*Int. J. Appl. Math. and Comp. Sci., 1999, Vol.9, No.1, 9–24*

# SOME ISSUES IN THE DESIGN OF PREDICTIVE CONTROLLERS[†]

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In the paper, we discuss how to design a predictive controller capable of addressing a number of important issues ranging from nominal stability to the model identification/controller design interplay. Nominal stability is ensured by resorting to Constrained Receding Horizon Predictive Control. As for robust stability, the connections between the frequency weighting $P$-polynomial in the cost function and the achievable robustness against multiplicative uncertainty are investigated. Then, a two-step design procedure is proposed in order to enhance the closed-loop robustness and obtain nominal performances. A correlation technique is also proposed as a tool to estimate uncertainty bounds to be used in controller design. Finally, the control and identification procedures are put together to form an iterative identification/control design methodology. A simulation example is reported to illustrate the approach.

**Keywords:** predictive control, robust control, two degree of freedom regulation, identification for control.

## 1. Introduction

Model Based Predictive Control (MBPC) has gained wide acceptance in the industrial environment due to its ability to obtain good performances starting from simple models and rather intuitive design principles (Clarke, 1994). Some of the reasons behind this success are the possibility of including explicit constraints on the future outputs and inputs and the flexibility allowed by a number of design knobs such as the control weights and the control and prediction horizons. Furthermore, experience has shown that reasonably good performances are usually obtained also when the design parameters are tuned according to more or less heuristic recipes.

At the same time, recent years have witnessed many theoretical developments in control theory which can be used to provide more systematic foundations to the design of predictive controllers. From a practical point of view any control design method should address the following issues:

† This paper has been partially supported by MURST Project *Model Identification, System Control, Signal Processing*.

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*Nominal stability:* For many years most of the stability results of MBPC algorithms have been asymptotic, i.e. they have held only for sufficiently large prediction horizons (Clarke *et al.*, 1987; Soeterboek, 1992), whereas in practice small horizons are used in order to save computations. Only in recent years, it has been shown that MBPC algorithms with guaranteed stability can be designed by introducing input and output terminal constraints (Clarke and Scattolini, 1991; Kouvaritakis *et al.*, 1992; Mosca and Zhang, 1992; Rawlings and Muske, 1993).

*Robust stability:* Traditionally (Clarke *et al.*, 1991; McIntosh *et al.*, 1991; Mohtadi, 1988; Robinson and Clarke, 1994), the robustness properties of MBPC algorithms have been improved by suitably tuning the available "design knobs", such as the control and prediction horizons, the output and control weighting functions (the so-called $P$ and $Q$ polynomials), or the observer polynomial (the $T$-polynomial). However, since the predictive approach mainly relies on $H_2$ (rather than $H_\infty$) arguments, robust stability with respect to model uncertainty is not guaranteed in general. Other ways to handle uncertainty in predictive control include those based on a contraction mapping property (Morari, 1994; Zafiriou, 1990), or the use of a linear cost function (Genceli and Nikolau, 1993; Zheng and Morari, 1993). Recently, systematic approaches to the robustification of MBPC with respect to unstructured perturbations have been developed by means of the Youla parametrization so as to achieve robustness while maintaining the servo dynamics of the nominal controller (Hrissagis *et al.*, 1995; Kouvaritakis *et al.*, 1992). Although this procedure is elegant and effective in addressing the robustness problem, it can be computationally demanding in some contexts, e.g. in adaptive control. Thus, there is still some interest in improving robustness of classical MBPC by a suitable choice of the standard design parameters (Ansay *et al.*, 1998; Yoon and Clarke, 1995).

*Performance*: The robustification of a predictive controller, motivated e.g. by the presence of high-frequency model uncertainty, can go to the detriment of the closed-loop performance even in nominal conditions. This is an emerging topic which has received attention only recently (De Nicolao *et al.*, 1996; Kouvaritakis *et al.*, 1992; Yoon and Clarke, 1995).

*Interplay between controller design and model identification*: The design of robust controllers calls for the identification of uncertainty bounds for the nominal system. Traditionally, the identification phase has been viewed as preliminary and separate with respect to the control design phase. A recent stream of research, however, has pointed out possible benefits coming from a joint design of identification and control (Gevers, 1993; Hjalmarsson *et al.*, 1996; Lee *et al.*, 1993; Schrama, 1992; Schrama and Bosgra, 1993; Van den Hof *et al.*, 1995). Again there is interest in incorporating these ideas in the MBPC design.

The aim of the present paper is to show how to design a predictive controller taking into account the above issues. The emphasis here is not on developing ultimate and optimal answers to the single questions but rather on outlining an overall design procedure. Specifically, the nominal stability issue is ipso facto solved by considering the Constrained Receding Horizon Predictive Control (CRHPC) algorithm (Clarke and Scattolini, 1991). As for robust stability, we provide some insight into the use of the classical method based on the $P$-polynomial. With respect to the performance issue, we observe that the intrinsic two-degrees-of-freedom structure of MBPC schemes has not been fully exploited so far. Therefore, we suggest a two-step design procedure where, after designing a feedback regulator ensuring robust stability, performance recovery is obtained by means of a suitable feedforward compensator (of predictive type, as well). Finally, we propose a joint control/identification scheme hinging on the iteration of a two-step procedure. In the identification step, input-output data collected from a closed-loop experiment are suitably filtered and used to identify a nominal plant model together with its uncertainty bounds. In the other step, the nominal plant model and the uncertainty bounds are used to design a controller to be used in the subsequent identification step. The effectiveness of the proposed approach is demonstrated through a simulated benchmark problem (Lee *et al.*, 1993).

