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Nonlinear Fuzzy Model Predictive Control of the TCP-100 Parabolic Trough Plant

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Abstract

Advanced control strategies can play an important role in improving the efficiency of solar plants. In particular, linear model predictive control strategies have been applied successfully when controlling solar trough plants. However, if the control algorithm uses a linear model associated only with one operating point, when the plant is working far from the design conditions, the performance of the controller may deteriorate.

In this paper, a fuzzy model-based nonlinear model predictive controller is applied to the new TCP-100 solar facility. The control strategy uses a fuzzy model of the plant for predicting the future evolution of the outlet temperature. This approach reduces the computational time of the nonlinear model predictive control strategy and allows to solve it much faster than using the full nonlinear model.

Keywords: Control, Model Predictive Controller, Fuzzy model, solar trough, Nonlinear MPC.

1 Introduction

There is a pressing need to increase the use of renewable energy sources. The need to reduce the environmental impact produced by the use of fossil energies is a very important objective as stated by the International Renewable Energy Agency, the European Commission and the National American Academy [1, 2]. As far as the renewable energy sources is concerned, solar energy is the most abundant renewable energy available. In fact, wind and most of the hydraulic energies depend on solar energy [7, 5].

Many solar energy plants have been built around the world in the last 20 years using multiple technologies: parabolic trough, solar power towers, Fresnel collector, solar dish, solar Furnaces etc. In this paper we focus on parabolic trough solar plants. Many examples of solar thermal plants can be found in [19]. One of the first operative solar trough plant was the ACUREX field at the Plataforma Solar de Almería and many control strategies for solar systems have been tested here [10, 29, 30].

The use of solar energy has to address two important problems. The first is to make it economical and competitive. This can be achieved by reducing investment and operating cost and by increasing the overall performance [6]. Advanced control and optimization techniques play a decisive role dealing with those issues.

The control objective in this kind of plants is to regulate the outlet temperature around a desired set-point. The application of control strategies to solar plants faces two problems: a) the primary energy source, solar radiation, cannot be manipulated acting as a disturbance and b) the highly nonlinear nature of the process [16]. This produces that conventional linear model predictive control strategies do not perform properly when working far from the design point. Nonlinear model predictive control strategies can be used but the problem is that the computational effort is much higher than solving the linear case and attaining the global optimum is not ensured [26]. Several approximations to solve the nonlinear problem can be found in literature [3, 22, 24] but they do not solve the full constrained nonlinear problem. One of the problems is that the use of the full nonlinear model to predict the future response is the computational time invested. One possible approach is using a fuzzy algorithm to learn the evolution of the distributed parameter model and using it as a prediction model.

Some examples of using fuzzy control strategies have been used in control of solar energy plants [9]. In

[15], a fuzzy predictive controller was applied to the ACUREX plant. The controller was tested on simulation and compared to a classical MPC strategy. More recently, in [8] a fuzzy algorithm was used to implement the selection of the operation mode for a solar cooling plant. This approach avoided the need of solving a hard nonlinear optimization problem.

Thanks to the structure of fuzzy systems, there have been several simplified ways of implementing Fuzzy Model-based Predictive Control (FMPC). Although with suboptimal solutions, FMPC presents better performance than strategies based on linear models. Some techniques take advantage of the structure of the Takagi-Sugeno models, designing a linear MPC controller $u_j(k)$ for each consequent, calculating the controller output as

$$u(k) = \sum_{j=1}^{L} \frac{\prod_{i=1}^{n} \mu_{ij}(k)}{\sum_{j=1}^{N} \prod_{i=1}^{n} \mu_{ij}(k)}(k) u_j(k) \qquad (1)$$

Where $\mu_{ij}(k)$ membership degree of input i to the membership function defined by the rule j for such input. N and n are number of rules and inputs respectively. This technique and its variants can be seen in [14, 18]. Although this technique is simple enough to be implemented in industry, it presents a serious problem with increasing fuzzy model rules, when it is accurate enough. In [13] a complexity reduction technique is presented to solve this issue. The global optimum is also not always found and the design may not guarantee stability. In [25] an explicit formulation of a Fuzzy Generalized Predictive Control (FGPC) is obtained without restrictions, guaranteeing stability. Some FMPC strategies linearize the fuzzy model around an operating point, solving a linear MPC problem [4, 27, 31, 28].

