



## **Model Predictive Control Strategy for a Combined-Cycle Power-Plant Boiler**

Burgasi Cushicagua, Dennis Fernando y Orrala Muñoz, Tania Brigitty

Departamento de Eléctrica y Electrónica

Carrera de Ingeniería Electrónica e Instrumentación

Artículo académico, previo a la obtención del título de Ingeniero en Electrónica e Instrumentación

Ing. Llanos Proaño, Jacqueline Del Rosario Ph.D

02 de marzo del 2021

# Model Predictive Control Strategy for a Combined-Cycle Power-Plant Boiler

Tania Orrala, Dennis Burgasi, Jacqueline Llanos, and Diego Ortiz-Villalba,

**Abstract**— Combined-cycle power plants recycle steam or gas to generate additional power and reduce emissions. In this research work, the boiler of a combined-cycle power plant is controlled using three control strategies, which are designed and compared, for the variables drum water level ( $L$ ) and superheated steam pressure ( $p_s$ ). A conventional PI controller is designed using the Lambda-tuning technique to obtain the optimal controller's gains. In addition, a fuzzy logic-based controller that considers the error and the error's rate-of-change is applied. Finally, a model predictive control (MPC) is applied, which objective function is to minimize the steady state error and the variation of the control actions, thus the fuel consumption is reduced. The controllers' performance is compared by analyzing maximum overshoot, settling time, steady-state error, and mainly fossil fuel consumption, which influences the operating cost. The results show a proper performance of the three control techniques. However, MPC control achieves a higher reduction of fuel consumption.

**keywords**—Combined-cycle power plant, fuzzy controller, model predictive control (MPC), proportional-integral controller (PI).

## I. INTRODUCTION

THE thermoelectric plants have allowed providing electrical energy to different cities, supplying high demands.

However, these plants in their basic configuration dissipate the steam, or gas, emitted by their turbines to the environment which generates a pollution degree [1]. For this reason, combined-cycle (CC) power plants were created, which allow using this steam to generate additional electric energy, while reducing environmental pollution [2].

Due to the advantages of CC power plants over conventional plants, in [3] a conversion from a conventional power plant to a combined-cycle plant is proposed. These conversions succeed in reducing energy losses. The key of CC lies in the reuse of waste heat from gas-turbine exhaust gases to produce additional electricity. This allows efficiency in fossil fuel-based power generation to increase by 50% [4]. These types of plants have become a topic of interest in recent years due to the growing demand for electrical energy; for instance, in [5] is illustrated how a combined-cycle power plant is more efficient with a relatively low investment cost. Furthermore, in [6], takes

Manuscript received; revised; accepted. This work was supported by Universidad de las Fuerzas Armadas ESPE (Control and Optimal Management of Isolated Microgrids project and VLIR-UOS project number EC2020SIN322A101).

Tania Orrala, Dennis Burgasi, J. Llanos and D. Ortiz-Villalba are with the Department of Electrical Engineering, Universidad de las Fuerzas Armadas ESPE, Sangolquí, Ecuador; emails: tborrara@espe.edu.ec, dfburgasi@espe.edu.ec, jdllanos1@espe.edu.ec, ddortiz5@espe.edu.ec.

advantage of the on/off characteristics of the CC plants, operating them during the day and shutting them down frequently at night.

Undoubtedly, the implementation of a combined-cycle power plant in big cities helps to produce clean energy with a higher capacity, decreasing pollution degree [7].

Although investment costs in CC plants are low, operating costs can be significant because depend on fossil fuel consumption for power generation [8]. Traditionally, these plants are controlled by Proportional-Integral-Derivative (PID) controllers [9]. Although, these controllers allow maintaining the variables in the desired values, they neither ensure low consumption of raw materials used for operation, nor allow for a detailed analysis of the system dynamics (i.e., transitory performance) [10].

