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IFAC PapersOnLine 52-13 (2019) 141–146

Economic Model Predictive Control for Optimal Operation of Combined Heat and Power Systems

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Abstract: The use of decentralized Combined Heat and Power (CHP) plants is increasing since the high levels of efficiency they can achieve. Hence, to determine the optimal operation of these systems in the changing energy market, the time-varying price profiles for both electricity as well as the required resources and the energy-market constraints should be considered into the design of the control strategies. To solve these issues and maximize the profit during the operation of the CHP plant, this paper proposes an optimization-based controller, which will be designed according to the Economic Model Predictive Control (EMPC) approach. The proposed controller is designed considering a non-constant time step to get a high sampling frequency for the near instants and a lower resolution for the far instants. Besides, a soft constraint to met the market constraints for the sale of electric power is proposed. The proposed controller is developed based on a real CHP plant installed in the ETA research factory in Darmstadt, Germany. Simulation results show that lower computational time can be achieved if a non-constant step time is implemented while the market constraints are satisfied.

Keywords: Combined heat and power systems, Profit maximization, Economic model predictive control, Mixed Integer Linear Programming

1. INTRODUCTION

The energy supply in Germany is increasingly changing from a centralized to a decentralized generation structure (Strasser et al., 2015). In particular, the use of decentralized Combined Heat and Power plants (CHP) is increasing, as they can achieve high levels of fuel utilization (Khaljani et al., 2015). The cost efficiency of a CHP is highly dependent on the operation strategy. However, identifying the optimal operation strategy in volatile energy markets while covering thermal demands can be challenging though. For this reason, optimization algorithms are often used for scheduling tasks (Zhang et al., 2017).

In order to take price fluctuations on the electricity market into account when choosing an operation strategy for CHPs in a microgrid, a sufficiently large optimization horizon is required. For intraday optimization, this horizon is usually assumed to be about one day, which is usually modeled with a temporal resolution of 15 minutes (Aluisio et al., 2017; Sasaki et al., 2018). Additionally, it must be ensured that the plant actually produces the amount of electricity traded, whereby a higher temporal resolution and more accurate modeling are required (Parisio et al., 2015). If both a long time horizon and a high temporal resolution are chosen, the number of time steps taken into account increases rapidly. This problem is aggravated by an increased requirement for model accuracy when mapping the transient behavior of the plant. Thus, in order to solve the optimization problem within a short time, the number of considered decision variables must be kept low.

One way to reduce the complexity of the problem is to divide it into a planning problem and a fulfillment or adaptation problem (Luo et al., 2017). The longer-term energy marketing is considered in the planning problem and then given as a target to the fulfillment problem. However, with the introduction of the continuous intraday market, the boundaries between the planning and compliance phases become blurred. Trading of electrical energy can be carried out within the control zones in Germany on the continuous intraday market up to 5 minutes before fulfillment (Epex-Spot, 2018). Thus, to make the best possible use of the resulting optimization opportunities on the market, an approach that combines the optimization of both problems in a single model is required.

In order to meet these requirements with respect to the optimization horizon, temporal resolution, and model accuracy, this paper presents a predictive-like controller

10.1016/j.ifacol.2019.11.166

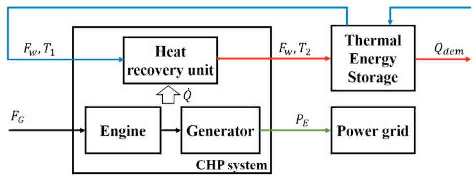

Fig. 1. Combined Heat and Power (CHP) system with an integrated Thermal Energy Storage (TES).

with a varying time step, designed using the Economic Model Predictive Control (EMPC) approach (Angeli et al., 2012; Rawlings et al., 2012). Some relevant applications of EMPC that combine the planning and tracking problems have been proposed in (Kuboth et al., 2019; Tian et al., 2019). In the proposed controller, the width of the time step increases for the future time steps, since if only the most recent time step is executed, the accuracy of the model can be maintained while the number of variables is reduced. Hence, the general idea of the proposed controller is to predict both the thermal and electrical power production to maximize the profit during the CHP operation considering its operating constraints and the energy market. The modeling of the operational behavior of CHP is based on a data-driven model obtained from subspace identification (SI) methods. These methods directly deliver a state-space model, which have a great application in the design of control strategies (Verhaegen and Hansson, 2016). Finally, the proposed approach is validated using a simulation model for a real cogeneration plant.

