DESIGN OF A MULTIOBJECTIVE PREDICTIVE CONTROLLER FOR MULTIVARIABLE SYSTEMS

F. Ben Aicha, F. Bouani and M. Ksouri
Laboratory of Analysis and Control of Systems, National Engineering School of Tunis
BP 37, le Belvedere 1002, Tunis, Tunisia

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Abstract: In this paper, a strategy for automatic tuning of decentralized predictive controller synthesis parameters based on multiobjective optimization for multivariable systems is proposed. This strategy integrates the genetic algorithm to generate the synthesis parameters (the prediction horizon, the control horizon and the cost weighting factor) making a compromise between closed loop performances (the overshoot, the variance of the control and the settling time). A simulation example is presented to illustrate the performance of this strategy in the on-line adjustment of generalized predictive control parameters.

1 INTRODUCTION

Processes with only one output being controlled by a single manipulated variable are classified as single-input single output (SISO) systems. Many processes, however, do not conform to such simple control configuration. These systems are known as multi-input multi-output (MIMO) or multivariable systems. As most of the multivariable systems present interactions, the interaction problem between control loops has long been recognised as an area for concern and many approaches to deal with this problem were proposed. The method used in this work is to design non-interacting or decoupling controllers to eliminate completely the effects of loop interactions. This is achieved via decouplers (Albertos and Sala, 2004). As a control technique**,** we have used the Generalized Predictive Control (GPC) which has achieved great success in practical applications in recent decades. This strategy of control requires the determination of synthesis parameters: prediction horizon, control horizon and cost weighting factor which give acceptable closed loop performances. But, there is not exact rules giving the values of required parameters. Some works deal with the automatic tuning of GPC such as (Ben Abdennour, Ksouri and Favier, 1998) in which, an on-line adjustment of GPC's synthesis parameters using the fuzzy logic is presented. But, this method does not give exact values of synthesis parameters but allows a fuzzy description of each parameter (small, average, big). On the other hand, in (Ben Abdennour, Ksouri and Favier, 1998) to determine the GPC parameters, each performance criterion is minimized without considering the others criteria, so the problem is considered as a single-objective one. In practice, the optimization problems are rarely single-objective; where from the interest of multiobjective optimization (MOO) based on the minimization of all performance criteria at every sample time. The MOO leads to a set of optimal solutions, i.e. the Pareto optimal solutions or the non dominated solutions (Collette and Siarry, 2002). In this context, many works such as (Popov, Farag and Werner, 2005), (Yang and Pedersen, 2006), (Bemporada and Muñoz de la Peñab, 2009) and (Muldera, Tiwari and Kothare, 2009) were interested in the synthesis of controllers based on multiobjective optimisation which has more and more interest. In this paper, we propose a new method allowing the on-line adjustment of synthesis parameters of predictive controller using the genetic algorithm and that for the multivariable systems. The performances' criteria to be simultaneously minimized are the settling time, the overshoot and the variance of the control. This paper is organized as follows. The problem is formulated in section two where the multivariable decoupling control and the predictive control principle are given. The proposed

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method allowing the tuning of synthesis parameters and the design of the multiobjective predictive controller are described in section three. The obtained simulation results are presented in section four. Conclusions are given in the last section.

2 PROBLEM FORMULATION

2.1 Multivariable System Representation

We consider a multivariable linear system with m inputs $u_i(k)$: $i=1,\ldots,m$ and n outputs $y_j(k)$: $j=1,\ldots,n$. The system equation is given by:

$$Y(k)=G(z^{-1})U(k) \tag{1}$$

with: $U(k)=[u_1(k),u_2(k),....,u_m(k)]^T$ is the control vector, $Y(k)=[y_1(k),y_2(k),.....,y_n(k)]^T$ is the output vector and $G(z^{-1})$ is the transfer function matrix having as dimension $m\times n$ given by:

$$G(z^{-1})=\begin{pmatrix} g_{11}(z^{-1}) & \cdots & g_{1m}(z^{-1}) \\ \vdots & \ddots & \vdots \\ g_{n1}(z^{-1}) & \cdots & g_{nm}(z^{-1}) \end{pmatrix} \tag{2}$$

