Fuzzy PID Control for an Overhead Crane Using Hybrid Optimization Approach

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Abstract: In this paper, a hybrid optimization approach is proposed to design fuzzy PID controllers for asymptotical stabilization of a three-dimensional overhead crane. In the proposed method, a fuzzy PID controller is expressed in terms of fuzzy rules, in which the input variables are the error signals and their derivatives, while the output variables are the PID gains. In this manner, the PID gains are adaptive and the fuzzy PID controller has more flexibility and capability than the conventional ones with fixed gains. To tune the fuzzy PID controller simultaneously, a hybrid optimization procedure integrating genetic algorithm (GA) and particle swarm optimization (PSO) method is proposed. The simulation results illustrate that the proposed controller can effectively perform the asymptotical stability of the prototype overhead crane.

Keywords: Three-dimensional overhead crane, particle swarm optimization, genetic algorithm, fuzzy PID control, hybrid optimization

I. INTRODUCTION

Overhead cranes are widely used in industry for transportation systems. However, the overhead cranes have several problems. Such that load swing usually degrades work efficiency and sometimes causes load damages and even safety accidents in the worst cases. Therefore, some researchers have endeavored to control the load swing [1-8]. However, the control of overhead cranes is not a simple task since the overhead cranes have fewer control inputs than degrees of freedom. Recently, many methods have been proposed for the design of controllers. Most industrial processes nowadays are still controlled by PID controllers [9-12]. However, a conventional PID controller may have poor control performance for nonlinear and/or complex systems that have no precise mathematical models. The main disadvantage is that they usually lack in flexibility and capability.

Fuzzy controllers provide reasonable and effective alternatives for conventional controllers. Many researchers attempted to combine conventional PID controllers with fuzzy logic [13,14]. Despite the significant improvement of these fuzzy PID controllers over their classical counterparts, it should be noted that they still have disadvantages. Furthermore, for nonlinear multivariable systems, how to reduce the number of fuzzy rules is unsolved.

Several evolutionary algorithms have been proposed recently to search for optimal PID controllers. Among them, genetic algorithm (GA) has received great attention and particle swarm optimization (PSO) method has been successfully applied to various fields [15,16]. In this paper, a hybrid optimization approach integrating GA and PSO will be adopted to perform the fuzzy PID control. In this manner, the proposed method is fully capable of creating a fuzzy PID controller and eliminates the need for human expertise information in the design process. To show the flexibility and capability of the proposed method, an overhead crane is adopted as an illustrative example. From the simulation results, one can find that the designed fuzzy PID controller guarantees not only prompt damping of load swing but also accurate control of crane positions.

II. FUZZY PID CONTROLLERS

In the proposed fuzzy PID controller, the input variables of the fuzzy rules are the error signals and their derivatives, while the output variables are the PID gains. The fuzzy PID control rules are expressed as

$$\text{If } e_1 \text{ is } X_1^i \text{ and } \dot{e}_1 \text{ is } X_2^j \text{ and } e_2 \text{ is } X_3^k \text{ and } \dot{e}_2 \text{ is } X_4^l,$$
$$\text{then } K_{P1} = Y_{P1}^{ijkl}, K_{I1} = Y_{I1}^{ijkl}, \cdots, K_{D2} = Y_{D2}^{ijkl}$$
$$\text{for } 1 \le i \le n_1,\ 1 \le j \le n_2,\ 1 \le k \le n_3,\ 1 \le l \le n_4 \quad (1)$$

where e_1, e_2 and $\dot{e}_1$, $\dot{e}_2$ are the error signals and their derivatives, $X_1^i, X_2^j, X_3^k, X_4^l$ are the membership functions of e_1, $\dot{e}_1$, e_2, and $\dot{e}_2$, $K_{P1}, K_{I1}, \cdots, K_{D2}$ are the PID gains, $Y_{P1}^{ijkl}, Y_{I1}^{ijkl}, \cdots, Y_{D2}^{ijkl}$ are real numbers, n_1, n_2, n_3, and n_4 denote the numbers of input membership functions, respectively.