Research works using predictive control strategies, implemented as centralized controllers, have been reported in the literature. In that context in [11], the design and evaluation of a MPC are presented at a supervision level. This MPC was applied to a dynamic simulator of a CC plant. The supervisory control strategy reduced fossil fuel consumption of the CC plant with integrated solar collectors. Similarly, in [12], a control strategy in the boiler level variable of a CC power plant is presented to determine the optimal references or set-points to minimize boiler operation cost. Finally, in [13], a comparison between a conventional PID controller and a generalized predictive control system is presented, where it is shown that advanced control has better results than a conventional controller.

All works described above use a centralized approach, where in addition to process controllers, a central controller is needed. The main problem occurs when the central control fails, which causes all controlled variables to stop operating properly. However, without adding an extra central controller it is still possible to ensure good performance of local controllers with a reduction of fossil fuel consumption. In this research work, different techniques of traditional proportional-integral (PI) and advanced control (fuzzy and MPC) are compared in order to select the strategy that allows obtaining a better performance of the controlled variables and less fossil fuel consumption.

### A. Combined-cycle plant description

A CC plant has two turbines, a gas turbine and a steam turbine, which generate electrical energy. These turbines are combined in a cycle so that the heat or gas flow is transferred between them. The CC configuration modeled and simulated in this work is shown in Fig. 1, as proposed in [9]. In these plants, a gas turbine generator produces electricity and the exhaust gases from gas turbine go to the boiler where most heat is extracted. In addition, water from the feed system enters the

economiser and is directed to the drum. The drum sends water to the elevator, where the heat produced by the furnace (which has fossil fuel and air as inputs) raises its temperature producing steam, which returns to the drum. This steam is sent to the superheater to increase its heat content. Superheated steam enters the high-pressure turbine and passes to the boiler superheater where its temperature is increased even further. Then, superheated steam is directed to the low-pressure steam turbines, and this turbine begins to turn producing mechanical energy which is transformed into electrical energy through a generator. Finally, the condenser located at the steam output causes the steam to condense and then be transformed into water that passes into feedwater and the process is repeated.

This research work focuses on boiler control as it is directly associated with fossil fuel consumption and the aim of this work is to improve controller performance, through advanced control strategies, in order to reduce fossil fuel consumption. This in turn reduces operating costs and environmental pollution.

The work content is organized as follows: Section II corresponds to the design of PI controllers, fuzzy logic-based control strategies, and model predictive control. Section III shows the results obtained for each implemented control strategy and their analysis. Finally, Section IV shows conclusions.

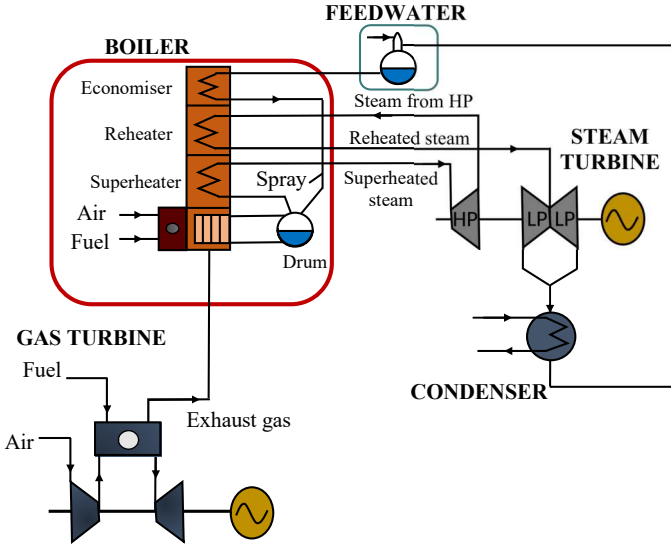


Fig. 1. Combined-cycle power plant configuration

## II. CONTROLLERS DESIGN

The boiler has four closed-loop control as shown in Fig. 2. In the first closed-loop control, the superheated steam pressure variable ( $p_s$ ) is controlled, and fuel flow variable ( $w_f$ ) is manipulated. In the second closed-loop control the drum water level variable ( $L$ ) is controlled and the feedwater flow variable ( $w_e$ ) is manipulated. In the third closed-loop control, the furnace gases pressure variable ( $p_G$ ) is controlled and air flow variable ( $w_A$ ) is manipulated. Finally, in the fourth closed-loop control, the superheated steam temperature variable ( $T_s$ ) is controlled and attemperator water flow variable ( $w_{att}$ ) is manipulated.

