Intelligent Tuning of PID Controller With Disturbance Rejection Using Immune Algorithm

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Abstract: Strictly maintaining the steam temperature can be difficult due to heating value variation to the fuel source, time delay changes in the main steam temperature, the change of the dynamic characteristics in the reheater. Up to the present time, PID Controller has been used to operate this system. However, it is very difficult to achieve an optimal PID gain with no experience, since the gain of the PID controller has to be manually tuned by trial and error. This paper focuses on tuning of the Controller with disturbance rejection for thermal power plant using immune based multiobjective approach. An ITSE(Integral of time weighted squared error) is used to decide performance of tuning results.

Key Words: PID control; Disturbance control; Immune algorithm, Multiobjective control; Power plant control.

1. Introduction

There has been a continuing interest in the study of large systems such as power plant [1-2]. This can be explained by the fact that many control problems of modern industrial system are associated with the control of complex interconnected systems. An electric power plant is divided into subsystems: boiler, turbine, and generator. Once a local controller is designed for each subsystem, the three components are connected together.

However, if the overall system is to be driven to an operating point different from the design point, the interaction variables are very likely to vary from their design values.

Therefore, the local controllers need to be robust in order to accommodate these variations. When control theory is applied to solve problems of power plant systems, the decentralized controller is usually required for an excessive information gathering and an extensive computational requirement to make such a controller system to apply.

Up to now, a Proportional – Integral – Derivative (PID) controller has been used in the control system of power plant. However, it cannot effectively control such a complicated or fast running system, since the response of a plant depends on only the gain P, I, and D. There are many well known PI and PID tuning formulas for stable processes that are suitable for autotuning and adaptive control [3, 4]. However, PID tuning formulas for unstable processes are less common. Of course, there are several approaches to tuning the PID controllers for unstable processes. De Paor and O'Malley [5] derived PID tuning methods of the Ziegler-Nichols type for unstable first-order plus time-delay processes.

This paper also addresses whether an intelligent tuning method by multiobjective based on an immune algorithm can be used effectively for disturbance rejection on control system of power plant.

2. Control Characteristics Of Thermal Power Plant For Controller Design

2.1 Control Characteristic in the Thermal Power Plant

A thermal power plant is mainly composed of one boiler whose steam output feeds one turbine, driving a generator. There are many available models for each subsystem with a varying degree of complexity and accuracy. The models are nonlinear MIMO system, obtained through both physical and empirical methods and compared well against actual plant data [6]. The boiler model is six states depending on modeling approaches for dynamics of the steam quality. In fact, they cause unnecessary spikes in the drum level response.

2.2 Turbine/Governor Models

The model is composed of a mechanical-hydraulic speed-governing system and a tandem compound, single reheat steam turbine.

2.3 Generator/Exciter Models

It is a nonlinear 7th order model, which is developed by Anderson and Fouad, described in terms of flux linkages [2]. The synchronous machine under consideration is assumed to have three stator windings, one field winding, and two damper windings. These windings are magnetically coupled and the magnetic coupling is a function of the rotor position.

Direct axis acquations [1-2]:

$$\frac{d\lambda_d}{dt} = \omega_b\left[\frac{r}{l_d}(\lambda_{AD} - \lambda_d) - \omega\lambda_q - v_d\right], \quad (1)$$

$$\frac{d\lambda_d}{dt} = \omega_B\left[\frac{r_F}{l_F}(\lambda_{AD} - \lambda_F) - v_F\right], \quad (2)$$

$$\frac{d\lambda_d}{dt} = \omega_B \left[\frac{r_D}{l_D} (\lambda_{AD} - \lambda_D \right], \quad (3)$$

Where $\lambda_d, \lambda_F, \text{ and } \lambda_D$ are the direct axis, field, and damper flux linkages, respectively, and ω_B and ω are the based frequency and actual frequency respectively.
The mutual flux linkage is given by:

$$\lambda_{AD} = L_{MD}(\lambda_d / l_d + \lambda_F + / l_F + \lambda_D / l_D) , \quad (4)$$

