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Model predictive control based on chaos particle swarm optimization for nonlinear processes with constraints

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Abstract

Purpose – The purpose of this paper is to propose a new type of predictive fuzzy controller. The desired nonlinear system behavior is described by a set of Takagi-Sugeno (T-S) model. However, due to the complexity of the real processes, obtaining a high quality control with a short settle time, a periodical step response and zero steady-state error is often a difficult task. Indeed, conventional model predictive control (MPC) attempts to minimize a quadratic cost over an extended control horizon. Then, the MPC is insufficient to adapt to changes in system dynamics which have characteristics of complex constraints. In addition, it is shown that the clustering algorithm is sensitive to random initialization and may affect the quality of obtaining predictive fuzzy controller. In order to overcome these problems, chaos particle swarm optimization (CPSO) is used to perform model predictive controller for nonlinear process with constraints. The practicality and effectiveness of the identification and control scheme is demonstrated by simulation results involving simulations of a continuous stirred-tank reactor.

Design/methodology/approach – A new type of predictive fuzzy controller. The proposed algorithm based on CPSO is used to perform model predictive controller for nonlinear process with constraints.

Findings – The results obtained using this the approach were comparable with other modeling approaches reported in the literature. The proposed control scheme has been show favorable results either in the absence or in the presence of disturbance compared with the other techniques. It confirms the usefulness and robustness of the proposed controller.

Originality/value – This paper presents an intelligent model predictive controller MPC based on CPSO (MPC-CPSO) for T-S fuzzy modeling with constraints.

Keywords Control systems, Optimization techniques, Fuzzy logic, Nonlinear systems

Paper type Research paper

1. Introduction

Various control methods have been utilized in industries, one of them being the model predictive control (MPC). This latter becomes one of the major control strategies because of its intuitive control concept. It has many successful applications including chemicals, food processing, automotive and aerospace applications (Qin and Badgwell, 2003).

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In recent years, several tuning techniques for the MPC have been developed in the literature. Lino *et al.* (1993) have proposed a parameter tuning method considering robust stability based on frequency response analysis. Later, Drogies and De Geest (1999) have proposed a heuristic tuning method based on expert rules, can be considered as that reported by Rowe and Maciejowski (2000). Other authors have proposed an MPC with constraints based on H-infinity loop shaping method. However, these methods have certain disadvantages. First, they require complicated computing procedures and they are difficult to use by unskilled ordinary controller designers. Second, they are difficult to deal with in the case of plants with constraints. Although most of MPC algorithms with constraints turn to linear matrix inequalities to take care of the constraints (Wan and Kothare, 2003), they are difficult to be realized due to some matrix calculations, especially the matrix inverse operation. They also involve a lot of mathematic operations which are difficult to be understood. That is why some researchers have proposed a new controller based on a combination with other techniques. Causa *et al.* (2008) used the genetic algorithm (GA) to minimize both the trajectory error and the control energy for the control strategy of the temperature of a batch reactor. But, GA has the disadvantage of premature, slow convergence rate and needed many parameter settings. Chen and Jiang (2009) have proposed Takagi-Sugeno (T-S) model fuzzy predictive controller based on intelligent optimization algorithm (Du Shi *et al.*). Recently, many studies have proposed the evolutionary computation technique based on Particle Swarm Optimization (PSO) (Shin and Park, 1998; Soltani *et al.*, 2012; Soltani and Chaari, 2013). They have been successfully applied to solve various optimization problems. Indeed, Coelho and Mariani (2009) present a predictive controller based on recursive linear models, where the optimization problem is solved using the PSO algorithm. In the same context, the PSO have been applied successfully to optimize the control law of a multivariable generalized predictive control (Yusuf *et al.*, 2009; Duwaish and Rizvi, 2010; Zheng, 2010a). While Pourjafari and Mojallali (2011) have proposed a voltage control scheme based on the MPC to overcome the Voltage stability problem. Their proposed method utilizes a modified discrete multi-valued PSO to perform the MPC. However, Hongbing *et al.* (2009) have been shown that PSO can be easily trapped in local optima and premature convergence. In order to overcome this problem, Jianchao and Han (2012) proposed the Gaussian PSO, but the use of this type of optimization needed more time to calculate the optimal control variable.