For the P canonical structure (Albertos and Sala, 2004)., in the case of a system with two inputs and two outputs, the outputs are related to the inputs according to:

$$y_1(k)=g_{11}(z^{-1})u_1(k)+g_{12}(z^{-1})u_2(k) \tag{3}$$

$$y_2(k)=g_{22}(z^{-1})u_2(k)+g_{21}(z^{-1})u_1(k) \tag{4}$$

2.2 Multivariable Decoupling Control

Generally, in the industry the distributed control is the most favorable and the most used thanks to its structure simplicity. During the decentralized control design for a two inputs two outputs (TITO) process, the input-output pairing is essential and determining for the obtained performances as well as for the stability of the system (Moaveni and Khaki-Sedigh, 2006). Several methods were proposed to solve the interaction problem (Bristol, 1966), (Khelassi, Wilson and Bendib, 2004). The method which will be applied in this work is the one using decouplers having as role to decompose a multivariable process into a series of independent single-loop sub-systems, and the multivariable process can be controlled using independent loop controllers. As well as the input-output representation of multivariable processes, different structures are possible, like P or V decouplers. Judging by the literature, the P-decoupler seems to be the most popular. In this work, we choose to use the decoupling network of Zalkind given in (Zalkind, 1967). The structure of the obtained decoupled process having as auxilliary inputs $v_1(k)$ and $v_2(k)$ is presented in the figure below.

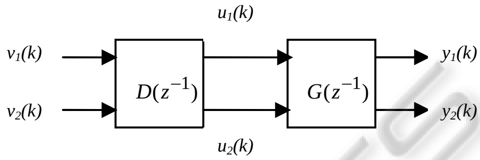

Figure 1: The structure of the decoupled process.

The control signals are given by:

$$u_1(k)=D_{11}(z^{-1})v_1(k)+D_{12}(z^{-1})v_2(k) \tag{5}$$

$$u_2(k)=D_{21}(z^{-1})v_1(k)+D_{22}(z^{-1})v_2(k) \tag{6}$$

where $D_{ij}(z^{-1}),\ i=1,2\ and\ j=1,2$ are the elements of the transfer function $D(z^{-1})$.

In taking into account equations (3), (4), (5) and (6), we shall have:

$$\begin{aligned} y_1(k) &= \left[D_{11}(z^{-1})g_{11}(z^{-1})+D_{21}(z^{-1})g_{12}(z^{-1})\right]v_1(k) \\ &+\left[D_{22}(z^{-1})g_{12}(z^{-1})+D_{12}(z^{-1})g_{11}(z^{-1})\right]v_2(k) \end{aligned} \tag{7}$$

$$\begin{aligned} y_2(k) &= \left[D_{11}(z^{-1})g_{21}(z^{-1})+D_{21}(z^{-1})g_{22}(z^{-1})\right]v_1(k) \\ &+\left[D_{22}(z^{-1})g_{22}(z^{-1})+D_{12}(z^{-1})g_{21}(z^{-1})\right]v_2(k) \end{aligned} \tag{8}$$

To have $y_2(k)$ independent of $v_1(k)$ and $y_1(k)$ independent of $v_2(k)$, we introduce the decouplers between the process and the controller such as :

$$D_{12}(z)=\frac{-g_{12}(z)D_{22}(z)}{g_{11}(z)} \tag{9}$$

$$D_{21}(z)=\frac{-g_{21}(z)D_{11}(z)}{g_{22}(z)} \tag{10}$$

Generally we take $D_{11}(z)=1$ and $D_{22}(z)=1$ except in case the delays are more important in the direct branches than in the crossed branches (Albertos and Sala, 2004).

By using (9) and (10) in (7) and (8), we obtain:

$$y_1(k)=\left(g_{11}(z^{-1})-\frac{g_{12}(z^{-1})\,g_{21}(z^{-1})}{g_{22}(z^{-1})}\right)v_1(k) \tag{11}$$

$$y_2(k) = \left(g_{22}(z^{-1}) - \frac{g_{12}(z^{-1})\, g_{21}(z^{-1})}{g_{11}(z^{-1})} \right) v_2(k) \qquad (12)$$

