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A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids

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HIGHLIGHTS

- MILP formulation is proposed to manage energy production and demand.
- Flexible demand profile has been considered by applying penalty terms.
- A rolling horizon approach is introduced to deal with uncertainty associated to production and consumption.
- This approach allows updating input parameters, in order to react to variations from the nominal schedule.

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ABSTRACT

This work focuses on the development of optimization-based scheduling strategies for the coordination of microgrids. The main novelty of this work is the simultaneous management of energy production and energy demand within a reactive scheduling approach to deal with the presence of uncertainty associated to production and consumption. Delays in the nominal energy demands are allowed under associated penalty costs to tackle flexible and fluctuating demand profiles. In this study, the basic microgrid structure consists of renewable energy systems (photovoltaic panels, wind turbines) and energy storage units. Consequently, a Mixed Integer Linear Programming (MILP) formulation is presented and used within a rolling horizon scheme that periodically updates input data information.

1. Introduction

The development of sustainable energy supply chains has led to advances in the area of Energy Systems Engineering, which involve all the decision-making procedures from the primary energy source to the final energy delivery to the costumer. The main objectives and challenges of managing energy systems are to reduce costs associated to the exploitation of the energy network, to reduce the environmental impact caused by the production and transmission of energy and to satisfy the energy demand subjected to unexpected internal and external disturbances.

Traditionally, power grids are based on centralized networks where large power plants generate electricity that is used posteriorly at industrial or domestic level [1]. This kind of energy supply chains involves energy losses in power transmission due to the physical distance between the electricity generation and consumption sites. Furthermore, the generation of energy in centralized networks usually exploits non-renewable sources (i.e., fossil fuels), which has a negative environmental impact (i.e., pollution, climate change).

Microgrids are based on the decentralized energy supply chain concept, which can integrate several renewable and non-renewable energy sources that are usually close to energy consumers. A major drawback of renewable energy systems is the apparent mismatch of the volatility of energy production from renewable sources and energy demand. Natural energy resources though, have the disadvantage of intermittent and unpredictable production, due to their dependence on natural phenomena, the forecast techniques of which are far from reliable [2]. Thus, the simultaneous consideration of energy production and demand is essential to manage appropriately a microgrid, in order to match

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Nomenclature

Indices and sets

$i \in I$	energy production generators
$j \in J$	energy consumers
$f \in F_j$	energy demand included in the overall scheduling horizon
$f \in F_jRH$	energy demand included in the current prediction horizon
$k \in K$	energy storage systems
$r \in R$	power grids
$t \in T$	time intervals included in the overall scheduling horizon
$t \in TRH$	time intervals included in the current prediction horizon

Parameters

CH	length of the control horizon (h)
$Cons_{j,f}$	individual energy consumption of each energy consumption task jf (kW h)
$cpen_{j,f,t}$	penalty cost (m.u./time)
$cpro_{i,t}$	production energy cost (m.u./kW h)
$csto_{k,t}$	storage energy cost (m.u./kW h)
DT	duration of the time interval (h)
$Dur_{j,f}$	remaining time consuming of consumption jf in the current prediction horizon (h)
$Dur_{0,j,f}$	time consuming of energy consumption jf in the overall scheduling horizon (h)
it	Iteration
$P_{i,t}^{min}$	minimum power supply of energy generator i at interval t (kW)
$P_{i,t}^{max}$	maximum power supply of energy generator i at interval t (kW)
PH	length of the prediction horizon (h)
$Price_{r,t}$	energy price to be sold to power grid r at interval t (m.u./kW h)
$SE_{k,t}^{min}$	minimum electricity storage of system k at interval t (kW h)
$SE_{k,t}^{max}$	maximum electricity storage of system k at interval t (kW h)
$SE_{0k,t}$	initial storage level of system k at interval t (kW h)
SH	length of the scheduling horizon (h)
$Ts_{j,f}^{max}$	maximum initial time of consumption jf in the current prediction horizon (h)
$Ts_{j,f}^{min}$	Target initial time of consumption jf in the current prediction horizon (h)
$Ts_{0,j,f}^{max}$	maximum initial time of consumption jf in the overall scheduling horizon (h)
$Ts_{0,j,f}^{min}$	target initial time of consumption jf in the overall scheduling horizon (h)
η_k^{in}	charging efficiency of energy storage system k
η_k^{out}	discharging efficiency of energy storage system k
α_k	percentage of the maximum energy storage system k

Continuous variables

$Benefit$	microgrid benefit (m.u.)
$CostPen$	total penalty cost (m.u.)
$CostPro$	total energy production cost (m.u.)
$CostSto$	total storage cost (m.u.)
$Costs$	total operation cost of the microgrid (m.u.)
Dem_t	total energy consumption at interval t (kW h)
$Incomes$	microgrid incomes (m.u.)
$Ld_{k,t}$	energy supplied to load system k during interval t (kW h)
$P_{i,t}$	power supply of energy generator i at interval t (kW)
$Pg_{r,t}$	power supplied to power grid r at interval t (kW)
$Profit$	total profit along the time horizon (objective function) (m.u.)
PT_t	total power supply at interval t (kW)
$SE_{k,t}$	electricity storage level of system k at the end of the interval t (kW h)
$\widehat{SE}_{k,t}$	linking variable determining the storage level of energy storage system k at the end of interval t in the current prediction horizon (kW h)
$SP_{k,t}$	energy supplied by storage system k during interval t (kW h)
$Tf_{j,f}$	finishing time of each consumption jf (h)
$Ts_{j,f}$	starting time of each consumption jf (h)
T_t	time corresponding to time interval t (h)

Binary variables

$X_{i,t}$	=1, if energy generator i is used at interval t
$Y_{j,f,t}$	=1, if consumption jf starts at interval t during the current prediction horizon
$\widehat{Y}_{j,f}$	=1, if consumption jf starts outside the current prediction horizon
$Z_{j,f,t}$	=1, if consumption jf finishes at interval t during the current prediction horizon
$\widehat{Z}_{j,f}$	=1, if consumption jf finishes outside the current prediction horizon
$W_{j,f,t}$	=1, if consumption jf is active at interval t during the current prediction horizon

energy production and demand. Moreover, the use of energy storage systems is a common way to alleviate this mismatch and tackle the uncertainty in energy demand forecasts. Furthermore, energy storage provides the necessary tools to schedule the flexible energy demand according to time-of-use market base pricing, introducing enough operational flexibility to efficiently exploit periods of low prices, avoiding pick prices and reducing energy costs.

As mentioned above, the behavior of natural energy sources involves the consideration of uncertainty in microgrids, in order to ensure the generation of good quality and practical management decisions. Particularly, the operations management of microgrids is affected by several types of uncertainty, such as energy demand variations and weather conditions which affect the availability and production capacity of renewable energy systems. The decision making process becomes more complex if the consideration of different sources of uncertainty in the models is essential to ensure the quality of the solution or even its practical feasibility. Different types of uncertainty sources can be found, including:

(i) External sources, including uncertainty in energy demand, prices and availability of resources.
(ii) Internal sources, like fluctuations in process parameters.
(iii) Other sources, such as measurements errors or strikes.

The approaches to address scheduling problems under uncertainty could be classified into reactive and proactive. On one hand, reactive approaches focus on modifying a nominal schedule obtained by a deterministic formulation in order to adjust it to different alterations, modifications or updated system data. On the other hand, proactive approaches are based on the consideration of all possible cases, and finding a good solution for all these cases. These approaches have the advantage that a feasible solution is found for all considered scenarios. However, this solution may be too conservative, since the model must take into account all the possibilities even the ones that do not occur eventually. The most broadly used proactive approaches are stochastic programming [3] and robust optimization [4].

In this work, a new discrete-time Mixed Integer Linear Programming (MILP) mathematical formulation is presented to cope with the underlying uncertainty through a rolling horizon approach with the purpose to optimally manage a microgrid (i.e., schedule the energy production and consumption). This approach will allow to update all input parameters and to react to any variation from the nominal or expected conditions. One of the main elements for the optimization of the microgrid operation problem is scheduling. But the term scheduling actually embraces several decisions (degrees of freedom), as unit assignment (usually known as unit commitment problems in this specific area) or timing decisions. The resulting optimization models may be different in terms of their capacity to manage a generalized microgrid network structure, their capacity to manage several technical constraints, and also the way the different types of uncertainty are addressed in the problem of interest. This paper focuses on this last point. Although the use of rolling horizon strategies to scheduling problems in uncertain scenarios is well-known, its application to this specific area (microgrid scheduling) and also the exploitation of the demand side flexibility to improve the matching between energy generation and energy requirements constitute a challenge in this area. For this reason, this work emphasizes on the simultaneous optimization of energy generation and demand side management as a means for improved decision making of scheduling problems in microgrids.

The paper is organized as follows. In the next section, the literature review on the energy management models and the use of rolling horizon approach is presented. Then, Section 3 describes the problem statement of this study. In Section 4, the proposed reactive scheduling approach for the simultaneous energy production and energy demand side management is described in detail, and some remarks on the proposed method are provided. In Section 5, a case study is presented. Then, Section 6 provides a discussion on the obtained results. Finally, some concluding remarks are drawn and future research directions are revealed in Section 7.

2. Literature review

The growing interest in energy microgrids has led to the development of several mathematical models and representation schemes related to their management [5–8], as well as to their design [9,10], including the energy production management, the energy demand side management and the simultaneous management of energy production and demand.

Regarding the energy production management, different mathematical models were developed in order to minimize the operational cost of a given network. In this field, Zamarripa et al. [11] have developed a mathematical model to determine the production and storage levels to satisfy a deterministic energy demand, by minimizing the operational cost. More recently, Chen et al. [12] have proposed a mathematical formulation of a microgrid, consisting of renewable energy systems and storage devices, with the objective of maximizing its profit. Morover, a MILP model for the energy production planning related to an energy supply chain network based on a residential microgrid, which consists of a number of interconnected combined heat and power systems, under the objective of minimizing the total operational cost, has been presented by Kopanos et al. [13]. These mathematical formulations take into account energy generation constraints, such as production limits, ramping limits and minimum startup and shutdown times. The aim of these approaches is to find how a given set of energy generators should satisfy a given demand in order to minimize the total operational costs. This is a very challenging optimization problem because of the large number of possible combinations of the statuses of the energy generation units of the network [14]. Several works focused on the management of energy production of deterministic energy demand. Carrión and Arroyo [15] presented a discrete-time MILP formulation which minimizes the energy cost of a given network. More recently, Zondervan et al. [16] developed a Mixed Integer Non-Linear Programming (MINLP) formulation for process industries, in which the objective was to minimize the operational cost according to the availability and price of energy, by determining the optimal schedule of processing tasks. With regards to energy prices, Velik and Nicolay [17] presented a simulated annealing approach for the profit maximization in a power grid under time-dependent prices.

The energy demand side management of industrial processes represents an emerging challenge. In this area, Della Vedova and Facchinetti [18] developed a real-time scheduling approach to model and control the electrical availability. The aim was to reduce the presence of peaks for power consumption, which are negative for energy providers, for the grid and for the users, due to the fact that the presence of peaks reduces the grid efficiency and also because energy prices are based in peaks.

