507	2.9252	17.2693	1.4900	4.5800	0
$W(1.5)$	1.7728	0.6619	2.6933	4.5904	1.8300	2.7700	0
$J(k)$	1.6316	0.4825	1.8000	0.4427	2.2600	3.4200	0

From Table 7 and Figure 3, it can be seen that the PID with the proposed cost function has better response in minimizing the overshoot and steady state error. In addition, the PID with $W(0.7)$ and $W(1.5)$ has smaller the rise time and settling time as compared to that of $J(k)$ and closer the same as IAE, $ITAE$ and $ITSE$. However, the table and figure indicate that PID controller tuned with CS based on the proposed cost function has generally the best performance while the others have the largest overshoot.

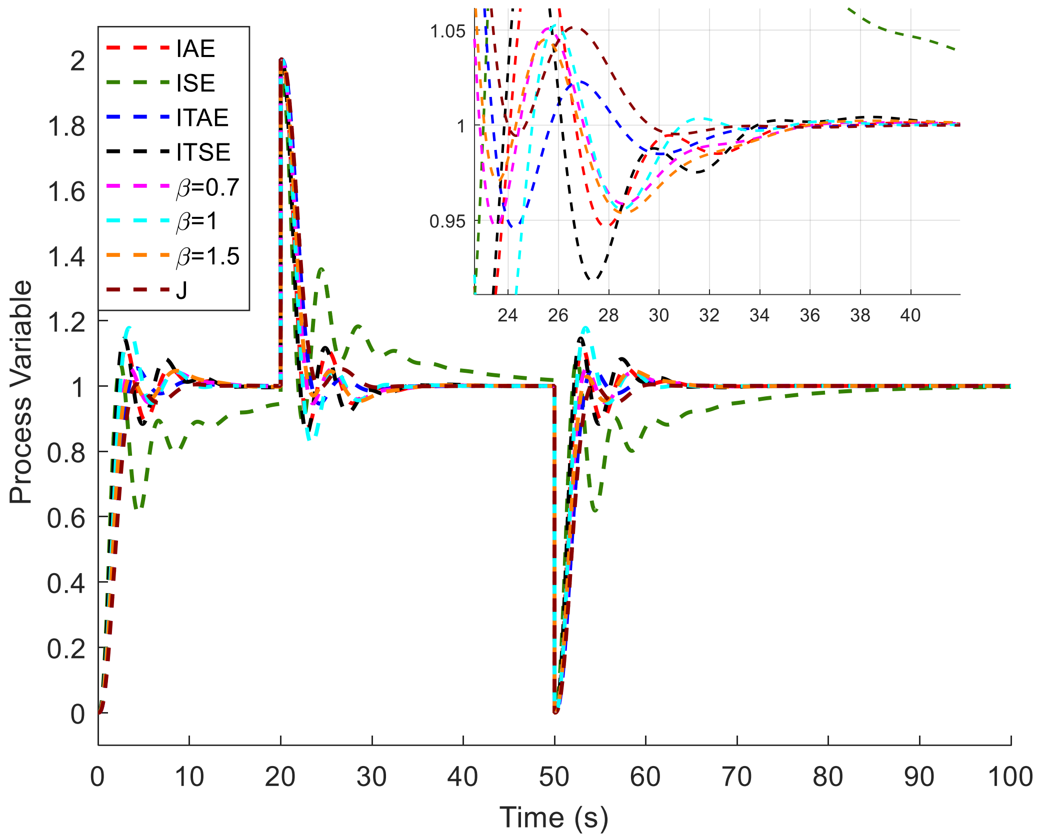

Figure 4. Reference tracking and disturbance rejection for the high order process.

For the purpose of comparing the performance of the tuned PID controllers based on the different objective functions, the superiority of the tuned controllers is examined under a load disturbance. For this process, two disturbance signals are used as +100% and −100% of the set point at times 20 s and 50 s, respectively as shown in Figure 4.

As observed from the results shown in Figure 4, the CS tuned PID controller based on the proposed cost function has better adaptability in the presence of a load disturbance as compared to the other optimized PID controller based on the different objective functions.

5. CONCLUSIONS

In this paper, CS based tuning approach for the PID controller based on the multi-objective optimization technique using the Pareto front solutions with GA has been presented for improved dynamic response of the different process systems. The optimal choice of the weights in the proposed multi-objective cost function has been obtained through multi-objective GA algorithm, based on simultaneous minimization of four conflicting objective function (overshoot, rise time settling time and steady state error). Also, the results obtained from the proposed cost function were compared with commonly used integral based performance index such as IAE, ISE, ITAE and ITSE and the time domain performance criteria based on the system dynamic output.

The results showed that the CS tuned PID controller designed by the proposed multi-objective cost function provides better control performance compared to the PID controller tuned with CS based on the other objective functions. The simulation results indicated that the proposed multi-objective cost function work well even for high order process producing a range of solutions on the Pareto front.

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