The remainder of the paper is organized as follows. The problem statement regarding the optimal operation of a CHP is presented in Section 2. Next, the proposed controller based on the EMPC approach is presented in Section 3. In Section 3.1 the way as the process model have been obtained by SI methods is reported. A detailed description of the case study is presented in Section 4. Then, the obtained results for the proposed approach by simulation are reported and analyzed in Section 5. Finally, conclusions and future work are drawn in Section 6.

2. PROBLEM STATEMENT

According to Figure 1, a gas flow F_G is feeding the CHP for generating electric power P_E, which is usually injected into the local grid point of common connection. During this combustion process, heat is generated as waste but a significant amount is recovered by heating a cooling fluid (e.g. water) from temperature T_1 up to T_2 via heat transfer. Afterward, the warm fluid is pumped with a constant flow rate F_W towards a Thermal Energy Storage (TES), from which the thermal power demand Q_{dem} is supplied. In this sense, the costs associated to F_G should be minimized to determine the optimal operation of the CHP that satisfies Q_{dem}. In addition, costs for the wear of the system caused by too many switching operations and operating hours should be minimized.

On the other hand, besides to minimize costs associated with the production of Q_{dem}, revenue for selling the produced electric power could be maximized taking into account the current energy-price profile in the market. Thereby, in order to determine the economic-optimal operation of a CHP along an operation time T, the following objectives could be defined:

- Minimization of cost by gas consumption F_G:
$$\theta_1 = \sum_{k=1}^{T} F_G(k)\ P_{r,g}, \tag{1}$$
being $k \in \mathbb{Z}_{\geq 0}$ the discrete-time index, $F_G(k) \in \mathbb{R}_{\geq 0}$ the gas consumption at instant k, and $P_{r,g} \in \mathbb{R}_{\geq 0}$ the gas price.
- Minimization of costs related to the CHP operation:
$$\theta_2 = \sum_{k=1}^{T} u(k)\ P_{r,on}, \tag{2}$$
with $u(k) \in \{0, 1\}$ the on/off state of system on at instant k, and $P_{r,on} \in \mathbb{R}_{\geq 0}$ the costs of keeping the system activated.
- Minimization of switching frequency, f_{sw}:
$$\theta_3 = \sum_{k=1}^{T} f_{sw}(k)\ P_{r,s}, \tag{3}$$
being $f_{sw}(k) = |u(k) - u(k-1)|, \in \{0, 1\}$ and $P_{r,s} \in \mathbb{R}_{\geq 0}$ costs for switching on/off the system.
- Maximization of revenue produced by the sale of P_E:
$$\theta_4 = \sum_{k=1}^{T} P_E(k)\ P_{r,e}(k), \tag{4}$$
with $P_E \in \mathbb{R}$ and $P_{r,e}(k) \in \mathbb{R}_{\geq 0}$ the energy price at instant k.