The use of (9) and (10) leads to the following control signals:

$$u_1(k) = \frac{-g_{12}(z^{-1})}{g_{11}(z^{-1})} v_2(k) + v_1(k) \qquad (13)$$

$$u_2(k) = \frac{-g_{21}(z^{-1})}{g_{22}(z^{-1})} v_1(k) + v_2(k) \qquad (14)$$

The ($m \times n$) multivariable process is treated as a set of n SISO processes. Each SISO process is characterized by a CARIMA (Controlled Auto Regressive Integrated Moving Average) dynamic model. This model is given by the following relation:

$$A(z^{-1})\, y(k) = z^{-d} B(z^{-1})\, v(k-1) + \frac{C(z^{-1})}{\Delta(z^{-1})}\, e(k) \qquad (15)$$

where

- $y(k)$ and $v(k)$ are respectively the output and the input of the system.
- $e(k)$ is a sequence of white noise with zero mean average and a finite variance.

-The polynomials $A(z^{-1})$, $B(z^{-1})$, $C(z^{-1})$ and $\Delta(z^{-1})$ are given by:

$$A(z^{-1}) = 1 + a_1 z^{-1} + ... + a_{nA} z^{-nA} \qquad (16)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + ... + b_{nB} z^{-nB} \qquad (17)$$

$$C(z^{-1}) = 1 + c_1 z^{-1} + ... + c_{nC} z^{-nC} \qquad (18)$$

$$\Delta(z^{-1}) = 1 - z^{-1} \qquad (19)$$

-The roots in z of $C(z^{-1})$ must be strictly inside the unit circle.

- d represents the time delay of the system.

2.3 The GPC Optimal Control

The generalized predictive control is based on the minimization of a quadratic criterion given by the following expression (Richalet, Lavielle and Mallet, 2005), (Clarke, Mohtadi and Tuffs, 1987):

$$J_{GPC} = \sum_{j=1+d}^{Hp+d} (r_c(k+j) - \hat{y}(k+j/k))^2 + \rho \sum_{j=0}^{Hc-1} (\Delta v(k+j))^2 \qquad (20)$$

where H_p is the prediction horizon, H_c is the control horizon, ρ is the cost weighting factor, $r_c(k)$ is the set point, $\hat{y}(k+j/k)$ is the predicted output and $\Delta v(k+j)$ is the future increments of the control given by:

$$\Delta v(k+j) = v(k+j) - v(k+j-1) \qquad (21)$$

By minimizing the criterion J_{GPC}, we can determine the expression of the optimal vector $\Delta V(k) = \left[\Delta v(k),...,\Delta v(k+H_c-1)\right]^T$ as follows:

$$\Delta V(k) = K_{GPC}\left[R_c(k) - \left[\frac{1}{C(z^{-1})}[Gy(k) + R\Delta(z^{-1})v(k-1)] \right]\right] \qquad (21)$$

where

$$K_{GPC} = [N_1^T N_1 + \rho I_{H_c}]^{-1} N_1^T \qquad (23)$$

$$R_c(k) = [r_c(k+1+d),...,r_c(k+H_p+d)]^T \;. \qquad (24)$$

N_1 is a (H_p, H_c) matrix, G and R are obtained by the resolution of Diophantine equations (Clarke, Mohtadi, and Tuffs, 1987). The optimal control to be applied to the process is defined from the vector given by (22) using the receding horizon principle. This optimal control $v(k)$ is computed from the first element $\Delta v(1)$ of the vector $\Delta V(k)$:

$$v(k) = v(k-1) + \Delta v(1) \qquad (25)$$

It is evident that the optimal predictive control depends on synthesis parameters $(H_p,\ H_c,\ \rho)$. So, in this paper, we present a new method allowing the automatic determination of required GPC's synthesis parameters in the case of multivariable systems.

3 MULTIOBJECTIVE GENERALIZED PREDICTIVE CONTROL

Multi-objective optimization (MOO) can be defined as the problem of finding a vector of parameters $X = \left[x_1,...,x_l\right]^T$, which optimizes a vector of objective functions $(J_1,...,J_n)$ (Gambier, 2008). In general, the MOO problem can be formulated as follows:

$$\min_X \; (J_1(X),\ J_2(X),...,J_n(X)) \qquad (26)$$

At present, a very huge number of methods to solve MOO problems can be found in literature (Collette and Siarry, 2002), (Gambier, 2008). The method applied in this work is the weighted sum method that belongs to the family of aggregative methods.