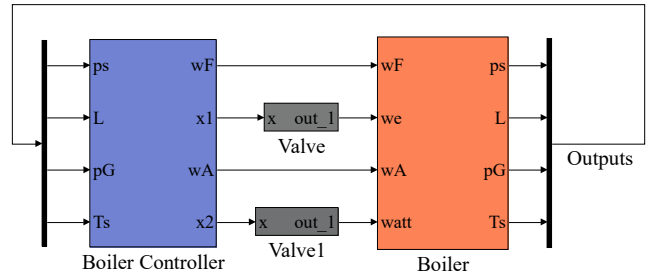


Fig. 2. Closed-loop control system of the CC plant boiler

In this section, the design of PI, fuzzy, and MPC controllers is performed for the local variables  $L$  and  $p_s$  of the CC plant boiler, which define the fuel consumption, therefore the operating cost of the plant. The other variables of the plant are controlled with PID algorithm, since they are not influencing the operating cost.

### A. PI Controller design

The PI control implemented is shown in (1), where  $K_p$  represents proportional gain,  $K_i$  the integral gain of the error  $e(s)$ . To obtain the gains, Lambda tuning technique is used considering the criteria  $\lambda = 3T$ , where  $\lambda$  is the tuning criteria. This requires a transfer function that represents the process described in (2), which contains the parameters  $K, T, \tau$  that represents the process gain, open-loop time constant of the process and delay respectively. With these parameters, tuning gains of the controller are obtained by replacing in (3) and (4) [14], [15].

$$U(s) = K_p e(s) + K_i \frac{e(s)}{s} \quad (1)$$

$$G(s) = \frac{K}{1 + Ts} e^{-\tau s} \quad (2)$$

$$K_p = \left(\frac{1}{K}\right) \left(\frac{\tau}{2} + \lambda\right) \quad (3)$$

$$K_i = \frac{K_p}{T + \frac{\tau}{2}} \quad (4)$$

The design gains obtained for PI controller, implemented in Section III of the results, are shown Table I.

TABLE I.  
DESIGN PARAMETERS OF PI CONTROLLERS

Variable	$K_p$	$K_i$
$p_s$	$2.3092 \times 10^{-6}$	$2.1756 \times 10^{-8}$
$L$	10	1

### B. Fuzzy logic-based control design

A fuzzy proportional-derivative (PD) controller with integral action at the output is designed and implemented. Fig. 3 illustrates the block-diagram model of the fuzzy controller. Control structure considers two inputs, error and error's rate of change, both multiplied by a proportional and a derivative gain,  $Kp_f$  and  $Kd_f$  respectively. As fuzzy output, the incremental

change in the manipulated variable is defined, which is multiplied by an integral gain  $Ki_f$ .

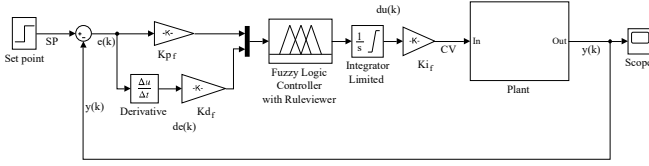


Fig. 3. PD fuzzy controller with integral action scheme

The two inputs, error and error's rate of change, are represented in 7 fuzzy sets, with trapezoidal membership functions at the ends and triangular functions at the rest, as shown in Fig. 4, with a membership degree between 0 and 1 for the output, on the other hand, 9 fuzzy sets with triangular membership functions are used, as shown in Fig. 5. The fuzzy sets in these figures are uniformly distributed on the boundaries  $[-1, +1]$  and are defined as NBB (negative biggest), NB (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medium), PB (positive big) and PBB (positive biggest) [16].

