INPUT WEIGHTING OPTIMIZATION FOR PID CONTROLLERS BASED ON THE ADAPTIVE TABU SEARCH

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ABSTRACT

Eitelberg introduced a useful method to recover system performance when a direct tuning of the PID's parameters was prohibited in 1987 [1]. Our work herein proposes the use of adaptive tabu search (ATS) [11] to optimally tune the input-weight factors according to Eitelberg's. We illustrate the effectiveness of our proposed method via two motor control problems.

1. INTRODUCTION

Over decades, PID controllers have been increasingly employed in feedback control systems for industrial applications. The three-term parameters are appropriately designed at the beginning by a number of design methods or tuning rules. In general, design of the PID controllers assumes that neither the controlled plant's nor the controller's parameters are changed due to working environment or use. This may thus degrade the system performance in long term. For industrial use, most controllers are hard-wired or prohibited from adjustment. On the other hand, the fixed configuration type control system has been commonly used in industries. The method to keep the system response at or near optimum whenever the parameter variation occurs in the control loop was introduced by Eitelberg [1] in 1987. Employing the leveling of input signals, called input weighting, the structure of the control system introduced by Eitelberg is shown in Fig.1. Due to the special feature of input-weighting parameter adjustment, the Eitelberg's method is extended to several applications such as feedback analog PID control [2], fuzzy-PID for DC motor speed regulation [3-4], performance adjustment of a fixed configuration type control system [5], and novel control strategy under alias situation [6].

Nowadays, artificial intelligent (AI) techniques have been accepted and widely used for the controller design in various industrial control applications. For example, designing of an adaptive PID controller by Genetic Algorithm (GA) [7], a self-tuning PID controller by GA [8], and a finite-precision PID controller by GA [9]. Although the GA is efficient to find the global minimum of the search space, it consumes too much calculation time. By literature, the ATS (Adaptive Tabu Search) method is an alternative, which also has global convergence property. Interestingly, it requires less time consumed, comparative to that spent by the GA method [10]. In addition, it is extended to linear and nonlinear identifications for some complex systems [11]. In this paper, the ATS method is exploited for the PID controller design problems proposed by Eitelberg.

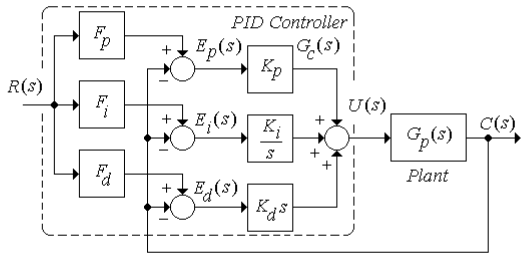

Fig. 1 Input weighting introduced by Eitelberg

This paper consists of five sections. Section 2 describes the problem formulation of the input weighting optimization. Section 3 provides the ATS method used in this work. The test of the proposed optimization method is illustrated in Section 4, while Section 5 gives the conclusions.

2. PROBLEM FORMULATION

Consider the structure of the control system introduced by Eitelberg as shown in Fig. 1. The parallel type PID controller receives the error signal $E_p(s)$, $E_i(s)$, and $E_d(s)$ as shown in Eq. (1) – (3), respectively. Then, the controller generates the control signal, $U(s)$, to regulate the output response, $C(s)$, referred to the input, $R(s)$, where $G_p(s)$ and $G_c(s)$ are the plant and the controller transfer functions, respectively. The transfer function of the system introduced by Eitelberg is shown in Eq. (4),

$$E_p(s) = F_p R(s) - C(s) \quad (1)$$

$$E_i(s) = F_i R(s) - C(s) \quad (2)$$

$$E_d(s) = F_d R(s) - C(s) \quad (3)$$

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$$\frac{C(s)}{R(s)} = \frac{\left(F_p K_p + \frac{F_i K_i}{s} + F_d K_d s\right) G_p(s)}{1 + \left(K_p + \frac{K_i}{s} + K_d s\right) G_p(s)} \quad (4),$$

where $E_p(s)$, $E_i(s)$, and $E_d(s)$ are the error signals, K_p, K_i, and K_d are the original parameters, and F_p, F_i, and F_d are the weighting factors of P-, I-, and D-elements, respectively.