Furthermore, the management of both energy production and demand has been studied in a sequential way, by adapting the process schedule to the energy availability from an external power grid. Regarding industrial processes, Nolde and Morari [19] have developed a continuous-time MILP in order to minimize the total energy cost, by managing the energy consumption. The aim of the proposed formulation was to adapt the schedule of a steel plant, introducing a penalization for any variation from the contracted energy consumption from the plant to the energy supplier. Other works related to the simultaneous management of production and demand were focused on adapting the scheduling of the industrial process to the energy price in each period of time. Mitra et al. [20] developed a discrete-time MILP in order to adjust production planning according to time-dependent electricity pricing schemes for a continuous process. Also, the demand response has been studied by Hadera et al. [21] for a steel plant, in order to reduce energy costs. Moreover, Mohsenian-Rad and León-García [22] developed an offline residential energy consumption scheduling approach based in electricity pricing models.

Although energy production management has been studied in the last years, the overall scheduling of a microgrid taking into account the simultaneous management of energy production and energy demand (including the possibility to shift energy consumptions) under uncertainty has not been reported and still represents an open challenge. The development of a new mathematical model to manage a microgrid can be applied to obtain the optimal schedule of energy consumptions, producing several benefits such as the reduction of energy peaks and the reduction of non-renewable energy requirements. Along this line, a discrete-time MILP formulation for the integrated management of energy production and demand was developed by Silvente et al. [23]. More recently, Silvente et al. [24] have presented a comparison between discrete-time and hybrid-time MILP formulations related to a microgrid under profit maximization. Also, a new MILP hybrid approach was presented by Silvente et al. [25] with the aim of minimizing the operational cost of the overall system, and very recently Marietta et al. [26], Silvente et al. [27] have presented a discrete-time MILP formulation with flexible time windows for the allocation of energy loads into a rolling horizon framework.

The presence of uncertainty is addressed by implementing a rolling horizon approach, which is a reactive scheduling method that solves iteratively the deterministic problem by moving forward the optimization horizon in every iteration; assuming that the status of the system is updated as soon as the different uncertain or not accurate enough parameters became to be known, the optimal schedule for the new resulting scenario (and optimization horizon) may be found. This approach considers: a prediction horizon, in which all the uncertain parameters related to this time horizon are assumed to be known with some certainty (due to the fact that the system under study receives feedback related to the unknown parameters) and a control horizon, where the decisions of the optimization for the actual prediction horizon are applied (Fig. 1). Rolling-horizon has been applied to several scheduling problems under uncertainty, and the interested reader can be referred to Kopanos and Pistikopoulos [28] for a brief review. As mentioned in the Introduction, the iterative procedure of this formulation allows to update or to modify all input parameters in order to optimize the problem according to the current available information. Model Predictive Control has also been studied to address the energy management of island microgrids [29]. Furthermore, the energy production management of microgrids under uncertain conditions has also been studied through the implementation of proactive approaches. For example, Mohammadi et al. [30] developed a scenario-based optimization model focused on the energy operation management considering uncertainty in energy consumption, production and market price. Also, Kuznetsova et al. [31] presented a management framework of a microgrid connected to an external power grid under operational and environmental parameters through the implementation of the robust optimization. Multi-objective optimization approaches have been used to take into account different factors, such as cost and emission minimization, considering types of uncertainty related to expected values for energy demand, energy production through renewable energy systems and market prices, under deterministic conditions [32] and under uncertain conditions, by formulating a scenario-based stochastic programming model [33].

This work is an extension of the previous works of the authors and proposes an energy planning model to optimize simultaneously energy production, storage and consumption to maximize the energy efficiency by optimally adjusting energy production and energy demand. One of the main features of this methodology is the presence of flexible energy requirements. In addition, another feature is the possibility to handle uncertainty, which improves the applicability of the model in the decision making process. The objective of this approach is to fully exploit the flexibility offered by a complete microgrid system that involves renewable energy systems, offering solutions which might be virtually continuously updated when an unexpected event occurs in either production or demand sides. The assessment of this methodology is presented through a case study addressing the optimal management of the energy generation, storage and consumption of several appliances within a microgrid.

3. Problem statement

The system under study consists of a set of interconnected elements (i.e. power generators, energy storages, energy consumptions) as well as a set of decisions (when, where, who, how much) that define a managerial problem (resource allocation and timing) under uncertain conditions.

The proposed formulation takes into account not only the production and storage levels to be managed by the microgrid, but also the possibility to modify the timing of the energy consumption within a certain time window, if this is considered acceptable. The proposed formulation contemplates energy selling to the main power grid as well as all the involved costs, including generation and storage costs, as well as penalty costs in case of deviations from the energy consumers' target, in order to maximize the profit. The mathematical model includes both the energy balance constraints required to describe the energy flows (generation, storage and consumption), and the constraints associated to the equipment and technologies involved in the microgrid. Consequently, the problem under study is described in terms of the following items:

(i) A given scheduling horizon SH, which is divided into a number of equal-size time intervals $t \in T$. Also, a given Prediction Horizon PH and a Control Horizon CH.
(ii) A set of energy generators $i \in I$, characterized by a minimum and maximum energy generation capacity, $P_{i,t}^{min}$ and $P_{i,t}^{max}$, and a given operational cost $cpro_{i,t}$.

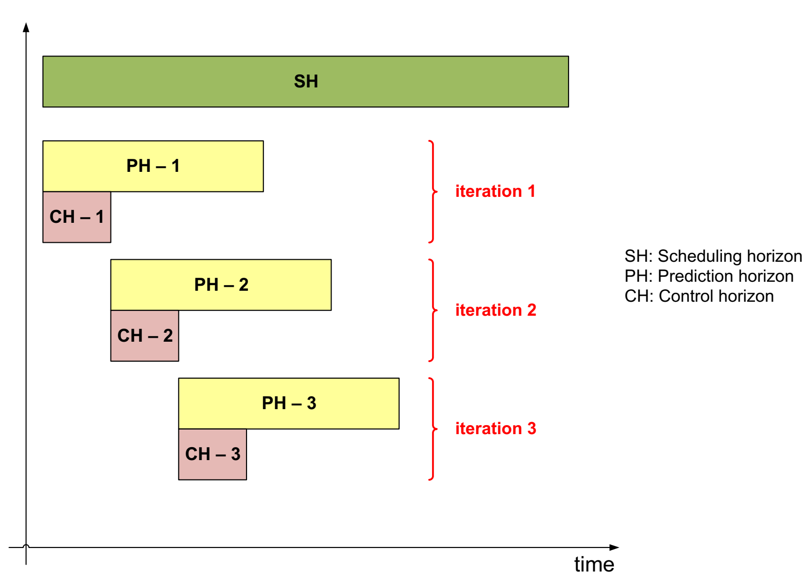

Fig. 1. Concepts associated to rolling horizon approach: scheduling, prediction and control horizon.

(iii) A set of energy storage systems $k \in K$, having a minimum and a maximum energy storage capacity, $SE_{k,t}^{min}$ and $SE_{k,t}^{max}$, and cost $csto_{k,t}$.
(iv) A demand for energy, given by the amount of energy required from a set of energy consumption tasks jf, where $f \in Fj$ denotes the number of times that a consumer j can be active. For any energy consumption, its duration $Dur_{0,j,f}$ and a target starting time $Ts_{j,f}^{min}$ are provided, although consumption tasks can be delayed within certain time limits generating a penalty cost $cpen_{j,f}$. The energy demand $Cons_{j,f}$ for consumption tasks is assumed to be constant.
(v) All energy consumption tasks which might be active during each iteration of the rolling horizon approach are included in the dynamic set F_jRH.
(vi) A given set of power grids $r \in R$, which can buy the excessive energy production, or sell additional energy to the microgrid if required.

The proposed reactive scheduling problem has been introduced into an iterative approach based on a rolling horizon framework (Fig. 2). The rolling horizon algorithm can be applied as shown in Fig. 3:

- Initially, set the initial conditions of the system as well as the length of the scheduling, prediction and control horizons.
- Next, establish the first scheduling period and solve the scheduling problem for the prediction horizon considered.
- Update the uncertain parameters and solve again the scheduling problem using data from the last optimization, by the use of linking variables (see Section 4.2).
- Then stop, if this new schedule corresponds to the last period of time. Otherwise, fix the values obtained in the optimization problem for that iteration, re-schedule and update the period of time until the last scheduling period has been reached.

The proposed formulation allows to update or modify the different uncertain parameters, such as the external variability in weather conditions (which affects the energy production) or the variability of the duration of the consumption tasks (which affects the energy demand).

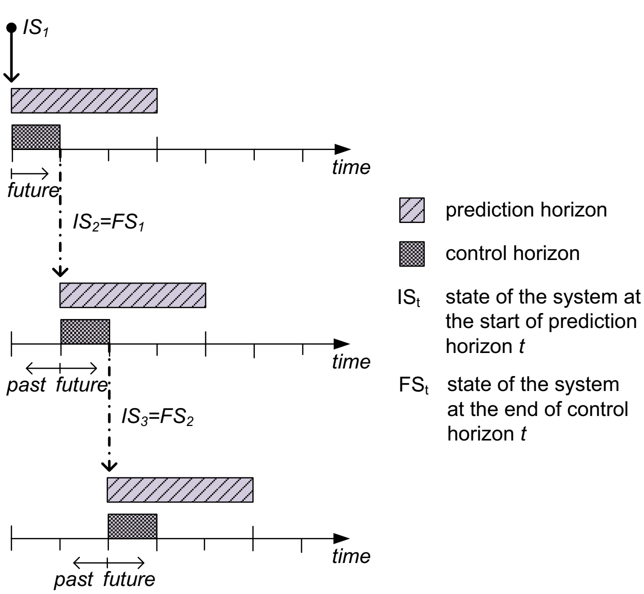

Fig. 2. Reactive scheduling via a rolling horizon framework [28].

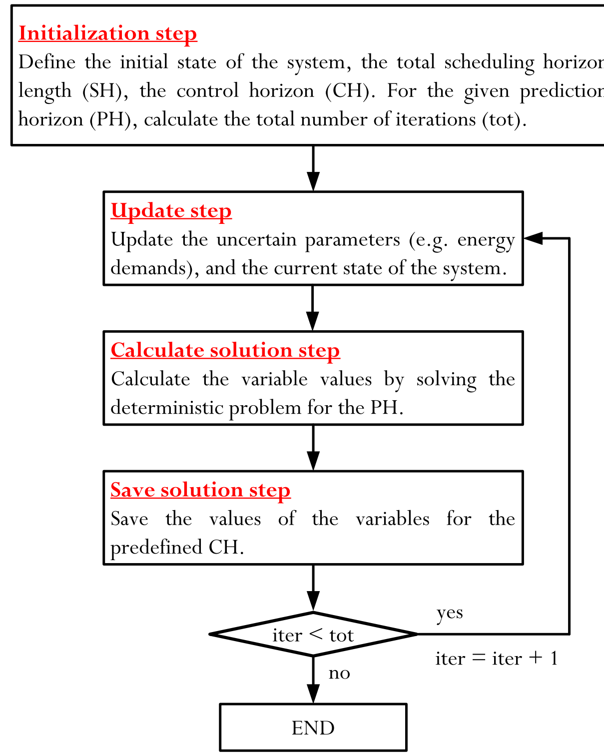

Fig. 3. Algorithm for the rolling horizon approach.

