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Model correction mechanishm for nonlinear time variant systems as support to predictive control strategies ⋆

A. Pérez-Castro ∗ J. Sánchez ∗ J. L. Guzmán ∗∗

∗ *Dep. of Computer Science and Automatic Control, National Distance Education University, Madrid, Spain (e-mail: agustinperezcastro@bec.uned.es jsanchez@dia.uned.es).*
∗∗ *Dep. of Computer Science, University of Almería, Almería, Spain (e-mail: joseluis.guzman@ual.es)*

Abstract: This work presents a strategy to estimate and to correct dynamics variations in nonlinear time variant systems. This correction is carried out by estimating the internal parameters of the process and determining the differences with an available nonlinear model of the system. The proposed approach has a double functionality; on the one hand, it allows a better performance of using nonlinear models for control purposes, like for nonlinear predictive controllers; and on the other hand, it can be used as a diagnosis mechanism since it provides relevant information about the current state of the system. Thus, in order to use this technique with nonlinear time variant systems, a nonlinear model predictive control strategy has been used. The estimator proposed within the framework of this work is similar to the Moving Horizon Estimation strategy. Experimental results on a real tank process are presented to show the main properties of the proposed architecture. © *Copyright IFAC 2014*

Keywords: Modeling, Model Predictive Control, Nonlinear Model Predictive Control, System diagnosis, Nonlinear time variant models, Moving Horizon Estimation

1. INTRODUCTION

One of the main difficulties to develop durable and robust control systems is the variation in the behaviour of the systems. Such variations can be due to the own dynamics nature of the system, or because of faults and deteriorations in someone of their components. These changes in the dynamics can suppose from economic losses until dangerous situations for the operators of the plant, as well as a bad performance of the system. In order to solve this problem, fault-tolerant control approaches are typically used (Puig et al., 2004). More specifically, a fault can be defined as a change in the behaviour of any component of the system (a not allowed deviation of any property or characteristic parameter), in such a way that it could not satisfy the function for which it has been designed (Blanke, 2000; Puig et al., 2004).

According to (Puig et al., 2004), the fault-tolerant control methodology must follow five different stages: analysis of the system, diagnosis, fault tolerance, supervision, and application. In addition, the fault tolerance stage is divided into three steps: detection, isolation, and estimation. Therefore, based on the definitions proposed by (Puig et al., 2004), the strategy proposed in this work can be used in the detection state. More specifically, it can be used as a failure detection mechanism based on quantitative models.

In this work, a strategy to correct nonlinear time variant models will be combined with a nonlinear model predictive control in order to obtain an adaptive control structure able to change the parameters associated with the prediction model. This variation provides a fault detection mechanism and an improvement in the performance of the system. Moreover, this improvement has several advantages in comparison to these strategies which only have an error corrective mechanism, as the corrective factor used by the Practical Nonlinear Model Predictive Control (PNMPC) approach (Plucenio, 2010; Andrade et al., 2013). Considering that although these strategies, which are based on error corrective mechanisms or robust techniques, allow the controller to follow the established references, they can achieve sub-optimal solutions. However, if the parameters of the model are directly corrected, results closer to the optimal can be achieved since, although it has a similar setpoint tracking, the optimization of other internal parameters can only be optimal if the prediction model is adjusted, in its internal behaviour, to the real process. Besides, the proposed technique avoids that the control loop hides faults, modeling errors and even variations in the system dynamics.

The estimator proposed within the framework of this work has as theoretical basis a Nonlinear Model Predictive Control (NMPC) technique and, as a result, it provides similar results to the Nonlinear Moving Horizon Estimation

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(MHE) with constraints approach (Kraus et al., 2013). In accordance with (Kraus et al., 2013), an Extended Kalman Filter (EKF) is mostly used to estimate parameters and states. This can be justified with linear or mildly nonlinear systems when disturbances are considered Gaussian, and constraints do not play an important role. Moreover, the constraints related to physical limitations cannot be incorporated to any framework of Kalman filter. A detailed discussion about the use of MHE with constraints can be found in (Robertson and Lee, 1995; Rao et al., 2003; Kühl et al., 2011).

