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Multistage day-ahead scheduling of the distributed energy sources in a local energy community

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***Abstract*—This paper presents a multistage approach for the day-ahead scheduling of a local energy community (LEC) aimed at considering the uncertainty associated to both the generation from renewable sources and the energy consumption. The considered LEC corresponds to a community of prosumers connected to the same distribution power network. In general, the considered prosumers are equipped with photovoltaic generating units, energy storage units, and local loads. The scheduling of the LEC is defined by a distributed optimization procedure based on the alternating direction method of multipliers (ADMM), which minimizes the total energy procurement costs. The adopted approach adjusts the operational planning according to the current operative conditions by means of a scenario-based multistage procedure. This paper describes the scenario tree generation and an intra-day decision-making procedure based on the day-ahead solution. Moreover, numerical tests are presented for several operating scenarios.**

Keywords—alternating direction method of multipliers, distributed optimization, energy management, local energy community, scenario reduction.

I. INTRODUCTION

This paper deals with the day-ahead energy management of a local energy community (LEC) in which direct energy transactions between the participants are allowed in addition to the transactions with the external energy provider. The regulatory challenges and opportunities for such entities are analyzed in e.g., [1], which also refers to the recent legal framework called "Clean Energy for all Europeans" approved by the European Union.

The expected gap between the prices of buying and selling energy from and to the external electricity provider, respectively, represents an attractive possibility for the implementation of local energy communities, and can be further increased by ancillary services, for instance.

The participants to the LEC are residential, small commercial or industrial sites connected to the same distribution network. Each participant can, in general, consume or produce electricity in different time periods, i.e. can be considered as a prosumer. In general, each prosumer may be equipped with local generation units (photovoltaic panels in this paper) and battery energy storage (BES) units, which help supplying its loads.

The LEC concept implies the implementation of an energy management system to achieve the common goals and the optimal operation of the installed energy resources [2]. According to several approaches presented in the literature (e.g., [3]–[6], and references therein), a day-ahead scheduling procedure is useful to minimize the total energy procurement costs of the community.

In a previous contribution [7], recently extended in [8], the authors of this paper have proposed a distributed approach based on the alternating direction method of multipliers (ADMM) which guarantees that each prosumer has an advantage in the participation to the LEC with respect to the case in which it can exchange energy only with the external provider. With respect to a centralized approach, a distributed approach appears more suitable for the scheduling of the resources inside of a community in which the participants will collaborate to a common goal, but they remain independent. In this context, the distributed approach, which may be implemented by using a distributed ledger technology [9], permits to limit the information that each participant needs to communicate to the others. This paper extends the study in [7], [8] by the presentation of a scenario-based ADMM approach that considers the uncertainties associated with the day-ahead forecasts of the photovoltaic (PV) generation and loads consumptions.

Stochastic optimization approaches are widely used to solve this kind of problems (e.g., [10]–[12]). Reference [13] considers the day-ahead scheduling of a single site, in which a multistage stochastic approach is employed to solve the scheduling problem of the battery. By applying this approach, the output set values of the BES units are adjusted at each stage according to the intra-day operating conditions (i.e. at the beginning of the day and at mid-day). In order to generate the scenario tree, which represents the multistage decision problem, a *k*-means clustering procedure has been implemented.

In this paper the scheme of [13] is adapted to the ADMM distributed approach. The main characteristics of the method proposed in this paper are the following:

- it considers the uncertainties of the forecasts of load and PV generation, represented with a scenario tree

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model that combines the different scenarios of the various prosumers;

- it includes a routine that merges the scenario tree of each prosumer in a common tree for the operation of the entire LEC;
- it includes a decision-making procedure that updates the BES units scheduling and the LEC internal transactions according to the intra-day operating conditions;

The results obtained by the intra-day scenario-based approach are compared with those given by both a day-ahead forecast-based solution and a deterministic one.

The structure of the paper is the following. Section II describes the distributed approach based on the ADMM method. Section III describes the scenario tree generation method. Section IV presents the intra-day decision-making procedure. Section V illustrates the test cases and the relevant results. Section VI concludes the paper.

II. Distributed Approach for the Scheduling of the LEC

One of the main challenges of the LEC is the definition of an optimal day-ahead scheduling of its energy sources. The set of participants to the LEC is denoted as $\Omega = \{1, 2, \ldots, N\}$, $T = \{1, 2, \ldots, t_{\text{end}}\}$ corresponds to the set of time intervals t in the optimization horizon (a day), and $B = \{1, 2, \ldots, b_{\text{end}}\}$ denotes the set of branches of the network inside the community.

The objective function is the minimization of the energy procurement cost of the LEC (1) given by the cost associated to the exchanges of electricity with the external energy provider during the day, taking into account the corresponding prices of buying and selling in €/kWh, (i.e. π_{buy}^{t} and π_{sell}^{t}) respectively. The prices associated with the energy transactions with the external provider are fixed (i.e. deterministic) for the next day.

$$OF = \sum_{\substack{t\in T\\ i\in\Omega}} \left(\pi_{\text{buy}}^{t} P_{\text{buy\_Grid}\,i}^{t} - \pi_{\text{sell}}^{t} P_{\text{sell\_Grid}\,i}^{t} \right) \Delta t \tag{1}$$

The quantities $P_{\text{buy\_Grid}\,i}^{t}\Delta t$ and $P_{\text{sell\_Grid}\,i}^{t}\Delta t$ are the energy bought from and sold to the utility grid, respectively, in a time step Δt. For the numerical tests included in this paper the powers are expressed in kW and Δt is equal to 0.25 h.

