Residential MPC Controller Performance in a Household with PV Microgeneration

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***Abstract*—The energy demand of the residential sector and the adjacent option for fossil fuels has negative consequences by both greenhouse gases (GHG), CO_2 and other air pollutants emissions. The home energy demand consists mainly of energy requirements for space and water heating along with the energy dedicated for appliances. Therefore, different strategies that aim to stimulate an efficient use of energy need to be reinforced at all levels of human activity. In this paper a comparison is made between a Model Predictive Control (MPC) model, the ON/OFF and proportional-integral-derivative (PID) control models of an air conditioning unit AC system controlling the temperature of a room. The model of the house with local Photovoltaic (PV) solar microgeneration is assumed to be located in a Portuguese city. The household of the case study is subject to the local solar irradiance, temperature and electricity tariff of a summer day.**

***Index Terms*—Model predictive control; Energy management controller; Photovoltaic system; Residential building.**

NOMENCLATURE

A_w	The wall area.
A	The state (or system) matrix.
B	The input matrix.
C	The output matrix.
C_{in}	The thermal capacitance of the indoor air.
C_{wl}	The thermal capacitance of the wall.
h_o	The combined convection and radiation heat transfer coefficient.
I	The identity matrix.
$J(k)$	Infinite horizon performance cost.
k	Sampling instant and the current control interval.
$k+i$	The time instant associated to the future state prediction for $i=1...N$.
N	The prediction horizon.
M	Positive definite matrix.
P	The control horizon.
Q_{ac}	The cooling power input to the room.
Q_s	The heat flow into an exterior surface of the house subjected to solar radiation
R_{wd}	The thermal resistance of the windows.
R_{wl}	The thermal resistance of the wall.
$S(t)$	A binary variable that emulates the turn-on and turn-off of the thermostat.
T_{in}	The temperature of the room.
T_{out}	The ambient temperature.
T_s	The wall surface temperature.
T_{wl}	The wall temperature.
U	The non-empty set described with linear inequalities.
$u(.\|k)$	Future control sequence.
$u(k+i\|k)$	Future control signals for $i=0...P-1$.
W	Positive definite matrix of the performance weights.
$x(k)$	The state vector.
$x(k\|k)$	The current state.
$y(k)$	The system output.
$y(k+i\|k)$	The estimated outputs.

Abbreviations:

AC	Air Conditioner
AC	Air Conditioning Unit
LQ	Linear Quadratic
MPC	Model Predictive Control
ON/OFF	Thermostat
SISO	Single-Input and Single-Output
ToU	Time of Use Tariff

I. INTRODUCTION

Increasing concerns regarding climate change are very present when confronted with the damaging consequences of rapid and uncontrolled urbanization. To cope with the current energy consumption growing rate, several efforts are necessary to oppose environmental threats [1]. Results published by the Intergovernmental Panel on Climate Change (IPCC) emphasized the requirement to preserve the GHG below 450 ppm CO_2 equivalence by 2050 in order to maintain the increase of the temperature of the planet under 2ºC [2].

Countries gradually concentrate their initiatives on reducing the negative environmental repercussions of careless energy consumption. The energy sector is experiencing substantial transformation driven by legislation with the purpose to reduce energy consumption and the consequently related environmental impacts [3]. Presently, the consumption of energy in buildings is responsible for circa 32% of the final energy consumption on the planet. In the case of primary energy consumption, the building sector embody about 40% in most of the IEA (International Energy Agency) nations are accountable for 36% of the European Union (EU) CO_2 emissions [4]. Also, the same sector absorbs 40% of EU final consumption and 60% of electricity consumption [5]. As part of the building sector, the residential sector is accountable for 60% of the final energy consumption and presents the highest prospective to decrease the peak demand which is described by the volatility of energy utilization [6].

