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A New General Type-2 Fuzzy Predictive Scheme for PID Tuning

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Abstract: The proportional-integral-derivative controller is widely used in various industrial applications. But, in many noisy problems the strong methods are needed to optimize the proportional-integral-derivative parameters. In this paper, a novel method is introduced for adjusting the proportional-integral-derivative parameters through the model predictive control and generalized type-2 fuzzy-logic systems. The rules of suggested fuzzy system are online adjusted and the parameters of proportional-integral-derivative are tuned based on the fuzzy model such that a cost function to be minimized. The designed controller is applied on continuous stirred tank reactor and the performance is compared with other traditional approaches. The main advantages are that the accuracy is improved by online modeling and optimization and a predictive scheme is added to the conventional proportional-integral-derivative controller.

Keywords: fuzzy systems; machine learning; model predictive control; proportional-integral-derivative controller; continuous stirred tank reactor; self-tuning

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1. Introduction

The proportional-integral-derivative (PID) controller is one of the prevalent controllers that is widely used because of its simple structure and acceptable performance. The PID has three control modes, proportional, integral and derivative modes. Proportional control mode is, in most cases, the driving force of the controller. This mode changes the output of the controller according to the level of error. If the error is large, the control action is also larger. If the controller gain is set to a very high value, the control loop will start to oscillate and become unstable. On the other hand, if the gain is too low, responding to disturbances or changes in the set point will not be effective enough. Adjustment of the proportional gain also affects the integral and derivative modes. That is why this parameter is also called the controlling gain. When there is an error, the integrated control mode continuously increases or decreases the output of the controller to reduce the error to zero. If the error is large, the integral mode rapidly increases or decreases the output of the controller, and if the error is small, changes will occur more slowly. The operation speed of the integral mode is set with the integral gain. A small gain causes a slow integral operation, and a big one leads to a fast integral operation. If the integral gain is too small, the controller will be very slow, and if it is too large, the control loop will be fluctuated and unstable. The third control mode

in a PID controller is derivative mode. Derivative control is rarely used in process control, but it is more commonly used in motion control. This type of controller is very sensitive to measurement noise in process control and makes adjustment using trial and error more difficult. However, the use of a derivative mode slightly increases the response speed [1,2]. Then developing of tuning algorithms are essential to improve the performance.

The model predictive control (MPC) is one of the most advanced control models for the practical systems. Because, the main control limitations and other state retractions can be taken into account in the control designing. However, but it is difficult to implement and many engineers are not familiar with it. To solve this problem, a novel combined scheme of MPC and PID controller implemented in a two-tier hierarchical structure is proposed. The performance of MPC is strongly depends on the model accuracy. However in many applications, the model is not available or not reliable in practical conditions. Commonly the mathematical model is perturbed by various factors and this problem undermines the MPC performance. We proposes a online optimized type-2 fuzzy model. The suggested identification scheme is updated sample-by-sample and guarantees the accurate model. Also the online tuned model can handle the unpredicted dynamic perturbations.

The main challenges and problems are summarized as follows:

- The PID is a simple and effective controller, but in many applications the gains should be tuned. The un-tuned parameters leads to undesired performance and/or instability.
- The most of existence regulation methods such evolutionary methods impose high computational cost.
- The predictive scheme in many applications improves the control accuracy, but its implementation is more difficult than PID.
- The MPC results in good performance, but its accuracy strongly depends on the model.

2. Literature Review

The computational intelligence is recently widely used in optimization problems [3–5]. The PID tuning by the neural-networks (NNs), FLSs and evolutionary optimization techniques have recently been studied. For example, in [6] the Kalman filter is developed for optimizing a PID in control of joint robotic manipulator. In [7], by the use of Matlab toolbox a model is estimated and then the parameters of PID are adjusted and evaluated on a robotic application. The harmony search technique is developed in [8] for destining an optimal PID. The gradient descent is suggested in [9] for tuning and the convergence speed is analyzed. In [10], the NNs are used to determine the gains of PID and the back-propagation scheme based on Smith predictor is developed for training of NNs. In [11], a NN is learned to tune the PID gains and effect of nonlinearities is investigated. In [12], using the NNs and FLSs, the gains of PID are calculated, and it is shown that the suggested approach has less settling time than the other models. In [13], a robust PID is introduced for Quadcopters that are constantly exposed to parametric changes as well as external disturbances. In [2], for tuning the parameters of PID, a deep learning NN is suggested and it is shown that, the number of attempts to adjust the controller is reduced, and also less data is needed for learning. In [14] to remote control operation of underwater vehicles with unknown disturbances, an NN based self tuning PID controller is designed to track the route, and it is shown that compared to conventional PIDs, suggested method shows better performance with less energy. In [15], a PID controller is optimized by NNs and it is applied for oxygen control system.

The other class of PID regulation methods is the evolutionary based algorithms. For example the weight beetle antenna method is developed in [16], for PID tuning and its performance is evaluated on hydraulic plant. The genetic algorithm is applied in [17] to tune the PID gains and the optimized PID is used for a temperature control problem. The various swarm-based tuning methods are studied in [18] and a new scheme is suggested by combining the bacterial foraging and particle swarm optimization (PSO) methods. In [19], the performance of PSO is improved by the use of chaotic systems and the optimized PID

is applied for a voltage control problem. The multi-objective PSO is formulated in [20] for optimizing the PID controller of a aerial vehicle. The Chien-Hrones-Reswick approach is analyzed in [21] and it is applied for glucose regulation problem.

The continuous stirred tank reactor (CSTR) is one of the units used in the industry to perform some chemical activities and produce products. As the operating level of the system changes, CSTRs exhibit nonlinear behavior. To better control of CSTR some PID based methods have been designed. For example, in [22], considering two input disturbances, a Particle Swarm optimization (PSO)-based PID is proposed. In [23], a PID-based fuzzy controller is designed to control the CSTR temperature. In this controller, the gain is controlled and determined by an adaptive stabilization block. By the results comparing, it is shown that FLS based PID has a much better performance in tracking than the conventional PIDs. In [24], the dynamically updated PID is suggested to control the CSTR units under variable parameterise. The gray wolf optimization scheme is suggested in [25] for PID tuning, and it is shown that the suggested tuning scheme gives better control accuracy than genetic and PSO algorithms.

