Model predictive controller for a retrofitted heat exchanger temperature control laboratory experiment

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Article Info

Article history:

Received Aug 3, 2021
Revised Dec 8, 2021
Accepted Dec 17, 2021

Keywords:

Heat exchanger
LabVIEW
MPC controller
PID controller
Real-time control
Signal converters

ABSTRACT

This paper aims to demonstrate the practical aspects of process control theory for undergraduate students at the Department of Chemical Engineering at the University of Bahrain. Both, the ubiquitous proportional integral derivative (PID) as well as model predictive control (MPC) and their auxiliaries were designed and implemented in a real-time framework. The latter was realized through retrofitting an existing plate-and-frame heat exchanger unit that has been operated using an analog PID temperature controller. The upgraded control system consists of a personal computer (PC), low-cost signal conditioning circuit, national instruments USB 6008 data acquisition card, and LabVIEW software. LabVIEW control design and simulation modules were used to design and implement the PID and MPC controllers. The performance of the designed controllers was evaluated while controlling the outlet temperature of the retrofitted plate-and-frame heat exchanger. The distinguished feature of the MPC controller in handling input and output constraints was perceived in real-time. From a pedagogical point of view, realizing the theory of process control through practical implementation was substantial in enhancing the student's learning and the instructor's teaching experience.

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1. INTRODUCTION

Model predictive control (MPC) refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant. At each control interval, an MPC algorithm attempts to optimize future plant behavior by computing a sequence of future manipulated variable adjustments [1]. MPC has gained interest from both industry and academia and it is considered as the only advanced control scheme compared to proportional integral derivative (PID) that has had a notable impact on the industry [2]-[4]. The traditional way of implementing MPC is that it is applied to large-scale processes and provides set points to PID controllers at the regulatory level. However, developments in computing and optimization technology are paving the way for the implementation of MPC controllers at the regulatory level [2]-[4]. Recently, predictive control started to combine with other algorithms to develop a class of advanced predictive control strategies [5]-[8]. Hence, teaching and practicing MPC is an important part of the process control engineering education. Several software packages are available to teach MPC controllers via simulations [9], however, simulations cannot replace real experience, since simulations only provide an approximation of the real plant environment.

In our process control laboratory, all practical control experiments are limited only to PID controllers. The manufacturer software supplied originally cannot be modified to implement other types of control algorithms. The latter becomes a real constraint for practical implementations of another type of controller. Such constraints certainly restricted the students' practical experience in implementing MPC controllers. Owing to that, this study aims to overcome these constraints and develop a process control laboratory setup that offers the possibility for students to understand, implement and test model predictive controllers in real-time.

A large number of undergraduate control laboratories experiments which address MPC and PID controllers design and testing are published [10]-[15]. In this work, a cost-effective solution for process control laboratory experiments is proposed. The experimental setup used is an armfield temperature control apparatus. The current setup uses a PID controller that is based on obsolete technology. The first objectives of this work are to locally retrofit the unit with a personal computer (PC), signal conditioning circuit, LabVIEW software interface, and national instruments USB 6008 data acquisition card. LabVIEW is preferred because it is to apply, adapt, and easily learn. LabVIEW features include hardware interfaces, built-in engineering-specific libraries of software functions, data analysis and visualization, and graphical user interface (GUI). It permits the user to select their input values and operate them in a manner that is similar to a real laboratory [16]-[17]. The second objective of the study is to develop a program to execute the MPC and PID control algorithms calculations. Since our students prefer to wire and block programing language rather than text-based programming, it was decided to use LabVIEW along with its control design and simulation modules. The program has been tailored to evaluate the performance of constrained and unconstrained single input single output (SISO) and multi-input multi-output (MIMO) MPC controllers.

To summarize, the objective of this paper is to propose an educational experimental module that allows students to control the outlet temperature of a heat exchanger by manipulating the hot water flow rate using the ubiquitous PID and MPC controllers. The educational experimental module can also be used to examine the effect of MPC tuning parameters on the control action. Furthermore, the student has the possibility to investigate the improvements MPC can offer against the PID controller when applied to the lag dominant process.

2. RETROFITTED LABORATORY EQUIPMENT

2.1. Process description

The process considered in this paper is a plate-type heat exchanger (HE) that is characterized by being highly nonlinear with a large time delay. The main aim of the HE is to maintain a specific temperature, which is achieved by controlling the exit temperature of one of the fluids despite any variations of the operating conditions. It is worth mentioning here that the HE used in this study is an Armfield temperature control apparatus (known commercially as PC4) where water serves as both the process fluid and the heating fluid. The PC4 apparatus is relatively an old apparatus in our lab, but most of its equipment and instrumentation are still in good condition. It has been retrofitted by replacing the analog PID controller and chart recorder with personal computer (PC), which made it valuable research and teaching resource. The arrangement adopted, water circuit, and control system are shown in Figure 1. All the hot water flow is directed through the pneumatically operated control globe valve (Air to Close) and heat exchanger. The cold water (process fluid) flows through a flow meter and then through the heat exchanger in the counter-flow direction. The input hot water flow rate is the manipulated variable and the process fluid outlet temperature is the controlled variable. A temperature transmitter (platinum resistance element) is fitted at the process fluid outlet point for control purposes.