The proposed approach adopted a distributed scheme based on the ADMM algorithm. Hence, the *OF* is decomposed in local subproblems, one for each prosumer *i*, by means of the Lagrangian decomposition. The objective function of each subproblem is

$$OF_i = \min_{\substack{P_{\text{buy\_Grid}\,i}^{t},\, P_{\text{sell\_Grid}\,i}^{t}\\ P_{\text{buy}\,i,j}^{t},\, P_{\text{sell}\,i,j}^{t}}} \sum_{t\in T} \begin{bmatrix} \pi_{\text{buy}}^{t} P_{\text{buy\_Grid}\,i}^{t}\Delta t - \pi_{\text{sell}}^{t} P_{\text{sell\_Grid}\,i}^{t}\Delta t + \\ \sum_{\substack{j\in\Omega\\ j\neq i}} \lambda_j^t P_{\text{buy}\,i,j}^{t}\Delta t - \lambda_i^t \sum_{\substack{j\in\Omega\\ j\neq i}} P_{\text{sell}\,i,j}^{t}\Delta t + \ell_i^t \end{bmatrix} \tag{2}$$

where

$$\ell_i^t = m\cdot\rho\cdot[\sum_{\substack{j\in\Omega\\ j\neq i}} (\hat{P}_{\text{buy}\,j,i}^{t} - P_{\text{sell}\,i,j}^{t})^2 + \sum_{\substack{j\in\Omega\\ j\neq i}} (P_{\text{buy}\,i,j}^{t} - \hat{P}_{\text{sell}\,j,i}^{t})^2] \tag{3}$$

The local *OF* (2) is given by the summation of three terms: costs and revenues associated to exchanges of energy with the external electricity provider, considering the respective prices; cost and revenues for the exchanges of *i* with the other prosumers, where λ_i^t and λ_j^t are the Lagrangian multipliers of the equilibrium between power sold and bought in each internal transaction; finally, the squared norm of the imbalance of each energy transaction between prosumer *i* and every other prosumer *j* (parameter ρ is a positive penalty coefficient and *m* is a scale factor).

The constraints of the implemented model are the following

$$\begin{gathered} P_{\text{PV}\,i}^{t} + P_{\text{dis}\,i}^{t} + P_{\text{buy\_Grid}\,i}^{t} + \sum_{\substack{j\in\Omega\\ j\neq i}} P_{\text{buy}\,i,j}^{t} = P_{\text{Load}\,i}^{t} \\ + P_{\text{ch}\,i}^{t} + P_{\text{sell\_Grid}\,i}^{t} + \sum_{\substack{j\in\Omega\\ j\neq i}} P_{\text{sell}\,i,j}^{t} + \frac{1}{2}\sum_{b\in B} L_{b,i}^{t} \qquad t\in T, i\in\Omega \end{gathered} \tag{4}$$

$$\begin{cases} P_{\text{buy\_Grid}\,i}^{t} = 0 \text{ and } P_{\text{buy}\,i,j}^{t} = 0 \text{ if } u_i^t = 0 & u_i^t \in \{1,0\} \\ P_{\text{sell\_Grid}\,i}^{t} = 0 \text{ and } P_{\text{sell}\,i,j}^{t} = 0 \text{ if } u_i^t = 1 & i \text{ and } j \in \Omega \end{cases} \tag{5}$$

$$0 \le P_{\text{buy\_Grid}\,i}^{t} \le P_{\text{buy}\,i}^{\max} \quad 0 \le P_{\text{sell\_Grid}\,i}^{t} \le P_{\text{sell}\,i}^{\max} \quad t\in T, i\in\Omega \tag{6}$$

$$0 \le P_{\text{buy}\,i,j}^{t} \le P_{\text{buy}\,i}^{\max} \quad 0 \le P_{\text{sell}\,i,j}^{t} \le P_{\text{sell}\,i}^{\max} \quad t\in T, i \text{ and } j\in\Omega \tag{7}$$

$$E_{\text{BES}\,i}^{t} = E_{\text{BES}\,i}^{t-1} + (P_{\text{ch}\,i}^{t}\eta_{\text{ch}\,i} - P_{\text{dis}\,i}^{t}/\eta_{\text{dis}\,i})\Delta t \qquad \begin{matrix} i\in\Omega \\ t\in T, t>1 \end{matrix} \tag{8}$$

$$\begin{cases} E_{\text{BES}\,i}^{t=1} = E_{\text{BES}\,i}^{\max} + (P_{\text{ch}\,i}^{t=1}\eta_{\text{ch}\,i} - P_{\text{dis}\,i}^{t=1}/\eta_{\text{dis}\,i})\Delta t & i\in\Omega \\ E_{\text{BES}\,i}^{t_{\text{end}}} = E_{\text{BES}\,i}^{\max} \quad i\in\Omega \end{cases} \tag{9}$$