3.1 Weighted Sum Method

This method allows the transformation of the objective functions vector in a single-objective function. It is known for its efficiency and suitability to generate a strongly non dominated solution that can be used as an initial solution for other techniques. The single criterion is obtained by the sum of the weighted criteria as follows (Gambier, 2008):

$$J = \sum_{i=1}^{n} w_i \; J_i \tag{27}$$

where the weights are chosen such that:

$$\sum_{i=1}^{n} w_i = 1 \;\; and \;\; 0 \le w_i \le 1 \tag{28}$$

The MOO leads to a set of solutions known as a Pareto set. This set is also called non-dominated solutions. When the non dominated solutions are collectively plotted in the criterion space, they constitute the Pareto front (Gambier, 2008). All points of the Pareto front are equally acceptable solution for the problem. However, it is necessary to obtain only one point in order to be able to implement the controller (Gambier, 2008).To choose one solution from the Pareto front, we can compute the following norm for each solution which gives a compromise between all criteria (Bouani, Laabidi, and Ksouri, 2006):

$$d_i = \sqrt{J_1^2 + J_2^2 + \ldots + J_n^2} \tag{29}$$

The quality of a control applied to a process is generally estimated by the closed loop performances of the system. Among these performances we choose as objective functions to optimize:

- The overshoot $D_{\%}$

$$D_{\%} = 100 \frac{|y_{\max} - r_c|}{r_c} \tag{30}$$

$y_{\max}$ is the maximum value of the output and r_c is the set point value.

- The variance of the control V_v

$$V_v = \frac{\sum_{N_1}^{N_2} v(k)^2}{N_2 - N_1} \tag{31}$$

N_1 is the first measure iteration and N_2 is the last one.

- The settling time T_s: It is the first instant after which, the system output doesn't exceed $\pm 5\%$ of the set point value.

So, to estimate the synthesis parameters for GPC, the following criterion will be minimized.

$$J = w_1 \; D_{\%} + w_2 \; V_v + w_3 \; T_s \quad . \tag{32}$$

such that:

$w_1 + w_2 + w_3 = 1$ and $0 \le w_i \le 1; \; i = 1,\ldots,3$.

3.2 Generating Optimal Solutions Using Genetic Algorithms

In genetic algorithms, each parameter is represented by a string structure. This is similar to the chromosome structure in natural genes (Goldberg, 1991). A group of strings are called population. It should be notice that GAs evaluate a set of solutions in the population at each iteration step. Every solution is formed by GPC's synthesis parameters. A number of genetic operators (selection, crossover and mutation) are available to generate new individuals in next generation.

In this paper, we propose an on-line supervisor for each classic predictive controller based on genetic algorithms. In figure 2, we present the structure of this supervisor. Each supervisor permits the on-line adjustment of the GPC algorithm parameters in order to optimize simultaneously closed loop performances.

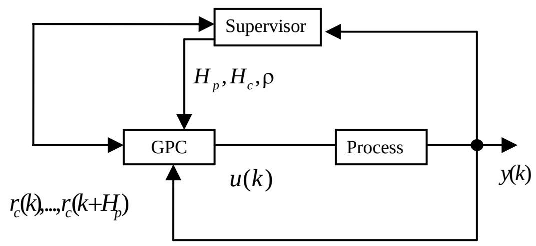

Figure 2: The Supervisor of the Classic Predictive Controller.

In our work, the GA population is formed by the synthesis parameters (H_p, H_c, ρ). The initial population is formed by arbitrary values, such as: $1 \le H_p \le 20$; $1 \le H_c \le 3$ and $0 < \rho \le 10$. For each individual of the population, we use the process model and the generalized predictive controller in order to compute, for a given set point, the output sequence along two hundreds sample times. Then, we evaluate the performance indices ($D_{\%}, V_v, T_s$)

and the fitness. To obtain the new population, we use the roulette wheel as a selection operator. To acquire more information in the new population, the crossover and the mutation operators are needed. This procedure will be repeated until a stop criterion (e.g. max number of generation) is reached. Then, we obtain the best individual (optimal values of H_p, H_c and ρ) that minimizes the performances indices. The steps used to compute the best synthesis parameters are given in algorithm 1. In this algorithm, we design by max_gen the maximum number of generations and by max_pop the maximum number of population.

Algorithm 1: The principal steps to design multi-objective predictive controller.