The paper is organized as follows: In Section 2, the control strategy used as basis to the development of the estimator is explained. Section 3 is devoted to show a complete description of the model estimator and its components. Section 4 presents the experimental setup used to validate the proposed control strategy. In Section 5, the obtained results are shown and widely commented. Finally, in Section 6, a summary of the main conclusions and future works is performed.

2. A PRACTICAL NON-LINEAR MODEL PREDICTIVE CONTROL (PNMPC)

The theoretical basis of the estimator proposed in this work is based on the PNMPC algorithm developed by (Plucenio, 2010; Andrade et al., 2013). Moreover, this algorithm will be used as the main control strategy combined with the resulting estimator.

The PNMPC strategy is characterized by the use of linearized models at each sample time. This allows a wide simplicity and a good fitting of the linearization which is independent of the current system operation point. Therefore, in this case, the predicted output data vector, $\overrightarrow{y_p}$, can be estimated as follows

$$\overrightarrow{y_p} = F_{lib} + G_{PNMPC} \cdot \overrightarrow{\Delta u} \tag{1}$$

where $\overrightarrow{y_p}$ are the predicted outputs within the prediction horizon, F_{lib} is the free response of the system obtained when the future control actions, $\overrightarrow{\Delta u}$, are equal to zero, and $G_{PNMPC} = \dfrac{\partial \overrightarrow{y_p}}{\partial \overrightarrow{\Delta u}}$ is the Jacobian of $\overrightarrow{y_p}$. Some examples of the use of this control approach can be found in (Castilla et al., 2012; Normey-Rico et al., 2011; Andrade et al., 2013).

Both, F_{lib} and G_{PNMPC}, have to be estimated at each sample time using the algorithm proposed in (Plucenio, 2010), and the modifications suggested in (Pérez-Castro, 2011), which are able to improve the robustness and velocity of the algorithm.

Moreover, in order to perform an appropriate treatment of the prediction error, noise and non-measurable disturbances, the PNMPC approach implements a corrective factor, F_c, which should be added to each one of the predictions. This corrective factor is estimated as

$$F_c(k+j|k) = F_c(k-1) \cdot (1+f_d) - F_c(k-2) \cdot f_d + e(k) \cdot k_i \quad \forall j = 1, \dots N \tag{2}$$

$$f_d = a_f^2; \quad k_i = 1 + a_f^2 - 2 \cdot a_f \tag{3}$$

that is, by means of the integral of the error, $e(k)$, filtered as a function of a tuning parameter, a_f. This parameter should be selected as a tradeoff between the speed of the response before step disturbances and the noise level.

Besides, the typical cost functions within the MPC framework will be used

$$J = \sum_{j=1}^{N} \|\overrightarrow{y_p}(k+j|k) - \overrightarrow{w_{ref}}(k+j|k)\|^2_{P_R} + \sum_{j=1}^{N_u} \|\overrightarrow{\Delta u}(k+j-1)\|^2_{P_Q} \tag{4}$$

where this cost function is subjected to typical constraints which affect to the changes in the control signal, the value of this control signal and the value of the output, respectively, as shown in the following

$$\overrightarrow{\Delta u_{min}} \leq \overrightarrow{\Delta u}(k+j) \leq \overrightarrow{\Delta u_{max}} \quad \forall j = 0, \dots N_u - 1 \tag{5}$$

$$\overrightarrow{u_{min}} \leq \overrightarrow{u}(k+j) \leq \overrightarrow{u_{max}} \quad \forall j = 0, \dots N_u - 1 \tag{6}$$

$$\overrightarrow{y_{min}} \leq \overrightarrow{y_p}(k+j|k) \leq \overrightarrow{y_{max}} \quad \forall j = 1, \dots N \tag{7}$$

In the previous equations $\overrightarrow{y_p}(k+j|k)$ are the predicted output of the system estimated at sample time $k+j$ with the information available at sample time k, $\overrightarrow{w_{ref}}$ are the future references, $\overrightarrow{\Delta u}$ are the control signal, P_R and P_Q are the weighting coefficients associated with the setpoint tracking and the control signal respectively, and finally, N and N_u are the prediction and control horizons.