2.2. Interface circuit

PC-based control system accepts the input from the temperature transmitter and generates control action which is sent to the plant through a DAQ card. The output of the DAQ is in the range of 0-5 volts is given to the voltage to the current converter, which gives an output in the range of 4-20 mA. The current signal is given to the current-to-pressure (I/P) converter and this latter gives an output in 3-15 psi pressure. The pressure signal is given to the actuator of the ½ inch pneumatic control valve which moves the stem position to vary the input hot water flow rate to the heat exchanger. As shown in Figure 2, the interface between the PC and the PC4 unit is provided by National Instruments USB 6008 data acquisition card. To match the signals to and from the PC4 within the ranges of the card, two appropriate signal conditioning circuits based on Texas Instruments 4-20 mA current loop transmitters (known commercially as XTR110 and XTR105) are designed and used as interfaces between the PC4 and the card. The developed arrangement is depicted in Figure 3.

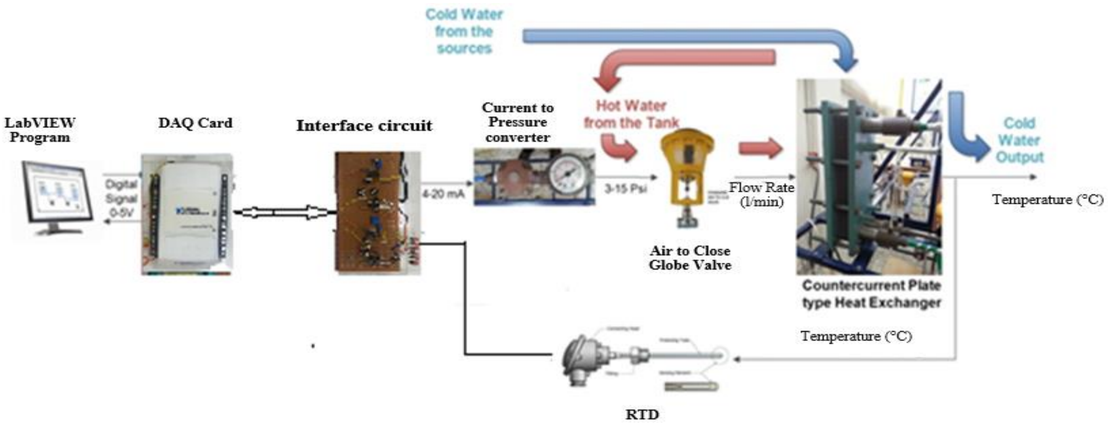

Figure 1. Main components and interface circuits of the closed control system

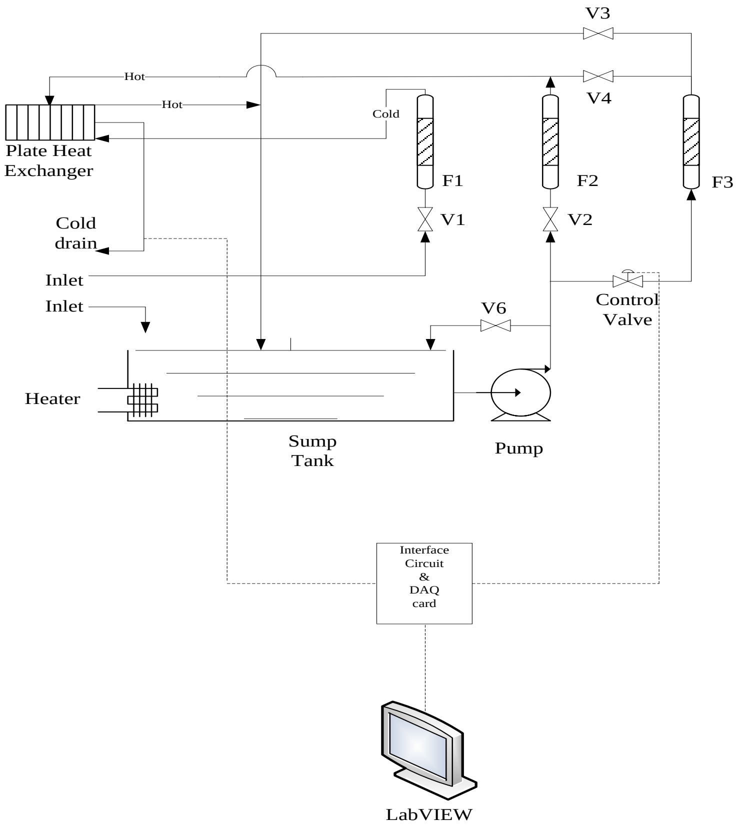

Figure 2. Diagram of the unit to be controlled

2.3. Software interface

In this work, LabVIEW software is used to develop an intuitive and easy-to-use human-machine interface (HMI) to allow the user to visualize the dynamic responses, dials, and data entry. The MPC and PID control algorithms calculations can be computed using either LabVIEW or MATLAB. Our students prefer to wire and block programing language rather than text-based programming. Thus, it was decided to use LabVIEW along with its control design and simulation modules to perform control algorithms calculations. However, if needed, LabVIEW features permit to perform the control calculation using m-script MATLAB code along with LabVIEW. This feature provides MATLAB script node block that permits for wiring the variables to and from the LabVIEW programming environment and the m-script text-based MATLAB program. Details of the state-space model-based MPC algorithm implemented in this work can be found in [18], [19]. The next section gives an overview of the theory behind MPC and PID control algorithms implemented in this work.

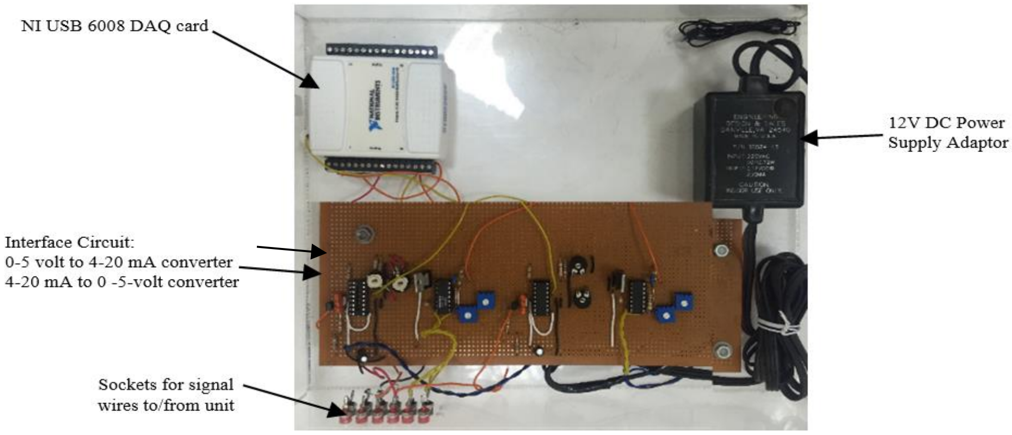

Figure 3. Interface circuit to link between PC and the unit

3. CONTROL ALGORITHMS

3.1. Model predictive control basic theory

MPC relies on a dynamic model of the plant, most often linear empirical models, obtained by system identification, and this model is used to predict the future behavior of a plant. This predictive capability makes MPC a good candidate for processes with significant time delay and therefore it could be an alternative to the PID controller. In addition, MPC exhibits superior performance in handling constraints. As depicted in Figure 4, MPC control scheme is building and optimizing feedback controllers at each sampling time. The discrete-time MPC main elements are the reference trajectory, the controlled output and the process input, which are denoted by *r*, *y*, and *u*, respectively.

