Adaptive Energy Management System for Self-consumption in Productive Processes

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Abstract. Productive processes are the largest consumers in power systems. The energy required by these processes is usually supplied by the power grid with its associated high operative costs. In this work, we propose a methodology to design energy management systems for self-consumption in productive processes with non-conventional local energy resources. Our goal is to maximize the use of the local energy resources to reduce the amount of energy contracted with the service supplier, and consequently to reduce production costs of the process. This methodology includes a robust-optimization-based energy management strategy to include power variability through the generation of a finite number of possible future scenarios of uncertain variables such as power demand and power from non-conventional energy sources. It allows improving the performance of the power supplies as our simulation results show.

Keywords: Non-conventional energy sources
Energy management system · Stochastic programming
Industrial processes

1 Introduction

According to the International Energy Agency, the world industrial sector consumes 42% of the total demanded energy around the world [5]. Furthermore, industry is the most pollutant end-user sector [4]. Then, in the near future the industry sector will face the dual challenge of implementing low energy and low pollution technologies while simultaneously maintaining its competitiveness [4]. Non-Conventional Energy Sources (NCES) are a suitable opportunity for industries to reduce their environmental impacts and to increase profitability. However, when NCES are integrated in productive processes, technical issues might arise due to their variability. Thus, the grid support and the dispatchable local energy sources must be coordinated through an energy management system (EMS) in such a way that a reliable supply of electric energy is achieved, despite of the unexpected power variations of the NCES and demand.

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Several EMS-based approaches have been presented in the literature to deal with the uncertainty associated with these power variations. Some examples of prediction-based EMS are reported in [7,9]. The main idea of these predictive strategies is to anticipate the performance of both NCES and power demand to maintain a suitable performance of the power system during power fluctuation. However, these strategies do not include the uncertainty directly in the EMS problem formulation, and single predictions are not enough to improve the robustness of the system. For this reason, some strategies such as those in [8,11] focus on this problem. In these works, authors represent uncertainty through prediction scenarios, but selecting them is still a research challenge. Furthermore, these methodologies have not clear strategies to determine a suitable number of scenarios to represent uncertainty, and they do not improve the uncertainty representation in real-time. In addition, all above applications are oriented to energy management in microgrids to supply energy on communities.

Particularly for productive processes, some EMS approaches with NCES integration have been proposed. In [2], the authors proposed a NCES integration based on a phenomenological process model. But they did not implement control actions over the local energy sources to correct any low performance in real-time. [10] presented a solar and wind source integration in a water desalination process through a model predictive control strategy. In this approach, the controller managed both sources and process. Nevertheless, it required a specific process model making it problem specific. In [3], a fuzzy controller was presented to manage a generation system with multiple types of sources and an experimental variable load. They did not implement an optimal control strategy in order to reduce the computational cost of the controllers.

In this work, we propose to tackle above mentioned drawbacks with an EMS design methodology based on the robust optimization strategy presented in [1]. Our goal is to include uncertainties as part of the energy management problem formulation in productive processes with NCES penetration. With this new approach, we expect to improve robustness of the energy supplied to the industrial process by reducing the possibility of collapse caused by unexpected variations associated with the NCES and power demanded by the process, which is basically the definition of robustness in this frame.

The proposed methodology consists of the following stages: Characterization of power demand and generation of available NCES; stochastic modeling of the power demand and power from the non-conventional resources (with the stochastic model, multiple possible future scenarios or realizations of the uncertain variables are computed in order to represent the future power variations); and design of a robust EMS to maximize the use of the available NCES. Realizations are included to improve the power system performance along the day. In this formulation, an additional constraint is included to avoid the energy surpluses injection into the main grid, and then to promote the self-consumption in countries where energy injection into the grid is not regulated.

The main advantages of the proposed methodology are: (i) it does not require an specific process model, i.e., it can be applied in any productive process; (ii) uncertainties are explicitly included in the proposed EMS through multiple scenarios in order to improve the robustness of the local power system under unexpected power flows variations; (*iii*) it is simple to implement because it only requires historical time series of the power demand and power from NCES to be designed; and finally, (*iv*) the parameters of the stochastic models are updated every sample time with the new measurements from the system; it allows improving the dynamic performance and the adaptive capabilities of the EMS.

