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Control Improvement of a C Sugar Cane Crystallization Using an Auto-Tuning PID Controller Based on Linearization of a Neural Network

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Abstract**—**The industrial process of the sugar cane crystallization produces a residual that still contains a lot of soluble sucrose and the objective of the factory is to improve its extraction. Therefore, there are substantial losses justifying the search for the optimization of the process. Crystallization process studied on the industrial site is based on the "three massecuites process". The third step of this process constitutes the final stage of exhaustion of the sucrose dissolved in the mother liquor.

During the process of the third step of crystallization (C-crystallization), the phase that is studied and whose control is to be improved, is the growing phase (crystal growth phase). The study of this process on the industrial site is a problem in its own. A control scheme is proposed to improve the standard PID control law used in the factory. An auto-tuning PID controller based on instantaneous linearization of a neural network is then proposed.

Keywords**—**Auto-tuning, PID, Instantaneous linearization, Neural network, Non linear process, C-crystallisation.

I. INTRODUCTION

OUR works deal with the improvement of sugar cane crystallisation control loop strategy. The crystallisation process is the final step of sugar production. Consequently, sugar quality and productivity are hardly dependent on an efficient control of operating conditions. In Bois-Rouge sugar mill (B.R.), crystallisation is performed in three stages. The final one named C crystallisation is the ultimate stage where the saccharose in solution can be converted into a solid form. In sugar cane industry, most of the processes deal with complex non linear phenomena.

Generally, in industries more than 95% of the control loops are based on Proportional-Integral-Derivative (PID) controllers [1]. Nevertheless the PID algorithm shows its limits when dealing with highly nonlinear and time varying chemical processes.

Several methods have been proposed to tune the PID parameters [2, 3, 4, 5, 6], but all these methods are based on linear model identification.

Otherwise, artificial neural networks (ANNs) have been successfully used in many process control applications. Their ability to approximate nonlinear functions [7], combined with dynamic elements has turned out to be a powerful tool for modelling nonlinear dynamical systems. Thus, an on-line updated PID algorithm is proposed. The linearization of the neural network model allows a piecewise linear PID control of the process.

This paper is organised as follows: the next section deals with the crystallisation process in sugar cane industry. The third section presents the main elements of the advanced control scheme based on instantaneous linearization and neural networks. The fourth section presents heuristic rules to improve the control scheme. The fifth section presents a comparison between results obtained by a standard and an advanced PID control.

II. CRYSTALLISATION PROCESS IN SUGAR CANE INDUSTRY

The final step in cane sugar mill is the transformation of concentrated syrup into crystals. To perform the process with the best energy efficiency, this liquid-solid transformation is stage-wise achieved.

The third stage of the crystallisation process: C crystallization is the ultimate stage where saccharose can be extracted from the massecuite solution. So, the efficiency of this extraction is of highest interest.

During the first phase of the C process, the solution of sucrose is heated to be concentrated (syrup concentration). Then, in order to manage the final dimension of crystals, slurry is introduced into the pan (secondary nucleation). The crystals are afterward growing up during a growing phase.

During the growing phase of crystals, complex phenomena can occur in the solution. The control of this phase is based on the following of an electrical conductivity setpoint. Fig. 1 gives the synoptic scheme of the control loop in BR. This control loop presents two major convenient. The first one is the choice of the observed variable: the conductivity. This variable doesn't give information about the transformation of saccharose into crystals. Nevertheless, the most important disadvantage is the nature of the control: PID control. This type of algorithm shows its limits for non linear complex process.

In order to improve the control of the process during the growing phase, we propose another methodology based on the identification of neural networks models.

Neural networks are well known to be non-linear model and universal approximators [7].

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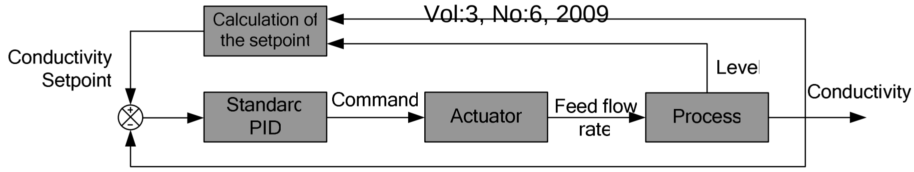

Fig. 1 Bois-Rouge standard control scheme of the C-crystallization process.