And the d-axis and field currents are given by

$$i_d = (1/l_d)(\lambda_d - \lambda_{AD}), \quad (5)$$

$$i_F = (1/l_F)(\lambda_F - \lambda_{AD}), \quad (6)$$

Quadrature axis equations:

$$\frac{d\lambda_q}{dt} = \omega_b \left[\frac{r}{lq} (\lambda_{AQ} - \lambda_q) - \omega\lambda_d - v_d \right] \quad (7)$$

$$\frac{d\lambda_Q}{dt} = \omega_b (\frac{r_Q}{l_Q} (\lambda_{AQ} - \lambda_Q) \quad (8)$$

Where λ_q and λ_Q are the quadrature axis and damper flux linkages, respectively. The mutual flux linkage is given by

$$\lambda_{AQ} = L_{MQ}(\lambda_q / l_q + \lambda_Q + / l_Q), \quad (9)$$

And the q-axis current is given by

$$i_q = (1/l_q)(\lambda_q - \lambda_{AQ}), \quad (10)$$

Equations for frequency and rotor angle:
The frequency deviation is given as a function of the mechanical torque and electric torque.

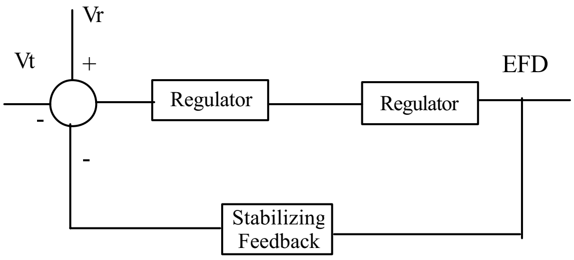
$$\frac{d\omega_{\Delta u}}{dt} = \frac{1}{2H} (T_m - T_e - D\omega_{\Delta u}) , \quad (11)$$

$$\frac{d\delta}{dt} = \frac{180\omega_R}{\pi} \omega_{\Delta u} , \quad (12)$$

Where $\omega_{\Delta u}, T_m, T_e, \text{ and } \delta$ are the per-unit frequency deviation, mechanical torque, electric torque, and rotor angle, respectively.

Exciter model:
The model used also includes an IEEE type 1 excitation system which is a combination of a regulator, an exciter, and a stabilizer. The block diagram of the excitation system is shown in Fig. 1.

A power system stabilizer and a saturation function are also included in the model. More details about the model can be found in [3]. It is worth mentioning at this point that the model includes an infinite bus through a transmission line. Table 1 presents some of the typical values used for the model.



$$\text{Regulator} = \frac{K_a}{1 + r_A s}, \ \text{Exciter} = \frac{1}{K_E + \tau_E s},$$

$$\text{Stabilizer} = \frac{K_F}{1 + \tau_F s}$$

Fig.1.IEEE Type 1 excitation system.

Table 1. Typical value for generator/exciter variable.

Exciter			
$K_a = 400$	$K_E = -0.17$	$K_F = 0.04$	$V_R = 1.1pu$
$\tau_A = 0.05$	$\tau_E = 0.5$	$\tau_F = 1.0$	
Generator			
$\omega = 377$	$r = 0.0011$	$l_q = 0.15$	$r_Q = 0.054$
$l_Q = 0.036$	$r_F = 0.0007$	$l_d = 0.15$	$l_F = 0.101$
$l_D = 0.055$	$L_{MD} = 0.02825$	$r_D = 0.0131$	$D = 2.0$
$H = 0.055$	$L_{MQ} 0.02848$		

3. Power Plant Control

The power plant under study in this paper is composed of boiler, turbine, and generator. The control strategy for disturbance rejection controller design is to decompose the plant into 3 subsystems of boiler, governor/turbine, and generator/exciter and to independently design a robust controller with disturbance rejection for each subsystem.

3.1 Boiler Local Controller

The two inputs to the boiler are the fuel valve (U_1) and the feedwater valve (U_3). The two outputs are steam pressure (P) and the drum water level deviation (δL). Note that the governor valve (U_2) affects the boiler. However, since this valve is under the control of the governor, it is considered as a constant interaction variable.
For a controller to meet these objectives, the immune algorithm based tuning approaches for disturbance rejection is used that controller is to be robust.

3.2 Governor/Turbine Controller

The input to the governor is the mechanical power demand (PO) and the output of the turbine is the mechanical power (PM). Also, the governor receives the speed deviation (DW) from the generator and the turbine receives pressure

effect from the boiler. However, since these two variables are outputs of the other subsystems, they are taken as constant boundary conditions with uncertainties.
Here, also, the immune algorithm based controller for disturbance rejection is chosen to meet these objectives.