$$\begin{cases} P_{\text{ch}\,i}^{t} = 0 \text{ if } u_{\text{BES}\,i}^{t} = 0 & u_{\text{BES}\,i}^{t} \in \{1,0\} \\ P_{\text{dis}\,i}^{t} = 0 \text{ if } u_{\text{BES}\,i}^{t} = 1 & i\in\Omega \end{cases} \tag{10}$$

$$0 \le P_{\text{dis}\,i}^{t} \le P_{\text{BES}\,i}^{\max} \quad 0 \le P_{\text{ch}\,i}^{t} \le P_{\text{BES}\,i}^{\max} \quad t\in T, i\in\Omega \tag{11}$$

$$E_{\text{BES}\,i}^{\min} \le E_{\text{BES}\,i}^{t} \le E_{\text{BES}\,i}^{\max} \quad t\in T, i\in\Omega \tag{12}$$

Constraint (4) corresponds to the power balance for prosumer *i* at each period *t*: where the forecast profiles of PV generation and load (in kW) are given by parameters $P_{\text{PV}\,i}^{t}$ and $P_{\text{Load}\,i}^{t}$, respectively; the charging and discharging power of the BES (in kW) are represented with the non-negative variables $P_{\text{ch}\,i}^{t}$ and $P_{\text{dis}\,i}^{t}$, respectively; $L_{b,i}^{t}$ represents an estimation of the losses in branch *b* originated from the energy transactions concerning the *i*-th prosumer. Since each transaction is between two prosumers, only half of the power loss is attributed to each prosumer. The omission of the concurrent presence of the transactions of all the prosumers is an approximation justified by the lack of counter-flows due to the assumed non-competitive behavior of the prosumers in the LEC.

$L_{b,i}^{t}$ in (4) is defined by the following constraints

$$L_{b,i}^{t} = \frac{R_b}{3V_n^2}\left(F_{b,i}^{t}\right)^2 \quad t\in T, b\in B, i\in\Omega \tag{13}$$

$$F_{b,i}^{t} = A_{\mathrm{Grid}\,b,i} P_{\mathrm{buy\_Grid}\,i}^{t} - A_{\mathrm{Grid}\,b,i} P_{\mathrm{sell\_Grid}\,i}^{t} + \sum_{j\in\Omega} A_{b,i,j} P_{\mathrm{buy}\,i,j}^{t} - \sum_{j\in\Omega} A_{b,i,j} P_{\mathrm{sell}\,i,j}^{t} \qquad t\in T, b\in B, i\in\Omega \quad (14)$$

In (13), the resistance of each branch b of the internal network is represented by R_b, V_{n} corresponds to the line-to-line rated voltage value, and $F_{b,i}^{t}$ represents the three-phase power flow in internal branch b, due to the energy transaction that involves the i-th prosumer. The relative transactions are assumed positive when directed from the substation to the end of the feeder, and negative in the opposite direction. The rms bus voltage values in constraint (13) are assumed equal to the rated value; the same constraint considers a balanced low voltage network and neglects reactive power flows.

In (14), the position of each branch with respect to the buses where the prosumers are connected, is described by the matrix A_{Grid} and array A, assuming a radial configuration:

- $A_{b,i}$ is the b,i element of the 2D-matrix A_{Grid}. When the power flow due to the energy transaction between the i-th prosumer and the external provider crosses the branch b, it takes the value 1, and 0 otherwise
- $A_{b.i,j}$ is the b,i,j element of the 3-D array A. If the power flow created when i buys from j, crosses the branch b in the assumed positive direction, then the value of the element is equal to 1. If the corresponding power flow crosses in the negative direction, the value of the element is -1. And the value is 0, if the branch b is not crossed by the power flow created by the corresponding energy transaction between prosumers i and j.

Indicator constraints (5) employ the binary variable u_i^t, to prevent simultaneous purchases and sales by the prosumer i.

Constraints (6) and (7) limit the energy bought and sold by prosumer i at each period t: where $P_{\mathrm{sell}\,i}^{\max}$ is the largest value between 0 and $P_{\mathrm{PV}\,i}^{t} - P_{\mathrm{Load}\,i}^{t} + P_{\mathrm{BES}\,i}^{\max}$; $P_{\mathrm{buy}\,i}^{\max}$ is the largest value between 0 and $P_{\mathrm{Load}\,i}^{t} - P_{\mathrm{PV}\,i}^{t} + P_{\mathrm{BES}\,i}^{\max}$; $P_{\mathrm{BES}\,i}^{\max}$ is the maximum power output of the i-th BES unit.

The state of energy (SoE) of the battery of prosumer i is given by (8) and (9), which represent a simple energy balance model, where $E_{\mathrm{BES}\,i}^{t}$ is the SoE at time t (in kWh), $E_{\mathrm{BES}\,i}^{\max}$ is the maximum storage capacity. The non-negative paremeters $\eta_{\mathrm{ch}\,i}$ and $\eta_{\mathrm{dis}\,i}$ are values lower than 1 and represent the charging and discharging efficiencies, respectively. In (9), the BES units are assumed fully charged at the beginning and at the end of the day. The binary variable $u_{\mathrm{BES}\,i}^{t}$ in indicator constraints (10), prevents the concurrent charging and discharging processes of the batteries. In (11), the discharging and charging power of the BES are bound within the maximum value $P_{\mathrm{BES}\,i}^{\max}$. Constraint (12) limits the value of the SoE between minimum level $E_{\mathrm{BES}\,i}^{\min}$ and maximum $E_{\mathrm{BES}\,i}^{\max}$.