Even though the flexibility related with home appliances and time varying prices can accomplish palpable positive results for consumers, the present residential load control operations are largely competed physically, thus signifying demanding challenges to consumers in planning the activity of their appliances in an optimal manner. Several clients might not have enough time to plan such type of scheduling operations and at times when the price variation is quick and recurrent scheduling might be perceived as significantly complex. Therefore, an energy management system (EMS) could be a solution to optimize the operation of appliances [7].

As a whole, two methodologies currently exist aiming to achieve energy savings: the inclusion of more energy efficient equipment in buildings, or the efficient management of the energy consumption through an EMS [8]. In the last ten years, the price of storage, data processing, and communication diminished while the incorporation of EMS has become increasingly effective. Such types of solutions offer additional possibilities for the project and implementation of forefront control methods [9].

The development of numerous control techniques has been proposed for AC systems and are classified into classical control, soft control, hard control, hybrid control, and other control methods. Yet, due to their simplicity, ON/OFF and PID controls are still utilized in several AC systems even though such settings might not be adequate for the entirety of the building. Thus, through the definition of set points for local controllers, the regulatory control is utilized to enhance the global system performance such as costs or energy consumption [10].

Driven by the recent improvements in data storage, communication devices, and computing, it is currently possible to materialize a suitable control technique to surmount the characteristic weaknesses in AC control. The implementation of EMS control strategies could be an auspicious solution for reaching improved results in AC systems when compared to other common control methods. By utilizing embedded EMS control units in AC systems, several improvements in energy efficiency could be obtained without the changes affecting the heating and cooling systems. Such types of controllers our found to be a reliable improvement for dwellings and can be without much effort installed, ran and replaced [11].

Several methods based on the MPC have been created and tested with the purpose to optimize the operation of AC systems [12]. The MPC is, in essence, an optimization based approach in which a clear model is used to predict the performance of the controlled plants over a receding horizon [13]. The popularity of the MPC ascended ever since its first application in the process industry in 1970s.

Presently, MPC is broadly utilized in several industry applications. The common research of MPC is mostly dedicated to a centralized implementation. On the other hand, with the accelerated improvement of energy efficiency technology and the required improvement for the economic behavior, large scale systems, such as EMS, are becoming more complex [14].

The aim of this paper is to compare the MPC performance with the ON/OFF and PID control of a domestic AC system controlling the temperature of a room. The model of the house with local solar microgeneration is assumed to be located in Portugal. Thus, the dwelling is subject to the local temperature, solar irradiance and electricity tariff. The MPC is considered to be superior to the classical control techniques such as ON/OFF and PID controls. PID controllers are inferior due to the reason that they display low accuracy in processes which are either non-linear or have a large time delay. For instance, PID controllers only manage efficiently single input single output (SISO) systems. On the other hand, the MPC is able to manage multiple input-multiple output (MIMO) systems, to show a greater accuracy, to operate with constraints, is robust when facing disturbances and has the capacity to predict the performance of the controlled plants over a receding horizon. However, such advantages are counterweighted with greater computational requirements [15]. The remainder of the paper is organized as follows: in Section II the proposed methodology is developed. Then, in Section III the modelled test case is presented while in Section IV obtained results are thoroughly discussed. Finally, conclusions are drawn in Section IV.

II. METHODOLOGY

The MPC is a control technique which is intended to optimize a series of manipulated variable adjustments bound by a prediction horizon. It functions as such through the use of a process model in order for the optimization predictions of process performance based on a linear or quadratic objective, restrained by equality or inequality constraints.

In such a control technique, the optimization is performed repeatedly on-line – the receding horizon which is the inherent contrast between MPC and other control methods. In perfect circumstances only the suboptimal result for the total solution can be achieved, this is the restriction of such finite-horizon optimization. Yet, the optimization of the receding horizon can efficiently include the uncertainties suffered by the model, also the time-varying disturbances and behavior [16].