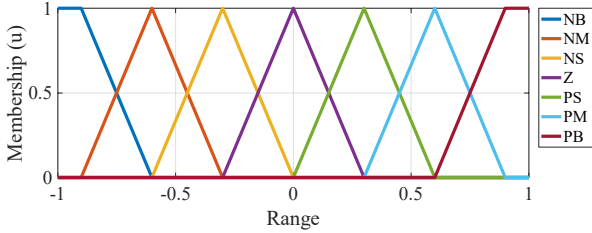


Fig. 4. Fuzzy sets of inputs variables

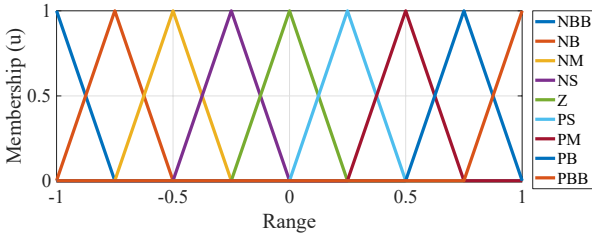


Fig. 5. Fuzzy sets of outputs variables

Combing the fuzzy sets of inputs and outputs, 49 control rules are generated. The established rules are based on the fuzzy control matrix proposed by McVicar-Whelan [17] [18], and are shown in Table II. The defuzzification is based on centroid.

TABLE II.  
FUZZY CONTROLLER RULES [18].

e/de	NB	NM	NS	Z	PS	PM	PB
NB	NBB	NBB	NBB	NB	NM	NS	Z
NM	NBB	NBB	NM	NM	NS	Z	PS
NS	NBB	NM	NS	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PS	PM	PBB
PM	NS	Z	PS	PM	PM	PBB	PBB
PB	Z	PS	PM	PB	PBB	PBB	PBB

The parameters design for fuzzy controller are obtained by trial and error technique, which are shown in Table III.

The design parameters obtained for fuzzy controller, implemented in Section III of the results, are shown in Table III.

TABLE III  
FUZZY CONTROLLER DESIGN PARAMETERS

Variable	$Kp_f$	$Ki_f$	$Kd_f$
$p_s$	0.1	1	8
$L$	0.7	10	5.8

### C. MPC controller design

The control architecture used for MPC controller is shown in Fig. 6, the components are the following: prediction model, optimization problem, and trajectory [19], [20].

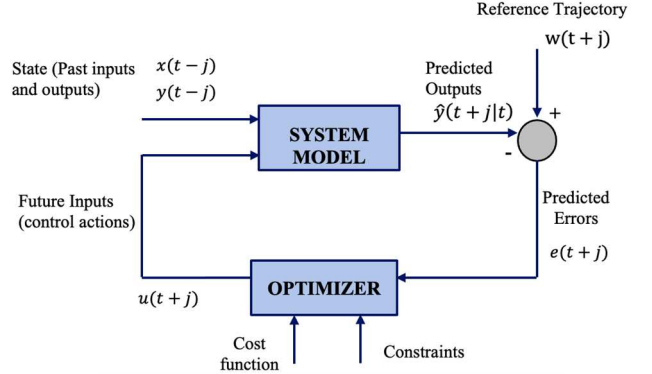


Fig. 6. MPC control architecture

Unlike PID and fuzzy controllers, MPC controllers minimize steady-state error while the variation in the control action is reduced, considering plant operation limitations. In this work, the objective function is defined by:

$$\begin{aligned} \text{Min } J(u) = & \sum_{j=1}^p \gamma_1 [\hat{y}(t+j|t) - w(t+j)]^2 \\ & + \sum_{j=1}^m \gamma_2 [\Delta u(t+j-1)]^2 \end{aligned} \quad (5)$$

Subject to:

$$y_{min} \leq y \leq y_{max} \quad (6)$$

$$u_{min} \leq u \leq u_{max} \quad (7)$$

where the term  $(\hat{y}(t+j|t) - w(t+j))^2$  corresponds to the quadratic steady-state error,  $w$  represents the set points or reference vector,  $\hat{y}$  is the output of the prediction model, and the second term  $[\Delta u(t+j-1)]^2$  corresponds to a minimum change in the control action, which allows proper actuator operation,  $\Delta u$  corresponds to the control action change.

