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Model Predictive Control for the Flowrate Control Loop of the FESTO MPS PA Compact Workstation

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Abstract: Model Predictive Control techniques offer favorable characteristics for the process control sector and have been used in industry since the 1980s. Some of the advantages of the Model Predictive Control techniques are that the process model can capture both static and dynamic interactions between input, output, and disturbance variables; the existing constraints on inputs and outputs are considered systematically, and the control calculations can be coordinated with the calculation of optimum set-points. This study aims to design and implement a Model Predictive controller for the flowrate control loop of the FESTO MPS PA Compact Workstation. The designed Model Predictive controller has an important advantage because it is easy to conFig. how much energy should be used using well-designed tuning parameters. First, a dynamic model of the plant is obtained using Pseudo-Random Binary Signal input. The obtained model is used to define the objective function, determine the aspects to be optimized and analyze and identify the restrictions and limitations of the control algorithm. For the implementation of the model predictive control algorithm, LabVIEW software was used because it can execute a graphic visualization of the operation of the plant, and it offers ActiveX controls that are needed for interfacing with the MPS PA compact workstation. Finally, the controller's behavior was analyzed, and comments about the obtained results and conclusions on this line of research are presented.

Keywords: model predictive control, system identification, flowrate control system.

費斯托自動化流程模塊化生產系統緊湊型工作站流量控制迴路的模型預測控制

摘要：模型預測控制技術為過程控制領域提供了有利的特性，並且自一千九百八十 年代以來一直在工業中使用。模型預測控制技術的一些優點是過程模型可以捕獲輸入、輸出和乾擾變量之間的靜態和動態交互；系統地考慮對輸入和輸出的現有約束，控制計算可以與最佳設定點的計算相協調。本研究旨在為費斯托自動化流程模塊化生產系統緊湊型工作站的流量控制迴路設計和實施模型預測控制器。所設計的模型預測控制器具有一個重要的優勢，因為它易於配置。使用精心設計的調諧參數應該使用多少能量。首先，使用偽隨機二進制信號輸入獲得植物的動態模型。得到的模型用於定義目標函數、確定需要優化的方面以及分析和識別控制算法的限制和局限。對於模型預測控制算法的實施，使用了實驗室視圖軟件，因為它可以執行工廠運行的圖形可視化，並且它提供了與自動化流程模塊化生產系統緊湊型工作站接口所需的活動 X 控件。最後，對控制器的行為進行了分析，並對所獲得的結果和結論進行了評論。

关键词：模型預測控制、系統辨識、流量控制系統。

1. Introduction

Model Predictive Control (MPC) is an advanced control strategy that has been in use in the process industries such as oil refineries, chemical plants,

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automotive, food processing, and aerospace applications since the 1980s. MPC's remarkable performance in the process industries is explained in [1] and was mainly attributed to its simplicity and ability to easily and efficiently manage complex systems with hard control constraints and multiple inputs and outputs. Model predictive controllers rely on dynamic process models, most often linear empirical models obtained by system identification [2]. In general, a model predictive control algorithm utilizes a definite system model to predict the future response that needs to be controlled. The MPC algorithm optimizes future system response by working out a sequence of future manipulated variable adjustments at each control interval. The first input in the obtained optimal sequence is sent to the system, and the entire calculation is reiterated at succeeding control intervals. Several recent publications give a good insight into the theoretical and practical aspects of MPC technology [6-13].

The MPS PA Compact Workstation (MPS PA CWS) developed by Festo Didactic is an educational system specially designed to meet several different industry-oriented training and vocational requirements. The system represents laboratory-scale equipment that resembles real industrial systems found in different fields, including chemical industries, oil refineries, paper, and pulp factories 0. Furthermore, the MPS PA CWS can be used for training in topics such as programmable logic controllers, closed-loop control design, fault-finding, and/or troubleshooting 0. The MPS PA CWS (Fig. 1) consists of several mechanical components, electrical components, sensors, and actuators. Please refer to the user manual for more information about the MPS PA CWS 0.