Although the solution obtained in each prediction horizon is optimal for this period of time, the solution of the overall problem could be suboptimal in practice, since future information outside the current prediction horizon is not taken into account. Therefore, the length of the prediction horizon must be appropriate in order to ensure the quality of the obtained results. The length of the prediction horizon depends on the characteristics of the problem [28].

The main decisions to be made in order to maximize the profit of the microgrid, are:

(i) The amount of power PT_t to be produced (or purchased) in each time interval t.
(ii) The energy generators that are in operation $X_{i,t}$ in each time interval t.
(iii) The energy storage level $SE_{k,t}$ at the end of time interval t.
(iv) The specific (nominal) time to execute an energy consumption.
(v) The amount of power $Pg_{r,t}$ to be sold to the power grid in each time interval t.

The decision variables include the determination of whether or not an energy generator i is switched on/off at a given time interval t, according to different energy consumers j, as well as decisions associated with the energy demand side management, which determines when to consume.

It is worth noting that the presented formulation is based on a discrete-time representation, in which the scheduling horizon is divided in a finite number of identical time intervals. This representaton of time forces the tasks to start at the beginning of each time interval [34]. The computational time to solve discrete-time models depends on the size of the problem, which strongly depends on the number of time intervals of the prediction horizon *PH*. The length of the time interval depends on the characteristics of the problem under consideration, since long time intervals could

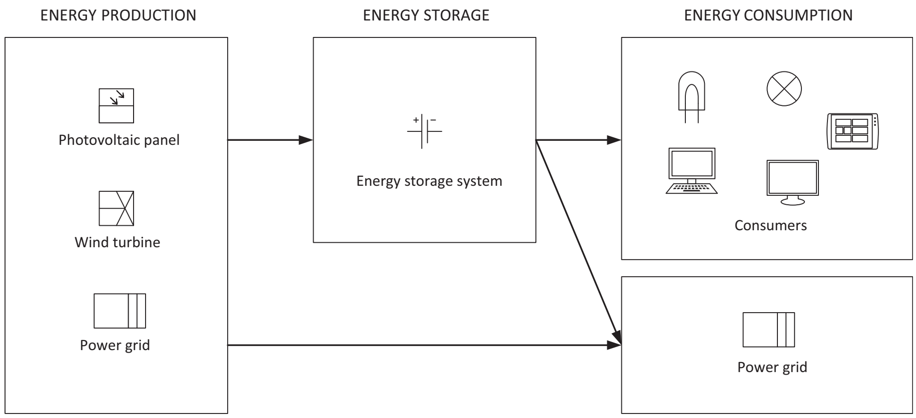

Fig. 4. Schematic representation of the case study.

Table 1
Economic data and capacity constraints.

Unit	Description	Cost (m.u./kW h)	P_i^{min} (kW)	SE_k^{min} (kW h)	SE_k^{max} (kW h)	α_k (–)
*i*1	Photovoltaic panel	0	0	–	–	–
*i*2	Wind turbine	0	0	–	–	–
*i*3	Power grid	0.153	0	–	–	–
*k*1	Energy storage system	$1 \cdot 10^{-6}$	–	13.44	16.80	0.05

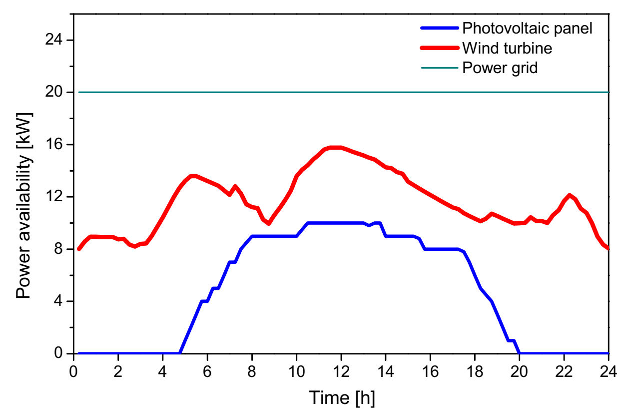

Fig. 5. Power availability.

lead to suboptimal solutions, and short time intervals could imply an unaffordable computational effort to reach the optimal solution [35].

4. Mathematical formulation

4.1. Microgrid schedule

The constraints associated to sequencing, allocation of energy consumptions and generators, and energy distribution of a given microgrid are presented next.

Bounds on energy production for every energy generator (including energy purchases to the external power grid) are specified by Eq. (1). For each energy generator i and time interval t included in the prediction horizon the binary variable $X_{i,t}$ indicates if this generator is being used or not. Thus, the total amount of energy produced at each interval t is given by Eq. (2):

$$P_{i,t}^{min} \cdot X_{i,t} \leqslant P_{i,t} \leqslant P_{i,t}^{max} \cdot X_{i,t} \quad \forall i, t \in TRH \tag{1}$$

$$PT_i = \sum_i^I P_{i,t} \quad \forall t \in TRH \tag{2}$$

The amount of energy in each energy storage k at each time interval t is bounded within a minimum and a maximum value, as given by Eq. (3). This maximum value corresponds to the full energy storage level. Eq. (4) represents the energy balance at a specific storage system and time k, t. This equation considers the storage level $SE_{k,t}$, the energy requirements covered by the storage $SP_{k,t}$, the supply flows arriving to the storage $Ld_{k,t}$ and the input and output efficiency of the energy storage system η. The maximum level of load is bounded by Eq. (5). Also, power constraints related to the charge and discharge of the energy storage systems must be considered. Thus, Eq. (6) indicates that the variation of the amount of energy in each energy storage k at each time interval t is bounded by a maximum variation level.

$$SE_{k,t}^{min} \leqslant SE_{k,t} \leqslant SE_{k,t}^{max} \quad \forall k, t \in TRH \tag{3}$$

$$SE_{k,t} = SE_{k,t-1} + \eta_k^{in} \cdot Ld_{k,t} - \frac{SP_{k,t}}{\eta_k^{out}} \quad \forall k, t \in TRH \tag{4}$$

$$\sum_k^K Ld_{k,t} \leqslant PT_t \cdot DT \quad \forall t \in TRH \tag{5}$$

$$-\alpha_k \cdot SE_{k,t}^{max} \leqslant SE_{k,t} - SE_{k,t-1} \leqslant \alpha_k \cdot SE_{k,t}^{max} \quad \forall k, t \in TRH \tag{6}$$

The proposed mathematical formulation allows to start the energy consumption tasks within a time window. Thus, the energy demand side management involves the determination of the starting time of each energy consumption task. Hence, some constraints are required regarding the time window within energy consumption task jk are allowed to consume. According to Eq. (7), the starting time is bounded by a minimum (target) and a maximum initial time. Moreover, the finishing time of each energy consumption task jf is given by the starting time plus its duration, according to Eq. (8).

$$Ts_{j,f}^{min} \leqslant Ts_{j,f} \leqslant Ts_{j,f}^{max} \quad \forall j, f \in F_j RH \tag{7}$$

$$Tf_{j,f} = Ts_{j,f} + Dur_{j,f} \quad \forall j, f \in F_j RH \tag{8}$$

The binary variable $Y_{j,f,t}$ is active (i.e., equal to 1) when the energy consumption task jf starts at time interval t. Accordingly, $Z_{j,f,t}$ is active if the energy consumption jf finishes its consumption at time interval t. These logical restrictions can be reformulated as a set of big-M constraints, given by Eqs. (9a)–(10b):

$$Ts_{j,f} \geqslant T_t - M \cdot (1 - Y_{j,f,t}) \quad \forall j, f \in F_j RH, \quad t \in TRH \tag{9a}$$

$$Ts_{j,f} \leqslant T_{t+1} - M\cdot(1 - Y_{j,f,t}) \quad \forall j,f \in F_jRH, t \in TRH \tag{9b}$$

$$Tf_{j,f} \geqslant T_t - M\cdot(1 - Z_{j,f,t}) \quad \forall j,f \in F_jRH, t \in TRH \tag{10a}$$

$$Tf_{j,f} \leqslant T_{t+1} - M\cdot(1 - Z_{j,f,t}) \quad \forall j,f \in F_jRH, t \in TRH \tag{10b}$$

Furthermore, energy loads of a given consumption cannot overlap in the same unit time:

$$Tf_{j,f} \leqslant Ts_{j,f'} \quad \forall j, \quad f \in F_jRH, \quad f < f' \tag{11}$$

Moreover, Eqs. (12) and (13) ensure a unique starting time for energy consumption jf. The binary variable $Y_{j,f,t}$ determines if consumption task jf starts during the current time interval included in the prediction horizon, and $\widehat{Y}_{j,f}$ determines if this consumption starts outside this time interval, forcing that all consumptions must start in the scheduling horizon. In the same way, Eqs. (14) and (15) determine the finishing time for energy consumption task jf. Also, Eq. (16) establishes when each energy consumption task jf is active at t.

$$\sum_{\substack{t\in T \\ T_t \leqslant Ts^{max}_{j,f}}}^{T} Y_{j,f,t} \leqslant 1 \quad \forall j, \ f \in F_jRH \tag{12}$$

$$\widehat{Y}_{j,f} + \sum_{t\in TRH}^{T} Y_{j,f,t} = 1 \quad \forall j, \ f \in F_jRH \tag{13}$$

$$\sum_{\substack{t\in T \\ T_t \leqslant Tf^{max}_{j,f}}}^{T} Z_{j,f,t} \leqslant 1 \quad \forall j, \ f \in F_jRH \tag{14}$$

$$\widehat{Z}_{j,f} + \sum_{t\in TRH}^{T} Z_{j,f,t} = 1 \quad \forall j, \ f \in F_jRH \tag{15}$$

$$W_{j,f,t} = \widehat{Y}_{j,f} + \sum_{\substack{t'\in TRH \\ t \geqslant t'}}^{T} Y_{j,f,t'} - \widehat{Z}_{j,f} - \sum_{\substack{t'\in TRH \\ t > t'}}^{T} Z_{j,f,t'} \quad \forall j, \ f \in F_jRH, \ t \in TRH \tag{16}$$

The total energy demand of the microgrid at time interval t, determined by all the active consumption tasks jf at this time interval t, is given by Eq. (17). The second term of this equation determines the exact energy consumption for those time intervals in which the energy consumption will not take place during the overall time interval.

$$Dem_t = \sum_{j}^{J}\sum_{f}^{F_j} Cons_{j,f}\cdot[W_{j,f,t}\cdot DT - Z_{j,f,t}\cdot(T_{t+1} - Tf_{j,f})] \quad \forall t \in TRH \tag{17}$$

Eq. (18) establishes the overall energy balance of the microgrid, considering the production, the consumption, the charge and discharge of the storage unit (i.e., battery), and the energy sales to the power grids.

$$\sum_{k=1}^{K} SP_{k,t} + PT_t\cdot DT - Dem_t - \sum_{k=1}^{K} Ld_{k,t} - \sum_{r=1}^{R} Pg_{r,t}\cdot DT = 0 \quad \forall t \in TRH \tag{18}$$

Hence, economic aspects related to the energy management are studied. The production cost is calculated in Eq. (19) as the amount of the costs associated to each energy generators, given by the unitary production cost multiplied by the energy units produced. The storage cost for each interval t is the amount of costs associated to each interval, which are the same as the unitary storage cost multiplied by the energy storage, according to Eq. (20). Finally, the penalty cost is determined as a function of the delay in satisfying each energy demand, and given by Eq. (21). The total operational cost of the microgrid is given by Eq. (22), which considers the previous costs.