The process model determines the predicted process outputs on the prediction horizon, denoted P. The algorithm of optimization is intended at determining the control sequence given by {u(k−1 + i), i = 1,2,..., M} for the control horizon, denoted *M*. Only the first element $u^*(k)$ of the optimized control sequence is applied to the process and the control input is updated at each sampling instant. The process of optimization is repeated at the next sampling time, based on the measured (or estimated from the measured output y(k)) state x(k). The optimization algorithm assumes that u(k-1+i) = u(k+M-1) for $M < i \leq P$.
The behavior of the controlled process is given as following discrete state space model:

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

$$y(k) = Cx(k) \tag{2}$$

This model is used to generate the predictions over a finite prediction horizon of P samples. Hence, for specified prediction and control horizons and at every sampling time, the MPC controller tries to minimize the following cost function:

$$J(k) = \sum_{i=1}^{i=P} (\hat{e}(k+i|k))^T Q (\hat{e}(k+i|k) + \sum_{i=0}^{i=M-1} \Delta u^T(k+i|k)\, R\, \Delta u(k+i|k) \tag{3}$$

where $\hat{e}(k+i|k) = \hat{y}(k+i|k) - r(k+i|k)$, $\hat{y}(k+i|k), r(k+i|k)\ and\ \Delta u(k+i|k)$ are the predicted process output, the output set-point profile, and the predicted change in control action at time *k*+*i*, given all measurements up to and including those at sampling time *k*, respectively. R and Q are weighting matrices on the control action increments and the output error respectively. The control signal applied to the process is given by $u^*(k) = u^*(k-1) + \Delta u^*(k)$, where $\Delta u^*(k)$ is the optimized control sequence first element, and it is computed at each sampling instant. The following constraints can be taken into consideration by MPC when calculating the future controls, namely constraints on the outputs: $y_{min} \leq y(k) \leq y_{max}$, constraints on the inputs: $u_{min} \leq u(k) \leq u_{max}$ and constraints on the change of inputs: $\Delta u_{min} \leq \Delta u(k) \leq \Delta u_{max}$. The constraints can be physical such as actuator limits, or safety constraints such as bounds on the temperatures, or even performance constraints such as the response overshoot. As mentioned previously, knowledge of the current states is crucial for the computation of the control signal. If the states are not measurable, then it can be computed using the input/output data of the model dynamic. If, however, the internal dynamic model is not accurate, an observer might be incorporated with MPC to reconstruct the current state based on available process inputs and outputs and eventually improve the robustness of the control system. The MPC controller within the LabVIEW uses a linear state-space internal model to design the controller. Nevertheless, LabVIEW supports different model structures e.g., transfer functions which can be converted internally to a state-space model.

