Demand Response for Renewable Energy Integration and Load Balancing in Smart Grid Communities

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***Abstract*—This paper proposes a demand response strategy for energy management within a smart grid community of residential households. Some of the households own renewable energy systems and energy storage systems (ESS) and sell the excess renewable energy to the residences that need electrical energy. The proposed strategy comprises methods that provide benefits for the residential electricity users and for the load aggregator. Specifically, we propose an off-line algorithm that schedules the renewable resources integration by trading energy between the renewable energy producers and buyers. Moreover, we propose a geometric programming based optimization method that uses the ESS for balancing the community's power grid load and for reducing the grid consumption cost. Simulations show that the proposed method may lead to a community's grid consumption cost reduction of 10.5%. It may also achieve balanced load profiles with peak to average ratio (PAR) close to unity, the average PAR reduction being 52%.**

***Index Terms*—smart grids, optimization, demand response, renewable energy, load balancing, geometric programming**

I. INTRODUCTION

The continuous growth of electricity demands and the global concern for carbon emissions calls for a significant increase of electricity generation from distributed renewable sources. This requires the development of methods that efficiently integrate the renewable energy supplies into the power grid. Some demand response approaches that use energy storage systems (ESS) to manage the renewable energy resources in a centralized or decentralized fashion have already been proposed [1], [2]. Other methods assure the efficiency of the power grid by facilitating the integration of renewable resources [3] and at the same time provide balanced demands for the utility company [4]. Different methods can provide significant cost reduction to the electricity consumers [5], [6]. Energy storage management methods can bring benefits for the grid operators by avoiding grid congestion [7].

In this paper we propose a novel demand response approach for optimizing the energy trade within a smart grid community of households. We consider a smart grid community composed of several residential households that are being served by the same load aggregator. Some of the households own nondispatchable renewable energy systems (RES), such as wind turbines or solar panels, as well as ESS. The amount of renewable energy that exceeds the demands of the RES owners is being sold to the other residential energy users in the community. The coordination of the energy flow is fully centralized and is performed by the load aggregator against a fee. The value of this fee and the price of the renewable energy are not discussed in this paper. It is assumed that all households in the community are equipped with smart energy-management meters that predict their energy demand profiles and the renewable energy availability profiles, for a finite time period ahead. Methods as the one in [8] perform such predictions. The households communicate these profiles to the load aggregator through a two-way communication infrastructure. The load aggregator knows the daily market electricity prices and finds the optimal energy trade solution for the given time period ahead. The main contributions of this paper are stated below:

- We propose an off-line algorithm for scheduling the integration of the renewable resources produced within the smart grid community. The algorithm calculates the amounts of renewable energy that need to be stored for meeting the demand of each RES owner during the given period ahead. The excess amounts of renewable energy are sold to the other energy users in the community. All the renewable energy sellers receive benefits in proportion to their renewable energy production. The algorithm makes sure that the energy is stored for the shortest period possible in order to prevent energy losses that occur when storing energy.
- We propose an optimization algorithm for balancing the power grid load and reducing the cost of the consumed grid energy. The solution for the problem is found using geometric programming (GP). The objective function of this optimization is derived using the Cobb-Douglas production function from consumer theory [9]. The optimization is performed by using the available storage capacity, not needed for storing renewable energy. Similar GP approach was used in [10] for balancing the grid electricity consumption of a single residential user. In this paper we extend this technique to perform load flattening for a whole community of households. The work in [10] is also extended by taking into account renewable energy sources.

Methods that approach the problem of community storage management for renewable energy integration were proposed in [1], [2]. The novelty of this work stands in the innovative use of multiple ESS to jointly achieve three objectives: integrate the renewable resources by energy trading, balance the community's power grid load and reduce the cost of the

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energy consumed from the power grid.

Simulation results demonstrate that the proposed energy management method achieves a balanced load with a peak to average ratio (PAR) close to unity. Average PAR reduction of 52% was achieved. The community's grid electricity cost may be reduced by 10.5% compared to the case when the RES owners would not sell their excess renewable resources. The proposed load balancing with cost reduction optimization method achieves a grid electricity cost reduction of 4%.