Fig. 1 shows the iterative procedure that implements the ADMM algorithm.

At the beginning of the procedure, Lagrange multipliers λ_i^t , penalization parameter ρ, and scale factor m are initialized. Then, at each iteration v, local subproblem (2) is solved by each one of the prosumers i considering the set of constraints (4)-(14).

Each prosumer communicates within the community the profiles of $P_{\mathrm{buy}\,i,j}^{t}$ and $P_{\mathrm{sell}\,i,j}^{t}$ obtained as a result of the local optimization. Then, each prosumer i updates the Lagrangian multipliers λ_i^t (i.e., the prices associated to the internal energy exchanges in the LEC) based on the imbalance between their local variables and the values communicated by the others prosumers, denoted by a hat in (3). The imbalances are equal to primal residual r_i^t .

In order to accelerate the convergence of the ADMM procedure, an updating scheme for parameter ρ and factor m has been implemented, as shown in Fig. 1.

The distributed optimization is iteratively carried out until the values that represent the imbalances (i.e. residuals r_i^t) are below the tolerance ε. A tolerance ε equal to 50 W has been assumed for the numerical tests.

Once the procedure converges, ℓ_i^t tends to zero and the value of the total OF for the community is equal to the summations of the objectives of the prosumers:

$$OF = \sum_{i\in\Omega} OF_i \qquad (15)$$

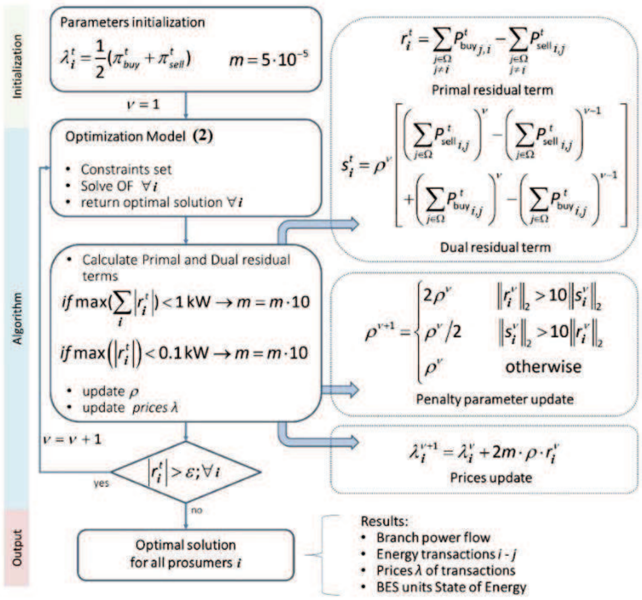


Fig. 1. Scheme of the implemented ADMM procedure.

III. Generation of the Scenario Tree

A significant issue in the operation of the community concerns the uncertainties associated with the distributed generation and loads consumption. In order to deal with this, the ADMM model has been extended to a multistage stochastic approach.

According to a multistage stochastic approach, the realization of the considered stochastic processes during the day (i.e., PV generation and energy consumption) is represented with a scenario tree.

The decisions are made at the beginning of each stage: i.e., at the beginning of the day and subsequently at the middle of the day (t=12). Variables $P^t_{\text{ch}\,i}$ and $P^t_{\text{dis}\,i}$ are assumed as the decision variables of the model. The other variables are calculated at the end of each stage, for all time intervals of the stage.

In the following, first the procedure adopted for the construction of the scenario tree for each prosumer i is described. Then, the routine implemented to merge the scenario tree of each prosumer in a common scenario tree for the operation of the entire LEC is presented. The obtained scenario tree is used for both the day-ahead scheduling and the intra-day decision-making procedure presented in section IV.

A. Generation of Scenario Tree for each Prosumer

The uncertainties associated to the operation of each prosumer have been represented by means of an individual scenario tree. For this purpose, we adopt a scenario generation technique that applies a Markov-process considering the autocorrelation between consecutive observations starting with the forecast profiles of PV production and load (i.e. $P^t_{\text{PV}\,i}$ and $P^t_{\text{Load}\,i}$ respectively), as described in [13].

The test case is a LEC composed of five prosumers, each connected to the same low voltage feeder. Fig. 2 shows the profile of the ratio between power output and the panel surface (reported in Table I) that is assumed equal for all the PV units. Fig. 2 also shows the price profile of the energy bought from the utility grid π^t_{buy}, for the numerical test $\pi^t_{sell} = 0.5\pi^t_{\text{buy}}$ has been assumed. Fig. 3 shows the load demand for each prosumer.

