A smooth gain scheduling generalized predictive control

Yassine Himour, Mohamed Tadjine, and Mohamed-Seghir Boucherit

Abstract− Nonlinear model predictive control is an emerging control technique dealing with high nonlinearities of industrial plants. However, it suffers from many hurdles such as the numerical problems related to the resulting no convex nonlinear optimization problem, time consuming, and difficulties in analyzing properties such as stability. In this paper, to side-step these difficulties, an infinite gain scheduling generalized predictive control is designed to control a benchmark high nonlinear plant instead of nonlinear predictive control. A neural model of the plant is identified and used as an internal model of the generalized predictive control scheme. The neural model is linearized successively and a filtering process is used to smooth the adaptation of the linearized model every sample time. The results show good performance in tracking the reference and rejecting abrupt changes in measured disturbances. The filtering process improved the results in terms of rapidity, overshoots damping, and smoothing the control signal.

***Keywords*− GPC, neural networks, gain scheduling, measured disturbances, high nonlinearities.**

NOMENCLATURE

ANN	Artificial neural network
ARX	Autoregressive exogenous inputs
CARIMA	Autoregressive integrated moving average
GPC	Generalized predictive control
HTF	Heat transfer fluid
MPC	Model predictive control
NLP	Nonlinear problem
NMPC	Nonlinear predictive control
PTC	Parabolic trough collector

I. INTRODUCTION

Model predictive control is the most used advanced control technique in industry. This is because it provides many advantages, among which constraints handling. Additionally, the principle of MPC is intuitive and its tuning is relatively straightforward— even practitioners with limited knowledge have the chance to work with. MPC can handle a panoply of processes that encompasses those with complex dynamics such as high nonlinearities, long delays, unstable characteristics and nonminimum phase systems[1]. MPC can be easily extended to multivariable cases, and it naturally includes feedforward action that allows it to exploit measured disturbances. For systems with high nonlinear dynamics, it's obvious that nonlinear predictive control is the first MPC technique to think to use with. However, NMPC relies on nonlinear optimization which shows many hurdles, especially in real time implementation. Among difficulties NMPC suffers from difficulty of theoretical analysis of properties such as stability[2]. Most solutions in this situation add more complexities and many computational problems may show up, for example the nonlinear optimization algorithm could not converge to the desired accuracy and/or can't converge in the needed time, especially in the case of fast systems. Moreover, numerical problems could occur and the obtained solution is not verified to be a global optimal solution. One interesting alternative to bypass those NMPC difficulties while treating high nonlinearities in a good way, is adaptive linear MPC, but again, adaptive MPC needs extra mechanisms to avoid adaptation problems such as persistent excitations which are crucial to obtaining good results. In such situation, scheduled gain MPC strategy has demonstrated better performance [3].

The gain scheduling MPC control strategy uses linearized models of the nonlinear process to predict the outputs over a prediction horizon, this results in poor modelling performance when using long prediction horizon, this is because the linearized models are supposed to be used near the operation points of their linearization. Some ideas have been appeared to cope with this problem. For example in [4], this is treated by interpolating the controller gains between four operating points chosen on the basis of the manipulated variable. Inspired by this idea, the authors in [5] used an interpolation of the linearized models' parameters.

This study aims to develop an MPC control strategy, namely, an infinite neural gain scheduling generalized predictive control, to overcome the aforementioned challenges. The remainder of this paper is organized as follows: the next section explains the control strategy, and gives details about its elements, namely, the generalized predictive control and the neural model and its linearization. In section III, the introduced control strategy is applied to a highly nonlinear process, the output temperature in the ACUREX parabolic trough collector field.