Fig. 1 FESTO MPS PA compact workstation

The rest of the paper is organized as follows. Section 2 briefly describes the MPS PA CWS; Section 3 describes the designed LabVIEW interface. Section 4 describes the system identification for the flowrate control loop; Section 5 describes the MPC algorithm; experimental results are demonstrated in Section 6, and the concluding remarks are presented in Section 7.

2. MPS PA CWS System Description

The MPS PA CWS combines four control loops: level, pressure, temperature, and flowrate control loop. The actuators in the system are centrifugal pump, proportional valve, and heating element. The sensors included in the MPS PA CWS are an ultrasonic sensor, flow rate sensor, temperature sensor, and a pressure sensor for measuring the level, flow rate, temperature, and pressure, respectively. The MPS PA CWS also has multiple proximity sensors and float switches. The MPS PA CWS has a terminal connection with 24 pins. The connection allows communication between the MPS PA CWS and a personal computer by using the EasyPort USB interface card. The components of the MPS PA CWS are shown in the P&ID given in Fig. 2. A short description of the components mentioned above is given in Table 1.

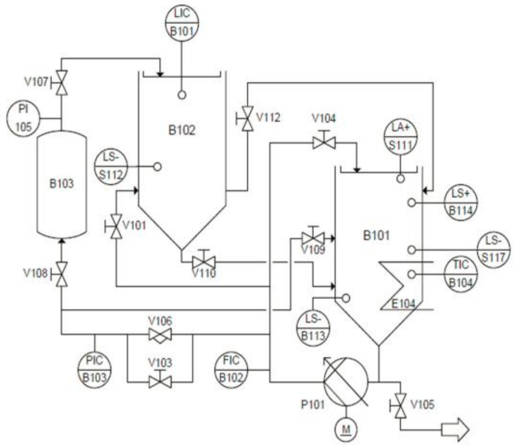

Fig. 2 P & ID for the FESTO MPS PA compact workstation

Table 1 MPS PA CWS components description

Labels	Description
B101 and B102	B101 and B102 refer to the upper and lower tanks storing the liquid. Both tanks have a measurement scale to observe the liquid level
B103	Pressurized air tank
P101	Centrifugal pump
E104	The heating element that is used to increase the liquid temperature in tank B101
V101, V103, V104, V105, V107, V108, V109, V110, and V112	Manual valves that control the flow rate through the pipes of the MPS PA CWS
V106	2/2 proportional valve for flow control
FIC/B102	Flow indicator controller
PIC/B103	Pressure indicator controller
ICT/B104	Temperature indicator controller
LIC/B101	Liquid-level indicator controller
PI/105	Pressure indicator
LS- B113 and S117	Switches for low liquid level
LS+ S111 and B114	Switches for high liquid level

3. LabVIEW Interface for the FESTO MPS PA Compact Workstation

3.1. Connect/Disconnect to/from EasyPort

The invoke node "Connect' method of the FESTO ActiveX control is used to initiate the login phase. This method checks all serial ports found within the system for EasyPort modules, as shown in Fig. 3.

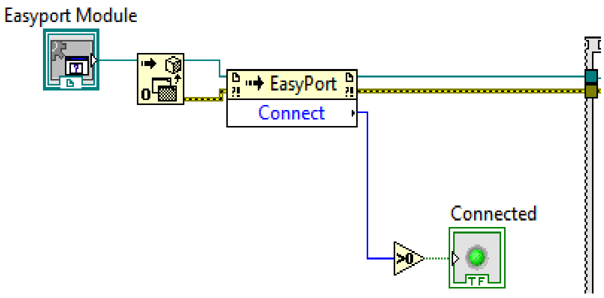

Fig. 3 Login to EasyPort

Fig. 4 shows the “Disconnect” invoke node method used to accomplish disconnection from the EasyPort module.

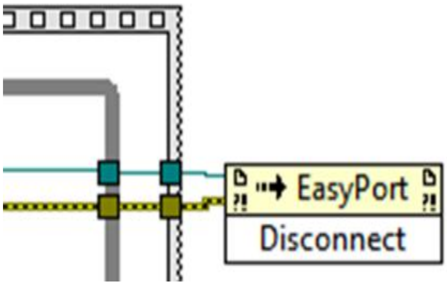

Fig. 4 Disconnect from EasyPort

3.2. Flowrate Sensor Reading

The output voltage mapping of the flowrate sensor is shown in Fig. 5. The sensor's reading is obtained using the Invoke Node method with the GetAnalogOutput1 action. The output of the flowrate analog sensors is an integer between the values 0 to 32767 due to the 12-bit resolution analog/digital conversion. In order to map the output voltage to a value between 0 and 10 V, the sensors' output is divided by 3276.7.