Recently, MPC for Programmable Logic Controller (PLC) have been presented [23], in which, using real-time optimization function blocks, developed under the IEC 61131 standard, allow the implementation of MPC (with constraints) in PLCs. This, together with the existence of the IEC 61131-7 part, which standardizes the fuzzy control language for PLCs, can allow a practical realization of the FMPC. In this paper, a fuzzy predictive controller is designed and tested for the new PTC TCP-100 research facility at the PSA, currently under construction, is presented. The control strategy is tested on the mathematical model of a loop described in [17], because the plant is not operative yet. A nonlinear fuzzy model is obtained to predict the future evolution of the plant. The main advantage of using a fuzzy model instead of the full nonlinear model is that the computation time is much faster.

The paper is organized as follows: section 2 describes the plant TCP-100. Section 3 presents the mathematical model used in this paper to test the controller. The fuzzy model of the plant is presented in section 4. Section 5 describes the fuzzy model-based predictive control strategy proposed in this work and some simulation results. Finally, a section providing some concluding remarks is included.

Figure 1: Lateral view of the first TCP-100 PTC in the first loop at Pataforma Solar de Almería (PSA-CIEMAT). It is composed of 8 modules of 12 meters length. Courtesy of PSA.

Figure 2: Top view of the TCP-100 field at Plataforma Solar de Almería (PSA-CIEMAT). Courtesy of the PSA.

2 TCP-100 solar field description

The TPC-100 solar facility has been built at the Plataforma Solar de Almería (CIEMAT) replacing the old ACUREX solar trough plants which operated more than 30 years. The new plant is designed to be an experimental plant to develop research in automatic control of parabolic trough solar field.

The new TCP-100 solar field is composed of three North-South oriented loops of parabolic trough collectors (PTC). Each loop consists of two PTCs of 96 m long each placed in series. Fig. 1 shows the first PTC in the first loop.

The PTCs in each loop are connected in the South extreme, and the *colder* PTC will be always the first in the row, placed at the right part of each loop in Fig. 2.

Some novel features are implemented in the new field compared to the old ACUREX plant. These aimed at implementing novel advanced control techniques which may use multiple measurements provided by all sensors located at several places along the loop. Some of these characteristics are:

- Inlet and outlet solar field temperature sensors.
- For each loop, inlet and outlet temperatures are measured. Inside the loop, for each PTC: inlet, outlet and middle point temperatures sensors are located.
- Volumetric flow rate for each loop.
- Control valves in each of the loops to regulate mass flow rate in each loop.

A more complete description can be found in [17].

3 Mathematical model of a parabolic trough loop

The mathematical model of the parabolic trough loop used in this paper is presented. Since the TCP-100 solar facility is formed by 3 parallel loops, the whole plant model can be implemented by connecting the model loops in parallel.

Each of the TCP-100 loops consists of two eight module PTCs suitably connected in series. Each collector measures 96 m long and the passive parts joining them (parts where solar radiation does not reach the tube) measures 24 m long.

This sort of systems can be modeled by using a lumped description (concentrated parameter model) or by a distributed parameter model [11]. The approach used here to simulate the plant is the distributed parameter model as it describes better the system dynamics.

3.1 Distributed parameter model

The model equations are the same used in the ACUREX solar field developed in [11] and [6]. The model consists of the following system of non-linear partial differential equations (PDE) describing the energy balance:

$$\rho_m C_m A_m \frac{\partial T_m}{\partial t} = I K_{opt} cos(\theta) G - H_l G (T_m - Ta) - L H_t (T_m - T_f) \quad (2)$$

$$\rho_f C_f A_f \frac{\partial T_f}{\partial t} + \rho_f C_f q \frac{\partial T_f}{\partial x} = L H_t (T_m - T_f) \quad (3)$$

Where the subindex m refers to metal and f refers to the fluid. The model parameters and their units are shown in table 1.