Based on the previous discussion, in order to determine the optimal activation sequence and the use of resources in a CHP with an integrated TES, the control objective can be defined as the profit maximization as follows:
$$J = -(\theta_4 - \theta_1 - \theta_2 - \theta_3), \tag{5}$$
being J the profit for operation of CHP along T, which is equal to total revenue (θ_4) minus total costs ($\theta_1, \theta_2, \theta_3$). Thus, in order to achieve the control objective in (5), the suitable instants for activation of the CHP and the optimal amount of gas to feed the system should be determined. Therefore, to compute both the revenue and total costs, dynamic expressions that relate the variables of interest for the CHP operation are required, i.e.,
$$\begin{aligned} P_E &= f_1(F_W, T_1, F_G, u), \\ T_2 &= f_2(F_W, T_1, F_G, u), \end{aligned} \tag{6}$$
where $f_1, f_2 : \{0, 1\} \times \mathbb{R} \mapsto \mathbb{R}$ are linear/non-linear maps in function of the inputs signals (F_W, T_1, F_G and u). Additional to the operation of the CHP, the dynamics of the TES should be modeled in order to guarantee the thermal power supply and its operating constraints. Thus, the dynamic of energy stored on a TES is defined as
$$Q_s(k+1) = Q_s(k) + \Delta t\left(Q_{CHP}(k) - Q_{dem}(k)\right), \tag{7}$$
with
$$Q_{CHP}(k) = F_W(k)\ C_p\ \left(T_2(k) - T1(k)\right), \tag{8}$$
being $Q_{CHP} \in \mathbb{R}$ the thermal flow produced by CHP at instant k, $Q_{dem} \in \mathbb{R}$ the required thermal power, $Q_s \in \mathbb{R}$ the energy stored in TES at instant k, $T_1(k), F_W(k)$ measured inputs, C_p the heat capacity of water, and Δt the sampling time. It should be noted that $\underline{Q}_s \leq Q_s \leq \overline{Q}_s$ for all k, with $\underline{Q}_s$ and $\overline{Q}_s$ the lower and upper bounds of Q_s, respectively. Finally, in addition to the models for the analyzed processes, other operating constraints, e.g., operating ranges, operation times, idle time, should be considered.

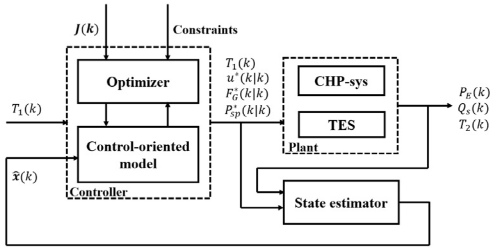

Fig. 2. Control scheme for the optimal operation of CHP with a integrated TES.

3. PROPOSED APPROACH

In order to determine the optimal operation of the CHP system from an economic viewpoint, the EMPC approach is addressed to design an optimization-based controller that allows maximize the revenue while minimize the total cost along a prediction horizon H_p. Thus, behind the design of such a controller, an optimization problem is solved at each discrete-time instant k, which considers the models for operation of the CHP and TES, as well as their operating constraints.

In this sense, based on the receding horizon approach and considering a fixed H_p, the general idea is to predict the optimal sequences u and F_G that allow maximizing the profit taking into account both the operating constraints and the price profiles in the market. Moreover, since the electric power traded P_{con} with the electric company is update each 15 minutes and, P_{con} must be approximately equal to P_E, a new control objective for minimizing the difference between P_E and P_{con} up to the next updating period $T_c = 15$min is defined as follows

$$\theta_5 = P_{r,\Delta P} \sum_{i=k}^{i=k+T_c} \|P_{con}(i) - P_E(i)\|^2. \tag{9}$$

Thus, at each instant k an optimal sequence is found along H_p and the predicted P_E from k up to $k + T_c$ is sold to the electric company. Then, for next iteration $k + 1$, the objective in (9) is minimized in order to guarantee that the sold electric power P_{con} can be achieved at instant $k + T_c$ avoiding economical penalties. Next, when $k = T_c$, a new electric power to be sold is predicted and updated, and the process is repeated again. Thereby, θ_5 is considered only for the first 15 minutes of H_p since P_{con} for this time period has been already selling while for the rest of H_p new targets can be defined according to the variations of the energy market. Thus, (5) can be redefined as follows

