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Extended Kalman filter based unconstrained model predictive control of a complex nonlinear system: the quadruple tank process

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ABSTRACT

This paper proposes the model predictive controller (MPC) based on the Kalman filter for a complicated nonlinear system—the quadruple tank process (QTP). The control of a multivariable and nonlinear system like a QTP is a difficult job. A number of nonlinear design techniques are implemented to ameliorate the pursuit performance of the QTP, however, the nonlinear techniques make implementation composite and computationally unsuitable. In this work, an unconstrained MPC is planed for the QTP experiences and it is controlled for both minimum and non-minimum sentence configurations in order to follow the wanted track. Its performance can be damaged once system is pass from minimum to non-minimum phase region and inversely. The unknown states required for model predictive control design are rebuilt using an extended Kalman filter. The design of model predictive control and extended Kalman filter is based on the QTP and the achievement of the proposed controller is checked for the monitoring of references. All results of simulation are affected using the MATLAB software. The results of the simulation show the capability and power of the suggested controller in respect of monitoring the trajectory and state estimation.

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1. INTRODUCTION

Model predictive control (MPC) is an involved control way in the automatic, also named as regressing horizon control, This is the most, indicated to manage the complex systems in industrial environments, such as petrochemicals, process engineering and the automotive sector where it has demonstrated its evidence. Its ability to jointly process operating specifications and operating constraints in the development of the order law made its success in the presence of disturbances and uncertainties [1]-[6], and it has a good capability to cope with MIMO systems, non-minimum phase and unstable systems [7]. The evolution of computer science is not foreign to its success either, because the powerful developed computers allowed automaticians to achieve their objectives with great precision in a record time. All these factors have propelled the predictive order to occupy a preponderant place in academic and industrial sector [8]-[13].

MPC is a particular case of the optimal control that uses a process model to calculate future anticipated outputs. These anticipated outputs are once exploited to count up a classification of control inputs that are transmitted to the system to optimize the future comportement of the plant and then optimizing again, consistently, which is different from a linear quadratic regulator (LQR). The MPC also has the capability to expect future events and take control effort consistently. PID controllers do not have this predictive power. The MPC is in all cases implemented as a numerical control, for all that research is an underway to achieve quick response times [14]. The MPC algorithm consists of an objective function, constraints and an anticipate model or model of the system [15]. The primary aspiration of this work is to develop a predictive controller on the basis of on the estimate of the states which reaches an absolute monitoring for the QTP, both for minimum and non-minimum illustration.

Often in practice not all states of a system are calculable; Consequently, the state estimation is considered. The Kalman filter is an essential expedient in control algorithms because of its power to alleviate the unwanted outcome of perturbations in the process [16]. The utilisation of the Kalman filter make known of the important advantages as the utilisation of its extended version in nonlinear systems. The QTP that accompany the law of mass equilibration and equations of energy are a non-linear process. attributable to perturbation it is more hard to take the calculations of the water position in the QPT. Here an extended Kalman filter based MPC algorithm is introduced to adapt the removal of improved disturbance in the four tank tracking system. Consequently, the estimate do the important job in estimating of the states parameters in real time. If the states variables are precisely valued, it is very facile to keep the magnitude of the system. In this article the state estimation is carried out by extended Kalman filter to make out the vector of state variable of the process. By using the valued state parameters the complication of the system is decreased.

The plan of this article is presented like so. Section 2 details the mathematical model for QTP for control design. In section 2, the classic formulation of unconstrained MPC controller algorithm is presented and the Kalman filter is then briefly introduced. Section 3 details the mathematical model for QTP for control design. In section 4 the result of simulations is shown and discussed. The conclusion is contributed in section 5.

2. ALGORITHM

This section is providing with the theoretical framework of state estimation based unconstrained MPC controller and the adapted variable for upgrading Kalman filter assessment.

