MODEL PREDICTIVE CONTROL SUITABLE FOR CLOSED-LOOP RE-IDENTIFICATION

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Resumen: The main problem of a closed-loop re-identification procedure is that, in general, the dynamic control and identification objectives are conflicting. In fact, to perform a suitable identification, a persistent excitation of the system is needed, while the control objective is to stabilize the system at a given equilibrium point. However, an abstraction or generalization of the concept of stability, from punctual stability to (invariant) set stability, allows a flexibility that can be used to avoid the conflict between these objectives. Taking into account that an invariant target set includes not only a stationary component, but also a transient one, the system could be excited without deteriorating the stability of the closed-loop. In this work, a MPC controller is proposed that assures the stability of invariant sets at the same time that a signal suitable for closed-loop re-identification is generated. Several simulation results show the propose controller formulation properties.

Palabras Claves: Model predictive control, closed-loop identification, target set control, persistent excitation.

1. INTRODUCTION

Model predictive control (MPC) is typically implemented as a lower stage of a hierarchical control structure. The upper level stages are devoted to compute, by means of a stationary optimization, the targets that the dynamic control stage (MPC) should reach to economically optimize the operation of the process. Since both, the dynamic and stationary optimizations are model based optimizations, a periodic updating of the model parameters are desired to reach meaningful optimums. In this context, a re-identification procedure should be developed in a closed-loop fashion, since the process cannot be stopped each time an update is needed. As it is known, the main problem of a closed-loop identification is that the dynamic control objectives are incompatible with the identification objectives. In fact, to perform a suitable identification, a persistent excitation of the system modes is needed, while the controller takes this excitation as disturbance that it tries to reject from the output to stabilize the system.

From a general point of view, the closed-loop identification methods fall into the following main groups (Soderstrom and Stoica (1989)). The direct approach ignores the feedback law and identifies the open-loop system using measurements of the input and the output. The indirect approach identifies the closed-loop transfer function and determines the open-loop parameters subtracting the controller dynamic. To do that, controller dynamic must be linear and known. The joint input-output approach takes the input and output jointly, as the output of a system produced by some extra input or set-point signal. Since the last two methods needs the exact knowledge of a linear

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controller, they are not directly applicable for closed-loops under constrained MPC controllers.

Several strategies were developed to perform closed-loop re-identification under MPC controllers: Genceli and Nikolaou (1996) proposed a controller named Model Predictive Control and Identification (MPCI) where a persistent excitation condition is added by means of an additional constraints in the optimization problem. This strategy, which was explored later in (Ballin (2008)), turns the MPC optimization problem non-convex, and so, most the well-known properties of the MPC formulation cannot be established. Sotomayor *et al.* (2009) proposed a strategy that manipulates the steady state target optimization (in the hierarchical MPC control structure) in order to excite the system. This strategy does not modify the MPC optimization problem structure, but the identification is performed on the whole closed-loop system. As a result, the controller dynamic should be linear and perfectly known, to make a clear distinction between the controller and the open-loop system. Bustos *et al.* (2011) proposed a simpler closed-loop identification strategy to estimate multivariable process gains directly from on line data. The control structure adopted to test the proposed strategy is an LP-MPC control structure frequently used in industrial applications. In the context of data driven MPC formulations (i.e., MPC that are designed to perform predictions directly from collected data), the subspace identification method is exclusively used (Overschee and Moor (1996)). In Kadali *et al.* (2003), Wahab *et al.* (2010) and Mardi (2010) several approaches were presented, where a closed-loop re-identification is needed to update the data for predictions. Though preliminary studies were made according to the trade-off between stability and excitation, no definitive results were presented.

In general, none of the reports cited in this section have shown results regarding the system stability of the MPC while the system is re-identifying. In this work, based on the concept of stability of an invariant set (as a generalization of stability of a point), a MPC controller with a extended domain of attraction is proposed, which assures stability at the same time that a persistent excitation can be generated to perform a closed-loop re-identification.

