Disturbance Rejection Control of Thermal Power Plant Using Immune Algorithm

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Abstract. A PID Controller has been used to operate this system because of its implementational advantages. 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 PID Controller with disturbance rejection using immune network algorithm. To decide the performance of response, an ITSE (Integral of time weighted squared error) is used in this paper.

1 Introduction

The normal power plant operation requires tracking the steam demand while maintaining the steam pressure and the steam temperature of at their respective setpoints, despite variations of the steam load. 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. 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. In this paper, an intelligent tuning method by a immune algorithm is suggested for robust control with disturbance rejection on control system of power plant.

2 Control Characteristics of Thermal Power Plant for Controller Design

A thermal power plant is mainly composed of one boiler whose steam output feeds one or two turbine, driving an electric generator. There can be many available models for each subsystem with a varying degree of complexity and accuracy. The models

M. Bubak et al. (Eds.): ICCS 2004, LNCS 3037, pp. 687–690, 2004.
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are nonlinear MIMO system, obtained through both physical and empirical methods and compared well against actual plant data [3].

$$\frac{d\lambda_d}{dt}=\omega_b\left[\frac{r}{l_d}(\lambda_{AD}-\lambda_d)-\omega\lambda_q-v_d\right],\ \frac{d\lambda_d}{dt}=\omega_B\left[\frac{r_F}{l_F}(\lambda_{AD}-\lambda_F)-v_F\right],\ \frac{d\lambda_d}{dt}=\omega_B\left[\frac{r_D}{l_D}(\lambda_{AD}-\lambda_D\right]$$

where $\lambda_d, \lambda_F,$ *and* λ_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 $\lambda_{AD}=L_{MD}(\lambda_d/l_d+\lambda_F+/l_F+\lambda_D/l_D)$, and the d-axis and field currents are given by $i_d=(1/l_d)(\lambda_d-\lambda_{AD}),\ \ i_F=(1/l_F)(\lambda_F-\lambda_{AD}),$

$$\frac{d\lambda_q}{dt}=\omega_b\left[\frac{r}{lq}(\lambda_{AQ}-\lambda_q)-\omega\lambda_d-v_d\right],\ \frac{d\lambda_Q}{dt}=\omega_b(\frac{r_Q}{l_Q}(\lambda_{AQ}-\lambda_Q)\ \ \lambda_{AQ}=L_{MQ}(\lambda_q/l_q+\lambda_Q+/l_Q),$$

$i_q=(1/l_q)(\lambda_q-\lambda_{AQ})$. The frequency deviation is given as a function of the mechanical torque and electric torque $\frac{d\omega_{\Delta u}}{dt}=\frac{1}{2H}(T_m-T_e-D\omega_{\Delta u})$, $\frac{d\delta}{dt}=\frac{180\omega_R}{\pi}\omega_{\Delta u}$, where $\omega_{\Delta u}, T_m, T_e,$ *and* δ are the per-unit frequency deviation, mechanical torque, electric torque, and rotor angle, respectively.

3 PID Controller Tuning with Disturbance Rejection Function by Immune Algorithms

3.1 Condition for Disturbance Rejection

In Fig. 1, the disturbance rejection constraint can be given by $\max_{d(t)\in D}\frac{\|Y\|}{\|d\|}=\left\|\frac{w(s)}{1+K(s,c)G(s)}\right\|_\infty\langle\delta$. Here, $\delta\langle 1$ is constant defining by the desired rejection level and $\|\bullet\|_\infty$ denotes the H_∞-norm, which is defined as $\|G(s)\|_\infty=\max_{\omega\in[0,\infty)}|G(j\omega)|$. The disturbance rejection constraint becomes

$$\begin{aligned}\left\|\frac{w(s)}{1+K(s,c)G(s)}\right\|_\infty&=\max_{\omega\in[0.\infty)}\left(\frac{w(j\omega)w(-j\omega)}{1+K(j\omega,c)G(j\omega,c)K(-j\omega,c)G(-j\omega,c)}\right)^{0.5}\\&=\max_{\omega\in[0.\infty)}(\sigma(\omega,c))^{0.5}\end{aligned}\tag{1}$$

The controller K (s, c) is written as $K(s,c)=c_1+\frac{c_2}{s}+c_3s$, $c=[c_1,\ c_2,\ c_3]^T$. Hence, the condition for disturbance rejection is given as $\max_{\omega\in[0.\infty)}(\sigma(\omega,c))^{0.5}\langle\delta$.

3.2 Performance Index for Optimal Controller Design

The performance index defined as ITSE (Integral of the Time-Weighted Square of the Error) is written by $PI = \int_0^{\infty} t(E(t))^2 dt$, $E(s) = B(s)/A(s) = \sum_{j=0}^{m} b_j s^{m-1} \bigg/ \sum_{i=0}^{n} a_i s^{n-1}$.