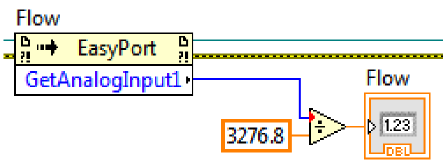

Fig. 5 Block diagram for reading the signal of the flowrate sensor

3.3. Sending Signals to the Actuators of the MPS PS CWS

The Invoke Node method with SetAlanogOutpt0 illustrated in Fig. 6 is used to set the desired supply voltage for operating the pump.

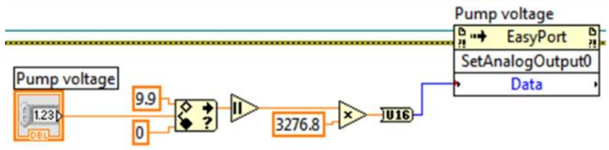

Fig. 6 Set the centrifugal pump voltage

4. Identification of the Flowrate Loop of the MPS PA Plant

The system identification for the flowrate control loop is achieved by applying a Pseudo-Random Binary Signal (PRBS) generated with the help of LabVIEW software. The resulting vectors of input and output signals are processed in the Ident tool of MATLAB to obtain the transfer function of the said loop. The generation of the PRBS signal in the LabVIEW software is done through the block "Generate Pseudo-Random Binary Sequence VI," as seen in Fig. 7.

The vectors representing the system input and output obtained by applying the PRBS are used to estimate the transfer function utilizing the Ident tool of MATLAB. The approximated transfer function according to the data entered for the flowrate loop is given in Equation 1.

The generated PRBS signal is shown in Fig. 8. By applying this PRBS to the system, the response vector shown in Fig. 9 is obtained.