II. System Model

We consider a smart grid model composed of a community of residential energy users. The energy management within the community is coordinated over a finite time horizon *T* which is divided into several equally long time slots indexed by $t = 1, \ldots, T$. Let $\boldsymbol{\xi}$ be the set of market electricity prices known ahead for each time slot of the period *T*: $\boldsymbol{\xi} = \{\xi(t)\}_{t=1}^{T}$.

Let $\mathcal{M} = \{1, \ldots, M\}$ be the set of residences from the community that own RES and ESS. The index of a household from this set is denoted by *m*. These residences produce renewable energy and sell the excess to the other residential energy users in the community. The per-time-slot amounts of renewable energy produced by each household $m \in \mathcal{M}$ are assumed to be known for the whole period *T*: $\mathbf{w}_m = \{w_m(t)\}_{t=1}^{T}$. The electricity demand of each household is also known for the whole period *T*: $\mathbf{u}_m = \{u_m(t)\}_{t=1}^{T}$. Each household $m \in \mathcal{M}$ has a maximum ESS_m capacity $C_m^{\max}$. Thus, the maximum storing capacity in the community is: $C^{\max} = \sum_{m \in \mathcal{M}} C_m^{\max}$. Let $\mathcal{P} = \{1, \ldots, P\}$ be the set of residences from the community that are sole energy consumers. The index of a household from this set is denoted by *p*. The energy demand of each household $p \in \mathcal{P}$ is also known for the entire period *T* and is denoted by: $\mathbf{u}_p = \{u_p(t)\}_{t=1}^{T}$. The total demand of the community at each time-slot is then: $u(t) = \sum_{m \in \mathcal{M}} u_m(t) + \sum_{p \in \mathcal{P}} u_p(t)$. We assume that the energy demand of each household is fixed over period *T* and cannot be changed.

A renewable energy amount shall be saved per-time-slot in each ESS_m such that the demand of RES owner $m \in \mathcal{M}$ is satisfied during the entire period *T*. The set of these amounts is denoted by: $\mathbf{r}_m = \{r_m(t)\}_{t=1}^{T}$. Each ESS_m stores also the amount of renewable energy that remains after selling renewable energy to the community at each time-slot. The set of total amounts of renewable energy existing per-time-slot in each ESS_m is devoted by: $\mathbf{s}_m = \{s_m(t)\}_{t=1}^{T}$.

If the energy demand of the community at certain time-slot cannot be fulfilled by the available renewable energy resources, the rest of the needed energy is then supplied by the load aggregator from the main power grid. We further denote by $\mathbf{g}$ the set of per-time-slot energy amounts required by the community from the power grid: $\mathbf{g} = \{g(t)\}_{t=1}^{T}$. The set of energy amounts actually consumed from the power grid after the load balancing optimization is denoted by: $\mathbf{b} = \{b(t)\}_{t=1}^{T}$. Part of the energy consumed from the power grid is instantly used for satisfying the community's demand, while the rest is stored in the community's ESS for load balancing and cost reduction purposes. These amounts are denoted by: $\mathbf{e} = \{e(t)\}_{t=1}^{T}$. Hence, the total amount of energy stored in the community's ESS is composed by the stored renewable resources and also by the power grid energy stored for balancing the load and reducing the community's grid energy costs: $\sum_{m \in \mathcal{M}} s_m(t) + e(t)$ such that $0 \leq \sum_{m \in \mathcal{M}} s_m(t) + e(t) \leq C^{\max}$.