2.1. MPC control algorithm

In this section, The MPC control with integral action is considered to solve the problems of the offset [17]. The discrete-time state space model with disturbance is given as follows:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + \zeta \\ y_k &= Cx_k + \vartheta \end{aligned} \tag{1}$$

where A, B and D are matrices of the system, $x_k \in R^n$ is a state variables vector, $u_k \in R^r$ is input vector, $y_k \in R^m$ output vector. ζ is process perturbation vector and ϑ is computation perturbation vector. From the equivalence (1), the state space model accords:

$$\begin{aligned} \Delta x_{k+1} &= A\Delta x_k + B\Delta u_k \\ y_k &= y_{k-1} + C\Delta x_k \end{aligned} \tag{2}$$

where,

$$\Delta x_{k+1} = x_{k+1} - x_k \tag{3}$$

$$\Delta x_k = x_k - x_{k-1} \tag{4}$$

$$\Delta u_k = u_k - u_{k-1} \tag{5}$$

The augmented form of the model is given as,

$$\begin{aligned} \underbrace{\begin{bmatrix} \Delta x_{k+1} \\ y_k \end{bmatrix}}_{\tilde{x}_{k+1}} &= \underbrace{\begin{bmatrix} A & 0 \\ C & I \end{bmatrix}}_{\tilde{A}} \underbrace{\begin{bmatrix} \Delta x_k \\ y_{k-1} \end{bmatrix}}_{\tilde{x}_k} + \underbrace{\begin{bmatrix} B \\ 0 \end{bmatrix}}_{\tilde{B}} \Delta u_k \\ y_k &= \underbrace{\begin{bmatrix} C & I \end{bmatrix}}_{\tilde{C}} \underbrace{\begin{bmatrix} \Delta x_k \\ y_{k-1} \end{bmatrix}}_{\tilde{x}_k} \end{aligned} \tag{6}$$

A strictly appropriate state model is as:

$$\tilde{x}_{k+1} = \tilde{A}\tilde{x}_k + \tilde{B}\Delta u_k \\ y_k = \tilde{C}\tilde{x}_k \tag{7}$$

$\tilde{A}, \tilde{B}, \tilde{C}$: matrices of extended model.

The anticipated value of the output alongside the range is going to be,

$$y_{k+1/L} = F_L + G_L u_{k/L} \tag{8}$$

where,

$$F_L = O_L \tilde{A}_L \tag{9}$$

$$G_L = [O_L \tilde{B} \quad H_L^d] \tag{10}$$

where O_L is augmented observability matrix for the $(\tilde{C}, \tilde{A})$, and $(\tilde{C}, \tilde{A}, \tilde{B})$ are matrices where Toeplitz matrix is H_L^d [18].

The objective function for optimization is given by:

$$J = \left(y_{k+1/L} - w_{k+1/L}\right)^T Q\left(y_{k+1/L} - w_{k+1/L}\right) + u_{k/L}{}^T P u_{k/L} + \Delta u_{k/L}{}^T R \Delta u_{k/L} \tag{11}$$

where **w** is the set point, **y** is the output, Δ**u** is the input changes, and **u** is the input. Q, R and P are the weight matrices. **L** prediction range.

The (8) and (11) can be combined and considered as a quadratic criterion according to the standard form as,

$$J_k = \Delta u_{k/L}^T H \Delta u_{k/L} + 2 f_k{}^T \Delta u_{k/L} + J_0 \tag{12}$$

where,

$$H = G_L^T Q G_L + R \tag{13}$$

$$f_k = G_L^T Q (F_L - w_{k+1/L}) \tag{14}$$

$$J_0 = (F_L - w_{k+1/L})^T Q (F_L - w_{k+1/L}) \tag{15}$$

The optimal control variation vector is as,

$$\Delta u_{k/L}^* = -H^{-1} f_k \tag{16}$$

2.2. Kalman Filter

It often happens that all states are not measured in this case the obligation to estimate the state arises. For a plant model [19],

$$x(k+1) = Ax(k) + Bu(k) + v(k) \\ y(k) = Cx(k) + w(k) \tag{17}$$

The steps for calculating the state estimation by the Kalman filter algorithm are given as [20],