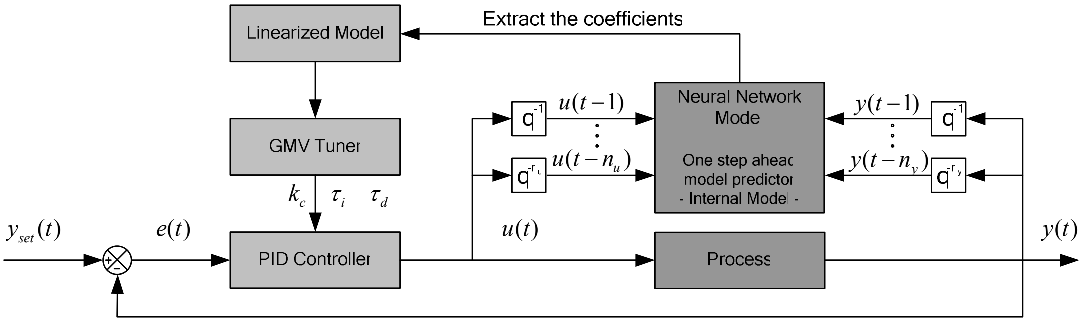

Fig. 2 Control structure using an tuning PID controller based on instantaneous linearization of a neural network

III. Tuning of PID Controller Based on Instantaneous Linearization of a Neural Network

A. Interest of the Method

The method proposed in this paper consists in updating controller parameters at each sampling time to control a non linear process. The main interests of this method are as follows [8,9]:
- this method is based on a popular control structure;
- the internal model is a one step ahead predictor, easier to obtain than a k-step ahead predictor;
- optimisation of the PID parameters is not iterative;
- the control of the process, with a non linear behaviour, is taken into account by an instantaneous change of the PID parameter.

B. Tools

This method is based on three main tools. Artificial neural networks (ANN): Identification of the one-step ahead internal model predictor. Instantaneous linearization of a neural network: Extracting coefficients of the linearized neural network. General minimum variance (GMV) control law: applied to the previous extracted coefficients to update the PID parameters.

Fig. 2 shows the control structure using a tuning of PID controller based on instantaneous linearization of a neural network. The parameters of the PID controller are updated by a loop composed of an instantaneously linearized neural network model estimator and a GMV control design calculation. In this study, a neural network model is trained off-line to model the nonlinear process. Then an instantaneous linearization of the neural network at each sampling time is performed to obtain a linearized model process whose dynamic respects quick process changes. The ANN internal model is trained off-line so that no extra computation load is needed for the current control design.

C. Advanced PID Control Law

This section presents the main steps of the calculation of the optimal PID parameters. The PID control law is as follows(1):

$$\Delta u(t) = k_c\left[\left(y_{set}(t)-y(t)\right)+\frac{1}{\tau_i}\int\left(y_{set}(t)-y(t)\right)dt + \tau_d\frac{d\left(y_{set}(t)-y(t)\right)}{dt}\right] \tag{1}$$

The command to be applied to the process is(2):

$$u(t) = u(t-1)+\Delta u(t) \tag{2}$$

A velocity form of the PID control law can be written as follows(3):

$$\Delta u(k) = k_c\left[\left(e(k)-e(k-1)\right) + \frac{\Delta t}{2\tau_i}\left(e(k)-e(k-1)\right) + \frac{\tau_d}{\Delta t}\left(e(k)-2e(k-1)+e(k-2)\right)\right] \tag{3}$$

The PID control law, based on (3) can be written as:
$\Delta u(k) = \mathbf{e}^T(k)\mathbf{k}(k)$
Where $e(k) = y_{set}(k)-y(k)$ with $\mathbf{e}(k) = \left[e(k) \quad e(k-1) \quad e(k-2)\right]^T$
And $\mathbf{k}(k) = \left[k_0 \quad k_1 \quad k_2\right]^T$ with $k_0 = k_c\left(1+\frac{\Delta t}{2\tau_i}+\frac{\tau_d}{\Delta t}\right)$, $k_1 = -k_c\left(1-\frac{\Delta t}{2\tau_i}+\frac{2\tau_d}{\Delta t}\right)$, and $k_2 = \frac{k_c\tau_d}{\Delta t}$

In the proposed methodology, the GMV control law is based on the minimisation of the following criterion(4):

$$\begin{cases} \min_{k_c,\tau_i,\tau_d} J = \frac{1}{2} \min_{k_c,\tau_i,\tau_d} \left[e^2(t+1) + \mu.\Delta u^2(t) \right] \\ e(t+1) = y_{set}(t+1) - y(t+1) \end{cases} \quad (4)$$

At time t, $y(t+1)$ is not available. To overcome this problem, an approximation of the process output at time $t+1$ can be obtained with the one step ahead neural predictor: $y(t+1) \cong \hat{y}(t+1)$.