The broadest state-space representation of a linear system with p inputs [17], q outputs and n state variables is represented as follows:

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

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

where:

$$x(k) \in \mathbb{R}^n,\ u(k) \in \mathbb{R}^p,\ y(k) \in \mathbb{R}^q \tag{3}$$

The consequence of such representation is that the system is observable and controllable.

As stated above, the MPC is an optimization based control law, and in an elemental MPC controller the performance measure is nearly each time a quadratic cost. Through the representation of the positive definite matrices as:

$$M = M^T \succ 0 \tag{4}$$

and the performance weights is given by:

$$W = W^T \succ 0 \tag{5}$$

The optimal control input has to be identified in order to minimize the infinite horizon performance cost:

$$J(k) = \sum_{j=k}^{\infty} x^T(j \mid k) M x(j \mid k) + u^T(j \mid k) W u(j \mid k) \tag{6}$$

In an unconstrained scenario, the solution to this equation is given by the linear quadratic (LQ) controller. Yet, in a constrained scenario, no analytic solution exists. As an alternative, the objective in the MPC is to establish a prediction horizon N and approximate the problem with a finite horizon cost:

$$J(k) = \sum_{j=k}^{k+N-1} x^T(j \mid k) M x(j \mid k) + u^T(j \mid k) W u(j \mid k) \tag{7}$$

The finite horizon is essential since it is due to it that it is possible to solve the problem, but simultaneously, other complications are brought by the finite horizon.

By utilizing the model from (1) and (2), it is possible to predict the state $x(k+j|k)$, given a future control sequence $u(\cdot|k)$ and the current state $x(k|k)$. In such a case, no state estimation is obligatory and it is assumed that $C=I$, therefore, $x(k|k) = x(k)$. Consequently, the prediction is represented as:

$$x(k+j \mid k) = A^j x(k \mid k) + \sum_{i=0}^{j-1} A^{j-i-1} B u(k+i \mid k) \tag{8}$$

By utilizing such predictions, it is possible to define the following optimization equation:

$$\min_{u} \sum_{j=k}^{k+N+1} x^T(j \mid k) M x(j \mid k) + u^T(j \mid k) W u(j \mid k) \tag{9}$$

which is subject to:

$$u(k+j \mid k) \in U \tag{10}$$

and

$$x(k+j \mid k) = Ax(k+j-1 \mid k) + Bu(k+j-1 \mid k) \tag{11}$$

and thus, it is possible to design a basic MPC controller.

III. CASE STUDY

The AC system clematises the room through a cooling capacity of 3.516 kW. The heat exchange with the exterior occurs through the outer wall of the room and it is the key cause of disturbance of the preferred thermal comfort level of the room. With the purpose of testing both control strategies, the rate of heat loss/generation through the model of the external wall of the room is simulated using a temperature based time series with significant wide thermal amplitude variation upon 24 hours. The thermostat (TH) and the MPC are set with a limit of +/1 ºC and having as reference 23ºC.

A. The model of the room

In order to build pleasant interior environments in terms of temperature in distinct rooms of a house - additional energy needs to be consumed with the purpose to remove or insert heat. Thus, the preferred comfort level is established by choosing a reference temperature and by assessing the space air temperature. The comfort level based on temperature is disrupted by the number of residents that inhabit the dwelling, the thermal mass of the space itself, and by the exchange of heat with the external environment through the external walls as can be observed in Fig. 1. Thus, the temperature dynamics of a room in the house derives from the balance of energy of the outside environment temperatures, the AC equipment that inserts or extracts heat from the room in permutation with the indoor thermal mass as shown in Fig. 1. The time of use (ToU) tariff in this studied case has three price levels: the valley price is quantified by 10.23 cent/kWh, the peak price is characterized by 17.68 cent/kWh and the critical peak price is 22.47 cent/kWh [18].