Nowadays it is well recognized that the success of predictive control lies in its capability to handle difficult control problems for highly constrained MIMO systems. However, in order to simplify the presentation and to focus on some basic aspects concerning the choice of the design parameters, we will restrict the attention to the simpler case of unconstrained SISO systems.

## 2. System Under Control and CRHPC Control Law

The system under control is described by the SISO linear, discrete, time-invariant nominal model:

$$A(q^{-1})y(t) = B(q^{-1})u(t) \tag{1}$$

where $q^{-1}$ is the backward shift operator, $u$ and $y$ are the input and the output signals respectively, while $A(q^{-1})$ and $B(q^{-1})$ are polynomials of order $n$ with $B(0) = 0$. In the following $z$ will represent the argument for $Z$-transforms (in operational terms $q^{-1} = z^{-1}$); polynomials and transfer functions will be either defined in terms of $q^{-1}$ or $z$ depending on the context.

Assuming that system (1) does not contain derivative terms, i.e. $B(1) \neq 0$, an integral action can be inserted to guarantee asymptotic zero error regulation for constant reference signals and load disturbances. Then, by letting

$$\begin{aligned} \delta(q^{-1}) &= 1 - q^{-1} \\ \mathrm{d}u(t) &= u(t) - u(t-1) = \delta(q^{-1})u(t) \end{aligned}$$

the system to be controlled is:

$$A(q^{-1})\delta(q^{-1})y(t) = B(q^{-1})\,\mathrm{d}u(t) \tag{2}$$

The CRHPC control law for system (2) is obtained by solving at any time $t$ the following optimization problem:

$$\min_{\mathrm{d}u(t),\mathrm{d}u(t+1),\ldots,\mathrm{d}u(t+N)} \sum_{i=1}^{N} \lambda_P \left[P(q^{-1})y(t+i) - \overline{P}y^o(t+i)\right]^2 + \sum_{i=1}^{N} \lambda_q \,\mathrm{d}u^2(t+i) \tag{3}$$

subject to (2) and

$$\begin{aligned} P(q^{-1})y(t+N+j) &= \overline{P}y^o(t+N), \qquad j>0 \\ du(t+N+j) &= 0, \qquad j>0 \end{aligned} \tag{4}$$

and by applying only the first computed control variation $du(t)$ according to the receding horizon strategy.

In problem (3)–(4) the reference signal $y^o$ is known in advance, $\lambda_P \geq 0$, $\lambda_q > 0$, $\overline{P} = P(1)$, while $P(q^{-1})$ represents a suitable frequency weighting transfer function, of order $n_p$, which must be selected in order to improve the closed-loop characteristics. Although the $P$-polynomial has a long-standing history in predictive control (Clarke and Gawthrop, 1975), its design is still generally performed on the basis of empirical considerations.

The receding horizon control law obtained by solving problem (3)–(4) takes the form (De Nicolao and Scattolini, 1994):

$$G(q^{-1})\,du(t) = H(q^{-1})y^o(t+N) + F(q^{-1})y(t) \tag{5}$$

where $G$, $H$, $F$ are suitable polynomials.

Concerning the control law (5), some comments are in order. First, it is easy to prove with Lyapunov-type arguments that, when $P(q^{-1}) = 1$, the closed-loop system (2)–(5) is asymptotically stable (De Nicolao and Scattolini, 1994) provided that $\lambda_P \geq 0$, $N \geq n+1$. Second, when $y^o = 0$, eqn. (5) can be viewed as the solution to a suitably defined infinite-horizon $LQ$ control problem (De Nicolao and Scattolini, 1994). Furthermore, when $N$ is sufficiently large, the CRHPC solution tends to the corresponding infinite horizon $LQ$ one. Hence, the connection between predictive techniques and $H_2$ control theory is well established. Finally, it is apparent that CRHPC has a two-degree-of-freedom structure since a feedback regulator (polynomials $G(q^{-1})$ and $F(q^{-1})$) and a feedforward compensator (polynomial $H(q^{-1})$) are synthesized. However, the potentialities of a two-degree-of-freedom scheme are not fully exploited, since the optimization problem (3)–(4) does not allow us to specify different requirements simultaneously, such as robust stability and nominal performances.

## 3. Improving Robustness with $P$-Polynomial

For many years, the $P$-polynomial has been used to accommodate the controller design for the presence of a high-frequency model uncertainty. The aim of this section is to give an assessment of its use for robustness enhancement.