Symbol	Description	Units
t	Time	s
x	Space	m
ρ	Density	Kgm^{-3}
C	Specific heat capacity	$JK^{-1}kg^{-1}$
A	Cross Sectional Area	m^2
$T(x,y)$	Temperature	K,°C
$q(t)$	Oil flow rate	m^3s^{-1}
$I(t)$	Solar Radiation	Wm^{-2}
$cos(\theta)$	Geometric efficiency	Unitless
K_{opt}	Optical efficiency	Unitless
G	Collector Aperture	m
$T_a(t)$	Ambient Temperature	K,°C
H_l	Global coefficient of thermal loss	Wm^{-2}°C^{-1}
H_t	Coefficient of heat transmission metal-fluid	Wm^{-2}°C^{-1}
L	wetted perimeter	m

Table 1: Parameters description

The density and specific heat of the fluid depend on the temperature. The coefficient of heat transmission depends not only on the temperature value but on the oil flow as explained in [20].

The heat transfer fluid (HTF) is Syltherm800. Its properties have been obtained using data in the datasheet. The mathematical expressions are described in detail in [17]. The density and the specific heat of the fluid can be computed as follows:

$$\rho_f = -0.00048098 T_f^2 - 0.811 T_f + 953.65 \quad (4)$$

$$C_f = 0.0000001561 T_f^2 + 1.70711 T_f + 1574.2795 \quad (5)$$

And the coefficient of heat transmission can be computed using the equation (6):

$$\begin{aligned} Hv(T) &= 2 \cdot (-0.00016213 T_f^3 + 1.221 T_f^3 \\ &\quad + 115.9983 T_f + 12659.697) \\ H_t &= Hv(T) q^{0.8} \end{aligned} \quad (6)$$

The thermal losses coefficient depends on the working temperature and the ambient temperature. It has been estimated considering that the overall thermal losses for 400 °C are about 265 W/m^2 as the design conditions for the metal tube stated [17].

The optical efficiency, K_{opt}, takes into account factors such as reflectivity, absorptance, interception factor and others. The peak optical efficiency is about 0.76 according to the plant technical report.

The geometric efficiency, $cos(theta)$, is determined by the position of the mirrors respect the radiation beam vector. It depends on hourly angle, solar hour, declination, Julianne day, local latitude and collector dimen-

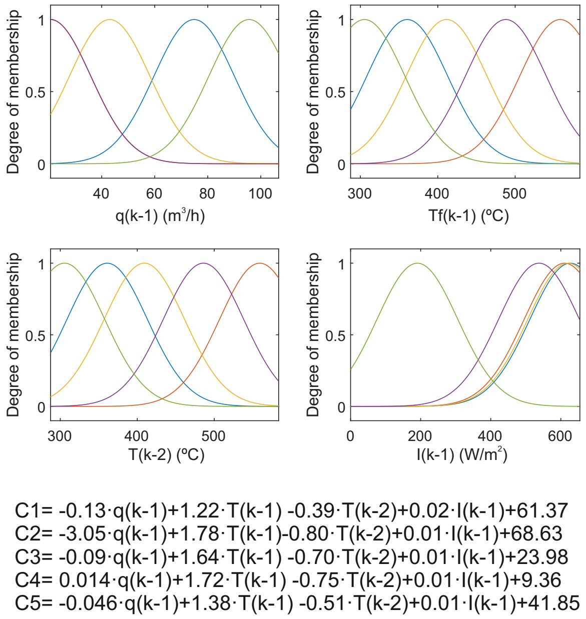

Figure 3: Membership functions and consequents results from SC over process data.