$$J = -(\theta_4 - \theta_1 - \theta_2 - \theta_3 - \theta_5). \tag{10}$$

According to the defined control objectives, the sequences for J and the system inputs along H_p are defined as

$$\mathbf{J}(k) \triangleq \{J(k|k), \ldots J(k + H_p - 1|k)\}, \tag{11a}$$
$$\mathbf{U}(k) \triangleq \{u(k|k), \ldots u(k + H_p - 1|k)\}, \tag{11b}$$
$$\mathbf{F_G}(k) \triangleq \{F_G(k|k), \ldots F_G(k + H_p - 1|k)\}, \tag{11c}$$
$$\mathbf{P_{sp}}(k) \triangleq \{P_{sp}(k|k), \ldots P_{sp}(k + H_p - 1|k)\}, \tag{11d}$$

with $\mathbf{J}(k) \in \mathbb{R}^{H_p}$, $\mathbf{U}(k) \in \{0,1\}^{H_p}$, $\mathbf{F_G}(k) \in \mathbb{R}^{H_p}$, and $\mathbf{P_{sp}}(k) \in \mathbb{R}^{H_p}$ being the set point for the generated electric power P_E. Then, the proposed economic predictive controller is based on the following open-loop optimization problem:

$$\min_{\mathbf{U(k)},\mathbf{F_G(k)},\mathbf{P_{sp}(k)}} \quad \mathbf{J}(k) \tag{12a}$$

subject to

$$P_E(k+1|k) = f_1\left(F_W(k), T_1(k), F_G(k), u(k)\right), \tag{12b}$$
$$T_2(k+1|k) = f_2\left(F_W(k), T_1(k), F_G(k), u(k)\right), \tag{12c}$$
$$Q_s(k+1|k) = q_1\left(F_W(k), T_1(k), u(k), T_2(k)\right), \tag{12d}$$
$$F_W(k|k) = F_w\ u(k|k), \tag{12e}$$
$$P_E(k|k) \leq P_{sp}(k|k), \tag{12f}$$
$$u(k|k) \in \{0, 1\}, \tag{12g}$$
$$Q_s(k|k) \in \left[Q_{min}, Q_{max}\right], \tag{12h}$$
$$T_2(k|k) \in \left[T_{min}, T_{max}\right], \tag{12i}$$

and the following logical conditions

$$u(k|k) = 1 \Longleftrightarrow F_G(k|k) \in \left[F_{min}, F_{max}\right], \tag{13a}$$
$$u(k|k) = 1 \Longleftrightarrow P_{sp}(k|k) \in \left[P_{min}, P_{max}\right], \tag{13b}$$
$$u(k|k) = 0 \Longleftrightarrow P_{sp}(k|k) = 0, \tag{13c}$$
$$u(k|k) = 0 \Longleftrightarrow F_G(k|k) = 0, \tag{13d}$$

being q_1 the right-hand side of equation (7), F_w the constant flow of water to recover heat produced by CHP, P_{sp} the set point for the electric power generated, and $F_{min}, F_{max}, P_{min}, P_{max}, Q_{min}, Q_{max}$ and T_{min}, T_{max} the lower and upper bounds for F_G, P_{sp}, Q_s and T_2, respectively.

Afterward, assuming that the optimization problem (12) is feasible, i.e., $\mathbf{U}(k) \neq \emptyset, \mathbf{F_G}(k) \neq \emptyset, \mathbf{P_{sp}}(k) \neq \emptyset$, the optimal sequences $\mathbf{U}^*(k), \mathbf{F_G}^*(k), \mathbf{P_{sp}}^*(k)$ exist and, according to receding horizon approach, the first components $u^*(k|k), F_G{}^*(k|k), P_{sp}{}^*(k|k)$ are sent to the plant. This process is repeated for the next instant $k+1$ once measurements of input signals and estimation of the required information about the plant is update for the next iteration. Thus, to obtain suitable estimations of model states for the next iteration an state estimator could be required. The proposed control scheme to determined the optimal inputs to system along H_p is shown in Figure 2.