For this purpose it is useful to recall some basic facts concerning robustness. Specifically, let $\mathcal{G}_n(z)$ and $\mathcal{G}(z)$ be the nominal and the true system transfer function, and consider a *multiplicative model uncertainty description:*

$$\mathcal{G}(z) = \mathcal{G}_n(z)\big(1 + \Delta_m(z)\big) \tag{6}$$

Now, assume that $y^o = 0$ and let $R(z)$ be the feedback regulator transfer function, i.e. $U(z) = -R(z)Y(z)$. The corresponding closed-loop scheme is reported in Fig. 1.

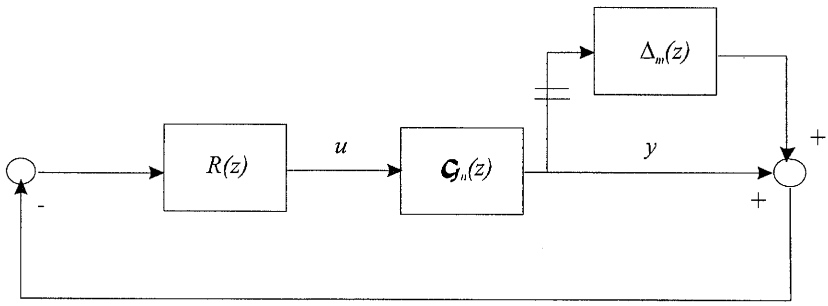


Fig. 1. Closed-loop system with multiplicative uncertainty.

By a standard $H_\infty$ argument (Doyle *et al.*, 1992), robust stability is achieved by imposing

$$\left\|T(e^{j\theta})\Delta_m(e^{j\theta})\right\|_\infty < 1, \qquad \theta \in [0, \pi]$$

where $T(z)$ is the complementary sensitivity function.

A main difficulty in guaranteeing robustness of predictive controllers is that they rely on an $H_2$-type cost functional, rather than an $H_\infty$ one. In the general $H_2$ setting, one aims at solving the problem

$$\min \left\|T(e^{j\theta})W(e^{j\theta})v\right\|_2^2 = \min \left\|W(e^{j\theta})y\right\|_2^2, \qquad \theta \in [0, \pi] \tag{7}$$

where $W(z)$ is a user-defined weight, $v(t) = \text{imp}(t)$ and $y(t)$ is the nominal closed-loop response to an impulse reference signal (Morari and Zafiriou, 1989). Now, consider the performance index (3)–(4) of CRHPC, and for ease of reasoning, assume that $\lambda_q \to 0$, and $N$ is sufficiently large. Then, CRHPC is substantially equivalent to an $H_2$ controller, where $P$ plays the same role as $W$ in (7). In most cases, minimizing the average magnitude (the $H_2$ norm) of $TW$ will have some beneficial effect on its peak value (the $H_\infty$ norm) as well. For this reason, the following (heuristic) criterion for choosing $P$ is expected to improve robustness:

*Whenever an estimate $\hat{\Delta}_m(e^{j\theta})$ of the multiplicative model uncertainty description $\Delta_m(e^{j\theta})$ is available, use a $P$-polynomial such that $\left|P(e^{j\theta})\right| \simeq \left|\hat{\Delta}_m(e^{j\theta})\right|$, $\theta \in [0, \pi]$.*

It is interesting to note that this rule of thumb is in accordance with the classical selection of the $P$-polynomial as a high-pass filter in the presence of high-frequency model uncertainty. In the particular case of the Clarke-Gawthrop one-step-ahead self-tuning controller with no weight on the control effort, $P^{-1}$ is actually the complementary sensitivity function of the closed-loop system (Gawthrop, 1977).

## 4. Two-Degree-of-Freedom Predictive Controller

The use of the $P$-polynomial to enhance robustness can lead to a very conservative design with a severe deterioration of the reference tracking performance. In order to

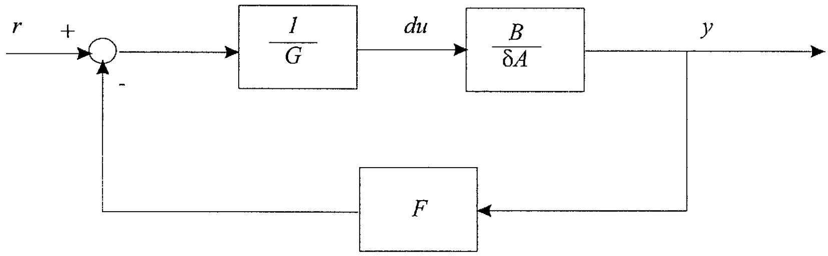


Fig. 2. Closed-loop system resulting from the first phase.

face this problem, we split the design into two phases. First, $P$ is selected according to the guidelines given in the previous section and the optimization problem (3)–(4) with $y^o = 0$ is solved. This leads to the feedback control law:

$$F(q^{-1})y(t) = G(q^{-1})\, du(t)$$

In the second phase, as described below, a feedforward compensator for the reference signal is synthesized, again with the aid of the predictive approach.

Observe that, if the feedback regulator $R(z) = F(z)/G(z)$ (of order $n_r$) is stabilizing, the closed-loop system depicted in Fig. 2 is stable and described by

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})G(q^{-1})\delta(q^{-1}) + B(q^{-1})F(q^{-1})} r(t) \cong \sum_{i=1}^{M} g_i r(t-i) \qquad (8)$$

where the last term is an $M$-th order FIR approximation.