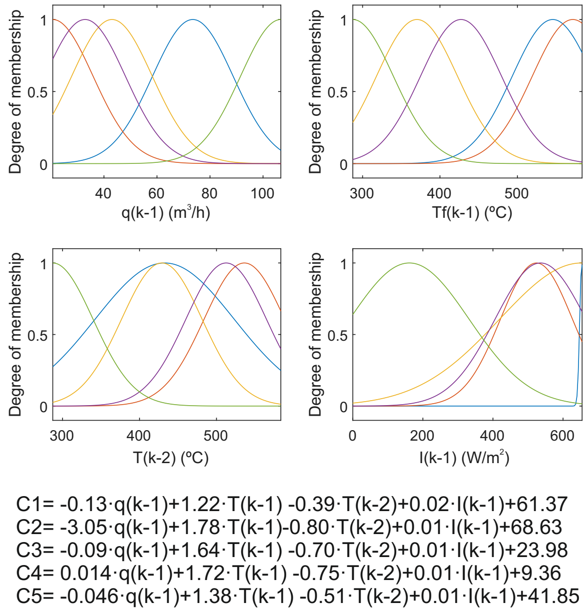

Figure 4: Membership functions and consequents final result.

sions. The complex calculations needed for obtaining these parameters are shown in [17].

4 Fuzzy model of a parabolic trough loop

For the design of the fuzzy inference system (FIS), the data generated by the distributed parameter model described above were used, with a sampling time of 25 s. Subtractive Clustering (SC) [12] is used to obtain an initial structure with which, through the grouping of data in areas of the input space, the membership and consequent functions are obtained, ready to be subsequently trained. Observing the relationships between the variables in equations 2 and 3 and considering second order local models, the following vector of inputs is chosen: $[q(k-1), T(k-1), T(k-2), I(k-1)]$, where q is the oil flow rate in m^3/h, T is the outlet temperature (in ^oC) and I, the Direct Normal Irradiance (DNI) in W/m^2.

Figure 3 shows the antecedents and the consequents after using SC. After obtaining the initial fuzzy system, a data set with different values of steps in the input flow rate and different days with irradiance perturbations has been prepared. With this data set, a Particle Swarm Optimization algorithm [21] has been used to fit the membership functions of the initial fuzzy system to the data. To avoid overfitting of the new adjusted FIS, validation data have been reserved separately. Figure 4 shows the result of the training.

Figure 4 shows the antecedents and the consequents after the optimization process. Using a validation data set for the resulting FIS, the root mean square error. It should be noted that the model is auto-regressive, and it uses its previous out to feed two inputs. Figure 5 depicts the difference between the actual temperature and the model result.

5 Fuzzy model predictive control strategy

The control scheme is shown in Figure 6. With the current sampling k, the fuzzy model predicts the output temperature value, if the system evolves forward in time N_p. An optimizer uses the fuzzy model to calculate what sequence of flow rate values q should be taken to minimize the following cost function:

$$J(N_p, N_c, \delta, \lambda) = \sum_{j=1}^{N_p} \delta \left[\widehat{T}(k+j \mid k) - T_{REF}(k+j) \right]^2 + \sum_{j=1}^{N_c} \lambda \left[\Delta q(k+j-1) \right]^2, \tag{7}$$

Where $\widehat{T}(k+j \mid k)$ is the predicted outlet temperature given by the FIS, from time k forward j samples (chosen, due to model structure, 25 s). $\Delta q(k) = q(k) - q(k-1)$ is the increase in control action. N_p and N_c are known as prediction horizon and control horizon, respectively.$\delta, \lambda \in \mathbb{R}$ are weights used to penalize each term. To improve the performance of the optimizer, a half-scale constrained nonlinear optimization algorithm, such as *active-set*, has been used. Once