This work is organized as follows: in Sect. 2 we present a methodology to manage energy in productive process where NCES are integrated. In Sect. 3, the proposed methodology is applied to design an EMS in a typical cooper extraction process, which is partially supplied with wind energy. In Sect. 4, simulations results are presented and discussed. Finally, conclusions are presented in Sect. 5.

2 Proposed EMS Design Methodology

The optimization problem with multiple scenarios presented in [1] can be written as an expected value minimization problem:

$$\begin{aligned} \min_{X} \quad & \mathbf{E}(F(X, \bar{a} + u)) \\ \text{subject to:} \quad & G(X, \bar{a} + u) \leq b \end{aligned} \tag{1}$$

Where X is the set of decision variables, which are calculated such that $F(X, \bar{a} + u)$ is minimum. $F(X, \bar{a} + u)$ is an objective function and $G(X, \bar{a} + u)$ represents a group of physical and operative constraints of the process. b is commonly expressed as a fixed parameter and a is an uncertain parameter. To consider uncertainties explicitly in the problem, a is expressed such as $a = \bar{a} + u$, where $\bar{a}$ and u are the mean and uncertainty components of a, respectively. However, this problem could not be mathematically tractable since the expected value of $F(X, \bar{a} + u)$ might not be differentiable. Nevertheless, it can be solved when a takes a finite number of values that represent the original population. Then, the problem can be reformulated as:

$$\begin{aligned} \min_{X} \quad & p_1 * F(X, a_1) + \ldots + p_K * F(X, a_K) \\ \text{subject to:} \quad & G(X, a_i) \leq b; \quad i = 1, \ldots, K \end{aligned} \tag{2}$$

Where K is a finite number of chosen scenarios for a and $p_i, \ldots, p_K$ are the occurrence probabilities of each scenario. The goal with this formulation is to find a value of X such that $F(X, a)$ can be minimized, whereas all constraints imposed by the a_i scenarios are simultaneously satisfied.

2.1 Generating and Selecting Scenarios

Power from NCES and power demand scenarios can be obtained from forecasting. An EMS with power forecasting models can achieve better planning of the power sources and improve the dynamic response of the system. We use a set of possible future scenarios obtained from a set of probability density functions (PDF), which are fitted via previous analysis of the historical time series of the uncertain variables, and their parameters are updated in every sample time to include the new measurements into the uncertainty representation process. The advantage of this method is that a suitable uncertainty representation can be achieved without the need of a complex model. In addition, this method allows updating historical information with every new measurement to update the parameters of the PDFs. The drawback of this method is that it is not possible to include exogenous variables in the process of the generation of the future scenarios, in other words, it is not possible to include the influence of exogenous variables on the uncertain variables. However, according to our simulations, it is a suitable strategy for average renewable NCES and demand conditions.

First, we combine historical time series from all uncertain variables to obtain only one time series. For example, the general form of the power balance with a renewable NCES is $P_G + P_R = P_D$, where P_G, P_R, and P_D are the power from grid, from the renewable NCES and demanded power respectively. Uncertain variables in this case are P_R and P_D, if we combine them in only one uncertain variable P_C we obtain, $P_C = P_D - P_R$, and then, power balance can be rewritten such as $P_G = P_C$, where now, there is only one uncertain variable, which is the combination of the two original ones. This process allows finding easily a PDF to represent the variability of the problem, and to reduce the computational effort of the final problem.

Then, possible future scenarios are generated using a method for uncertainty representation which is proposed based on [1,7,9]. Thereafter, we need to select those scenarios that represent the uncertainty of the historical data. Our goal is to represent uncertainties in the historical information through a finite number of possible future variations of the variable in order to improve the robustness of our EMS as follows:

1. Classifying historical information: Combined initial time series is disaggregated according to their resolution; then, we obtain a time series for every sample time along a day. For example, a time series of 365 days with 1 h resolution provides 24 disaggregated time series, each with 365 points.
2. Fitting time series: Disaggregated time series are fitted through a PDF; then, parameters of every time series are calculated. From the example of step 1, we obtain parameters of 24 PDFs for the 24 time series.
3. Generating scenarios: With the parameters of all PDFs, a finite number of realizations or future scenarios are generated for every sampling time. On our example, K scenarios are generated for each hour according to the respective PDFs.
4. Estimating the minimum number of scenarios: The goal with the generated scenarios is to represent uncertainties in the historical information, which will allow to the EMS having into account the K possible variations that the uncertain variables could have in the future, in other words, the control actions of the EMS will satisfy all the operational conditions that could impose each of those K possible future variations; achieving in this way to improve the robustness of the EMS. In this regard, K scenarios must be

selected such that the PDF parameters calculated from the generated scenarios and from the original disaggregated time series are as close as possible. In this work, the maximum allowed difference was 5%. Finally, minimum number of scenarios can be determined through a plot of K vs. PDF parameters difference as we show in the next section. This step is only performed once in the EMS design stage. When the EMS is in operation mode, only steps 1 to 3 are executed every sample time to update PDF parameters with new measurements.

2.2 Robust EMS Formulation

Based on the selected realizations, a robust EMS is proposed to maximize the use of NCES and to improve robustness of the power system when unexpected variations occur. The objective of the multiple scenarios explained in Subsect. 2.1 is to anticipate the future behavior of the NCES and demand and to improve the robustness of the whole power system in the long term, even under unexpected power flow variations.

Since we promote the self-consumption in productive processes, our EMS approach is formulated as an uni-nodal problem, i.e., we assume that all loads and sources are connected to the same connection point. In other words, the transmission constrain is not included. In (3) the formulation of the problem in an uni-nodal form and including single prediction is presented according to [7,9]:

$$\min_{P_{gi}^{(r)},P_{ns}^{(r)},P_{lo}^{(r)}} \sum_{r=1}^{N_p} \left(\sum_{i=1}^{M} (C_{gi} P_{gi}^{(r)}) + (C_{ns} P_{ns}^{(r)}) + (C_{lo} P_{lo}^{(r)}) \right) \tag{3}$$

subject to $r = 1, \ldots, N_p$ constraints:

$$\sum_{i=1}^{M} P_{gi}^{(r)} + P_{ns}^{(r)} - P_{lo}^{(r)} - \sum_{j=1}^{N} P_{dj}^{(r)} + \sum_{m=1}^{O} P_{Rm}^{(r)} = 0$$

$$P_{gi}^{\min}, P_{ns}^{\min}, P_{lo}^{\min} \leq P_{gi}^{(r)}, P_{ns}^{(r)}, P_{lo}^{(r)} \leq P_{gi}^{\max}, P_{ns}^{\max}, P_{lo}^{\max}$$

with $i = 1, \ldots, M$. P_{gi} is the power from the i-th controllable energy source. C_{gi} is the cost associated with the i-th energy source. P_{ns} and C_{ns} are the non-supplied power and their associated cost, respectively. P_{lo} and C_{lo} are the lost power and their associated cost, respectively. P_{Rm} is the power from the m-th renewable energy source. P_{dj} is the demanded power of the j-th load. $P_{gi}^{\min}$, $P_{ns}^{\min}$, $P_{lo}^{\min}$, $P_{gi}^{\max}$, $P_{ns}^{\max}$ and $P_{lo}^{\max}$ are the minimum and maximum physical constraints of the decision variables. M, N and O are the number of dispatchable energy sources, loads, and renewable sources respectively. Superscript $\bullet^{(r)}$ refers to the number of the step along to the prediction horizon of the variable $\bullet$. And N_P is the prediction horizon.

The optimization problem formulation (3) includes the single prediction of the available energy from the NCES and the demand to improve the performance of the system in the long term via anticipation of the possible variations.

However, predictions are not enough to improve the robustness of the system under unexpected future power variations. For this reason, we directly include uncertainties in the optimization problem formulation [1]. This inclusion is performed through the generation of a finite number of possible future scenarios with their respective occurrence probability. But first, we define uncertain sets for every renewable energy source P_{Rm} and power demand P_{dj}:

$$[P_{Rm}^{(1)}, \ldots, P_{Rm}^{(N_P)}] \in:= \{(P_{Rm(1)}^{(1)}, \ldots, P_{Rm(1)}^{(N_P)}), \ldots, (P_{Rm(K)}^{(1)}, \ldots, P_{Rm(K)}^{(N_P)})\}$$

$$[P_{dj}^{(1)}, \ldots, P_{dj}^{(N_P)}] \in:= \{(P_{dj(1)}^{(1)}, \ldots, P_{dj(1)}^{(N_P)}), \ldots, (P_{dj(K)}^{(1)}, \ldots, P_{dj(K)}^{(N_P)})\}$$