II. CONTROL STRATEGY AND DESIGN

The strategy is to use an artificial neural network model to reduce the computations[6]and to assure a maximum performance and capture of the plant nonlinear dynamics. In

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Y.HIMOUR, M. TADJINE and M.S. BOUCHERIT are with Process Control Laboratory at EcoleNationale Polytechnique, Algiers, Algeria. (e-mail: yassine.himour@g.enp.edu.dz, mohamed.tadjine@g.enp.edu.dz, ms.boucherit@g.enp.edu.dz)

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every sampling time, the neural model is linearized around the actual operating point, and a linear GPC control law is applied using the linearized model. This strategy avoids NLPs and results in more precise local linear models than considering only some operating regimes.

A. Generalized predictive control

The generalized predictive control is an MPC control technique based oncontrolled autoregressive integrated moving average model(CARIMA model):

$$A(q^{-1})y(t) = q^{-d_u}B(q^{-1})u(t-1) + \frac{C(q^{-1})\xi}{\Delta} \quad (1)$$

Where, q^{-1} is the time backward shift operator, the differencing operator: $\Delta = (1-q^{-1})$, $y(t)$ and $u(t)$ are the output and the input of the model, d_u is the dead time according to the input $u(t)$. And $\xi(t)$ is a zero mean white noise.$A(q^{-1})$and$B(q^{-1})$ are the model polynomial with $A(q^{-1})$is monic.

In GPC the cost function is usually defined by:

$$J = \frac{1}{2}\sum_{i=N_1}^{N_2}(r(k+i) - \hat{y}(k+i|k))^2 + \frac{1}{2}\sum_{i=1}^{N_u}\lambda\,(\quad (2)$$

Where, $r(k+i)$is the reference signal, $\hat{y}(k+i|k)$is the predictions at time $k+i$ calculated at time k,$\Delta u(k)$ is the control increments, $\lambda$is the penalty factor of the control increments, $N_1$and$N_2$are the first and second prediction horizons, and N_u is the control horizon.

When there is no constraints, the GPC control can be given by the following analytical expression[7]:

$$\Delta U = [G^T G + \lambda I]^{-1} G^T (R - \phi) \quad (3)$$

Where, ΔU is the vector of the control increments over the control horizon, G is a matrix whose elements are the step response coefficients[7],ϕ is the free response depending on past and present signals, and R is the known reference over the control prediction horizon.

Every sampling time, only the first element of ΔU is applied to the real system, and the calculations are repeated for the next sample where new measurements are obtained. The control horizon N_u is commonly chosen less than the prediction horizon, hence the elements of ΔUafter the$N_u$element are taken equal to zero, this reduces the computations, particularly those of the inverse matrix whose dimensions become $N_u \times N_u$.

B. Neural network modeling and linearization

In[8] it was demonstrated that with a one hidden layer, an ANN is able to model any measurable function to any desired degree of accuracy. On the basis of that result, in this work, a two-layer perceptron is used; its output is given as follows:

$$\hat{y}(t) = \sum_{j=1}^{p} W_j \tanh\left(\sum_{i=1}^{l} w_{ji} z_i(t) + w_{j0}\right) + W_0 \quad (4)$$

Where, W_j *and* w_{ji} are the weights of the hidden to output layer and the input to hidden layer respectively. W_0 and w_{j0} are the biases of the nodes. p is the number of the hidden neurones, and l is the length of the input vector $z(t)$.

As mentioned before, this neural model is linearized every sampling time to get a linear CARIMA model appropriate to be used as an internal model in the GPC control law.

Let the whole function in(4) be expressed by the shorter expression:

$$y(t) = g(z(t)) \quad (5)$$

Where $z(t)$ is the input vector of the neural network:

$$z(t) = [y(t-1) \ldots y(t-n)\; u(t-d_u-1) \ldots u(t-d_u-1-m)]$$

Linearizing the ANN model g around an operating point $z(\tau)$ gives:

$$y(t) = -a_1\tilde{y}(t-1) - \ldots - a_n\tilde{y}(t-n) + b_0\tilde{u} \quad (6)$$

