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Full Length Research Paper

Optimized proportional integral derivative (PID) controller for the exhaust temperature control of a gas turbine system using particle swarm optimization

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In this paper, the particle swarm optimization (PSO) technique is used in optimising the proportional integral derivative (PID) controller parameters for the exhaust temperature control of a gas turbine system. The performance of the PID controller whose parameters are tuned based on the PSO method (PSO-PID) is compared with the conventional PID (CPID) controller that employs the Ziegler-Nichols method. A new performance criterion, known as multipurpose performance criterion (MPPC) is proposed and used in the PSO algorithm. Time domain performance of the PSO-PID controller, such as the maximum overshoot (M_p), rise time (t_r), settling time (t_s) and absolute error (AE) are being optimized based on the MPPC and compared with other performance criteria such as the integral of time multiplied by absolute error (ITAE), integral of time multiplied by square error (ITSE), integral square error (ISE) and integral of absolute error (IAE). Result shows that the PSO technique, combined with the MPPC performance criterion is very effective to yield optimal transient response of the gas turbine exhaust temperature. An adjustable weighting factor in the MPPC technique makes it more reliable, consistent and flexible as compared to the commonly used performance criteria.

Key words: Proportional integral derivative (PID) controller, particle swarm optimization, multipurpose performance criterion, gas turbine exhaust temperature.

INTRODUCTION

Gas turbine has become increasingly popular in different areas of industry due to their lower greenhouse emission and higher efficiency compared to other types of engine, such as diesel engines, especially when connected in a combined cycle setup (Yee et al., 2008). The control of gas turbine system, particularly its exhaust temperature control, is of primary concern. During transient, the system's transient response period should be as short as possible and the temporal peaks of the main parameters, such as turbine inlet temperature and rotational speed should not exceed certain reference values required for a safe and reliable operation (Kim et al., 2001). However, this is the main problem of the gas turbine; it suffers from undesirable transient response during start-up, load changes and shutdown as well as under abnormal conditions.

In most cases, proportional integral derivative (PID) controller is applied to control the exhaust temperature of the gas turbine system (Rowen, 1995). This is because PID controller is regarded as the workhorse of the process control industry (Rowen, 1983). Its widespread use and universal acceptability is attributed to its simple algorithm, the relative ease with which the controller effects can be adjusted, the broad range of applications where it has reliably produced excellent control performances and the familiarity with which it is perceived amongst researchers and practitioners within the process control community (Rowen, 1983). In spite of its wide-spread use, one of its main shortcomings is that there is no

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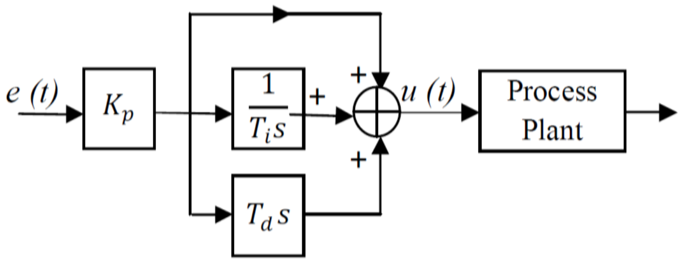

Figure 1. PID controller block diagram.

efficient tuning method for this type of controller (Åström and Häagglund, 1995). Despite some advantages of the CPID controller, such as simplicity of tuning, intuitive structure and easy implementation, it does not work sufficiently for non-linear systems, particularly, when fluctuation happens.

In this study, particle swarm optimization (PSO) algorithm is used to optimize the coefficients of the PID controller. It can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods (Kennedy and Eberhart, 1995). The main objective of this study is to develop a tuning methodology of a PID controller parameters in controlling the exhaust temperature of a gas turbine system so that the closed-loop system is able to adapt to the variation of ambient temperature, not only by reducing the error but also the values of rise time, settling time and maximum overshoot. The use of multipurpose performance criterion (MPPC) in the PSO algorithm is proposed to provide consistent and optimal solution to the control problem posed in this paper.

PID CONTROLLER

There are several parameters that most process control systems aim to control. These include the rise time (the time required for the controlled parameters to go from 10 to 90% of the final desired values), settling time (the time required for the transient's damped oscillations to reach and stay within $\pm 2\%$ of the steady-state value) and the maximum overshoot (the maximum amount that the controlled parameters overshoot the desired values). PID controller is the most commonly used controller in the process control industry (Åström and Hägglund, 2004). It was an essential element of early governors and it became the standard tool when process control emerged in the 1940s. PID control is often combined with logic, sequential functions, selectors and simple function blocks to build the complicated automation systems used for energy production, transportation and manufacturing (Åström and Hägglund, 2004). Its widespread use is attributed to its simple structure and robust performance over a wide range of operating conditions (Gaing, 2004).

The PID control signal is given by Equation 1:

$$u(t) = K_p(e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau + T_d\frac{de(t)}{dt}) \quad (1)$$

where $u(t)$ is the control signal and $e(t)$ is the control error, which is difference between the desired set point and the measured process variable. The control parameters consists of the proportional gain (K_p), the integral time (T_i) and the derivative time (T_d).