3. MODEL ESTIMATOR

Through the measurement of past prediction errors and using the inputs and outputs of the system which had produced these errors, the model estimator recalculates the parameters of the model to minimize such errors. This setting will produce an improvement in the future outputs prediction. Figure 1 shows the proposed corrective mechanism architecture, which is composed of three main elements: the PNMPC estimator, a parameter model block, and a trigger. These elements are described in the subsequent sections.

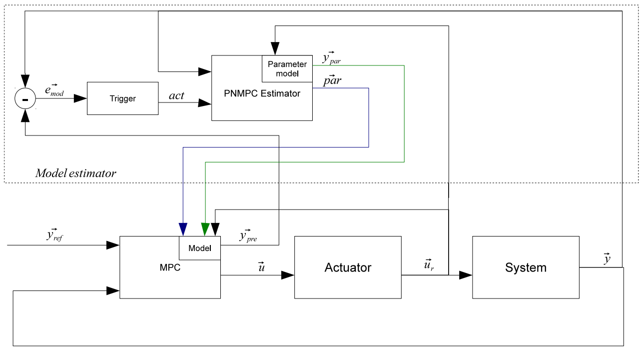

Fig. 1. Control scheme with a model estimator

3.1 PNMPC estimator

Whereas the PNMPC approach, as any typical predictive controller (Camacho and Bordóns, 2004), usually works with future predictions, in the case of the PNMPC estimator only the past will be used. In this way, the prediction and control horizons, N and N_u, respectively, are replaced by the correction and parameters variation horizons, N_{cor} and N_{par}, respectively. N_{cor} represents the number of sample times which are considered to correct the output of the model in relation to the output of the system, and N_{par} is the number of sample times in which the controller can perform changes in the model parameters. Moreover, the cost function to optimize by the PNMPC estimator is proposed as follows

$$J = \sum_{j=N_{cor}-1}^{0} \|\overrightarrow{y_{par}}(k-j) - \overrightarrow{y}(k-j)\|^2_{P_{cor}} + \sum_{j=N_{par}}^{1} \|\overrightarrow{\Delta par}(k-j)\|^2_{P_{par}} \quad (8)$$

where k is the current sample time, $\overrightarrow{y_{par}}(k-j)$ are the outputs estimated by the parameter model at sample time $k-j$, $\overrightarrow{y}(k-j)$ are the real outputs of the system at sample time $k-j$, $\overrightarrow{\Delta par}(k-j)$ are the parameters variation at sample time $k-j$, P_{cor} are the weighting coefficients associated with the correction mechanism (that is, they weight the order of magnitude of the different outputs and the priority among them), and P_{par} are the weighting coefficients associated with the parameters variation (they weight the order of magnitude among different parameters and the priority in the modification of them).

The cost function (8), as in the PNMPC approach, is subjected to several constraints, which in this case are over the outputs, the parameters, and the parameters variation

$$\overrightarrow{y_{min}} \leq \overrightarrow{y_{par}}(k-j) \leq \overrightarrow{y_{max}} \quad \forall j = N_{cor}-1, \dots 0 \quad (9)$$

$$\overrightarrow{par_{min}} \leq \overrightarrow{par}(k-j) \leq \overrightarrow{par_{max}} \quad \forall j = N_{par}, \dots 1 \quad (10)$$

$$\overrightarrow{\Delta par_{min}} \leq \overrightarrow{\Delta par}(k-j) \leq \overrightarrow{\Delta par_{max}} \quad (11)$$
$$\forall j = N_{par}, \dots 1$$

It is important to highlight that the calibration process of a model taking into account the output of the system is not unique, that is, for the same set of outputs, in a certain operation point, it is possible to obtain different parameter sets which provide equivalent results. For example, if the volume of a container is being modeled and its characteristic parameters are the height and width, these parameters could exchange their values providing the same output under an equivalent calibration process. Nevertheless, it would not be the same model but an equivalent one. To solve this problem, the constraints described previously can be used, and thus, it is possible to limit the ranges of the parameters in absolute value, and also, their variation as a function of time. On the other hand, by using the weighting coefficients of the cost function, it is possible to establish a certain priority in the variation of the different parameters.