a) Calculate the state one-step predicting

$$\hat{x}(k/k-1) = A\hat{x}(k-1/k-1) + Bu(k-1) \tag{18}$$

b) Assess the one step anticipation of approximation error covariance

$$P(k/k-1) = AP(k-1/k-1)A^T + Q \tag{19}$$

c) Calculate Kalman gain

$$K(k) = P(k/k-1)C^T(CP(k/k-1)C^T + R^{-1}(k))^{-1} \quad (20)$$

d) Compute the filter approximate value

$$\hat{x}(k/k) = \hat{x}(k/k-1) + K(k)(y(k) - C\hat{x}(k/k-1)) \quad (21)$$

e) Renovate estimation error covariance

$$P(k/k) = (I - K(k)C)P(k-1/k) \quad (22)$$

where v is the white system perturnation, w is white frequency perturbation $Q(k)$ and $R(k)$ are noise covariance matrices.

3. PROCESS DESCRIPTION

This section will presente a theoretical model for the QTP. The QTP contains four acossiated liquid tanks and two devoted pumps [21], [22]. The illustrative sketch of the QTP is given in Figure 1.

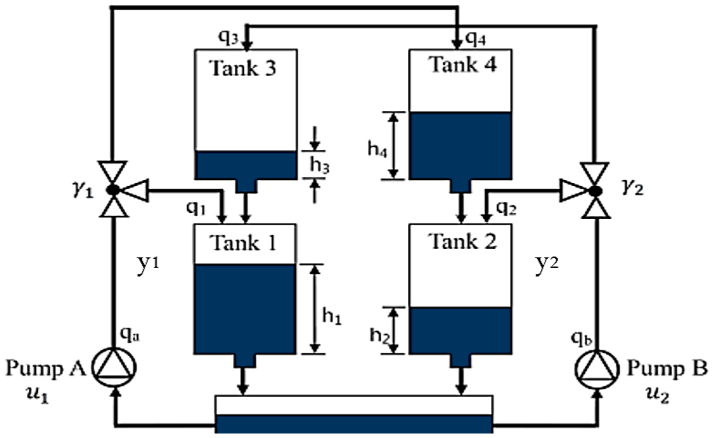

Figure 1. Schematic diagram of the QTP

The inputs of the process are u1 and u2 and the outputs are $y_1 = k_c h_1$ and $y_2 = k_c h_2$. The mathematical model of four tank systems is as follows [23]-[25]:

$$\frac{dh_1}{dt} = -\frac{a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_1}{A_1}u_1 \quad (23)$$

$$\frac{dh_2}{dt} = -\frac{a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_2}{A_2}u_2 \quad (24)$$

$$\frac{dh_3}{dt} = -\frac{a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_2}{A_3}u_2 \quad (25)$$

$$\frac{dh_4}{dt} = -\frac{a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_1}{A_4}u_1 \quad (26)$$

where,
A_i: Surface of cross section of the tank i;
a_i: Surface of cross section of the exit hole i;
h_i: Level of water in the tank i;
u_i: Voltage of the pump i;
γ_i: Constant of valve i;
k_i: Constant of pump i;
g: Acceleration of gravity;
k_c: Pump gain.

The nonlinear equations of four-tank process is linearized with the operation point given by the liquid height of the tanks h_1^0, h_2^0, h_3^0 and h_4^0 and voltage u_1^0 and u_2^0. The previous nonlinear differential equations are changed to linearized state space model by way of Jacobian matrix.
The Jacobian matrix is as follows,

$$\frac{\partial f}{\partial h} = \begin{bmatrix} \frac{\partial f_1}{\partial h_1} & \frac{\partial f_1}{\partial h_2} & \frac{\partial f_1}{\partial h_3} & \frac{\partial f_1}{\partial h_4} \\ \frac{\partial f_2}{\partial h_1} & \frac{\partial f_2}{\partial h_2} & \frac{\partial f_2}{\partial h_3} & \frac{\partial f_2}{\partial h_4} \\ \frac{\partial f_3}{\partial h_1} & \frac{\partial f_3}{\partial h_2} & \frac{\partial f_3}{\partial h_3} & \frac{\partial f_3}{\partial h_4} \\ \frac{\partial f_4}{\partial h_1} & \frac{\partial f_4}{\partial h_2} & \frac{\partial f_4}{\partial h_3} & \frac{\partial f_4}{\partial h_4} \end{bmatrix} \tag{26}$$