The use of AI searching techniques to optimize the input weighting factors of PID controllers can be depicted in Fig. 2, where $C(s)$ and $C^*(s)$ are actual and desired responses, respectively. The error between $C^*(s)$ and $C(s)$ is fed back to the AI tuning block. The cost function, J, stated in Eq. (5) is therefore minimized to obtain a set of appropriate parameters that give a satisfactory response. In this paper, the ATS method is introduced and then applied in order to minimize the cost function, J.

$$J = \int_0^T \left| c^*(t) - c(t) \right|^2 dt \quad (5)$$

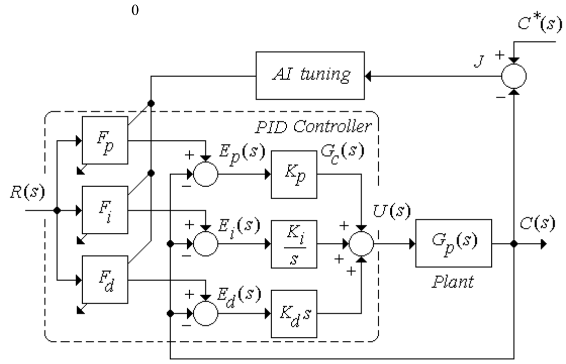

Fig. 2 AI-based PID controller optimization

3. ATS METHOD [11]

The ATS method is one of the efficient AI searching techniques. It is based on iterative neighborhood search approach for solving combinatorial and nonlinear problems. The Tabu list, one important feature of this method that has first-in-last-out property, is used to record a history of solution movements, which may lead to a new direction that could escape a local minimum trap. In addition, the ATS method has two additional mechanisms, namely back-tracking and adaptive-radius, to enhance its convergence. The ATS algorithm is summarized, step-by-step, as follows.

Step 1) Initialize a search space, radius R, *count* and *MAX_count*.

Step 2) Randomly select an initial solution x_0 from the search space. Let x_0 be a current local minimum.

Step 3) Randomly generate N solutions around x_0 within a certain radius R. Store the N solutions, called neighborhood, in a set X.

Step 4) Evaluate a cost function of each member in X. Set x' as a member that gives the minimum cost in X.

Step 5) If $x' < x_0$, put x_0 into the Tabu list and set $x_0 = x'$, otherwise, store x' in the Tabu list instead.

Step 6) Activate the back-tracking mechanism, when solution cycling occurs.

Step 7) If the termination criteria: *count* $\geq$ *MAX_count* (maximum search round), or desired specifications are met, then stop the searching process. The solution x_0 is the best solution (global minimum), otherwise go to Step 8.

Step 8) Activate the adaptive-radius mechanism, when a current solution x_0 is relatively close to a local minimum to refine searching accuracy.

Step 9) Update count, and go to Step 2.

The back-tracking mechanism described above is active when the number of solution cycling is equal to the maximum solution-cycling allowance. This mechanism selects an already visited solution stored in the Tabu list as an initial solution for the next search round to enable a new search path that could escape the local deadlock towards a new local minimum. For the adaptive-radius mechanism, it is invoked when a current solution is relatively close to a local minimum. The radius is thus decreased in accordance with the best cost function found so far. The less the cost function, the smaller the radius. With these two features, a sequence of solutions obtained by the proposed method rapidly converges to the global minimum.

4. INPUT-WEIGHT OPTIMIZATION BY ATS

Refering to Fig. 2, the AI tuning block can be alternatively represented by the ATS block. Thus, the input-weighting factor tuning process is repeatedly performed to minimize J until one of the termination criteria is satisfied. To demonstrate the ATS-based Eitelberg's PID controller design, DC servo and three-phase induction motor control system are used to perform the tests.