Another important issue is the elimination of the correction filter associated with the modeling error that is used by the PNMPC approach, as shown in the previous section. Due to the fact that PNMPC estimator corrects the modeling error, it is not necessary to use the corrective factor, which unlike the PNMPC estimator has a constant sampling. Notice that, as the PNMPC estimator only acts when the mean error exceeds from a certain level within the correction horizon, N_{cor}, the necessity of estimating again the parameters of the model due to the effect of noise at the output is diminished.

3.2 Parameter model

The parameter model will be equivalent to the model which describes the system, with the main difference that the configuration parameters of the model are transformed into inputs, and the inputs of the model are considered as disturbances, such as shown in Figure 2. Hence, a nonlinear model able to provide the outputs of the system as a function of their parameters, without having to perform any modification in its internal equations, is obtained.

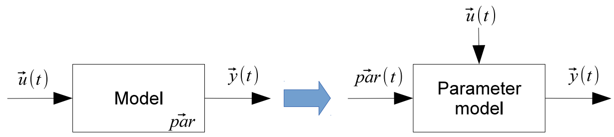

Fig. 2. Parameter model

3.3 Trigger

The trigger block (see Figure 1) has the function of activating or deactivating the PNMPC estimator as a function of the error in the past predictions of the model, by activating the correction, $act = 1$, when the root mean square error, $eRMSE$, surpasses a certain sensibility, sen_{cor} according to the following equations

$$act = \begin{cases} 1 \ si \ eRMSE \geq sen_{cor} \\ -1 \ si \ eRMSE < sen_{cor} \end{cases} \quad (12)$$

$$eRMSE = \sqrt{\frac{\sum_{j=N_{cor}-1}^{0} \|\overrightarrow{y}_{pred}(k-j) - \overrightarrow{y}(k-j)\|^2}{N_{cor}}} \quad (13)$$

Therefore, when sen_{cor} is equal to zero, the PNMPC corrective mechanism will be executed in a continuous way, and when sen_{cor} is greater than zero it will be computed as an event-based execution.

4. EXPERIMENTAL SETUP

To validate the modeling and control approach proposed in this work, a the level control problem in a tank will be used. This system, whose description can be observed in Fig. 3, is a classic tank system but where time variations on its parameters are considered. These variations are based on realistic situations, for example, when using an intermediate tank within a water treatment system. In this tank, the input water can contain some sediments which can join to the tank surface, and thus, to provoke changes of cross section area, A, or partially block the outlet hole of the tank by varying its corresponding area, a. In addition, as it can be in a real water treatment system, it is supposed that the block of the outlet hole of the tank, that is, the output area of the tank a, cannot be directly measured. The tank level dynamics is given by the following equation

$$\frac{dh(t)}{dt} = \frac{q(t)}{A(t)} - \frac{a(t)}{A(t)}\sqrt{2gh(t)} \qquad (14)$$

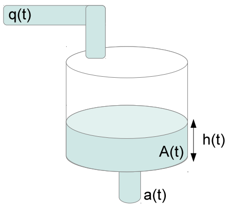

Fig. 3. Tank system

where $A(t)$ is the area of the base of the tank in $[m^2]$, $a(t)$ is the area of the output aperture of the tank in $[m^2]$, $q(t)$ is the input flow of fluid to the tank in $[m^3\ s^{-1}]$, $h(t)$ is the height of the fluid inside the tank in $[m]$, and finally, g is the gravity constant in $[m\ s^{-2}]$. Notice how, A and a are considered to be time variant parameters.

In order to test the strategy proposed in this work, a four tank plant located in the University of Almería and whose description can be found in (García et al., 2006; Pasamontes et al., 2012) has been used. More specifically, with the main objetive of evaluate the performance of this strategy only one tank has been used. This work is centered on the development of the optimization and adaptation layers, and thus, the regulatory control layer is not within the framework of this work. However, as it can be observed in Fig. 1, both the prediction model and the estimator receive feedback from this layer. To do that, in a previous step to the estimation of the control signals and the update of the parameters, both the prediction and parameter models are updated with the control signal measured at the output of the actuator, $\overrightarrow{u_r}$.