With,

$$\tilde{y}(t-i) = y(t-i) - y(\tau-i)$$

$$\tilde{u}(t-i) = u(t-i) - u(\tau-i)$$

And

$$a_i = -\left.\frac{\partial g(z(t))}{\partial y(t-i)}\right|_{z(t)=z(\tau)}$$

$$b_i = -\left.\frac{\partial g(z(t))}{\partial u(t-d_u-i)}\right|_{z(t)=z(\tau)}$$

Putting the elements of the current instant τ in(6) on one side gives:

$$y(t) = \left(1 - A(q^{-1})\right)y(t) + q^{-d_u}B(q^{-1})u(t-1) + \zeta(\tau)$$

Or

$$A(q^{-1})y(t) = q^{-d_u}B(q^{-1})u(t-1) + \zeta(\tau) \quad (7)$$

Taking $C(q^{-1})$ in(1) equals to 1, and modelling $\zeta(\tau)$ as an integrated white noise makes this model identical to the model used in the MPC control law.

C. Smoothing the adaptation of the linearized model's parameters

As mentioned earlier, using a linearized model, which is supposed to give good predictions just near the operating point of linearization, to predict the output of the process over long prediction horizon can result in poor performance of the model. For this reason, it is proposed here to use a filtering parameter to smooth the adaptation of the linear model's parameters. The filter expression is given by[9]:

$$\hat{P}_k(q^{-1}) = (1-d)P_k(q^{-1}) + d\,\hat{P}_{k-1} \quad (8)$$

Where $P_k(q^{-1})$ is every polynomial of the model in (7), k is the actual sample time, and d is the introduced tuning parameter.

This filtering process has the effect of smoothing the variation of the parameters of the successively linearized models. Increasing the parameter d slows the adaptation of the model and vice versa. The filtering process would improve the performance of the gain-scheduled GPC controller when there are disturbances or abrupt changes in the reference. In the absence of these two factors, the filter would have no noticeable effect.

III. Case Study

In this section, the strategy developed above is applied to the ACUREX solar parabolic trough field.

A. Plant description and modelling

The ACUREX plant is a PTC based distributed solar collector field. It is located in the desert of Tabernas, in southern of Spain. It is an experimental facility that has a maximum energy of 0.5 MW. The concentrators are aligned east-west in 10 parallel loops, every loop is composed of two rows. The length of one loop is 172 m, and only 142 m of the tube per loop receive the concentrated sun rays. The heat transfer fluid (HTF) used in the ACUREX field decompose for temperatures bigger than 300°C. The HTFflows in the absorber tube through the field area to collect solar energy in the form of heat.

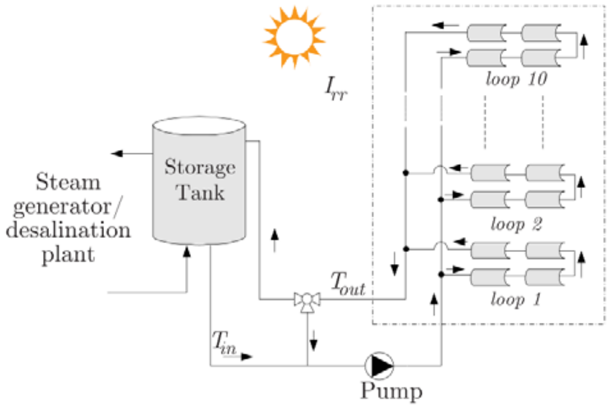

Fig 1: ACUREX Distributed Solar Field Schematics[10]

The HTF flow is limited between 2.0 and 12.0 l / s[11], or 0.2 and 1.2 l/s for every loop. This is to ensure safety especial to avoid the risk of the HTF decomposition.

he following hypothesis are considered in elaborating the model used in the present work[12]:

1. The properties of the heat transfer fluid are functions of the actual temperature value, and the flowequals to its average value.
2. Tube wall temperature variations are not taken into account.
3. Losses caused by the conduction of axial heat on both sides of the wall are negligible.

