COMPUTING PARITY SPACE RESIDUALS' COMPUTATIONAL FORM WITH MIMO PREDICTIVE MODELS

Dionísio, R.V. [*,†,1] **Lemos, J.M.** [**,†]

[*] *ESTSetúbal/Instituto Politécnico de Setúbal*
Campus do IPS, Estefanilha, 2910-761 SETÚBAL, Portugal
[**] *Instituto Superior Técnico, Portugal*
[†] *INESC-ID, R. Alves Redol 9, 1000-029 LISBOA, Portugal*
[*] *rvilela@est.ips.pt;* [**] *jlml@inesc.pt*

Abstract

This paper presents a simplified way of computing the parity space residuals' computational form through MIMO predictive models used for control synthesis. It is possible to derive a parity equation in the predictive models framework starting from a plant model description in pseudo-state space variables. From this equation, after a time transformation, the resultant set of predictors is compared with the respective predictors of the discrete linear plant MIMO models. The comparison results in a simpler way of computing matrices K and J of the parity space residuals' computational form. This result shows that predictive controllers and parity space residuals naturally fit and an integrated strategy allows computational savings, in particular in adaptive schemes where system parameters estimation dependent matrices need to be recalculated at each sampling interval.

Keywords: MIMO predictive models; Generalized Predictive Controller; Discrete linear systems; Parity Space; Residuals computational form.

1. INTRODUCTION

An active fault-tolerant control system is designed following performance objectives under either normal, or faulty operation (Zhang and Jiang, 2003). For a system to achieve good performance, faults need to be detected and diagnosed as fast as possible so that a reconfigurable controller may be activated. All this should be done on-line and in real-time, in particular, residuals generation. In this paper, residuals generation through parity space computational form is integrated in the MIMO predictive models framework with the intention of its use with adaptive predictive controllers, namely the Generalized Predictive Controller (GPC) (Clarke et al., 1987). Writing this equation in this framework, and after a time transformation, reveals a set of predictors with the same structure as the one of the MIMO predictive models. Both the parity space residuals' computational form and the MIMO predictive models allow a very simple way of computing the former predictors' vectorial equations matrices from the later. This results in an important economy of computations in an on-line real-time strategy such as the one of active fault-tolerant control systems. This holds in particular when using adaptive structures, where matrices for residuals generation and controller gains need to be recalculated, each time sample, through plant parameters recursive estimation. Hence, the approach proposed here is well suited for the combined strategy of an adaptive GPC with an adaptive residuals generation presented in (Dionísio et al., 2003).

The paper follows with the introduction of some notation and the plant description, in section 2. Section 3 presents the set of MIMO predictive models for later comparison with the set of predictors generated by the residuals' computational form, from section 4. In section 5, comparison

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results are presented. Finally, section 6 presents a numerical example, and in section 7 conclusions are drawn.

2. PLANT MODEL

Consider a discrete I/O MIMO description of a plant subjected to actuators and sensors faults, and to sensors noise. The plant has $u \in \mathbb{R}^m$ inputs, $y \in \mathbb{R}^l$ outputs, $\Delta u \in \mathbb{R}^m$ actuators faults, $\Delta y \in \mathbb{R}^l$ sensors faults, and $\xi \in \mathbb{R}^l$ sensors noise.

$$y(t) = \begin{bmatrix} H_{11}(q^{-1}) & H_{12}(q^{-1}) & \cdots & H_{1m}(q^{-1}) \\ H_{21}(q^{-1}) & H_{22}(q^{-1}) & \cdots & H_{2m}(q^{-1}) \\ \vdots & \vdots & \ddots & \vdots \\ H_{l1}(q^{-1}) & H_{l2}(q^{-1}) & \cdots & H_{lm}(q^{-1}) \end{bmatrix} \cdot [u(t) + \Delta u(t)] + I_{l\times l}\Delta y(t) + \begin{bmatrix} N_1(q^{-1}) & 0 & \cdots & 0 \\ 0 & N_2(q^{-1}) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & N_l(q^{-1}) \end{bmatrix} \cdot \xi(t) \quad (1)$$

where $I_{l\times l}$ is an $[l] \times [l]$ identity matrix, and the transfer functions are