5. EXPERIMENTAL RESULTS

This section describe the results obtained for the estimator, and the benefits of the proposed framework.

A clear application of the model corrective strategy presented in this work is its combination within a predictive control framework, in such a way that the process model used in the MPC algorithm is updated when faults or variations on the process dynamics are observed. In this way, apart from a mechanism to identify the behaviour and state of the system, an element to improve the performance of the controller is also provided. A possible configuration of this application can be observed in Figure. 1, where a PNMPC approach is used. More specifically, the initial parameters associated with the model and the system are shown in Table 1, where $h_{pre}(0)$ is the height for the tank model in $[m]$, $A_{pre}(0)$ is the area of the base for the tank model in $[m^2]$, and $a_{pre}(0)$ is the area of the output aperture for the tank model in $[m^2]$. Table 2 shows the parameters used to configure the controller, and finally, the PNMPC estimator parameters can be observed in Table 3.

The obtained results can be observed in Figure 4. In this experiment, variations in the reference at time instants $t = 200s$ and $t = 400s$, and also, variations in the outlet of

Table 1. Initial parameters

Param.	Value	Param.	Value
$h(0)$	$0[m]$	$h_{pre}(0)$	$0[m]$
$A(0)$	$0.038916[m^2]$	$A_{pre}(0)$	$0.038916[m^2]$
$a(0)$	$0.00014[m^2]$	$a_{pre}(0)$	$0.00017[m^2]$

Table 2. PNMPC parameters

Param.	Value	Param.	Value
N	$10[-]$	N_u	$10[-]$
a_f	$0.6[-]$	Δu_{min}	$-10^{-4}[m^3s^{-1}]$
Δu_{max}	$10^{-4}[m^3\ s^{-1}]$	u_{min}	$10^{-4}[m^3s^{-1}]$
u_{max}	$3.8 \cdot 10^{-4}[m^3\ s^{-1}]$	Y_{min}	$0[m]$
Y_{max}	$0.2[m]$	P_r	$1[-]$
P_q	$10^5[-]$		

Table 3. PNMPC estimator parameters

Param.	Value	Param.	Value
N_{cor}	$8[-]$	N_{par}	$8[-]$
Δpar_{min}	$[-0; -10^{-4}][m^2]$	sen_{cor}	$0.01[m]$
Δpar_{max}	$[0; 10^{-4}][m^2]$	P_{cor}	$[1; 1][-]$
par_{max}	$[0.05; 0.00026][m^2]$	P_{par}	$[1; 10^5][-]$
par_{min}	$[0.02; 0][m^2]$	Y_{min}	$0[m]$
Y_{max}	$0.2[m]$		

the tank, a, at time instants $t = 600s$ and $t = 950s$ have been considered. In the real experiments, variations on a were provoked by covering the outlet area of the tank with an smaller hole element. Besides, as it can be observed in Table 1, the prediction model is not tuned correctly at time instant in which the experimental plant is connected. From Figure 4, it can be seen as the output is able to follow the established references, and also, to reject the disturbances derived from the variations in the output aperture of the tank. Moreover, it is shown as the predicted output is similar to the real output in both instants in which the reference is modified, and thus the operation point, and when disturbances derived from variations in the system dynamics are introduced. In addition, as it is shown in Figure 5, the flow provided by the pump is different from the requested by the control signal estimated with the controller.

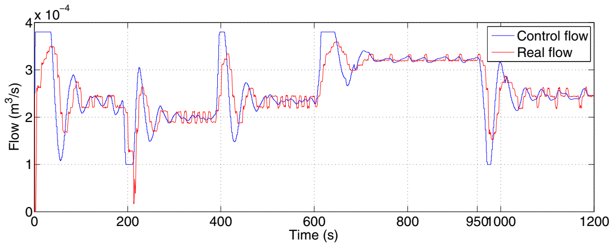

Fig. 5. Flow

Furthermore, Fig. 6 shows as the model is corrected almost exclusively at these time instants in which the system changes its internal parameters, and therefore its dynamic. In addition, it also provides information about the state of the real system.

