Prioritized adaptive Model Predictive Control using evolutionary algorithms

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Abstract–**Adaptive Model Predictive Control (MPC) configurations are quite popular methodologies for successful control of dynamic time varying systems. Most adaptive schemes include the persistent excitation requirement as an additional hard constraint of the optimization problem. In this paper an alternative approach is attempted, by using the principles of multiobjective optimization. A prioritized optimization problem is formulated, considering the persistent excitation as the top priority objective. Afterwards, an objective function is assigned to each one of the remaining control goals. This way, the adaptive capabilities of the methodology are exploited and the time consuming tuning procedure to weigh the different control goals in one objective function, is avoided. An additional innovation of the proposed configuration is the utilization of an improved evolutionary algorithm in order to meet the complexity and non convexity introduced by the persistent excitation requirement. The overall proposed configuration is evaluated through the application to a continuous stirred tank reactor. The produced results are superior compared to the performance of a conventional MPC scheme.**

Index Terms - Model Predictive Control, Multiobjective Optimization, Adaptive Control, Closed Loop Identification, Evolutionary Algorithms.

I. INTRODUCTON

Model Predictive Control (MPC) refers to a category of particularly popular computer control algorithms with successful industrial applications including chemicals, automotive and aerospace [9, 10]. It is an optimal control method that implements a process model in order to predict the response of the controlled variable to a future sequence of the manipulated variables. This future sequence is the result of an optimization problem which minimizes the weighted sum of the differences of the output variable from their set points and the control moves. The main advantages of these methodologies is that they can be applied in cases of linear or non linear process models without significant modifications and can also include constraints on the input and the output variables. Even though the theory of MPC is considerably matured, many challenging issues to improve its performance and applicability still exist [9].

Such an issue concerns the performance of the MPC methods in cases where more than one control goals must be satisfied simultaneously. In these cases the conventional MPC configurations assign weights to the different objectives in order to formulate one optimization problem. A quite common example is the multi input multi output (MIMO) systems. In such systems, the different controlled variables are often competitive. Consequently, to achieve a satisfactory performance or to assign the correct importance to all the output variables, a time consuming tuning effort is required, in order to choose the appropriate weight values. A different approach to confront this problem is to exploit the advantages of a prioritized multiobjective structure, where the different objectives are lined up according to their importance and equal in number optimization problems are solved. Reference [15] used integer variables to prioritize and optimize a number of different objectives. Reference [6] proposed the formulation of a hierarchy of objectives that represent the different control targets and solved such a multiobjective optimization problem [8].

An also important advantage of the MPC configurations is that they are in general characterized by great robust capabilities. However, there are situations where the process dynamics change significantly with time and thus, adaptation of process model is necessary in order to retain a good closed loop performance. Considering that a process operating in closed loop cannot provide enough information for a successful adaptation, a persistent excitation constraint for the manipulated variables is usually added [1, 14]. The persistent excitation requirement can be implemented either as a hard constraint [1], which may result to infeasible optimization problems, or as a soft constraint. Reference [4] utilized the soft constraint approach, by augmenting appropriately the typical MPC objective function.

Another significant aspect concerning MPC methods that will be taken into account in this work is the type of optimization problem that is formulated and solved on-line and the optimization techniques that are utilized. If the inputs and/or the outputs of the process are limited and the model describing the process is non-linear, conventional optimization algorithms often fail to provide acceptable solutions due to the increased computational effort and convergence to local minima. Inclusion of the persistent excitation constraint into the MPC framework introduces an additional complexity due to the non-convex nature of the constraint. Recognizing the difficulty of the optimization problem, in a number of publications [4, 12, 13] the persistent excitation criterion is transformed to a relaxed LMI formulation, and the problem is solved using an iterative procedure.

During the last years, evolutionary algorithms and particularly genetic algorithms have found great acceptance in control systems engineering [2]. They are effective search and optimization algorithms that have borrowed their basic operations from the natural evolution and improvement of species. Their advantages are that they can be used for solving optimization problems where the objective function and/or the constraints are noncontinuous and/or nonconvex functions and they can be applied to a wide range of optimization problems without significant modifications. In the field of control system engineering, the off-line applications seem to be more appropriate for evolutionary algorithms. However, there are on-line cases where common algorithms cannot find a feasible solution, while evolutionary algorithms, supplied with good initial conditions, can provide near optimum solutions in acceptable time periods.