4.1 DC Servo Motor Controlled System

The DC servo motor [3] is commonly used in industrial applications. Its open-loop transfer function is given in Eq. (6). The $K_p = 25.6$, $K_i = 282.35$, and $K_d = 0.1$ are the PID parameters obtained from the modulus optimum design method [3]. Such parameters are assumed to be variant in the control loop.

$$G_p(s) = \frac{1}{(1 + 8.5\times10^{-2}s)(1 + 1.77\times10^{-3}s)(1 + 5.55\times10^{-3}s)} \quad (6)$$

The desired specifications are given by $T_r \leq 0.01$ s, $P.O. \leq 20\%$, $T_s \leq 0.03$ s, and $E_{ss} \leq 0.001$. They are therefore set as inequality constraints of the problem described in Eq. (7). The ATS method is used to obtain the input weighting factors of the PID controller shown in Eq. (4). The optimization framework can be defined as in Eq. (7).

$$\begin{array}{ll} \textit{Minimize} & J \\ \textit{Subject to} & T_r \leq 0.01\ s \\ & P.O. \leq 20\% \\ & T_s \leq 0.03\ s \\ & Ess \leq 0.001 \end{array} \quad (7)$$

The ATS-based optimization used in this application is summarized as follows. The back-tracking mechanism is activated when *MAX_cycling* (maximum cycling allowance) = 15. The adaptive-radius mechanism is used as well. In each search round, 40 neighborhood members are randomly generated and *MAX_count* is set as 1000. The tests are demonstrated by three cases of parameter variation. After the searching process stopped, the input weighting factors in each case are successfully obtained. The step response of the satisfied system, one of the unsatisfied system when the parameter variation occurs, and one after optimization are shown in Fig. 3 – Fig. 5. In addition, the variable limits to form the search space are given as $F_p = F_I = F_d = [0,1]$.

4.2 Induction Motor Controlled System

The induction motor control [12] is widely used in industries. Its open-loop transfer function is given in Eq. (8). The $K_p = 8.5$, $K_i = 0.5$, and $K_d = 0.62$ are the PID parameters obtained from the trial-and-error design method. Such parameters are assumed to be variant in the control loop.

$$G_p(s) = \frac{168.0436}{s(s^2 + 25.921s + 168.0436)} \quad (8)$$

$$\begin{array}{ll} \textit{Minimize} & J \\ \textit{Subject to} & T_r \leq 0.5\ s \\ & P.O. \leq 20\% \\ & T_s \leq 2\ s \\ & Ess \leq 0.001 \end{array} \quad (9)$$

The desired specifications are given by $T_r \leq 0.5$ s, $P.O. \leq 20\%$, $T_s \leq 2$ s, and $E_{ss} \leq 0.001$. They are therefore set as inequality constraints of the problem described in Eq. (9). The ATS method is used to obtain the input weighting factors of the PID controller shown in Eq. (4).

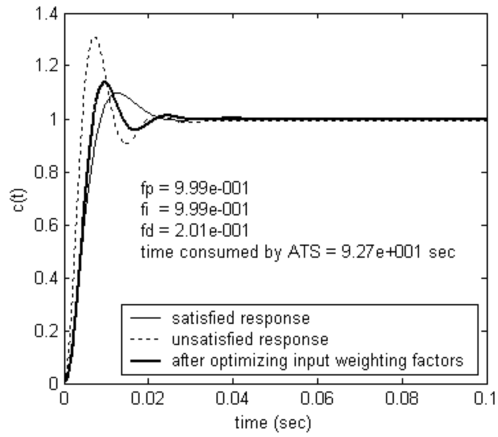

Fig. 3 Step responses of the DC servo motor control system (case 1)

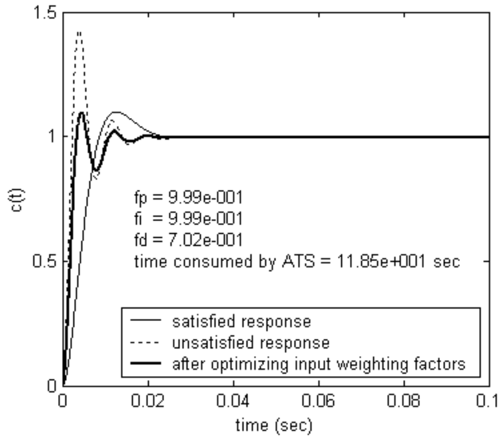

Fig. 4 Step responses of the DC servo motor control system (case 2)