The objective function (5) is subject to the linear inequality constraints of limits (6) and (7). Equation (6) corresponds to the constraint of the output variable or controlled variable ( $y$ ), which has an operating range between  $y_{min}$  to  $y_{max}$ . Also, the control action ( $u$ ) is restricted to ranges  $u_{min}$  to  $u_{max}$ , as shown in (7).

Finally,  $\gamma_1$  and  $\gamma_2$ , corresponds to the weights associated with the control objectives. Prediction horizon is defined by  $p$ , and control horizon by  $m$ . These parameters have been obtained by trial and error technique in order to reduce the steady-state error and a best performance of the actuators.

The state-space prediction model is defined by:

$$\dot{x}(t+1) = Ax(t) + Bu(t) \quad (8)$$

and

$$y(t) = Cx(t+1), \quad (9)$$

where the state matrices A, B (input matrices), and C (output matrix), are obtained using Matlab system identification toolbox, taking the input and output data from CC plant [16].

The design described above is applied to control the variables  $p_s$  and  $L$ .

The MPC design parameters used for the drum water level and superheated steam pressure, are shown in Table IV.

TABLE IV  
MPC DESIGN PARAMETERS

MPC design parameters	Variable	
	$p_s$	$L$
$p$	150 s	300 s
$m$	17 s	20 s
$\gamma_1$	8	15
$\gamma_2$	1.8	10
$u_{min}$	$4.525 \times 10^{-6}$ Pa	4.138 m
$u_{max}$	$5.3 \times 10^{-6}$ Pa	4.2 m
$y_{min}$	$4.525 \times 10^{-6}$ Pa	4.138 m
$y_{max}$	$5.3 \times 10^{-6}$ Pa	4.2 m

The matrices A, B and C of the state-space model of (8) and (9) for superheated steam pressure are shown in Tables V, VI and VII.

TABLE V  
MATRIX A OF THE VARIABLE  $p_s$

A	$x_1$	$x_2$	$x_3$	$x_4$
$x_1$	-0.01493	0.02806	0.003499	-0.008516
$x_2$	-0.060079	-0.02134	-0.01581	0.03992
$x_3$	-0.02427	-0.01429	-0.006907	0.07748
$x_4$	-0.1443	-0.1944	-0.2243	-0.2224

TABLE VI  
MATRIX B OF THE VARIABLE  $p_s$

B	$U_1$
$x_1$	$-1.087 \times 10^{-8}$
$x_2$	$8.955 \times 10^{-8}$
$x_3$	$1.082 \times 10^{-8}$
$x_4$	$7.386 \times 10^{-7}$

TABLE VII  
MATRIX C OF THE VARIABLE  $p_s$

C	$x_1$	$x_2$	$x_3$	$x_4$
$y_1$	$7.773 \times 10^5$	$9.708 \times 10^5$	6028	3114

The values of matrices A, B and C of the state-space model for drum water level are shown in Tables VIII, IX and X.

TABLE VIII  
MATRIX A OF THE VARIABLE  $L$

A	$x_1$	$x_2$	$x_3$	$x_4$
$x_1$	-0.07332	0.07459	-0.01205	-0.002709
$x_2$	-0.2536	-0.0372	0.008694	0.001265
$x_3$	0.2969	0.09247	-0.08235	-0.02581
$x_4$	0.5947	0.1243	-0.2166	-0.1611

TABLE IX  
MATRIX B OF THE VARIABLE  $L$

B	$U_1$
$x_1$	-2.23
$x_2$	-7.562
$x_3$	9.353
$x_4$	19.67

TABLE X  
MATRIX C OF THE VARIABLE  $L$

C	$x_1$	$x_2$	$x_3$	$x_4$
$y_1$	-0.03368	-0.003028	$5.007 \times 10^{-5}$	$2.721 \times 10^{-5}$

### III. RESULTS

This section shows the results obtained by implementing the three control strategies described in Section II.