Because *E(s)* contains the parameters of the controller *(c)*, the value of performance index, *PI* for a system of n*th* order can be minimized by adjusting the vector c as $\min_c PI(c)$, The optimal tuning is to find the vector c, such that the ITSE performance index, *PI (c)* is a minimum and the constraint $\max_{\omega \in [0.\infty)} (\sigma(\omega,c))^{0.5} \langle \delta$ is satisfied through real coded immune algorithms.

3.3 Evaluation Method for Disturbance Rejection Based on Immune Algorithms

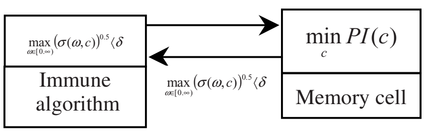

Fig. 1. Immune algorithm based computational structure for optimal parameter selection.

Let the ITSE performance index be *PI(c)*. Then the value of the fitness of each individual of immune network $c_i (i = 1, \ldots\ldots n)$ is determined by the evaluation function, denoted by $\Gamma(c_i)$ as $\Gamma_1(c_1) = -(PI_n(c_i) + \Phi(c_i))$,

The penalty function $\Phi(c_i)$ is discussed in the following. Let the disturbance rejection constraint be $\max(\alpha(\omega,c_i))^{0.5}$. The value of the fitness of each individual of memory cell $\omega_j (j = 1,\ldots,m)$ is determined by the evaluation function, denoted by $\Omega(\omega_j)$ as $\Omega(\omega_j) = \alpha(\omega,c_i)$. The penalty for the individual c_i is calculated by means of the penalty function $\Phi(c_i)$ given by

$$\Phi(c_i) \{ M_2 \ \textit{if} \ c_i \ \textit{is unstable}, \ M_1 \max(\omega, c_i) \ \textit{if} \ \max(\alpha(\omega,c_i))^{0.5} \rangle \delta, \ 0 \ \textit{if} \ \max(\alpha(\omega,c_i))^{0.5} \langle \delta.$$

3.4 Computational Procedure for Optimal Selection of Parameter

[Step 1.] Initialization and recognition of antigen: That is, initialize the populations of network $c_i \ (i = 1,\ldots,n)$ and memory cell $\omega_j (j = 1,\ldots,m)$.

[Step 2.] Product of antibody from memory cell: For each individual c_i of the network population, calculate the maximum value of $a(\omega,c_i)$ using memory cell. If no individuals of the network satisfy the constraint $\max(a(\omega,c_i))^{0.5} < \delta$,

[Step 3.] Calculation for searching a optimal solution: Calculate the fitness value for each individual c_i .

[Step 4.] Stimulation and suppression of antibody: The expected value η_k of the stimulation of the antibody is given by $\eta_k = m_{\varphi k} / \sigma_k$,where σ_k is the concentration of the antibodies. Through this function, for each individual c_i of the network, calculate $\max(a(\omega, c_i))$ using memory cell, and initialize the gene of each individual $\omega_j (j = 1,...,m)$ in the population.

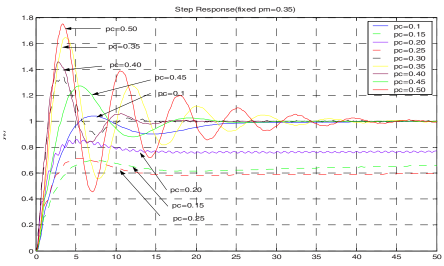

Fig. 2. Response to average values on parameter learning of immune network. (Pm=0.35, Pc=0.1 to

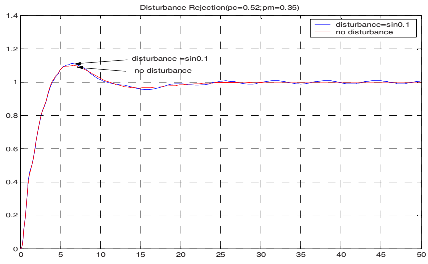

Fig. 3. Response to disturbance rejection. (Pc=0.52, Pm=0.35)

[Step 5.] Stimulation of Antibody: If the maximum number of generations of memory cell is reached, stop and return the fitness of the best individual $\max(a(\omega, c_i))$ to network; otherwise, go to step 3.

4 Simulations and Discussions

The simulation results are shown as Fig. 2-3. Fig. 2 represents response to average values on parameter learning of immune network on parameters, Pm=0.35, Pc=0.1 to 0.5. Fig. 3 illustrates comparison between immune based PID control depending on generation variation and genetic algorithm based PID control depending on generation variation.

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