Based on Figure 2, the optimization problem in (12) is solved into the controller module in order to determine the optimal inputs $u^*(k|k), F_G{}^*(k|k), P_{sp}{}^*(k|k)$. Next, the first component of each optimal signal $\mathbf{U}^*, \mathbf{F_G}^*, \mathbf{P_{sp}}^*$ is sent to the plant and the estimator. Then, from these signals as well as the real measurements from the CHP, the current states of CHP model are estimated and fed back to the controller for the next iteration. Thereby, a Kalman filter to estimate the states of the CHP based on the real system outputs is proposed in this paper.

Since the optimization problem (12) explicitly considers models for the generation of both electric and thermal power (12b) and (12c), respectively, suitable expressions for maps f_1 and f_2 are required. Due to the complexity of these systems, this paper proposes the identification of data-driven models by SI methods, as explained in the next section.

3.1 Model of a Combined Heat and Power System

Although the expression for map q_1 is given by (7), suitable expressions for the maps f_1 and f_2 can be determined based on real data. Different methods for model identification have been developed during the last years, however, the SI methods have been selected in this paper due to allow obtaining a state space representation from input-output data (Sinquin and Verhaegen, 2017). Thus, this paper considers a linear approximation for maps f_1 and f_2, which will be obtained from these methods and real data of the system.

The general idea of SI methods is to determine the model order N and the set of model matrices $A \in \mathbb{R}^{nx\times nx}, B \in \mathbb{R}^{nx\times nu}, C \in \mathbb{R}^{ny\times nx}$ and $D \in \mathbb{R}^{ny\times nu}$, which satisfy a unknown state space realization (Overschee and De Moor, 1996), with nx, nu and ny the dimension of the state ($\mathbf{x}$), input ($\mathbf{u}$), and output vectors ($\mathbf{y}$), respectively, i.e.,

$$\mathbf{x}(k+1) = A\mathbf{x}(k) + B\mathbf{u}(k), \quad (14a)$$
$$\mathbf{y}(k) = C\mathbf{x}(k) + D\mathbf{u}(k). \quad (14b)$$

Then, in order to determine model matrices and N, first, a state estimation $\hat{x}$ based on the projection of input-output data is performed. Next, the model matrices are determined according to the obtained $\hat{x}$ (Verhaegen and Hansson, 2016). Some examples of these algorithms are the Canonical Variate Analysis (CVA) and Numerical algorithm for Subspace IDentification (N4SID). However, due to the great application and implementation in software of N4SID algorithm, this paper focuses on it to get proper expressions for maps f_1 and f_2. Finally, to obtain a suitable state space representation, proper experiments should be performed for getting information about the real system behavior at different operating conditions.

4. CASE STUDY

The system to be analyzed in this paper is based on a real CHP system with a integrated TES installed in the ETA research factory at Technische Universität Darmstadt, Germany. As shown in Figure 1, a CHP system is formed by an engine, a generator and a heat recovery unit. However in this paper, the model for each component is not addressed, and instead all elements are considered as a unique system, i.e., CHP. Therefore, the analyzed system has three inputs T_1, F_W and F_G, which feed the system to produce the outputs P_E and T_2. Although the direct output of the CHP is T_2, from this variable the thermal power Q_{CHP} can be computed by using 8.

The considered CHP has a maximum electric power capacity $P_{E,max} = 6$kW when the maximum flow of gas F_{max} is fed to the system. Thus, when the system is turned on, the produced P_E is sold to the power grid in order to maximize revenue and mitigate the cost associated to the thermal power production, which is the main objective of the CHP in the ETA research factory. Therefore, the warm water flow F_W is transported towards a TES with a maximum capacity of 1MWh, from which the required Q_{CHP} is supplied to the building. It should be noted that a pump with a constant flow rate $F_W = 2753.4$ L/h is assumed, and since the fluid is recirculated through the system there are no costs associated.