In this paper, a new type of MPC is proposed using Chaos Particle Swarm Optimization (CPSO). First, for the modelling phase, the T-S fuzzy model is employed to approximate the nonlinear system. Second, we introduce CPSO into MPC using a modified performance criterion in order to provide less computational controller's expression.

The remainder of this paper is organized as follows. In Section 2, a brief overview of T-S fuzzy model and weighted recursive least squares method are given. The iterative distributed MPC is presented in Section 3. The proposed MPC tuning algorithm based on CPSO is detailed in Section 4. Simulation results and conclusion are given in Sections 5 and 6, respectively.

2. T-S fuzzy model

We consider a class of nonlinear systems defined by:

$$y(k+1) = f(X(k)) \tag{1}$$

with the regressor vector $X(k)$ is:

$$X(k) = [y(k), y(k-1), \ldots, y(k-n), u(k), u(k-1), \ldots, u(k-m)]$$

Here, k denotes the discrete time, n and m define the number of delayed output and input. The unknown function $f(X(k))$ is approximated by a T-S fuzzy model which is charities by consequent rules that are linear function of the input variables (Lagrat *et al.*, 2007). A T-S model consists of a set of fuzzy rules, each describing a local input-output relation as follows:

$$R^i: \; if \; X_1 \; is \; A_1^i \text{ and if } X_z \; is \; A_z^i \; THEN \; y_i(k) = [X(k) \;\; 1].\theta_i^T \tag{2}$$

where R^i denotes the ith IF-THEN rule, r is the number of rules, $A_j^i\,(j = 1, \ldots, z)$ is the fuzzy subset, $u(k)$ is the system input variable, $y(k)$ is the system output, $\theta_i = [a_{i1}, \, a_{i2}, \ldots a_{iz}, \; b_{i0}]$ is the parameter vector of the corresponding local linear model. Let $\mu_i(X(k))$ is the normalized membership function of the inferred fuzzy set A^i, where $A^i = \prod_{j=1}^{s} A_j^i$.

The output of T-S fuzzy model is computed:

$$\hat{y} = \sum_{i=1}^{r} \mu_{ik} y_i \tag{3}$$

The membership values μ_{ik} have to satisfy the following conditions:

$$\mu_{ik} \in [0 \; 1] \quad i = 1, \ldots, r \tag{4}$$

$$\sum_{i=1}^{r} \mu_{ik} = 1 \quad k = 1, \ldots, N \tag{5}$$

$$0 < \sum_{k=1}^{N} \mu_{ik} < N \quad i = 1, \ldots, r \tag{6}$$

The weighted recursive least squares method (WRLS) can be applied to estimate the consequent parameters for each rule. The WRLS algorithm is described as follows (Kung and Su, 2007):

$$\theta_i(k) = \theta_i(k-1) + L_i(k)\left[y_i(k) - [X(k) \;\; 1]\theta_i^T(k-1)\right] \tag{7}$$

$$L_i(k) = \frac{P(k-1)[X(k) \;\; 1]^T}{1/\mu_{ik} + [X(k) \;\; 1]P(k-1)[X(k) \;\; 1]^T} \tag{8}$$

$$P_i(k) = P_i(k-1) - L_i(k)[X(k) \;\; 1]P_i(k-1) \tag{9}$$

where $p(k)$ is a covariance matrix and $L(k)$ referred to the estimator gain vector. A common choice of initial value is to take $\theta_i(0) = 0$ and $P_i(0) = \alpha I$, where α is a large number.