Here, $m = 1, \ldots, O$ and $j = 1, \ldots, N$, where O and N are the amount of NCESs and power demands respectively. Now, every scenario can be defined as follows considering all NCES and demands (contraction Scen means Scenario):

$$\text{Scen}\#s = \{(P_{Rm(s)}^{(1)}, \ldots, P_{Rm(s)}^{(N_P)}), (P_{dj(s)}^{(1)}, \ldots, P_{dj(s)}^{(N_P)})\}$$

for $s = 1, \ldots, K$ generated scenarios. Finally, we formulate an optimization problem for the robust EMS where uncertainties are included through the inclusion of above scenarios in form of K sets of constraints, one set per considered scenario. Every step time of every realization or scenario has an occurrence probability. However, the numerical tractability of the problem can be affected when the number of constraints increases. Therefore, following the procedure presented in [1], the expected value optimization problem is reformulated in its equivalent epigraph form:

$$\min_{P_{gi}^{(r)}, P_{ns}^{(r)}, P_{lo}^{(r)}, t_{(s)}^{(r)}} \sum_{r=1}^{N_p} \left(\sum_{i=1}^{M} (C_{gi} P_{gi}^{(r)}) + (C_{ns} P_{ns}^{(r)}) + (C_{lo} P_{lo}^{(r)}) \right) + \sum_{s=1}^{K} \left(\sum_{r=1}^{N_p} p_{(s)}^{(r)} t_{(s)}^{(r)} \right)$$

subject to:

$$\text{set}\#s \begin{cases} \sum_{i=1}^{M} P_{gi}^{(1)} + P_{ns}^{(1)} - P_{lo}^{(1)} + \sum_{m=1}^{O} P_{Rm(s)}^{(1)} - \sum_{j=1}^{N} P_{dj(s)}^{(1)} \leq t_{(s)}^{(1)} \\ \vdots \\ \sum_{i=1}^{M} P_{gi}^{(N_P)} + P_{ns}^{(N_P)} - P_{lo}^{(N_P)} + \sum_{m=1}^{O} P_{Rm(s)}^{(N_P)} - \sum_{j=1}^{N} P_{dj(s)}^{(N_P)} \leq t_{(s)}^{(N_P)} \end{cases}$$

$$P_{ns}^{(r)}, P_{lo}^{(r)} \geq 0; \quad P_{gi}^{\min} \leq P_{gi}^{(r)} \leq P_{gi}^{\max}; \quad t_{(s)}^{(r)} >= 0$$

with $s = 1, \ldots, K$, $i = 1, \ldots, M$, and $r = 1, \ldots, N_p$. Here, subscript $\bullet_{(s)}$ is the counter of the selected scenarios. p is the probability of each step in every scenario, and t is the additional decision variable that appears because of the epigraph form transformation. The selection of the number of scenarios is carried out according to the procedure proposed on Subsect. 2.1.

3 Simulation Set-Up

We tested our proposed methodology via simulation with a robust EMS for a typical copper extraction process supplied from the bulk grid, a local conventional generator, and a NCES (a wind generator in this case). In general, mining process is considered as an intensive energy process because it consumes around 700 kWh/tone mined [6]. Simulations were performed with power curves of a real process and real historical information of wind speed in the same location. The EMS controls the amount of power imported from the main grid and the local generator, so that they can compensate power fluctuations from the NCES and the demanded power.

IEEE benchmark of nine nodes and three generators was used to represent the electric grid of the selected productive process. Mathematical nomenclature is defined as: **g2** is the energy source in node 2 and it represents power from main grid; **g3** is the energy source in node 3 and it represents the local generator; **w** is the energy source in node 1 and it represents a NCES, a wind energy source for this case; **L5, L6, L8** are the system loads connected in nodes 5, 6 and 8 respectively, and they represent the total power demand of the copper extraction process.