Notation: Matrix $I_n \in \mathbb{R}^{n\times n}$ denotes the identity matrix, and matrix $0_{n,m} \in \mathbb{R}^{n\times m}$ denotes the null matrix. Given a matrix $M \in \mathbb{R}^{m\times n}$, $\mathcal{R}(M) = \{x \in \mathbb{R}^m : x = M\alpha,\ \alpha \in \mathbb{R}^n\}$ and $\mathcal{K}er(M) = \{x \in \mathbb{R}^n : Mx = 0_{1,m}\}$ are the range (column space) and the kernel (null space) of matrix M, respectively. Consider a convex set $\mathcal{X} \subseteq \mathbb{R}^n$. Then $d_M(z,\mathcal{X}) \triangleq \inf_{x\in\mathcal{X}} \|z-x\|_M^2$, with $M > 0$, denotes the distance from an element z to the set $\mathcal{X}$. Consider two sets $\mathcal{U} \subseteq \mathbb{R}^n$ and $\mathcal{V} \subseteq \mathbb{R}^n$, containing the origin, and a real number λ. The Minkowski sum $\mathcal{U} \oplus \mathcal{V} \subseteq \mathbb{R}^n$ is defined by $\mathcal{U} \oplus \mathcal{V} = \{(u+v) : u \in \mathcal{U}, v \in \mathcal{V}\}$; the set $(\mathcal{U}\backslash\mathcal{V}) \subseteq \mathbb{R}^n$ is defined by $\mathcal{U}\backslash\mathcal{V} = \{u : u \in \mathcal{U} \ \wedge\ u \notin \mathcal{V}\}$; and the set $\lambda\mathcal{U} = \{\lambda u : u \in \mathcal{U}\}$ is a scaled set of $\mathcal{U}$.

2. PROBLEM STATEMENT

Consider a system described by a linear time-invariant discrete time model

$$\begin{aligned} x^+ &= Ax + Bu \\ y &= Cx \end{aligned} \tag{1}$$

where $x \in \mathrm{I\!R}^n$ is the system state, x^+ is the successor state, $u \in \mathrm{I\!R}^m$ is the current control and $y \in \mathrm{I\!R}^p$ is the system output. The solution of this system for a given sequence of control inputs $\mathbf{u} = \{u(0), \cdots, u(j-1)\}$ and an initial state x is denoted as $x(j) = \phi(j; x, \mathbf{u})$, $j \in \mathbb{I}_{\geq 1}$, where $x = \phi(0; x, \mathbf{u})$. The state, the control input and the output at sampling time k are denoted as $x(k)$ and $u(k)$ respectively.

The system is subject to hard constraints on state and input:

$$x(k) \in X, \quad u(k) \in U \tag{2}$$

for all $k \geq 0$, where $X \subset \mathbb{R}^n$ and $U \subset \mathbb{R}^m$.

It is assumed that the following assumption holds.

Assumption 1. Matrix A is stable, the pair (A, B) is controllable and the state is measured at each sampling time.

Assumption 2. The set X is convex and closed, U is convex and compact and both sets contain the origin in their interior.

2.1 Steady state characterization

If we consider the joint variable (x, u), the state and input equilibrium subspace, associated to model (1), is given by

$$\mathcal{V}_{ss} = \mathcal{K}er([(A-I) \ \ B]) \subseteq \mathbb{R}^{n+m},$$

where $\mathcal{K}er$ is the null space operator.

We define now the set of admissible stationary states as $X_{ss} = \{x \in X \mid (x,u) \in \mathcal{W}_{ss}\}$, which is the projection of $\mathcal{W}_{ss}$ on the state space.

2.2 Invariance generalization

In the definitions above, the concept of steady state points, and the concept of equilibrium subspace or set - as the mere aggregation of steady state points - were presented. However, the generalization of the concept of equilibrium point is not the concept of equilibrium set, but the concept of invariant set (associated to an equilibrium point), in the sense that both, the equilibrium point and the invariant set are geometric entities such that, if the system reaches them, it remains in them indefinitely. This fact suggests the idea of using the dynamic degree of freedom that the generalized equilibriums (i.e., the invariant sets) allows for to excite the system with the objective of identification. It should be noted that in this way, some kind of stability, i.e., the stability to a (possibly robust) invariant set, instead of the stability to an equilibrium point could be assured, avoiding the conflicting objectives of exciting and stabilizing a system.

Now we will present the following definitions (Blanchini and Miani (2008), Kerrigan (2000)):

Definition 1. **(Equilibrium set)** A set Ω is an equilibrium set for the autonomous system $x^+ = Ax$ if for every point $x \in \Omega$ the condition $x = Ax$ holds.

It is clear that if A is assumed to be stable, the only equilibrium point is the origin.