$$H_{ij}(q^{-1}) = q^{-1} \frac{b_0^{ij} + b_1^{ij} q^{-1} + \ldots + b_{n_b^{ij}}^{ij} q^{-n_b^{ij}}}{1 + a_1^i q^{-1} + \ldots + a_{n_a^i}^i q^{-n_a^i}}$$

$$N_i(q^{-1}) = \frac{1}{1 + a_1^i q^{-1} + \ldots + a_{n_a^i}^i q^{-n_a^i}}$$

Define the following polynomials

$$A_i^*(q^{-1}) := 1 + \sum_{p=1}^{n_a^i} a_p^i q^{-p}; B_{ij}^*(q^{-1}) := \sum_{p=0}^{n_b^{ij}} b_p^{ij} q^{-p} \quad (2)$$

A_i^* and B_{ij}^* being coprime and $i = 1, \ldots, l$, and $j = 1, \ldots, m$. Rewriting (1) as

$$\begin{aligned} \mathcal{A}^*(q^{-1}) \cdot y(t) =& \mathcal{B}^*(q^{-1}) \cdot [u(t-1) + \Delta u(t-1)] \\ &+ \mathcal{A}^*(q^{-1}) \cdot [\Delta y(t) + \xi(t)] \end{aligned} \quad (3)$$

with $\mathcal{A}^*(q^{-1}) = diag\big(A_1^*(q^{-1}), \ldots, A_l^*(q^{-1})\big)$, and

$$\mathcal{B}^*(q^{-1}) = \begin{bmatrix} B_{11}(q^{-1}) & B_{12}(q^{-1}) & \cdots & B_{1m}(q^{-1}) \\ B_{21}(q^{-1}) & B_{22}(q^{-1}) & \cdots & B_{2m}(q^{-1}) \\ \vdots & \vdots & \ddots & \vdots \\ B_{l1}(q^{-1}) & B_{l2}(q^{-1}) & \cdots & B_{lm}(q^{-1}) \end{bmatrix}$$

The vectors in (1) and (3) are, by definition,

$$\begin{aligned} u(t) &:= [u_1(t) \ldots u_m(t)]' \\ \Delta u(t) &:= [\Delta u_1(t) \ldots \Delta u_m(t)]' \\ y(t) &:= [y_1(t) \ldots y_l(t)]' \\ \Delta y(t) &:= [\Delta y_1(t) \ldots \Delta y_l(t)]' \\ \xi(t) &:= [\xi_1(t) \ldots \xi_l(t)]' \end{aligned}$$

Introduce the pseudo-state $s(t)$

$$\begin{aligned} s(t) :=&[y_1(t) \ldots y_1(t - n_a^1 + 1)\ y_2(t) \ldots \\ & y_2(t - n_a^2 + 1) \ldots y_l(t) \ldots y_l(t - n_a^l + 1) \\ & u_1(t-1) \ldots u_1(t - n_b^1)\ u_2(t-1) \ldots \\ & u_2(t - n_b^2) \ldots u_m(t-1) \ldots u_m(t - n_b^m)]' \end{aligned}$$

Where $n_b^j = max\{n_b^{ij} : i = 1, \ldots, l\}$, for each $j = 1, \ldots, m$. The following vectors are also considered

$$\begin{aligned} \Delta\breve{u}(t) &:= [\Delta u_1(t) \ldots \Delta u_1(t - n_b^1 + 1) \ldots \\ &\qquad \Delta u_m(t) \ldots \Delta u_m(t - n_b^m + 1)]' \\ \Delta\breve{y}(t) &:= [\Delta y_1(t+1) \ldots \Delta y_1(t - n_a^1 + 1) \ldots \\ &\qquad \Delta y_l(t+1) \ldots \Delta y_l(t - n_a^l + 1)]' \\ \breve{\xi}(t) &:= [\xi_1(t+1) \ldots \xi_1(t - n_a^1 + 1) \ldots \\ &\qquad \xi_l(t+1) \ldots \xi_l(t - n_a^l + 1)]' \\ f(t) &= [\Delta\breve{u}(t)\ \Delta\breve{y}(t)]' \end{aligned}$$

Finally, it is possible to write a pseudo-state space representation of the plant

$$\begin{aligned} s(t+1) &= \Phi s(t) + \Gamma u(t) + S_F f(t) + S_N \breve{\xi}(t) \\ y(t) &= H s(t) \end{aligned} \quad (4)$$