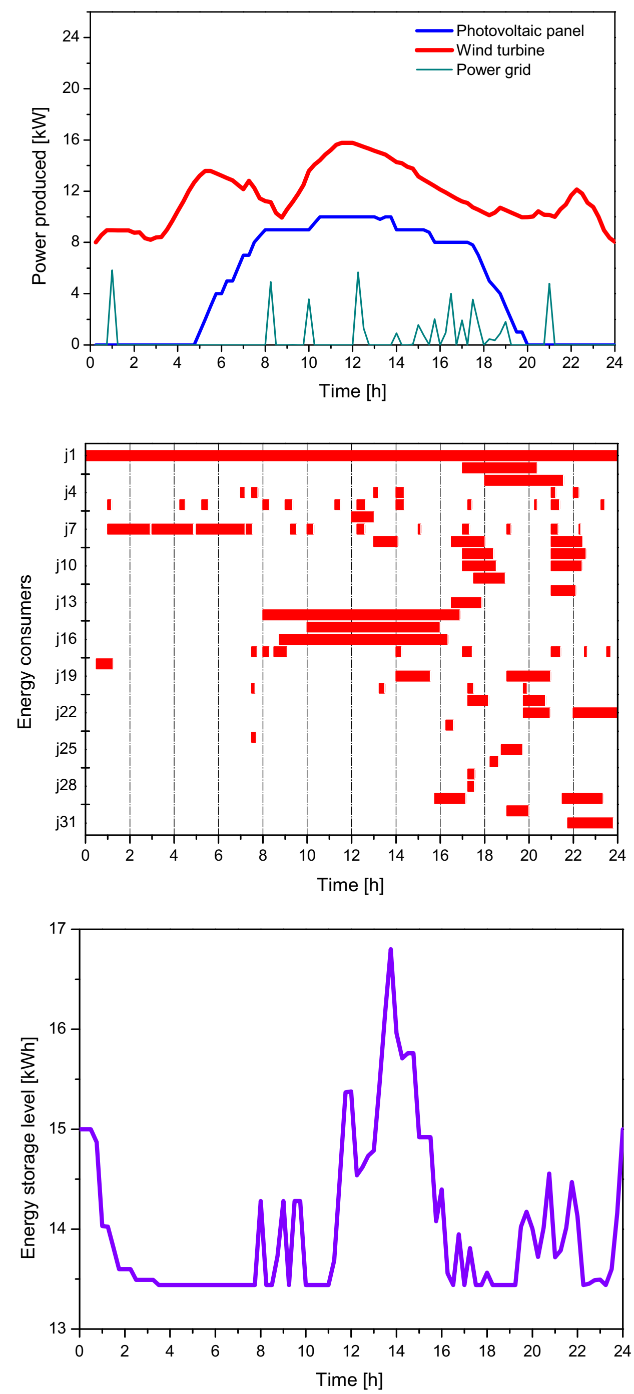

Fig. 6. Daily schedule for energy production, consumption and storage ($PH = 20$).

$$CostPro = \sum_{\substack{t=1 \\ t\in TRH}}^{T}\sum_{i=1}^{I} cpro_{i,t}\cdot P_{i,t}\cdot DT \tag{19}$$

$$CostSto = \sum_{\substack{t=1 \\ t\in TRH}}^{T}\sum_{k=1}^{K} csto_{k,t}\cdot SE_{k,t} \tag{20}$$

$$CostPen = \sum_{j=1}^{J}\sum_{\substack{f=1 \\ f\in F_jRH}}^{F_j} cpen_{j,f}\cdot(Ts_{j,f} - Tin_{j,f}) \tag{21}$$

$$Costs = CostPro + CostSto + CostPen \tag{22}$$

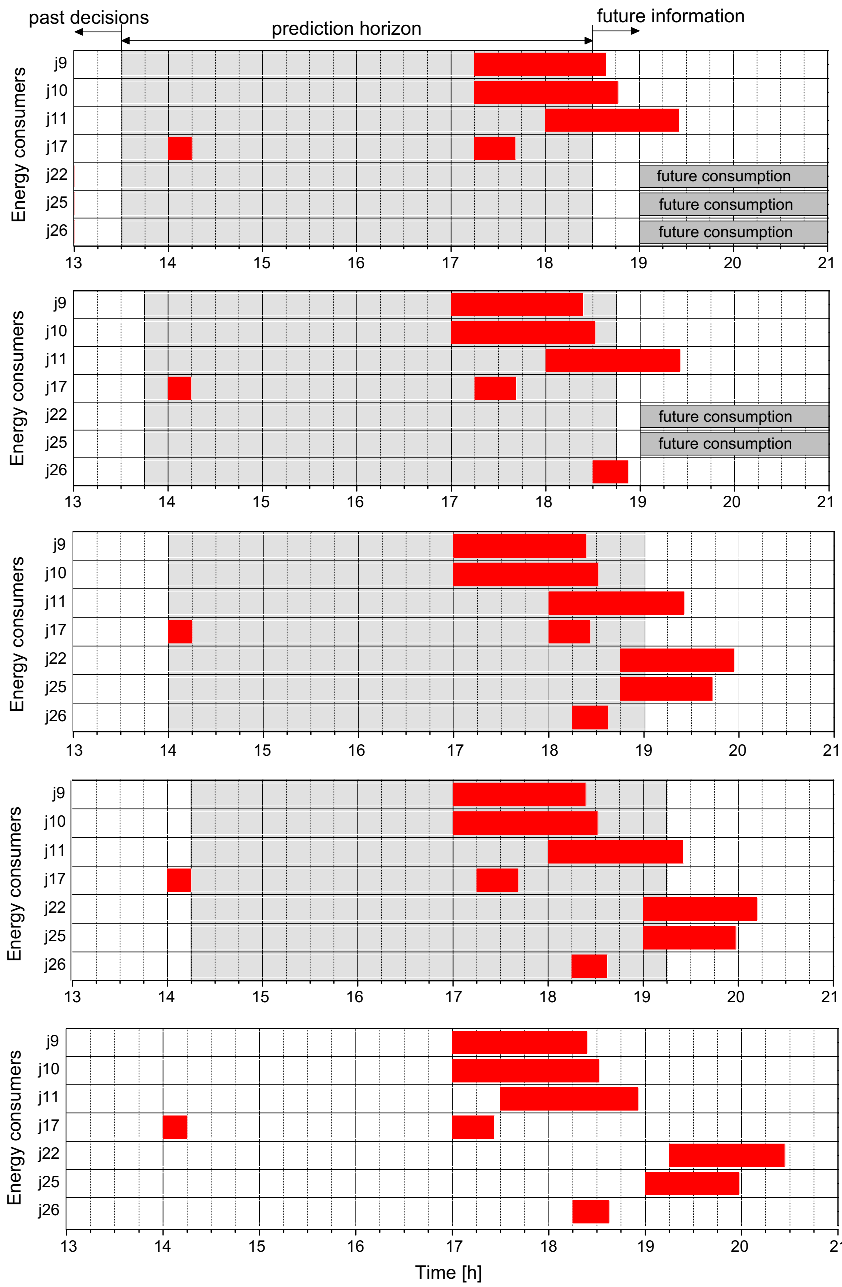

Fig. 7. Evolution of the energy consumption scheduling for $PH = 20$ in iterations 54, 55, 56, 57 and final iteration.

Also, energy revenues to the power grid have been taken into account. Thus, incomes are given by Eq. (23) considering the energy sales to each power grid.

$$Incomes = \sum_{\substack{t=1 \\ t \in TRH}}^{T} \sum_{r=1}^{R} Price_{r,t} \cdot Pg_{r,t} \cdot DT \tag{23}$$

In this study, the objective function is the profit of the microgrid that includes total incomes and costs, as given by:

$$Profit = Incomes - Costs \tag{24}$$

4.2. Rolling horizon approach

In order to use the proposed model in a rolling horizon scheme, the following set of variables and equations are used to link past decisions with the current prediction horizon. Minimum and maximum starting times of energy consumption tasks at each iteration are given by Eqs. (25) and (26), considering the minimum/-maximum starting time of the previous iteration and the duration of the control horizon (CH). The duration of the energy consumption tasks is also updated at each iteration, as indicated by Eq. (27). And finally, the energy storage level of the previous control horizon is linked to the initial energy storage level of the current prediction horizon by Eq. (28). The optimization problem will be iteratively solved according to the rolling horizon approach. This reactive approach will be used to adjust all input parameters to the current available information.

$$Ts_{j,f}^{min} = Ts_{0,j,f}^{min} - CH \cdot it \quad \forall j, f \in F_jRH \tag{25}$$

$$Ts_{j,f}^{max} = Ts_{0,j,f}^{max} - CH \cdot it \quad \forall j, f \in F_jRH \tag{26}$$

$$Dur_{j,f} = Dur_{0,j,f} - (CH \cdot it - Ts_{j,f}) \cdot \widehat{Y}_{j,f} \quad \forall j, f \in F_jRH \tag{27}$$

$$SE_{k,t-1} = \widehat{SE}_{k,t'} \quad \forall k, t, t' \in TRH, \quad t' = T_t \cdot DT \tag{28}$$