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The membership functions of an FLC are usually parametric functions such as triangular functions, trapezoidal functions, Gaussian functions, and singletons. Though the proposed method is equally applicable to all these kinds of membership functions, asymmetric Gaussian ones are used as the antecedent fuzzy sets in this paper. This means that input membership functions are represented as

$$X_k^{m_k}(x_k) = \begin{cases} \exp\left[-\left(\dfrac{x_k - \rho_k^{m_k}}{\sigma_{kl}^{m_k}}\right)^2\right] & \text{if } x_k \le \rho_k^{m_k} \\ \exp\left[-\left(\dfrac{x_k - \rho_k^{m_k}}{\sigma_{kr}^{m_k}}\right)^2\right] & \text{if } x_k > \rho_k^{m_k} \end{cases}$$

$$\text{for } k = 1, 2, \cdots, 4,$$

$$1 \le m_1 \le n_1, 1 \le m_2 \le n_2, 1 \le m_3 \le n_3, 1 \le m_4 \le n_4 \quad (2)$$

where x_k represents the input linguistic variables, $\rho_k^{m_k}$, $\sigma_{kl}^{m_k}$, and $\sigma_{kr}^{m_k}$ denote the values of the centers, the left widths, and the right widths of the input membership functions, respectively. For the output membership functions, singleton sets are adopted. In the defuzzification process, Wang [17] used the center of gravity method to determine the output crisp values. Then, if the PID control law is used and the control signal is determined as

$$u(t) = K_{P1}e_1(t) + K_{I1}\int e_1(t)dt + K_{D1}\dot{e}_1(t) + K_{P2}e_2(t) + K_{I2}\int e_2(t)dt + K_{D2}\dot{e}_2(t) \quad (3)$$

From the above description, one can find that the gains of the fuzzy PID controller are adaptive such that the controller should have more flexibility and capability than the conventional ones. However, it is very difficult, if not impossible, to determine the parameters directly. Therefore, a novel method integrating PSO and GA is proposed to search for the optimal values of these parameters simultaneously.

III. A SIMULATION EXAMPLE

1. Dynamic of An Overhead Crane

In practice, load swing is suppressed as much as possible for safety considerations. This study considers this practical case of small load swing around the stable equilibrium. Then, for the generalized coordinates x, θ_X y, and θ_Y, in Fig. 1 the following linearized dynamic model [5] can be derived:

$$(M_X + m)\ddot{x} + mL\ddot{\theta}_X = F_X - D_X\dot{x} \quad (4)$$

$$\ddot{x} + L\ddot{\theta}_X + g\theta_X = 0 \quad (5)$$

$$(M_Y + m)\ddot{y} + mL\ddot{\theta}_Y = F_Y - D_Y\dot{y} \quad (6)$$

$$\ddot{y} + L\ddot{\theta}_Y + g\theta_Y = 0 \quad (7)$$

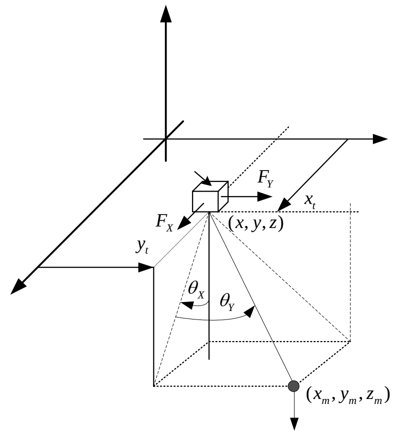

Fig. 1. Coordinate systems of an overhead crane.

where m is the load mass; L is the rope length; M_X and M_Y are the *x* and *y* components of the crane mass including the moment of inertia of the gear train and motors, respectively; D_X and D_Y denote the viscous damping coefficients of the crane in the *x* and *y* directions, respectively; F_X and F_Y are the force inputs to the crane in the x and y directions, respectively; g denotes the gravitational acceleration.