3.1 Robust Energy Management System Formulation

The efficiency of generators and loads of the power system when exchanging power among them mainly depends on the management of those power flows through the EMS. Then, in (4), the proposed robust EMS for the power system of the copper process is presented. In this robust problem formulation, uncertainties are included through the inclusion of K possible future scenarios of the uncertain variables, which are expressed as K constraints:

$$
\begin{aligned}
\min_{t_{(s)}^{(r)}, P_{g2}^{(r)}, P_{g3}^{(r)}, P_{ns}^{(r)}, Plo^{(r)}} & (C_{g2}P_{g2}^{(1)} + C_{g3}P_{g3}^{(1)} + C_{ns}P_{ns}^{(1)} \\
& \vdots \\
+C_{g2}P_{g2}^{(N_p)} + C_{g3}P_{g3}^{(N_p)} + C_{ns}P_{ns}^{(N_p)} + C_{lo}P_{lo}^{(N_p)}) & + (p_{(1)}^{(1)}t_{(1)}^{(1)} + \ldots + p_{(1)}^{(N_P)}t_{(1)}^{(N_P)} \\
& \vdots \\
& +p_{(K)}^{(1)}t_{(K)}^{(1)} + \ldots + p_{(K)}^{(N_P)}t_{(K)}^{(N_P)})
\end{aligned} \tag{4}
$$

subject to $s = 1, \ldots, K$ sets:

$$
\text{set}\#s \begin{cases} P_{g2}^{(1)} + P_{g3}^{(1)} + P_{ns}^{(1)} - P_{lo}^{(1)} + P_{w(s)}^{(1)} - P_{d5(s)}^{(1)} - P_{d6(s)}^{(1)} - P_{d8(s)}^{(1)} \leq t_{(s)}^{(1)} \\ \vdots \\ P_{g2}^{(N_p)} + P_{g3}^{(N_p)} + P_{ns}^{(N_p)} - P_{lo}^{(N_p)} + P_{w(s)}^{(N_p)} - P_{d5(s)}^{(N_p)} - P_{d6(s)}^{(N_p)} - P_{d8(s)}^{(N_p)} \leq t_{(s)}^{(N_p)} \end{cases}
$$

and to the following constraints:

$$
\begin{aligned}
& P_{g2}^{\min} \leq P_{g2}^{(r)} \leq P_{g2}^{\max} \qquad P_{g3}^{\min} \leq P_{g3}^{(r)} \leq P_{g3}^{\max} \\
& P_{ns}^{(r)}, P_{lo}^{(r)} \geq 0; \qquad t_{(s)}^{(r)} >= 0; \quad r = 1, \cdots, N_p
\end{aligned}
$$

where P_{g2} and P_{g3} are the two power flows from the two controllable energy sources, grid and local generator respectively for this case. C_{g2} and C_{g3} are the costs associated with the controllable energy sources mentioned above. P_{ns} and C_{ns} are the non-supplied power and its associated cost. P_{lo} and C_{lo} are the lost power and its associated cost. P_w is the power from wind energy source. P_{d5}, P_{d6}, P_{d8} are the demanded power of the three loads of the test system. $P_{g2}^{\min}$, $P_{g3}^{\min}$, $P_{ns}^{\min}$, $P_{lo}^{\min}$, $P_{g2}^{\max}$, $P_{g3}^{\max}$ $P_{ns}^{\max}$ and $P_{lo}^{\max}$ are the minimum and maximum physical constraints of the decision variables. Finally, $\{\text{set}\#1, \cdots, \text{set}\#K\}$ are the power balance constraints that need to be satisfied for each $s = 1, \ldots, K$ scenario.

The robust solution obtained with this formulation reduces the possibility of the power system to collapse when an unexpected power variation occurs. Thereby, our robust energy management strategy helps to improve the dynamical performance of the system during unexpected power flow variations.

4 Simulation Results

The minimum number of scenarios was selected through the procedure presented in Sect. 2.1. Figure 1 shows the relation between the number of considered scenarios and the error of the statistical parameters. In this case, a normal distribution was used to represent the uncertainty of the historical time series (it is only one time series because of the combination of all uncertain variables that we presented in Sect. 2.1). We found that 1500 is a suitable number of scenarios to reduce the error of the mean (μ) and standard deviation (σ) to around 5%. It means that the uncertainty on the historical data is represented by this amount of scenarios with 95% representation percentage.