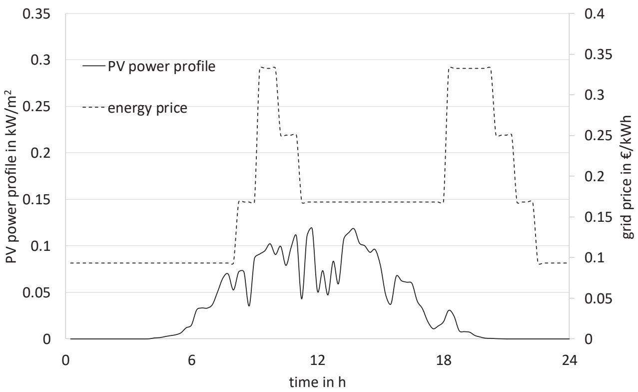


Fig. 2. Profile of the PV production and grid purchase price.

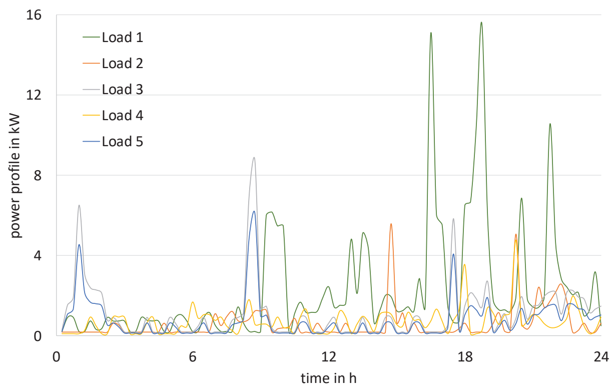


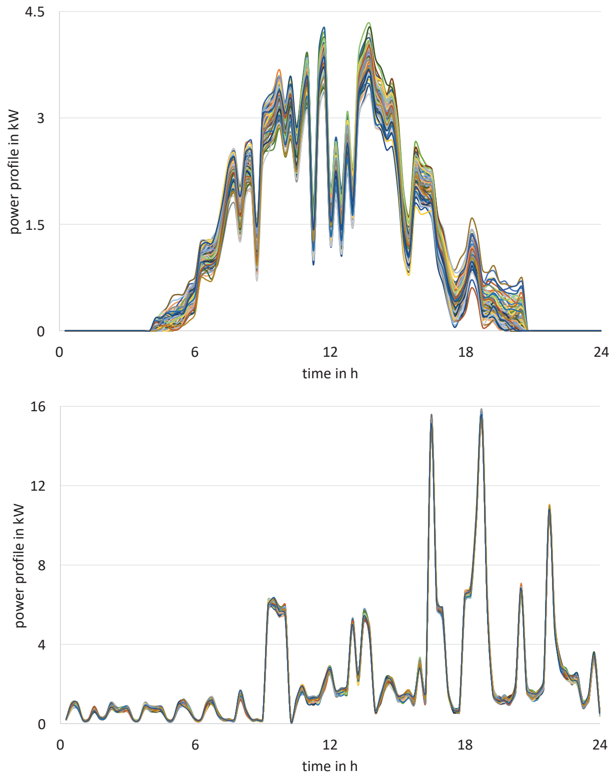
Fig. 3. Load profile for each prosumer.

TABLE I. PV PANEL SURFACE FOR EACH PROSUMER.

prosumer	1	2	3	4	5
area (m^2)	32	14	21	32	28

The obtained set of scenarios for prosumer i is denoted with Φ_i, φ_i denotes the scenario index, and s corresponds to the various stages (i.e. 1, 2, and 3). The scenario generation procedure limits the maximum deviation so that it does not exceed the ±20% band with respect to both P^t_{Load} (for all the 24 hours) and to P^t_{PV} (for 75% of the periods). The definition of these tolerance bands avoids unrealistic scenarios and guarantees that the generated scenarios are coherent with the forecast profiles.

A first set of 100 scenarios has been obtained for each prosumer. For instance, Fig. 4 shows those of prosumer 1.



a)

b)

Fig. 4. Initial Scenarios for prosumer 1: a) PV production; b) load.

Denoting scenario $\xi^t_{\varphi_i}$ as the normalized difference between PV production and load for prosumer i, namely

$$\xi^t_{\varphi_i} = \frac{P^t_{\text{PV}\,\varphi_i} - P^t_{\text{Load}\,\varphi_i}}{P^t_{\text{PV}\,i} - P^t_{\text{Load}\,i}} \qquad \forall\, s, \forall\, t \in s \qquad (16)$$

the scenario tree is obtained by a k-means clustering procedure applied to the total set of initial scenarios, with the scenario reduction technique described in [13].

The numerical results presented in this paper have been obtained assuming 3 centroids in the k-means procedure

Fig. 5 shows the scenario tree obtained for prosumer 1. A scenario tree with similar structure has been obtained for each one of the prosumers of the LEC.