The predictive controller is one of the interesting approaches to cope with system restrictions and improve the tracking performance. However, this technique has been rarely used for accuracy improvement of PID. For example, in [26], a PID is optimized by the use of FLSs and a predictive controller is used to improve the performance. In [27], the MPC is developed for control of eco-driving and it is compared with PID. In [28], the wavelet NNs are used to construct a predictive scheme for PID. The PSO algorithm is developed in [29], to design a predictive PID. The Hägglund's controller [30] is developed for second-order processes and it is called a predictive PID and the effect of dead time is investigated. In [31], a predictive sequence of output of a power system is obtained and then a PID is designed. In [32], the bacterial foraging algorithm is used to determine the parameters of the PID and it is combined with a predictive controller in parallel. In the most of above reviewed papers, the designed predictive controllers can not handle the high noisy nonlinear conditions and also the designed controller just can be applied for special case-study systems. Also, some optimization algorithms with high computational cost are used that are not appropriate for high speed practical plants.

The main contributions are as follows:

- A simple practical controller is proposed based on good features of popular PID and MPC methods.
- A type-2 fuzzy approach is suggested for online modeling that improves the MPC performance.
- An online optimization scheme is presented to handle the online unpredicted disturbances.
- The better performance is shown by several simulations.

3. Identification by Fuzzy System

This section illustrates the generalized type-2 fuzzy-logic systems (GT2-FLS) that is used for online modeling. The general scheme of the proposed control system is depicted in Figure 1. As it is seen from Figure 1, the system model is online identified by the suggested GT2-FLS. The structure of GT2-FLS is depicted in Figure 2 and details are illustrated as follows.

(1) The inputs of GT2-FLS are control signal and system output at previous sample times.
(2) The suggested membership function (MF) is shown in Figure 3. For β slice level, we have:

$$\begin{aligned}\bar{\vartheta}_{\tilde{\psi}^h_{i,\beta}}(x_i) = \tfrac{1}{2}\left(\bar{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i) + \underline{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i)\right) + \\ \tfrac{1}{2\ln(1/\varepsilon)}\left(\bar{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i) - \underline{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i)\right)\sqrt{\ln(1/\beta)}\end{aligned} \quad (1)$$

$$\begin{aligned}\underline{\vartheta}_{\tilde{\psi}^h_{i,\beta}}(x_i) = \tfrac{1}{2}\left(\bar{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i) + \underline{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i)\right) - \\ \tfrac{1}{2\ln(1/\varepsilon)}\left(\bar{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i) - \underline{\vartheta}_{\tilde{\psi}^h_{i,0}}(x_i)\right)\sqrt{\ln(1/\beta)}\end{aligned} \quad (2)$$

where,

$$\bar{\vartheta}_{\tilde{\psi}_{i,0}^{h}}(x_i) = \exp\left(-\frac{\left(x_i - c_{\tilde{\psi}_{i,0}^{h}}\right)^2}{\bar{\sigma}^2_{\tilde{\psi}_{i,0}^{h}}}\right) \tag{3}$$

$$\underline{\vartheta}_{\tilde{\psi}_{i,0}^{h}}(x_i) = \exp\left(-\frac{\left(x_i - c_{\tilde{\psi}_{i,0}^{h}}\right)^2}{\underline{\sigma}^2_{\tilde{\psi}_{i,0}^{h}}}\right) \tag{4}$$

where $\tilde{\psi}_{i,0}^{h}$ denotes the h^{th} MF for $i-th$ input, $c_{\tilde{\psi}_{i,0}^{h}}$ represents the center of MF, ε is the small constant and $\underline{\sigma}_{\tilde{\psi}_{i,0}^{h}}$ and $\bar{\sigma}_{\tilde{\psi}_{i,0}^{h}}$ are the standard divisions.

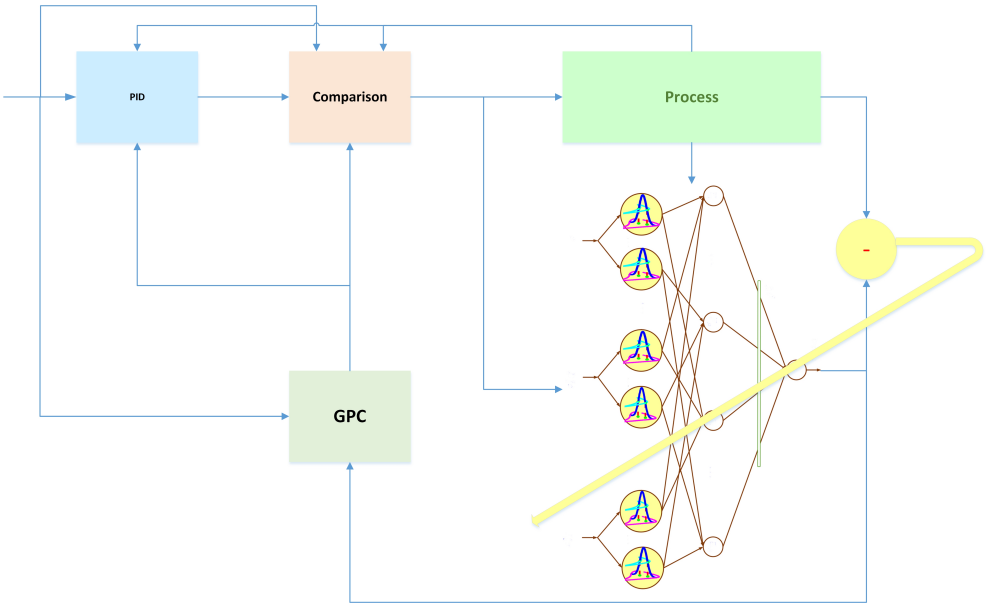


Figure 1. Schematic of the proposed control scheme.