2. GA-PSO tuning Fuzzy PID Controller

In the overhead crane, the desired value of $x(t)$ and $\theta(t)$ are denoted by x_d and θ_d. If the PID control law is employed, then the input-output relation of the crane system is expressed as

$$\tau(t) = k_{P1}e_1(t) + k_{I1}\int e_1(t)dt + k_{D1}\dot{e}_1(t) + k_{P2}e_2(t) + k_{I2}\int e_2(t)dt + k_{D2}\dot{e}_2(t) \quad (8)$$

where $e_1(t) = x(t) - x_d$, $e_2(t) = \theta(t) - \theta_d$, $\dot{e}_1(t) = \dot{x}(t) - \dot{x}_d$, and $\dot{e}_2(t) = \dot{\theta}(t) - \dot{\theta}_d$.

3. Fitness

In designing the fuzzy PID controller, the primary goal is to drive an overhead crane system from the given initial state to the desired final state. However, if the number of fuzzy rules is large, then heavy computation burden and huge memory requirement are inevitable. Therefore, the primary goal and the way to reduce the number of fuzzy rules should be taken into account simultaneously in defining the fitness function. This means that two performance criteria are chosen as follows:

$$f = \frac{1}{[(1+\sum_{i=1}^{n_1} p_i)\cdot(1+\sum_{j=1}^{n_2} p_j)\cdot(1+\sum_{k=1}^{n_3} p_k)\cdot(1+\sum_{l=1}^{n_4} p_l)]^2} + \frac{1}{\int t[e_1^2(t) + e_2^2(t)]dt} \quad (9)$$

where p_i, p_j, p_k, and p_l, are the binary elements to indicate which ones of the membership functions are activated. From the definition (9), the fitness value can be calculated to evaluate the performance of the fuzzy PID controller and a higher fitness value denotes a better performance.

IV. INTEGRATION OF PSO AND GA

PSO is a population-based stochastic searching technique developed by Kennedy and Eberhart [18]. It is similar to the GA in that it begins with a random population matrix and searches for the optima by updating generations.

1. Particle Representations

Before applying the novel auto-tuning method, how to encode the parameters must be introduced firstly. In the proposed method, a mixed coding method is used, in which n_1, n_2, n_3, and n_4 are encoded as binary numbers and $\rho_k^{m_k}$, $\sigma_{kl}^{m_k}$, $\sigma_{kr}^{m_k}$, Y_{P1}^{ijkl}, Y_{I1}^{ijkl}, Y_{D1}^{ijkl}, Y_{P2}^{ijkl}, Y_{I2}^{ijkl}, Y_{D2}^{ijkl} are encoded as real numbers. This means that the positions of particles are represented as

$$\boldsymbol{P} = [\boldsymbol{p}_{binary}\ \ \boldsymbol{p}_{real}] \tag{10}$$

The particle $\boldsymbol{p}_{binary}$ contains binary variables taking the value of one or zero. The elements of $\boldsymbol{p}_{binary}$ are used to indicate which ones of the membership functions are activated. As for the real particles $\boldsymbol{p}_{real}$, the elements of $\boldsymbol{p}_{real}$ are used to represent the values of $\rho_k^{m_k}$, $\sigma_{kl}^{m_k}$, $\sigma_{kr}^{m_k}$, Y_{P1}^{ijkl}, Y_{I1}^{ijkl}, Y_{D1}^{ijkl}, Y_{P2}^{ijkl}, Y_{I2}^{ijkl}, and Y_{D2}^{ijkl}.

2. Evolutionary Algorithms

In evolutionary strategies, the real particles $\boldsymbol{p}_{real}$ will employ the PSO method. As for binary particles $\boldsymbol{p}_{binary}$, it will adopt the GA because of their nature and simplicity. In PSO method, the particles update their velocities and positions based on the local best and global best solutions [19]. In the evolutionary procedure, the inertia weight, the cognitive parameter, and the social parameter are linearly adaptable over the evolutionary procedure [19]. In the proposed GA-based method for binary particles, one cut-point crossover operator and single-point mutation operator will be employed [20].