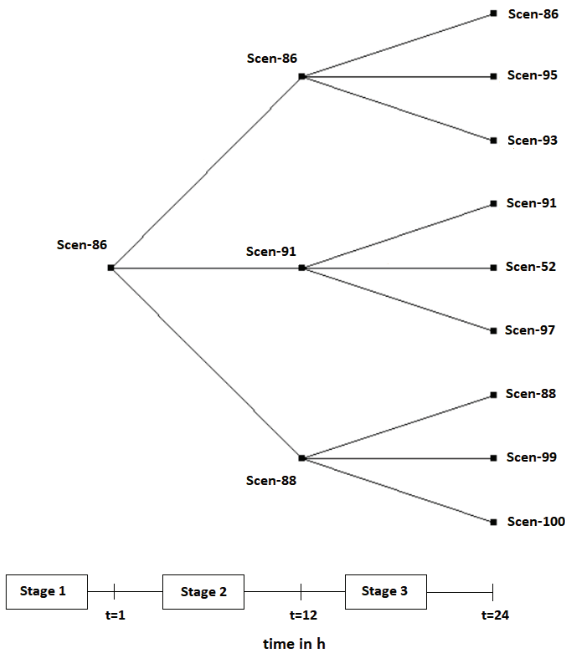


Fig. 5. Scenario tree for prosumer 1: obtained for 100 initial scenarios and using 3 cluster centers.

B. *Combination of Scenarios*

Ultimately, we want to obtain a common tree for the LEC, to achieve a coordinated response to the uncertainties associated to the operation of the community.

For this purpose, each prosumer communicates $\xi^{s}_{\varphi_i}$ (i.e. the scenarios of the individual tree) to the others within the community and uses as an input for the procedure illustrated by Fig. 6.

At each stage, a set of combinations conformed to individual prosumer scenarios is generated. Denoting the set of combinations ψ with Γ, then combination $\gamma \in \Gamma$ at stage s is built as:

$$\psi^{s}_{\gamma} = \left[\xi^{s}_{\varphi_1}, \xi^{s}_{\varphi_2}, \ldots, \xi^{s}_{\varphi_i}\right] \quad i \in \Omega \tag{17}$$

With the introduction of these combinations, the LEC is able to coordinate a response to the uncertainties associated to the operating conditions, while preserving the distributed nature of the scheduling approach.

Then, a routine based on a recursive k-means clustering algorithm merges the information of the scenario tree of each prosumer in a common tree of scenario combinations.

At stage s=1 (i.e., at the beginning of the optimization horizon), all the prosumers consider only the scenario root, i.e. $\xi^{s=1}_{\varphi_i} = \xi_{1_i}$. At stage s=2 (t=1…12 hours), set $\Gamma^{s=2}_{k'}$ is obtained from the combinations of scenarios $\xi^{s=2}_{\varphi_i}$. Then the set is divided in the predefined number K of desired clusters C^{s}_{k} , which has been assumed equal to 3 for the numerical tests presented in this paper.

At the following stage, the k-means clustering algorithm is applied independently to each cluster defined in the previous stage (s=2). For each $C^{s=2}_{k'}$, a set of combinations $\Gamma^{s=3}_{k'}$ is obtained by the combinations of scenarios $\xi^{s=3}_{\varphi_i}$ that correspond to one of scenarios $\xi^{s=2}_{\varphi_i}$ assigned to the same centroid k' at stage 2.

With the proposed procedure, the number of combinations generated and considered for the k-means clustering procedure at each stage is limited to K. The tree obtained for the numerical test using 3 centroids (i.e. K=3) is shown in Fig. 7. At stage 2 the generated set of combinations has 243 elements. At the last stage, three sets of combinations (one set for each centroid in stage 2) have been generated with 26420, 13121 and 19682 elements, respectively.

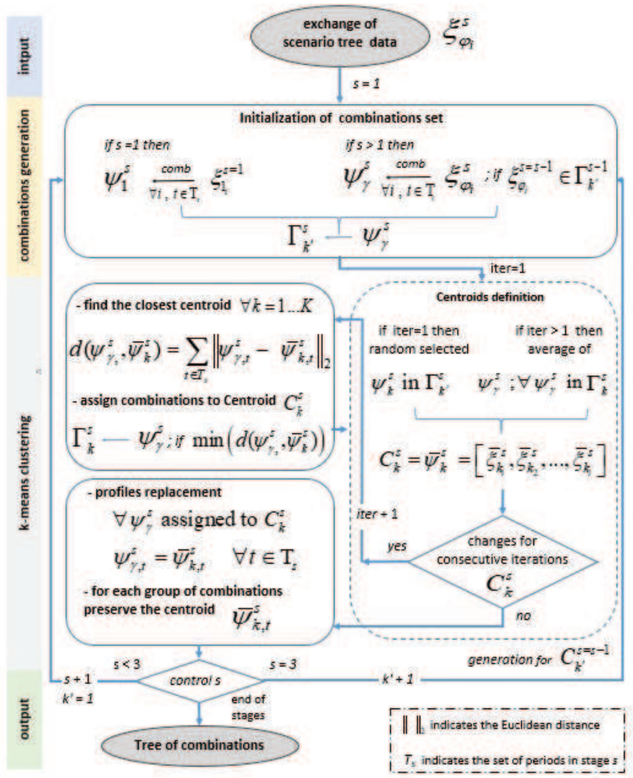


Fig. 6. Scheme for the generation of combinations tree.