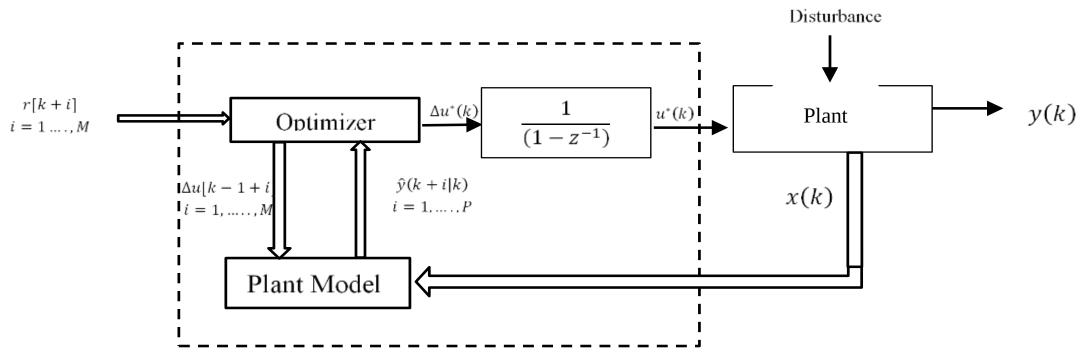

Figure 4. MPC control structure

3.2. MPC tuning parameters

Following the same research trend on PID tuning, several tuning guidelines for MPC controllers were developed and made available in the literature. Garriga [20] provides an outstanding review of the existing tuning guidelines for model predictive control, from theoretical and practical viewpoints. Based on process dynamic parameters, prediction (P) and control horizons (M) can be calculated using the following simple relations [19]:

$$P = [(5\tau + \theta)/2]/T_s \tag{4}$$

$$M = int(P/4) \tag{5}$$

where, τ, θ and T_s are process time constant, time delay, and sampling time respectively.

In general, the states are not measured and state observers might be used in real-time based on measured process inputs and outputs. Hence, the poles of the observer are also parameters that need to be fixed. The current tuning procedure [21] is to fix the above parameters to appropriate values, and then focus on weightings matrices R and Q adjustment to achieve the best possible control performance.

3.3. PID control

The PID control law to be considered in this study is as (6):

$$u(t) = K_c[e(t) + \frac{1}{\tau_I}\int_0^t e(\sigma)d\sigma + \tau_D \frac{de(t)}{dt}] \tag{6}$$

The error, e(t), refers to the difference between the set-point, r, and the value of the controlled variable y(t), i.e., e(t)= r(t) – y(t). Kc, τ_I, and τ_D are the controller gain, integral time, derivative time parameters respectively. The setting of these parameters can be calculated using the internal model control (IMC) relations [22], [23].

$$K_c = \frac{\tau + \frac{\theta}{2}}{k(\tau_c + \frac{\theta}{2})} \qquad \tau_I = \tau + \frac{\theta}{2} \qquad \tau_D = \frac{\tau\theta}{2\tau + \theta} \tag{7}$$

The PID controller performance will be compared with that of the MPC algorithm.

4. TESTING OF EQUIPMENT

Experimental set up arrangement adopted, water circuit and control system are shown in Figure 2. The hot water flow is directed through the pneumatically control valve (air to close), flow meter F3, valve V4 and heat exchanger. The cold-water flows through valve V1, flow meter (F1) and heat exchanger in the counter-flow direction. The valves V2, V3 and V6 are set fully closed. To test the hardware and software of the experiment developed, we started first by identifying the process model using experimental data collected. The identified process model is then used to test the MPC controller developed first via simulation and then in real-time.