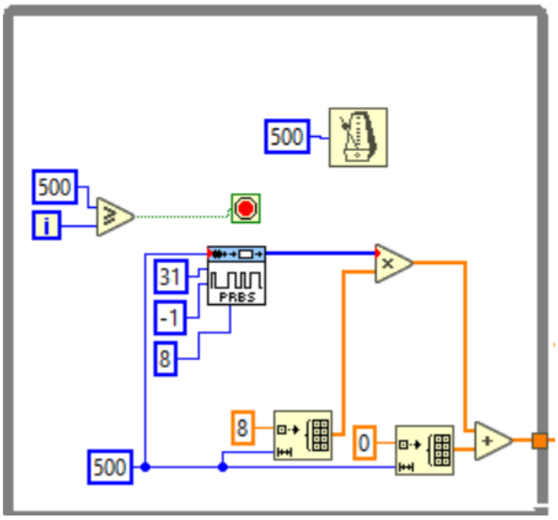

Fig. 7 Generation of PRBS signal in LabVIEW

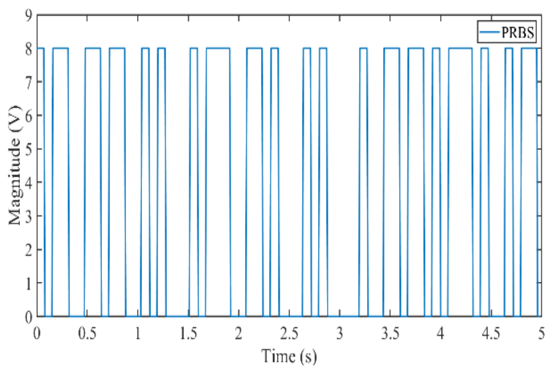

Fig. 8 PRBS signal used for system identification

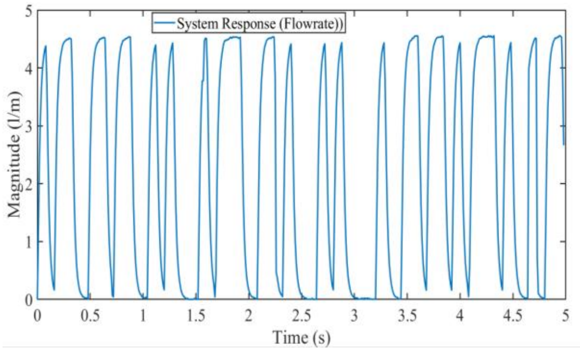

Fig. 9 System response to the applied PRBS

$$G(s) = \frac{-0.3021 + 4.094}{s^2 + 8.701s + 4.079} \tag{1}$$

5. Model Predictive Controller (MPC)

Model Predictive Control (Fig. 9 and 10) is considered an advanced control technique for control action optimization. The control action is related to the system's future behavior along a horizon of time. The design of MPC is based on three parameters: the prediction model, the cost function, and the optimization.

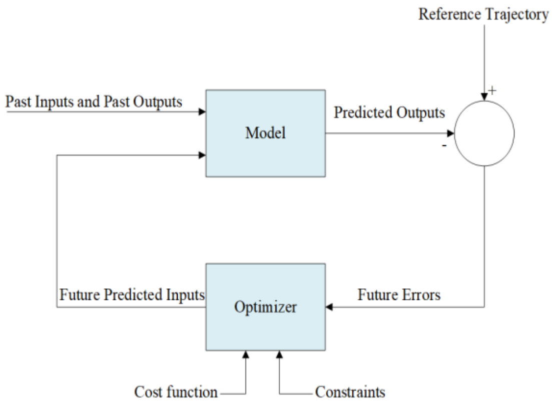

Fig. 10 The general structure of predictive model controllers

5.1. Mathematical Formulation Using State-Space

Model predictive control is designed based on a system's mathematical model. The model to be used in the control design is taken to be a state-space model. The current state variables represent the current information required for predicting. The flowrate system that needs to be controlled is a single input and single output system; therefore, the stat-space model can be described by equations 2 and 3.

$$x(k+1) = Ax(k) + Bu(k) \tag{2}$$

$$y(k) = Cx(k) + Du(k) \tag{3}$$

where $u(k)$ is the manipulated variable $y(k)$, is the process output, and $x(k)$ is the state variable vector with assumed dimension n_1. This system model has $u(k)$ as its input. Note that the direct term from the input $u(k)$ to the output $y(k)$ is zero due to the principle of receding horizon control where current information of the system is required for prediction and control. Therefore, the input $u(k)$ cannot affect the output $y(k)$ at the same time.

$$x(k+1) = Ax(k) + Bu(k) \tag{4}$$

$$y(k) = Cx(k) \tag{5}$$

The formulation of the MPC in state-space, see equations 4 and 5, should start from a model with an embedded integrator to account for various modeling uncertainties and external disturbances. Thus, we need to change the model to suit our design purpose in which an integrator is embedded.

The stat-space model with an embedded integrator is represented in a matrix form by equations 6 and 7. This model is obtained by taking the difference operation on both sides of equation 2. For more information, please refer to [2].

$$\overbrace{\begin{bmatrix} \Delta x(k+1) \\ y(k+1) \end{bmatrix}}^{x(k+1)} = \overbrace{\begin{bmatrix} A & o_m^T \\ CA & 1 \end{bmatrix}}^{Ae} \overbrace{\begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix}}^{x(k)} + \overbrace{\begin{bmatrix} B \\ CB \end{bmatrix}}^{B_e} \Delta u(k) \tag{6}$$

where A_e, B_e and C_e are the matrices of the augmented model, o_m is a matrix of zeros with length equals to the order of the system and $\Delta u(k)$ represents the difference of the control variable.

$$y(k) = \overbrace{\begin{bmatrix} o_m & 1 \end{bmatrix}}^{C_e} \begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix} \tag{7}$$

Fig. 11 shows the MATLAB script used to transform the previously obtained transfer function into its representation in state space and the formulation of the augmented model with an embedded integrator.