With reference to the FIR approximation (8), it is possible to solve, at any time instant $t$, the auxiliary optimization problem:

$$\min_{r(t),r(t+1),\ldots,r(t+N)} \sum_{i=1}^{N} \lambda_y \Big[y(t+i) - y^o(t+i)\Big]^2 + \sum_{i=0}^{N} \lambda_r \Big[r(t+i) - \bar{r}\Big]^2 \qquad (9)$$

subject to (8) and

$$y(t+N+j) = y^o(t+N) = \bar{y}, \quad \forall j > 0 \qquad (10)$$

$$r(t+N+j) = \bar{r}, \qquad \forall j > 0 \qquad (11)$$

with $\lambda_r > 0$ and $\bar{r} = F(1)\bar{y}$. Again, a receding horizon approach is adopted so that, at any time only the first computed value $r(t)$ is applied. The solution to (9)–(11), requires some remarks. First, it is easy to show that, if the $FIR$ representation (8) is used, the resulting control law is open-loop:

$$r(t) = H(q^{-1})y^o(t+N)$$

Second, provided that $N \geq n+1+n_r$, the control law is stabilizing, since the transfer function $H(q^{-1})$ is asymptotically stable. Third, the constraint (11) guarantees zero-error steady-state regulation, i.e. $y_\infty = y^o$, for any constant reference signal $y^o$.

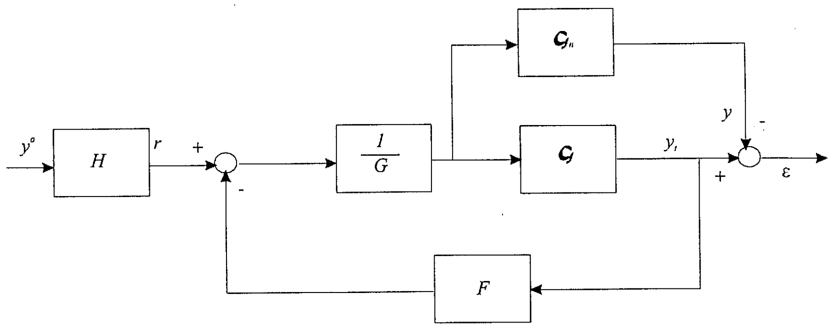


Fig. 3. The identification scheme for multiplicative uncertainty.

It is apparent that the second phase of the suggested procedure aims at obtaining a nominal performance (no uncertainty description is considered in this phase), while the first one takes care of robust stability.

The idea of splitting the stabilization problem from the need of performance enhancement by generating the reference trajectory in a receding horizon way has also been considered in other approaches which recently appeared in the literature, see e.g. (Bemporad and Mosca, 1996; Bemporad *et al.*, 1997). Notably, in these papers the so-called reference governor is determined also by considering the presence of input saturations.

## 5. Model Uncertainty Estimation and Iterative Identification/Controller Design Procedure

In recent years, several techniques have been proposed for the estimation of the model uncertainty, see (Banerjee and Shah, 1995; Hjalmarsson *et al.*, 1996; Van den Hof *et al.*, 1995) and references cited therein. In particular, the use of signal processing methods appears to be promising for evaluating the model/plant mismatch in the frequency range of interest. The scope of this section is to give some guidelines for the identification of the term $\Delta_m(z)$ appearing in (6). To this end, consider the scheme of Fig. 3, where $y_t$ denotes the true output and the nominal system output $y$ can be obtained by simulation, so that the error $\varepsilon(t) = y_t(t) - y(t)$ can be assumed as known. Now suppose that $y^o$ is a stochastic process and let $\phi_{\varepsilon y^o}(\theta)$ and $\phi_{yy^o}(\theta)$ be the cross spectral densities of the pair $(\epsilon(t),\ y^o(t))$ and $(y(t),\ y^o(t))$, respectively. Simple computations lead to

$$\frac{\phi_{\varepsilon y^o}(\theta)}{\phi_{yy^o}(\theta)} = \frac{\mathcal{G}(e^{j\theta}) - \mathcal{G}_n(e^{j\theta})}{\mathcal{G}_n(e^{j\theta})} = \Delta_m(e^{j\theta}) \tag{12}$$

This will be typically done by means of $FFT$ algorithms complemented with suitable windowing techniques in order to reduce the variance of the estimates (Oppenheim and Schafer, 1975).

In view of the above result, it is now possible to develop an iterative identification/control synthesis procedure in order to progressively enlarge the bandwidth of the closed-loop system until the limits imposed by the adopted model structure are reached.

The estimation of the parameters $a_i$ and $b_i$ of the system polynomials $A(q^{-1})$ and $B(q^{-1})$ can be performed by means of the Least Squares method, i.e. by solving the following optimization problem:

$$(a_i, b_i) = \arg\min \sum_{t=0}^{t_f-1} \left(L(q^{-1})\varepsilon(t)\right)^2$$

where $t_f$ is the number of available data and the filter $L(q^{-1})$ is used to focus the modelling procedure on a particular frequency band (Ljung, 1987). If, for example, a good model fit is required at low frequency ($\theta < \bar{\theta}$), $L(q^{-1})$ is chosen as a low-pass filter with cut-off frequency $\bar{\theta}$.