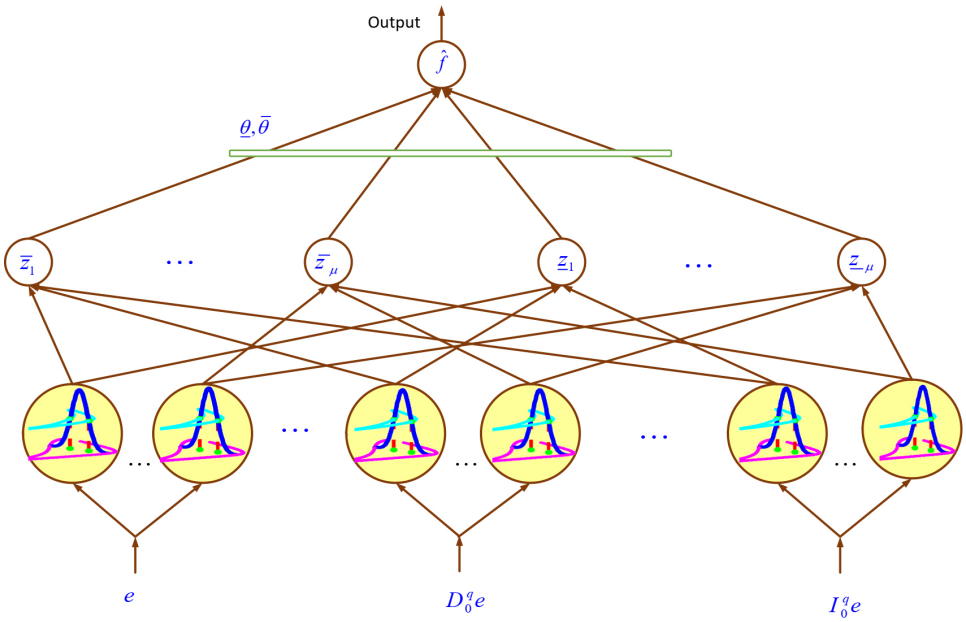


Figure 2. The structure of the proposed GT2-FLS.

(3) The rule firings are written as:

$$\bar{z}_{h,\beta} = \bar{\vartheta}_{\tilde{\psi}^h_{1,\beta}}(x_i) \times \cdots \bar{\vartheta}_{\tilde{\psi}^h_{n,\beta}}(x_i) \tag{5}$$

$$\underline{z}_{h,\beta} = \underline{\vartheta}_{\tilde{\psi}^h_{1,\beta}}(x_i) \times \cdots \underline{\vartheta}_{\tilde{\psi}^h_{n,\beta}}(x_i) \tag{6}$$

where, $h = 1, ..., \mu$ and μ are rules number.

(4) The output is written as:

$$\hat{f} = \frac{\sum_{h=1}^{\mu} \beta \left(\bar{z}_{h,\beta} \bar{\theta}_h + \underline{z}_{h,\beta} \underline{\theta}_h \right)}{\sum_{\beta} \sum_{h=1}^{\mu} \bar{z}_{h,\beta} + \underline{z}_{h,\beta}} \tag{7}$$

where, $\bar{\theta}_h$ and $\underline{\theta}_h$ are rule parameters.
The rule parameters are leaned by the following adaptation law:

$$\bar{\theta}_h(t+1) = \bar{\theta}_h(t) + \gamma \sum_{\beta} \frac{\beta \bar{z}_{h,\beta}}{\sum_{h=1}^{\mu} \bar{z}_{h,\beta} + \underline{z}_{h,\beta}} e \tag{8}$$

$$\underline{\theta}_h(t+1) = \underline{\theta}_h(t) + \gamma \sum_{\beta} \frac{\beta \underline{z}_{h,\beta}}{\sum_{h=1}^{\mu} \bar{z}_{h,\beta} + \underline{z}_{h,\beta}} e \tag{9}$$

where, γ is a constant and e represents the tracking error.

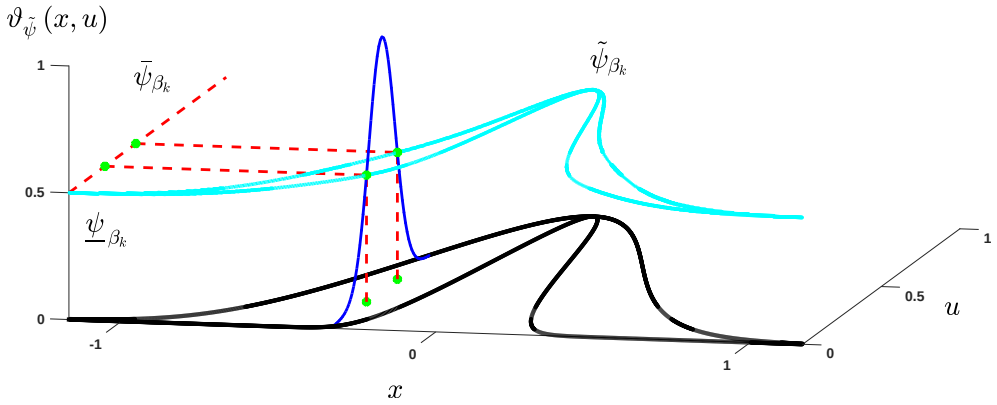


Figure 3. Proposed membership function.

4. Predictive Control

The prediction model is a model-based controller that has the same design for different models, but its performance varies according to the output model of the system. This model, which can take into account the limitations of the system, is quite suitable for complex systems. Generalized predictive control (GPC) and nonlinear model predictive control (NMPC) are the most widely used types of this controller. Predictive controllers can be designed as multiple inputs, multiple outputs (MIMO), and can be combined, but they are generally considered separately. Considering $U(K)$ as the controller output, $Y(K)$ as the system output, and $Y_s(K)$

as the optimal system output at moment K, we can define the Equation (10). Also P can be considered for the predictive horizon and M for the control horizon.

$$\begin{array}{l} U = \\ [u(k), u(k+1), \ldots, u(k+M-1)]^T \\ \hat{Y} = \\ [\hat{y}(k+1), \hat{y}(k+2), \ldots, \hat{y}(k+P)]^T \\ w = \\ [\mathrm{y}_s(k+1), \mathrm{y}_s(k+2), \ldots, \mathrm{y}_s(k+P)]^T \end{array} \tag{10}$$

By minimizing the following objective function, we can obtain the vector u, which is used to obtain the desired value of the system. In this case, λ is the weight on the output of the controller and $\hat{y}$ is the system forecast.

$$\begin{array}{l} min \;\; J = \\ \sum_{i=1}^{P} [\hat{y}(k+i) - \mathrm{y}_s(k+1)]^2 \\ \quad +\lambda \sum_{j=0}^{M} [\Delta u(k+j)]^2 \end{array} \tag{11}$$

By predicting the state of the system up to moment $k+p$, we can give only the first state to the system instead of using the U vector, and then recalculate the information with the new system specifications at a later time. In this way we can consider input disturbance and errors in embedding.