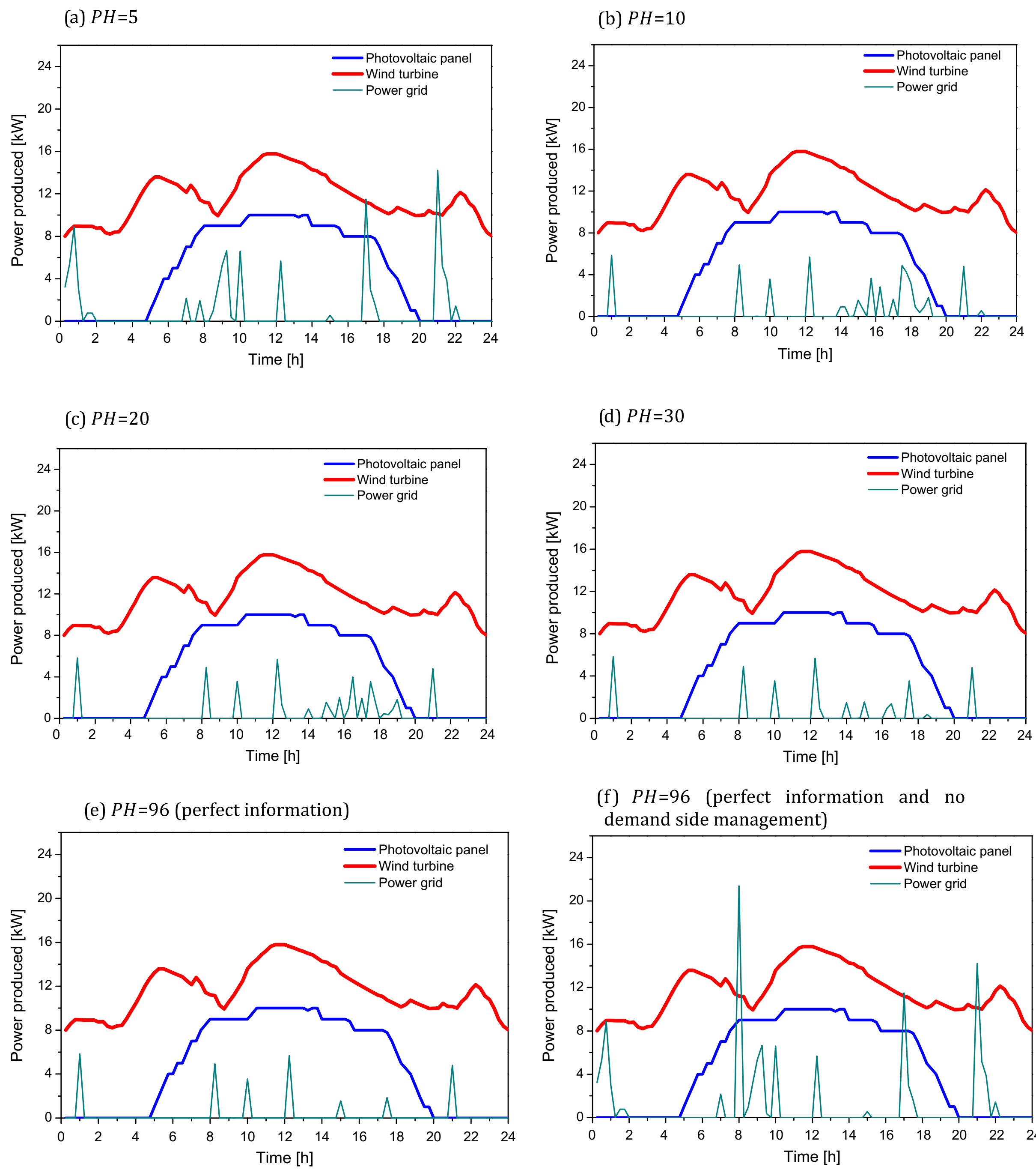

Fig. 8. Power source in each time interval for different *PH* lengths.

This mathematical formulation involves a MILP model. However, this mathematical formulation can be extended by introducing some features of the typical unit commitment problem associated to energy problems, such as ramping constraints and minimum up and down time constraints, as well as non-convex production costs and time-dependent startup costs, which may introduce non-linearities in the model. Moreover, the discrete-time representation has been chosen instead of the hybrid or the continuous-time formulation. Although the optimal solution could be improved by the use of hybrid or continuous-time representations, the resulting models involve more computational time. Also, the proposed model does not consider the presence of fixed costs associated to the investment and installation of energy production generators, since the design of the energy network related to the microgrid has not been taken into account and only short-term decisions are addressed.

5. Case study

The proposed MILP formulation has been applied to a case study. The microgrid of the case study consists of a photovoltaic panel and a micro-wind turbine. In addition, this microgrid is connected to the main power grid. The possibility to purchase energy from the power grid ensures the feasibility of the optimization problem, disregarding weather conditions and unexpected

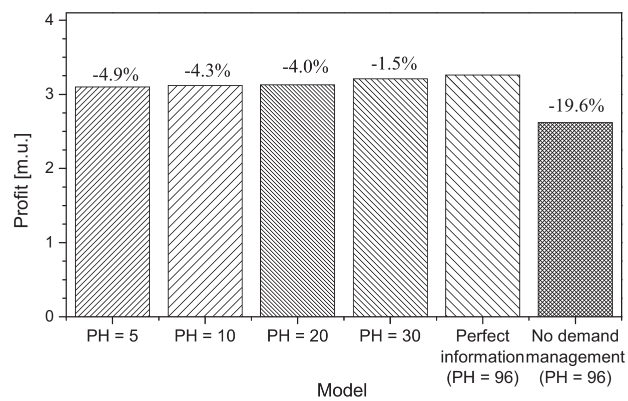

Fig. 9. Profit for different *PHs*, perfect information and no demand management case.

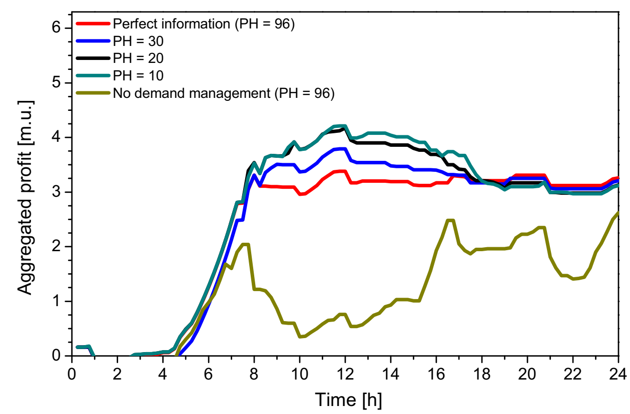

Fig. 10. Aggregated profit for different *PHs*, perfect information and no demand management case.

Table 2
Comparison of the results for scenario 1 (demand side management).

Unit	$PH = 5$	$PH = 10$	$PH = 20$	$PH = 30$	$PH = 96$
Profit (m.u.)	3.10	3.12	3.13	3.21	3.26
Consumed energy (kW h)	359.0	359.0	359.0	359.0	359.0
Total delays (h)	18.00	12.75	12.50	12.25	11.75
Energy produced or purchased (kW h)	416.0	405.4	403.7	400.7	399.0
Energy from photovoltaic panels (kW h)	112.7	112.7	112.7	112.7	112.7
Energy from wind turbines (kW h)	279.2	279.2	279.2	279.2	279.2
Energy from power grid (kW h)	24.0	13.5	11.7	8.8	7.0
Energy from energy storage systems (kW h)	19.5	14.2	10.3	11.2	11.9
Energy sold to the power grid (kW h)	58.5	58.5	44.3	42.1	38.9
Energy to load the storage system (kW h)	12.4	12.2	13.6	14.5	14.9
Energy loses (kW h)	16.2	0.3	0.3	0.3	0.3

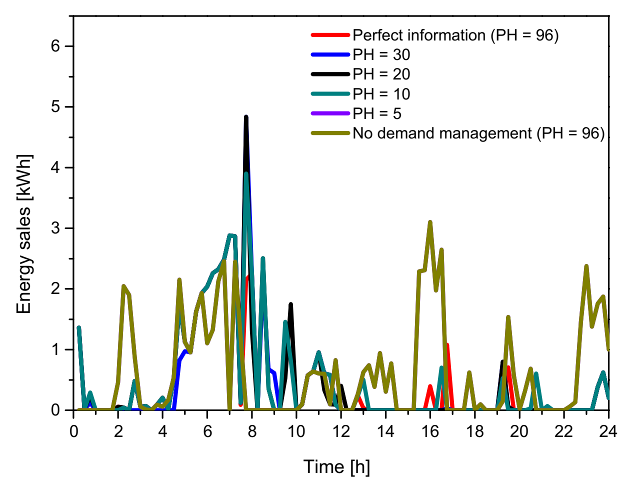

Fig. 11. Energy sales for different *PHs*, perfect information and no demand management case.

Table 3
Comparison of the results for cenario 2 (non-demand side management).

Unit	$PH = 5$	$PH = 10$	$PH = 20$	$PH = 30$	$PH = 96$
Profit (m.u.)	2.61	2.62	2.62	2.62	2.62
Consumed energy (kW h)	359.0	359.0	359.0	359.0	359.0
Total delays (h)	0.00	0.00	0.00	0.00	0.00
Energy produced or purchased (kW h)	422.1	420.8	420.8	420.8	420.8
Energy from photovoltaic panels (kW h)	112.7	112.7	112.7	112.7	112.7
Energy from wind turbines (kW h)	279.2	279.2	279.2	279.2	279.2
Energy from power grid (kW h)	30.3	28.9	28.9	28.9	28.9
Energy from energy storage systems (kW h)	18.2	19.5	19.5	19.5	19.5
Energy sold to the power grid (kW h)	60.2	58.5	58.5	58.5	58.5
Energy to load the storage system (kW h)	21.1	22.8	22.8	22.8	22.8
Energy loses (kW h)	0.1	0.1	0.1	0.1	0.1

Table 4
Comparison of optimal solution and model statistics.

Unit	$PH = 5$	$PH = 10$	$PH = 20$	$PH = 30$	$PH = 96$
Number of iterations	92	87	77	67	1
Equations per iteration	481	1216	3726	8016	93,604
Continuous variables per iteration	360	855	2,424	5,004	54,615
Discrete variables per iteration	80	260	1001	2411	33,468
Computational time per iteration (CPU, s)	0.1	0.3	0.3	0.4	0.8
Relative gap (%)	0.0	0.0	0.0	0.0	0.0

demand profiles. Also, an energy storage system has been considered.

Moreover, a total number of 30 different energy consumers j has been taken into account, with different energy consumption task jf. The possibility that the same consumer j will be active several times is considered. These energy consumptions are modelled allowing a certain delay from the initial target, depending on the availability and demand of energy. Each energy consumption task is associated with a penalty cost, in case of deviation from the target. A schematic representation of the considered microgrid can be found in Fig. 4.

The underlying scheduling problem includes energy production, storage and consumption tasks to be optimized. Data and decisions related to energy production are given for every 15 min, according to energy demand and the current weather forecast. Also, decisions related to energy demand are considered for every 15 min, as well as production decisions. The total scheduling horizon considered is 24 h, and the duration of each time interval is 15 min (i.e., 96 time

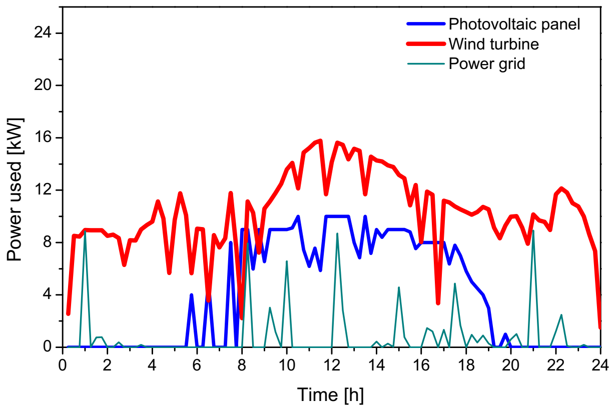

Fig. 12. Schedule of energy production with no sales to the power grid ($PH = 20$).

intervals in total). Prediction Horizons (*PHs*) of 5, 10, 20 and 30 time intervals have been considered. It has been considered that input data (e.g., energy demands, weather conditions) are updated at the beginning of each time interval, so the control horizon has been set also equal to 15 min (i.e., one time interval).

Data related to energy production cost for each generator and energy storage cost are presented in Table 1. Also, the same table displays the minimum and maximum values for energy supply and storage. The energy resource availability from different energy generators is displayed in Fig. 5. Data related to maximum power availability can be found in Table A2 in Appendix A. It is important to remark that variable production costs related to the energy production through solar panels and wind turbines are considered to be zero. Also, fixed costs (related to the investment, installation and maintenance of the generators) are not considered since the design of the energy supply chain related to the microgrid has not been taken into account in the operational level. Thus, only short-term decisions are considered. The minimum energy level of the energy storage system is determined by the 80% of the maximum capacity, because forcing lower energy levels shorten the life cycle of the energy storage system. All data used in this case study have been adapted to a domestic scenario within a single household served by a simple microgrid. However, input parameters can be modified in order to take into account the characteristics of other kind of problems, such as real situations at industrial level.