Figure 1 shows the conventional PID controller, in which, each term has its own characteristic regarding to the control of the process. The effect of K_p is to reduce the steady state error by increasing the value of gain, but it never eliminates the error. The other action of K_p is to reduce the rise time. The action of integral gain, $K_i = K_p/T_i$, is to eliminate the steady state error by reducing the value of T_i, but the tendency for oscillation also increases by this action. The derivative gain, $K_d = K_p T_d$ has the effect of increasing the stability of the system, reducing its overshoot as well as improving the settling time (Åström and Murray, 2008). Figure 1 shows the block diagram of the PID controller in controlling a process plant.

Determination of the parameters that represent the specification and robustness of the closed loop and control loop performance over a wide range of operating condition is the main aim of PID controller tuning. However, it is often difficult to simultaneously obtain all the desirable qualities simultaneously. Therefore, a more systematic method is required to ensure an optimized performance of the control system every time the PID controller is used.

The dynamical nature of the process control loop, which in this study is the exhaust temperature system of the gas turbine, leads to changes of operating conditions within the loop, and hence the loop performance. Changes in system performance may be attributed to the presence of process nonlinearities within the control channel, process aging, production strategy changes, modifications to the properties of raw materials and changes over equipment maintenance cycles (Poulin et al., 1996). Considering these dynamical conditions, tuning of the PID control parameters is necessary to ensure a continuously adequate performance of the control loop.

PARTICLE SWARM OPTIMISATION (PSO)

In a PSO system, a swarm of individuals (called *particles*) fly over the XYZ coordinate within a three-dimensional search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position according to its own experience, which is called the 'personal best position' (*p-best*) and the position of the best particle in the entire population, which is known as the 'global best position' (*g-best*). The performance of each particle (that is, how close is the particle to *g-best*) is measured using a fitness function that depends on the optimization problem it is dealing with. The particles memorise both their own best positions and the global best position in each iteration step. Each particle has its own velocity that is expressed by *vx, vy and vz (*the velocity along the X-axis, Y-axis and Z-axis, respectively) (Kennedy et al., 2001).

Modification of the particles position is realized based on the previous position and velocity information according to Equations 2 and 3 (Kennedy and Eberhart, 1995).

$$v_i^{k+1} = v_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest - s_i^k\right) \quad (2)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (3)$$

where v_i^k is the current velocity of particle *i* at iteration *k*, v_i^{k+1} is the new velocity of particle *i* at next iteration *k* +1, s_i^k is the current position of particle *i* at iteration *k*, s_i^{k+1} is the new position of particle *i* at the next iteration *k* +1, c_1 *and* c_2 are adjustable cognitive and social acceleration constants, $rand_1, rand_2$ are random number between 0 and 1, $pbest_i$ is the personal best of particle *i* and $gbest$ is the global best of the population. To control the convergence of the swarm, an inertia weighting function such as the one given in Equation 4 can be used (Clerc, 1999).

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (4)$$

where w is the inertia weight, w_{max} is the initial inertia weight, w_{min} is the final inertia weight, $iter_{max}$ is the maximum number of iterations and *iter* is the current iteration.

The inertia weight controls the impact of the previous velocities where a large inertia weight enhances the global exploitation and a small inertia weight creates a better space for local exploitation. This is why Equation 4 that results in the reduction of the inertia weight value is employed (Eberhart and Shi, 1998). The effect of the time-decreasing coefficient is to narrow the search to induce a shift from an exploratory to an exploitative mode (Kennedy et al., 2001). The inertia weight is then multiplied by the current velocity component, to give:

$$v_i^{k+1} = w v_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest - s_i^k\right) \quad (5)$$

A constriction factor has also been proposed in Clerc (1999) to achieve a better convergence performance. Unlike other evolutionary computing techniques, the constriction factor approach to PSO ensures the convergence of the search procedures and that the amplitude of each particle's oscillation decreases as it focuses on a previous best point.

The modified velocity update equation is given by Equation 6:

$$v_i^{k+1} = \chi\left[v_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest - s_i^k\right)\right] \quad (6)$$

where χ represents the constriction factor and is defined in Equation 7:

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \quad (7)$$

The constant parameter in Equation 7, φ, is defined as:

$$\varphi = c_1 + c_2 , \varphi > 4 \quad (8)$$

Eberhart and Shi (2000) showed empirically that using both the constriction factor and velocity clamping parameter (V_{max}) generally improves both the performance and the convergence rate of the PSO.

The termination criterion for the PSO algorithm depends on the type of performance criterion used for the fitness function evaluation, such as the integral of time multiplied by square error (ITSE), integral of time multiplied by absolute error (ITAE), integral of absolute error (IAE) or integral square error (ISE). In this paper, the proposed MPPC is applied. The detailed explanation on this criterion is provided in subsequently in this paper. The PSO algorithm can be summarized as shown in Figure 2.