In this work, we propose a new MPC configuration that addresses the above three issues. The formulation of the problem is based on the prioritization of the targets, so that the most important objectives are satisfied first. In the case of time varying systems, the idea is further extended to include the simultaneous closed-loop adaptation of the model into the MPC framework. This is achieved by considering the persistent excitation of the manipulated variables as an additional top priority control objective. The methodology that is utilized to solve the non-convex multi-objective optimization problem is based on the LUDE evolutionary algorithm [11], which has proved to be more efficient than common optimization routines in many nonconvex test cases. The proposed MPC formulation was applied to a nonisothermal continuous stirred tank reactor (CSTR) where the value of the heat transfer coefficient gradually decays. The proposed MPC framework is compared to the conventional MPC configuration.

The rest of this article is formulated as follows: in section II the proposed multiobjective controller is described in details. In section III the evolutionary algorithm used to solve the optimization problem is presented briefly and in section IV the application and the results are depicted. The most important conclusions are outlined in the last section of this paper.

II. The Proposed Multiobjective Adaptive Model Predictive Controller

A. *Recursive least squares (RLS) model adaptation*

An adaptation procedure for a process model that has been identified off line from input/output data, ensures that this model will be able to track on line the dynamic changes of the process in the best possible way. In this work, time varying processes modeled by simple linear Finite Impulse Response (FIR) adaptive models are assumed. The general form of such model is described by (1)

$$\hat{\mathbf{y}}(k+1 \mid k) = \mathbf{\Theta}\left(k \middle| k\right)^T \cdot \boldsymbol{\varphi}\left(k+1\right) \tag{1}$$

where $\hat{\mathbf{y}}\left(k+1 \middle| k\right)$ is the prediction, made at time k for the future output vector of nc controlled variables at time k+1, $\boldsymbol{\varphi}\left(k\right)$ is the regression vector containing n past input vectors and $\mathbf{\Theta}\left(k \mid k\right)$ is the $(nm \cdot n+1) \times nc$ matrix of the model parameters:

$$\boldsymbol{\varphi}(k)^T = \left[\mathbf{u}\left(k-1\middle|k\right)^T \mathbf{u}\left(k-2\middle|k\right)^T \ldots\ \mathbf{u}\left(k-n\middle|k\right)^T\ 1\right] \tag{2}$$

$$\mathbf{\Theta}\left(k \mid k\right) = \left[\boldsymbol{\theta}_1\left(k \mid k\right)\ \boldsymbol{\theta}_2\left(k \mid k\right)\ \ldots \boldsymbol{\theta}_n\left(k \mid k\right)\ \mathbf{d}\left(k \mid k\right)\right]^T \tag{3}$$

In (2), $\mathbf{u}\left(k\right)$ is the vector of nm manipulated variables. In (3), $\boldsymbol{\theta}_j\left(k \mid k\right)$, $j = 1,\ldots,n$ are the time varying $nc \times nm$ model coefficients and $\mathbf{d}\left(k \mid k\right)$ is the estimated disturbance at time point k.

For the on line adaptation of the model parameters the Recursive Least Squares (RLS) methodology, described in details in [1, 7, 14], is implemented. The concept behind RLS is to modify the estimation made at point k-1 using the information contained into the new data received at point k. The set of RLS equations for the FIR model described previously is:

$$\mathbf{\Theta}\left(k\right) = \mathbf{\Theta}\left(k-1\right) + \mathbf{K}\left(k\right) \cdot \left(\mathbf{y}\left(k\right) - \boldsymbol{\varphi}\left(k\right)^T \mathbf{\Theta}\left(k-1\right)\right) \tag{4}$$

$$\mathbf{K}\left(k\right) = \mathbf{P}\left(k-1\right) \cdot \boldsymbol{\varphi}\left(k\right) \cdot \left(\lambda + \boldsymbol{\varphi}\left(k\right)^T \cdot \mathbf{P}\left(k-1\right) \cdot \boldsymbol{\varphi}\left(k\right)\right)^{-1} \tag{5}$$

$$\mathbf{P}\left(k\right) = \left(\mathbf{I} - \mathbf{K}\left(k\right) \cdot \boldsymbol{\varphi}\left(k\right)^T\right) \mathbf{P}\left(k-1\right) / \lambda \tag{6}$$

where $\mathbf{y}(k)$ $(1 \times nc)$ are the current measured values of the output parameters, λ is the forgetting factor, $\mathbf{K}(k)$ is a $(nm \cdot n+1) \times 1$ vector and $\mathbf{P}(k)$ is a $(nm \cdot n) \times (nm \cdot n)$ matrix [1, 14].