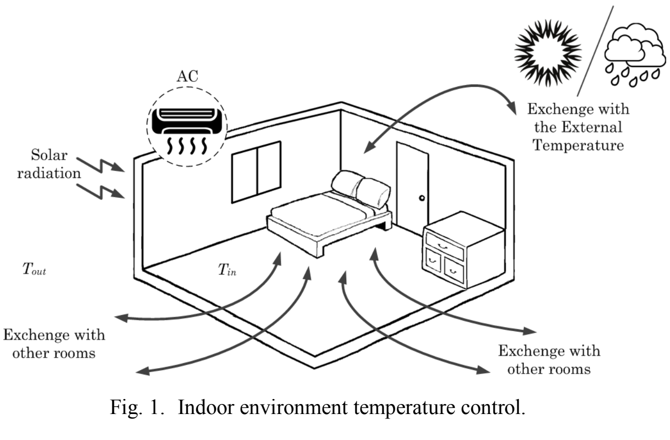

Fig. 1. Indoor environment temperature control.

With the intention of assessing and comparing the behavior of the controller a thermal mass model utilizing a resistance-capacitance circuit analogy is modelled. The aforementioned model contains the heat flow balance between the thermal capacitance of the internal air and the external wall and windows of the room of a house [18]. The following expressions were withdrawn from [19]:

$$\frac{dT_{wl}}{dt} = \frac{Q_s}{C_{wl}} + \frac{T_{in} - T_{wl}}{R_{wl} C_{wl}} \tag{12}$$

$$\frac{dT_{in}}{dt} = \frac{Q_{ac} \times S(t)}{C_{in}} + \frac{T_{out} - T_{in}}{C_{in} R_{wd}} + \frac{T_{wl} - T_{in}}{C_{in} R_{wl}} \tag{13}$$

$$Q_s = \mathrm{A_w} h_o (T_{out} - T_s) \tag{14}$$

where the cooling power input to the room is represented by Q_{ac}, the ambient temperature by T_{out}, T_{in} quantifies the temperature of the room, the wall temperature is given by T_{wl}, the thermal capacitance of the wall by C_{wl}, and the thermal resistance of the wall by R_{wl}, R_{wd} represents the thermal resistance of the windows, the thermal capacitance of the indoor air is given by C_{in} and the heat flow into an exterior surface of the house subjected to solar radiation by Q_s. The combined convection and radiation heat transfer coefficient is quantified by h_o, the wall area is represented by $\mathrm{A_w}$, T_s represents the wall surface temperature. Finally, *S(t)* represents a binary variable that emulates the turn-on and turn-off of the ON/OFF. For this study, the operation of AC is represented by a power switch block without internal losses. All the data of the physical parameters are acquired from [20].

B. The photovoltaic microgeneration system

With the purpose of modelling a Photovoltaic (PV) microgeneration system it was used PV panels from a German enterprise operating and manufacturing in the PV market. The manufacturing enterprise offers 25 years of linear performance.

In order to simulate the microgeneration PV system, Solarworld-SW-250 monocrystalline panels were selected for this study. This panel performance under standard test conditions presents a maximum power of 250Wp, an open circuit voltage 37.8V, a maximum power point voltage 31.1V, a short circuit current 8.28A and a maximum power point current 8.05A [21].

The PV system for this study contains 4 parallel strings and each one of them contains 10 PV panels signifying that the total installed capacity is 10kWp.

The typical thermostatic and PID control function as a reference to the MPC. As a result, the energy needed to control the appliances, the cost of consuming the energy throughout the off-peak, mid-peak, and on-peak along with the temperature variation are intended as function of weight selection related to the manipulated variable and process output as a portion of the cost function. The calculation of the energy cost depends on the electricity tariff of the Portuguese residential market employed during a period of 24 hours. For the assessment of the time horizon, *P* control moves number is set to 4 and the *N* predicted outputs is set to 20.