MULTI PURPOSE PERFORMANCE CRITERION (MPPC) IN PSO ALGORITHM

The work in this paper involves the application of PSO algorithm to optimize the coefficients of PID controller (K_p, K_i and K_d) for improving the performance of the exhaust temperature of a single shaft gas turbine. In this regard, each particle has three dimensions. Supposing K_j is the *j*th particle, $K_{pj}, K_{ij} and\ K_{dj}$ are the representatives of the proportional, integral and derivative gains of PID controller, respectively. Following the previous PSO algorithm, firstly, the initial population are generated $[K_{pj}, K_{ij}$

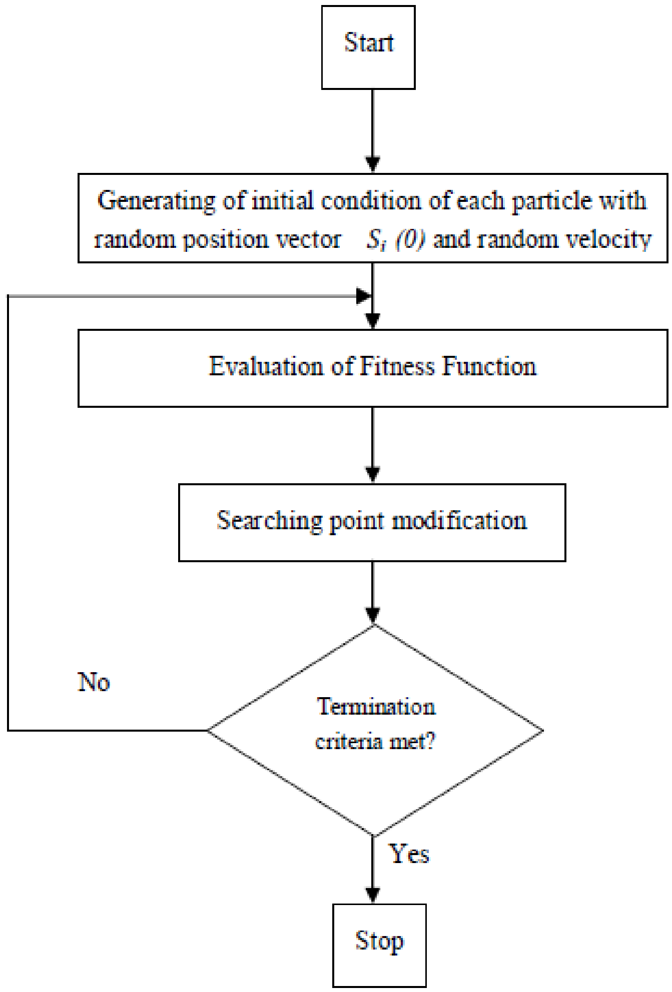

Figure 2. Flowchart of the PSO algorithm.

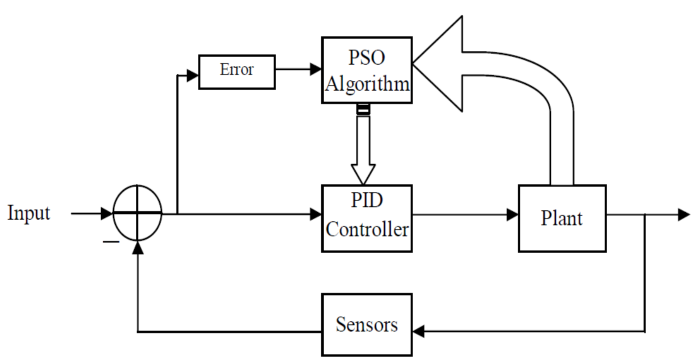

Figure 3. PSO-PID general block diagram.

$and\ K_{dj}]$. Then, the iteration and weight are updated and the rise time, settling time and overshoot are calculated for each set of particles. To find the best personal position for each particle and the best global position for the swarm, suitable performance criterion should be calculated (Ali Marzoughi et al., 2010). In optimal PID, typical performance criteria used in the evaluation of closed-loop system response include ISE index, ITSE index, IAE index and ITAE index (Zhao et al., 2005). Each of these indices has its own characteristic. For instance, the ISE penalizes large errors heavily and small errors lightly. A system designed by this criterion tends to show rapid decline in a large initial error. Hence, the response is fast and oscillatory leading to a system that has poor relative stability. On the other hand, ITSE places little emphasis on initial errors, but penalizes errors occurring late in the transient response to a step input heavily. Systems based on the IAE index penalizes the control error and overshoot, whereas a well damped oscillation is achieved using the ITAE criterion. Also, systems designed using ITAE criterion have small overshoots and well damped oscillations (Ogata, 2010). Despite the advantages of these performance criteria, there is no accurate control on overshoot, rise time and settling time. So, in this paper, a time domain performance criterion is developed and applied to evaluate the PID parameters, which is called the MPPC. The innovated formula is as shown in Equation 9.

$$J(k) = \left(1 - e^{-\beta}\right).\left(M_p\right) + \left(1 + e^{-\beta}\right).\left(t_s + t_r\right) \quad (9)$$

where M_p is maximum peak, t_s is settling time, t_r is rise time and β is a weighting factor whose value depends on the requirement of the control designer. Smaller β reduces t_s and t_r, whereas large β reduces over shoot. The advantage of the proposed technique compared to the other performance criteria is that the overshoot, rise time and settling time of the system can be controlled more accurately by choosing the suitable value for β.