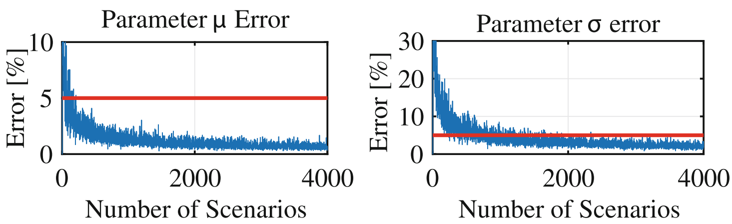

Fig. 1. Error of the statistical parameters vs. Number of considered scenarios. For this example, the error goes below 5% (red lines) with 1500 scenarios. (Color figure online)

We carried out simulation experiments with different EMS strategies during one day. All experiments were executed with conditions presented in Fig. 2. The figure shows a situation where the total power demand is always greater than the wind power, except in some intervals where the wind power is greater than the power demand. These mismatches have some consequences, which were analyzed.

Historical time series used for simulation was measured from the power consumed by a real copper mining process, and from a wind power plant (close to the place where power demand data were obtained). The sampling time of all tested controllers was 15 min.

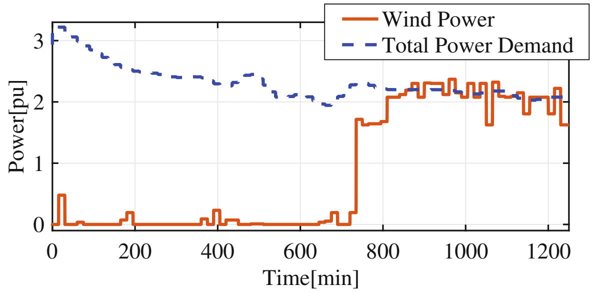

Fig. 2. Power delivered by the wind turbine and the total power demand of the system. The simulations were performed under these conditions.

The power system was tested on a typical situation to analyze its dynamic behavior with the proposed robust EMS and a non-robust EMS. In minute 1000 and along the 30 following minutes, wind speed decreased unexpectedly to zero. Although this is a totally unpredictable event, the controller had to react and try to compensate it. Figure 3 shows the dynamic performance of the power on the dispatchable sources, it means, grid and conventional local generator.

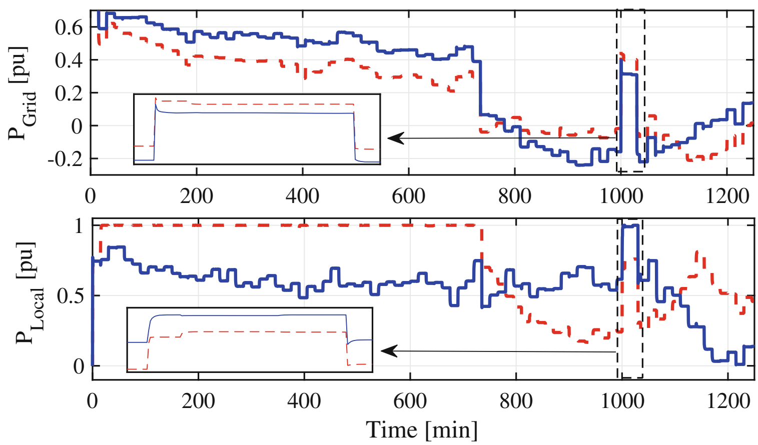

Fig. 3. Power from grid (top panel) and from local generator (bottom panel) under an unexpected absence of wind power. Proposed robust EMS (solid blue line). Non-robust EMS (dash red line) (Color figure online)

Table 1. Maximum variation of the delivered power from the dispatchable sources with the proposed robust EMS and a non-robust EMS caused by a wind event.

Max. power change		
Source	EMS	Max ΔP [MW]
Grid	Non-robust	10.7
	Robust	1.3
Local generator	Non-robust	9.6
	Robust	1.4