GPC Controller

Using the function conversion model, this controller is designed and can be run on unstable systems. It also requires less system parameters to model this controller than other methods. Equation (12) can be considered for a linear system

$$\begin{array}{l} \Delta A\left(z^{-1}\right) y(k) = \\ \quad B\left(z^{-1}\right) \Delta u(k-1) + C\left(z^{-1}\right) e(k) \end{array} \tag{12}$$

The expression $e(k)$ in (12), which is related to disturbance signals, can be chosen definitively or randomly. A and B are also polynomials of the expression z^{-1}. In this formula, C is also considered as random disturbance and it can be considered as one in the case of white noise. By minimizing the objective function of (11) and using the linear model shown in (12), the system can be predicted up to moment $k+p$. Also, for modeling nonlinear systems and those systems that are variable at any time, we can estimate the system at any time with a linear model. In this method, where variables A and B are constantly changing, we can model the behavior of the system well. This model is a GPC controller that can be used as an adaptive controller.

5. Obtain PID Parameters with Predictive Control

The PID controller is usually continuous and its overall structure is described by Equation (13) .

$$\frac{U(s)}{e_s(s)} = k_c + \frac{1}{T_I s} + T_D s \tag{13}$$

The general structure of the discontinuous PID control can also be described as Equation (14). In this relation, r_2, r_1, r_0 are the control parameters and S also determines the response speed.

$$\frac{u_{PID}(k)}{e_s(k)} = \frac{r_0 + r_1 z^{-1} + r_2 z^{-2}}{(1 - z^{-1})(1 + s z^{-1})} \tag{14}$$

$$e_s(k) = y_s(k) - y(k) \tag{15}$$

Equation (15) also indicates the error between the system output value and the desired value at moment k. By calculating Equation (14), the output of the control is obtained in accordance with Equation (16). Using this relation, the output of the controller can be obtained at moment k. We also consider the parameter $y(k)$ to consider the delay between system input and output.

$$\begin{aligned} u_{PID}(k) &= (1-s)u(k-1) + su(k-2) \\ &+(r_2 + r_1 + r_0)y_s(k) - r_0 y(k) \\ &-r_1 y(k-1) - r_2 y(k-2) \end{aligned} \tag{16}$$

If we consider the output of the controller at moment k as $U_{GPC}(k)$, we can consider an objective function such as equation (17) for it.

$$l_i \prec u_{PID}(k+i) \prec L_i \tag{17}$$

In above equation, L_i is the maximum and l_i is the minimum value that the system can consider as input at the moment $k+p$. Also, U_{GPC} can be obtained by minimizing Equation (11). The value of u_{PID} is also calculated according to Equation (18). In this equation, we can use the predicted value instead of the system output value.

$$\begin{aligned} u_{PID}(k) &= (1-s)u_{PID}(k-1) + su_{PID}(k-2) \\ &+(r_0 + r_1 + r_2)y_s(k) - r_0 y(k) \\ &-r_1 y(k-1) - r_2 y(k-2) \end{aligned}$$

$$\begin{aligned} u_{PID}(k+1) &= (1-s)u_{PID}(k) + su_{PID}(k-1) \\ &+(r_0 + r_1 + r_2)y_s(k+1) \\ &-r_0 \hat{y}(k+1) - r_1 y(k) - r_2 y(k-1) \end{aligned}$$

$$\begin{aligned} u_{PID}(k+i) &= (1-s)u_{PID}(k+i-1) \\ &+su_{PID}(k+i-2) \\ &+(r_0 + r_1 + r_2)y_s(k+i) \\ &-r_0 \hat{y}(k+i) - r_1 \hat{y}(k+i-1) \\ &-r_2 \hat{y}(k+i-2) \end{aligned} \tag{18}$$

6. Observer Controller

For the observer controller, we use GPC. A PID controller with fixed parameters can control many chemical processes well due to their low speed. And if the system changes or there is a disturbance in the system input, it is better not to change the parameters of the PID controller and to control the system by changing the system appropriately. Given the above, we need to use a observer controller to observe the proper operation of the PID controller, and if the PID controller did not work properly, using Equation (16), with the new parameters, the controller return to the normal PID again. For the observer controller, we use the GPC controller. With this design, in addition to greatly reducing the amount of calculations, the parameters of the PID controller can be changed only if necessary. We also no longer need to apply the prediction strategy at any time.

7. Temperature Control of CSTR Units

7.1. Control Performance

By considering a CSTR (see Figure 4), and assuming that the physical properties of the reactor and its volume are constant and that its composition is complete, we can model the reactor according to Equations (19)–(21).

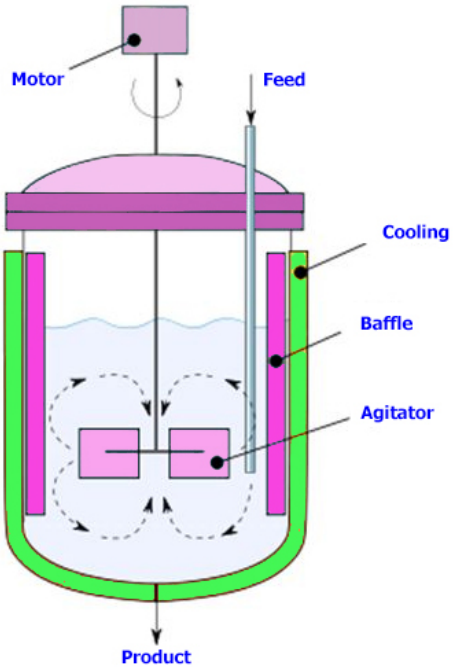


Figure 4. CSTR Unit performance process.