6. Results and discussion

The resulting MILP model has been implemented in GAMS 24.1 [36] and solved using CPLEX 12, to zero optimality in a Pentium Intel® Core™ i7 CPU 2600 @ 3.40 GHz. The resolution of the model provides the daily optimal schedule for energy generation and consumption in order to maximize the profit of the given microgrid. The rolling horizon approach, used to address the presence of uncertainty, has allowed to update input information related to weather conditions and consumption durations. Fig. 6 displays the daily schedule for energy production and energy consumptions for a prediction horizon of 20 time intervals. Some energy consumption tasks have been delayed (i.e., energy demand has right-shifted). According to this figure, the microgrid produce the maximum energy capacity from energy renewable sources, in order to satisfy the energy demand and to sell this energy to the power grid. The purchases of energy from the power grid are required if the use of both renewable energy systems and the energy storage system is not enough to meet the energy demand.

The application of the rolling horizon, in which the problem formulation is solved iteratively, can produce constant changes in the

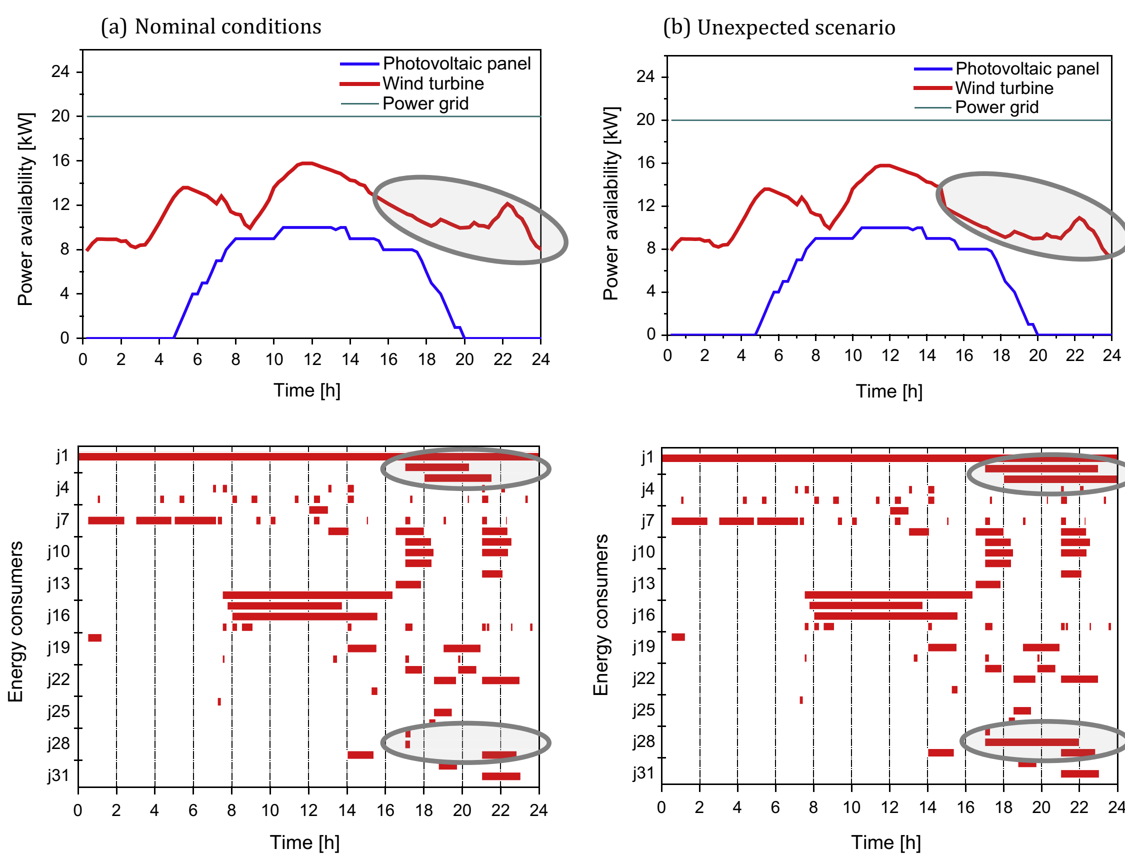

Fig. 13. Power availability and target schedule for the nominal conditions scenario and the unexpected scenario.

expected schedule (Fig. 7). This is produce because the input information is updated and future information is introduced in the system. To highlight these changes, only some consumption tasks have been plotted. At the beginning, some consumption tasks do not appear in the plot because in the current time there is no information related to the mentioned consumptions.

Different lengths of the prediction horizon have been considered, in order to compare, analyse and highlight the characteristics of the proposed rolling horizon and the simultaneous management of energy production and demand. Thus, prediction horizons of 5, 10, 20 and 30 time intervals has been taken into account. Moreover, the perfect information case ($PH = 96$), which corresponds to the situation in which the length of the prediction horizon is equal to the length of the scheduling horizon, has been considered.

In all these situations, the control horizon is equal to one time interval. According to the obtained results, longer prediction horizons involve a significant reduction in the use of the power grid to satisfy the demand (Fig. 8), since more future information is received to solve the optimization problem. As a consequence, the profit increases for longer prediction horizons (Fig. 9 and Table 2). In order to compare how the simultaneous energy production and demand management affects the final solution, Table 3 shows the obtained results in the case of managing only the energy production, in which energy consumptions cannot be shifted. As expected, the obtained profit decreases in comparison with that of the simultaneous management.

Fig. 10 shows the aggregated objective value for the rolling horizon approach under different prediction horizons in comparison with the perfect information case. Not surprisingly, as the length of the prediction horizon increases, the total objective is improved and closes the gap from the perfect information solution. Shorter prediction horizon involve more energy sales to the power grid (Fig. 11), because there is no information about future energy demand, requiring energy purchases from the power grid and more delays in the energy consumptions. Model statistics for the proposed model using different lengths for the prediction horizon can be found in Table 4.

Finally, in order to show how the energy production is managed, a variation from the initial model was solved. This model variation minimizes the total cost of the microgrid, without taking into account possible energy sales. Thus, the objective function will be to minimize Eq. (22) subject to constraints (1)–(21). This fact explains that in specific time intervals, all energy generators can be switched off, in order to match energy production and consumption. However, if the energy generator cannot be controlled (i.e., if produces, the production corresponds to the maximum power availability for this source), the excess of energy will be dissipated to an external load. For example, Fig. 12 shows the schedule of energy production that will be used to satisfy all energy consumptions for a prediction horizon equal to 20 time intervals. However, this figure indicates just the power used from each energy generator to perform all energy consumption tasks, without taking into account energy dissipations. Notice that in this case in contrast to the previous solution approach, the energy production does not reach the maximum energy production capacity, since only the energy to be consumed or stored is produced. In this case, 378.8 kW h were produced (30.3% produced from the photovoltaic panel and 69.7% from the wind turbine), reducing the energy requirements by 5.3%.

Moreover, the reactive scheduling approach allows updating input parameters to react to variations from the nominal/initial plan, including alterations in the power availability or in the duration of energy consumptions. This means that this approach is able to handle the types of uncertainty associated to the microgrid (i.e., prediction in the wind turbine and photovoltaic panel forecasts and energy consumption predictions). For instance, Fig. 13 shows an unexpected scenario in which there is a reduction in the power availability as well as an increased duration of some duration consumptions, with the objective of maximizing the profit of the microgrid. This variation is due to the uncertainty to predict accurately the weather forecast which directly affects the power availability.

Table 5
Comparison of the results for the demand side management for the unexpected scenario.

Unit	$PH = 20$	$PH = 96$
Profit (m.u.)	0.47	0.45
Consumed energy (kW h)	368.6	368.6
Total delays (h)	12.25	11.75
Energy produced or purchased (kW h)	405.0	399.4
Energy from photovoltaic panels (kW h)	112.7	112.7
Energy from wind turbines (kW h)	269.2	269.2
Energy from power grid (kW h)	23.0	17.5
Energy from energy storage systems (kW h)	16.9	19.3
Energy sold to the power grid (kW h)	34.2	27.0
Energy to load the storage system and energy loses (kW h)	19.0	23.1

The rolling horizon approach allows to react to any eventual alteration from the initial conditions. Table 5 compares the results for the simultaneous energy production and demand management, for $PH = 20$ and the perfect information case. According to the results, energy purchases are required in both cases to satisfy the energy demand. However, the use of the rolling horizon approach allows the benefit to be more than 3% higher compared with the perfect information case.

7. Conclusions

In this work, a discrete-time MILP formulation for the simultaneous optimization of energy production and consumption tasks in microgrids has been presented. The objective function considered is the maximization of the total profit. The proposed approach has proven the advantages of managing the energy demand by optimizing the management of the microgrid, which allows enhancing its flexibility and autonomy.

A rolling horizon approach has been introduced in the formulation to address the presence of uncertainty. As expected, longer prediction horizons favor the generation of better solutions, under the assumption of accurate demand predictions. This approach allows updating input parameters, in order to react to variations from the nominal schedule, which allows to adapt energy production and energy demand to update parameters.

The proposed approach has been used to solve a case study of a microgrid and also it could be used as the basis for solving further problems with higher complexity by combining a reactive and proactive technique to take into account the presence of uncertainty, as well as the simultaneous consideration of different factors (i.e., costs, environmental impact) through the implementation of multi-objective optimization approaches. Finally, in the same line with Kopanos et al. [37], rescheduling actions penalties could be included to the proposed optimization framework to avoid major changes in the initial schedule after the occurence of an unexpected event.

Acknowledgements

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Table A1
Input parameters.