Definition 2. **(λ-invariant set)** A set Ω is λ-invariant, with $0 < \lambda \leq 1$, for the autonomous system $x^+ = Ax$ if $x \in \Omega$ implies $Ax \in \lambda\Omega$.

For the case of $\lambda = 1$, we say that the set Ω is simply an invariant set. From the later definition it is clear that any equilibrium set is also an invariant set. Let us consider now a disturbed system $x^+ = Ax+Ew$, where E is the disturbance matrix, $w \in W$ is the disturbance vector, and W is a compact convex set that contains the origin. Then, we can define a robust invariant set as follows:

Definition 3. **(Robust invariant set)** A set Ω is robust invariant for the disturbed system $x^+ = Ax + Ew$, $w \in W$, if $x \in \Omega$ implies $x^+ \in \Omega$, for all $w \in W$.

From the definition above, it is clear that a robust invariant set for the disturbed system $x^+ = Ax + Ew$ is also a invariant set for the nominal system $x^+ = Ax$ (since $w = 0$ is a possible realization for the disturbance).

2.3 Convergence generalization

The concept of invariant set, as a generalization of an equilibrium point, allows us the generalization of the concept of stability of an equilibrium point. This generalization is one of the key points of this work, since based on this concept, an MPC formulation suitable for persistent excitation will be presented in the next sections. Let us denote the solution of the autonomous system $x^+ = Ax$, associated to an initial state x as $\phi(i;x) = A^i x$, $i \in \mathbb{I}_{\geq 0}$, where $x = \phi(0;x)$. Then, we can define the attractivity of an invariant and robust invariant set as follows (Rawlings and Mayne (2009)):

Definition 4. **(Local attractivity of an invariant set)** The (closed and invariant) set $\Omega \subseteq X$ is locally attractive for the autonomous system $x^+ = Ax$, $x \in X$, if for each x in a vicinity of Ω (that we call the domain of attraction), it follows that $d_M(\phi(j;x),\Omega) \to 0$, $\phi(j;x) \in X$, for $j \to \infty$ and for some $M > 0$.

This definition could be easily extended to the case of robust invariant set, if we consider a bounded disturbance vector $w \in W$.

2.4 Target invariant set for identification

In this subsection some target sets will be defined with the objective of proposing an MPC formulation suitable for re-identification. Let us consider first a state objective box-type set, X^{pe}, with a volume large enough to allows for an appropriate persistent excitation for identification. Furthermore, this set should be such that the variability of the system inside its volume is safe for the whole process. Now, let X^t be the largest robust invariant set inside X^{pe} for the disturbed system $x^+ = Ax+Bw$, with a bounded disturbance variable $w \in W \subset U$. Furthermore, because of the structure of system (1), X^t will contain the set $X^t_{ss} \triangleq (I_n - A)^{-1}BW$, which is the set of stationary points that the system will reach if a fixed disturbance signal $w \in W$ is continuously applied to the system (notice that such a constant signal is a possible realization for the disturbance). The output target set could be defined as

$$Y^t \triangleq CX^t.$$

3. MPC FOR TRACKING EQUILIBRIUM SETS

In this section an MPC controller for tracking the *equilibrium sets* X^t_{ss} (i.e., an aggregation of equilibrium points) is presented. This controller is formulated following a similar strategy to the one presented in Ferramosca *et al.* (2010); Gonzalez and Odloak (2009). The controller cost function is given by:

$$V_N^{ES}(x, X_{ss}^t; \mathbf{u}) = \sum_{j=0}^{\infty} d_Q(x_j, x_{ss}) + d_R(u_j, u_{ss}) + d_S(x_{ss}, X_{ss}^t)$$

where $Q > 0$, $R \geq 0$ and $S > 0$ are penalization matrices and N is the control horizon. For any current state $x \in X$, the optimization problem $P_N^{ES}(x, X_{ss}^t)$ to be solved is given by:

Problem $P_N^{ES}(x, X_{ss}^t)$

$$\begin{aligned}
&\min_{\mathbf{u}} V_N^{ES}(x; \mathbf{u}) \\
&s.t. \\
&\quad x_0 = x, \\
&\quad x_{j+1} = Ax_j + Bu_j, \qquad j \in \mathbb{I}_{0:N-1} \\
&\quad x_j \in X,\, u_j \in U, \qquad j \in \mathbb{I}_{0:N-1} \\
&\quad u_j = u_{ss}, \qquad j \in \mathbb{I}_{N:\infty} \\
&\quad x_{ss} = (I_n - A)^{-1} B u_{ss} \qquad .
\end{aligned}$$

In this optimization problem, x and X_{ss}^t are the parameter, while the sequence

$$\mathbf{u} = \{u(0), \cdots, u(N-1)\}$$

is the optimization variable. The control law, derived from the application of a receding horizon policy, is given by $\kappa_N(x, X_{ss}^t) = u^0(0; x)$, where $u^0(0; x)$ is the first element of the solution sequence $\mathbf{u}^0(x)$.