Then applying instantaneous linearization on the ANN leads to approximating the output at time $t+1$ with: $y(t+1) \cong \hat{y}^{lin}(t+1)$.

The J criterion can be approximated as follows(5):

$$\begin{cases} \min_{k_c,\tau_i,\tau_d} J \approx \min_{k_c,\tau_i,\tau_d} L \\ \min_{k_c,\tau_i,\tau_d} L = \frac{1}{2} \min_{k_c,\tau_i,\tau_d} \left[\left(\hat{e}^{lin}(t+1) \right)^2 + \mu.\Delta u^2(t) \right] \end{cases} \quad (5)$$

With $\hat{e}^{lin}(t+1) = y_{set}(t+1) - \hat{y}^{lin}(t+1)$

The ANN model can be written as(6):

$$\begin{cases} \hat{y}(t) = Z_o(m_o(t)) \\ m_o(t) = \sum_{c=1}^{N_{cc}} w_c^o.Z_c(m_c(t)) + w_b^o \\ m_c(t) = \sum_{\substack{i=1 \\ i_y=i}}^{n_y} w_{c,i_y}^h.y(t-i) + \sum_{\substack{i=1 \\ i_u=i+n_y}}^{n_u} w_{c,i_u}^h.u(t-i) + w_{b,c}^h \end{cases} \quad (6)$$

Z_o, Z_c are the activation functions of the output neuron / hidden layer neurons. $m_o(t), m_c(t)$ are the potentials arriving to the output neuron / hidden layer neurons. $w_b^o, w_{b,c}^h$ are the bias of the output neuron / hidden layer neurons. w_c^o is composed of the weights between hidden layer neurons and the output neuron. w_{c,i_y}^h, w_{c,i_u}^h are composed of the weights between the input layer neurons and the hidden layer neurons.

Instantaneous linearization of an ANN is considered as a first order Taylor development and can be written as(7):

$$\hat{y}^{lin}(t)|_{t=\tau} = -\sum_{i=1}^{n_y} a_i.y(t-i) + \sum_{i=1}^{n_u} b_i.u(t-i) + bias \quad (7)$$

With: $$\begin{cases} \hat{y}^{lin}(t) = \left(1 - A(q^{-1})\right).y(t) + B(q^{-1}).u(t) + bias \\ A(q^{-1}) = 1 + a_1 q^{-1} + \ldots + a_{n_y} q^{-n_y} \\ B(q^{-1}) = \quad b_1 q^{-1} + \ldots + b_{n_u} q^{-n_u} \end{cases}$$

and $$\begin{cases} a_i = -\frac{\partial \hat{y}(t)}{\partial y(t-i)}|_{t=\tau} & i = 1,2,\ldots,n_y \\ b_i = \frac{\partial \hat{y}(t)}{\partial u(t-i)}|_{t=\tau} & i = 1,2,\ldots,n_u \end{cases}$$

and $bias = y(\tau) + \sum_{i=1}^{n_y} a_i.y(\tau-i) - \sum_{i=1}^{n_u} b_i.u(\tau-i)$