#### A. Simulated plant parameters

The boiler has the following physical operating limits that are considered in the MPC controllers.

- The drum water level ( $L$ ) must have a minimum level 4.138m.
- The feedwater flow ( $w_e$ ) must be injected a minimum of 10 Kg/s and a maximum of 14 Kg/s.
- The fossil fuel flow ( $w_f$ ) must be injected a minimum of 13 Kg/s and a maximum of 16 Kg/s.

#### B. Performance and comparative analysis between the proposed control strategies for superheated steam pressure $p_s$

The controllers designed in Section II are implemented and the results are shown in Fig. 7, for a total simulation time of 2400 seconds. Controllers performance are analyzed by giving a reference change in  $p_s$  at 1000 seconds and a disturbance (reference change in  $L$ ) at 2000 seconds. Fig. 7 illustrates how the PI controller presents overshoot, while the fuzzy controller and MPC do not. For the MPC controller, the settling time is shorter, even when there is a disturbance. Table XI shows the performance parameters of the controllers. This table shows that MPC controller has better performance.

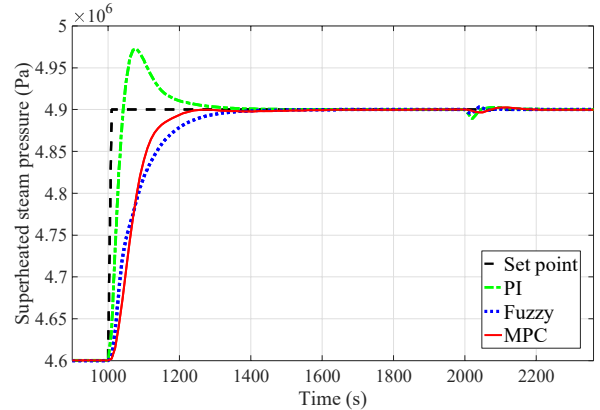


Fig. 7. System response in variable  $p_s$  with PI, fuzzy and MPC controllers

Parameters	PI	Fuzzy	MPC
Overshoot	1.47%	0 %	0%
Settling time	368.26 s	314.15 s	211.24 s
Steady-state error	17.86 Pa	2.72 Pa	1.79 Pa

### C. Performance and comparative analysis between the proposed control strategies for drum water level $L$ .

Fig. 8 shows the results for the control of the drum water level  $L$ . The PI controller presents overshoot again, whereas fuzzy controller and MPC do not present overshoot at reference changes in  $L$ . However, for this experiment, the MPC's settling time is greater than the fuzzy controller. Table XII shows the performance parameters of the controllers, which also illustrates the greater settling time of MPC controller compared to the other controllers. This is a result of the tuning strategy of the MPC controller, because its design priority was to reduce fossil fuel consumption; thus, the response of the MPC presents a longer settling time compared to other control strategies in order to achieve the required minimum fossil fuel consumption.

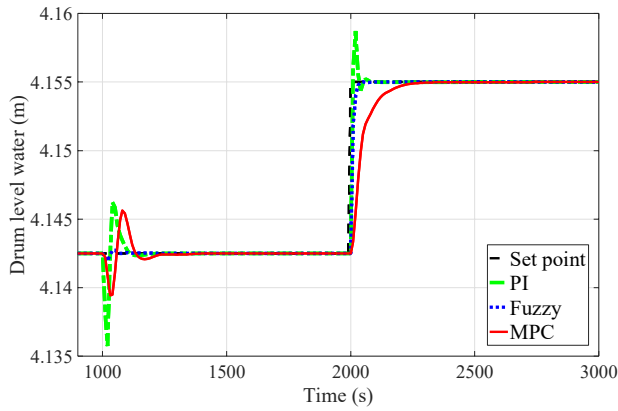


Fig. 8. System response in variable  $L$  with PI, fuzzy and MPC controllers

Parameters	PI	Fuzzy	MPC
Overshoot	0.0898%	0.000514%	0%
Settling time	67.23 s	49.87 s	228.61 s
Steady state error	$6.95 \times 10^{-11}$ m	$1.06 \times 10^{-12}$ m	$8.84 \times 10^{-10}$ m