Remark 1. The domain of attraction of the controller derived from the iterative application of Problem $P_N^{ES}(x)$ is given by the maximal invariant set contained in X.

Following similar procedures that the one shown in Ferramosca *et al.* (2010); **?**); Gonzalez and Odloak (2009), it can be shown that the closed-loop system converges asymptotically to zero.

4. MPC FOR TRACKING INVARIANT SETS

Now, a generalization of the MPC controller for tracking *equilibrium points* will be presented. To this end, we will consider the *robust invariant set* $X^t \supset X_{ss}^t$ presented in subsection 2.4. The controller cost function is given by:

$$V_N^{IS}(x, X^t; \mathbf{u}) = \sum_{j=0}^{\infty} d_Q(x_j, X^t) + d_R(u_j, W).$$

For any current state $x \in X$ than can be feasibly steered to X^t in N steps, the optimization problem $P_N^{IS}(x, X^t)$ to be solved is given by: **Problem** $P_N^{IS}(x, X^t)$

$$\begin{aligned}
&\min_{\mathbf{u}} V_N^{IS}(x, X^t; \mathbf{u}) \\
&s.t. \\
&\quad x_0 = x, \\
&\quad x_{j+1} = Ax_j + Bu_j, \qquad j \in \mathbb{I}_{0:N-1} \\
&\quad x_j \in X,\, u_j \in U, \qquad j \in \mathbb{I}_{0:N-1} \\
&\quad u_{N-1} \in W \subset U \\
&\quad x(N) \in X^t
\end{aligned}$$

As it can be seen, the main difference between this problem and problem $P_N^{ES}(x, X_{ss}^t)$ is that the target set is a (robust) invariant set, instead of an equilibrium set. The controller derived form this formulation also assures the convergence of the closed-loop system to the robust invariant. In fact, the controller only steers the system to the invariant set X^t, and then, once the state is there, nothing can be said about the system evolution.

To see this fact clearly, let us consider the MPC cost function for a state in X^t. First, it should be noted that from its definition, the cost $V_N^{IS}(x, X^t; \mathbf{u})$ will be zero along every trajectory starting in a initial state inside X^t, because it penalizes the distance from the trajectory to the invariant set, and using a control sequence $\mathbf{u}$ inside W is a feasible solution. Furthermore, by the definition of the invariant set, the system $x^+ = Ax + Bu$, $u \in W$, will maintain any state inside X^t, following feasible trajectories that do not leave X^t. From this fact the control action obtained from the optimization will not take any given value, and so, the system keep, in some sense, in open-loop operation.

Remark 2. It can be shown, following similar procedures as in González *et al.* (2011), that X^t is a contractive invariant set, for the closed-loop system obtained with the MPC controller derived from the formulation above. Furthermore, recursive feasibility can also be assured, for every initial state that can be steered to X^t in N steps.

5. INCLUDING THE EXCITING MODE

Form the discussion in the last section, we see that inside the robust invariant set X^t the proposed MPC controller actually left the system in open loop. This fact suggests the idea of using this condition, i.e., when the system is in X^t, to excite the system and perform a re-identification. As it is known, to be able to estimate a model from measured input and output data, the input signal should contain enough information. This property is generally indicated by the notion of persistency of excitation (Ljung (1999)).