A fitness function is given in Equation 10 for evaluating the value of each particle in the swarm (Gaing, 2004).

$$f = \frac{1}{J(k)} \quad (10)$$

Next, the velocity, position, *p-best* and *g-best* are updated and the constriction condition for velocity (v_i^{k+1}) and position (s_i^{k+1}) are implemented using Equation 11.

$$\begin{cases} v_{i\,min}^{k+1} \le v_i^{k+1} \le v_{i\,max}^{k+1} \\ s_{i\,min}^{k+1} \le s_i^{k+1} \le s_{i\,max}^{k+1} \end{cases} \quad (11)$$

Finally, if the maximum iteration is reached, the process is stopped and if not, it is repeated. The general control loop block diagram for the PID controller that is optimized using the PSO algorithm is illustrated by Figure 3.

OPTIMIZATION OF PID GAINS USING PSO TO CONTROL THE EXHAUST TEMPERATURE OF A SINGLE SHAFT GAS TURBINE SYSTEM

A gas turbine consists of a compressor, a combustion chamber and a turbine operating under the Brayton cycle (Cohen et al., 1996). Four irreversible processes: isentropic compression, constant pressure heat addition, isentropic expansion and constant pressure heat rejection, are the main constitutive elements of the ideal Brayton cycle. First, air is compressed in an adiabatic process with constant entropy (isentropic compression) within the compressor, which is usually an axial compressor. A pressure of 13 to 20 times higher than the atmospheric pressure is usually achieved after the

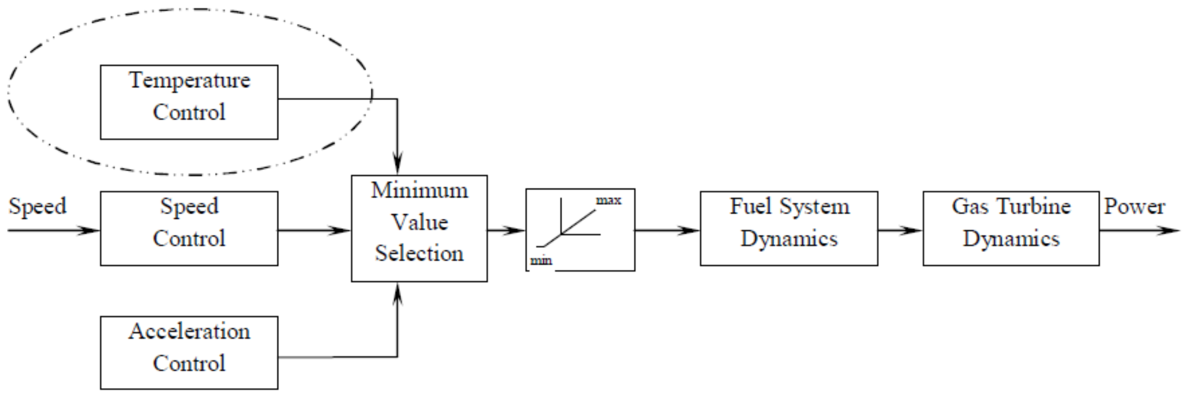

Figure 4. Simplified representation of a single shaft gas turbine model proposed by Rowen (1992).

compression stage (Cengel and Boles, 1989). Fuel, either liquid or gas is then mixed with the compressed air and is burnt in the combustor (constant pressure heat addition). After this, the hot gas is allowed to expand through the turbine (isentropic expansion). This gas expansion drives the blades of the turbine and consequently the shaft of the generator connected to it.

The typical model of gas turbines in stability studies consists of three control loops:

1. Load frequency/speed control loop that controls the power demand by the load.
2. Temperature control loop, which is responsible for controlling the inlet temperature of the compressor and turbine, but because of some technical constraints, exhaust temperature is usually measured and controlled rather than the inlet temperature itself.
3. Acceleration control loop that control the rotation speed of the shaft of the turbine (Rowen, 1995).

Figure 4 illustrates three control loops of a single shaft gas turbine. Referring to Figure 4, the load-frequency/speed control loop is the main control loop during normal operating conditions. The temperature and acceleration control will be active in the case of abnormal operating condition. The maximum power output of a gas turbine depends on the shaft speed and the ambient temperature. The temperature control of a gas turbine limits the exhaust temperature by reducing the fuel flow as the air flow decreases with the shaft speed (Kunitomi et al., 2001). For a GE frame 5011M gas turbine, the firing temperature is 927°C and the reference temperature is 513°C, as shown in Table 1. The maximum allowable overshoot of the temperature during transient time should not exceed the firing temperature (that is, approximately 80% higher than the reference temperature).

Figure 5 represents a simplified block diagram for a single shaft gas turbine, together with its control and fuel systems. The control system includes the speed control, temperature control, acceleration control and upper and lower fuel limits (Rowen, 1983). In Figure 5, parameters a, b and c are the fuel system transfer function coefficients, T_{fe} is the fuel system time constant and K_f is the fuel system feedback evaluated based on Table 2.

The turbine torque polynomial is shown by:

$$f(u) = 1.3(W_f - 0.23) + 0.5(1 - N) \tag{12}$$

K_d is the governor gain and is considered to be 25, typically for 4% droop setting. W_f is the per unit fuel flow, *N* is the rotor speed, T_x (exhaust temperature) is expressed in Equation 13, and is dependent on the reference temperature, fuel flow and rotor speed.

$$f_1 = T_x = T_r \text{ -390(1- } W_f \text{) +306(1-}N\text{)} \tag{13}$$

The variation of the reference temperature is related to the fluctuation of the ambient temperature and is calculated using Equation 14.

$$T_{ra} = T_r \text{ -0.6 (15-} \quad \text{14)}$$

In Equation 14, T_a and T_{ra} represent the values of ambient temperature and the rated exhaust temperature in degree Celsius, respectively (Rowen, 1992).