In order to keep track of vectors and matrices dimensions:

- $s(t)$ is $[n_a^1 + n_a^2 + \cdots + n_a^l + n_b^1 + n_b^2 + \cdots + n_b^m] \times [1]$
- $\Delta\breve{u}(t)$ is $[n_b^1 + n_b^2 + \cdots + n_b^m] \times [1]$
- $\Delta\breve{y}(t)$ is $[n_a^1 + n_a^2 + \cdots + n_a^l + l] \times [1]$
- $f(t)$ is $[dim(\Delta\breve{u}(t)) + dim(\Delta\breve{y}(t))] \times [1]$
- $\breve{\xi}(t)$ is $[n_a^1 + n_a^2 + \cdots + n_a^l + l] \times [1]$
- Φ is $[dim(s(t))] \times [dim(s(t))]$
- Γ is $[dim(s(t))] \times [m]$
- S_F is $[dim(s(t))] \times [dim(f(t))]$
- S_N is $[dim(s(t))] \times [dim(\breve{\xi}(t))]$
- H is $[l] \times [dim(s(t))]$

where $dim(x(t))$ means the number of lines of a generic column vector $x(t)$. A note about vectors $\Delta\breve{u}(t)$, $\Delta\breve{y}(t)$ and $\breve{\xi}(t)$ dimensions' should be given at this point: consider that only m_f actuators and l_f sensors are faulty, and that noise affects only

l_d sensors ($0 \leq m_f \leq m$, $0 \leq l_f \leq l$, and $0 \leq l_d \leq l$), meaning that the remaining n_b^j actuators, and n_a^i sensors entries' on vectors $\Delta\breve{u}(t)$, $\Delta\breve{y}(t)$, and $\breve{\xi}(t)$ are zero (index j corresponds to fault free actuators, and index i corresponds to fault free and/or noise free sensors), then these vectors can be shortened in length including only faulty actuators and sensors, and noisy sensors.

Since matrices Φ, Γ, S_F, S_N, and H are generally of large dimensions, their structure is not represented here. Nevertheless, they are easily obtained when taking into consideration vectors $s(t)$, $u(t)$, $y(t)$, $f(t)$, and $\breve{\xi}(t)$ definitions, as well as plant description (3).

Notice that vectors and matrices dimensions are explicitly shown here and throughout the paper (whenever justified) for the sake of better understanding of the comparative study and of the numerical example, sections 5 and 6, respectively.

3. MIMO PREDICTIVE MODELS

Starting with the plant description given by (3), discarding faults but considering noise (admitted to be zero mean white Gaussian), it is possible (Mosca, 1995) to obtain a set of predictive equations for the outputs, over a prediction time horizon T, written as

$$\hat{Y}_{t+1}^{t+T} = \Pi' s(t) + W U_t^{t+T-1} \tag{5}$$

with

$$\hat{Y}_{t+1}^{t+T} = \begin{bmatrix} \hat{y}(t+1) \\ \hat{y}(t+2) \\ \vdots \\ \hat{y}(t+T) \end{bmatrix} \quad U_t^{t+T-1} = \begin{bmatrix} u(t) \\ u(t+1) \\ \vdots \\ u(t+T-1) \end{bmatrix}$$

and $\hat{y}(t)$ meaning an estimate of $y(t)$. Matrices W and Π', with dimensions $[l \times T] \times [m \times T]$ and $[l \times T] \times [dim(s(t))]$, respectively, are

$$W = \begin{bmatrix} W_1 & 0 & & \\ W_2 & W_1 & & \\ \vdots & \vdots & \ddots & \\ W_T & W_{T-1} & \cdots & W_1 \end{bmatrix} \quad \Pi' = \begin{bmatrix} \Pi_1' \\ \Pi_2' \\ \vdots \\ \Pi_T' \end{bmatrix} \tag{6}$$

and

$$W_i = \begin{bmatrix} w_i^1 & \cdots & w_i^1 \\ w_i^2 & \cdots & w_i^2 \\ \vdots & \ddots & \vdots \\ w_i^l & \cdots & w_i^l \end{bmatrix} \qquad \Pi_i' = \begin{bmatrix} \pi_i^{1\prime} \\ \pi_i^{2\prime} \\ \vdots \\ \pi_i^{l\prime} \end{bmatrix} \tag{7}$$

with $i = 1, \ldots, T$. Matrices W_i and Π_i' have dimensions $[l] \times [m]$, and $[l] \times [dim(s(t))]$, respectively, and, although not entirely defined in this paper, they can be easily found in the literature (Mosca, 1995).