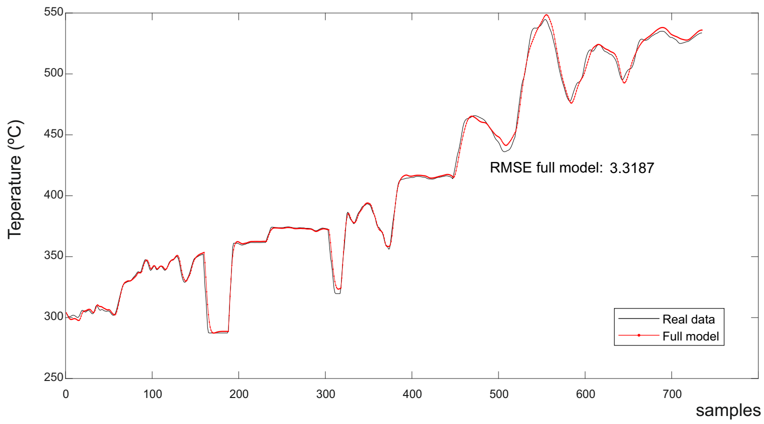

Figure 5: Comparison between real temperature output data and FIS output.

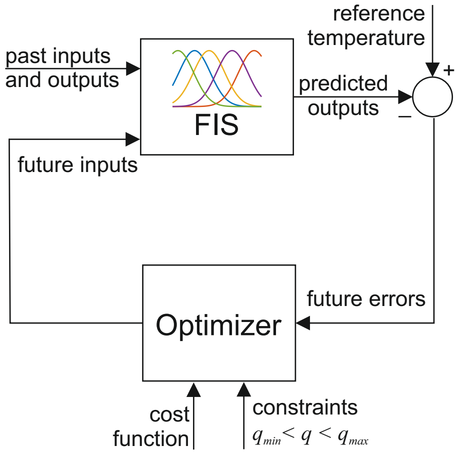

Figure 6: FMPC scheme

Table 2: Control strategies performance.

Control strategy	IAE	Average comp. time
FMPC	$5,65^oC$	0,43s
DPMPC	$5,35^oC$	29,72s

the $\Delta q(k+j-1)$ ahead sequence is solved, only the first element $\Delta q(k)$ of the sequence is applied on the system and the optimization process is recalculated again, after advancing an instant of time. Figure 2 shows the result of the FMPC control strategy using real irradiance data from a day with many irradiance perturbations. The following values were chosen: $N_p = 12, N_c = 6, \delta = 1, \lambda = 25$. It can be seen that the performance of the controller is quite good following references and rejecting disturbances.

Figure 8 shows a comparison between this strategy and another one where the model is based on the distributed parameters model (DPMPC) described in equations 2 and 3. In fact, the IAE is similar but, as can be seen in Table 2, the average computation time for the calculation of the control action makes the FMPC strategy suitable for plant control.

6 Conclusion

In this work a nonlinear predictive controller based on a fuzzy model is applied to the new TCP-100 solar installation. The control strategy uses a Takagi-Sugeno fuzzy model of the plant to predict the future evolution of the output temperature. The approach reduces the computational time of the nonlinear model predictive control strategy and allows it to be solved much faster than using the full nonlinear model. The strategy has been tested in simulation, using a concentrated parameter model of the plant under construction and real irradiance data. In addition, thanks to new developments in the use of MPC in mid-range PLCs and the use of the IEC 61131-7 standard, the strategy can be implemented in industrial controllers.