Figure 6 shows the block diagram of the exhaust temperature block that includes the thermocouples used as the temperature sensors and radiation shields (Wang et al., 2008). In Figure 6, the exhaust temperature is measured using a thermocouple and is labelled T_x. All the parameters in Figure 6 are determined according to Table 1 and 2. ε_{CR} is the combustion reaction time delay and ε_{TD} is the turbine and exhaust system transport delay which are very small and negligible (Rowen, 1995).

RESULTS AND DISCUSSION

Here, the performances of the PSO-PID and CPID controllers in controlling the exhaust temperature of a gas turbine system are compared. The coefficients of the CPID controller used are calculated using the Ziegler-Nichols tuning method and are as follows: K_p= 2.152, K_i= 0.0791 and K_d= 14.633.

These parameters are also used as the initial values for the PSO algorithm when finding the PSO-PID controller gains. The performance criteria used in evaluating the PID controller parameters in the PSO tuning method are the ITSE, ISE, ITAE, IAE and MPPC. The number of particles used (*n*) is 50 and the maximum number of iteration ($iter_{max}$) is 25. Also, 0.1 ≤ *w* ≤ 0.7 and c_1 = 2.5 and c_2 = 2.5. In the simulation work, it is assumed that

Table 1. ISO package rating the specification of gas turbine GE model 5001M (Rowen, 1983).

Model	Turbine speed (RPM)	Rating(MW)	T_r (°C)	Torque (Kg-M)	Inertia (Kg-M²)	Firing temperature(°C)
5001M	5100	18.2	513	3.484	1.037	927

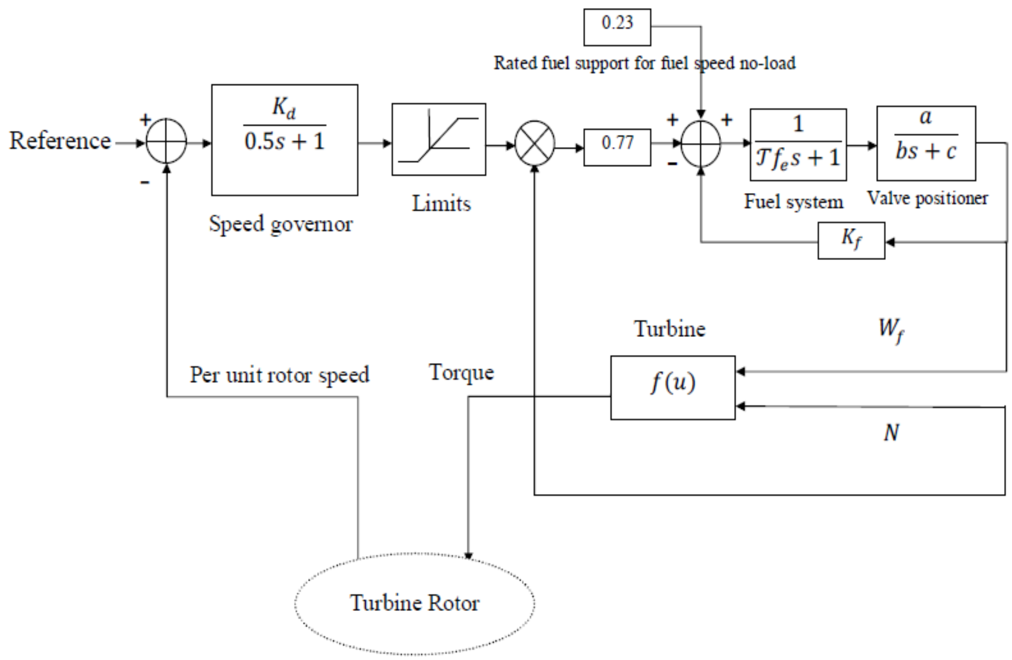

Figure 5. Simplified block diagram of a gas turbine.

Table 2. The values of exhaust temperature of gas turbine model 5001M (Rowen, 1983).