It should be noticed that the RLS adaptation mechanism is a particular case of the more general Recursive Prediction Error Methods (RPEM) [7, 14]. In this work it is assumed that only white noise deteriorates the process. So, an FIR model is adequate to describe the real process and a dynamic noise model is not required. In this case the RPEM can indeed be substituted by RLS. The extension of the proposed algorithm described subsequently in cases where colored noise exist, is under investigation. It should also be clarified that the noise contribution to the final output is assumed to be small (the signal to noise ratio is large) so that the RLS (and more general the PEM) can be used for systems operating in closed loop. A survey of the closed loop identification methods and their limitations can be found in [3].

B. *Model Predictive Control and Identification*

Most popular MPC methods are based on the idea that at sampling time k a set of future manipulated variables (control horizon) are selected in order to minimize an appropriate objective function. The objective function includes both the deviations of the predicted outputs from their set point over a future prediction horizon and the control effort over a control horizon. Then, only the first control move is implemented and the optimization problem is solved again at the next time step $k+1$. The future outputs are predicted based on an available linear or nonlinear dynamic model of the process. Constraints on the manipulated and the controlled variables, as well as the control moves can be easily incorporated in the MPC configurations. The estimated error between the process measurement and the model prediction at the current time step is added on the predicted future outputs and assumed to remain constant, during the entire prediction horizon. The above are described by the following set of equations:

$$\min_{\substack{\mathbf{u}(k+i-1|k)\\ i=1,\ldots,c}} \sum_{i=1}^{p}\left\|\mathbf{W}\left(\hat{\mathbf{y}}(k+i\,|\,k)-\mathbf{y}^{sp}\right)\right\|_2^2+\sum_{i=1}^{c}\left\|\mathbf{R}\Delta\mathbf{u}\left(k+i-1\,|\,k\right)\right\|_2^2 \quad (7)$$

$$\mathbf{u}_{\min}\le \mathbf{u}(k+i-1\,|\,k)\le \mathbf{u}_{\max},\ i=1,\ldots,c \quad (8)$$

$$-\Delta\mathbf{u}_{\max}\le \Delta\mathbf{u}(k+i-1\,|\,k)\le \Delta\mathbf{u}_{\max},\ i=1,\ldots,c \quad (9)$$

$$\mathbf{u}(k+c+i-1\,|\,k)=\mathbf{u}(k+i-1\,|\,k),\ i=1,\ldots,p-c \quad (10)$$

In (7) $\overset{\wedge}{\mathbf{y}}\left(k+i\right)$ is calculated according to (1), **W** and **R** are diagonal weight matrices. Equations (8)-(9) are hard constraints that bound the manipulated variables and the control moves respectively. Equation (10) assures that the future inputs will follow a periodic sequence.

Despite the great robust capabilities of MPC schemes, there are situations where adaptation is necessary in order to preserve the accuracy of the model and maintain the good control performance. In order to collect sufficient information, update the model parameters correctly and avoid nonsingularities, some additional conditions must be enforced. Such a condition is that the system information matrix $\mathbf{M}(k)$ which is formulated each time step k based on the last $l > mn\cdot N+1$ regression vectors $\boldsymbol{\varphi}(k)$

$$\mathbf{M}\left(k\right)=\sum_{m=0}^{l-1}\lambda^{m}\boldsymbol{\varphi}\left(k+1-m\middle|k\right)\,\boldsymbol{\varphi}\left(k+1-m\middle|k\right)^{T} \quad (11)$$

must be well conditioned. This is guaranteed if a real positive number ρ exists such that the following matrix is positive semidefinite [1, 4, 14]:

$$\mathbf{M}\left(k\right)-\rho\cdot\mathbf{I}\ge 0 \quad (12)$$

So, an adaptive MPC configuration should also include the following constraint (Persistent Excitation, PE):

$$\sum_{m=0}^{l-1}\lambda^{m}\boldsymbol{\varphi}\left(k+i-m\middle|k\right)\,\boldsymbol{\varphi}\left(k+i-m\middle|k\right)^{T}\ge\rho\cdot\mathbf{I},\ \rho>0 \quad (13)$$

for $i=1,\ldots,p$. The above MPC configuration has a serious drawback. Depending on the value of the parameter ρ in (13), there will probably exist situations that the persistent excitation requirement is not satisfied. This leads to infeasibilities, which are totally unacceptable in an on-line optimization problem, since they can seriously deteriorate the closed–loop performance.

