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Pareto Optimal Tuning of Adaptive PID Controller using Model Predictive Strategy

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Abstract

In this paper, the gains of PID controller are obtained online using Model Predictive Control (MPC). In fact MPC tries to tune the PID-controller parameters by predicting system's behavior in some time steps ahead. In this way, the nonlinear differential equation of system is approximated by a linear polynomial with unknown parameters. These unknown parameters are obtained using genetic algorithm to minimize the deviation between the real plant and approximated model. Moreover, multi-objective approach has been used to capture the parameters of MPC which are prediction horizon, control horizon and weight factor to minimize simultaneously two objective functions that are control effort and Integral time absolute error (ITAE) of the system response. Results mentioned at the end, obviously declare that the proposed method surpasses conventional MPC and PID-tuning method.

Article history

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1. Introduction

PID controller is one of the most common control methods in literature which has a great application in industrial and mechanical systems. Proven performance of PID controller attracted many authors' attention. Various techniques are introduced to tuning the PID parameters, i.e., proportional gain, integral gain and derivative gain. For SISO system, tuning methods of Cohen-Coon (C–C) and Ziegler–Nichols (Z–N) are frequently used to find gains of PID controller. In the past, the PID self-tuning methods based on the relay feedback technique have also usually presented for SISO systems [1] and MIMO systems [2]. Loop shaping, Ziegler Nichols tuning, biggest log modulus tuning (BLT) method [3], self-tuning by Lyapunov approach [4] and many other methods are some examples amongst all tuning rules for PID parameter adjustment. As the need to control performance increased and systems with more complex structure must be controlled, more reliable tuning methods are needed. Some authors have recently published methods for automatic tuning involving neural networks [5-7]. As almost the majority of these techniques to tune PID parameters work off-line and since off-line techniques rarely show an appropriate performance during changes in system properties, self-tuning and automatic PID controllers were established. In recent decades multiple type of auto-tuning PID controllers including self-tuning techniques and adaptive controller are introduced [3, 7]. Unfortunately most of the auto-tuning PID controllers do not pay attention to control effort as well and almost ever decrease the error in the system.

Model predictive control (MPC) is an advanced control strategy that can be used to predict the future action by minimizing its cost function. Combination of such property with PID control seems to improve the performance of system. In this way, PID parameters can be predicted at any time instant before the error applied to the response of the system. Sato obtained the discrete PID constants using a linear form of GPC to control an industrial heat exchanger [8]. Savran is presented a multi-variable fuzzy PID controller by a combination of a fuzzy PID controller with predictive control strategy [9]. In these works three PID constants obtained in the whole procedure of controlling the output of the system.

To design MPC, choosing an accurate model for the plant to predict its future response is vital and as solving the differential equations in nonlinear systems is Time-consuming. There

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are several indirect techniques for solving nonlinear differential equations of system such as, neural networks, fuzzy model, adaptive neuro-fuzzy inference system (ANFIS) and etc. Majd-abadi et al. have been used Model Predictive Control for optimal selection of PID controller gains [7]. They employed evolved group method of data handling (GMDH) neural networks to obtained a polynomial meta-models to simply simulate the time response of the dynamic system.

In this paper, the nonlinear dynamic equation of system is approximated by a linear polynomial with unknown parameters. These unknown parameters are then obtained using genetic algorithm to minimize the deviation between the real plant and approximated model. The proposed method is applied to control an inverted pendulum. Moreover, a multi-objective optimization with two cost functions, namely, the absolute area under the error curve and the maximum of absolute control effort, has been applied to optimally obtain the parameters of the MPC.

2. Model predictive control

The predictive control method is based on an online receding horizon optimization. Model predictive control (MPC) based on linear models is a mature control technique with multiple applications in industrial process. In some cases taking the nonlinearities of the plant into account is essential. Otherwise, the previous linear models cannot handle the process in some situation. Furthermore, the model that takes the nonlinearities into account implies an improvement in the performance of the plant by reducing the impact of the disturbances and improving the tracking capabilities of the control system [7]. In this paper, the representation of the plant nonlinearities is given based on a sub-model which requires less computation respect to its state space model.