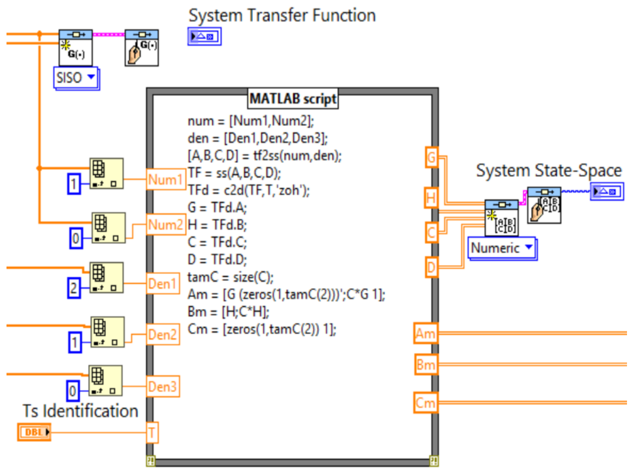

Fig. 11 The transformation of the system transfer function into the state space augmented model

5.2. Prediction Control within One Optimization Window

The state variables can be calculated sequentially by using the set of future control parameters and the state model A_e B_e and C_e. The following equations describe the predictions of the state and output variables for the present instan k_i ces. The state predictions are shown in Equations 8, 9, and 10.

$$x(k_i+2\,|\,k_i)=A_e^2x(k_i)+A_eB_e\Delta u(k_i)+B_e\Delta u(k_i+1) \quad (8)$$

$$x(k_i+1\,|\,k_i)=A_ex(k_i)+B_e\Delta u(k_i) \quad (9)$$

$$\begin{aligned} x(k_i+N\,|\,k_i)&=A_e^{N_p}x(k_i)+A_e^{N_p-1}B_e\Delta u(k_i)\\ &\quad+A_e^{N_p-N_c}B_e\Delta u(k_i+N_c-1) \end{aligned} \quad (10)$$

where N_c and N_p are the control and prediction horizons, respectively. And $x(k_i+N\,|\,k_i)$ represents the future state variables and k_i denotes the sampling instant. The same criteria can be used to obtain the predictions for the system's output. The output variables are obtained by substitution of the predicted state variables.

$$y(k_i+1\,|\,k_i)=C_eA_ex(k_i)+C_eB_e\Delta u(k_i) \quad (11)$$

$$\begin{aligned} x(k_i+2\,|\,k_i)&=C_eA_e^2x(k_i)+C_eA_eB_e\Delta u(k_i)\\ &\quad+B_e\Delta u(k_i+1) \end{aligned} \quad (12)$$

$$\begin{aligned} x(k_i+N\,|\,k_i)&=C_eA_e^{N_p}x(k_i)+C_eA_e^{N_p-1}B_e\Delta u(k_i)\\ &\quad+C_eA_e^{N_p-2}B_e\Delta u(k_i+1)\\ &\quad+C_eA_e^{N_p-N_c}B_e\Delta u(k_i+M-1) \end{aligned} \quad (13)$$

The set of output predictions can be represented by equation 14.

$$Y=Fx(k_i)+\Phi\Delta U \quad (14)$$

where matrices F and Φ, see equations 15 and 16, are constants formulated based on the matrices of the augmented model.

$$F=\begin{bmatrix} C_eA_e & C_eA_e^2 & C_eA_e^3 & \cdots & C_eA_e^{Np} \end{bmatrix}^T \quad (15)$$

$$\Phi=\begin{bmatrix} C_eB_e & 0 & \cdots & 0\\ C_eA_eB_e & C_eB_e & \cdots & 0\\ C_eA_e^2B_e & C_eA_eB_e & \cdots & 0\\ \vdots & \vdots & \vdots & \vdots\\ C_eA_e^{N_p-1}B_e & C_eA_e^{N_p-2}B_e & \cdots & C_eA_e^{N_p-N_c}B_e \end{bmatrix} \quad (16)$$

5.3. Optimization

For a given set-point signal $r(ki)$ at sample time ki within a prediction horizon, the objective of the predictive control system is to bring the predicted output as close as possible to the set-point signal, where we assume that the set-point signal remains constant in the optimization window. This objective is then translated into a design to find the 'best' control parameter vector ΔU such that an error function between the set-point and the predicted output is minimized.