C. Multiobjective formulation of the adaptive MPC configuration

In the proposed multiobjective MPC methodology, the idea of relaxing the persistent excitation requirement is exploited, by considering model adaptation as the most important objective. This is achieved by creating a hierarchy of objectives and placing the relaxed persistent excitation requirement at the top of this hierarchy. More specifically, the persistent excitation constraint (13) is transformed to an optimization problem, which is formulated as follows:

$$\min_{\mathbf{u}(k|k),\ldots,\mathbf{u}(k+p|k),\mu}\mu,\quad \mu>0 \quad (14)$$

subject to (8)-(10) and:

$$\sum_{m=0}^{l-1}\lambda^{m}\boldsymbol{\varphi}\left(k+i-m\middle|k\right)\boldsymbol{\varphi}\left(k+i-m\middle|k\right)^{T}\ge(\rho-\mu)\cdot\mathbf{I}>0 \quad (15)$$

for $i=1,\ldots,p$ and $\rho>0$. The optimization problem consisting of (14) and (15) is always feasible, since when $\mu\to\rho$, (15) is trivially satisfied.

The optimized value μ_{opt} of the parameter μ is then used in the subsequent optimization problems that will be formulated and solved sequentially. In order to proceed, the proposed method assumes that the nc controlled variables have been sorted according to their importance, so that the highest priority variable is placed first in the hierarchy. If the system is square (same number of manipulated and controlled variables, $nc=nm$) a different manipulated variable can be assigned to each controlled variable, so that pairs u_j-y_j, $j=1,\ldots,nc$ are constructed. For the selection of pairs, the designer can use his intuition or knowledge of the process, but can also adopt systematic methods that are utilized for designing decoupling control systems [16]. Then, the proposed multiobjective MPC scheme proceeds in the following way:

FOR $j=1$ to nc

$$\min_{\substack{\mathbf{u}(k+i-1|k)\\ i=1,\ldots,c}}\sum_{i=1}^{p}\left[\left(\hat{y}_j\left(k+i\middle|k\right)-y_j^{sp}\right)^2+\left\|\mathbf{R}_j\Delta\mathbf{u}\left(k+i-1\middle|k\right)\right\|_2^2\right] \quad (16)$$

subject to (1), (8)-(10), the constraints on the output responses which are consecutively added to the constraint set and the persistent excitation equation, which is modified as follows:

$$\sum_{m=0}^{l-1}\lambda^{m}\boldsymbol{\varphi}\left(k+i-m\middle|k\right)\,\boldsymbol{\varphi}\left(k+i-m\middle|k\right)^{T}\ge(\rho-\mu_{\text{opt}})\cdot\mathbf{I} \quad (17)$$

for $i=1,\ldots,p$

Add the following constraint to the set of constraints:

$$\sum_{i=1}^{p}\left(\hat{y}_j(k+i\,|\,k)-y_j^{sp}\right)^2 \le \sum_{i=1}^{p}\left(\hat{y}_j^{\,\text{opt}}(k+i\,|\,k)-y_j^{sp}\right)^2 \quad (18)$$

where $\hat{y}_j^{\,\text{opt}}\left(k+i|k\right)$ are the optimal response values for the controlled variable.

END

Consideration of the PE requirement as a top priority objective offers a great advantage compared to the MPC configuration described by (7)-(10), (13) since it avoids the infeasibility problems that may be encountered due to the hard constraint (13). Compared to a soft constraint approach presented in [4] the proposed methodology has two advantages. The first improvement is that it avoids the extra tuning effort introduced in the problem, by weightening the PE in the MPC objective function. Furthermore, the proposed method guarantees that the maximum possible excitation (up to the limit imposed by ρ) is introduced to the sequence of manipulated variables.