Now we can define a *persistent excitation* signal, $\mathbf{u}_{PE}$, contained in W, to perform a suitable identification. The persistent excitation input might be of several form, going from a Pseudo-random Binary Signal (PRBS) signal to a Filtered Gaussian White Noise Signal (Ljung (1999)). The proposed *persistent excitation MPC* formulation is as follows:

$$V_N^{EXC}(x, X^t, \mathbf{u}_{PE}, k; \mathbf{u}) = \sum_{j=0}^{\infty} \{d_Q(x_j, X^t) + d_R(u_j, W)\} + \rho(x)\|u_0 - u_{PE,k}\|$$

where

$$\mathbf{u}_{PE} = \{u_{PE}(0), \cdots, u_{PE}(T_{id})\} \in W,$$

is the *persistent excitation* signal, T_{id} is the length of the data necessary to perform a suitable identification, and $\rho(x)$ is the following function:

$$\begin{aligned} \rho(x) &= 1 \quad if \quad x \in \quad X^t \\ &= 0 \quad otherwise. \end{aligned}$$

For any current state $x \in X$, than can be feasibly steered to X^t in N steps, the optimization problem $P_N^{EXC}(x, X^t, \mathbf{u}_{PE}, k)$, to be solved at each time instant k, is given by:

Problem $P_N^{EXC}(x, X^t, \mathbf{u}_{PE}, k)$

$$\begin{aligned} &\min_{\mathbf{u}} V_N^{EXC}(x, X^t, \mathbf{u}_{PE}, k; \mathbf{u}) \\ &s.t. \\ &\quad x_0 = x, \\ &\quad x_{j+1} = Ax_j + Bu_j, \qquad j \in \mathbb{I}_{0:N-1} \\ &\quad x_j \in X,\ u_j \in U, \qquad j \in \mathbb{I}_{0:N-1} \\ &\quad u_{N-1} \in W \subset U \\ &\quad x(N) \in X^t \end{aligned}$$

Notice that the function $\rho(x)$ is a discontinuous function necessary to zero the persistent excitation in case that an external disturbance takes the system away from the robust invariant set X^t. Notice also, that the input increment penalization is not included in this formulation, since this cost term would disturb the excitation procedure.

Remark 3. It can be said that the MPC control formulation presented above has two main modes: if the state is inside X^t, only the excitation objective is present in the cost; if the system is in $X \backslash X^t$, then only the dynamic control objective is present in the cost. Shortly, it can be said that the MPC formulation presented above does not deal with the two objectives of controlling and identifying simultaneously.

Remark 4. As in the controller for tracking invariant sets, X^t is an attractive invariant set for the closed-loop system obtained with the MPC controller derived from the iterative solution of $P_N^{EXC}(x, X^t, \mathbf{u}_{PE}, k)$. Furthermore, recursive feasibility can also be assure, for every initial state that can be steered to X^t in N steps.

Remark 5. Because of the definition of the target robust invariant set X^t the persistent excitation signal $\mathbf{u}_{PE}$ cannot take the state outside the set. Furthermore, since inside X^t the dynamic MPC cost is null, the persistent excitation cost can also be zeroed, which means that the input increment can be equal to $\mathbf{u}_{PE}$. This fact guarantees that the persistent excitation of the system will be made.

Remark 6. Notice that once the system is inside X^t, if an external disturbance moves the state outside X^t, then the MPC controller suspends the excitation procedure to act as the MPC for tracking invariant sets, ensuring in this way the automatic switching between the two modes, and the whole stability of the controller.

6. OPERATION OF THE LOOP

Based on the above discussion, the MPC controller operation will be presented. We have two Operation modes:

- *Control operation mode*: in this mode no re-identification is needed, and the *MPC for tracking equilibrium* set is implemented (**Problem** $P_N^{ES}(x, Xss^t)$). No further comments are needed for this controller, since it has been extensively analyzed in the literature (Ferramosca *et al.* (2010); Gonzalez and Odloak (2009)).
- *Re-identification operation mode*: this mode is activated only when there is a suspect that the model is not working properly, and a re-identification is needed. In this mode the *persistent excitation MPC* is used (**Problem** $P_N^{EXC}(x, X^t, \mathbf{u}_{PE}, k)$).

6.1 Model mismatch

It should be noticed that the target set X^t, which is a parameter of the MPC optimization cost, depends on the model. Since the excitation scenario is precisely given when we suspect that the current model is no longer accurate, a comment about the effect of the model mismatch on the computation of X^t is needed. In fact, if a difference between the model and plant does exist, the current state x will be different from the predicted state x^+ corresponding to the precedent optimization problem, and the invariant condition of X^t could be no longer true. In this case, a second robustness condition should be imposed to X^t (different from the robustness associated to the input variability). For instance, consider that model mismatch can be modeled by means of an additive disturbance,

$$x^+ = Ax + Dd,$$

where D is the disturbance matrix, $d \in Dist$ is the disturbance vector that describe model mismatch, and $Dist$ is a compact convex set. Then, we can define the target robust invariant set X^t as the robust invariant set for the disturbed system given by:

$$x^+ = Ax + \begin{bmatrix} B & 0 \\ 0 & D \end{bmatrix} \begin{bmatrix} w \\ d \end{bmatrix}, \quad \begin{bmatrix} w \\ d \end{bmatrix} \in W \times Dist.$$

The details of this discussion, however, are not in the scope of the present work, and will be delayed for future studies.