Form the initial population
For j=1 To max_gen
  For i=1 To max_pop
   - Take the ith individual of the population,
   - Use the GPC with the process model,
   - Compute the model output,
   - Evaluate the criteria: $D_{\%}, V_v, T_s$
   - Evaluate the fitness using (32)
  End
  Use the GA operators (selection, crossover and mutation) to form the new population.
End
Take the best individual (H_p, H_c, ρ).

Once the non dominated solutions are computed, the problem is which solution can be used with the GPC to handle the real process. To choose one solution from the Pareto front, we compute the following norm for each solution:

$$d_i = \sqrt{D_{\%}^2 + V_v^2 + T_s^2} \quad . \tag{33}$$

The steps allowing to find the synthesis parameters which minimize the performance criteria, given by the proposed algorithm is executed twice because the TITO system is decomposed into two monovariable systems controlled each by multiobjective predictive controller.

4 SIMULATION RESULTS

To estimate the closed loop performances obtained by applying the approach presented in this paper, we consider the TITO process given in (Miskovic, Karimi, Bonvin and Gevers, 2007) characterized by the next transfer functions matrix:

$$G(z^{-1}) = \begin{pmatrix} \dfrac{0.09516\ z^{-1}}{1-0.9048\ z^{-1}} & \dfrac{0.03807\ z^{-1}}{1-0.9048\ z^{-1}} \\ \dfrac{-0.02974\ z^{-1}}{1-0.9048\ z^{-1}} & \dfrac{0.04758\ z^{-1}}{1-0.9048\ z^{-1}} \end{pmatrix} \tag{34}$$

4.1 Generating Optimal Solutions

To apply the genetic algorithm, we choose a population of 20 individuals and a maximum number of generations equals to 150. The crossover probability and the mutation probability are fixed respectively to $c_p = 0.7$ and $m_p = 0.3$. We vary w_1 between 0 and 0.9, and w_2 and w_3 are computed by:

$$w_2 = w_3 = \frac{1-w_1}{2} \quad . \tag{35}$$

For every set of (w_1, w_2, w_3), the genetic algorithm evaluates the criterion given by (32) and generates the best individual (H_p, H_c, ρ).

In tables 1 and 2, we have, respectively reported the values of the best individuals corresponding to every set of weights for the first and the second SISO systems.

Table 1: The values of best individuals corresponding to every set of weights for the first SISO system.

i	Weights			Best individuals		
	w_1	w_2	w_3	H_p	H_c	ρ
1	0	0.5	0.5	2	1	5.75
2	0.1	0.45	0.45	3	2	6.71
3	0.2	0.4	0.4	3	2	6.71
4	0.3	0.35	0.35	2	2	7.98
5	0.4	0.3	0.3	3	2	6.72
6	0.5	0.25	0.25	3	2	6.77
7	0.6	0.2	0.2	3	1	9.40
8	0.7	0.15	0.15	2	2	9.99
9	0.8	0.1	0.1	3	1	9.42
10	0.9	0.05	0.05	2	2	5.62

Table 2: The values of best individuals corresponding to every set of weights for the second SISO system.

i	Weights			Best individuals		
	w_1	w_2	w_3	H_p	H_c	ρ
1	0	0.5	0.5	6	3	7.51
2	0.1	0.45	0.45	5	3	7.43
3	0.2	0.4	0.4	7	2	8.36
4	0.3	0.35	0.35	4	2	6.43
5	0.4	0.3	0.3	5	3	7.41
6	0.5	0.25	0.25	4	2	6.47
7	0.6	0.2	0.2	2	1	9.78
8	0.7	0.15	0.15	2	1	9.76
9	0.8	0.1	0.1	6	3	7.43
10	0.9	0.05	0.05	7	2	8.31

Figures 3 and 4, describe respectively the non dominated solutions which constitute the Pareto front for the first and the second SISO systems.

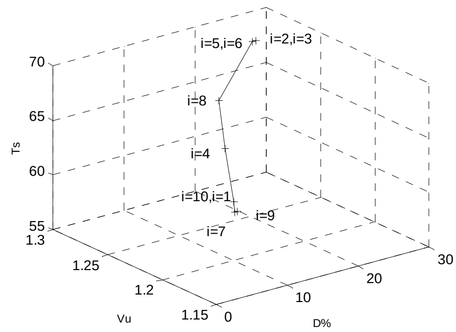

Figure 3: The Pareto front for the first SISO system.