Extracted coefficients a_i (8) and b_i (9) are calculated as follows, based on the neural notations(6):

$$\begin{aligned} a_i &= -\frac{\partial \hat{y}(t)}{\partial y(t-i)} \qquad i = 1,2,\ldots,n_y \\ &= -\sum_{c=1}^{N_{cc}} w_c^o.\frac{\partial Z_c(t)}{\partial m_c(t)}.\frac{\partial m_c(t)}{\partial y(t-i)} = -\sum_{c=1}^{N_{cc}} w_c^o.\frac{\partial Z_c(t)}{\partial m_c(t)}.w_{c,i}^h \end{aligned} \quad (8)$$

$$\begin{aligned} b_i &= \frac{\partial \hat{y}(t)}{\partial u(t-i)} \qquad i = 1,2,\ldots,n_u \\ &= \sum_{c=1}^{N_{cc}} w_c^o.\frac{\partial Z_c(t)}{\partial m_c(t)}.\frac{\partial m_c(t)}{\partial u(t-i)} = \sum_{c=1}^{N_{cc}} w_c^o.\frac{\partial Z_c(t)}{\partial m_c(t)}.w_{c,i+n_y}^h \end{aligned} \quad (9)$$

The control law error, estimated by the instantaneous linearization of the ANN model, can be written as(10):

$$\begin{aligned} \hat{e}^{lin}(t+1) &= y_{set}(t+1) + \sum_{i=1}^{n_y} a_i.y(t-i+1) \\ &\quad - \sum_{i=1}^{n_u} b_i.u(t-i+1) - bias \\ &= \left[y_{set}(t+1) + \sum_{i=1}^{n_y} a_i.y(t-i+1) \right. \\ &\quad \left. - \sum_{i=2}^{n_u} b_i.u(t-i+1) - bias \right] - b_1.u(t) \\ &= \Omega - b_1.\mathbf{e}^T(t)\mathbf{k}(t) \end{aligned} \quad (10)$$

With: $$\Omega = y_c(t+1) + \sum_{i=1}^{n_y} a_i.y(t-i+1) - \sum_{i=2}^{n_u} b_i.u(t-i+1) - b_1.u(t-1) - bias$$

To obtain the optimal command and PID parameters, the L criterion has to be minimized(11):

$$L = \frac{1}{2}.\left\{ \Omega - b_1.\mathbf{e}^T(t)\left[\mathbf{k}(t-1) + \Delta\mathbf{k}(t)\right] \right\}^2 + \frac{\mu}{2}.\left\{ \mathbf{e}^T(t)\left[\mathbf{k}(t-1) + \Delta\mathbf{k}(t)\right] \right\}^2 \quad (11)$$

Calculation of the gradient, to optimize the criterion, can be written as(12):

$$\begin{aligned} \nabla L(\Delta\mathbf{k}(t)) &= \frac{\partial L(\Delta\mathbf{k}(t))}{\partial \Delta\mathbf{k}(t)} \\ &= \mathbf{A}(t).\Delta\mathbf{k}(t) + \mathbf{d}(t) \end{aligned} \quad (12)$$

With $\mathbf{A}(t) = (b_1^2 + \mu).\mathbf{e}(t).\mathbf{e}^T(t)$

and $\mathbf{d}(t) = -b_1.\Omega.\mathbf{e}(t) + (b_1^2 + \mu).\mathbf{e}(t).\mathbf{k}(t-1).\mathbf{e}^T(t)$

Optimization of the gradient is obtained as follows:

$\nabla L(\Delta\mathbf{k}(t)) = 0 \quad \Leftrightarrow \quad \Delta\mathbf{k}(t) = -\mathbf{A}^{-1}(t).\mathbf{d}(t)$

And PID parameters can be calculated as(13):

$$\begin{cases} k_c = \frac{1}{2}.(k_0 - k_1 - 3.k_2) \\ \tau_i = \frac{\Delta t}{2}.\frac{k_0 - k_1 - 3.k_2}{k_0 + k_1 + k_2} \\ \tau_d = \frac{2}{\Delta t}.\frac{2.k_2}{k_0 - k_1 - 3.k_2} \end{cases} \tag{13}$$

Knowing: $\Delta\mathbf{k}(t) = \mathbf{k}(t) - \mathbf{k}(t-1)$ and

$$\Delta\mathbf{k}(t) = -\mathbf{k}(t-1) + \left[\mathbf{e}(t).\mathbf{e}(t)^T\right]^{-1}.\mathbf{e}(t).\frac{\Omega.b_1}{b_1^2 + \mu}.$$

IV. Heuristic Rules

A. Improving the Command Smoothness: Momentum Filter

Application of the controller action will result in amplification of the noise when the controlled variable is obtained around the desired setpoint. In order to avoid oscillations of the control parameters in the control action, the control parameters should be smoothed out. The momentum filter(14), like the first-order filter that reduces the variations, has been added to the control parameter changes. γ is a forgetting factor whose range is between 0 and 1.