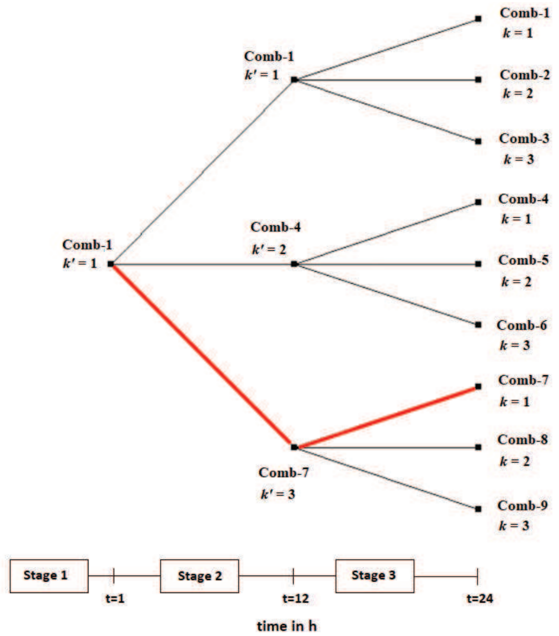


Fig. 7. Scenario tree for the LEC obtained from the combination of the individual scenario tree of each prosumer using 3 cluster centers. In red, an example of the solution given by the intra-day decision-making procedure.

As a result, the above-mentioned procedure locally generates the same common tree for each prosumer, obtaining at each stage s, the corresponding nodes $\bar{\psi}_k^{t \in T_s}$ and the branches that associate those nodes from the root to the leaves in the tree.

C. Solution of the scenario-based multistage day-ahead scheduling

By using the obtained tree, the solution of the scenario-based multistage scheduling provides the optimal set values of the decision variables in each node of the combination tree at the beginning and at the middle of the day.

The solution for each one of the final combinations in the tree is found by means of the ADMM procedure described in Section II, where the values of $P^t_{\mathrm{PV}\,i}$ and $P^t_{\mathrm{Load}\,i}$ are given by the corresponding ψ_γ in the tree. In order to satisfy the conditions required for a feasible multistage stochastic solution and to assure the coherence of the stochastic variables during the day for combinations with common nodes in the tree, the usual non-anticipativity constraints have been included for ψ_γ and $\psi_{\gamma'}$ with ($\gamma < \gamma'$):

$$\begin{cases} P^t_{\mathrm{ch}\,i} = P'^t_{\mathrm{ch}\,i} & \forall t \in T_s \ \text{ if } \ \psi^s_\gamma = \psi^s_{\gamma'} = \bar{\psi}^s_k \\ P^t_{\mathrm{dis}\,i} = P'^t_{\mathrm{dis}\,i} & \end{cases} \tag{18}$$

IV. Intra-Day Decision-Making Procedure

The decision-making procedure for the intra-day operation aims at identifying the most suitable decision at each stage among those given by the multistage day-ahead scheduling, considering the current PV generation and load of each prosumer.

By means of the Euclidean distance, the intra-day decision-making procedure is able to identify at the middle of the day, using the common tree, the combination that best matches the profile of the difference between the local generation and the energy demand from the previous 12 hours. Each prosumer performs its own comparison of the local profiles and shares the corresponding distance with the others, in order to make a joint decision based on the structure of the common scenario tree. Then, each prosumer implements the calculated $P^t_{\mathrm{ch}\,i}$, $P^t_{\mathrm{dis}\,i}$, $P^t_{\mathrm{sell}\,i,j}$, and $P^t_{\mathrm{buy}\,i,j}$ for the following 12-hours.

In order to guarantee the feasibility of the intra-day solution, each prosumer solves the problem with objective function (2) with $\ell^t_i = 0$ and constraints (4)-(14), by assuming that the values of the BES charges and discharges ($P^t_{\mathrm{ch}\,i}$ and $P^t_{\mathrm{dis}\,i}$) and the energy exchanges among the prosumers in the LEC ($P^t_{\mathrm{sell}\,i,j}$ and $P^t_{\mathrm{buy}\,i,j}$) are fixed to the values associated with to the most similar node of the common scenario tree. In this way, the differences between the current PV generation and energy demand with reference to the profiles used by the day-ahead optimization are compensated by the exchange of energy with the external utility grid ($P^t_{\mathrm{buy\_Grid}\,i}$ and $P^t_{\mathrm{sell\_Grid}\,i}$) in order to satisfy (4).

In Fig. 7, there is an example in red of the solution provided by the intra-day decision-making procedure. At the beginning of the day, the LEC implements for the first 12 hours the set values corresponding to the combination referred to Comb-1 in the tree. Then, at mid-day, based on what occurred during the first 12 hours, the LEC updates in a coordinated way the set values to the solution of the most similar and in a certain way expected combination of scenario for the rest of the day (i.e. Comb-7 in the example).

V. Numerical Test

The procedures have been implemented in an AIMMS Developer environment and tested by using the solver Cplex V12.9. The numerical results have been obtained on a 2-GHz Intel-i7 computer with 8 GB of RAM, running 64-bit Windows 10. The MIQP (mixed integer quadratic programming) solver has been employed to solve the day-ahead ADMM procedure and the MILP (mixed integer linear programming) solver for the intra-day decision-making tests.