On the other hand, in order to get real data, the CHP is equipped with several sensing devices that provide information in near real time about inputs and outputs of the system. Due to the nature of these systems, their settling times, and the number of variables to be sensed, a sampling time of $\Delta t = 10$s was fixed to provide data

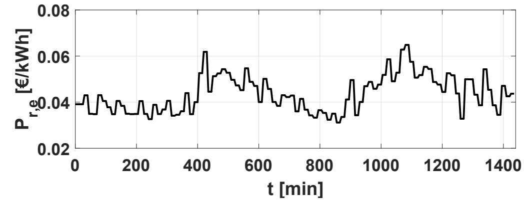

Fig. 3. Time-varying price profile for the sale of P_E.

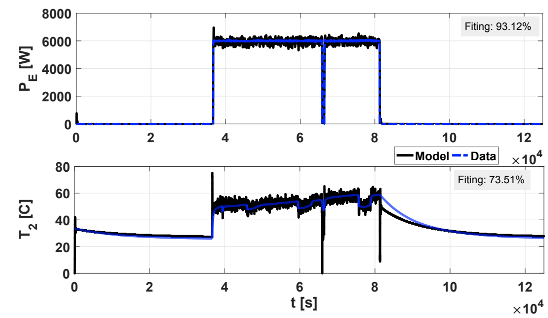

Fig. 4. Validation of the model for the CHP system.

about the real system operation. This information will be available for both model identification and its validation.

In order to maximize the profit and satisfying both the operating and market constraints, a total simulation time $T_s = 24$h and a prediction horizon of $H_p = 24$h were established to test the proposed approach. However, since $\Delta t = 10$s implicates a high computational cost due to the amount of variables to be optimized, a higher sampling time for optimization might be required. In this sense, this paper proposes to use a non-constant time step t_s with the aim to reduce the computational burden. The considered daily price profile for electric power is shown in Figure 3.

5. SIMULATION RESULTS

5.1 Model identification

According to Section 3.1, the modeling process for the analyzed CHP was identified by using the routine `n4sid` of the System Identification Toolbox™ provided by Matlab®. Thus, according to real data sets of the CHP in the ETA factory, different values of N were tested, and then, the model matrices A, B, C, and D were identified searching the highest fitting degree between the real and the modeled outputs. The obtained results for the system outputs (i.e., P_E and T_2) are presented in Figure 4. It should be noted that the dynamic for the TES is given by equation (7) and not obtained from data.

5.2 Proposed control scheme

Based on the case study in Section 4, a non-constant time step t_s is defined. This last is established considering a higher sampling time during the first hour with the aim to obtain a high-performance respect with the market constraints for the sale of P_E. Thereby, t_s will be $t_s = 5$min during the first 30 minutes of H_p, then, $t_s = 15$min along the next 30 minutes, and after 1 hour, it will be equal $t_s = 60$min. Although a non-constant t_s is defined, the model for CHP keeps running each 10s, and a short sub-sampled time scale is defined into the optimization loop. Thus, taking into account the receding horizon philosophy

Table 1. Simulation parameters of the CHP.

Parameter	Value	Parameter	Value
$P_{r,g}$	0.0218 € /kWh	P_{gas}	11.384 kW/m^3
$P_{r,on}$	10 € /kWh	$P_{r,s}$	5 € /kWh
$\overline{Q}_s$	1 MW	$\underline{Q}_s$	2 kW
C_p	4.180 kJ/kmol K	ρ	1000 kg/m^3
T_{min}	25 °C	T_{max}	80 °C
F_{min}	0.5 m^3/h	F_{max}	2.4 m^3/h
P_{min}	3000 W	T_{max}	6000 W

in which only the first component of the optimal sequence is sent to the system, the proposed control will be executed each 5 minutes, with a total number of iterations of N_{It} = 288 that corresponds to a whole day.