The enthalpy accumulated in the Δl element, between two instants time t and $t + \Delta t$ is given by the thermodynamics law:

$$E = \rho_f c_f A_f\, \Delta l\, [T(l, t+\Delta t) - T(l,t)] \quad (9)$$

Where, l is the space variable (m), A_f is thecross-sectional area of the tube (m^2), ρ_f is thefluid mass density (Kg/m^3), c_f is the fluid specific heat capacity (J /Kg °C), and $T(l,t)$ is the fluid temperature (°C).

This enthalpy is the sum of two enthalpies. The first is the difference between the enthalpy entering and the enthalpy leaving the Δl element due to fluid flow in Δt time:

$$E_1 = \rho_f c_f \bar{u}(t)\Delta t\, \left(T(l,t) - T(l+\Delta l, t)\right) \quad (10)$$

Where $\bar{u}(t)$ is the fluid volumetric flow rate (m^3 /s).

The second is due to the harvested solar energy between the two points l and Δl in Δt time:

$$E_2 = \eta\, G\, R\, \Delta l\, \Delta t \quad (11)$$

Where, R is the solar irradiance (W/m^2), η is the optical efficiency (Unit-less), and$G$ is the concentrator aperture (m).

By putting $E = E_1 + E_2$, we obtain the expression of the temperature evolution in every element $i\,\Delta l$:

$$\frac{\partial T(i\,\Delta l, t)}{\partial t} = -\frac{u(t)\left(T(i\,\Delta l, t) - T\left((i-1)\Delta l,\right.\right.}{\Delta l} \quad (12)$$

$$i = 1, \ldots n, \text{ and } \; n \times \Delta l = L$$

L is the total length of the absorber tube (m), $u(t) = \frac{\bar{q}(t)}{A_f}$, and

$$\alpha \triangleq \frac{\eta G}{\rho_f c_f A_f}$$

Define now,$T(i\Delta l, t) \stackrel{\text{def}}{=} x_i(t), that$ gives $x_0(t) = T(0, t))$.

And noting $\alpha_i = \alpha(x_i)$. Then, the set of differential equations defining the temperature process in a PTC field is:

$$\dot{x_1}(t) = -\frac{u(t)}{\Delta l}\left(x_1(t) - x_0(t)\right) + \alpha(x_1(t))R(t$$

$$\dot{x_2}(t) = -\frac{u(t)}{\Delta l}\left(x_2(t) - x_1(t)\right) + \alpha(x_2(t))R(t$$

$$\dot{x_3}(t) = -\frac{u(t)}{\Delta l}\left(x_3(t) - x_2(t)\right) + \alpha(x_3(t))R(t \quad (13)$$

$$\vdots \quad \vdots \quad \vdots \quad \vdots$$

$$\dot{x_n}(t) = -\frac{u(t)}{\Delta l}\left(x_n(t) - x_{n-1}(t)\right) + \alpha(x_n(t))R$$

B. *Neural identification of the ACUREX plant*

In the first principal model in (13),the solar irradiance $R(t)$ and the inlet temperature $x_0(t)$(or T_{in}: the HTF inlet temperature) are unmanipulated inputs, i.e., they have a direct effect on the output $x_n(t)$ (or T_{out}: the HTF outlet temperature) but are not commands, they are measured disturbances. However, in this work it's the model (13) which is being identified by the neural network but not the real plant. This gives the possibility to use the irradiance and the inlet temperature with the HTF flow as excitation signals in the identification task.

Fig. 2 depicts the curves of the used excitation signals over range of 12 hours. The irradiance signal is shaped likewise to imitate real solar irradiance during a day. The database is divided into two datasets, one for training and the other for validation. The total length is 18000 samples, with a time sampling of 15s.