The aim of the paper is to compare the MPC performance with the ON/OFF and PID control of a domestic AC system controlling the temperature of a room. The model of the house with local solar microgeneration is assumed to be located in Portugal, specifically in the city of Covilhã. The dwelling of the case study is subject to the local solar irradiance, temperature and electricity tariff of a specific day of summer – 8th August, 2016. The daily exterior air temperature of the aforementioned city is presented in Fig. 2. The local solar irradiance is shown in Fig. 3.

IV. RESULTS AND ANALYSIS

By taking into account the exterior temperature of Covilhã on 8th August, 2016, the solar radiation of the same day, a three level ToU tariff was used during the 24h time frame and the transient thermal model of the room equations several results can be obtained. In Fig. 4 can be seen the temperature of the room controlled by the MPC solution. In Fig. 5 can be seen the temperature of the room controlled by the ON/OFF solution. Finally, the behavior of the temperature of the room controlled by the PID solution can be observed in Fig. 6. By comparing the behavior presented in Figs. 4-6 it can be observed that the MPC presents the most erratic performance while the ON/FF the most stable one.

The energy consumed by the AC during the period in question when controlled by the MPC is lower than the one consumed by the PID and ON/OFF. This can be seen in the Table I. Fig. 7 shows the energy consumed by the AC during the same period of time while controlled by the MPC solution. The consumed energy by using the solutions ON/OFF and PID show a similar behavior. The results presented in the Table I concerning the PV microgeneration confirm that the cost of the energy consumption from the grid is significantly less while showing that the PID is the best solution with PV and MPC without PV.

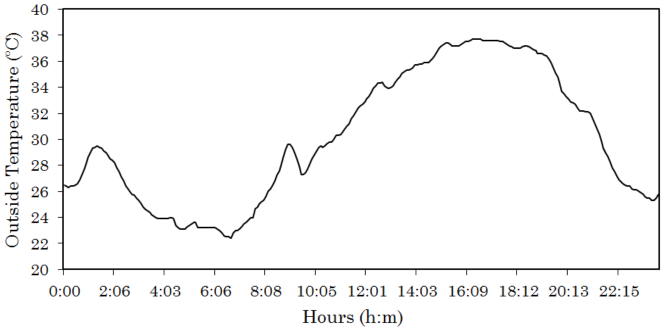

Fig. 2. The exterior temperature of Covilhã on 8th August, 2016.

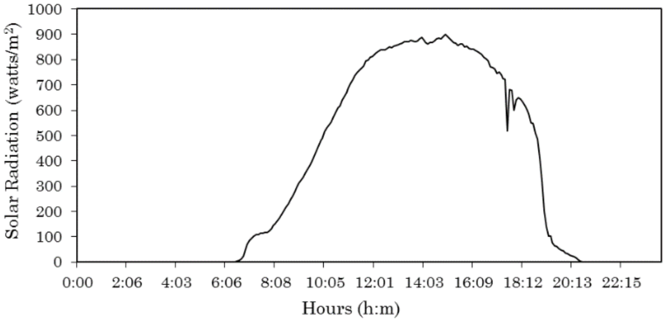

Fig. 3. Solar Radiation (watts/m^2) of Covilhã on 8th August, 2016.

TABLE I. THE ENERGY CONSUMPTION AND THE COST

	Without PV		With PV		
	Energy (kWh)	Cost (€)	Energy from grid (kWh)	Energy from PV (kWh)	Cost (€) from grid
ON/OFF	42,3637	7,5234	12,7563	29,6074	2,0203
PID	42,0281	7,4409	12,6780	29,3502	1,9882
MPC	41,5006	7,3898	12,4873	29,0132	1,9916

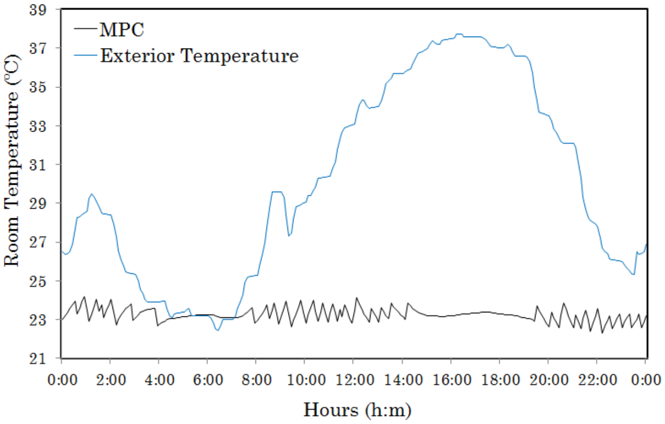

Fig. 4. The temperature of the room controlled by the MPC.