$$\begin{array}{l} \frac{dC_A}{dt} = \frac{q}{V}(C_{AF} - C_A) \\ -k_0 C_A exp\left(\frac{-E_a}{RT}\right)\varphi_c(t) \end{array} \tag{19}$$

$$\begin{array}{l} \frac{dT}{dt} = \frac{q}{V}(T_F - T) \\ \quad -\frac{\Delta H}{pc_P}k_0 C_A exp\left(\frac{-E}{RT}\right)\varphi_c(t) \\ +\frac{\rho_C C_{PC} q_C}{pc_P V}\left(1 - \exp\left(-\frac{h_A}{q_C \rho C_P}\varphi_h(t)\right)\right)\left(T_{cf} - T\right) \end{array} \tag{20}$$

$$\frac{dT_j}{dt} = \frac{UA}{pc_P V}(T - T_j) + \frac{u}{V_j}(T_{jF} - T_j) \tag{21}$$

The parameters used in Equations (19)–(21) are as given in Table 1.

Table 1. System description.

C_A	Concentration of the substance A inside the reactor
T	Temperature inside the reactor
Q	feed fluid flow, 0.2 m^3/min
V	reactor volume, 2 m^3
T_F	feed temperature, 30 °C
P	Medium density of material, 1000 kg/m^3
k_0	constant reaction speed, 3.5×10^6 L/min
E_a	activation energy, 49.88 Kj/mol
UA	heat transfer coefficient, 252 kj/min°C
R	gases constant, 8.134×10^{-3} kj/mol°C
V_j	jacket volume, 0.4 m^3
H_r	heat of reaction, 500 kj/mol
T_{jF}	inlet fluid temperature to the jacket, 10 °C
C_{AF}	Concentration of substance A in feed, 100 mol/m^3
$\varphi_c(t)$	Deactivation coefficient, 1
$\varphi_h(t)$	Fouling coefficient, 1
h_A	Heat transfer term, 7 × 105 cal/(min · k)
T	Reactor temperature, 438.7763 K

7.2. CSTR Temperature Control

Using a PID controller that has a GPC controller as the controller, we control the temperature of the CSTR units. Also, by minimizing the error function, the parameters of the PID controller can be obtained, which are as follows:

$$k_c = 0.521 \qquad T_I = 0.135 \qquad T_D = 0.706 \tag{22}$$

The system can be controlled using a PID controller whose parameters are determined by the GPC controller. In this method, the GPC controller can provide a linear model according to Equation (23) using the error squared minimization method, with an adaptive forgetting factor to define the system.

$$T(k) = \frac{b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} u(k) + \frac{e_s(k)}{\Delta} \tag{23}$$

The GPC controller is implemented according to the obtained model and determines the parameters of the PID controller, and the values of P, M and λ for the forecast horizon, control horizon and weight on the controller output are as follows, respectively. Also, the value of N is equal to 4.

$$P = 8 \qquad M = 3 \qquad \lambda = 0.23 \tag{24}$$

Equation (25) indicates the allowable range of the controller output. Also, the PID controller parameter correction index is set to one percent.

$$0.01 \leq u \leq 0.3 \tag{25}$$

8. Simulation Results

To evaluate the performance of the proposed method in this paper, we compare it with other existing methods such as traditional PID and MPC Self Tuning PID. In the simulation results, the less oscillating the output figure, shows the better performance of the method . Figure 5 shows the results of this comparison. By zooming in on part of this figure, Figure 6 is obtained, and it is observed that the performance of suggested Self Tuning PID method has less fluctuations than the other two methods. So it is clear that our proposed method performs better than the other two methods. Temperature changes are one of the conditions that should be considered to evaluate the performance of the proposed method. As shown in Figure 7, temperature changes are applied to the system and, as can be seen, decrease from 360 k to 350 k at t = 50 s and then increase from 350 k to 360 k at t = 150 s. Figure 8, the control signal is related to Figure 7, and the control signal shows the three methods mentioned. By zooming in, Figure 9 is obtained and it is seen that MPC self tuning PID is much better than traditional PID, but suggested self tuning PID method, is much better than both methods.

Tank parameters can be changed for various reasons, such as temperature increase, and its equations can be completely disrupted. Considering the ±20% change in tank parameters, we evaluate the performance of the three methods used to control the system and the results are shown in Figure 10. By zooming in on a part of Figure 10, Figure 11 is obtained, and as can be seen, the GT2-FLS method has a much better performance than the other two methods for controlling the system with the mentioned conditions. In other words, Figures 10 and 11 clearly show the superiority of our method over other methods. According to the results obtained from the simulations, we find that the FLS method has the least changes and has a significant advantage over the other two methods.

Figures 5–11, show that the designed PID controller gives better regulation performance. We see that the overshoots for the suggested PID is significantly less than other PIDs. Also, the settling time is much better than the compared PIDs. It should be noted that the suggested PID uses a strong tool based on GT2-FLSs for adjusting the gains that is more applicable in noisy environment. Also the suggested predictive scheme, improves

the accuracy. Furthermore, the online optimization technique ensures the better robustness against the disturbances.