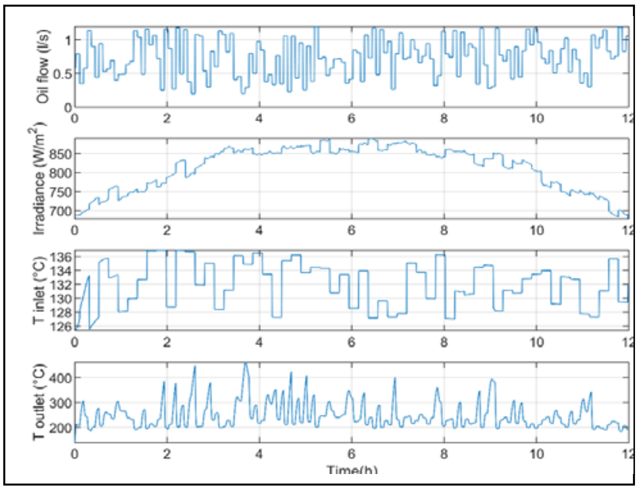

Fig. 2: The identification database[9]

Trial and error tests were held to find the convenient parameters of the ANN. The results in Fig. 3 and Fig. 4 were obtained for an ARX structure with 12 neurons in the hidden layer, one sample dead time for the three inputs, 5 order of the past delayed output, 4 for the control flow, and 3 for both the irradiance and the inlet temperature.

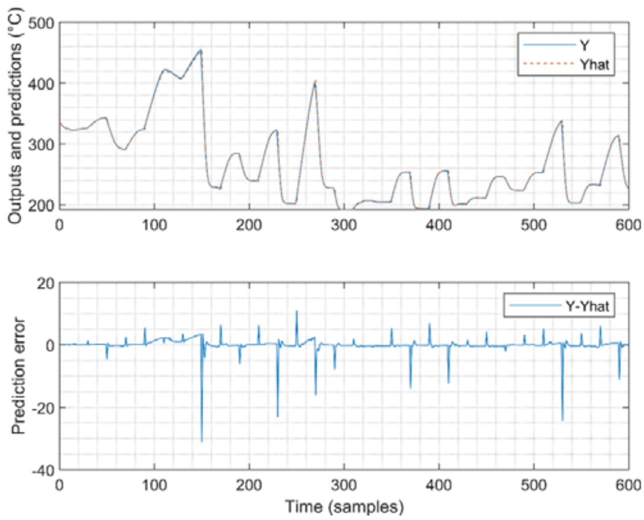

Fig. 3: The output, the prediction and error

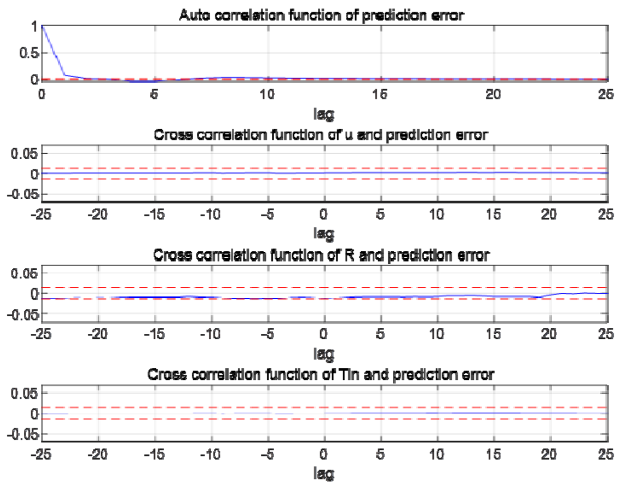

Fig. 4: Cross correl3ations of the inputs and the prediction error

It's to notice that the prediction error peaks in second subplot of Fig. 4 is due to big instantaneous changes of the output temperature, which is not usual in the real plant. The autocorrelation of the error and its cross-correlation with the inputs is null, and this is a good index of the good performance of the identified model.