By means of the (26), the linearized model for QTP is as,

$$\begin{aligned} \frac{dh}{dt} &= Ah + Bu \\ y &= Ch \end{aligned} \tag{27}$$

$$\frac{dh}{dt} = \begin{bmatrix} -\frac{1}{T_1} & 0 & \frac{A_3}{A_1 T_1} & 0 \\ 0 & -\frac{1}{T_2} & 0 & \frac{A_4}{A_2 T_2} \\ 0 \quad 0 & & -\frac{1}{T_3} & 0 \\ 0 \quad 0 & & 0 & -\frac{1}{T_4} \end{bmatrix} h + \begin{bmatrix} \frac{\gamma_1 k_1}{A_1} & 0 \\ 0 & \frac{\gamma_2 k_2}{A_2} \\ 0 & \frac{(1-\gamma_2)k_2}{A_3} \\ \frac{(1-\gamma_1)k_1}{A_4} & 0 \end{bmatrix} u \tag{28}$$

$$y = \begin{bmatrix} k_c & 0 & 0 & 0 \\ 0 & k_c & 0 & 0 \end{bmatrix} h \tag{29}$$

The discrete model of QTP is as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y_k &= Cx_k \end{aligned} \tag{30}$$

where,

$$A = \begin{bmatrix} 0.9984 & 0 & 0.0026 & 0 \\ 0 & 0.9989 & 0 & 0.0018 \\ 0 \quad 0 & & 0.9974 & 0 \\ 0 \quad 0 & & 0 & 0.9982 \end{bmatrix}; B = \begin{bmatrix} 0.0048 & 0 \\ 0 & 0.0035 \\ 0 & 0.0077 \\ 0.0056 & 0 \end{bmatrix}; C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{31}$$

The plant can be transfered from minimum to non-minimum phase region and inversely directely by switching a valve managing the flux fraction γ_1 and γ_2 between lessen and higher tanks. The minimum-phase structure corresponds to $1 < (\gamma_1 + \gamma_2) < 2$ and the non-minimum phase one to $0 < (\gamma_1 + \gamma_2) < 1$.

4. RESULTS AND DISCUSSIONS

For many different control algorithms, one of the most encountered problems is that the state variables of the controlled systems are not measurable. In reality, the process output is often measurable and the state variables are very rarely accessible. In this case, the state estimation process does an important job in the implementation of process control. Therefore, the Kalman filter is a needed means in control algorithms brcause of its capability to mitigate the unwanted consequences of noise and load perturbations. The primary attention of this work is to implimente a state estimation based unconstrained model predictive controller (MPC) for tank liquid level control for four interconnected tanks in both operating status i.e. minimum and non-minimum phase cases.

The chosen operating status correspond respectively to, $(h_1^0 = 12.3;\ h_2^0 = 12.8;\ h_3^0 = 1.63;\ h_4^0 = 1.41;)$ and $(h_1^0 = 12.4;\ h_2^0 = 13.2;\ h_3^0 = 4.73;\ h_4^0 = 4.99;)$. The constant weight matrices Q and R are selected in terms to obtain the better results accurately, $Q = \begin{bmatrix} 150 & 0 \\ 0 & 150 \end{bmatrix}$, and $R = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}$. The prediction horizon of 10 is used.

The set point is selected as a square wave. The simulation results are developed with newly created MATLAB script files for numerical simulation of the four-tank process.

4.1. Performance of state estimation based unconstrained MPC controller for QTP in minimum phase region

In this section, the implementation of state estimation based unconstrained MPC controller for four-tank process in minimum phase region is executed by substituting the set point. The simulations results are illustrated in Figure 2 and are discussed.

The Kalman filter based MPC controller is performed to approximate the siyuations of the QTP. The levels are estimated and measured in tanks 1, 2, 3 and 4. It could be observed out of the Figure 2 that there is a small contrast in estimated and calculated levels in tanks 1 and 2, however there is a big difference in levels for tanks 3 and 4. The tracking performance of estimated levels is achieved successfully in all tanks which is different from a PID controllers do not have this ability to estimate the states variables and it was noticed that the MPC control is more robust and quick than the classical controller. It was proven that the MPC is a powerful method to control the MIMO system. It can be seen also the measured levels give an undershoots and overshoots especially in reservoirs 1, 3, and 4.