3. MPC

MPC has been proposed by Richalet *et al.* (1978). MPC estimates future behavior of the control target within a certain period using a model of the control target inside the controller. Then, it determines manipulated signals so that an objective function is minimized (Qin and Badgwell, 2003; Maciejowski, 2002). MPC utilizes predictive outputs $\hat{y}$, which is estimated within N_y steps (prediction horizon) in the future using an internal model.

Figure 1 shows the basic strategy of a model-based predictive controller.

The objective function of MPC is defined by:

$$J = J_1 + J_2 \tag{10}$$

$$J_1 = \sum_{j=1}^{N_y} [y_r(k+j) - \hat{y}(k+j)] \tag{11}$$

$$J_2 = \sum_{i=1}^{N_u} \lambda[\Delta u(k+1-i)]^2 \tag{12}$$

with $\Delta u(k+1) = u(k+i+1) - u(k+i)$.

Here λ is weight coefficient for the future behavior, y_r is the future reference trajectory, $\hat{y}(k)$ corresponds to the prediction of the controlled variable, $u(k)$ is the increment of the future control actions and $\Delta u(k+j)$ is the increment of control variable.

A MPC problem can be formulated as an optimization problem, which determines input signals $[u(k), \ldots, u(k+N_u-1)]$ with in N_u steps (control horizon) in the future so that the objective function is minimized considering the following constraints (Shin and Park, 1998):

$$u_{\min} < u(k+i) < u_{\max}, \quad i = 1, \ldots, N_u - 1$$

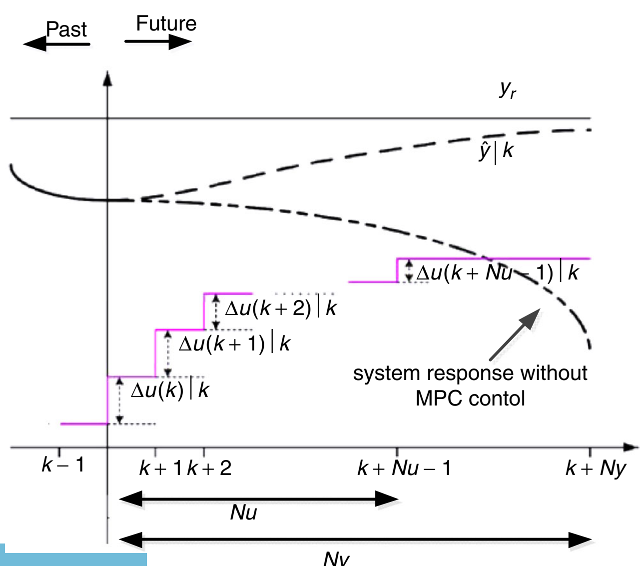

Figure 1.
Basic strategy of a model-based predictive controller

$$\Delta u_{\min} < \Delta u(k+i) < \Delta u_{\max}, \quad i = 1, \ldots, N_u - 1$$

$u_{\max}$ and $u_{\min}$ are the constraints for u. $\Delta u_{\max}$ and $\Delta u_{\min}$ are the constraints for Δu.

4. Nonlinear MPC based on CPSO

The quadratic optimization problem defined by Espinosa *et al.* (1999) must be solved using a nonlinear optimization method where the optimization variables are given by the future control actions. The conventional controllers are designed based on the linearized model, but in many cases, such a model is very difficult to build due to the presence of strong nonlinear dynamics in the behavior of the system. When the nonlinearity is strong, such controllers may produce big errors or even be out of control. Although CPSO is a relatively new technique, it has been used in many fields of applications related to optimal control of industrial processes (Coelho, 2009). It offers a high degree of flexibility and robustness in dynamic environments. Conventional nonlinear optimization methods are not capable of providing a solution in reasonable time (Shin and Park, 1998). For this reason, we propose the CPSO as an optimization method.