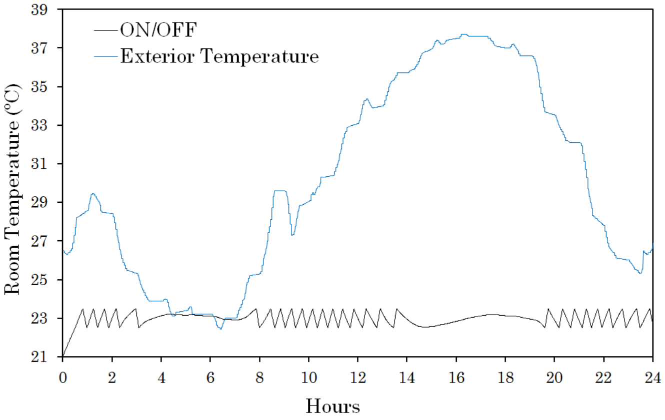

Fig. 5. The energy consumed by the AC by using the ON/OFF solution.

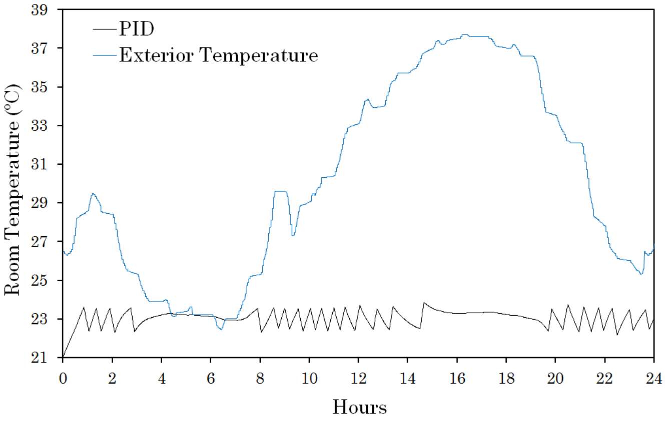

Fig. 6. The energy consumed by the AC by using the PID solution.

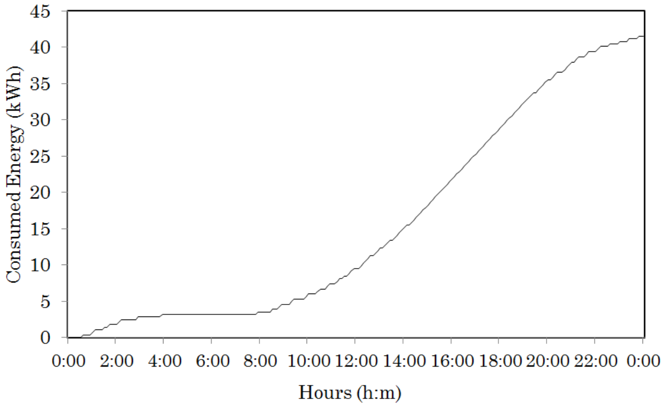

Fig. 7. The energy consumed by the AC by using the MPC solution.