$$\begin{cases} \Delta u^m(t) = \gamma.\Delta u^m(t-1) + (1-\gamma).\Delta u(t) \\ u(t) = u(t-1) + \Delta u^m(t) \end{cases} \tag{14}$$

B. Improving the Control Performance: Performance Criterion

Although the control design in the adaptive control structure should keep on-line calculating adaptive parameters of the controller, the computation of the new control action is redundant when the controlled output is close to the desired setpoint. Besides, the new computed control action in the processes which are not usually free of noise is susceptible to process noise. To overcome this problem, the concept of the statistical process control algorithm can be applied. The updated criterion, by a cumulative sum of the past error with the fixed window size, is designed to detect the deterministic shift in the desired setpoint. The combination of the most current error data sets is defined as a performance criterion(15):

$$C(t) = \frac{1}{m}\sum_{i=t-m+1}^{t}\left(y_{set}(t) - y(t)\right)^2 \tag{15}$$

Where $C(t)$ is the current control performance. m is the size of moving window which contains $m-1$ past outputs until now. The updated criterion is based on the performance of the current moving window. An old error data would be removed and a new error data would come into the picture with the moving of the rectangular window at each sampling time. Consequently, whenever the current performance $C(t)$ is below its control limit $C(t) \le \sigma^2$, the current controller parameters are assumed to be fixed until $C(t) > \sigma^2$. σ^2 is the threshold. It can be estimated from the steady-state process data when there is no change in the control action or it is based on the prior knowledge of the operating process.

C. Improving the Feasibility of the Command: Penalty Adjustment

The control parameters obtained from the quadratic objective function may not be particularly optimal, because the parameters are determined through an approximation of the objective based on the instantaneous linearization of the ANN model, L. It is expected that the control parameters are valid only in a neighbourhood around the current state. Here the penalty term μ in (16) is used to adjust the change of the control action in order to let L be close to the true criterion J. The accurate measure of the approximation can be defined if the difference is close to a small value. This indicates that the approximated model is good enough in the current design region; otherwise, the penalty should be adjusted by some factors to reduce or expand the region. Thus, the algorithm provides a nice compromise between the approximated linear model and the neural network model to compute the feasible control actions

$$\min_{\Delta x} J = \frac{1}{2}\min_{\Delta x}\left(e^2(t+1) + \mu.\Delta x^2(t)\right) \tag{16}$$

$$\eta = \left|\hat{y}(t+1) - \hat{y}^{lin}(t+1)\right| \tag{17}$$

$$\begin{cases} \eta \in [\varepsilon_1, \varepsilon_2] & \Rightarrow \quad \mu(t+1) = \mu(t) \\ \eta > \varepsilon_2 & \Rightarrow \quad \mu(t+1) = \frac{1}{2}.\mu(t) \\ \eta < \varepsilon_1 & \Rightarrow \quad \mu(t+1) = 2.\mu(t) \end{cases}$$

With ε_1 and ε_2 values to be determined by the expert.

D. Final Control Scheme

Including all the heuristic rules leads to the following control scheme *Fig. 3*.

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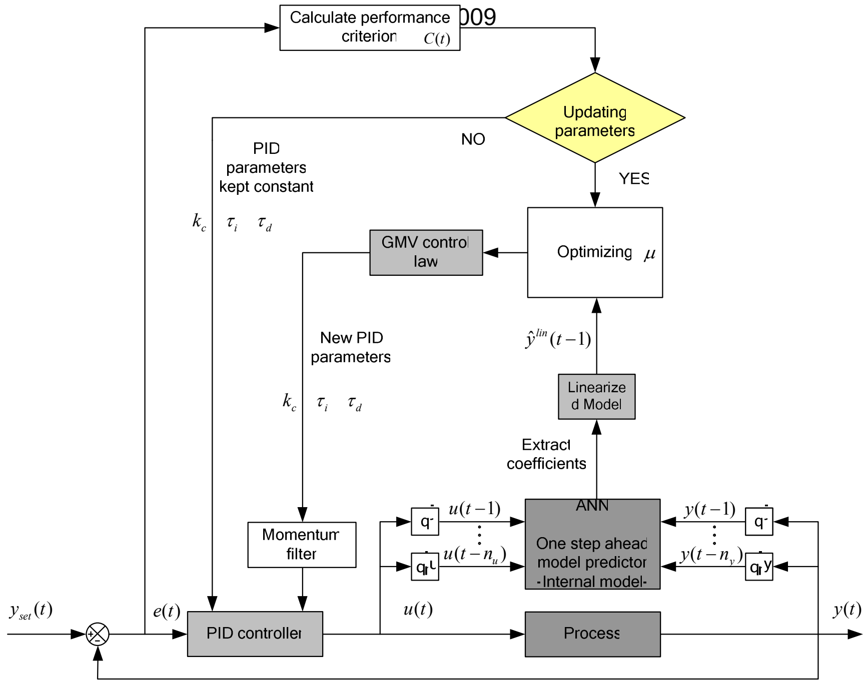