C. Application of the control strategy

The control strategy introduced in section II is applied here using the identified neural model. Fig. 5 shows the profile of the measured disturbances, i.e., the solar irradiance and the inlet HTF temperature. Two aggressive changes were added on the two signals to simulate two disturbances. Artificial estimations are made by adding made-up estimation errors, and are to be used in the GPC prediction horizon instead of the real signal.

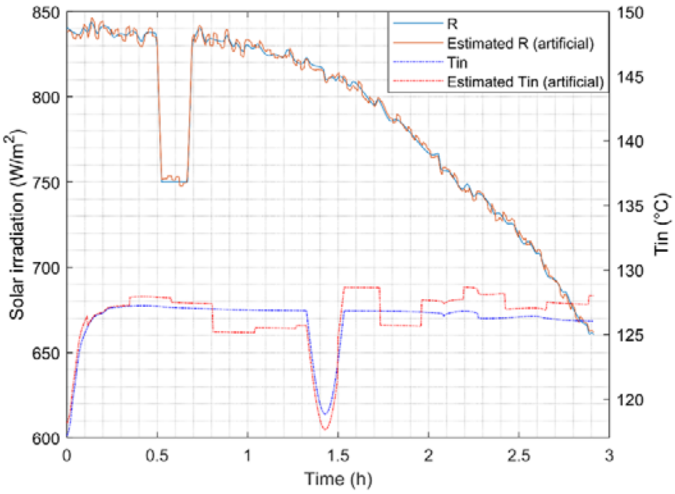

Fig. 5: The measured disturbances profile[9]

To test the robustness of the control law, model mismatch has been added to the first principal model which is used as a simulator of the real plant, and the reference signal was chosen to cover a wide range of the plant dynamics. Fig. 6 and Fig. 11 illustrate the output and the command behaviors respectively for different values of the smoothing parameter ***d***.

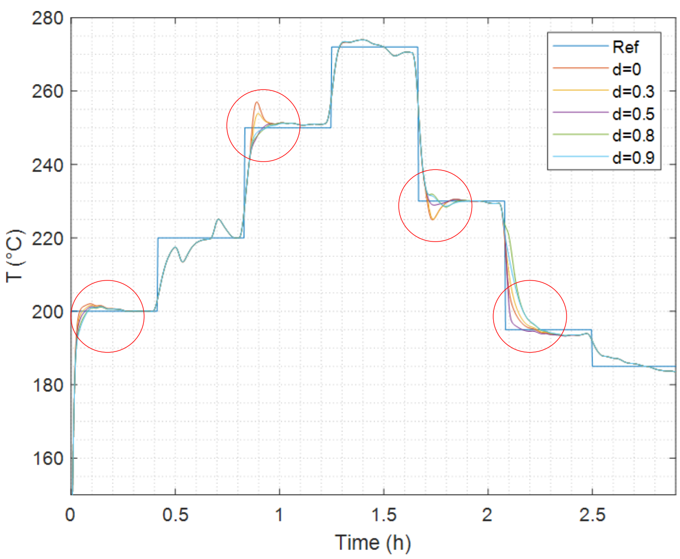

Fig. 6: Output versus the reference for different values of the smoothing parameter

Fig. 6 shows the performance of the control scheme in rejecting the two disturbances injected on the solar irradiance and the HTF inlet temperature, and the performance of tracking the reference. Fig. 7, Fig. 8, Fig 9 and Fig. 10, bellow, are a zoom into the red circles in Fig. 6, to show better the effect of the parameter ***d***. The figures are ordered corresponding to the circles from left to the right, i.e., the circle most to the left is in Fig. 7, the next to it is in Fig. 8, … etc.