4.1. Process identification

To identify the process model [23], the outlet temperature was first allowed to reach steady state after setting the cold water and hot water flow rates to 3 lit/min. Different level step changes are applied to the valve to change the hot water flow rate and outlet temperature changes are recorded with a sampling time equal to 0.1 seconds. Consequently, a first-order plus dead time transfer function was fitted to the experimental data with the aid of control station V3.7 [24]. The first-order plus time delay (FOPTD) models' approximation, given in Table 1, shows a fitness coefficient over 0.98 for the four identified models. The results show that the FOPTD models obtained have different gains, time constant, and time delay. This is due to the inherent nonlinearity of the heat exchanger as well as to the hysteresis and dead band present in the pneumatic control valve. The characteristic of the valve flow rate versus actuator input is depicted in Figure 5. A hysteresis is present and the control signal outside the range leads to saturation. The hot water flow rate is unchanged if the control signal is less than 1.8 volts and greater than 3 volts. The input span of the valve is only limited to 40% of the full range of 0-5 volts which means inherent constraint on the controller action. The open-loop responses to step input changes are shown in Figure 6.

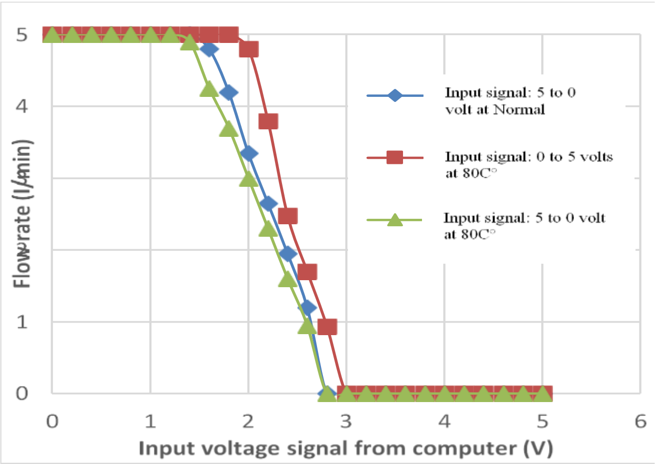

Figure 5. Open loop step responses of the unit output temperature

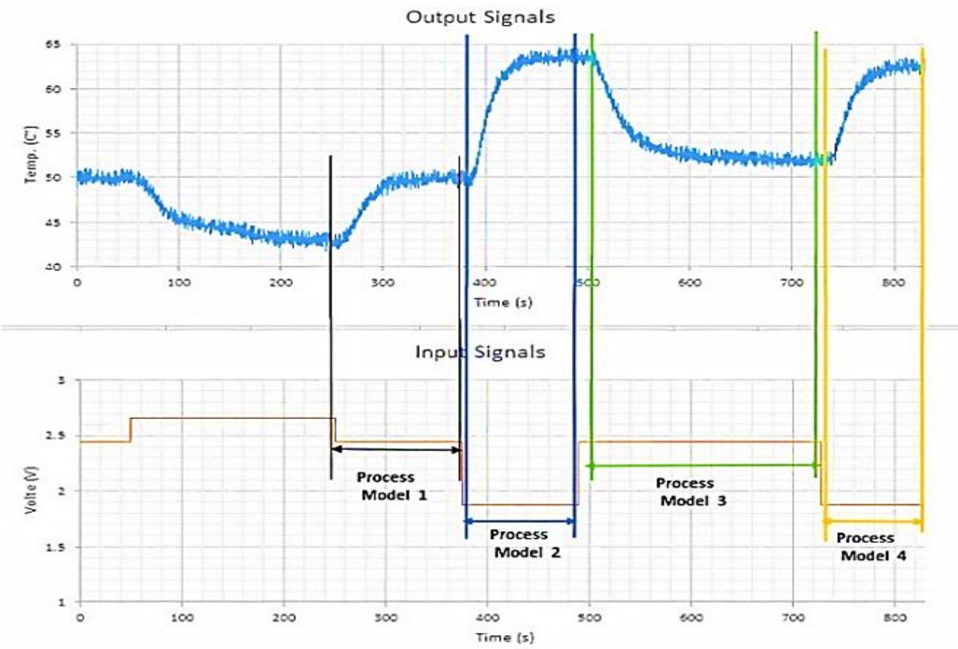

Figure 6. Installed pneumatic valve characteristic including voltage to current (V/I) and current to pressure (I/P) converters placed upstream the valve

Table 1. Process transfer functions obtained based on results shown in Figure 6

	Process Transfer Function	Goodness of Fit
1	$\frac{Y(s)}{U(s)} = \frac{-33.57\, e^{-14.897s}}{20.645\, s+1}$	0.9875
2	$\frac{Y(s)}{U(s)} = \frac{-23.22\, e^{-16.882s}}{17.434\, s+1}$	0.9794
3	$\frac{Y(s)}{U(s)} = \frac{-19.88\, e^{-15.362s}}{29.659\, s+1}$	0.9903
4	$\frac{Y(s)}{U(s)} = \frac{-18.81\, e^{-13.4.32s}}{17.165\, s+1}$	0.9958

4.2. Simulation test of MPC controller

As mentioned above, the MPC algorithm requires that the model be in a linear state-space model form. A built-in function in LabVIEW is used to convert the FOPTD to a linear state-space model. For control purposes [21], the sampling time is chosen equal to 2 seconds. The students have the option to perform control based on simulation of the process model or to control the process directly in real-time. Figure 7 shows simulation results of the outlet temperature response using the PID controller. The settings used for PID are obtained using the IMC relations given above: K_c=-0.04, τ_I=27.60, and τ_D=5.22. This latter setting can be fine-tuned for improved performance.