Assuming that the data vector that contains the set-point information is

$$Rs^T=\overbrace{\begin{bmatrix}1 & 1 & 1 & \cdots & 1\end{bmatrix}}^{N}r(k_i)$$

We define the cost function J that reflects the control objective as

$$J(y,u)=(Rs-Y)^T(Rs-Y)+\Delta U^TR\Delta U \quad (17)$$

This function minimizes the error between the predicted output and the set-point Rs while considering the increments of the ΔU signal. R is a tuning parameter that focuses on the control action increments ΔU. When there are no restrictions, the cost function can be derived and equalized to zero to clear ΔU. The result of this procedure is shown in equation 18.

$$\Delta U=H\Phi^T[Rs.r(k_i)-Fx(k_i)] \quad (18)$$

where $H=(\Phi^T\Phi+R)^{-1}$ is known as a Hessian matrix. The dimension of ΔU depends on the control horizon and only the first term of the ΔU vector is sent to the plant at each sampling time.

Fig. 12 shows the MATLAB script used to read the tuning parameters from the front panel and the calculation of F and Φ in Equation 15 and 16, respectively. The abovementioned tuning parameters are the prediction horizon (Np), control horizon (Nc), penalty parameter (rw), and the parameters necessary for the state observer.

Fig. 13 shows the MATLAB script used to calculate the control action for the MPC.

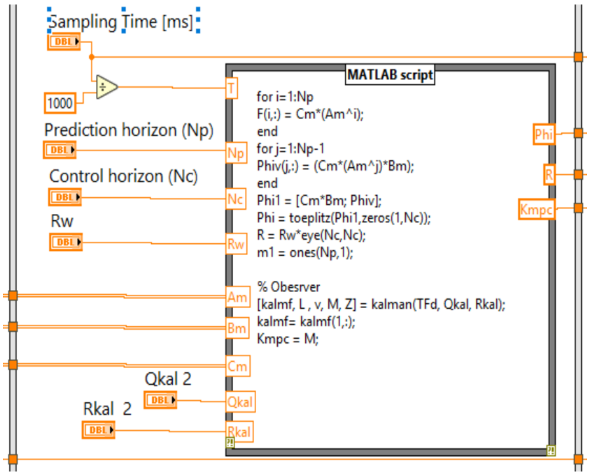

Fig. 12 Calculation of F , Φ , and observer gains

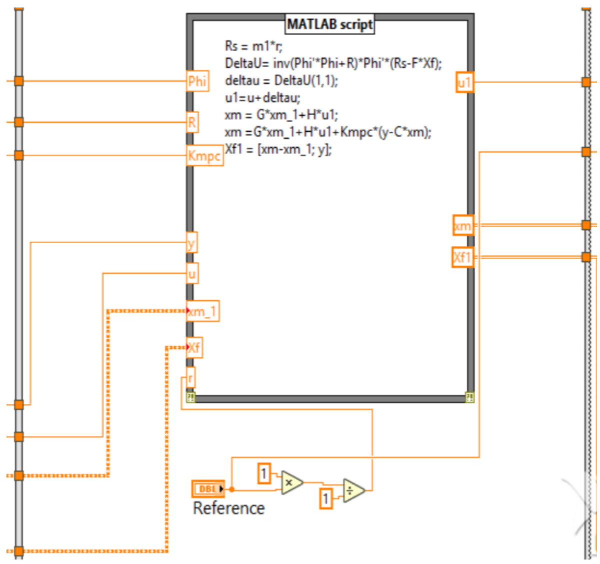

Fig. 13 Calculation of control action for MPC

6. Experimental Results

The front panel of the developed virtual instrument for the MPC controller of the flowrate control loop is presented in Fig. 14.