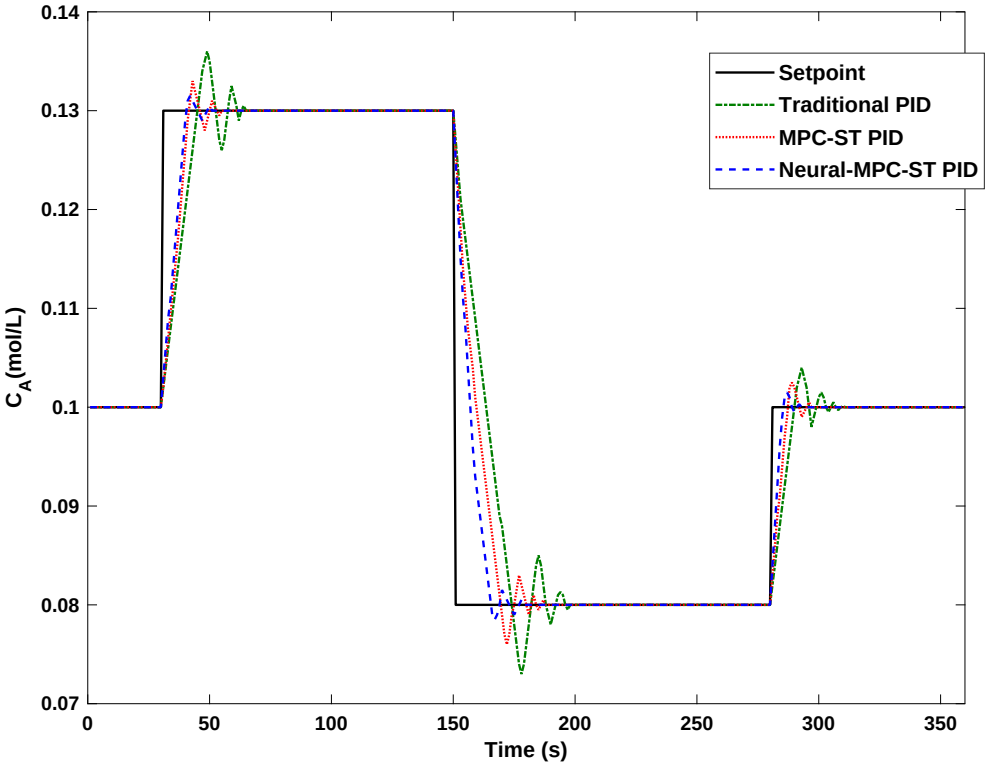


Figure 5. Comparison of suggested MPC Self Tuning PID method performance with traditional PID and MPC Self Tuning PID.

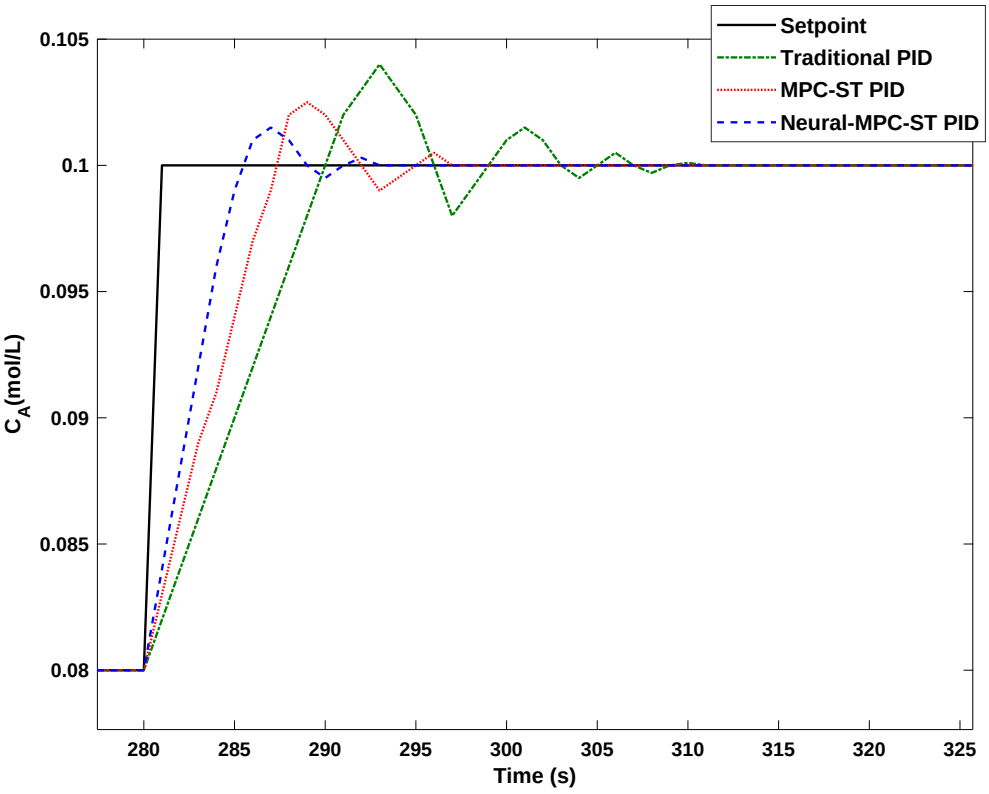


Figure 6. A closer look at a part of Figure 5.

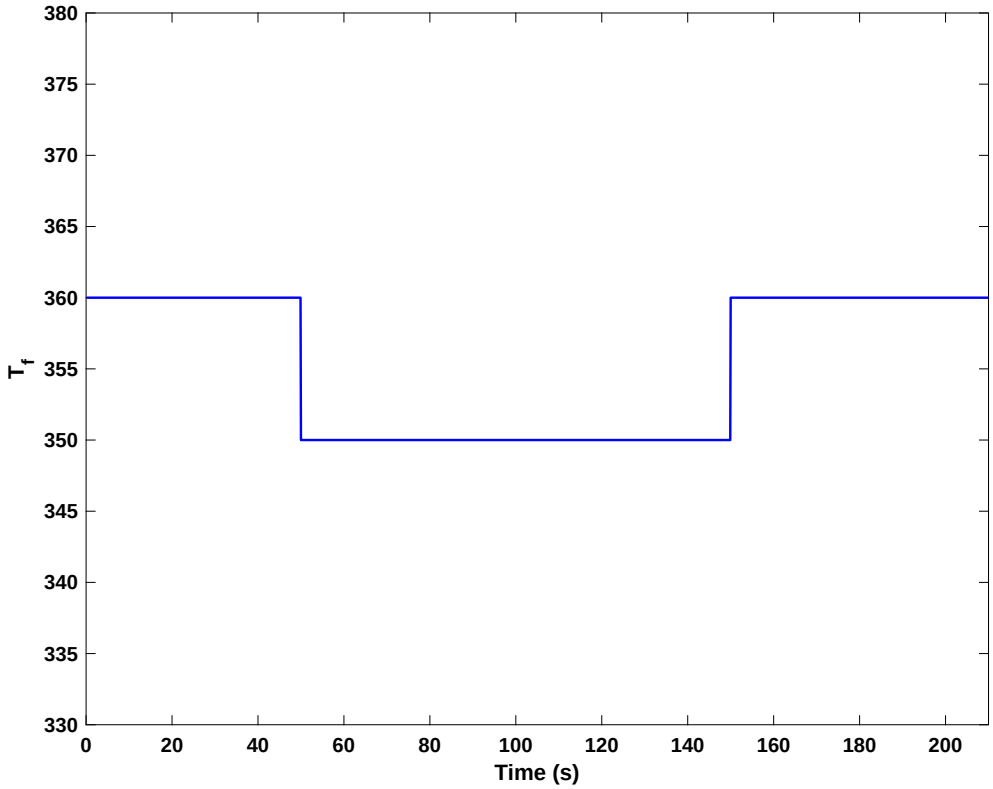


Figure 7. Temperature changes applied to the system.