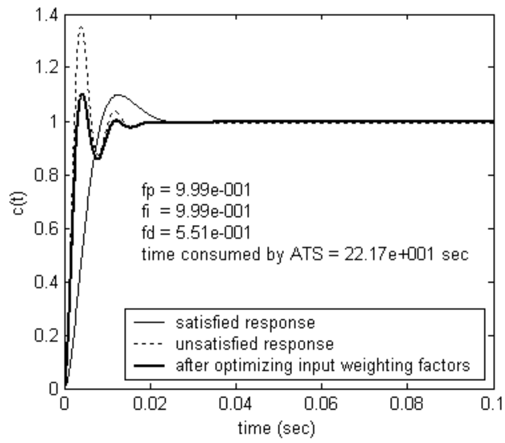

Fig. 5 Step responses of the DC servo motor control system (case 3)

The ATS-based optimization used in this application is summarized as follows. The back-tracking mechanism is activated when *MAX_cycling* = 15. The adaptive-radius mechanism is used as well. In each search round, 40 neighborhood members are randomly generated and *MAX_count* is set as 1000.

The tests are demonstrated by three cases of parameter variation. After the searching process stopped, the input weighting factors in each case are successfully obtained. The step response of the satisfied system, one of the unsatisfied system when the parameter variation occurs, and one after optimization are shown in Fig. 6 – Fig. 8. In addition, the variable limits to form the search space are given as $F_p = F_I = F_d = [0,1]$.

5. CONCLUSIONS

The ATS-based input weighting optimization of the PID controller according to the method introduced by Eitelberg was presented in this paper. Based on the ATS method, the appropriate input weighting factors are obtained to retrieve the system responses. As a result, the two demonstrated examples, DC servo motor controlled system and three-phase induction motor controlled system, show that the input weighting factors can be appropriately optimized by the ATS method to gain better responses.

6. REFERENCES

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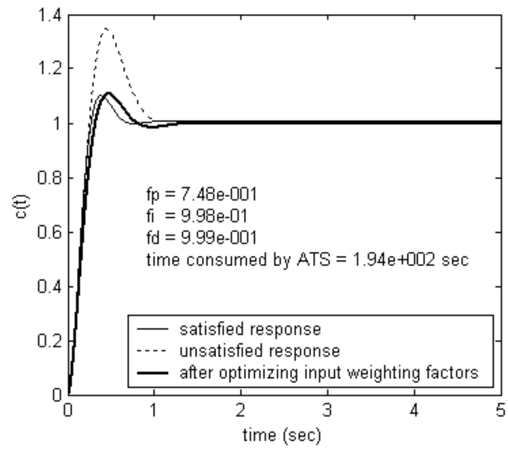

Fig. 6 Step responses of the induction motor control system (case 1)

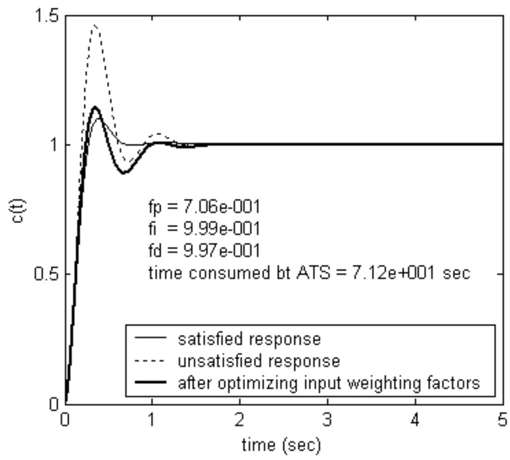

Fig. 7 Step responses of the induction motor control system (case 2)

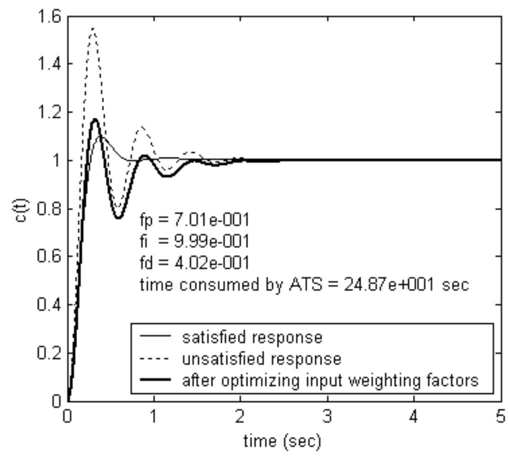

Fig. 8 Step responses of the induction motor control system (case 3)