Model	K_f	*a*	*B*	*c*	T_{fe}	ε_{CR}	ε_{TD}
5001M	0	1	0.05	1	0.4	0.01	0.02

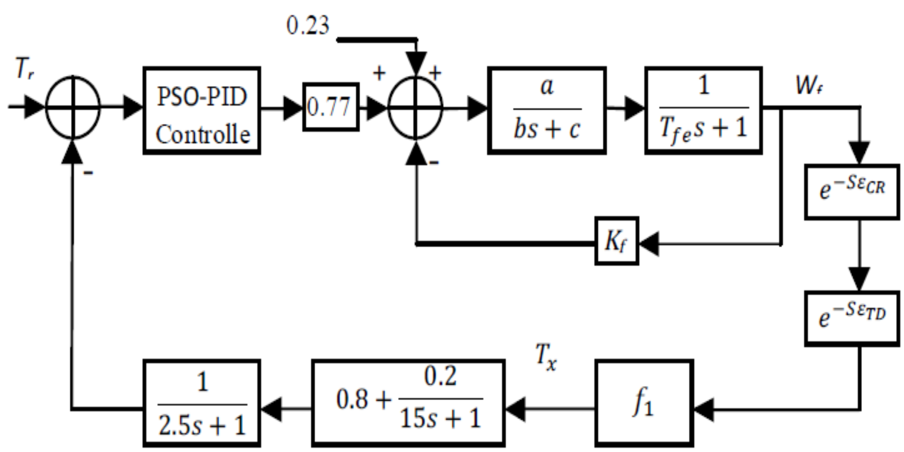

Figure 6. Exhaust temperature control block diagram.

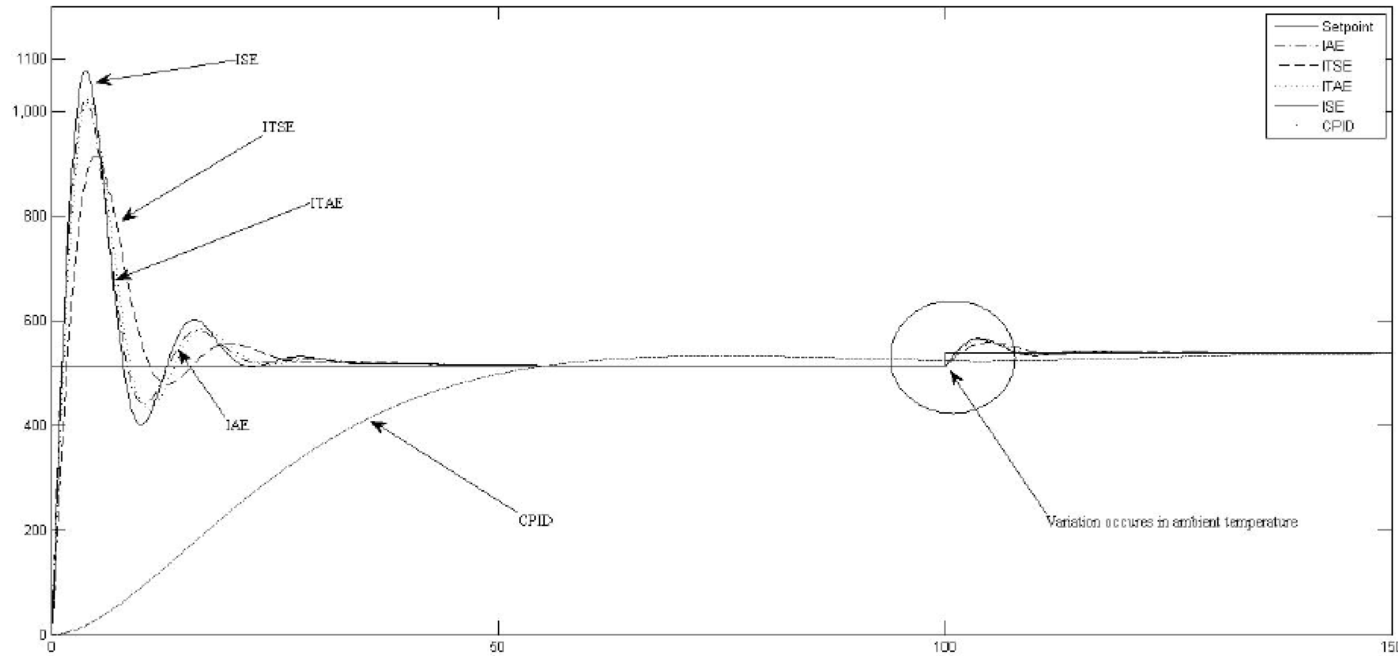

Figure 7. Output temperature response for PSO-PID and CPID controllers.

Table 3. Comparison of overshoot, rise time, settling time and absolute error using PSO-PID including MPPC and the other performance criteria and CPID.

	PSO-PID								CPID
	MPPC				ITAE	ITSE	ISE	IAE	
β	**0.001**	**0.01**	**0.1**	**1**	-	-	-	-	-
M_p(%)	89	27	6	2	99	78	110	99	3.5
t_s(s)	22	27	45	58	13.20	12.5	12.5	12.5	99
t_r (s)	0.80	2.90	8.50	13.00	0.85	1.05	0.77	0.71	26.35
AE	0.0001	0.0004	0.0045	0.0745	1.1538×10^{-4}	1.6131×10^{-4}	1.0721×10^{-4}	1.2287×10^{-4}	3.631×10^{-1}
K_i	0.0390	0.0663	0.0757	0.0731	6.6571	1.8189	1.2507	13.8704	0.0791
K_p	0.0495	0.2759	0.8433	1.2111	7.4525	2.8320	1.3207	16.5736	2.152
K_d	0.00012	0.000102	0.00077	0.0951	0.0024	0.2423	0.1362	1.6731	14.633

initially, the ambient temperature is 15°C. Thus, referring to Equation 14, the reference temperature should be 513°C. The step response of the exhaust temperature using CPID and PSO-PID controllers are shown in Figure 7. Table 3 summarizes the more detailed results of the comparison. As can be observed from Figure 7 and Table 3, the rise time, settling time and absolute error of the PSO-PID control are smaller than the CPID control. However, it can also be observed that the overshoot of PSO-PID control is greater than that of the CPID control. As discussed earlier, the firing temperature for this gas turbine is 927°C, which means that maximum overshoot must not be greater than this, that is, M_p < 80%. According to Table 3, ITSE is the only performance criterion used in the PSO-PID control that results in M_p < 80%, but the rise time, settling time and absolute error are still quite large.