Figure 8 shows the outlet temperature response using the MPC controller. The tuning parameters of the MPC controller are obtained using (4) and (5), with *P*=*N*=20, *M*=5. The control weight is adjusted to *r*= 20 and the output error weight is adjusted to *q*=1. The simulation results in Figure 7 and Figure 8 clearly demonstrate the superiority of MPC over PID controller. With MPC, the response follows the set-point with less lag and overshoot. Whereas in the case of PID controller the response exhibits large delay and overshoot. The controllers' performance evaluation is carried out qualitatively by visual inspection of the closed-loop output time responses using criteria such as settling time, overshoot, and oscillations. While time-integral performance criteria such as integral of the squared error (ISE) and integral of the absolute value of the error (IAE) can be used to evaluate the control system performance, it was intentionally intended to qualitatively assess the closed response as it is the commonly preferred approach in the industry. In the practical setup, a low pass digital exponential filter is used to filter the sampled measured controlled variable before inputting it to the controller [23].

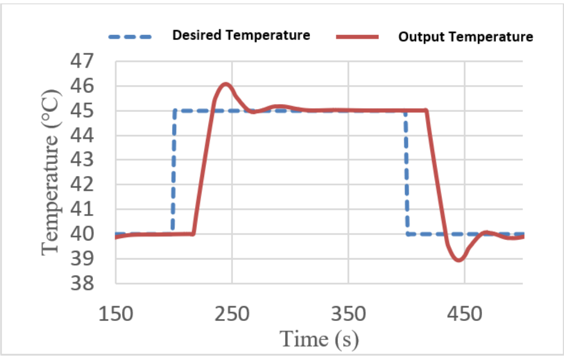

Figure 7. Response under PID control

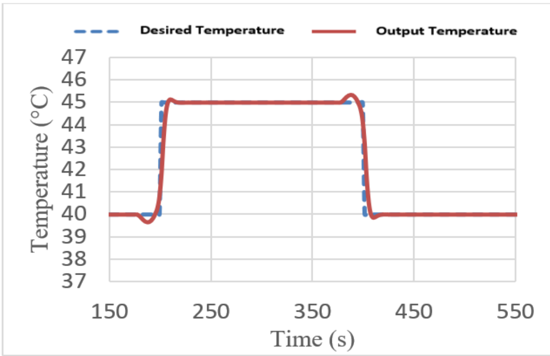

Figure 8. Response under MPC control

5. PRACTICAL TEST OF MPC CONTROLLER

Using the same parameter settings as those used in the simulation (i.e., K_c=-0.04, τ_I=27.60, and τ_D=5.22), the response under the PID controller is shown in Figure 9. As shown, the response is sluggish and presents a large time delay; it takes 150 seconds to reach the set point. The real-time response under MPC controller with *M*=5, *P*=20, *Q*=1, and *R*=1 is unable to ensure a good response as obtained in simulation. This is maybe due to factors such as nonlinear valve characteristics, variation of temperature in the tank, and high nonlinearity of the heat exchanger. These latter are a result of the plant/model mismatch that ultimately can deteriorate the robustness and performance of the MPC [25], [26].

To improve the performance of the MPC controller, a discrete state observer is added to the controller to improve the robustness of controller. The results obtained using MPC with observer and M=5, P=20, Q=1, and R=1 are shown in Figure 10. As shown the observer improved significantly both the robustness and prediction properties of the MPC controller. The MPC constraints on output variables can be included in the control calculations in various different ways [1], [27]. The performance of MPC under constraint is investigated as shown in Figure 11. The controller does not allow the output response to exceed the constraint 45 °C despite that the setpoint being 50 °C.