### D. Comparative analysis of fossil fuel consumption

Fossil fuel consumption under the same conditions indicated in the previous section is presented in Fig. 9. It can be seen that MPC controller is one with the lowest fossil fuel consumption. Table XIII shows the parameters corresponding to the manipulated variable  $w_f$  and the saving percentage.

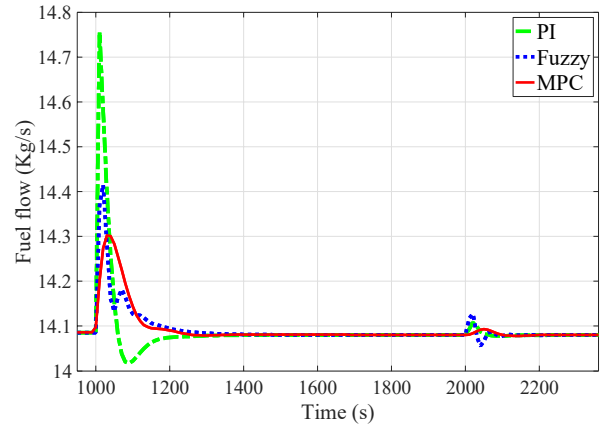


Fig. 9. Comparative graph of fossil fuel flow

Parameters	PI	Fuzzy	MPC
Maximum peak value	14.76 Kg/s	14.42 Kg/s	14.30 Kg/s
Saving	0%	2.31%	3.08%

Considering the proposed objective of reducing fossil fuel consumption, MPC controller is the one that should be selected in a real scenario, because it achieved lower fossil fuel consumption compared to other controllers.

## IV. CONCLUSIONS

A conventional PI controller and two advanced controllers, fuzzy and MPC, have been designed for the variables superheated steam pressure and drum water level of the boiler of the CC power plant. The results show that the MPC controller presents a lower fossil fuel consumption, with a saving of 3.08%, due to its better performance in terms of maximum overshoot and steady-state error compared to the fuzzy and PI controllers. The water level of the dome, with the fuzzy controller, stabilizes faster than the MPC controller, however the fossil fuel consumption is higher. Since the main objective is to reduce fossil fuel consumption, the MPC is established as the best controller.

Since the good performance of predictive control has been verified in this research work, MPC is a promising control strategy for future applications. For instance, it might be applied in the design of distributed predictive control algorithms, including the minimization of fossil fuel consumption in the formulation, which might be considered as a consensus variable.

## ACKNOWLEDGMENT

This work is part of the projects CONTROL AND OPTIMAL MANAGEMENT OF ISOLATED MICROGRIDS, and 2020-EXT-007 from the Research Group of Propagation, Electronic Control, and Networking (PROCONET) of Universidad de las Fuerzas Armadas ESPE. This work has been partially supported by VLIR-UOS project number EC2020SIN322A101.