Then, an increase of 35°C in the ambient temperature is assumed at t = 100 s resulting in T_{ra} of 534°C (Equation 14). Figure 8 shows the temperature control results when this temperature variation occurs. When ambient temperature variation occurs, Figure 8 shows that, unlike the CPID controller, the PSO-PID controller is able to track the reference temperature well. However, the high temperature overshoot problem remains unsolved. Therefore, the only critical problem with the PSO-PID controller is the large value of overshoot during

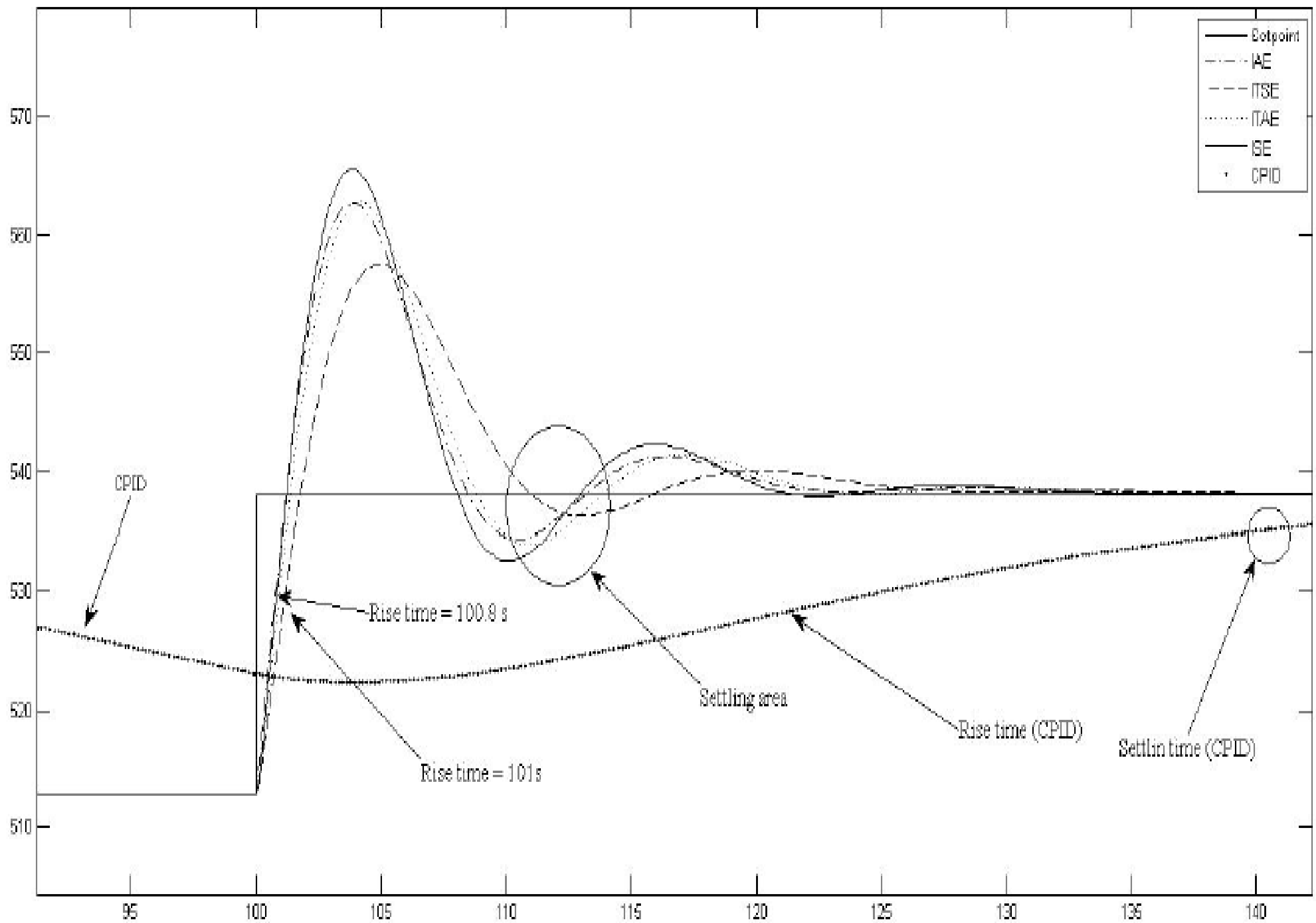

Figure 8. Output temperature response for PSO-PID and CPID controller when the ambient temperature changes from 15 to 35°C after t = 100 s.

transient. To overcome this problem, MPPC is used in the PSO algorithm in search of a more optimum PID gain parameter values. As explained in MPPC in PSO algorithm, the choice of the weighting factor β in Equation 9 is important and depends on the controller design requirements. Figure 9 shows the exhaust temperature control results of the gas turbine system when the PSO-PID controller employing MPPC with different *β* values are used.