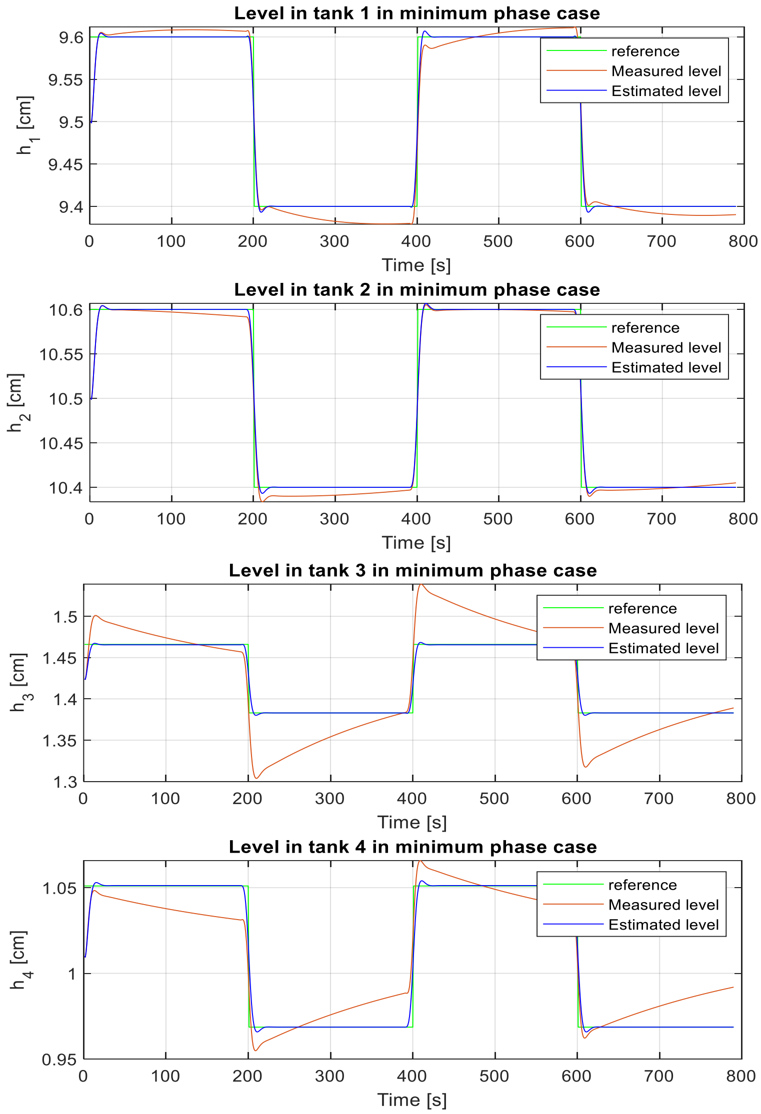

Figure 2. The simulation result of QTP in minimum phase region under state estimation based unconstrained MPC control

4.2. Performance of state estimation based unconstrained MPC controller for QTP in non-minimum phase region

In this section, the Kalman filter based unconstrained MPC controller is implemented to estimate the states of the QTP in non-minimum phase region. The levels are estimated and measured in tanks 1, 2, 3 and 4. It can be seen from the Figure 3 that there is a minor variation in estimated and measured levels in tanks 2, on the other hand there is a big gap in levels for tanks 1, 3 and 4. The tracking performance of estimated levels is achieved successfully in all tanks which is different from a PID controllers do not have this ability to estimate the states variables and to suporte multivariable non-linear system, however the measured levels give an undershoots and overshoots in all tanks.