The move suppression matrix $\mathbf{R}_j$ in the sequential formulation of the optimization problems described above, are selected so that small weights are assigned to the inputs $1,2,...,j$ and large weights to the inputs $j+1$, $j+2,\ldots,nm$. In this way, energy is preserved to control the next outputs in the hierarchy. Thus, the method guides the user in selecting proper values of the matrices $\mathbf{R}_j$, in contrast to the classical MPC configuration, where the matrices $\mathbf{W}$ and $\mathbf{R}$ in (7) are selected based on a time consuming trial and error approach.

Constraint (18) assures that once an optimal response profile has been calculated for a controlled variable, only improvements are allowed in subsequent iterations regarding the predicted response of the variable.

The above procedure can be easily extended to non-square systems by assigning more than one manipulated variables to some of the controlled variables. Also, in case of large systems, the variables can be partitioned in groups containing more than one input and output in order to reduce the number of objective functions that have to be minimized.

III. Evolutionary Algorithm for Solving the Optimization Problem

Inclusion of the persistent excitation requirement resolves a number of adaptive closed-loop identification problems, but introduces an extra computational complexity. The persistent excitation requirement is a non-convex constraint and thus the entire MPC optimization problem cannot be solved efficiently by standard methods. In this work, we use evolutionary computation to solve the sequential non-convex constrained optimization problems that are formulated. More specifically, a method based on the line up differential evolutionary algorithm (LUDE) is used, which has already been tested in numerous non-convex optimization examples [11]. The innovation of this evolution algorithm is that the constraints are introduced in the objective function in the form of a Lagrange penalty function, whose parameters are adapted during the execution of the algorithm. Thus, the algorithm consists of two iterative procedures: the inner loop where an evolutionary algorithm solves the unconstrained optimization problem with fixed Lagrange multipliers and penalty parameters and the outer loop where adaptation of the parameters is taking place.

One advantage of the LUDE algorithm is that contrary to conventional genetic algorithms, it uses a limited number of tuning parameters. For example, the probabilities of mutation and crossover, which are key tuning parameters in most genetic algorithms are not specified by the user, but are calculated independently for each individual inside the algorithm. In summary, the tuning parameters are the following: the size of the population (number of chromosomes), the maximum number of inner and outer iterations, which are limited by the time which is available to solve the multiobjective optimization problem, and the parameters which control the rate by which the Lagrange multipliers and the penalty parameters are modified between outer iterations. It should be noted that the convergence of the algorithm can be accelerated, by using in each time step as initial choices for the population of solutions, the optimal solutions calculated in the previous time step. The interested reader can find all the details of the LUDE algorithm in [11].

IV. Case Study: The Control of a CSTR Reactor

The proposed methodology is applied to a control problem concerning a non isothermal continuous tank (CSTR) reactor with two inputs and two outputs. The differential equations (19)-(20) describe the real behavior of the process:

$$dC_{\mathrm{A}}/dt = F\left(C_{\mathrm{A,in}}-C_{\mathrm{A}}\right)/F - k_{\mathrm{o}}\exp\left(-E/RT\right)\cdot C_{\mathrm{A}}^2 \quad (19)$$

$$\begin{aligned} dT/dt = {} & F\left(T_{\mathrm{in}}-T\right)/V + (-\Delta H)_{\mathrm{R}}\,k_o\exp\left(-E/RT\right)\cdot C_{\mathrm{A}}^2/\left(\rho c_p\right) \\ & -UA(T-T_j)/\left(V\rho_{\mathrm{A}}c_p\right) \end{aligned} \quad (20)$$

where V is the volume of the reactor, U, A are the overall heat transfer coefficient and the surface of the exchanger respectively, k_{o}, $(-\Delta H)_{\mathrm{R}}$, ρ_{A}, c_p, E/R are constants of the process, T_{in} is the inlet temperature, $C_{\mathrm{A,in}}$ is the inlet concentration of the reactant A, T_j is the temperature of the coolant, F is the flow rate, C_{A} is the concentration inside the reactor and T is the temperature inside the reactor.