Therefore, given the mixed-integer linear programming nature of the optimization problem in (12), and the need to solve this problem fast enough to react in real time, simulations were developed in Matlab® using the solver IBM ILOG CPLEX Optimization Studio (ILOG, 2013) and YALMIP toolbox (Löfberg, 2004) for stating the problem optimization in an intuitive format. Besides, the proposed algorithms were developed using a processor *Intel*® Core^{TM} i7-5500U CPU 2.40GHz and RAM of 8.0 GB. The obtained results using both the proposed control approach (EMPC) and a typical rule-based control (RBC) implemented in these systems are presented and discussed below. It should be noted that the proposed Kalman filter for estimation of the model states was validated by simulation although the result is not shown here by space limitations. The simulations were performed using the parameters in Table 1.

In Figure 5 the optimal sequences obtained for the activation of the CHP, and both the water and gas flows, which are fed to CHP are presented. From these results is possible to observe that RBC has a higher switching frequency than EMPC, which increases the wear of systems and therefore the associated cost. Besides, for each activation of the CHP the optimal value found for F_G presents some small variations regarding its maximum value. This last fact could be a consequence of the trade-off between control objectives of maximizing revenue for selling P_E and compensate the total costs. Then, according to optimal input sequences, in Figure 6 the corresponding outputs are shown. Thus, in order to maximize the sale of P_E, the operation of CHP is always set at the highest level, while the resulting Q_{CHP} vary according to the current value of T_1 to the system. However, it should be noted that the produced Q_{CHP} is higher than Q_{dem} for each time the CHP is turned on. Thus, the excesses in the thermal power production are sent to the TES for its later use when the system is turned off or even for supplying an unexpected demand.

According to the control objective for the sale of P_E in the market, and the energy trading constraints, Figure 7 shows a comparison between the generated P_E and the reported P_{con} at each 15 minutes. In this sense, a high fitting degree between P_E and P_{con} can be achieved with an error percentage near 0.33%. It should be noted that results are only shown for EMPC strategy because using RBC it is not possible to get a prediction of electric power generation, and therefore, economic penalties can no be reduced. Thus, including θ_5 in (10), the economic penalties can be reduced or even avoided if a suitable analysis of

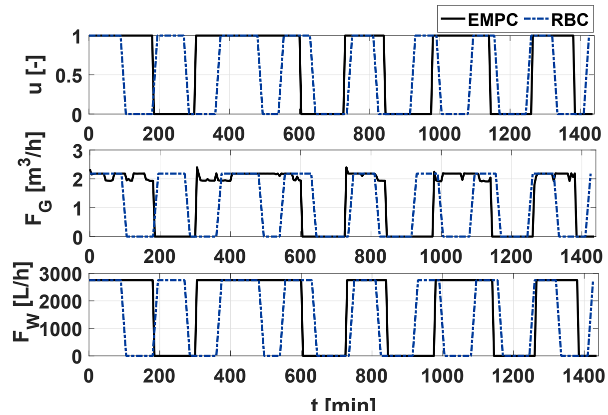

Fig. 5. Optimal sequences for the CHP activation (a), gas flow (b) and water flow (c) for both control strategies.

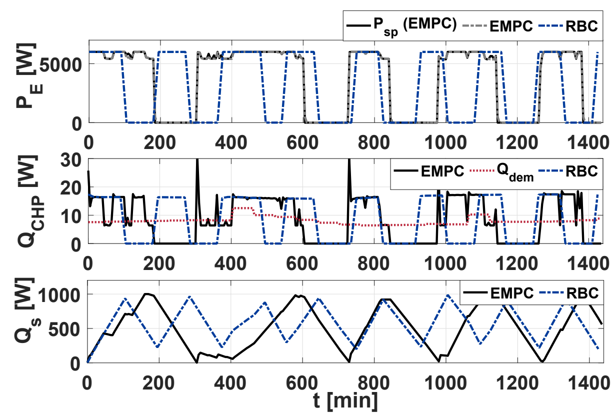

Fig. 6. Generated electric power (a), production of thermal power (b), and thermal power level in TES (c) for both control strategies.