As already mentioned, the considered optimization horizon corresponds to one day, which is divided into 96 periods of 15 minutes each. To complete the description of the test case (in addition to Fig. 2, Fig. 3, and Table I), Table II shows the sizes of the BES units ($E^{\max}_{\mathrm{BES}}$). The corresponding values of $P^{\max}_{\mathrm{BES}}$ are assumed equal to the ratio $E^{\max}_{\mathrm{BES}} / \Delta t$. Each branch of the internal network has a resistance of R_b = 189 mΩ.

Table II. Sizes of the BES Units.

prosumer	1	2	3	4	5
size (kWh)	5	3	4	2	3

The ADMM procedure takes few minutes to find the solution of the scheduling problem of the LEC for a given combination.

For each combination of the tree in Fig. 7, Fig. 8 shows the comparison between the *OF* values calculated by using the intra-day decision-making procedure (multistage solution) and those given by the day-ahead scheduling that takes into account only the forecast profiles (forecast-based). Multistage scheduling provides better results with respect to a forecast-based solution. Fig. 8 also shows the *OF* values of the deterministic solutions, in which the profiles employed by the ADMM correspond to the current PV generation and loads during the intra-day.

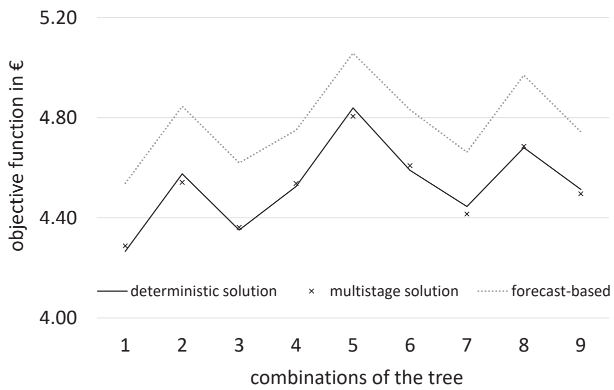


Fig. 8. Comparison between the values of the total objective function of the LEC for each combination of the tree.

During the day, small corrections in the power exchanged with the external network occur to compensate the imbalances (which are lower than the defined ADMM tolerance of 50W). Notwithstanding this, Fig. 8 shows that the values for the scenario-based and deterministic solution are very similar.

Fig. 9 shows the comparison of *OF* values, using 45 new combinations of scenarios, i.e. operating conditions during the intra-day different from those included in the common scenario tree. In general, the results of Fig. 9 confirm the advantage of the multistage day-ahead scheduling with respect to the forecast-based solution.

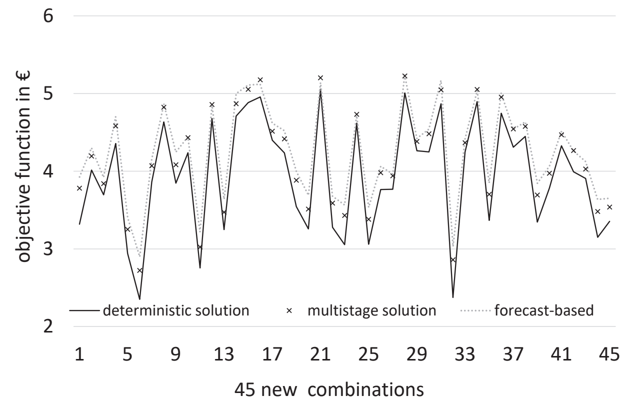


Fig. 9. Comparison between the values of the total objective function of the LEC for 45 new combinations.

TABLE III. PERCENTAGE INCREASE IN THE *OF* WITH RESPECT TO THE DETERMINISTIC SOLUTION.

comparison	average	min.	max.
multistage solution - deterministic	6%	2%	20%
forecast-based - deterministic	9%	2%	28%

Table III reports the percentage increase in the *OF* value with respect to the deterministic solution of the combinations in Fig. 9, by applying the multistage and forecast-based solution respectively. The average increase and the higher deviation (i.e. the maximum value) confirm the advantage of the implemented multistage day-ahead scheduling over the forecast-based solution.

An alternative method applied to solve optimization problems considering uncertainties is given by the calculation of average value of the deterministic solutions for a predefined set of scenarios. In the case of the set of combinations included in the tree, the average value of the objectives functions is € 4.53, whilst for the set of additional 45 combinations the average is € 3.94. In general, this method does not provide feasible profiles for the decision variables (i.e., charge and discharge profiles of the BES units). For such a reason, with respect to this method, the multistage procedure has the advantage to provide a feasible solution that can be adapted to the intra-day conditions.

VI. CONCLUSIONS

This paper has presented an ADMM-based day-ahead scheduling procedure of a local renewable energy community, suitably conceived to consider the uncertainties of the photovoltaic generation and energy consumption.

A tree generation method based on the *k*-means algorithm is adopted to deal with the problem of merging the stochastic information of the several prosumers in a common tree. By using the obtained tree, multiple decisions during the day are made. A decision-making procedure is proposed to identify the most suitable solution.

The proposed multistage scheduling provides in general improved results with respect to the corresponding forecast-based solution of the LEC, exploiting the chance to adapt the set values of the BES units and the energy transactions among the prosumers, according to the current operational conditions of the day.

The implementation of the proposed multistage solution based on the intra-day decision-making procedure allows for a flexible and cost-efficient solution.

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