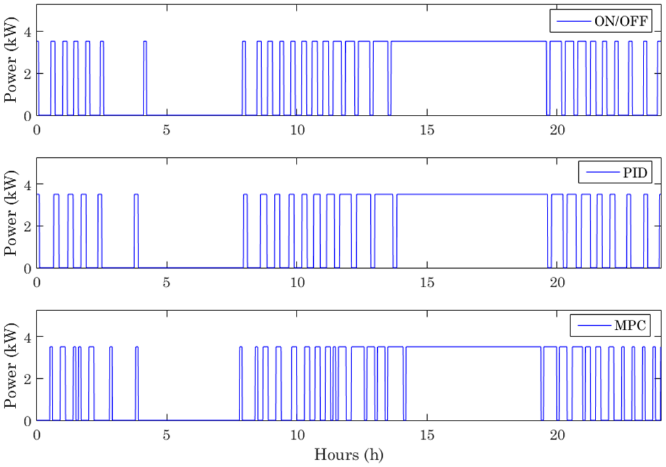

Fig. 8. Periods of operation of the ON/OFF, PID and MPC.

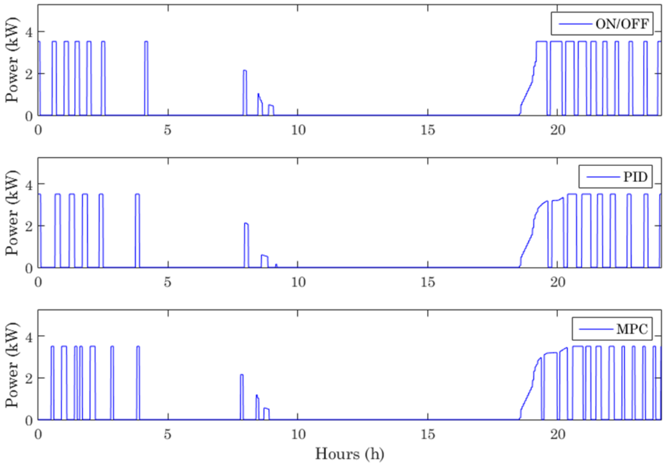

Fig. 9. The power and the consumed energy with PV microgeneration.

By having a PV microgeneration system installed for the house it will significantly lower the bill for the customer as shown in Table I. However, the PID presents a better result by using the PV microgeneration since it operates with a higher activity than others during the day in detriment of the night. Since the PV generates power during the daytime the PID solution is the one that benefits the most from the microgeneration. Fig. 8 shows the behavior of each of the three solutions and the periods of time during the day that they operate. Fig. 9 shows the power and the consumed energy from the grid with PV microgeneration. As can be observed, the energy consumed form the grid is lower during daytime since the AC system consumes a certain amount of energy produced by the PV microgeneration system during daytime.

V. CONCLUSION

In this paper, an MPC strategy with the purpose of stimulating an efficient use of home heating energy has been presented. A comparison was made between the MPC model, the ON/OFF and PID control models of a domestic AC system controlling the temperature of a room. The model of the house with local solar PV microgeneration was assumed to be located in Portugal, namely in the city of Covilhã. The household of the case study was subject to the local solar irradiance, temperature and a summer ToU electricity tariff with three price levels. The results showed that the PV system significantly lowered the electricity bill for the customer. The MPC presented a better behavior when the electricity is consumed only from the grid, while the PID solution is the one that presents a slightly better behavior from the microgeneration, since it operates more during the daytime.

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REFERENCES

[1] R. Nishant, T. S. H. Teo, and M. Goh, "Energy Efficiency Benefits: Is Technophilic Optimism Justified?," *IEEE Transactions on Engineering Management*, vol. 61, no. 3, pp. 476-487, 2014.

[2] B. Han, E. Bompard, F. Profumo, and Q. Xia, "Paths Toward Smart Energy: A Framework for Comparison of the EU and China Energy Policy," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 2, pp. 423-433, 2014.

[3] M. E. Morales Udaeta, F. Minoru Maruyam, A. L. Veiga Gimenes, and L. C. Ribeiro Galvao, "Integrated Energy Resources Planning for the Electricity Sector: Targeting Sustainable Development," *IEEE Technology and Society Magazine*, vol. 34, no. 1, pp. 31-38, 2015.