7. SIMULATION RESULTS

In this section some simulations results will be presented, to show the proposed control strategy properties. To this end, a simple 3-state integrating-stable system is used:

$$x^+ = Ax + Bu$$
$$y = Cx,$$

where

$$A = \begin{bmatrix} 0.51 & 0.24 & 0.35 \\ -0.20 & 0.30 & -0.20 \\ 0.18 & -0.20 & 0.50 \end{bmatrix}, \; B = \begin{bmatrix} 0.85 \\ -0.67 \\ 0.40 \end{bmatrix}$$
$$C = \begin{bmatrix} -0.54 & 0.80 & 0.20 \\ 0.30 & -1.10 & 0.70 \end{bmatrix}.$$

The constraints of the system are given by:

$$\begin{bmatrix} -30 \\ -30 \\ -30 \end{bmatrix} \leq x \leq \begin{bmatrix} 30 \\ 30 \\ 30 \end{bmatrix}, \quad -1.5 \leq u \leq 1.5$$

The persistent excitation input set has been selected to be $W = [-0.8 \quad 0.8]$, while the persistent excitation signal was selected to be a Random Gaussian White Noise Signal. Also, a target robust invariant set, X^t, was computed according to W. Figure 1 shows the relation between the feasible state space X and the target robust invariant set X^t.

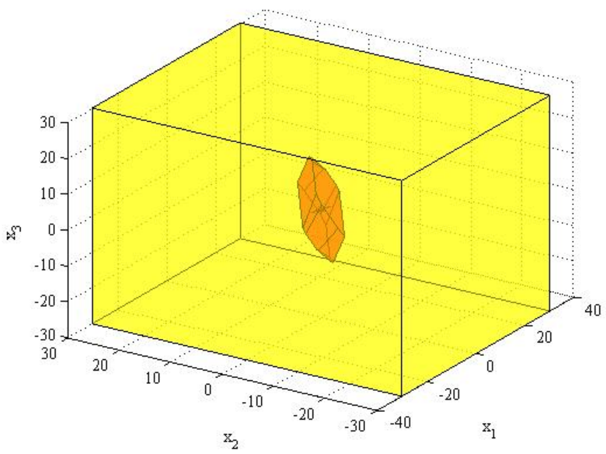

Fig. 1. Feasible state set, X, and robust invariant target set, X^t, for the 3-state system, for $W = [-0.8 \quad 0.8]$.

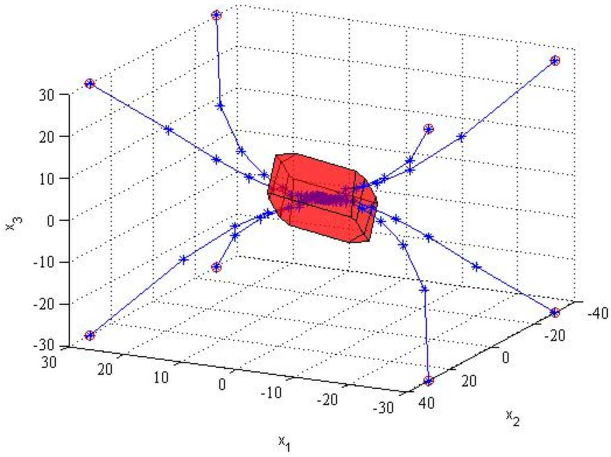

Fig. 2. State evolution corresponding to several initial states. Notice that the controller steers the system to X^t, and there, a persistent excitation is implemented.