Note that the choice of $\bar{\theta}$ is critical when, as usually happens, the identified plant underestimates the order of the true plant. Due to this underestimation, a substantial frequency response mismatch between the true and the identified plant is inevitable. The main problem however is how the mismatch is distributed along the frequency axis. By a proper choice of $\bar{\theta}$, it is possible to ensure accurate frequency response identification at low frequency so that the high-frequency uncertainty can be successfully coped with by means of robust control design techniques.

Since the data are collected in closed-loop, the consequent implicit frequency weighting guarantees a satisfactory identification only within the bandwidth. In some sense, the choice of $\bar{\theta}$ is bounded by the bandwidth, whereas the achievable bandwidth is limited by the availability of a model which is accurate over a sufficiently large frequency range. This kind of considerations have motivated the development of iterative identification/control procedures progressively enlarging the bandwidth of the control system (Gevers, 1993; Lee *et al.*, 1993; Schrama, 1992; Schrama and Bosgra, 1993).

In the context of our predictive control design scheme, a possible iterative identification/control procedure consists of the following steps:

- **Step 0:** let iteration# = 0; initialize $\mathcal{G}_n(z)$ and select $P$ according to the presumed model uncertainty. Typically one assumes a large high-frequency multiplicative uncertainty, and selects $P$ as a stable high-pass filter with cut-off frequency $\theta_p$. Then design a regulator possibly according to the two-degree-of-freedom synthesis procedure of Section 4.

- **Step 1:** iteration# = iteration# + 1; collect input-output data by means of a closed-loop experiment under a suitable reference signal $y^o$ (in particular $y^o$ should have sufficient energy in all over the frequency range of interest).

- **Step 2:** from the nominal closed-loop bandwidth determine the cut-off frequency $\theta_{id}$ of the filter $L(z)$. Estimate a new nominal model $\mathcal{G}_n(z)$ with the adopted identification algorithm. The corresponding model uncertainty description $\Delta_m(z)$ is obtained through (12).

- **Step 3:** determine a new cut-off frequency $\theta_p$ of the high-pass filter $P(z)$ according to the estimated uncertainty $\Delta_m(z)$ and synthesize a new CRHPC regulator possibly according to the two-degree-of-freedom synthesis procedure of Section 4.
- **Step 4:** iterate Steps $1 \div 3$ until convergence of $\theta_{id}$ and $\theta_p$ is reached.

## 6. Simulation Example

In this section, the control/identification algorithm is applied to the following benchmark plant (Lee *et al.*, 1993):

$$\mathcal{G}(s) = \frac{9}{(s+1)(s^2+0.06s+9)}$$

Assume that the true transfer function of the plant is not known and consider the following nominal transfer function:

$$\mathcal{G}_n(s) = \frac{9}{s+10}$$

In this case the multiplicative uncertainty is:

$$\Delta_m(s) = \frac{\mathcal{G}(s) - \mathcal{G}_n(s)}{\mathcal{G}_n(s)} = \frac{-9s^3 - 9.54s^2 - 72.54s + 9}{9s^3 + 9.54s^2 + 81.54s + 81} \tag{13}$$

whose frequency response, discretised with sampling time $T_s = 0.1$, is shown in Fig. 4.

If the nominal transfer function is used to synthesize the controller according to (3)–(4), with $P = 1$, the CRHPC law applied to $\mathcal{G}(s)$ yields an unstable closed-loop system. On the contrary, if a $P$-polynomial (Fig. 5) reflecting the multiplicative uncertainty (13) is introduced in (3)–(4), then the closed-loop stability is preserved in the face of the mismatch between the true system and the nominal one. In fact, as shown in Section 3, the $P$-polynomial produces a decrease in the complementary sensitivity function at the frequency where the model error is high (Figs. 6–7). However, the response to a reference signal (Fig. 8) is very sluggish.

Consider now the synthesis of the two-degree-of-freedom controller proposed in Section 4. The plot of the step response (Fig. 9) shows that robust stability is preserved, and a clear performance improvement with respect to the one-degree-of-freedom scheme is obtained.