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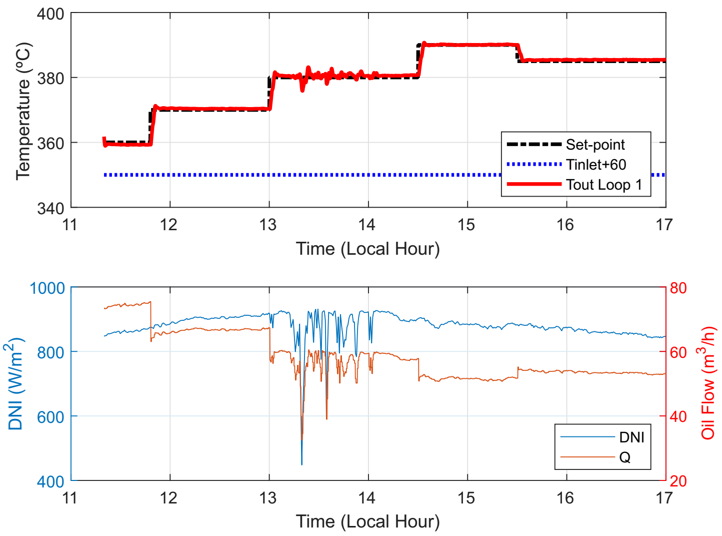

Figure 7: FMPC performance. Day with irradiance perturbations

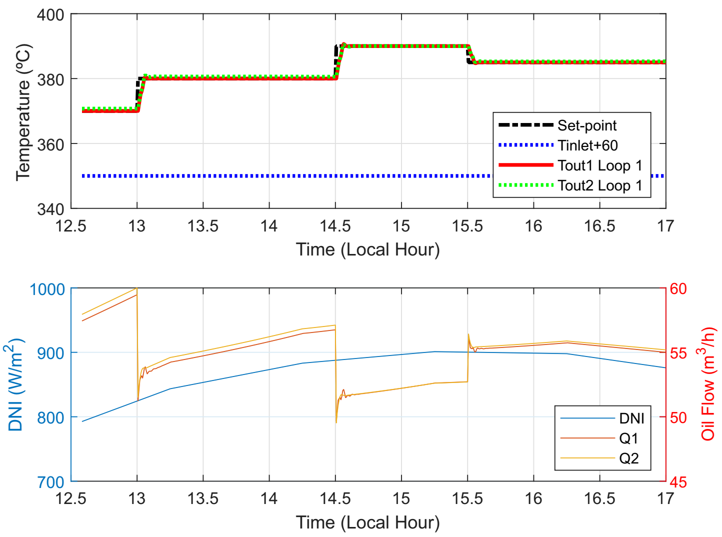

Figure 8: FMPC (Tout 1) performance Vs DPMPC (Tout 2)

References

[1] N. Academy, National academy of engineering. grand challenges for engineering (2008).
URL www.engineeringchallenges.org

[2] I. R. E. Agency, International renewable energy agency (November 2012).
URL http://www.irena.org

[3] G. A. Andrade, D. J. Pagano, J. D. Álvarez, M. Berenguel, A practical NMPC with robustness of stability applied to distributed solar power plants, Solar Energy 92 (2013) 106–122.

[4] R. Babuska, J. Sousa, H. Verbruggen, Predictive control of nonlinear systems based on fuzzy and neural models, European control conference (1999) 667.

[5] M. J. Blanco, L. R. Santigosa, Advances in Concentrating Solar Thermal Research and Technology, 1st Edition, Woodhead Publishing, 2017.

[6] E. F. Camacho, M. Berenguel, F. R. Rubio, D. Martinez, Control of Solar Energy Systems, Springer-Verlag, 2012.

[7] E. F. Camacho, A. J. Gallego, Optimal operation in solar trough plants: a case study, Solar Energy 95 (2013) 106–117.

[8] E. F. Camacho, A. J. Gallego, J. M. Escano, A. Sánchez, Hybrid nonlinear mpc of a solar cooling plant, Energies 12.

[9] E. F. Camacho, F. R. Rubio, M. Berenguel, Advanced control of solar plants, Springer-Verlag, 1997.

[10] E. F. Camacho, F. R. Rubio, M. Berenguel, L. Valenzuela, A survey on control schemes for distributed solar collector fields. part ii: advanced control approaches, Solar Energy 81 (2007) 1252–1272.

[11] R. Carmona, Analysis, modeling and control of a distributed solar collector field with a one-axis tracking system, Ph.D. thesis, Universidad de Sevilla (1985).