C. Generator Local Controller

The generator model has as input the reference voltage (V_r), and as output the terminal voltage (V_t).

4. PID Controller Tuning With Disturbance Rejection By Immune Algorithms

4.1 Immune Algorithm

The coding of an antibody in an immune network is very important because a well designed antibody coding can increase the efficiency of the controller. As shown in Fig. 2, there are three types antibodies in this paper: 1) antibody type 1 is encoded to represent only P gain in the PID controller; 2) antibody type 2 is encoded to represent I gain; 3) antibody is encoded to represent D gains. The value of the k locus of antibody type 1 shows P gain allocated to route 1. That is, the value of the first locus of antibody type 1 means that P gain allocated to route 1 is obtained by route 2 [12].

P	2	1	0.5	• • •	0.2	0.1
I	2	1	0.5	• • •	0.2	0.12
D	2	1	0.5	• • •	0.2	0.1

Fig. 2. Allocation structure of P, I, D gain in locus of antibody of immune algorithm.

On the other hand, the k locus of antibody 2 represents I gain for tuning of the PID controller with disturbance rejection function. Here, the objective function can be written as follows. This algorithm is implemented by the following procedures.
[step 1] Initialization and recognition of antigen: The immune system recognizes the invasion of an antigen, which corresponds to input data or disturbances in the optimization problem.
[step 2] Product of antibody from memory cell: The immune system produces the antibodies that were effective to kill the antigen in the past. This is implemented by recalling a past successful solution from memory cell.
[step 3] Calculation for searching a optimal solution.
[step 4] Differentiation of lymphocyte: The B -lymphocyte cell, the antibody that matched the antigen, is dispersed to the memory cells in order to respond to the next invasion quickly.
[step 5] Stimulation and suppression of antibody: The expected value η_k of the stimulation of the antibody is given by

$$\eta_k = \frac{m_{\varphi k}}{\sigma_k} \tag{13}$$

where σ_k is the concentration of the antibodies. The concentration is calculated by affinity based on phenotype but not genotype because of the reduction of computing time. So, σ_k is represented by

$$\sigma_k = \frac{sum\ of\ antibodies with\ same\ affinity\ as\ m_{\varphi k}}{sum of\ antibodies}. \tag{14}$$

Using equation (6), a immune system can control the concentration and the variety of antibodies in the lymphocyte population. If antibody obtains a higher affinity against an antigen, the antibody stimulates. However, an excessive higher concentration of an antibody is suppressed. Through this function, an immune system can maintain the diversity of searching directions and a local minimum.
[step 6] Stimulation of Antibody: To capture the unknown antigen, new lymphocytes are produced in the bone marrow in place of the antibody eliminated in step 5. This procedure can generate a diversity of antibodies by a genetic reproduction operator such as mutation or crossover. These genetic operators are expected to be more efficient than the generation of antibodies.

4.2 Optimized Parameter Selection for Disturbance Rejection by Immune Algorithm

Conventional optimization techniques, such as gradient-based and simplex-based methods, were not designed to cope with multiple-objectives search problems, which have to be transformed into single objective problems prior to optimization.
On the other hand, evolutionary algorithms are considered to be better tailored to multiple-objectives optimization problems. This is mainly due to the fact that multiple individuals are sampled in parallel, and the search for multiple solutions can be more effective. This section Stats by reviewing some basic approaches utilized in conjunction with evolutionary computation for multiple-objective optimization. Later, we propose a novel technique to handle this problem.

Evolutionary algorithms typically work with a scalar number to reward individuals' performance, the fitness value. In the case of a single-objective optimization problem, we call this scalar $f(x)$ where x is a particular individual. Considering a multiple-objective problem, we can now define the fitness vector $f(x)$:

$$f(x) = (f_1(x), f_2(x), \ldots, f_n(x)) \tag{15}$$

where $f_i(x)$ represent the scalar components of $f(x)$. The search problem is now restated to the me of seeking for optimal values for all the functions $f_i(x)$. This is the most straightforward approach, to transform the objective vector in a scalar. It is simply accomplished by the traditional weighted sum, i.e.,

$$f(x)=\sum_{i=1}^{n} w_i f_i(x) \qquad (16)$$

Chromosome representation: there are six control parameters $[K_p, K_i, K_d, \alpha, \beta, \eta]$ to be determined for an adaptive optimal control. Now, the chromosome is given as

$$f=[K_p, K_i, K_d, \alpha, \beta, \chi, T_1, T_2], \qquad (17)$$
$$f=w_1 f_t + w_2 f_t, \quad f_t = f_1+f_2+f_3,$$
$$w_1=[\alpha, \beta, T_1, T_2],\; w_2=[K_p, K_i, K_d, \eta],$$

with a real-number representation.