Energy consumer j	Energy demand f	Power (kW)	$Ts_{j,f}^{min}$ (h)	$Dur_{j,f}$ (h)	$Ts_{j,f}^{max}$ (h)	Penalty cost (m.u./h)
$j1$	$f1$	2.557	0.00	0.250	0.00	40
$j1$	$f2$	1.012	0.25	0.250	0.25	40
$j1$	$f3$	0.957	0.50	0.250	0.50	40
$j1$	$f4$	0.916	0.75	0.250	0.75	40
$j1$	$f5$	0.955	1.00	0.250	1.00	40
$j1$	$f6$	1.693	1.25	0.250	1.25	40
$j1$	$f7$	1.705	1.50	0.250	1.50	40
$j1$	$f8$	0.520	1.75	0.250	1.75	40
$j1$	$f9$	0.605	2.00	0.250	2.00	40
$j1$	$f10$	0.728	2.25	0.250	2.25	40
$j1$	$f11$	0.683	2.50	0.250	2.50	40
$j1$	$f12$	0.174	2.75	0.250	2.75	40
$j1$	$f13$	0.157	3.00	0.250	3.00	40
$j1$	$f14$	1.187	3.25	0.250	3.25	40
$j1$	$f15$	1.341	3.50	0.250	3.50	40
$j1$	$f16$	1.606	3.75	0.250	3.75	40
$j1$	$f17$	1.143	4.00	0.250	4.00	40
$j1$	$f18$	1.843	4.25	0.250	4.25	40
$j1$	$f19$	1.684	4.50	0.250	4.50	40
$j1$	$f20$	1.719	4.75	0.250	4.75	40
$j1$	$f21$	1.776	5.00	0.250	5.00	40
$j1$	$f22$	1.686	5.25	0.250	5.25	40
$j1$	$f23$	1.672	5.50	0.250	5.50	40
$j1$	$f24$	1.070	5.75	0.250	5.75	40
$j1$	$f25$	1.008	6.00	0.250	6.00	40
$j1$	$f26$	0.565	6.25	0.250	6.25	40
$j1$	$f27$	0.565	6.50	0.250	6.50	40
$j1$	$f28$	0.945	6.75	0.250	6.75	40
$j1$	$f29$	0.335	7.00	0.250	7.00	40
$j1$	$f30$	0.492	7.25	0.250	7.25	40
$j1$	$f31$	0.560	7.50	0.250	7.50	40
$j1$	$f32$	0.233	7.75	0.250	7.75	40
$j1$	$f33$	0.288	8.00	0.250	8.00	40
$j1$	$f34$	0.260	8.25	0.250	8.25	40
$j1$	$f35$	0.230	8.50	0.250	8.50	40
$j1$	$f36$	0.348	8.75	0.250	8.75	40
$j1$	$f37$	0.386	9.00	0.250	9.00	40
$j1$	$f38$	0.163	9.25	0.250	9.25	40
$j1$	$f39$	0.481	9.50	0.250	9.50	40
$j1$	$f40$	0.168	9.75	0.250	9.75	40
$j1$	$f41$	0.600	10.00	0.250	10.00	40
$j1$	$f42$	1.129	10.25	0.250	10.25	40
$j1$	$f43$	1.311	10.50	0.250	10.50	40
$j1$	$f44$	0.400	10.75	0.250	10.75	40
$j1$	$f45$	0.200	11.00	0.250	11.00	40
$j1$	$f46$	0.655	11.25	0.250	11.25	40
$j1$	$f47$	0.694	11.50	0.250	11.50	40
$j1$	$f48$	0.494	11.75	0.250	11.75	40
$j1$	$f49$	0.681	12.00	0.250	12.00	40
$j1$	$f50$	0.436	12.25	0.250	12.25	40
$j1$	$f51$	0.723	12.50	0.250	12.50	40
$j1$	$f52$	1.195	12.75	0.250	12.75	40
$j1$	$f53$	0.212	13.00	0.250	13.00	40
$j1$	$f54$	0.295	13.25	0.250	13.25	40
$j1$	$f55$	0.342	13.50	0.250	13.50	40
$j1$	$f56$	0.209	13.75	0.250	13.75	40
$j1$	$f57$	0.421	14.00	0.250	14.00	40
$j1$	$f58$	0.179	14.25	0.250	14.25	40
$j1$	$f59$	0.296	14.50	0.250	14.50	40
$j1$	$f60$	0.236	14.75	0.250	14.75	40
$j1$	$f61$	0.174	15.00	0.250	15.00	40
$j1$	$f62$	0.155	15.25	0.250	15.25	40
$j1$	$f63$	0.423	15.50	0.250	15.50	40
$j1$	$f64$	0.734	15.75	0.250	15.75	40
$j1$	$f65$	0.075	16.00	0.250	16.00	40
$j1$	$f66$	0.680	16.25	0.250	16.25	40
$j1$	$f67$	0.573	16.50	0.250	16.50	40
$j1$	$f68$	0.171	16.75	0.250	16.75	40
$j1$	$f69$	0.465	17.00	0.250	17.00	40
$j1$	$f70$	0.461	17.25	0.250	17.25	40
$j1$	$f71$	0.479	17.50	0.250	17.50	40
$j1$	$f72$	0.010	17.75	0.250	17.75	40
$j1$	$f73$	0.457	18.00	0.250	18.00	40
$j1$	$f74$	0.077	18.25	0.250	18.25	40

(*continued on next page*)

Table A1 (*continued*)

Energy consumer j	Energy demand f	Power (kW)	$Ts_{j,f}^{min}$ (h)	$Dur_{j,f}$ (h)	$Ts_{j,f}^{max}$ (h)	Penalty cost (m.u./h)
j1	f75	0.224	18.50	0.250	18.50	40
j1	f76	0.632	18.75	0.250	18.75	40
j1	f77	0.441	19.00	0.250	19.00	40
j1	f78	0.028	19.25	0.250	19.25	40
j1	f79	0.088	19.50	0.250	19.50	40
j1	f80	0.743	19.75	0.250	19.75	40
j1	f81	0.931	20.00	0.250	20.00	40
j1	f82	0.792	20.25	0.250	20.25	40
j1	f83	0.906	20.50	0.250	20.50	40
j1	f84	1.299	20.75	0.250	20.75	40
j1	f85	0.918	21.00	0.250	21.00	40
j1	f86	0.894	21.25	0.250	21.25	40
j1	f87	0.572	21.50	0.250	21.50	40
j1	f88	0.193	21.75	0.250	21.75	40
j1	f89	0.725	22.00	0.250	22.00	40
j1	f90	0.187	22.25	0.250	22.25	40
j1	f91	0.443	22.50	0.250	22.50	40
j1	f92	0.259	22.75	0.250	22.75	40
j1	f93	0.689	23.00	0.250	23.00	40
j1	f94	0.631	23.25	0.250	23.25	40
j1	f95	0.862	23.50	0.250	23.50	40
j1	f96	0.312	23.75	0.250	23.75	40
j2	f1	1.500	16.75	3.375	16.75	0.4
j3	f1	1.500	17.75	3.550	17.75	0.4
j4	f1	0.350	6.75	0.200	6.75	0.04
j4	f2	0.350	7.25	0.275	7.25	0.04
j4	f3	0.350	12.75	0.225	12.75	0.04
j4	f4	0.350	13.75	0.375	13.75	0.04
j4	f5	0.350	20.75	0.200	20.75	0.04
j4	f6	0.350	21.75	0.250	21.75	0.04
j5	f1	2.000	0.75	0.175	0.75	0.04
j5	f2	2.000	4.00	0.250	4.00	0.04
j5	f3	2.000	5.00	0.300	5.00	0.04
j5	f4	2.000	7.75	0.300	7.75	0.04
j5	f5	2.000	8.75	0.350	8.75	0.04
j5	f6	2.000	11.00	0.250	11.00	0.04
j5	f7	2.000	12.00	0.375	12.00	0.04
j5	f8	2.000	13.75	0.375	13.75	0.04
j5	f9	2.000	17.00	0.175	17.00	0.04
j5	f10	2.000	20.00	0.125	20.00	0.04
j5	f11	2.000	20.75	0.375	20.75	0.04
j5	f12	2.000	23.00	0.175	23.00	0.04
j6	f1	2.640	11.75	1.025	11.75	0.04
j7	f1	8.000	0.25	1.925	0.75	0.04
j7	f2	8.000	2.75	1.875	3.00	0.04
j7	f3	8.000	4.75	2.200	5.00	0.04
j7	f4	8.000	7.00	0.275	7.00	0.04
j7	f5	8.000	9.00	0.275	9.00	0.04
j7	f6	8.000	9.75	0.300	9.75	0.04
j7	f7	8.000	12.00	0.350	12.00	0.04
j7	f8	8.000	14.75	0.125	14.75	0.04
j7	f9	8.000	16.75	0.325	16.75	0.04
j7	f10	8.000	18.75	0.200	18.75	0.04
j7	f11	8.000	20.75	0.325	20.75	0.04
j7	f12	8.000	22.00	0.100	22.50	0.04
j8	f1	0.400	12.75	1.100	13.00	0.02
j8	f2	0.400	16.25	1.525	16.50	0.02
j8	f3	0.400	20.75	1.375	21.25	0.02
j9	f1	0.240	16.75	1.400	17.00	0.02
j9	f2	0.240	20.75	1.575	21.25	0.02
j10	f1	0.240	16.75	1.525	17.00	0.02
j10	f2	0.240	20.75	1.400	21.25	0.02
j11	f1	12.000	16.75	1.425	17.75	0.02
j12	f1	2.000	20.75	1.125	21.00	0.02
j13	f1	8.000	16.25	1.375	16.50	0.02
j14	f1	7.000	7.25	8.900	7.75	0.02
j15	f1	7.000	7.50	6.000	9.75	0.02
j16	f1	7.000	7.75	7.600	8.50	0.02
j17	f1	2.000	7.25	0.250	7.50	0.02
j17	f2	2.000	7.75	0.300	7.75	0.02
j17	f3	2.000	8.25	0.600	8.50	0.02
j17	f4	2.000	13.75	0.250	14.25	0.02
j17	f5	2.000	16.75	0.450	17.00	0.02
j17	f6	2.000	20.75	0.250	20.75	0.02
j17	f7	2.000	21.00	0.175	21.50	0.02

Table A1 (*continued*)

Energy consumer j	Energy demand f	Power (kW)	$Ts_{j,f}^{min}$ (h)	$Dur_{j,f}$ (h)	$Ts_{j,f}^{max}$ (h)	Penalty cost (m.u./h)
j17	f8	2.000	22.25	0.125	22.50	0.02
j17	f9	2.000	23.25	0.200	23.25	0.02
j18	f1	7.500	0.25	0.750	0.75	0.02
j19	f1	1.500	13.75	1.550	14.50	0.02
j19	f2	1.500	18.75	1.975	19.00	0.02
j20	f1	0.240	7.25	0.150	7.50	0.004
j20	f2	0.240	13.00	0.250	13.25	0.004
j20	f3	0.240	16.75	0.250	17.00	0.004
j20	f4	0.240	19.50	0.175	19.50	0.004
j21	f1	0.350	16.75	0.925	17.00	0.004
j21	f2	0.350	19.50	1.000	19.50	0.004
j22	f1	5.000	18.25	1.200	19.50	0.004
j22	f2	5.000	20.75	2.000	21.75	0.004
j23	f1	10.000	15.00	0.350	16.25	0.004
j24	f1	20.000	7.00	0.200	7.25	0.004
j24	f2	20.000	7.75	0.250	9.75	0.004
j25	f1	4.000	18.25	0.975	18.75	0.004
j26	f1	0.192	18.00	0.375	18.25	0.004
j27	f1	0.440	16.75	0.325	17.00	0.004
j28	f1	0.660	16.75	0.300	17.00	0.004
j29	f1	4.000	13.75	1.400	15.50	0.004
j29	f2	4.000	20.75	1.850	21.50	0.004
j30	f1	0.200	18.50	1.000	18.75	0.004
j31	f1	1.500	20.75	2.050	21.50	0.004

Table A2
Maximum availability of power for each energy generator i at interval t.