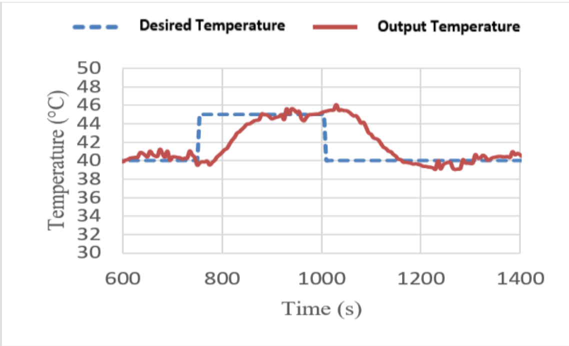

Figure 9. Response under PID control

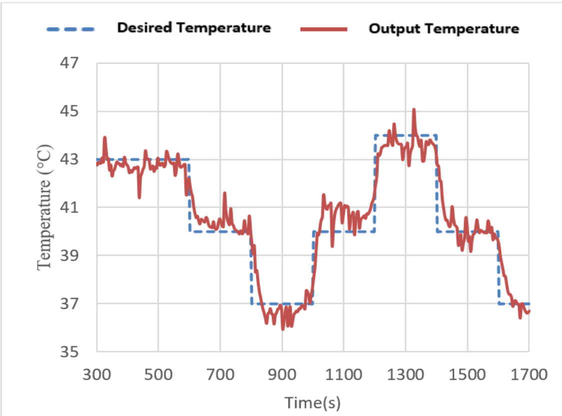

Figure 10. Response under MPC controller with state observer without constraint

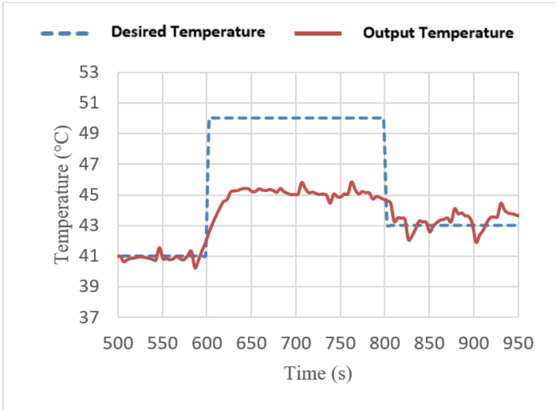

Figure 11. Response under MPC controller with constraint

6. DISCUSSION

Discussion with students revealed that this project stimulated their interest and laid down the foundation for future learning in this important technology area and improved their ability to apply modern software and techniques in industrial control. Overall, students appreciated that they are able to apply quite complex control algorithms to real processes and it works. Nevertheless, the stages of designing up the setup have been explained to the student. The latter was of importance to the students to appreciate the challenges associated with real-time setup compared to the simulation cases that they used to encounter in their normal classes. In addition, the real-time experiment allows the student to restress many of the concepts that they used to underestimate e.g., sampling, noise filtering, model/plant mismatch, and non-minimum phase system, constraint.

7. CONCLUSIONS

In this study, we have developed an experiment, which offers our fourth-year students a unique opportunity to experience and understand the design and implementation of MPC controllers in real-time. The experiment was retrofitted by replacing the analog PID controller and chart recorder with personal computer (PC). The experiment enables the students to investigate the effect of tuning parameters on a real control system and observe physically how constraints affect system performance. Additionally, the students are able to investigate the system performance without and with state observer along with their poles. While the present experience is limited to single input single output, multivariable MPC control will be considered in future work.

Overall, this experiment shows a great impact on students' performance and supports their efforts in understanding MPC control. Students learned the importance of model accuracy in the development of MPC controllers and how a state observer can improve control performance in case of model inaccuracy. They also learned that the selection of tuning parameters plays a key role in closed-loop performance as well as constraints. Students also appreciated that they are able to apply quite a complex control algorithm to real processes and, as a result, they were very proud of their achievement. Future work is to improve further the experimental set-up with new linear pneumatic control valves for manipulating the flow of cold and hot water and extend the experiment to multivariable MPC control.

REFERENCES

[1] S J. Qina and T. A. Badgwellb, "A Survey of İndustrial Model Predictive Control Technology," *Control Engineering Practice*, vol. 11, no. 7, pp. 733-764, 2003, doi: 10.1016/S0967-0661(02)00186-7.

[2] J. Richalet, "Industrial Applications of Model-Based Predictive Control," *Automatica*, vol. 29, no. 5, pp. 1251-1274, 1993, doi: 10.1016/0005-1098(93)90049-Y.

[3] M. Alam *et al.*, "Comprehensive Review on Model Predictive Control Applied to Power Electronics," *Recent Advances in Electrical & Electronic Engineering Journal*, vol. 13, no. 5, 2020, doi: 10.1109/PEDES.2018.8707833.

[4] J. Han, Y. Hu, and S. Dian, "The State-of-the-art of Model Predictive Control in Recent Years," *CACRE IOP PublishingIOP Conf. Series: Materials Science and Engineering*, vol. 428, 2018, p. 012035, doi: 10.1088/1757-899X/428/1/012035.

[5] J. Zhang, "Design of a new PID controller using predictive functional control optimization for chamber pressure in a coke furnace," *ISA Transactions*, vol. 67, pp. 208-214, 2016, doi: 10.1016/j.isatra.2016.11.006.

[6] M. Killian, B. Mayer, and M. Kozek, "Cooperative fuzzy model predictive control for heating and cooling of buildings," *Energy & Buildings*, vol. 112, pp. 130-140, 2016, doi: 10.1016/J.ENBUILD.2015.12.017.

[7] P. N. Chikasha and C. Dube, "Adaptive Model Predictive Control of a Quadrotor," *IFAC-Papers Online*, vol. 50, no. 2, pp. 157-162, 2017, doi: 10.1016/j.ifacol.2017.12.029.