Finally, it is sufficient to apply only once the iterative identification/control procedure to obtain further improvements. In fact, the first-order model identified in the first iteration of the procedure is more representative of the true system than the one used at iteration #0 (Fig. 10). In this respect, a square-wave of period 8 s has been used as a reference signal during a closed-loop experiment of length 40 s. Correspondingly, the model uncertainty $\Delta_m(e^{j\theta})$ has been computed by means of (12). A comparison of this uncertainty and the actual one is reported in Fig. 11, where the mismatch is due to the limited number of data used in the computation of the

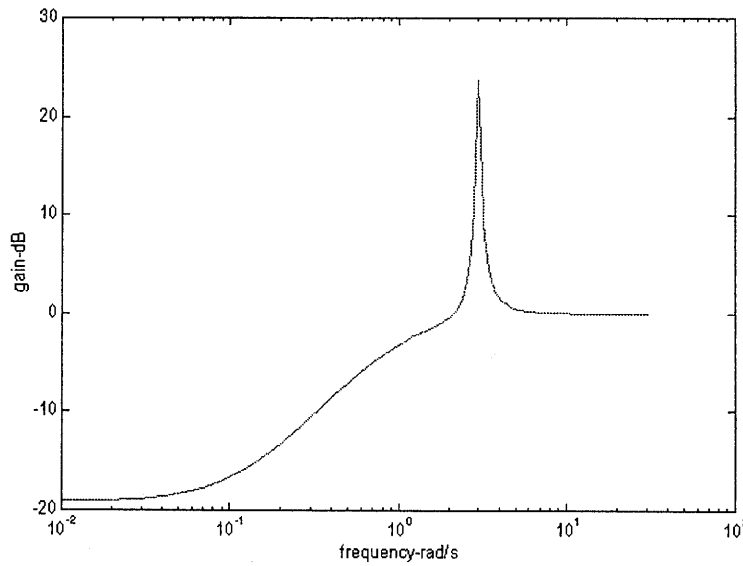


Fig. 4. Magnitude of $\Delta_m(z)$.

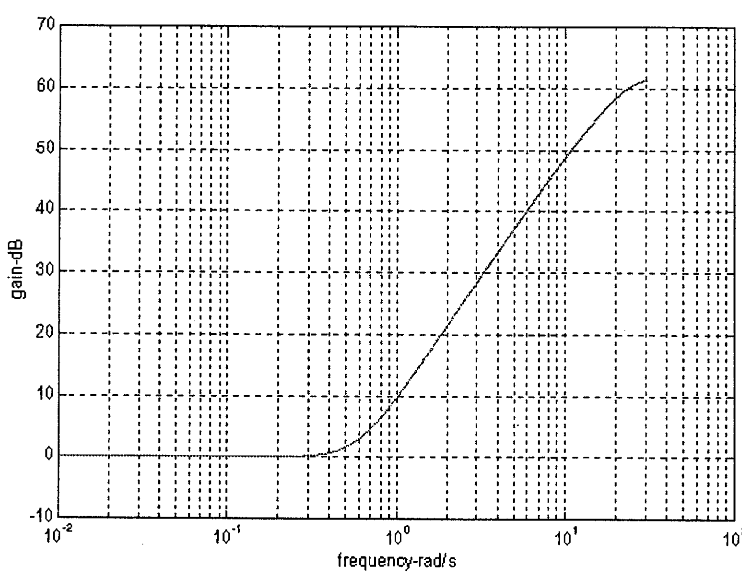


Fig. 5. Magnitude of the $P$-polynomial.

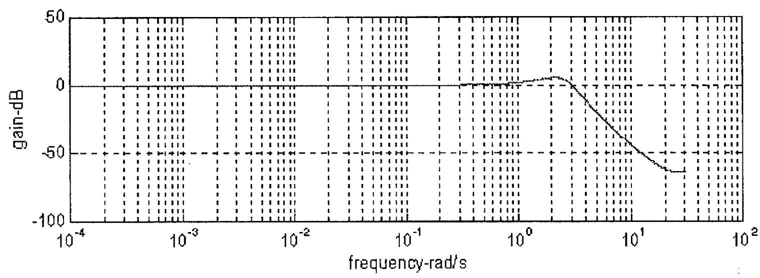


Fig. 6. CRHPC without $P$-polynomial: Complementary sensitivity function.

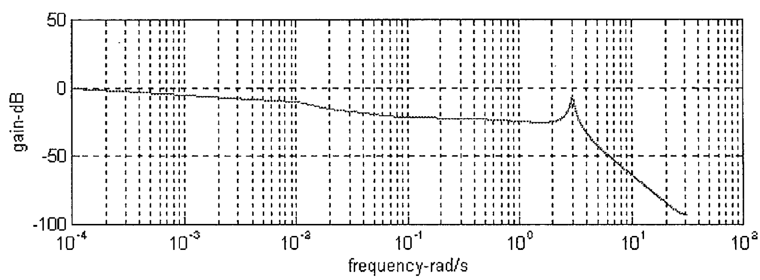


Fig. 7. CRHPC with $P$-polynomial: Complementary sensitivity function.

spectral densities $\phi_{\varepsilon y^o}(\theta)$ and $\phi_{yy^o}(\theta)$. A more refined estimate of the model uncertainty being available, the cut-off frequency $\theta_p$ of the high-pass filter $P(q^{-1})$ becomes less conservative. This entails a performance improvement of the corresponding one-degree-of-freedom CRHPC with $P$-polynomial (Fig. 12). The results obtained with the two-degree-of-freedom controller designed at iteration #1 are reported in Fig. 13.