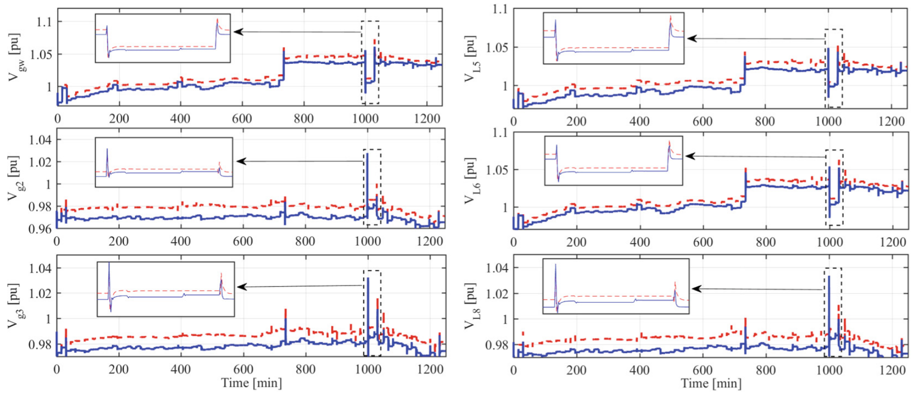

Fig. 4. Voltages in the main nodes of the power system under unexpected reduction of the wind power. Proposed robust EMS (solid blue line). Non-robust EMS (dash red line). (Color figure online)

When the wind turbine stopped producing energy, the grid and the local generator increased their delivered power to compensate this event. However, according to the used EMS, the dynamical performance was different. Figure 3 shows that the changes in the delivered power from the controllable energy sources with the proposed robust EMS are smaller than in the non-robust EMS during the unexpected outage of the wind generator. In the case of the local generator, it means that the energy consumption efficiency was improved, suggesting that the useful life of the machine was extended. The magnitudes of these changes are presented in Table 1.

Regarding the voltage performance, Fig. 4 and Table 2 show a faster response when the proposed EMS was used. In addition, the overshoot voltage magnitude was also reduced. In general, the stability of the power system was improved with the proposed EMS. Furthermore, the figure shows that voltages are always lower when the robust EMS was used, i.e., there is a wider range to regulate reactive power through the voltage manipulation in the case of considering voltage as a control variable.

Table 2. Numerical differences between a non-robust EMS and the proposed robust EMS under an unexpected wind power reduction*.

Voltages in unexpected wind event					
Node	EMS	IST [s]	FST [s]	Iovsh [%]	Fovsh [%]
1	Non-robust	90	90	−2.2	2.5
	Robust	60	45	−1.7	2.3
2	Non-robust	90	75	3.6	2.1
	Robust	60	45	4.9	1.8
3	Non-robust	90	90	3.5	2.7
	Robust	60	45	4.6	2.5
5	Non-robust	90	90	−2.1	2.4
	Robust	60	45	−1.6	2.2
6	Non-robust	90	90	−2.4	2.6
	Robust	60	45	−1.9	2.4
8	Non-robust	90	90	3.5	2.4
	Robust	60	45	4.8	2.2

*Here, **IST** and **FST** are the initial (min 1000) and final (min 1030) stabilization times respectively, **Iovsh** and **Fovsh** are initial (min 1000) and final (min 1030) overshoot respectively. The wind turbine is connected to Node 1. Nodes 2 and 3 are the connections of the bulk grid and the local generator, respectively. Nodes 5, 6, and 8 are the loads L5, L6 and L8 connections, respectively.

5 Conclusions

In this work, we proposed a methodology to manage energy in productive processes with NCES penetration via a robust EMS. Unlike other works in the literature [7–9,11,12], our methodology is manly oriented to promote self-consumption in productive processes in countries where it is not possible to sell energy surpluses to the main grid. The EMS includes a method to consider uncertainties in the NCES and power demand using historical information updated on real-time, with the objective of minimizing the operative costs. Our methodology allows avoiding large power variations in the local generator. A desirable characteristic in systems with NCES, because in productive processes it is a common practice to use thermal generation units to supply part of the power consumption of the process and they show a slow power response by nature. Furthermore, the proposed robust EMS ensures a suitable dynamical performance of the power system, which is not the case with a non-robust EMS.

A typical industrial process includes sensitive voltage devices, i.e., the dynamic behavior of the voltage is a critical aspect in power systems. Thereby, the proposed EMS has several advantages because it reduces the time response and voltage overshoot during abrupt unexpected power variations. In addition, our approach reduces the voltage level in all nodes of the power system (inside the permissible limits), which allows increasing the span to control the reactive power of the system.

Although a non-robust EMS allows having lower operative costs of the system, the proposed approach improves several dynamic aspects of an industrial power system such as the energy efficiency, the useful life of its components, and economic savings in the long term.

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