In these simulations F and T_j were used as the manipulated variables and the two remaining inputs $C_{\mathrm{A,in}}$, T_{in} were considered as disturbances. The controlled variables were the concentration of the reactant C_{A} and the outlet temperature T. The model parameters and the steady state values can be found in [5]. The differential equations were solved using the ode45 Matlab function using a sample time of 1min. A Gaussian distributed noise is added to the measured outputs with standard deviation 0.0001 for the reactant concentration and 0.1 for the reactor temperature. The process was also assumed to be time varying due to the following gradual decrease of the heat transfer coefficient U:

$$U \cdot A = 20000 \cdot \exp\left(-0.001t\right) \tag{21}$$

The multiobjective MPC configuration described in section 2 was applied using a FIR model consisting of n=20 past values of each manipulated variables. The rest of the algorithm parameters are summarized in Table I. The overall algorithm was implemented in the following way: First the persistent excitation optimization problem was solved using the evolutionary algorithm and gives an optimal value μ_{opt}. Then, the concentration of the reactant at the outlet of the reactor was controlled using the coolant temperature as the main manipulated variable (a large move suppression coefficient was assigned to the flow rate). Finally the temperature of the reaction mixture was optimized, using both the manipulated variables, provided that both the persistent excitation optimal value μ_{opt} and the optimal concentration profile were preserved. The manipulated variables and their moves are bounded for i=1,…p:

$$9 \text{ l/min} \le F(k+i) \le 25 \text{ l/min} \tag{22}$$
$$170\text{K} \le T_j(k+i) \le 290\text{K} \tag{23}$$
$$\left|\Delta F(k+i-1)\right| \le 1 \text{ l/min} \tag{24}$$
$$\left|\Delta T_j(k+i-1)\right| \le 5\text{K} \tag{25}$$

TABLE I
PARAMETERS OF THE MPC ALGORITHMS

Parameters	Conventional MPC	Multiobjective adaptive MPC
Nv	2	2
C	6	6
P	10	10
N	20	20
W	$\begin{bmatrix} 10 & 0 \\ 0 & 1 \end{bmatrix}^*$	-
R	$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^*$	-
$\mathbf{R_1}, \mathbf{R_2}$	-	$\begin{bmatrix} 1 & 0 \\ 0 & 0.1 \end{bmatrix}, \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}^*$
L	-	50
Λ	-	1
P	-	0.001
Adaptation method	-	RLS

In order to explore the advantages of an adaptive algorithm, a simulation containing two set point changes for both variables was performed. More precisely, the set points enforced at time point 70 for the concentration and the temperature were 0.07 mol/l and 370K respectively, while after some time the process was forced to return to the original set points (0.07545 mol/l and 376.3K). Adaptation of the model parameters also started at time point 70, using l=50 past values of the input variables.

Fig. 1 depicts the results produced by a conventional (nonadaptive) MPC approach consisting of (7)-(10), where the future input variables are forced to remain constant after the end of the control horizon. The optimization *fmincon* function of Matlab is used to solve the optimization problem. In order to show a fair comparison, a much larger weight was assigned to the deviation between the output concentration and the desired set point. The responses produced by the proposed methodology and the LUDE optimization algorithm are given in Fig. 2. The manipulated variables for both configurations are depicted in Fig. 3.

Comparison results are in favor of the proposed methodology. Although dynamic behaviors are comparable for the concentration of the reactant in the outlet stream, an improved response, due to adaptation, is observed for the reactor temperature. Furthermore, the proposed approach

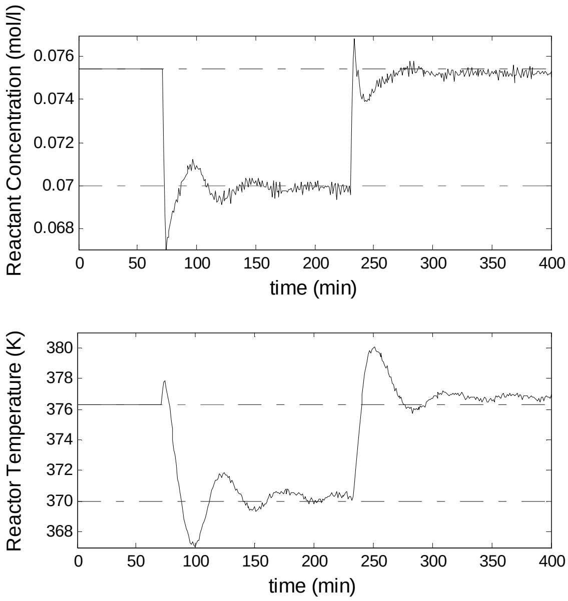

Fig. 1 Responses of the controlled variables using the conventional MPC configuration.