4.1 PSO

PSO is a stochastic optimization technique based on the social behavior of swarms off locking animals (Kennedy and Eberhart, 1995). The aim of this algorithm is to minimize a defined function. We assume that the swarm consists of N_p particles, which is as a point in this D-dimensional search space. Each particle has a position vector $p_i = [p_{i1}, p_{i2}, \ldots, p_{id}]$ {\rm \, and\, a\, velocity\, vector} $V_i = [V_{i1}, V_{i2}, \ldots, V_{id}]$. The particle adjusts the velocity and position according to the best experience called the pbest, found by itself, and gbest, found by all its neighbors (Chen and Jiang, 2009):

$$V_{id}(s+1) = w\, V_{id}(s) + r_1 c_1 (\text{pbest}_{id}(s) - p_{id}(s)) + r_2 c_2 (\text{gbest}_{gd}(s) - p_{id}(s)) \quad (13)$$

$$p_{id}(s+1) = p_{id}(s) + V_{id}(s+1) \quad (14)$$

where s is the number of iteration, r_1 and r_2 are two random numbers in the interval [0, 1]. c_1 and c_2 are positive constants. pbest and gbest are the memory of the particle and w is the inertia weight, it is a parameter used to control the impact of the previous velocities on the current velocity. It influences the tradeoff between the global and local exploitation abilities of the particles. w is updated as:

$$w = w_{\max} \left(\frac{w_{\max} - w_{\min}}{s_{\max}} \right) s \quad (15)$$

where $w_{\min}$, $w_{\max}$ are minimum, maximum values of w, respectively. The PSO algorithm uses a swarm consisting of N_u particles each control-increment vector: $\Delta u(k+j)$, $(j = 1, \ldots, N_u - 1)$ to get an optimal solution $\Delta u(k+j)^*$ which minimizes the optimization problem:

$$\Delta u(k+j) = [\Delta u_1(k+j) \;\; \Delta u_2(k+j) \ldots \Delta u_{N_u}(k+j)],$$
$$\Delta v(k+j) = [\Delta v_1(k+j) \;\; \Delta v_2(k+j) \ldots \Delta v_{N_u}(k+j)]$$

where the position of the particle $\Delta u(k+j)$ is update by Equation (14).

4.2 CPSO
Hongbing *et al.* (2009) have shown that PSO can be easily trapped in local optimal convergence. In order to overcome this problem, CPSO has been used by Clerc (1999) as well as Kennedy and Clerc (2002). In CPSO, a constriction factor χ is added in the velocity equation of PSO algorithm. Consequently, the velocity Equation (13) begins:

$$V_{id}(s+1) = \chi(V_{id}(s) + r_1c_1(\text{pbest}_{id}(s) - p_{id}) + r_2c_2(\text{gbest}_{gd}(s) - p_{id})) \tag{16}$$

where the constriction coefficient χ is expressed as:

$$\chi = \frac{2}{\left\| 2 - \ell - \sqrt{\ell^2 - 4\ell} \right\|} \tag{17}$$

with $l = c_1 + c_2$ and $l > 4$. Usually, l is set to 4.1 ($c_1 = c_2 = 2.05$), and the constriction coefficient χ is 0.729. Other possible choice for the constriction coefficients is available. Kennedy and Clerc (2002) found that the system behavior could be controlled so that the system behavior has the following features:

(1) the system does not diverge in a real value region and finally can converge; and

(2) the system can search for different regions efficiently by avoiding premature convergence.

4.3 The proposed algorithm
The proposed approach is composed of two phases of learning algorithm. In the first phase, the FCM is employed to construct the fuzzy model. In the second phase, the CPSO is used to finally tune predictive control law of the obtained fuzzy model by minimizing a defined objective function. Figure 2 shows the structure of the proposed control system (MPC-CPSO).

The proposed predictive control algorithm is summarized as follows:

Phase 1: construction of the fuzzy model using FCM algorithm:

Step 1. Given data $S = \{(x_1, y_1), \ldots, (x_k, y_k)\}\quad k = 1, \ldots, N$, set $m > 1$ and the metric matrix $A = I$. Select a termination threshold $\varepsilon > 0$ and initialize U^0 (e.g. random).