Moreover, if the sensors noise is not considered in an ideal plant description, than $\hat{y}(t) = y(t)$ and (5) can be rewritten as

$$Y_{t+1}^{t+T} = \Pi' s(t) + W U_t^{t+T-1} \tag{8}$$

4. RESIDUALS' COMPUTATIONAL FORM

Consider a time window of dimension σ and backward iterate the pseudo-state space described by (4) over this time window in order to obtain the following parity equation (Chow and Willsky, 1984; Gertler, 1998).

$$Y_{t-\sigma}^{t} = Js(t-\sigma) + KU_{t-\sigma}^{t} + L_F F_{t-\sigma}^{t} + L_D \Xi_{t-\sigma}^{t} \tag{9}$$

where vectors $Y_{t-\sigma}^t$ and $U_{t-\sigma}^t$ have the same structure as previously defined for vectors Y_{t+1}^{t+T} and U_t^{t+T-1}, respectively. The other vectors and matrices are

$$F_{t-\sigma}^{t} = \begin{bmatrix} f(t-\sigma) \\ f(t-\sigma-1) \\ \vdots \\ f(t) \end{bmatrix} \quad \Xi_{t-\sigma}^{t} = \begin{bmatrix} \breve{\xi}(t-\sigma) \\ \breve{\xi}(t-\sigma-1) \\ \vdots \\ \breve{\xi}(t) \end{bmatrix}$$

and

$$J = \begin{bmatrix} H \\ H\Phi \\ H\Phi^2 \\ \vdots \\ H\Phi^{\sigma} \end{bmatrix}$$

$$K = \begin{bmatrix} 0 & & & \\ H\Gamma & 0 & & \\ H\Phi\Gamma & H\Gamma & & \\ \vdots & \vdots & \ddots & \\ H\Phi^{(\sigma-1)}\Gamma & H\Phi^{(\sigma-2)}\Gamma & \cdots & H\Gamma \;\; 0 \end{bmatrix} \tag{10}$$

Matrices L_F and L_D have the same format as matrix K, being Γ replaced by S_F and S_N, respectively. Dimensions of vectors and matrices are:

- $Y_{t-\sigma}^t$ is $[l \times (\sigma+1)] \times [1]$
- $U_{t-\sigma}^t$ is $[m \times (\sigma+1)] \times [1]$
- $F_{t-\sigma}^t$ is $[dim(f(t)) \times (\sigma+1)] \times [1]$
- $\Xi_{t-\sigma}^t$ is $[dim(\breve{\xi}(t)) \times (\sigma+1)] \times [1]$
- J is $[l \times (\sigma+1)] \times [dim(s(t))]$
- K is $[l \times (\sigma+1)] \times [m \times (\sigma+1)]$
- L_F is $[l \times (\sigma+1)] \times [dim(F_{t-\sigma}^t)]$
- L_D is $[l \times (\sigma+1)] \times [dim(\Xi_{t-\sigma}^t)]$

Equation (9) can be rewritten as

$$Y_{t-\sigma}^t - KU_{t-\sigma}^t = Js(t-\sigma) + L_F F_{t-\sigma}^t + L_D \Xi_{t-\sigma}^t \tag{11}$$

being the left hand side of (11) called the *residuals' computational form*, and the right hand side the *residuals' internal form.*