The performed simulations were designed to show the *Re-identification operation mode* of the controller. To this end several initial states in $X \backslash X^t$ was selected. As can be seen in Figure 2, every (feasible) state is steered to the target set X^t, and once the system is inside this set, the exciting procedure is activated. Figure 3 shows the input increment, outputs and cost function time evolutions. Notice that there are two clear modes: first, from time $k = 0$ to time $k = 10$, the system is steered to the target set, with a decreasing cost function. Then, from time $k = 11$ on, the cost function remains null, which corresponds to a persistent excitation determined by the Gaussian signal $\mathbf{u}_{PE}$. The two time periods have been separated by a dotted-line in Figure 3. Notice also, that the input increment is on its upper bound in the first time periods, because the controller tries to do the best for the system to reach the target. Furthermore, in the excitation mode, the input remain inside set W, whose limits are also plotted in solid lines. Next, a pure persistent excitation scenario is simulated. An initial state $x = [0 \ 0 \ 0]^T \in X^t$ has been selected. The state evolution can be seen in Figure 4, where two plots, with different time scales, are presented. Finally, the input increment, outputs and cost function time evolutions corresponding to the later case is shown in Figure 5. Notice that the MPC cost function is null throughout all the simulation, which is consistent with a pure persistent excitation of the system. This can be clearly inferred by the input increment and outputs time evolutions.

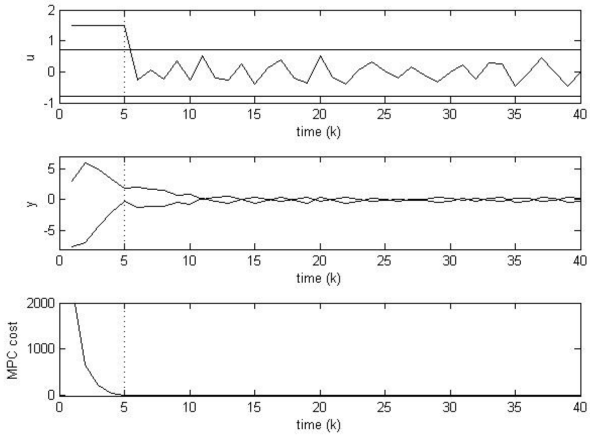

Fig. 3. Input increment, output and cost evolution.

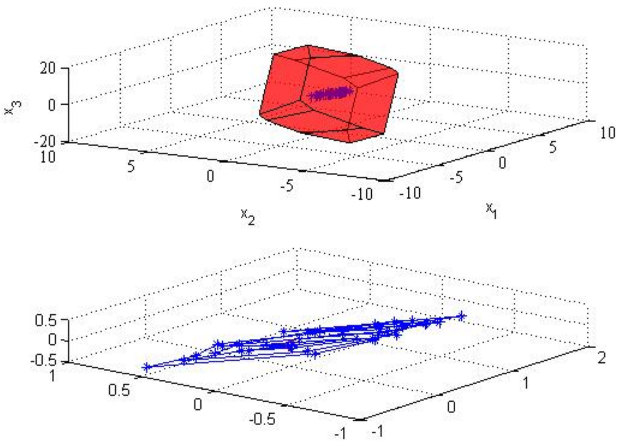

Fig. 4. State evolution corresponding to persistent excitation.

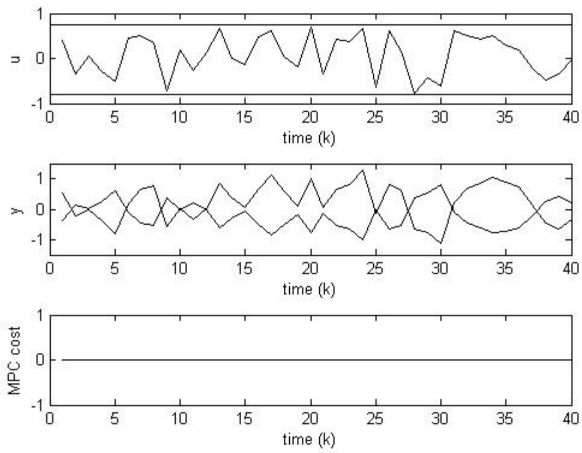

Fig. 5. Input increment, output and cost evolution. Notice that the MPC cost is null throughout all the simulation.

8. CONCLUSIONS

In this work, some preliminary results regarding a new MPC formulation suitable for closed-loop re-identification was presented. The main advantages of the method is that it assures closed-loop stability and recursive feasibility, together with a guarantee of persistent excitation. The key concept to mixture these two opposite objectives is the concept of stability of a robust invariant set, inside which the excitation of the system can be made, without affecting the stability itself. A preliminary drawback of the method is that a robust invariant set, which could be conservative even for reduced exciting sets, needs to be computed for each target change. Future research clearly includes the study of the relation between these two sets (the robust invariant and the exciting set), in order to obtain a less conservative formulation.

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