## 7. Conclusions

In this paper, some issues concerning the synthesis of predictive controllers have been investigated. The first issue has to do with the problem of improving robust stability with respect to multiplicative model uncertainties while maintaining nominal performances. This has been obtained by means of a two-step synthesis procedure, where the first step is devoted to the enhancement of the robustness properties of the closed-loop system, while the second one aims at improving the servo properties of the compensated system. Obviously, in many cases it is sufficient to perform only the first synthesis step. However, the design of the open-loop compensator $H(q^{-1})$ as described in Section 4 opens the way to different strategies for the design of robust predictive controllers. For instance, it could be possible to design a feedback regulator by means of standard $H_\infty$ theory, thus achieving guaranteed stability, and then to design the feedforward term $H(q^{-1})$ with the technique proposed here in order to

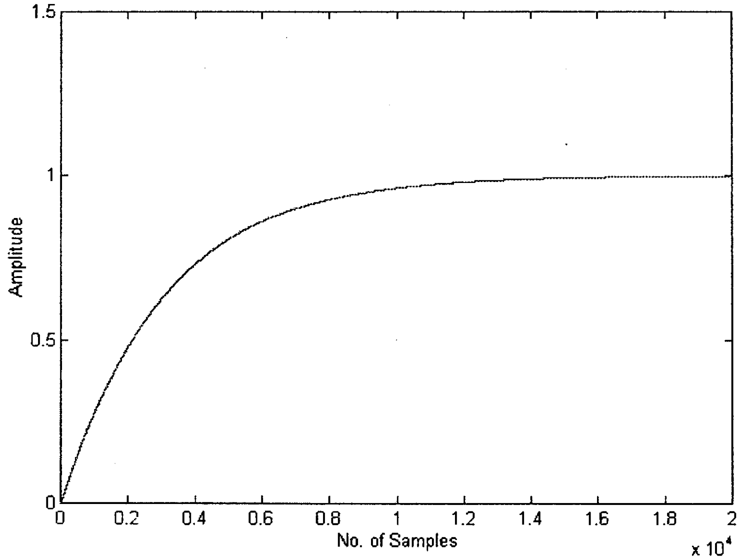


Fig. 8. CRHPC with $P$-polynomial (iteration #0): Step response.

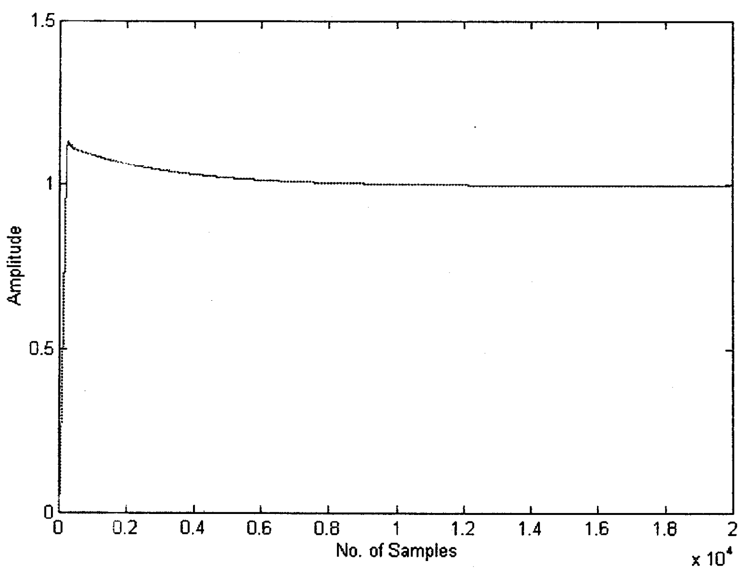


Fig. 9. Two-degree-of-freedom controller (iteration #0): Step response.

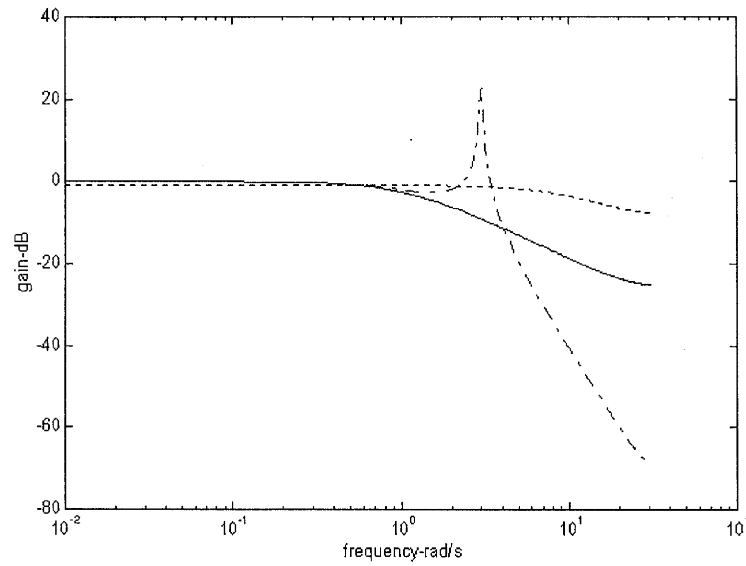


Fig. 10. Model comparison (solid line: identified model (iteration #1); dashed line: initial model (iteration #0); dash-dot: true system).