Repeat for $l = 1, 2, \ldots$

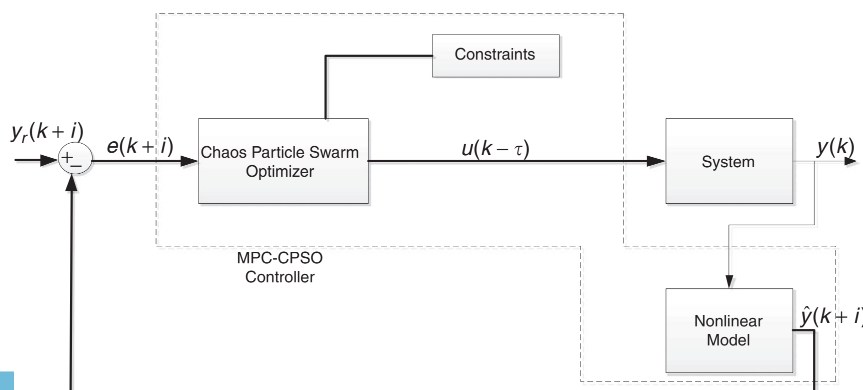

Figure 2.
Structure of proposed MPC-CPSO controller

Step 2. Calculate the cluster centers as follows:

$$v_i^l = \frac{\sum_{k=1}^{N} (\mu_{ik}^{l-1})^m x_k}{\sum_{k=1}^{N} (\mu_{ik}^{l-1})^m} \qquad i = 1, 2, \ldots, r \quad k = 1, 2, \ldots, N \tag{18}$$

m is the fuzzy weighting exponent.

Step 3. Calculate distances as follows:

$$\rho_{ik} = (x_k - v_i^l)^T A (x_k - v_i^l) \tag{19}$$

Step 4. Update U^l with ρ_{ik} satisfy:

$$U_{ik}^l = \begin{cases} \mu_{ik}^l = \frac{1}{\sum_{j=1}^{r} (\frac{\rho_{ik}}{\rho_{jk}})^{\frac{2}{m-1}}} & \text{if } \rho_{ik} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

Until $\|U^l - U^{l-1}\| < \varepsilon$ then stop. Otherwise, set $l = l + 1$ and return to *Step 2*.

Step 5. Calculate values for r model parameters θ_i^r using WRLS method.

Phase 2: optimization predictive control algorithm:

Step 1. Fix the parameters of the algorithm c_1, c_2, N_p,N_u, N_y, $w_{\min}$ and $w_{\max}$. Choose $u_{\max}$,$u_{\min}$,$V_{\min}$ and $V_{\max}$.

Step 2. Calculate the fitness value of each particle according to Equation (10).

Step 3. Updating of each particles velocity and position according to Equations (16) and (14).

Step 4. Find the individual best pbest for each particle and the global best gbest.

Step 5. Check each parameter of the particle's position by the corresponding bounds $V_{\min}$ and $V_{\max}$.

Step 6. Return to Step 2 until a good fitness is met.

5. Simulation results

In this section, we are going to examine the performance of the proposed control predictive algorithm developed above.

In this paper, the Relative Error (RE), Mean Relative Error (MRE) and Overshoot Value (OV) are used as the performance indexes, which are defined as:

$$RE = \frac{|y(k) - y_r(k)|}{y_r(k)} \tag{21}$$

$$MRE = \frac{\sum_{k=1}^{N} RE(k)}{y_r(k)} \tag{22}$$

$$OV = \frac{y_{\max} - y_{\infty}}{y_{\infty}} \times 100\% \tag{23}$$

$y_{\max}$ is the maximum value of $y(k)$, y_{∞} is the value when the predicted output arrives at its steady state.