Figure 7 show the results obtained when the same controller under the same configuration is used, but without the integration of the estimated model. More specifically, it can be inferred that the modeling error corrective technique including in the PNMPC strategy is able to follow

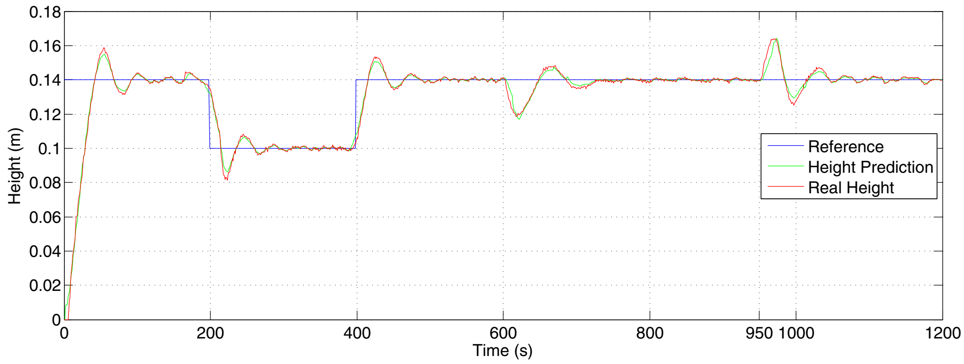

Fig. 4. Reference tracking with the PNMPC estimator

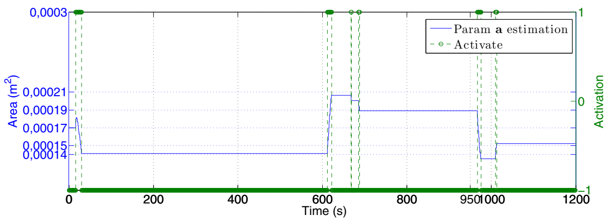

Fig. 6. Parameters estimation

the established reference. However, this architecture does not allow to obtain information about the real state of the system, and besides, it has a worst performance as shown in Table 4.

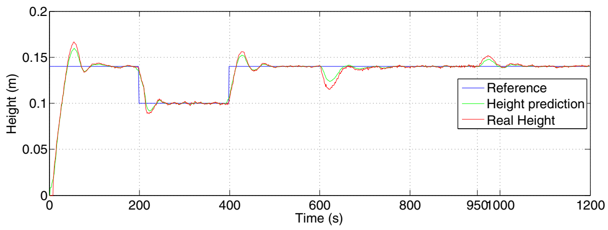

Fig. 7. Reference tracking without the PNMPC estimator

Table 4. Tracking errors

PNMPC estimator	**Error type**	**Error**
No	*RMSE*	0.01742
Yes	*RMSE*	0.01737
No	*ISE*	0.36444
Yes	*ISE*	0.36245

It is necessary to consider that the proposed techniques to correct nonlinear time variant models is based on the PNMPC approach developed by (Plucenio, 2010). For nonlinear systems, this controller linearizes the prediction model at each sample time, hence, it does not work with the nonlinear model but linearizing it at different operation points. This implies that the PNMPC estimator does not adjust the parameters of a nonlinear model, but the parameters of a linearized model at a certain operation point.

For that reason, once that the model is adjusted, variations in the operation point can provoke, as a function of the modeled system and the magnitude of the variation, that the estimator considers the necessity of estimating the model parameters. It also depends of the selected correction sensibility, sen_{cor}, and the correction horizon, N_{cor}. Nevertheless, as it can be observed in Fig. 6, in the performed test, variations in the reference does not cause a new estimation of the model parameters and they remain constant generating only a new calibration when the plant is connected and when there are variations in the output aperture area of the tank. Moreover, it can be also observed that thanks to the combined use of the trigger and the correction factor of the PNMPC approach, the number of samples in which it is necessary to estimate again the parameters is minimal, and therefore, the computational cost derived from the estimator is quite limited.