Referring to Figure 9, smaller *β* value produces smaller t_s and t_r, but increases the value of M_p, whereas larger *β* value reduces the percentage of over shoot but increases t_s and t_r. Therefore, with careful choices of *β* value, the values of t_s, t_r and M_p can be controlled considerably. In this case, the maximum temperature over shoot can be controlled so that it always remains less than the firing temperature. Table 3 compares the exhaust temperature control performance of the CPID controller and PSO-PID controller using different performance criteria in the PSO algorithm.

Conclusion

The paper presents a new approach in optimizing the PID controller parameters to control the exhaust temperature of a single-shaft gas turbine system. Results have shown that although the proposed PSO-PID controller incurporating ITSE, ISE, ITAE and IAE performance criteria are able to produce system responses with small rise time, settling time and absolute error as well as coping with ambient temperature variation, they results in high maximum temperature overshoot, most of which are greater than the allowable limit: the firing temperature. To overcome this problem, the new performance criterion, MPPC, has been incorporated in the PSO algorithm in place of the ITSE, ISE, ITAE and IAE. Results have shown that the PSO-PID controller, with MPPC and a

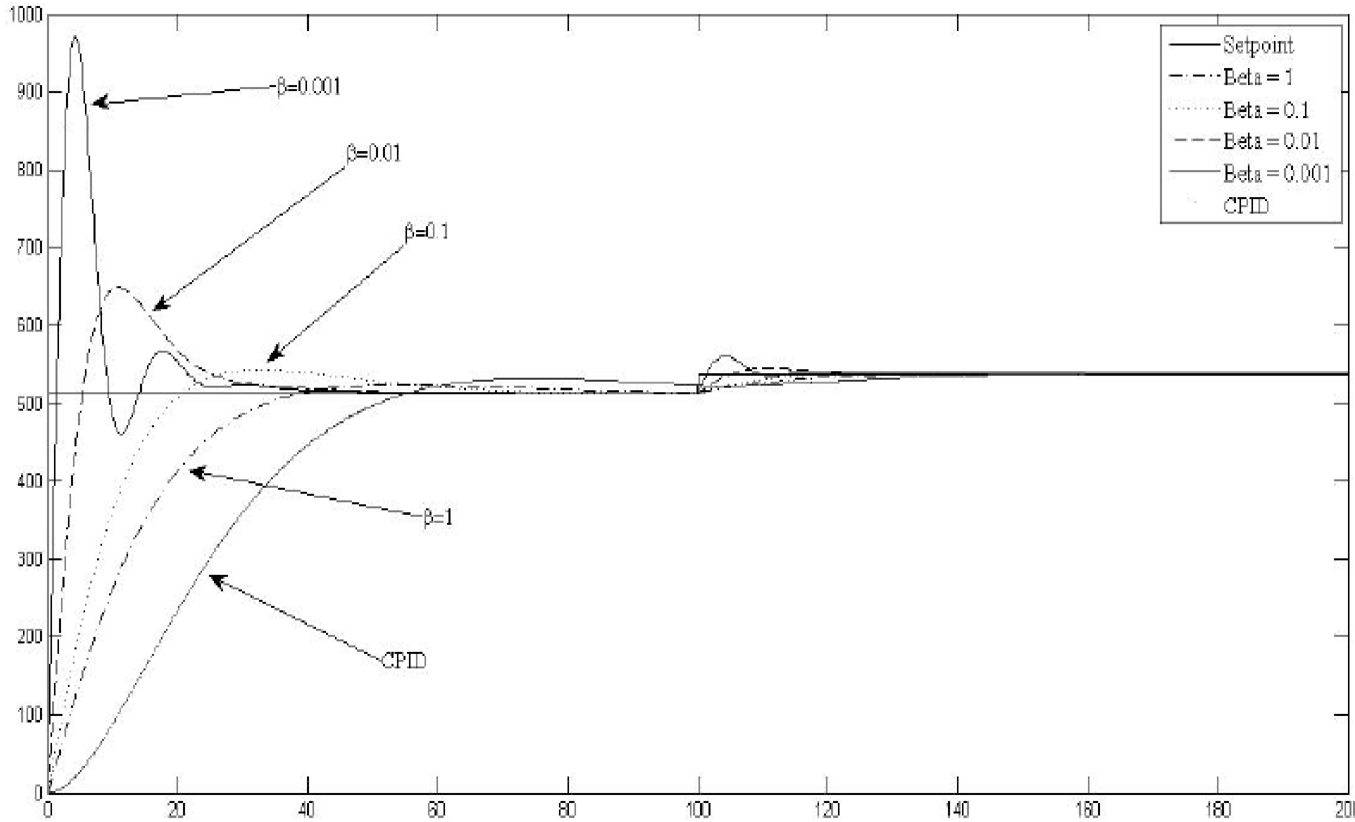

Figure 9. Response of the gas turbine exhaust temperature with different β values.

suitable choice of β value, is able to simultaneously maintain reasonably small values of all transient response characteristics including the rise time, settling time and absolute error, as well as maximum overshoot.

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