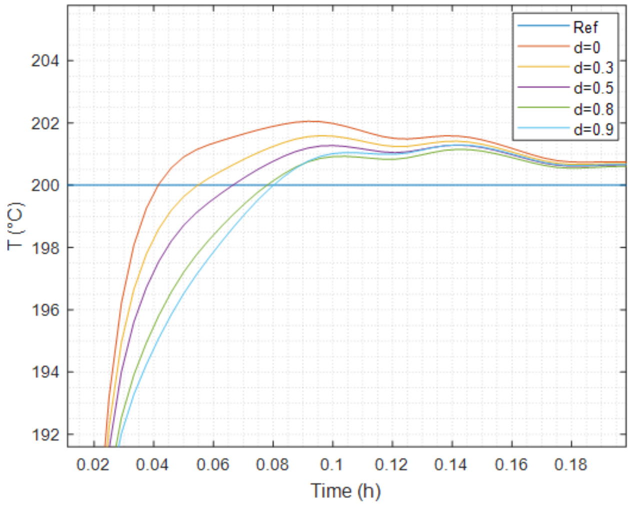

Fig. 7: Zoom on the first red circle from the left in Fig. 6

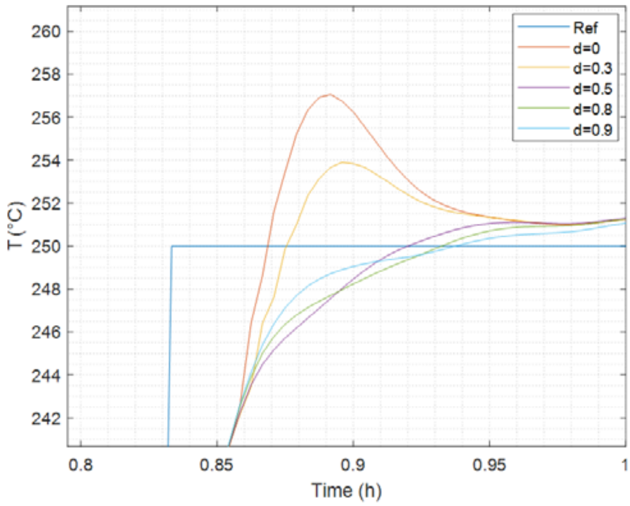

Fig. 8: Zoom on the second red circle from the left in Fig. 6

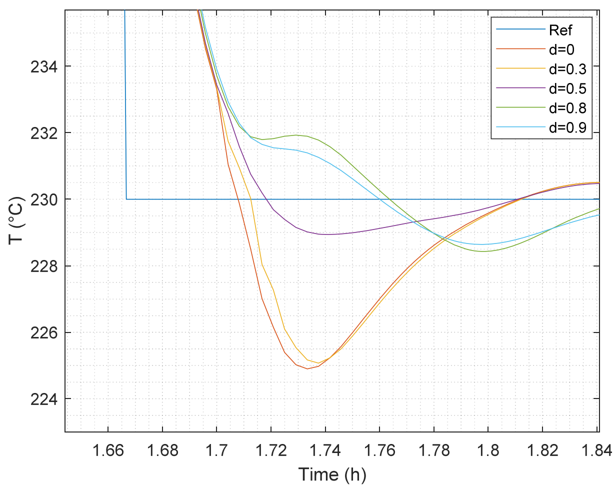

Fig. 9: Zoom on the third red circle from the left in Fig. 6

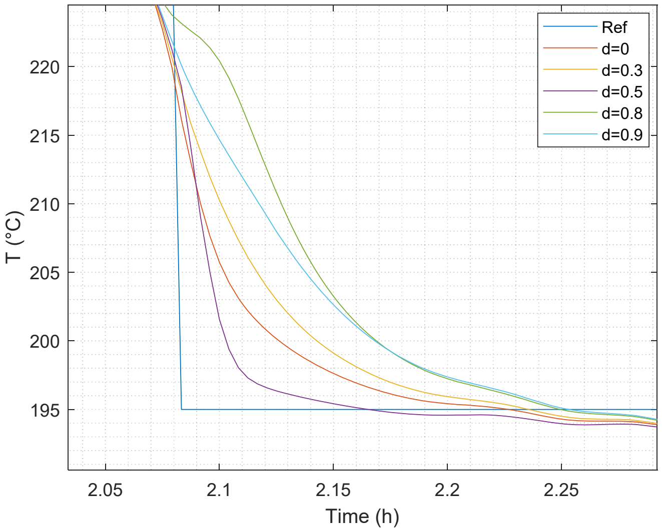

Fig. 10: Zoom on the fourth red circle from the left in Fig. 6

These figures clearly depict the improvement brought by the introduction of the filtering process of the polynomials of the successively linearized models. As it was expected, the filtering has no effect when the plant is in steady state, i.e., when there is no abrupt change of the reference. The best