5.1 Example 1

We consider the nonlinear system (Song *et al.*, 2007):

$$y(k) = \frac{y(k-1)y(k-2)(y(k-1)+2.5)}{1+y(k-1)^2+y(k-2)^2} + u(k-1) \tag{24}$$

$y(k)$ is the output and $u(k)$ is the input which is uniformly bounded in the region $[-2,2]$. We choose $[y(k-1), y(k-2), u(k-1), u(k-2)]$ as input variables, and the number of fuzzy rules is four. The desired setpoints $y_r(k)$ are switched between 0 and 3 every 100 iterations and the initial conditions are set as $y(-1)=y(-2)=0$. The parameter settings of the proposed method are: $Np=20$, $N_u=5$, $u_{max}=2$, $u_{\min}=0$, $\Delta u_{\max}=0.5$, $\Delta u_{\min}=-0.5$, $w_{\max}=0.9$, $w_{\min}=0.5$ and $c_1=c_2=2.05$.

The fuzzy rules obtained by the FCM clustering algorithm are:

$$R_1:\ y(k) = 1.05y(k-1) - 0.271y(k-1) + 0.213u(k-1) + 0.354u(k-2) + 1.201$$

$$R_2:\ y(k) = 0.947y(k-1) - 0.013y(k-1) + 0.3143u(k-1) + 0.337u(k-2) + 0.941$$

$$R_3:\ y(k) = 1.121y(k-1) - 0.073y(k-1) + 0.223u(k-1) + 0.291u(k-2) + 0.921$$

$$R_4:\ y(k) = 0.897y(k-1) - 0.093y(k-1) + 0.178u(k-1) + 0.199u(k-2) + 0.798$$

Table I compares our results with those obtained with different MPC methods such as MPC (Qin and Badgwell, 2003) and MPC based on PSO (MPC-PSO) (Coelho and Mariani, 2009). From Table I, we can note that the performance of the MPC based on CPSO with constraints is better than those of other methods (MPC and MPC-PSO) in terms of MRE, OV and rise time (RT). Figures 3-5 show the control signal and

Table I.
MRE, OV and rise time results

Performance	MPC	MPC-PSO	MPC-CPSO
MRE	0.0074	0.0052	0.0011
OV (%)	1.13	0.1567	0.0033
Rise Time	1.3192	1.4311	0.7976