Objective functions: for the general control problem, it is desirable to optimize a number of different system performances. Consider a step input R(t) and the output response Y(t). The following objectives are stated for design.

- Minimizing the maximum overshoot of the output

$$f_1 = OV = \max_t\ Y(t) \qquad (18)$$

- Minimizing the settling time of the output

$$f_2 = ST = t_s \qquad (19)$$

such that $0.98R \le Y(t) \le 1.02R, \forall t \ge t_s$.

- Minimizing the rise time of the output

$$f_3 = RT = t_1 - t_2 \qquad (20)$$

such that $Y(t_1)=0.1R \; and \; Y(t_2)=0.9R.$

4.3 Disturbance Rejection Based on Immune Algorithms

For the solution of the constrained optimization problem, two real-coded IMs are employed, i.e., IM_1 to minimize the performance index $I_n(\mathrm{k})$, and IM_2 to maximize the disturbance rejection constraint $\alpha(\omega,\mathrm{k})$, as depicted in Fig. 2. Initially, IM_1 is started with the controller parameters within the search domain as specified by the designer. These parameters are transferred then to IM_2, which is initialized with the variable frequency ω.

IM_2 maximizes the disturbance rejection constraint during a fixed number of generations for each individual of GA 1. Next, if the maximum value will be associated to the corresponding individual of IM_1. Individuals of IM_1 that satisfy the disturbance rejection constraint will not be penalized. In the evaluation of the fitness function of IM_1, individuals with higher fitness values are selected automatically and those penalized will not survive the evolutionary process.

For the implementation of the IM, we used tournament selection, arithmetic crossover, and mutation [10].

A. Representation

In the immune based representation, the parameters of the controller were coded in floating - point and concatenated in an individual for IM_1. For IM_1, an individual consists of only one gene (frequency ?). The IMs were initialized randomly.

B. Fitness Function

An approach using penalty function [10] is employed to solve the constrained optimization problem.

Let the ITSE performance index be $I_n(\mathrm{k})$. Then the value of the fitness of each individual of IM_1 $\mathrm{k}_i (i=1,.......\mu_1)$ is determined by the evaluation function, denoted by $F_1(\mathrm{k}_i)$ as

$$F_1(\mathrm{k_i}) = -(I_n(\mathrm{k}_i)+P(\mathrm{k}_i)) \qquad (21)$$

where μ_1 denotes the population size of GA_1. The penalty function $P(\mathrm{k}_i)$ is discussed in the following.

Let the disturbance rejection constraint be $\max(\alpha(\omega,\mathrm{k}_i))^{0.5}$. The value of the fitness of each individual of IM_2 $\omega_j(j=1,...,\mu_2)$ is determined by the evaluation function, denoted by $F_2(\omega_j)$ as

$$F_2(\omega_j)=\alpha(\omega,k_i) \qquad (22)$$

where μ_2 denotes the population size of IM_2.

The penalty for the individual k_i is calculated by means of the penalty function $P(k_i)$ given by

$$P(k_i)\begin{cases} M_2 & if\ \ k_i\ \ is\ unstable \\ M_1 \max(\omega,\ k_i) & if\ \ \max(\alpha(\omega,k_i))^{0.5} \succ \gamma \\ 0 & if\ \ \max(\alpha(\omega,k_i))^{0.5} \prec \gamma. \end{cases} \qquad (23)$$

If the individual k_i does not satisfy the stability test applied to the characteristic equation of the system, then k_i is an unstable individual and it is penalized with a very large positive constant M_2. Automatically, k_i does not survive the evolutionary process. If k_i satisfies the stability test, but not the disturbance rejection constraint, then it is an infeasible individual and is penalized with $M_1 \cdot \max\ a(\omega,k_i)$, where μ_1 is a positive constant to be adjusted. Otherwise, the individual k_i is feasible and is not penalized.