The general objective design of MPC is to compute a trajectory of a future manipulated variable u to optimize the future behavior of the plant output y. In the proposed method, MPC predicts the PID controller's optimal manipulated variable u to track the reference trajectory by the output y. The optimal manipulated variable derived by minimizing the quadratic cost function that is very similar to the one obtained as

$$J = (r - y)^T (r - y) + \Delta U^T \bar{R}\, \Delta U \qquad (1)$$

$$\bar{R} = r_w\, I \qquad (2)$$

Subjected to

$$x(k+1) = A_{DT}\, x(k) + B_{DT}\, u(k) \qquad (3)$$

$$y(k) = C_{DT}\, x(k) \qquad (4)$$

In equation (2), r_w is used as a tuning parameter for the desired closed-loop performance and I is the identity matrix. A_{DT}, B_{DT}, and C_{DT} in equations (3) and (4) are the discrete state space matrices. MPC method tries to predict the response of the system some time steps ahead, by minimizing J in Equation (1). The method then, gives a vector of control effort that can lead the system response to converge to the reference trajectory as closely as possible. The first member of this predicted control signal is applied to the system and after that by the use of the behavior of the system which is concluded from the mentioned control effort, MPC tries again to predict the future manner of the system response in the same amount of time steps ahead and produce a control effort to lead the system to the desired response and the procedure goes on in the same way.

3. Emerging predictive control with PID structure

PID controller is a controller with three terms that has a long history in the field of automatic control. Because of being easy to understand, simplicity and its satisfactory performance, it can be applied to a wide range of processes. This controller has become a standard controller in industrial applications in practice. Transfer function and the control variable of PID controller respectively are shown in equations (5) and (6),

$$G_c(s) = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) \qquad (5)$$

$$U = K_P\, e(t) + K_i \int e(t)\, dt + K_d\, \dot{e}(t) \qquad (6)$$

Although in the recent decades many advanced controllers are introduced because of the mentioned properties of PID controllers, they kept their vast usage in industry. In this article despite keeping the PID controller's properties, MPC strategy is used for tuning the parameters of PID controller.

To design the PID controller by concepts of predictive control, the control effort in equation (6) is replaced by ΔU which given in equation (1). Respect to the variation of manipulating variable ΔU, the optimal PID controller parameters are on-line tuned by minimizing the quadratic cost function is given in equation (1).

Some effective parameters, as prediction horizon, control horizon and r_w can have had a great influence on the performance of the controller. So these parameters are tuned with a multi-objective optimization respect to two cost functions. The first cost function is the minimization of maximum control effort as follows,

$$F1 = \text{Minimize}\ (\text{Max}\ (|U|)) \tag{7}$$

And the second objective function is the integral of absolute error (IAE) as follows,

$$F2 = \text{minimize}\left(\int_0^{\infty} |e(t)|\, dt\right) \tag{8}$$

Pareto multi-objective genetic algorithm is used to obtain optimum non-dominated solutions of such two objective functions optimization problem.

4. Simulation and results

The control of an inverted pendulum Fig. 1. is a well-known benchmark problem to compare with different methodologies. The inverted pendulum is required to stay as perpendicular as possible, i.e., θ=0°. The dynamic equations of this system are [7].

$$\dot{x}_1 = x_2 \tag{9}$$

$$\dot{x}_2 = \frac{g\sin x_1 - \frac{m l x_2^2 \cos x_1 \sin x_1}{m_c + m} + \frac{\cos x_1}{m_c + m} u}{l\left(\frac{4}{3} - \frac{m \cos x_1^2}{m_c + m}\right)} \tag{10}$$

Where, x_1 and x_2 are the angle and angular velocity of pendulum. Parameters of inverted pendulum in equation (10) are selected as, m_c=0.455, m=0.210, l=0.610 and g=9.81 which are, mass of the cart, mass of the pendulum, length of the pendulum, and the gravity acceleration, respectively. Genetic algorithm is used to take the nonlinearities of the plant into account. In conventional system to create the state-space matrices, if the angle is inside the linear region (θ ≤ ±12°) (it is considered as sin (θ) = θ and cos(θ) = 1). Otherwise, if the point is out of the linear region the mentioned state-space model does not work as well. So the proposed method is presented to let the plant work more precisely, and take the nonlinearities of the system into account. For this purpose the equation (11) that consists of a series of nonlinear terms substituted with a linear polynomial that its coefficients obtained using genetic algorithm (GA).

$$\dot{x}_2 \approx \hat{\dot{x}}_2 = a x_1 + b x_2 + c u \tag{11}$$

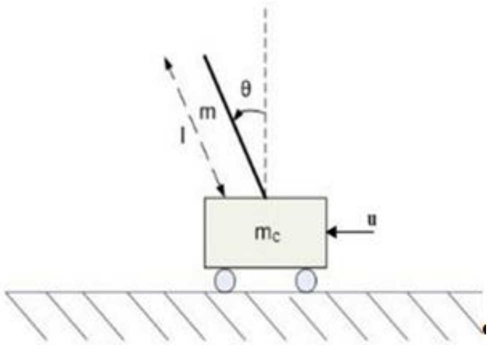

Fig. 1. a schematic of gripper

$$\text{Error} = \dot{x}_2 - \hat{\dot{x}}_2 \tag{12}$$

To get the best fitness, equation (13) is minimized respect to a, b and c as the optimization variables. Using GA algorithm, the coefficients in equation (12) are derives as a=0.5834, b=-0.8055 and c=1.3759. So the modified dynamic equations are as follows:

$$\dot{x}_1 = x_2 \tag{13}$$

$$\dot{x}_2 = 0.5834\, x_1 - 0.8055\, x_2 + 1.3759\, u \tag{14}$$

Theses state space model is now used to design a PID controller based on MPC for nonlinear inverted pendulum model.

Multi-objective genetic algorithm with population size of 100, generation number of 500, probability of crossover, 0.92, and probability of mutation, 0.1, have been used to tune the PID parameters.

By minimizing two objective functions, the 13 non-dominated solutions are obtained and given in Fig. 2. In this figure, the design points A and B stand for the best control effort and IAE, respectively. As shown in this figure, moving from one placement on the aforementioned curve to another one changes the value of one of the corresponding objective function to a lower level in relation to the last placement. But, astonishingly the other one's ascends to a better level with respect to the last position. Accordingly, such treatment of those two objective functions shows a kind of confliction which none of them has any superiority on the other one. By this way, none of the results obtained by the optimization approach of this work overlook each other and, therefore, they are non-dominated and can be chosen for the purpose of designing. The corresponding values of the design variables of the Pareto front are the best feasible ones which can be obtained by the process of optimal designing. So that, by selecting any others groups of design variables the values of the corresponding objective functions situate an area with lower status in relation to the proposed optimum points of this methodology. This so-called inferior location is seen in the top/right side of the curved presented in Fig. 2. Point C can be optimally chosen from a trade-off point of view for objectives control effort and IAE.

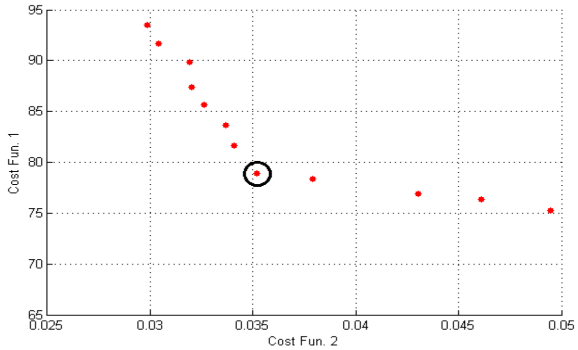

Fig. 2. Pareto front of 2-objective optimization

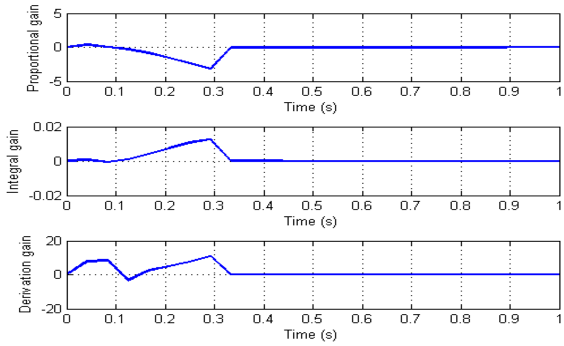

Fig. 3. Trends of PID parameters belong to proposed controller

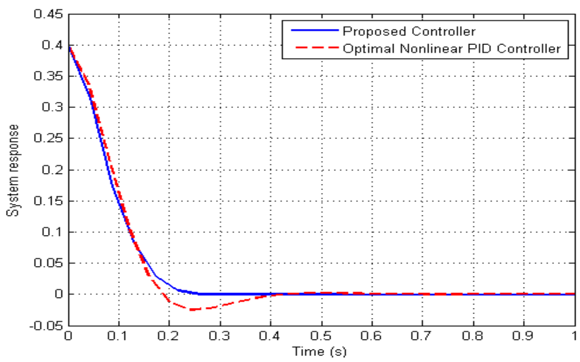

Fig. 4. Comparison of the responses between proposed controller and Optimal N-PID

As considered before, in each sample time three PID controller parameters Kp, Ki, Kd exist that the trend of them are demonstrated in Fig. 3. The time response and control effort of the design point C are shown in Figs. 4 and 5, respectively.

Table 1. Comparison of the presented controllers

Type	$\int_0^\infty \lvert e(t)\rvert\,dt$	Max $\lvert U\rvert$
Proposed Controller	0.0352	78.9182
Optimal Nonlinear PID Controller	0.0395	80.1268

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