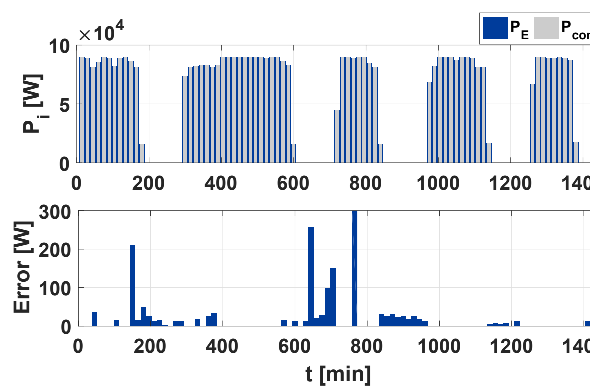

Fig. 7. Comparison between P_E and P_{con} for the proposed approach (a), and its corresponding error (b).

variance between these values is performed and reported to the electric company.

Finally, taking into account the importance to reduce the sampling time, in Figure 8 the computing time t_c[s] by iteration along T_s is presented. It should be noted that for each iteration a H_p = 24 hours is considered with the suitable update of price profiles and thermal power demand. Thus, it can be observed that even for a great number of decision variables and long prediction horizon, values of t_c lower than 7s could be achieved. Then, considering the updating time for the price profiles is equal

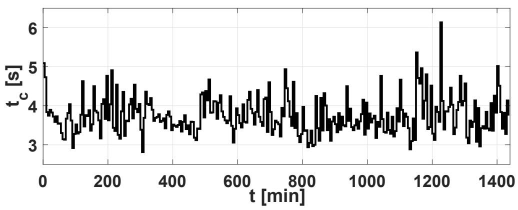

Fig. 8. Computational time by iteration along T_s.

Table 2. Total costs for daily operation by using both EMPC and RBC.

Approach	Cost
EMPC	201.3814 €
RBC	208.3417 €

15min, and the optimal inputs are found and sent to plant at each 5min, there is time enough for the implementation of the proposed control strategy in real time. Afterward, in Table 2 the total cost for one day of operation using both the proposed control strategy and RBC are reported. Thus, even if the economic penalties by the difference between P_E and P_{con} are neglected when the RBC is used, a cost reduction near 3.4% per day with respect to RBC can be achieved if the proposed EMPC is implemented.

6. CONCLUSION

A predictive-like controller has been designed considering a non-constant time step and a soft constraint in order to include the energy market constraints and minimize the total costs during the operation of cogeneration plants. Thus, a high resolution has been defined for near instants with the aim to include more decision variables in the near future, from which significant cost reductions per day were achieved while satisfying the traded electric power with small differences. Based on the obtained results, lower computational cost for long prediction horizons and a considerable number of decision variables were achieved.

As further work, the energy balance in the TES could be improved in order to include the energy losses and to represent a more realistic scenario. Besides, a stage of co-design for the implementation of the proposed control strategy in the real system could be developed. Finally, the proposed control strategy could be tested for disturbed and more complex systems, e.g., a microgrid with two or more different CHP systems and only one TES to validate its performance.

ACKNOWLEDGEMENTS

Authors would like to thank the FI-AGAUR scholarship of the Catalan Government and the project IKERCON ref. c-10683 for their financial and scientific support in this work, respectively. Besides, parts of this work are funded by the German Federal Ministry of Education and Research (BMBF) in the project SynErgie and the German Federal Ministry of Economic Affairs and Energy (BMWi) in the project PHI-Factory.

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