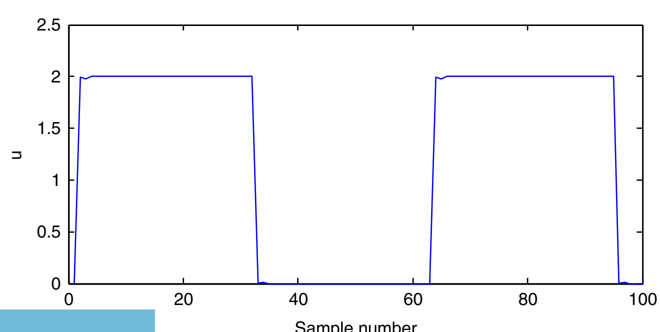

Figure 3.
Control signal

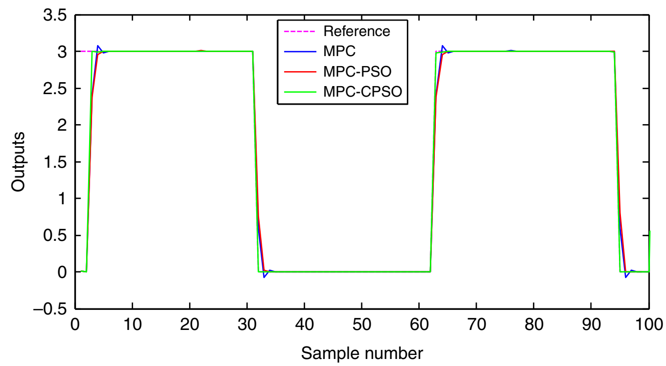

Figure 4.
System response of different methods

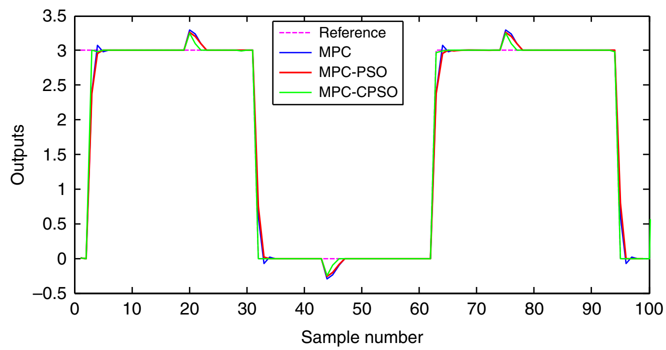

Figure 5.
System response with disturbance of different methods

the output responses, respectively, of predictive control under setpoints changes. As shown in these figures, the proposed control system MPC-CPSO has a good tracking capability and control performance. Furthermore, the MPC-CPSO design has a short setting time, small maximum overshoot fast response, reasonable control activity, and good setpoint tracking ability regarding Figure 4. In the presence of disturbance, Figure 5 discloses that MPC and MPC-PSO have an unstable tracking performance and produce a big overshoot. These results clearly indicate that the proposed controller outperforms the other methods (MPC and MPC-PSO) taking into account the square responses to reference changes and the disturbance rejection. Consequently, we can note that our proposed controller always keep the best performance with and without disturbance. Thus, it confirms the usefulness and robustness of the proposed controller.

5.2 Example 2

The proposed method has been tested also for the control of a Continuous Stirred-Tank Reactor (CSTR) as shown in Figure 6. The discrete dynamic equations for the CSTR are (Chen and Peng, 1997):

$$\begin{cases} x_1(k) = x_1(k-1) + Te(-x_1(k-1) + Da(1 - x_1(k-1)) \exp\frac{x_2(k-1)}{1+x_2(k-1)/\gamma}) \\ x_2(k) = x_2(k-1) + Te(-(1-\beta)x_2(k-1) + \mathrm{B}Da(1 - x_1(k-1)) \exp\frac{x_2(k-1)}{1+x_2(k-1)/\gamma}) + \beta u(k-1) \\ y(k) = x_2(k) \end{cases} \quad (25)$$

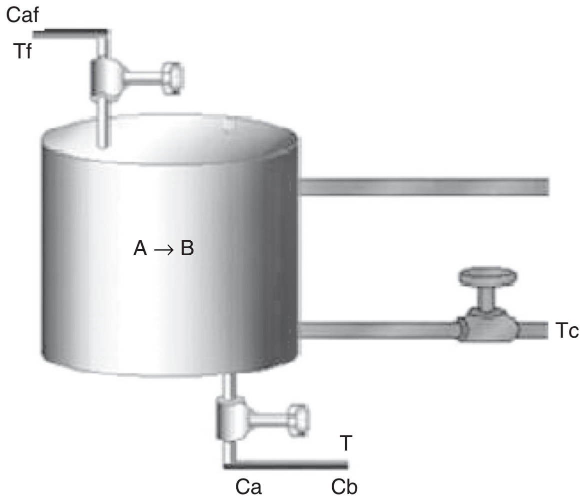

Figure 6.
CSTR plant

Source: Chen and Peng (1997)

where x_1 and x_2 represent the dimensionless reaction concentration and reactor temperature, respectively, and u is the control input representing the dimensionless cooling jacket temperature. The physical parameters of the CSTR model equations are Da, γ, B and β which correspond to the Damköhler number, the activate energy, the heat of reaction and the heat transfer coefficient, respectively. Nominal system parameters are $Da = 0.072$, $\gamma = 20$, $B = 8$, $\beta = 0.8$ and Ts is the sampling time ($Ts = 0.2s$). The FCM algorithm gave a fuzzy model that consists of two fuzzy rules in the following form:

$$R_1 : y(k) = 0.562y(k-1) + 0.324y(k-2) - 0.123u(k-1) + 1.432$$

$$R_2 : y(k) = 0.472y(k-1) - 0.007y(k-2) + 0.109u(k-1) + 1.002$$

The responses for the servo essays are given in Figure 6. For the analysis of this behavior, the reference signal changes as follows:

$$y_r = \begin{cases} 1 & 0 < k \leqslant 150 \\ 2 & 150 < k \leqslant 300 \\ 3 & 300 < k \leqslant 450 \\ 4 & 450 < k \leqslant 600 \end{cases} \tag{26}$$

The simulation results of different methods are given in Table II. The comparisons results between the control law and the estimated obtained by MPC, MPC-PSO and our

Table II.
MRE, OV and rise time results

Performance	MPC	MPC-PSO	MPC-CPSO
MRE	0.0026	0.0023	0.0016
OV (%)	1.13	0.0031	00
Rise Time	5.7171	4.6649	4.6345

method are shown in Figure 7. As it is presented in Table II, the simulation results demonstrate the superiority of MPC-CPSO method comparing to the other algorithms. Indeed, the performance index MRE obtained by our method is 0.0016. In terms of overshoot OV, MPC-CPSO has a lower overshoot by 0.0031 percent than MPC-PSO algorithm and 1.13 percent than MPC algorithm. In addition, MPC-CPSO has minimum RT equal to 4.6345. However, Qin and Badgwell (2003) and Coelho and Mariani (2009) their method are 5.7171 and 4.6649, respectively. A similar analysis can be seen also in Figure 8. This figure shows the RE performance of the different methods. On the whole, we note that, our method retained a good performance with good tracking capability and control performance.

6. Conclusions

This paper presents an intelligent model predictive controller based on CPSO. Indeed, the proposed MPC is designed taking into account the constraints. The application of CPSO improves the performance of the MPC of nonlinear systems without recourse to use a complicated mathematical calculation. The robustness and the quality of this modification in the MPC method are demonstrated by simulation results of two benchmark problems. Through these results, the proposed control scheme has shown favorable results either in the absence or in the presence of disturbance compared with the techniques reported in the literature.

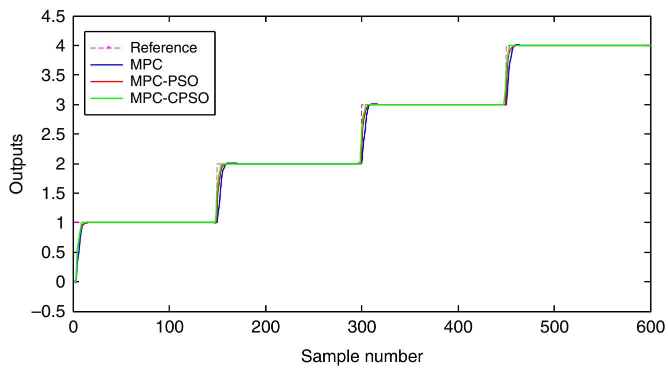

Figure 7.
Servo response

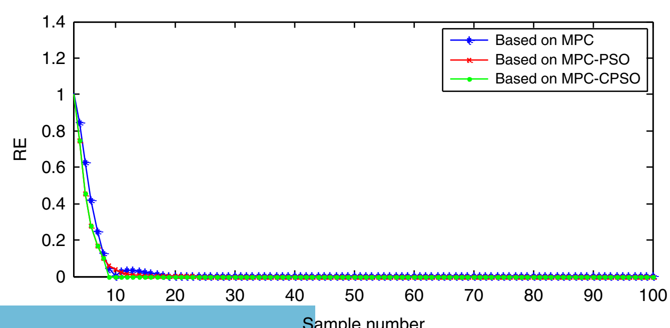

Figure 8.
RE results

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