In particular, if the plant is fault free and noise free, (9) becomes

$$Y_{t-\sigma}^t = Js(t-\sigma) + KU_{t-\sigma}^t \tag{12}$$

5. COMPARATIVE STUDY

It is now possible to perform a comparison between predictive MIMO models and residuals' computational form in parity space. To start with, consider (12) written for a generic time instant t'. Applying a $t' = t + T$ time translation to (12) yields

$$Y_{t+T-\sigma}^{t+T} = Js(t+T-\sigma) + KU_{t+T-\sigma}^{t+T} \tag{13}$$

Next, consider $T = \sigma$, as a restriction,

$$Y_t^{t+T} = Js(t) + KU_t^{t+T} \tag{14}$$

In (8) it is easily seen that there are T predictors, and that in (14) there are $(T+1)$ predictors, the extra one (first line of (14)) corresponding to a zero order predictor (notice there is no time delay between Y and U). Comparing the T predictors of (8) (T lines of (8)) directly with the last T predictors of (14) (disregard the first line of (14)), allows to conclude that

$$\begin{aligned} W_1 &= H\Gamma & \Pi'_1 &= H\Phi \\ W_2 &= H\Phi\Gamma & \Pi'_2 &= H\Phi^2 \\ &\vdots & &\vdots \\ W_T &= H\Phi^{T-1}\Gamma & \Pi'_T &= H\Phi^T \end{aligned}$$

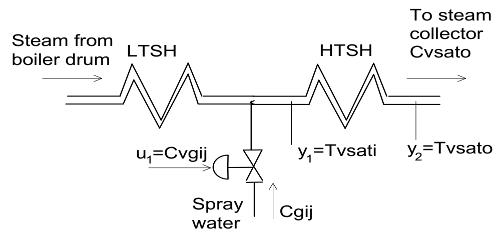

Fig. 1. Plant schematic view.

or, more generally,

$$W_i = H\Phi^{i-1}\Gamma \quad \Pi'_i = H\Phi^i \quad (i = 1, \ldots, T)$$

also based on the comparison of matrices W and Π' (6) with K and J (10).

Notice that the restriction $T = \sigma$ has been made only for convenience, and that in practice σ is normally smaller than T (specially for a reduced number of faults), implying that only the first $\sigma < T$ predictors should be considered out of the T predictors defined in (8).

6. NUMERICAL EXAMPLE

A simulation example illustrating the computational savings achieved with the proposed algorithm is presented hereafter.

6.1 *Plant and model description*

The plant considered in this example is the steam super-heating subsystem of a boiler (Barreiro thermoelectric power plant of CPPE). Fig.1 shows a simplified overview of this subsystem referring the main variables. The steam coming from the boiler drum passes through the low-temperature super-heater (LTSH) and receives a spray water injection before passing through the high-temperature super-heater (HTSH) to the steam collector. From the collector, the steam is extracted for use, either by the turbine or by industrial clients. The process variable to be controlled is $y_2 = T_{vsato}$, the steam temperature at the output of the HTSH. The manipulated variable is $u_1 = C_{vgij}$, the command of the spray water valve, which influences the spray water flow, C_{gij}. The overall plant dynamics is quite slow ($\tau \simeq 230s$) and changes due to the influence of the load imposed on the system, the super-heated steam flow, C_{vsato}. This variable affects the dynamic behaviour between $y_1 = T_{vsati}$, an intermediate temperature measure, and $y_2 = T_{vsato}$.

The physical based model is described in (Dionísio et al., 2001, 2003); nevertheless, a brief presentation of model essential characteristics' follows. Two sampled models were identified in open loop with discrete linear time-invariant models. The first model, corresponding to the discrete transfer function between C_{vgij} and T_{vsati}, has 3 poles, 2 zeros and 1 unit delay ($n_a^1 = 3$, and $n_b^{11} = 2$), and was obtained at the equilibrium point defined by $C_{vgij}(0) = 30\%$ and $T_{vsati}(0) = 426.31^oC$. The second model, corresponding to the overall discrete transfer function between C_{vgij} and T_{vsato}, has 4 poles, 2 zeros and 2 units delay ($n_a^2 = 4$, and $n_b^{21} = 3$; $n_b^1 = 3$), and was obtained at the equilibrium point defined by $C_{vgij}(0) = 30\%$ and $T_{vsato}(0) = 535.15^oC$. For both models the sampling period was $T_s = 5s$ and the input signal was a band-limited white noise with variance of 3.3% of $C_{vgij}(0)$, superimposed to the constant input $C_{vgij}(0)$. A RLS algorithm with directional forgetting was running in parallel, with a forgetting factor $\lambda = 0.98$, estimating both plant models parameters. The identified overall discrete plant model is of non-minimum phase having a static incremental negative gain. With this set of parameters and a new collection of data, the overall discrete linear model was validated, having an accumulated quadratic tracking error of 0.43^oC^2.