## REFERENCE

- [1] C. Mardones and C. García, "Effectiveness of CO<sub>2</sub> taxes on thermoelectric power plants and industrial plants," *Energy*, vol. 206, no. 118157, 2020.
- [2] M. Zoghi, H. Habibi, A. Chitsaz and M. Ayazpour, "Multi-criteria performance comparison between a novel and two conventional configurations of natural gas – driven combined cycle power plant based on a hybrid multi-objective optimization.," *Thermal Science and Engineering progress*, vol. 19, no. 100597, 2020.
- [3] R. Pérez and I. Gerson, "Reconversión de una planta termoeléctrica convencional en una central de ciclo combinado.," Universidad Nacional de Ingeniería, Nicaragua, 2016.
- [4] M. I. Hossain, I. A. Zissan, M. S. M. Khan, Y. R. Tushar and T. Jamal, Prospect of Combined Cycle Power Plant over Conventional Single Cycle Power Plants in Bangladesh: A Case Study, International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT) 2014, 2014.
- [5] D. Sáez and A. Cipriano, "Fuzzy Models Based Economic Predictive Control for a Combined Cycle Power Plant Boiler," in *Proceedings of the 1999 IEEE International Symposium on Intelligent Control Intelligent Systems and Semiotics*, Cambridge, 1999.
- [6] B.-K. Lee and Y.-H. Shin, "The integrated monitoring and control system for the combines cycle power plant.," in *International Conference on Control, Automation and Systems.*, Seoul, 2008.
- [7] D. Sáez and A. Cipriano, "Economic optimal control with environmental constraints for combined cycle power plants.," in *IECON '98. Proceedings of the 24th Annual Conference of the IEEE Industrial Electronics Societ*, 1998.
- [8] J. Kotowicz, M. Brzeczek and M. Job, "The thermodynamic and economic characteristics of the modern combined cycle power plant with gas turbine steam cooling.," *Energy*, no. 164, pp. 359-376, 2018.
- [9] A. Ordys, A. Pike, M. Johnson, R. Katebi and M. Grimbale, *Modelling and Simulation of Power Generation Plants*, Scotland: Springer, 1994.
- [10] J. Rúa, M. Hillestad and L. O. Nord, "Model predictive control for combined cycles integrated with CO<sub>2</sub> capture plants," *Computers & Chemical Engineering*, vol. 146, 2021.
- [11] C. Ponce, "Model Predictive Control Strategy Evaluation of an Integrated Solar Combined Cycle Plant," in *IEEE International Conference on Automatica (ICA-ACCA)*, 2016.
- [12] D. Sáez and A. Cipriano, "Economic optimal control for a combined cycle power plant boiler," in *1999 European Control Conference (ECC)*, Karlsruhe, 1999.
- [13] X. Liu, G. Hou and C. Yin, "An Energy Saving Control for Combined Cycle Power Plant by Supervisory Predictive Scheme.," in *Proceedings of the European Control Conference 2007*, Kos, 2007.
- [14] E. Pruna, E. Sasig and S. Mullo, "PI and PID controller tuning tool based on the lambda method.," *2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON)*, pp. 1-6, 2017.
- [15] E. Pruna, I. Escobar, J. Llanos, A. Navas and J. Zambrano, "Evaluación del desempeño de los controladores lógico y difuso y proporcional integral derivativo en una estación de caudal.," *Revista Científica INFOCIENCIA. ESPE extensión Latacunga*, vol. 8, no. ISSN 1390 – 339X, pp. 72-77, 2014.
- [16] B. Dennis, T. Orrala, J. Llanos, D. Ortiz-Villalba, A.-A. Diego and C. Ponce, "Fuzzy and PID controllers performance analysis for a combined-cycle thermal power plant," *CIT 2020, XV International Multidisciplinary Congress on Science and Technology*, 2020, to be published.
- [17] P. MacVicar-Whelan, "Fuzzy sets for man-machineinteraction," *International Journal of Man-Machine Studies*, vol. 8, pp. 687-697, 1976.
- [18] B. Jager, P. Neugebauer, R. Kriesten, N. Parspour and C. Gutenkunst, "Torque-Vectoring Stability Control of a Four Wheel Drive Electric Vehicle," in *IEEE Intelligent Vehicles Symposium*, Seoul, 2015.
- [19] C. Bordons, F. García-Torres and M. Ridao, *Model Predictive Control of Microgrids*, Sevilla: Springer, 2020, pp. 25-32.
- [20] J. Llanos-Proaño, M. Pilatasig, D. Curay and A. Vaca, "Design and implementation of a Model Predictive Control for a pressure control plant (Diseño e implementación de un Controlador Predictivo basado en Modelo MPC para una planta de control de presión)," *2016 IEEE International Conference on Automatica (ICA-ACCA)*, pp. 1-7, 2016.