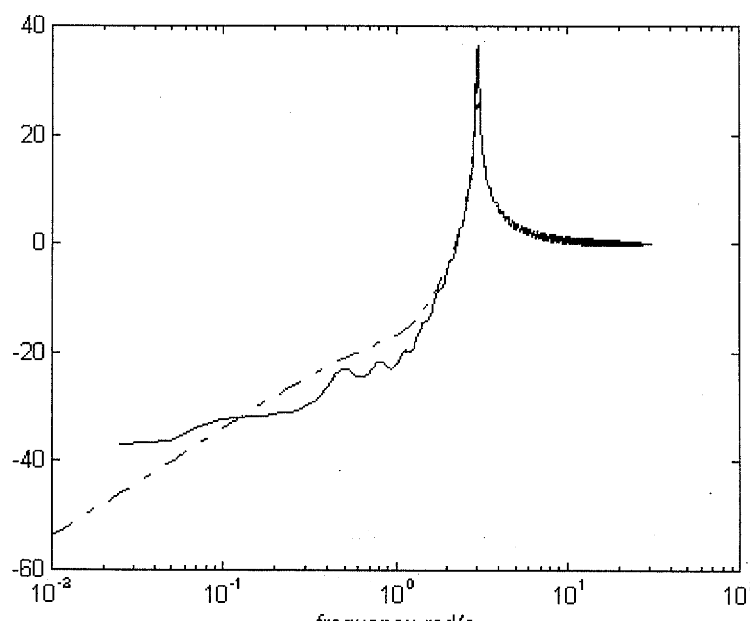


Fig. 11. Estimated (solid line) vs. actual (dash-dot line) model uncertainty (iteration #1).

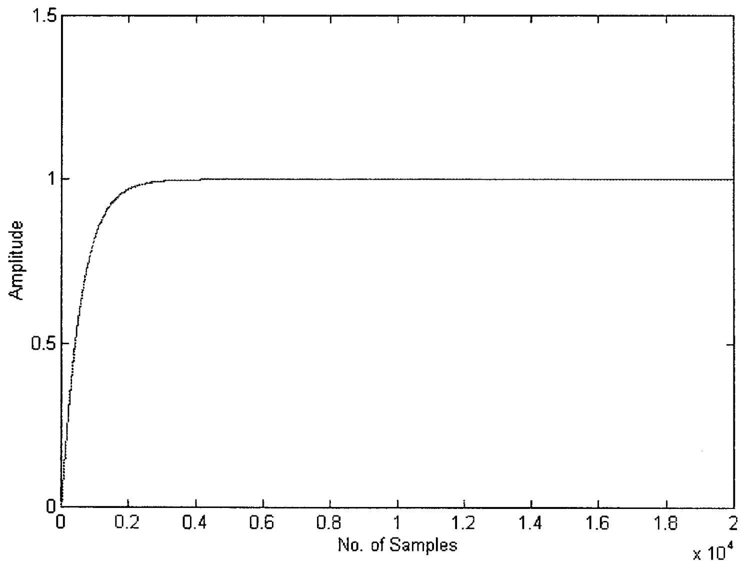


Fig. 12. CRHPC with $P$-polynomial (iteration #1): Step response.

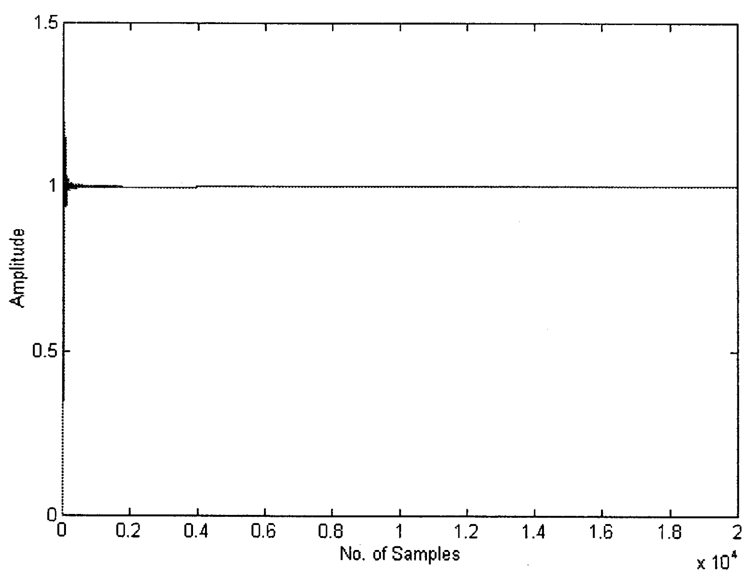


Fig. 13. Two-degree-of-freedom controller (iteration #1): Step response.

obtain the desired response to reference signals. A scheme for model uncertainty estimation has also been proposed. Having linked the $P$-polynomial to the model uncertainty and a method for uncertainty estimation being available, it comes natural to develop an iterative model-identification/controller-design strategy whose potentialities have been illustrated through the control of a nontrivial simulated benchmark problem. Future developments of the main issues considered in this paper, namely nominal and robust stability, performances, iterative identification/control procedures, could concern the extension of the proposed methods to the case of input constrained systems and multivariable systems.

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