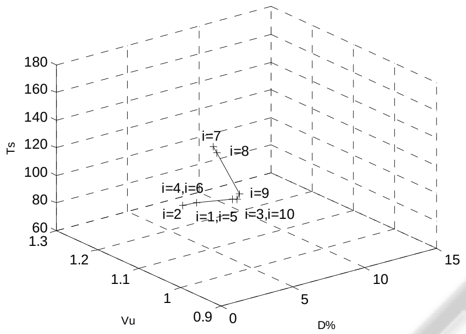

Figure 4: The Pareto front for the second SISO system.

4.2 Multiobjective Predictive Controller

To implement the controller, it is necessary to choose a single solution among all non dominated solutions. This choice is made by the user, if he decides to give the priority to the minimization of overshoot, he will choose the solution giving the overshoot minimum value. If the most important criterion to be minimized for the user is the settling time, he will choose the solution giving the minimum settling time. In this paper we choose to make a compromise between the three closed loop performances. For that, the step to be followed is to calculate the norm given by (33) for every set of w_i and to choose the synthesis parameters corresponding to the smallest value of d_i .

For the first SISO system, the synthesis parameters giving a minimal value of the norm d_i are given in Table 3. For the second SISO system the synthesis parameters chosen by the supervisor are presented in table 4. So we can notice that this proposed method allows automatic adjusting of synthesis parameters.

Table 3: The Synthesis Parameters Chosen by the Supervisor for the first SISO system.

H_{p1}	H_{c1}	ρ_1
2	2	7.98

Table 4: The Synthesis Parameters Chosen by the Supervisor for the second SISO system.

H_{p2}	H_{c2}	ρ_2
5	3	7.43

The obtained synthesis parameters, given in Table 3 and Table 4 are used with the two predictive controllers to control the multivariable process.

The obtained results are shown in Figure 5 and Figure 6 which respectively present the evolution of the system outputs and the set points and the evolution of the control signals. From these figures, we can notice that this proposed method allows automatic adjusting of synthesis parameters permitting a compromise between closed loop performances.

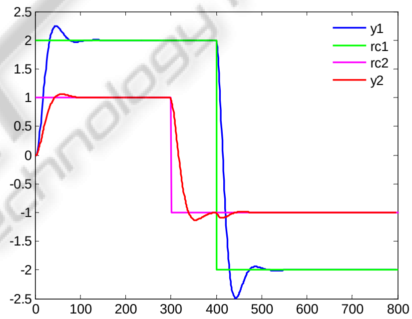

Figure 5: Evolution of the outputs and the set points.

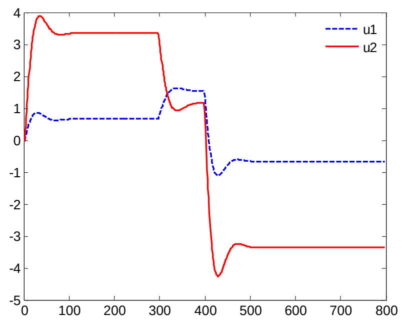

Figure 6: Evolution of the control signals.

The tables 5 and 6 recapitulate respectively the overshoots, the settling times values and the variances of the controls found for the first and the second SISO system.

Table 5: Closed loop performances Values Obtained for the First SISO System.

	Overshoot ($D_{\%}$)	Settling time (T_s)	Variance of the control (V_v)
k ∈ [0;400]	12	64s	0.69
k ∈ [401;800]	24	66s	

Table 6: Closed loop Performances values for the Second SISO System.

	Overshoot ($D_{\%}$)	Settling time (T_s)	Variance of the control (V_v)
k ∈ [0;300]	05.8	71s	10.06
k ∈ [301;800]	12.8	77s	

5 CONCLUSIONS

In this paper, a new method allowing the on line adjustment of the predictive controller synthesis parameters for multivariable systems has been presented. The decentralized control using the decoupling network is applied to decouple the different subsystems and to control the MIMO system using multiple SISO controllers. Genetic algorithms and the weighted sum method are exploited to find the synthesis parameters by minimizing simultaneously three criteria which are the overshoot, the settling time and the variance of the control. The obtained simulation results have shown that the proposed method can lead to acceptable closed loop performances.

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