5. Simulations And Discussions

5.1 Simulation of the immune algorithm based PID Controller on the Thermal Power Plant

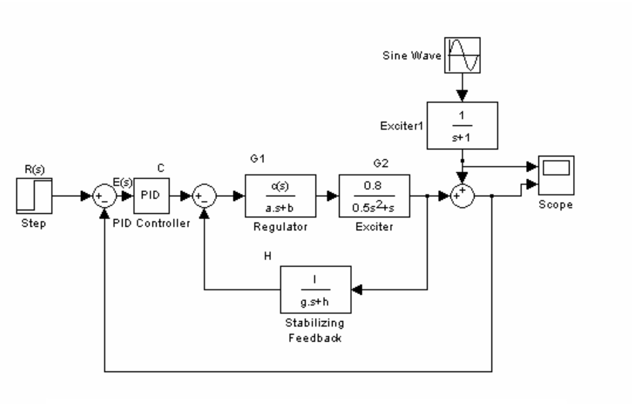


Fig. 3. Block diagram of power plant under consideration.

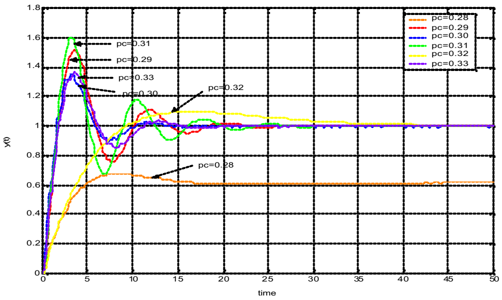


Fig. 5. Response to average values on parameter learning of immune network. (Pm=0.35, Pc=0.28 to 0.33)

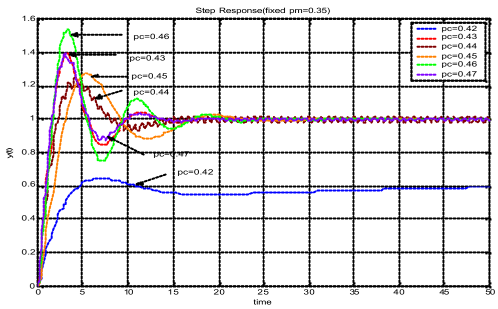


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Fig. 6. Response to average values on parameter learning of immune network. (Pm=0.5, Pc=0.42 to 0.47)

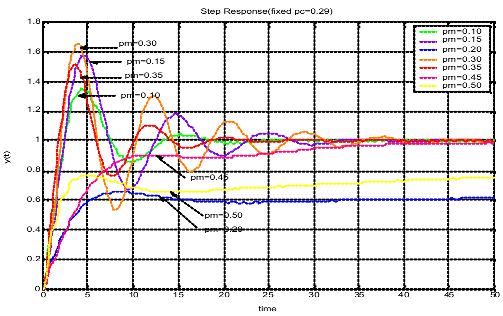

Fig. 7. Response to average values on parameter learning of immune network. (Pc=0.29, Pm=0.1 to 0.5)

Simulation results are shown as Fig. 4-7. Fig. 5 represents response to average values on parameter (Pm=0.35, Pc=0.1

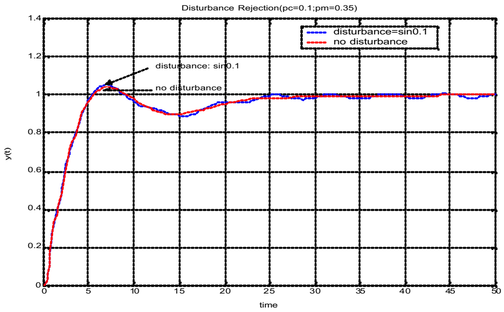

Fig. 8. Response to disturbance rejection. (Pc=0.1, Pm=0.35)

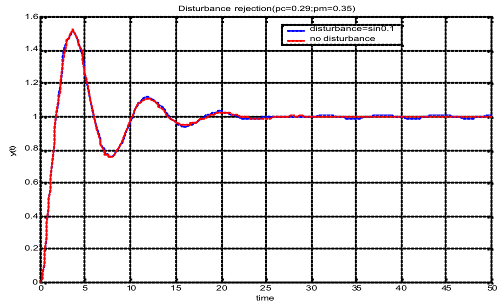

Fig. 9. Response to disturbance rejection. (Pc=0.29, Pm=0.35)