Figure 8 shows how when the model estimator is used, in comparison what happens when it is not used, as presented in Fig. 9, the correction factor is closer to zero. It implies that in the presence of variations at the operation point or at the real parameters of the model, the prediction model will be quickly adapted to the new situation which implies to obtain a better performance of the controller. Table 5 shows the prediction errors obtained with and without the model estimator.

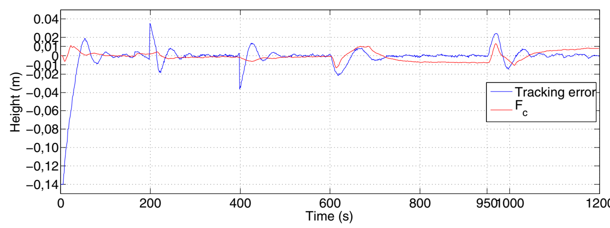

Fig. 8. Tracking error and F_c with the PNMPC estimator

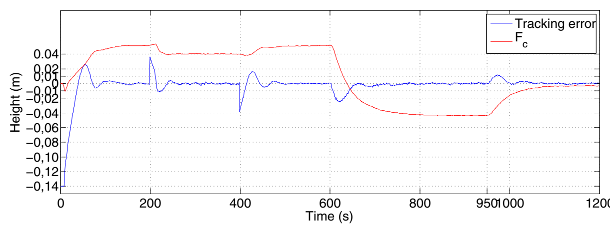

Fig. 9. Tracking error and F_c without the PNMPC estimator

Furthermore, it is possible to use only the PNMPC estimator to correct the prediction model by completely deac-

Table 5. Prediction errors

PNMPC estimator	Error type	Error
No	$RMSE$	0.00223
Yes	$RMSE$	0.00178
No	ISE	0.00601
Yes	ISE	0.00381

tivating the use of the correction factor. To do that, there are two different options: i) to perform the correction when the trigger acts, which should be the ideal solution for an event-based controller, or ii) to allow that the controller work in a continuous way deactivating the trigger, that is, $sen_{cor} = 0$.

6. CONCLUSIONS AND FUTURE WORKS

The strategy proposed to correct nonlinear time variant models allows to obtain some improvements in the performance of a predictive controller, and also, in the diagnosis of systems. The main advantages derived from the use of a prediction model able to adjust its dynamic to the real system are a better reference tracking, possible costs saving due to the adjustment of the internal parameters, and the possibility of obtaining an adaptive controller which changes its performance from a robustness point of view as a function of the real state of the system. In addition, the adjustment of the model parameters reduces the necessity of the output adjustment in a continuous way, and thus, it is easier to develop an event-based nonlinear model predictive control.

The noise at the output can be responsible of a constant and unnecessary re-estimation of the model parameters. This can be avoided by filtering output measurements. However, as the estimator only works when the mean error, $eRMSE$, exceeds the sensibility, sen_{cor}, within a correction horizon, N_{cor}, if the noise at the output measurements is a zero mean white noise, and the sensibility and the correction horizon are high enough, the own trigger mechanism of the estimator will act as a noise filter.

The greatest potential of the strategy described in this work lies in the correction of nonlinear time variant models where its dynamics change due to the own system nature, or undesirable faults or deteriorations. Furthermore, the benefit of using the proposed strategy instead of other ones as the MHE proposed by (Kraus et al., 2013) is in the use of an NMPC technique as theoretical basis, since it allows to take advantage of the knowledge and the implementation of these techniques to correct nonlinear time variant models. Besides, it also allows a quick adaptation to other NMPC techniques as NMPC approaches based on intelligent control.

As future works, four different research lines are proposed: i) the comparison with other strategies to correct nonlinear time variant models, ii) the implementation of a mechanism for diagnosis of errors and fault-tolerant control, iii) the development of an event-based nonlinear model predictive control approach, and iv) an optimal tuning of the parameters associated with the controller and the PNMPC estimator. A first approach could be to tune the parameters of the constraints according to the physical constraints of the system, ie, a volume can not be negative; to select the weights of the cost function as function of the order of the parameters and the likelihood that these vary; besides, the sensitivity correction parameter should be selected based on the measurements noise; and the horizons will depend on the speed of the system dynamics.

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