[12] S. L. Chiu, Fuzzy model identification based on cluster estimation, Journal of intelligent and Fuzzy systems 2 (3) (1994) 267–278.

[13] J. M. Escaño, C. Bordons, K. Witheephanich, F. Gómez-Estern, Fuzzy model predictive control: Complexity reduction for implementation in industrial systems, Int. J. Fuzzy Syst. 21 (2019) 2008–2020.

[14] J. Escaño, C. Bordons, C. Vilas, M. García, A. Alonso, Neurofuzzy model based predictive control for thermal batch processes, Journal of Process Control 19 (9) (2009) 1566 – 1575.

[15] A. Flores, D. Sáez, J. Araya, M. Berenguel, A. Cipriano, Fuzzy predictive control of a solar power plant, IEEE Transactions on Fuzzy Systems 13 (1) (2005) 58–68.

[16] A. J. Gallego, G. M. Merello, M. Berenguel, E. F. Camacho, Gain scheduling model predictive control of a fresnel collector field, Control Engineering Practice 82 (2019) 1–13.

[17] A. J. Gallego, L. J. Yebra, E. F. Camacho, A. J. Sánchez, Mathematical modeling of the parabolic trough collector field of the tcp-100 research plant, in: 9th EUROSIM Congress on Modelling and Simulation, 12-16 September (Finland), 2016.

[18] Y. L. Huang, H. H. Lou, J. P. Gong, T. F. Edgar, Fuzzy model predictive control, IEEE Transactions on Fuzzy Systems 8 (6) (2000) 665–678.

[19] M. T. Islam, N. Huda, A. B. Abdullah, R. Saidur, A comprehensive review of state of the art concentrating solar power (csp) technologies: Current status and research trends, Renewable and Sustainable Energy Reviews 91 (2018) 987–1018.

[20] R. Karwa, Heat and Mass Transfer, 1st Edition, 2020.

[21] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proceedings of ICNN'95 - International Conference on Neural Networks, Vol. 4, 1995, pp. 1942–1948 vol.4.

[22] B. Khoukhi, M. Tadjine, M. S. Boucherit, Nonlinear continuous-time generalized predictive control of solar power plant, International Journal for Simulation and Multidisciplinary Design Optimization A3 (6) (2015) 1–12.

[23] P. Krupa, D. Limon, T. Alamo, Implementation of model predictive control in programmable logic controllers, IEEE Transactions on Control Systems Technology (2020) 1–14.

[24] D. M. Lima, J. L. Normey, T. L. M. Santos, Temperature control in a solar collector field using filtered dynamic matrix control, ISA Transactions 62 (2016) 39–49.

[25] C.-H. Lu, C.-C. Tsai, Generalized predictive control using recurrent fuzzy neural networks for industrial processes, Journal of Process Control 17 (1) (2007) 83 – 92.

[26] L. Magni, D. M. Raimondo, F. Allgower, Nonlinear Model Predictive Control: Towards New Challenging Applications, Springer Verlag, 2009.

[27] P. Marusak, P. Tatjewski, Stability analysis of nonlinear control systems with unconstrained fuzzy predictive controllers, Archives of Control Sciences Vol. 12, no. 3 (2002) 267–288.

[28] S. Mollov, R. Babuska, J. Abonyi, H. B. Verbruggen, Effective optimization for fuzzy model predictive control, IEEE Transactions on Fuzzy Systems 12 (5) (2004) 661–675.

[29] A. N. Reviriego, F. H. del Olmo, L. Álvarez-Barcia, Nonlinear adaptive control of heat transfer fluid temperature in a parabolic trough solar power plant, Energies 10 (2017) 1–12.

[30] A. J. Sánchez, A. J. Gallego, J. M. Escaño, E. F. Camacho, Temperature homogenization of a solar trough field for performance improvement, Solar Energy. 165C (2018) 1–9.

[31] P. Tatjewski, Advanced control of industrial processes: structures and algorithms, Advances in industrial control, Springer, 2007.