Time interval	Photovoltaic panel, i1 (kW)	Wind turbine, i2 (kW)	Power grid, i3 (kW)
t1	0.0000	8.0101	20.0000
t2	0.0000	8.5800	20.0000
t3	0.0000	8.9637	20.0000
t4	0.0000	8.9509	20.0000
t5	0.0000	8.9374	20.0000
t6	0.0000	8.9325	20.0000
t7	0.0000	8.9365	20.0000
t8	0.0000	8.7540	20.0000
t9	0.0000	8.7881	20.0000
t10	0.0000	8.3396	20.0000
t11	0.0000	8.2092	20.0000
t12	0.0000	8.3976	20.0000
t13	0.0000	8.4325	20.0000
t14	0.0000	8.9991	20.0000
t15	0.0000	9.6991	20.0000
t16	0.0000	10.4340	20.0000
t17	0.0000	11.2057	20.0000
t18	0.0000	12.0160	20.0000
t19	0.0000	12.6966	20.0000
t20	1.0000	13.2275	20.0000
t21	2.0000	13.5921	20.0000
t22	3.0000	13.5921	20.0000
t23	4.0000	13.4062	20.0000
t24	4.0000	13.2221	20.0000
t25	5.0000	13.0399	20.0000
t26	5.0000	12.8595	20.0000
t27	6.0000	12.5023	20.0000
t28	7.0000	12.1522	20.0000
t29	7.0000	12.8092	20.0000
t30	8.0000	12.2730	20.0000
t31	8.5000	11.4436	20.0000
t32	9.0000	11.2207	20.0000
t33	9.0000	11.1461	20.0000
t34	9.0000	10.2857	20.0000
t35	9.0000	9.9391	20.0000
t36	9.0000	10.5947	20.0000
t37	9.0000	11.1518	20.0000
t38	9.0000	11.7933	20.0000
t39	9.0000	12.4862	20.0000
t40	9.0000	13.5857	20.0000
t41	9.5000	14.0864	20.0000
t42	10.0000	14.4237	20.0000

(*continued on next page*)

Table A2 (*continued*)

Time interval	Photovoltaic panel, *i*1 (kW)	Wind turbine, *i*2 (kW)	Power grid, *i*3 (kW)
*t*43	10.0000	14.8724	20.0000
*t*44	10.0000	15.2228	20.0000
*t*45	10.0000	15.6293	20.0000
*t*46	10.0000	15.7856	20.0000
*t*47	10.0000	15.7856	20.0000
*t*48	10.0000	15.7856	20.0000
*t*49	10.0000	15.6277	20.0000
*t*50	10.0000	15.4715	20.0000
*t*51	10.0000	15.3167	20.0000
*t*52	10.0000	15.1636	20.0000
*t*53	9.8000	15.0119	20.0000
*t*54	10.0000	14.8618	20.0000
*t*55	10.0000	14.5646	20.0000
*t*56	9.0000	14.2733	20.0000
*t*57	9.0000	14.1878	20.0000
*t*58	9.0000	13.9081	20.0000
*t*59	9.0000	13.7669	20.0000
*t*60	9.0000	13.1652	20.0000
*t*61	9.0000	12.9019	20.0000
*t*62	8.8000	12.6439	20.0000
*t*63	8.0000	12.3910	20.0000
*t*64	8.0000	12.1432	20.0000
*t*65	8.0000	11.9003	20.0000
*t*66	8.0000	11.6623	20.0000
*t*67	8.0000	11.4291	20.0000
*t*68	8.0000	11.2005	20.0000
*t*69	8.0000	11.0765	20.0000
*t*70	7.8000	10.7569	20.0000
*t*71	7.0000	10.5418	20.0000
*t*72	6.0000	10.3310	20.0000
*t*73	5.0000	10.1244	20.0000
*t*74	4.5000	10.3310	20.0000
*t*75	4.0000	10.7234	20.0000
*t*76	3.0000	10.5290	20.0000
*t*77	2.0000	10.3384	20.0000
*t*78	1.0000	10.1516	20.0000
*t*79	1.0000	9.9686	20.0000
*t*80	0.0000	9.9892	20.0000
*t*81	0.0000	10.0134	20.0000
*t*82	0.0000	10.4412	20.0000
*t*83	0.0000	10.1723	20.0000
*t*84	0.0000	10.1459	20.0000
*t*85	0.0000	10.0069	20.0000
*t*86	0.0000	10.5880	20.0000
*t*87	0.0000	10.9698	20.0000
*t*88	0.0000	11.6925	20.0000
*t*89	0.0000	12.1341	20.0000
*t*90	0.0000	11.8204	20.0000
*t*91	0.0000	11.1056	20.0000
*t*92	0.0000	10.7717	20.0000
*t*93	0.0000	9.9986	20.0000
*t*94	0.0000	8.9664	20.0000
*t*95	0.0000	8.3550	20.0000
*t*96	0.0000	8.0446	20.0000

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Appendix A

See Tables A1 and A2.

References

[1] Wang L, Singh C. Multicriteria design of hybrid power generation systems based on a modified particle swarm optimization algorithm. IEEE Trans Energy Convers 2009;24:163–72.

[2] Girard R, Laquaine K, Kariniotakis G. Assessment of wind power predictability as a decision factor in the investment phase of wind farms. Appl Energy 2013;101:609–17.

[3] Shapiro A, Tekaya W, da Costa JP, Soares MP. Risk neutral and risk averse stochastic dual dynamic programming method. Eur J Oper Res 2013;224:375–91.

[4] Li Z, Ding R, Floudas CA. A comparative theoretical and computational study on robust counterpart optimization: I. Robust linear optimization and robust mixed integer linear optimization. Ind Eng Chem Res 2011;50:10567–603.

[5] Giaouris D, Papadopoulos AI, Ziogou C, Ipsakis D, Voutetakis S, Papadopoulou S, et al. Performance investigation of a hybrid renewable power generation and storage system using systemic power management models. Energy 2013;61:621–35.

[6] Giaouris D, Papadopoulos AI, Seferlis P, Papadopoulou S, Voutetakis S, Stergiopoulos F, et al. Optimum energy management in smart grids based on power pinch analysis. Chem Eng Trans 2014;39:55–60.

[7] Manfren M, Caputo P, Costa G. Paradigm shift in urban energy systems through distributed generation: methods and models. Appl Energy 2011;88:1032–48.

[8] Mehleri ED, Sarimveis H, Markatos NC, Papageorgiou LG. A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level. Energy 2012;44:96–104.

[9] Pruitt KA, Braun RJ, Newman AM. Evaluating shortfalls in mixed-integer programming approaches for the optimal design and dispatch of distributed generation systems. Appl Energy 2013;102:386–98.
[10] Zhao B, Zhang X, Li P, Wang K, Xue M, Wang C. Optimal sizing, operating strategy and operational experience of a stand-alone microgrid on Dongfushan Island. Appl Energy 2014;113:1656–66.
[11] Zamarripa MA, Vasquez JC, Guerrero JM, Graells M. Detailed operation scheduling and control for renewable energy powered microgrids. Comput Aided Chem Eng 2011;29:1819–23.
[12] Chen YH, Lu SY, Chang YR, Lee TT, Hu MC. Economic analysis and optimal energy management models for microgrid systems: a case study in Taiwan. Appl Energy 2013;103:145–54.
[13] Kopanos GM, Georgiadis MC, Pistikopoulos EN. Energy production planning of a network of micro combined heat and power generators. Appl Energy 2013;102:1522–34.
[14] Bhardwaj A, Kamboj VK, Shukla VK, Singh B, Khurana P. Unit commitment in electrical power system – a literature review. In: IEEE international power engineering and optimization conference; 2012. p. 275–280.
[15] Carrión M, Arroyo JM. A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem. IEEE Trans Power Syst 2006;21:1371–8.
[16] Zondervan E, Grossmann IE, de Haan AB. Energy optimization in the process industries: unit commitment at systems level. Comput Aided Chem Eng 2010;28:931–6.
[17] Velik R, Nicolay P. Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer. Appl Energy 2014;130:384–95.
[18] Della Vedova ML, Facchinetti T. Real-time scheduling for industrial load management. In: IEEE international energy conference and exhibition; 2012. p. 770–776.
[19] Nolde K, Morari M. Electrical load tracking scheduling of a steel plant. Comput Chem Eng 2010;34:1899–903.
[20] Mitra S, Grossmann IE, Pinto JM, Arora N. Optimal production planning under time sensitive electricity prices for continuous power-intensive processes. Comput Chem Eng 2012;38:171–84.
[21] Hadera H, Harjunkoski I, Grossmann IE, Sand G, Engell S. Steel production scheduling optimization under time-sensitive electricity costs. Comput Aided Chem Eng 2014;33:373–8.
[22] Mohsenian-Rad A, León-García A. Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans Smart Grid 2010;1:120–33.
[23] Silvente J, Graells M, Espuña A, Salas P. An optimization model for the management of energy supply and demand in smart grids. In: IEEE international energy conference and exhibition; 2012. p. 424–429.
[24] Silvente J, Aguirre A, Zamarripa MA, Méndez CA, Graells M, Espuña A. Improved time representation model for the simultaneous energy supply and demand management in microgrids. Energy 2015. http://dx.doi.org/10.1016/j.energy.2015.05.028.
[25] Silvente J, Aguirre A, Crexells G, Zamarripa MA, Méndez CA, Graells M, et al. Hybrid time representation for the scheduling of energy supply and demand in smart grids. Comput Aided Chem Eng 2013;32:553–8.
[26] Marietta M, Graells M, Guerrero JM. A rolling horizon rescheduling strategy for flexible energy in a microgrid. In: Energy conference (ENERGYCON), 2014 IEEE international; 2014. p. 1297–1303.
[27] Silvente J, Kopanos GM, Pistikopoulos EN, Espuña A. A reactive scheduling for the coordination of energy supply and demand management in microgrids. Comput-Aided Chem Eng 2014;33:493–8.
[28] Kopanos GM, Pistikopoulos EN. Reactive scheduling by a multiparametric programming rolling horizon framework: a case of a network of combined heat and power units. Ind Eng Chem Res 2014;53:4366–86.
[29] Parisio A, Rikos E, Tzamalis G, Glielmo L. Use of model predictive control for experimental microgrid optimization. Appl Energy 2014;115:37–46.
[30] Mohammadi S, Soleymani S, Mozafari B. Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices. Int J Electr Power Energy Syst 2014;54:525–35.
[31] Kuznetsova E, Li YF, Ruiz C, Zio E. An integrated framework of agent-based modelling and robust optimization for microgrid energy management. Appl Energy 2014;129:70–88.
[32] Dufo-López R, Bernal-Agustín JL, Yusta-Loyo JM, Domínguez-Navarro JA, Ramirez-Rosado IJ, Lujano J, et al. Muliti-objective optimization minimizing cost and life cycle emissions of stand-alone PV–wind–diesel systems with batteries storage. Appl Energy 2011;23:4033–41.
[33] Niknam T, Azizipanah-Abarghooee R, Narimani MR. An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation. Appl Energy 2012;99:455–70.
[34] Méndez CA, Cerdá J, Grossmann IE, Harjunkoski I, Fahl M. State-of-the-art review of optimization methods for short-term scheduling of batch processes. Comput Chem Eng 2006;30:913–46.
[35] Harjunkoski I, Maravelias CT, Bongers P, Castro PM, Engell S, Grossmann IE, et al. Scope for industrial applications of production scheduling models and solution methods. Comput Chem Eng 2014;62:161–93.
[36] Rosenthal RE. GAMS – a user's guide. Washington (United States): GAMS Development Corporation; 2012.
[37] Kopanos GM, Capón-García E, Espuña A, Puigjaner L. Costs for rescheduling actions: A critical issue for reducing the gap between scheduling theory and practice. Ind Eng Chem Res 2008;47:8785–95.