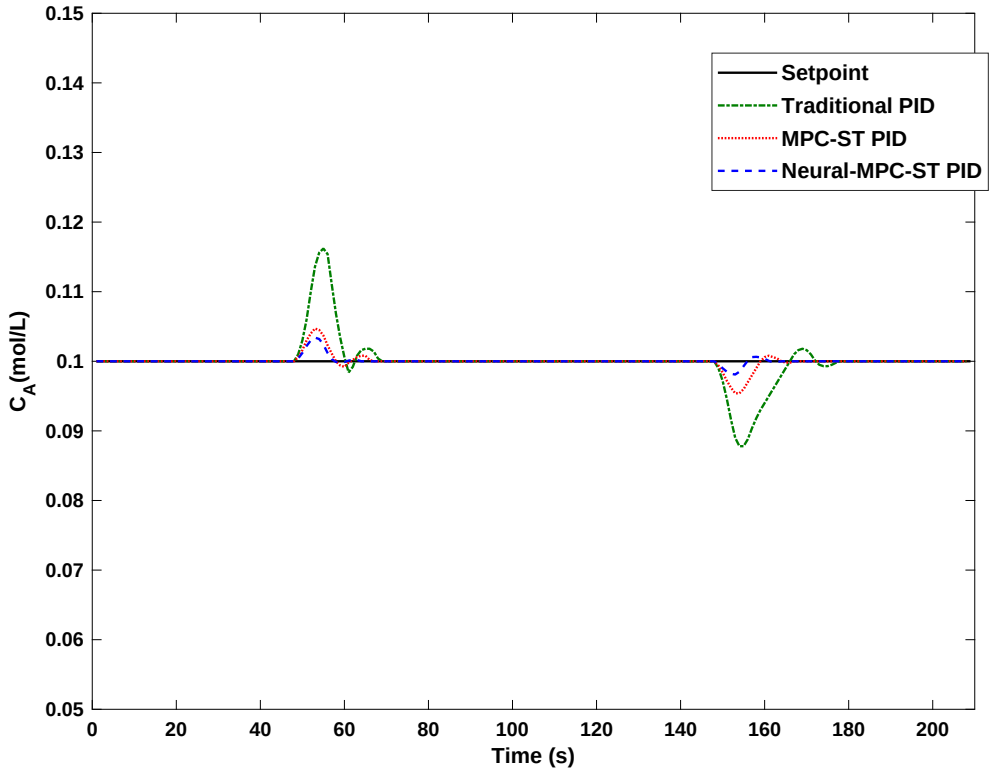


Figure 8. Control signal related to applied temperature changes.

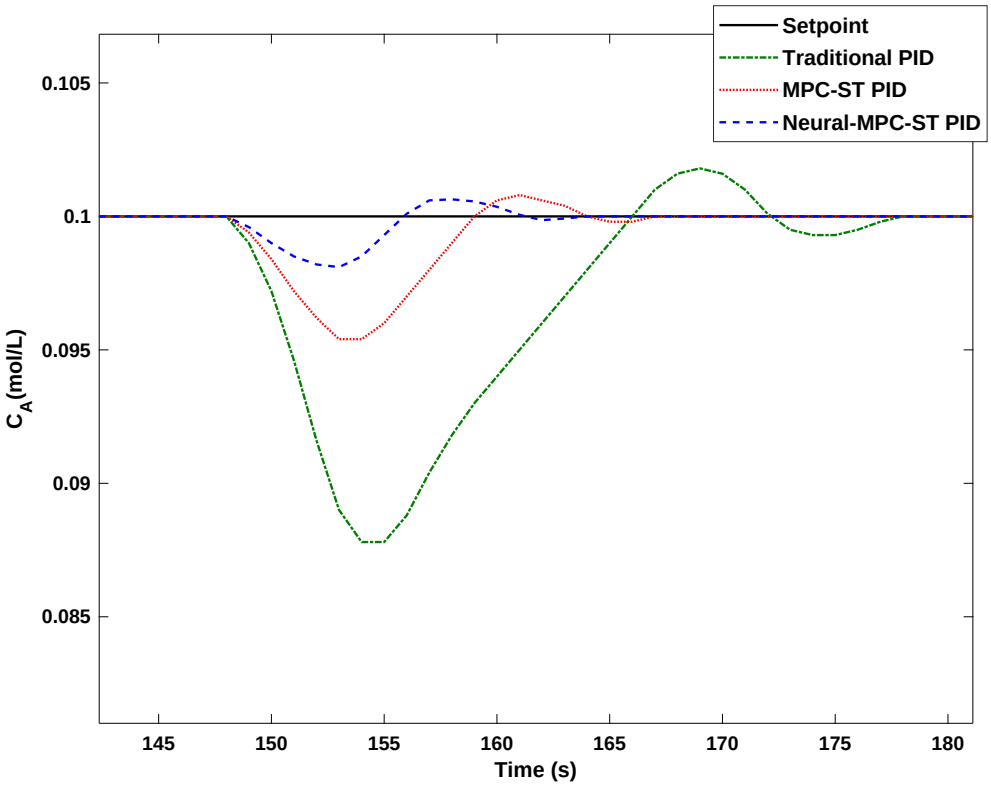


Figure 9. A closer look at a part of Figure 8.