6.2 *Simulation results*

The simulation starts at the linearized equilibrium point defined by $C_{vgij}(0) = 30\%$, $T_{vsati}(0) = 426.31^oC$ and $T_{vsato}(0) = 535.15^oC$, which is considered the nominal model. It is assumed that additive faults can only occur on actuator $u_1 = C_{vgij}$ and on sensor $y_2 = T_{vsato}$, and both sensors' noise is neglected, meaning that $m_f = m = 1$, $l_f = 1 < l = 2$, and $l_d = 0 < l = 2$. Therefore, matrix L_F is shortened by those columns related with non-faulty sensor $y_1 = T_{vsati}$, and matrix L_D is not considered at all.

Adaptive residuals that react to additive faults (r_1 sensitive to sensor 2 fault and r_2 sensitive to actuator fault) and do not react to set-point changes were designed as referred in (Dionísio et al., 2003), and considering $\sigma = 4$. These residuals are computed on-line for every simulation discrete time interval, since they are adaptive and system parameters may change at any time. Residuals are designed according to a certain fixed off-line criteria (e.g., structured residuals), but need to be computed on-line according to the estimated system parameters. This means that the adaptive residuals algorithm is run every simulation discrete time interval.

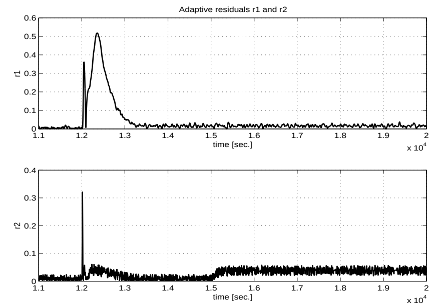

Fig. 2. Adaptive residuals r_1 and r_2 during a change of set-point. Actuator fault occurs.

In order to quantify the number of floating point operations saved by the direct assignment of matrices K and J, from matrices W and Π', respectively, vs. their algorithmic computation, in the adaptive residuals generation algorithm, the same simulation was performed under each one of the two possibilities.

Consider Fig.2 where it is shown the time evolution of adaptive residuals r_1 and r_2, respectively, during the occurrence of an actuator incipient fault (-0.8% at $t = 15000s$) after a change of the set-point (-1.8^oC at $t = 12000s$). Both residuals are shown in absolute value and after low-pass filtering. Residual r_1 remains insensitive to the fault occurrence and residual r_2 reacts (as designed) making detection possible. Attention should be payed to the set-point change instant where both residuals show some peaks. Even though they are not significant in amplitude they could mask incipient faults. Therefore, it was assumed (Dionísio et al., 2003) that during set-point changing instants no faults occur.

Under the possibility of assigning directly matrices K and J from matrices W and Π', respectively, the total number of floating point operations per simulation discrete time interval in the adaptive residuals generation algorithm was approximately 42185 for residual r_1, and approximately 31944 for residual r_2. Under the possibility of the algorithmic computation of matrices K and J, both previous results were increased by the amount of approximately 16481 extra floating point operations per simulation discrete time interval. These results reflect approximately a reduction of 28% and 34% on the number of floating point operations per simulation discrete time interval, respectively. Different results were obtained for residuals r_1 and r_2 because their computation is based on different design specifications.

A final remark: the numerical results for the floating point operations are highly dependent on the dimensions of all vectors and matrices involved in (11), and on the number of faults to detect and of noisy sensors to decouple. Therefore, these results are specific of this simulation and are not to be seen as a general rule, though they give a reasonable indication.

7. CONCLUSIONS

In this paper, the parity space formulation was integrated within a pseudo-state space representation valid for MIMO predictive models. This integration lead to the conclusion that both parity space residuals' computational form and MIMO predictive models represent the same predictors, allowing a simpler way of computing the former predictors' vectorial equations matrices from the later. This results in an important economy of computations in an on-line real-time strategy such as the one of active fault-tolerant control systems, particularly in an adaptive strategy. A numerical example is given highlighting the savings for the on-line computation of matrices K and J, in an adaptive residual generation in parity space.

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