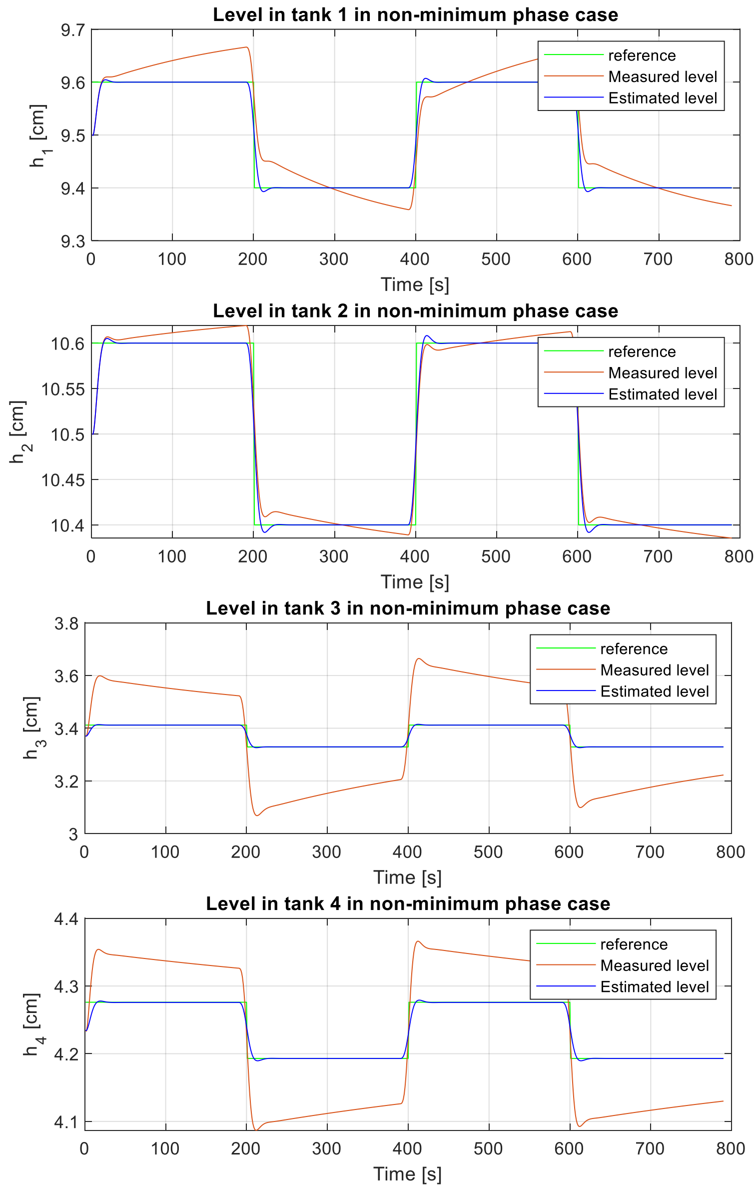

Figure 3. The simulation result of QTP in non-minimum phase region under state estimation based unconstrained MPC control

5. CONCLUSION

Liquid postion reservoirs are used in large number of manufactured, and environmental fields. Their level be obliged to maintained at a well-defined reference point. Liquid level regulation in tank systems is a fundamental problem in manufactory sector. The aim of the current study was to propose a state estimation based unconstrained MPC controller to control the liquid levels in nonlinear QTP in minimum and non-minimum phase configuration. The implementation of the proposed controller was designed and simulated in MATLAB environment with appropriate tuning parameters. Out of the results of simulation, it could be deduced that, the Kalman filter based unconstrained MPC controller allows to solve the problem of unknown states variables because in practice, often the state variables are very rarely accessible and it was exhibited better performance in the estimated levels than the measured levels. It was also shown that the suggested optimal controller performed superbly under both operating conditions and responded optimally to desired values.

The work could be extended to provide a constrained form for the MPC controller because the consideration of constraints is amongst the most demanded methods in the theory of control systems, often all industrial applications impose constraints. How to handle them in the configuration of the control system is a crucial question. The crucial power of MPC control is its capability to manage strict constraints on commands, outputs and states. Imposing constraints or ignoring them on the control signal cause performance degradation or even instability, especially for unstable systems. Give consideration of the constraints in the construction phase impose the solution of the advance problem under constraints. We hope also implemente the purported controller in other standard processes such as chemical reactors, three-phase separator and distillation columns.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Zohra Zidane	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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