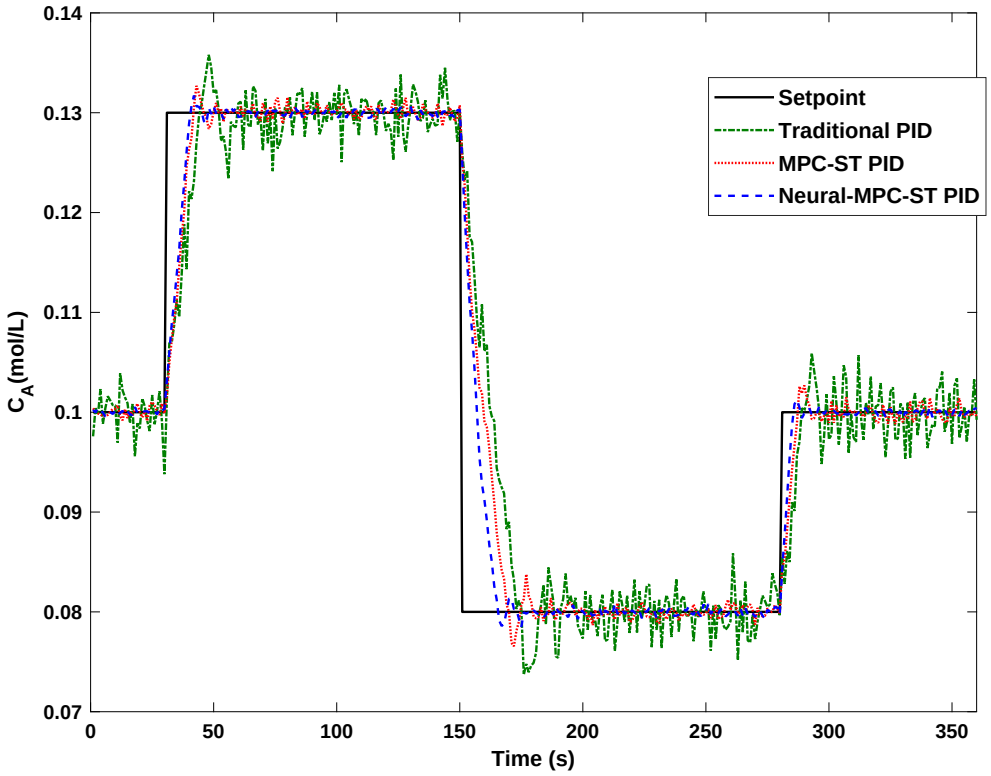


Figure 10. Comparison of the performance of the three control methods, taking into account the ±20% change in tank parameters.

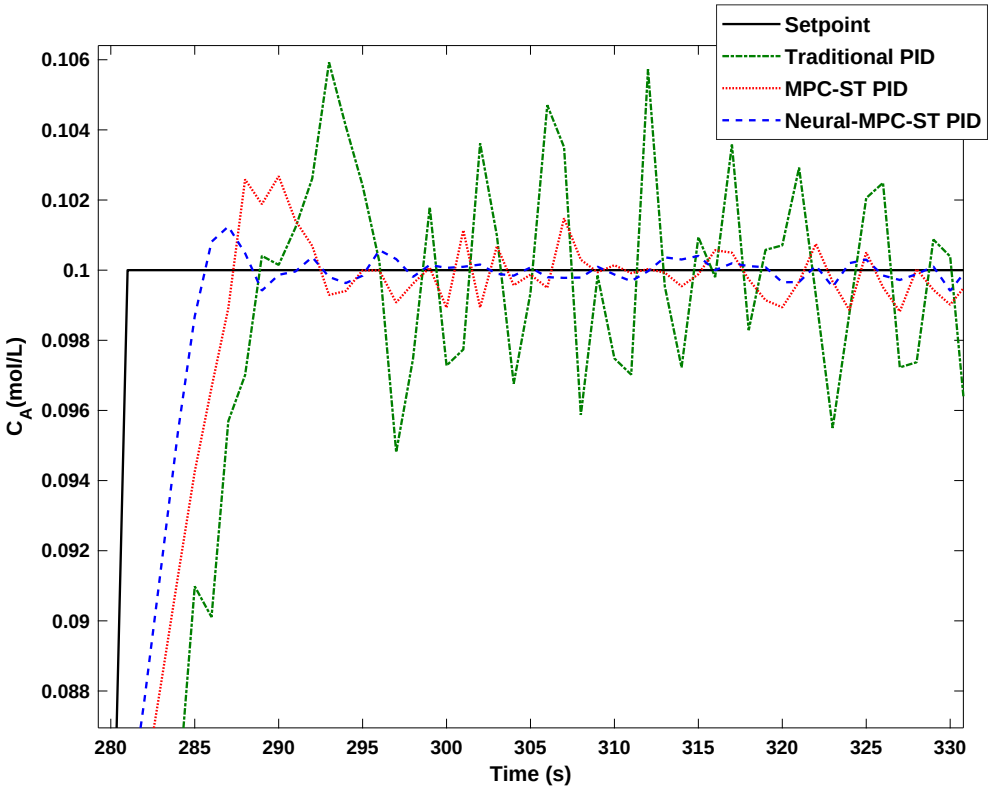


Figure 11. A closer look at a part of Figure 10.

9. Conclusions

The PID controller is extensively used in industrial applications. The PID gains are commonly tuned in an off-line approach. In other words, the PID gains are adjusted on basis of the plant information such as mathematical model, input-output data sets and transfer function, and then it is applied on system. By a small disturbance, the gains commonly get out of the desired range and the gains should be re-adjusted. For better automatic adjusting, in this paper a better self-tuning scheme is proposed. In this paper, a new method for adjusting the parameters of the PID controller using the generalized type-2 FLS and MPC scheme is presented and it is used to control the CSTR units. The suggested PID has the predictive property and it is online updated based on the online optimized GT2-FLS model. The generalized type-2 FLSs have better efficiency in noisy and practical applications. According to the simulations presented, suggested self tuning PID method is clearly superior to the traditional PIDs and other similar methods. The main difficulties that have been overcome by the suggested scheme are that: (1) The controller dependency on the mathematical model of the plant is eliminated, (2) The performance is improved by the suggested GT2-FLS modeling, (3) Online optimization scheme improves the robustness against unpredicted disturbances, (4) A predictive scheme is added to the conventional PID.

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