V. SIMULATION RESULTS

The parameters of the overhead crane system shown as Fig. 1 are chosen as [2]

$$M_X = 1440\ kg,\ D_X = 480\ N \cdot s/m$$

$$M_Y = 110\ kg,\ D_Y = 40\ N \cdot s/m$$

$$m = 10\ kg,\ L = 1\ m,\ g = 9.8\ m/s^2$$

and the constraints shown as

$$-4800\text{ N} \le F_X \le 4800\text{ N},\ -200\text{ N} \le F_Y \le 200\text{ N}$$

$$-\pi/12\text{ rad/s} \le \theta \le \pi/12\text{ rad/s}$$

$$-\pi/6\text{ rad/s} \le \dot{\theta} \le \pi/6\text{ rad/s}$$

$$0\ m \le x \le 5.5\ m,\quad 0\ m \le y \le 3.5\ m$$

$$-0.5\ m/s \le \dot{x} \le 0.5\ m/s,\ -2\ m/s^2 \le \ddot{x} \le 2\ m/s^2$$

$$-0.3\ m/s \le \dot{y} \le 0.3\ m/s,\ -1.5\ m/s^2 \le \ddot{y} \le 1.5\ m/s^2$$

The initial state and the desired final state of the overhead crane are $(x, y, \theta) = (1, 1, \pi/18)$ and $(x, y, \theta) = (0, 0, 0)$. In the proposed algorithm, the population size, the maximal iteration number, the crossover rate, and mutation rate are chosen to be 40, 2000, 0.8, and 0.2, respectively. Moreover, it is assumed that the values of n_1, n_2, n_3, and n_4 are all chosen as five, and the singletons of the output linguistic variables are all chosen as real numbers. According to the procedure of the GA-PSO algorithm, the minimal fuzzy rules and the optimal membership functions of the input linguistic variables are determined. Moreover, the optimal values of $\boldsymbol{p}_{binary}$ and $\boldsymbol{p}_{real}$ can be determined. The former is found to be [00101010010101010010] and it means that only the membership functions X_1^3, X_1^5, X_2^2, X_2^5, X_3^2, X_3^4, X_4^1, and X_4^4 are activated. Meanwhile, this also means that there are 16 ($= 2\times 2\times 2\times 2$) fuzzy rules in the fuzzy PID controller. Since the number of fuzzy rules is reduced from 625 ($= 5^4$) to 16, the computation burden in implementation of this fuzzy PID controller will also be reduced significantly.

The simulation results shown as Fig. 2 through Fig. 5 illustrate that the proposed fuzzy PID controller can effectively complete the asymptotical stability of the prototype overhead crane.

VI. CONCLUSION

In fuzzy PID tuning techniques, the parameters of fuzzy sets and PID gains are difficult to obtain the optimal values for stabilizing an overhead crane. In this paper, we present a hybrid optimization approach integrating GA and PSO to design a fuzzy PID controller to asymptotically stabilize the prototype overhead crane.

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REFERENCES

[1] Yu J, Lewis FL, Huang T (1995), Nonlinear feedback control of a gantry crane. Proc of American Control Conf, pp. 4310-4315

[2] Lee HH (1998), Modeling and control of a three-dimensional overhead crane. J of Dyn Systs, Meas, and Control 120: 471-476

[3] Singhose W, Porter L, Kenison M, Kriikku E (2000), Effects of hoisting on the input shaping control of gantry cranes. Control Eng Pract 8:1159-1165

[4] Moustafa KAF, Ebeid AM (1988), Nonlinear modeling and control of overhead crane load sway. J of Dyn Syst, Meas, and Control 110:266-271

[5] Cho SK, Lee HH (2002), A fuzzy-logic antiswing controller for three-dimensional overhea cranes, ISA Trans 41:235-243

[6] Hua YJ, Shine YK (2007), Adaptive coupling control for overhead crane systems. Mechatronics 17:143-152

[7] Chang CY (2007), Adaptive fuzzy controller of the overhead cranes with nonlinear disturbance. IEEE Trans on Ind Inform 3(2):164-172

[8] Park MS, Chwa DY, Hong SK (2008), Antisway tracking control of overhead cranes with system uncertainty and actuator nonlinearity using an adaptive fuzzy sliding-mode control. IEEE Trans on Ind Electronics 55(11):3972-3984

[9] Keel LH, Rego JI, Bhattacharyya SP (2003), A new approach to digital PID controller design. IEEE Trans on Automatic Control 48(4):687-692

[10] Cervantes I, Garrido R, Jose AR, et al (2004), Vision-based PID control of planar robots. IEEE Trans on Mechatronics 9(1):132-136