value of $d$in this simulation is 0.5, using this value eliminates the overshoots of the case without filtering, see Fig. 8 and Fig. 9, and also improves rapidity, see Fig. 10. The filtering has also good effect on the command, see Fig.11, It smooths the control signal, thus it helps reducing the control effort and increasing the lifetime of the pump.

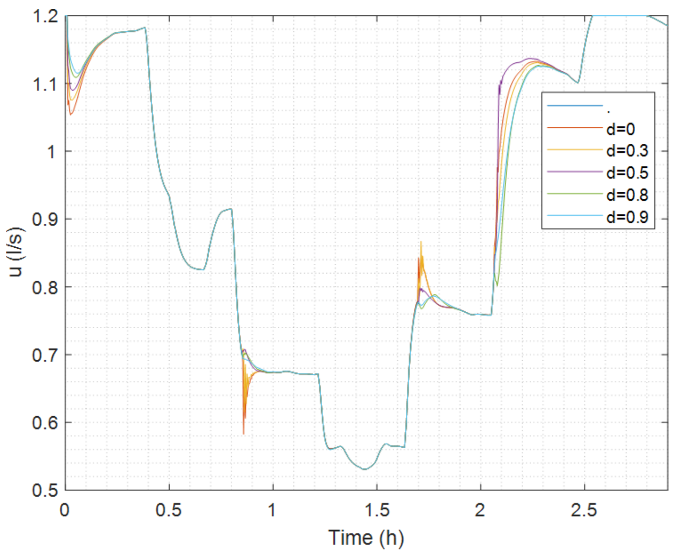

Fig. 11: Flow rate for different values of the smoothing parameter

IV. Conclusion

In this work, a gain scheduling control strategy based on GPC with real time linearization of a neural internal model was introduced and implemented. To improve the performance of the designed controller, a filtering process is used to smooth the adaptation of the linearized model polynomials. The whole strategy is applied to a highly nonlinear benchmark system: the ACUREX solar parabolic trough collector plant. The results showed satisfying results in rejecting the effects of abrupt changes of the two measured disturbance and in reference tracking. After applying the smoothing process, improvements are introduced in terms of overshoots damping, rapidity increasing and smoothing the control signal. Finally, as an idea of a future work , d could be updated according to the variation of the reference and the measured disturbances.

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Yassine Himour received Engineering anddegree in Control Engineering in 2004 from Skikda university, Algeria. He is actually a PhD student in Automatic Control inEcole Nationale Polytechnqiue (ENP) of Algiers, Algeria, and an assistant professor at Khemis Miliana university, Ain Defla, Algeria. His current research interests are control ofthermal solar systems, nonlinear predictive control.

Mohamed Tadjine received her PhD degree in Control and Manufacturing Management from 'Institut National Polytechnique de Grenoble' (INPG), (France) in 1994. In 1997, he joined the Ecole Nationale Polytechnique where he is currently Professor in Control Engineering Department. His main research areas are: Non Linear and Robust Control, Observer Design, Fault Detection and Fault Tolerant Control, Application in healthcare and biological systems.

Mohamed SeghirBoucherit was born in Algiers, Algeria. He is a Professor and University Research Professor in the Ecole Nationale Polytechnique. His fields of research are nonlinear control, power electronics, and variable-speed drives. He has contributed to several national and international journals and conferences for several years.