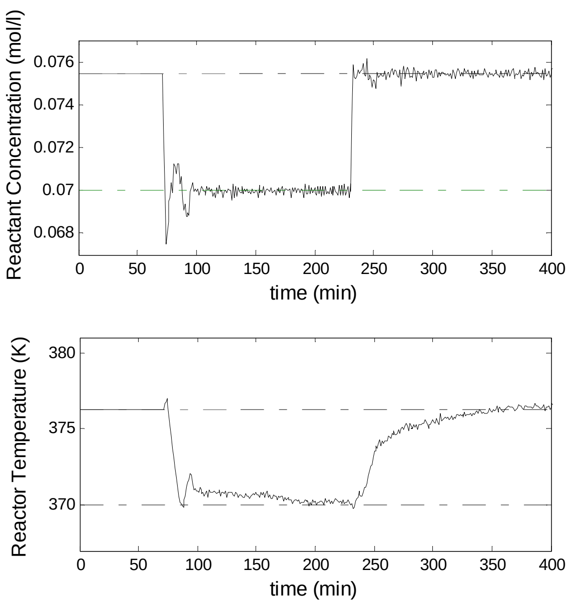

Fig. 2 Responses of the controlled variables using the multiobjective adaptive MPC configuration.

*Matrices **W**, **R**,$\mathbf{R_1}$, $\mathbf{R_2}$ refer to the scaled values of the input and output variables.

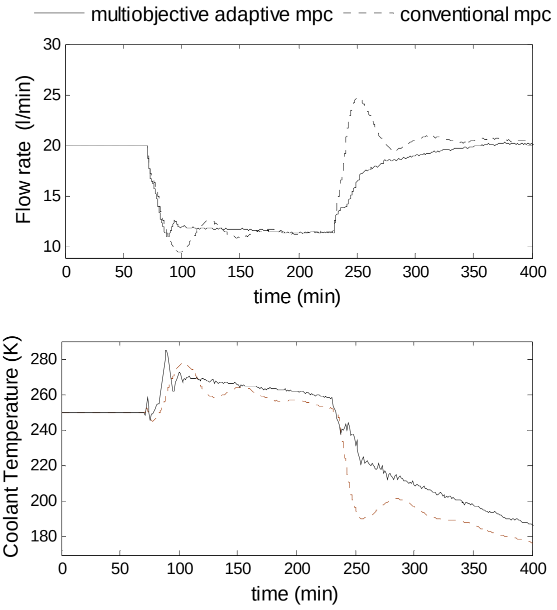

Fig. 3 Comparison between the proposed scheme and a typical MPC configuration: The manipulated variables.

manages to produce zero set point offsets for both controlled variables and both set point changes. This is not achieved by the non adaptive MPC, since it does not have the capability to correct the model according to the gradual changes in the dynamics of the process. It is important to notice that the improvement is more obvious during the second set point change, where due to the more intense modification of the heat transfer coefficient, permanent deviations from the actual set points are observed, when the conventional MPC approach is utilized. In summary, the advantages of the proposed MPC configuration compared to the classical MPC scheme are: a) the adaptation of the dynamic model that maintains a good performance even in the cases of severe and/or sudden modifications in the dynamics of the process or changes in the operating range and b) the utilization of an evolutionary algorithm that solves successfully the non-convex optimization problem that is formulated on-line. The algorithm is computationally efficient, given that a good guess is usually available as an initial solution, which is the input sequence calculated at the previous time step.

V. Conclusions

In this paper a prioritized multiobjective MPC approach is suggested for time varying systems. An advantage of this work is that it avoids the significant tuning effort, which is necessary in order to combine various control goals of different importance in a single optimization problem. A significant modification compared to the standard MPC formulation, is the substitution of the persistent excitation constraint of the manipulated variables by a top priority optimization problem. Satisfaction of the first objective guarantees that the process produces adequate information to identify dynamic modifications even in closed loop mode. Then, the rest of the control goals are satisfied according to their relative importance. The simulation examples of a time varying CSTR proved that the closed loop performance of the proposed scheme is superior to the standard MPC scheme.

The paper also explored the utilization of evolutionary computation for solving the non-convex nonlinear optimization problems that are formulated by including the persistent excitation requirement in the MPC configuration. The evolutionary algorithm that was tested proved to be very efficient for solving such problems. The idea of using an evolutionary algorithm to solve MPC-related optimization problems can also be extended to the cases where nonlinear models are used for predicting the future behavior of the controlled variables.

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