[4] Rim Missaoui, Hussein Joumaa, Stephane Ploix, and Seddik Bacha, "Managing energy Smart Homes according to energy prices: Analysis of a Building Energy Management System," *Energy and Buildings*, vol. 71, pp. 155-167, 2014.

[5] Jean-Nicolas Louis, Antonio Caló, Kauko Leiviskä, and Eva Pongrácz, "Modelling home electricity management for sustainability: The impact of response levels, technological deployment and occupancy," *Energy and Buildings*, vol. 119, pp. 218-232, 2016.

[6] S. Heinen, D. Elzinga, S.-K. Kim, and Y. Ikeda, "Impact of smart grid technologies on peak load to 2050," Paris, 2011.

[7] Chen Chen, Jianhui Wang, Yeonsook Heo, and S. Kishore, "MPC-Based Appliance Scheduling for Residential Building Energy Management Controller," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1401-1410, 2013.

[8] Jingran Ma, S. Joe Qin, and Timothy Salsbury, "Application of economic MPC to the energy and demand minimization of a commercial building," *Journal of Process Control*, vol. 24, no. 8, pp. 1282-1291, 2014.

[9] Wei Liang, Rebecca Quinte, Xiaobao Jia, and Jian-Qiao Sun, "MPC control for improving energy efficiency of a building air handler for multi-zone VAVs," *Building and Environment*, vol. 92, pp. 256-268, 2015.

[10] Abdul Afram and Farrokh Janabi-Sharifi, "Theory and applications of HVAC control systems – A review of model predictive control (MPC)," *Building and Environment*, vol. 72, pp. 343-355, 2014.

[11] W. H. Allen, A. Rubaai, and R. Chawla, "Fuzzy Neural Network-Based Health Monitoring for HVAC System Variable-Air-Volume Unit," *IEEE Transactions on Industry Applications*, vol. 52, no. 3, pp. 2513-2524, 2016.

[12] D. Oliveira et al., "Enhancing home appliances energy optimization with solar power integration," in *IEEE EUROCON 2015 - International Conference on Computer as a Tool (EUROCON)*, Salamanca, 2015.

[13] D. Oliveira et al., "MPC weights tunning role on the energy optimization in residential appliances," in *2015 Australasian Universities Power Engineering Conference (AUPEC)*, Wollongong, 2015.

[14] Michael G. Forbes, Rohit S. Patwardhan, Hamza Hamadah, and R. Bhushan Gopaluni, "Model Predictive Control in Industry: Challenges and Opportunities," in *9th International Symposium on Advanced Control of Chemical Processes*, Whistler, British Columbia, 2015.

[15] Evan M. Wanjiru, Lijun Zhang, and Xiaohua Xia, "Model predictive control strategy of energy-water management in urban households," *Applied Energy*, vol. 179, pp. 821-831, 2016.

[16] Y. Zong et al., "Model Predictive Controller for Active Demand Side Management with PV self-consumption in an intelligent building," in *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, Berlin, 2012.

[17] Liuping Wang, *Model Predictive Control System Design and Implementation Using MATLAB®*. London: Springer London, 2009.

[18] R. Godina, E. M. G. Rodrigues, E. Pouresmaeil, J. C. O. Matias, and J. P. S. Catalão, "Model predictive control technique for energy optimization in residential sector," in *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*, Florence, 2016.

[19] Yashen Lin, Timothy Middelkoop, and Prabir Barooah, "Issues in identification of control-oriented thermal models of zones in multi-zone buildings," in *51st IEEE Conference on Decision and Control*, Maui, Hawaii, USA, 2012.

[20] Yunus A. Cengel, *Heat Transfer: A Practical Approach*, 2nd ed.: Mcgraw-Hill, 2002.

[21] "SW 250 mono / Version 2.0 and 2.5 Frame," SolarWorld,.