[11] Whidborne JF, Istepanian RSH (2001), Genetic algorithm approach to designing finite-precision controller structures, IEE Proc of Control Theory Applications 148(5):377-382

[12] Lin L, Jan HY, Shieh NC (2003), GA-based multiobjective PID control for a linear brushless dc motor. IEEE Trans on Mechatronics 8(1):56-65

[13] Tao CW, Taur JS (2005), Robust fuzzy control for a plant with fuzzy linear model. IEEE Trans on Fuzzy Syst 13(1):30-41

[14] Wu CJ, Liu GY, Cheng MY, et al (2002), A neural-network-based method for fuzzy parameter tuning of PID controllers. J of the Chin Inst of Eng 25(3): 265-276

[15] Gaing ZL (2004), A particle swarm optimization approach for optimum design of PID controller in AVR system. IEEE Trans on Energy Conversion 19(2): 384-391

[16] Habib SJ, Al-kazemi BS (2005), Comparative study between the internal behavior of GA and PSO through problem-specific distance functions. The 2005 IEEE Congress on Evolutionary Computation, pp. 2190-2195

[17] Wang LX (1997), A Course in Fuzzy Systems and Control. Prentice-Hall, New Jersey

[18] Kennedy J, Eberhart R (1995), Particle swarm optimization. Proc of the IEEE Int Conf on Neural Networks, pp. 1942-1948

[19] Ratnaweera A, Halgamuge SK, Watson C (2004), Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients. IEEE Trans on Evolutionary Comput 8(3):240-255

[20] Haupt RL, Haupt SE (2004), Practical Genetic Algorithms, 2nd edition. John Wiley & Sons, New York

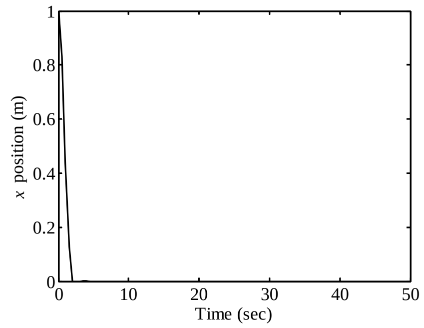

Fig. 2. Plot of *x*-position $x(t)$ for the overhead crane using the proposed fuzzy PID controller.

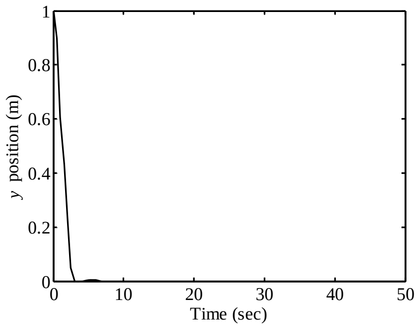

Fig. 3. Plot of *y*-position $y(t)$ for the overhead crane using the proposed fuzzy PID controller.

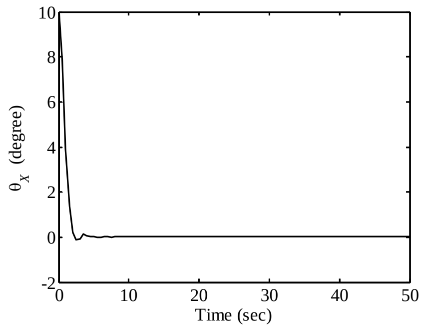

Fig. 4. Plot of *X*-angle $\theta_X(t)$ of the overhead crane using the proposed fuzzy PID controller.

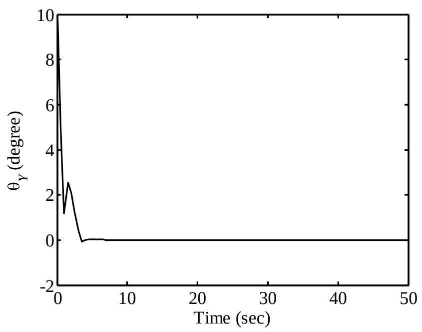

Fig. 5. Plot of *Y*-angle $\theta_Y(t)$ of the overhead crane using the proposed fuzzy PID controller.