Fig. 3 Control structure using an tuning PID controller augmented the heuristic rules

V. Advanced PID Control Scheme Results

Common PID control compared to the advanced PID with tuned parameters control is interesting. Applying these techniques to the C-crystallization process shows the efficiency of the proposed control law. Main results are presented (TABLE).

Standard deviation σ of the feed flow rate is shown to highlight the smoothness of the command. The mean squared error *MSE* is given to show the efficiency of the target tracking.

Four C-crystallization process have been studied to obtain the Table I, and Fig. 4 and Fig. 5 show the results of the control for example 1 and example 2, based on the *Fig. 3* control scheme.

TABLE I
ADVANCED VS STANDARD PID CONTROL RESULTS.

	PID control	Examples			
		Ex. 1	Ex.2	Ex.3	Ex.4
Conductivity [%] (*MSE*)	Standard	20.72	45.25	15.56	10.87
	Advanced	9.92	9.24	8.57	9.20
Feed flow rate [$m^3.h^{-1}$] (σ)	Standard	17.85	15.03	19.58	17.87
	Advanced	8.22	7.98	10.08	4.64

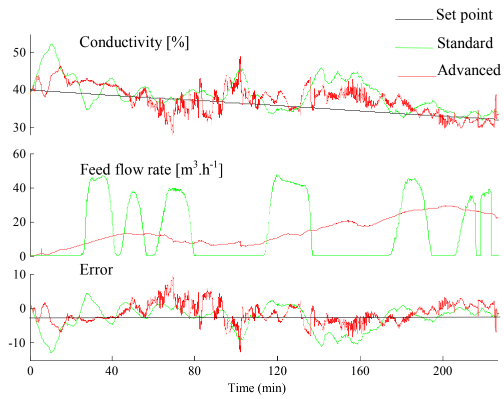

Fig. 4 *Ex. 1 Results*

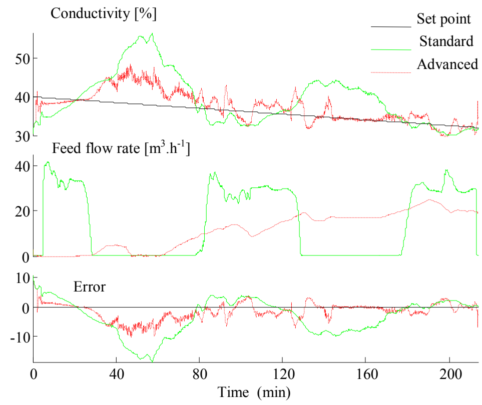

Fig. 5 *Ex. 2 Results*

VI. Conclusion

We compared two different control schemes to improve the performances of a sugar cane C-crystallisation. The first one is the control strategy employed in the industry, the

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second one is an auto tuning PID controller based on the instantaneous linearization of an ANN. Neural network-based modelling has been used to control a growing of a C-crystallization process. Results showed an efficient improvement of the control strategy, with the tuning of the PID parameters, which allows taking into account the non linearity of the process. On the whole, the results of this investigation suggest that the growing phase of the C-crystallization process can be effectively optimised by employing neural network model-based control. The main interests of this method were shown. This method is based on a popular control structure. The internal model is a one step ahead predictor, easier to obtain than a k-step ahead predictor. The optimisation of the PID parameters is not iterative, and the control of the process, with a non linear behaviour, is taken into account by an instantaneous change of the PID parameters.

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