[8] A. Vasičkaninová, M. Bakošová, A. Mészáros, and J. J. Klemeš, "Neural network predictive control of a heat exchanger," *Applied Thermal Engineering, Elsevier*, vol. 31, no. 13, pp. 2094-2100, 2011, doi: 10.1016/j.applthermaleng.2011.01.026.

[9] E. Yilmazlar and E. Kaplanoğlu, "Design of the Model Predictive Control Education and Application Interface," *Journal of Software Engineering and Applications*, vol. 5, no. 9, pp. 677-681, 2012, doi: 10.4236/jsea.2012.59080.

[10] F. Haugen, "Laboratory assignment: Model-based predictive control (MPC)," Telemark University College (Norway)/Finn Haugen (finn.haugen@hit.no) http://www2.hit.no/tf/fag/scev3106, 2009 (accessed Jul, 2021).

[11] D. Honc, R. Sharma, A. Abraham, F. Dušek, and P. Natarajan, "Teaching and Practicing Model Predictive Control," *11th IFAC Symposium on Advances in Control Education (ACE), Bratislava-Slovakia*, vol. 49, no. 6, pp. 34-39, June 1-3, 2016.

[12] P. Richmond and D. Chen, "A model predictive control package for undergraduate education," *Education For Chemical Engineers, Elsevier*, vol. 7, no. 2, pp. e43-e50, 2012, doi: 10.1016/j.ece.2012.02.001.

[13] A. L. R.-Sandoval, W. Blankespoor, and H. M. Budman, "Testing a Constrained MPC Controller in a Process Control Laboratory," *Chemical Engineering Education*, vol. 44, no. 2, pp. 127-133, 2010.

[14] M. Oliveria and J. D. Hedengren, "An APMonitor Temperature Lab PID Control Experiment for Undergraduate Students," 2019 24th IEEE *International Conference on Emerging Technologies and Factory Automation (ETFA)*, pp. 790-797, 2019, doi: 10.1109/ETFA.2019.8869247.

[15] S. M. Sundaram, "Design of visual process laboratory (VPCL) using first principle method and interactive PID control toolkits using Labview," 2017 9th *International Conference on Information Technology and Electrical Engineering (ICITEE)*, 2017, pp. 1-5, doi: 10.1109/ICITEED.2017.8250460.

[16] N. Ertuggrul, "Towards virtual laboratories: a survey of LabVIEW-based teaching/learning tools and future trends," *Int. J. Eng. Edu*. vol. 16, no. 2, pp 1-10, 2000.

[17] E. Luther, "Introduction to Control Design and Simulation using LabVIEW," *Rice University, Houston, Texas., Chemical Engineering Education*, vol. 44, no. 2, pp. 127-133, 2012.

[18] L. Wang, "Model Predictive Control System Design and Implementation Using MATLAB," *Springer-Verlag London Limited*, 2009, doi: 10.1007/978-1-84882-331-0.

[19] J. M. Maciejowski, "Predictive control: with constraints," *Prentice-Hall*, Pearson Education. *Limited*, Harlow, UK, 2002.

[20] J. L. Garriga, "Model predictive Control Tuning Methods: Review," *Industrial Engineering Chemistry Research*, vol. 49, no. 8, pp. 3505-3515, 2010, doi: 10.1021/ie900323c.

[21] M. L. Derouiche, S. Bouall`egue, J. Hagg`ege, and G. Sandou, "LabVIEW Perturbed Particle Swarm Optimization Based Approach for Model Predictive Control Tuning," *4th IFAC International Conference on Intelligent Control and Automation Sciences (ICONS 2016)*, Jun 2016, doi: 10.1016/j.ifacol.2016.07.138.

[22] K. Astrom and T. Hagglund, "The future of PID control," *Control Engineering Practice, Elsevier*, vol. 9, no. 11, pp. 1163-1175, 2001.

[23] D. E. Seborg, T. F. Edgar, and D. A. Melllichamp, "Process dynamics and control," *3rd edition Wiley*, 2011.

[24] Doog Cooper and Danielle Dougherty, "Control Station: An Interactive Simulator for Process Control Education," *Int. J. Engng Ed.*, vol. 17, no. 3, pp. 276-287, 2001.

[25] H. Wang, Z. Song, and L. Xie, "Parametric Mismatch Detection and Isolation in Model Predictive Control System," *Preprints of the 8th IFAC Symposium on Advanced Control of Chemical Processes, The International Federation of Automatic Control*, vol. 45, pp. 154-159, 2012, doi: 10.3182/20120710-4-SG-2026.00120.

[26] L. D. Tufa and C. Z. Ka, "Effect of Model Plant Mismatch on MPC Performance and Mismatch Threshold Determination," 4th *International Conference on Process Engineering and Advanced Materials, Procedia Engineering, Elsevier*, vol. 148, pp. 1008-1014, 2016, doi: 10.1016/j.proeng.2016.06.518.

[27] J. M. Maciejowski, "Predictive Control with Constraints," *Prentice-Hall, Upper Saddle River*, NJ, 2002.

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