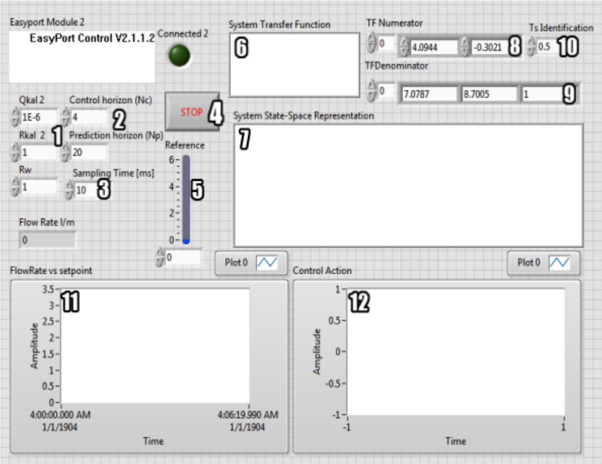

Fig. 14 MPC flowrate controller front panel

The Front Panel of the virtual instrument is made up of the elements listed below:

1. Numerical control for entry and modification of observer covariance
2. Numerical control for entry and modification of tuning parameters
3. Numerical control for entering the sampling time in milliseconds
4. Stop button of the instrumentation platform for the MPC controller
5. Slider to modify the system reference
6. Representation of the system's transfer function
7. Representation of the transfer function in state space
8. Entry vector for the numerator of the system transfer function
9. Entry vector for the denominator of the system transfer function
10. Numerical control for entering the system identification sampling time in seconds
11. Graphic display of the reference signal and the response of the system
12. Graphic display of the control signal.

The MPC PA Compact workstation was conFig.d to work on flowrate control loop mode with the Centrifugal pump (P101) acting as an actuator. The reference flowrate value was varied from 0 to the maximum possible flow rate of 5 l/m. Fig. 15 depicts the Set-point vs. the actual flowrate signals under MPC. Fig. 15 shows a very good response with a maximum settling time of 3.6 s, maximum steady-state error of 0.012 l/m, and max overshot of 0.58%. The control action signal is shown in Fig. 16.

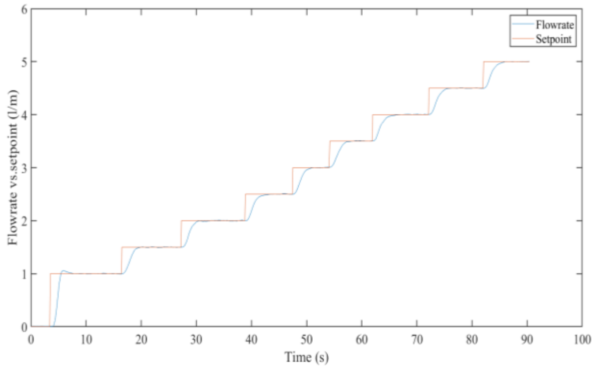

Fig. 15 Set-point vs. the actual flowrate signals under MPC

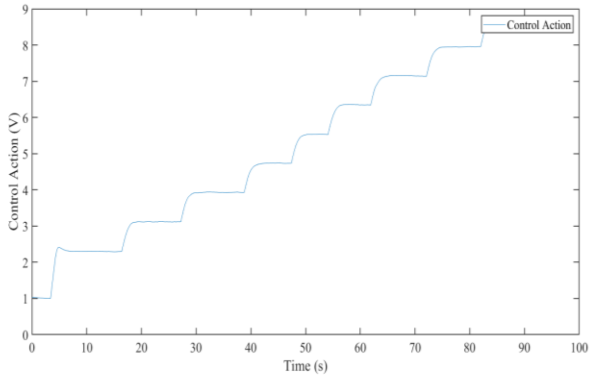

Fig. 16 The control action signal of the MPC for the flowrate control loop

7. Conclusion

An MPC controller was implemented and applied to a flowrate control system. The results showed that the identified model, the MPC control strategy, and the optimization configuration were adequate to achieve a high control performance with constraint handling. The novel implementation of the MPC control system presented advantages such as the easy configuration of how much energy should be used through the parameter R. Various configurations of prediction and control parameters have been tested. Among the configurations tested, the best configurations with high performance concerning minimizing error and energy were selected and presented in this paper. For the model-based predictive controllers (MPC), one must remember that increasing the tuning parameters of the controller causes a greater demand for computer resources and time for processing since the equations established in the Matlab script are based on a matrix calculation that depends on the size of the parameters chosen. For the computational cost of the implanted MPC controller, it was found that the average cost remained between 5 ms and 8 ms, guaranteeing the complete execution of the control. Thus, a safety margin was maintained to the 10 ms sampling period.

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