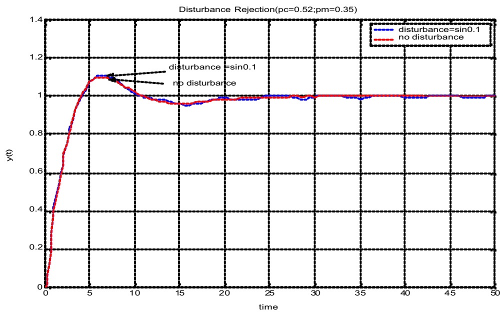

Fig. 10. Response to disturbance rejection. (Pc=0.52, to Pm=0.35)

0.5) learning of immune network on parameters of the given power plant model.

Also, Fig. 6 illustrates response to the average of crossover based learning parameter (Pm=0.5, Pc=0.42 to 0.47) of immune network and Fig. 7 is response to the average of mutation based learning parameter (Pc=0.29, Pm=0.1 to 0.5) of immune network. On the other hand, Figs. 8-10 show response to disturbance rejection depending on parameter variation when crossover and mutation change, respectively. The table 1 and 2 depict parameter value depending on permutation variation (Pc).

6. Conclusions

Up to now, the PID controller has been used to operate the power plants. However, achieving an optimal PID gain is very difficult for the steam temperature control loop with disturbances and without any control experience since the gain of the PID controller has to be tuned manually by trial and error the design of the PID controller may not cover a plant with complex dynamics, such as large dead time, inverse response, and a highly nonlinear characteristic.

To design an optimal controller that can actually be operated on a generating system, this paper focuses on tuning of PID controller with disturbance rejection using immune algorithm For this purpose, we suggest an immune algorithm based multiobjective tuning method for the PID controller. Parameters P, I, and D encoded in antibody are randomly allocated during selection processes to obtain an optimal gain for plant.

Table 1. Parameter value depending on permutation variation (Pc).

	Kp	Td	*A. Ti*	a	b	c	d	e	f
Pc=0.10	5.8454	1.6732	19.865	348.57	271.61	177.66	314.14	67.779	359.92
Pc=0.15	7.4582	0.05142	26.412	358.43	266.33	243.17	314.14	67.779	359.92
Pc=0.20	16.201	0.02176	27.842	237.77	244.69	279.14	314.14	67.779	359.92
Pc=0.25	7.322	0.00958	18.72	300.68	258.62	224.93	314.14	67.779	359.92
Pc=0.30	21.339	20.489	33.092	185.22	250.58	180.56	302.75	102.6	306.81
Pc=0.35	5.7534	15.607	26.966	305.97	235.63	211.14	300.52	77.984	281.62
Pc=0.40	16.026	22.067	27.995	211.55	283.94	198.09	268.08	97.794	128.67
Pc=0.45	8.2225	4.9614	24.898	294.16	240.15	148.32	311.11	68.524	352.67
Pc=0.50	6.9902	29.222	38.304	280.48	277.11	253.82	265.11	103.09	139.72

Table 2. Parameter value depending on permutation variation (Pc).

	Kp	Td	*B. Ti*	a	b	c	d	e	f
Pc=0.28	7.5935	0.020934	32.17	235.34	162.8	157.75	314.14	67.779	359.92
Pc=0.29	11.086	17.803	29.326	218.24	301.42	198.53	298.1	143.31	226.88
Pc=0.30	21.339	20.489	33.092	185.22	250.58	180.56	302.75	102.6	306.81
Pc=0.31	10.028	21.443	26.728	167.39	303.41	131.84	358.29	275.84	318.73
Pc=0.32	6.9831	0.66115	30.341	153.25	279.98	103.38	358.37	275.84	318.73
Pc=0.33	12.288	12.176	24.555	258.26	253.67	278.87	276.81	63.038	294.76

The object function can be minimized by gain selection for control, and the variety gain is obtained as shown in Table 1 and 2. The suggested controller can also be used effectively in the power plant since the controller needs no feedforward or cascade loop.

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