III. Renewable energy integration

In this section we propose an off-line algorithm that schedules the integration of the renewable energy resources produced within the community. The algorithm is performed individually for each RES owner $m \in \mathcal{M}$. The algorithm first determines the proportion of the renewable energy, $r_m(t)$, produced by the household at a time slot that must be saved in ESS_m such that the demand of that household is fulfilled during the whole time period *T*. The excess renewable energy from each time-slot is then sold to the other residences in the community. The method encourages fast consumption of available renewable energy. The energy demand at a time-slot must be first satisfied by the renewable energy supplies available at that particular time-slot. If at a time-slot the renewable energy supplies are insufficient to satisfy the demand, then the rest of the needed energy is supplied from the power grid. The algorithm is designed in such a way that the excess renewable energy is stored for the shortest possible period. This prevents the renewable energy losses that occur when storing energy. Most storage systems are losing a small part of the stored energy during a specific time duration.

In order to have a fair energy trade, it is assumed that each RES owner can only sell an amount of energy proportional to his renewable supplies available at each time-slot. For the realisation of the energy trade, we assume that the total energy demand of the community at every time-slot *t*, $u(t)$, is reallocated to the RES owners. The total energy demand of the community becomes the energy demand of the RES owners only. The new per-time-slot energy demand of a household $m \in \mathcal{M}$ will be proportional to the available energy supplies of that household in comparison to the total energy supply of the community at that time slot:

$$\mu_m(t) = \left[\frac{w_m(t) + s_m(t)}{\sum_{m \in \mathcal{M}} (w_m(t) + s_m(t))} \right] u(t), \tag{1}$$

where $\mu_m(t)$ represents a new notation for the energy demand. The term inside the brackets represents the weighting factor showing the above mentioned proportion. The difference between the available renewable energy supplies of a household $m \in \mathcal{M}$ and the energy demand at time-slot *t* is:

$$\Delta_m(t) = w_m(t) + s_m(t-1) - \mu_m(t), t = 1, \ldots, T. \tag{2}$$

The energy needed by the RES owner *m* from the main power grid at each time-slot in order to fulfill the allocated demand is $g_m(t)$ and can be calculated as following:

$$g_m(t) = |\min\{\Delta_m(t), 0\}|, t = 1, \ldots, T. \tag{3}$$

The total amount of renewable energy stored in ESS_m at the end of a time slot is equal to:

$$s_m(t) = \min\left\{\max\left\{\Delta_m(t), 0\right\}, C_m^{\max}\right\}, t = 1, \ldots, T. \quad (4)$$

The proposed renewable energy integration algorithm involves four steps. The algorithm starts by considering that the RES owner may sell at each time-slot all the excess renewable energy not needed for his own demand at that time-slot. Consequently, in the first step the energy demand of the RES owner is the one described in (1). The ESS_m profile, $s_m(t)$, and the amounts of energy needed from the power grid, $g_m(t)$, during the period T are calculated using (3) and (4). If the computed $g_m(t)$ amounts show that energy is required from the power grid ($g_m(t) > 0$ for any $t = 1, \ldots, T$), then the algorithm proceeds to the following step.

The second and third steps involve only the RES owner's personal demand. In the second step we recalculate using (3) the amounts of energy, $g_m(t)$, needed from the power grid by the RES owner alone in order to satisfy his personal demand, $u_m(t)$. These amounts are recalculated at every time-slot using the storage values $s_m(t)$ determined at the previous step. Here the energy demand of the RES owner is $\mu_m(t) = u_m(t)$. If at any time-slot t the RES owner would need to purchase electricity from the power grid in order to fulfill his own personal demand ($g_m(t) > 0$, at any $t = 1 \ldots T$), then the algorithm proceeds to the third step.

In the third step we go through all time-slots at which the RES owner requires energy from the power grid one by one: $\boldsymbol{y} = \arg_t\{g_m(t) > 0\}_{t=1}^{T}$. For each such time slot $t \in \boldsymbol{y}$, we check for the excess amounts of renewable resources existing at previous time-slots, $t-1, \ldots, 1$. We save in storage one by one the amount of the renewable energy available at previous time-slots, starting with $t-1$, until the consumption of the owner at each time slot $t \in \boldsymbol{y}$ is satisfied. These amounts, $\mathbf{r}_m$, would be otherwise sold to the other energy consumers in the community. In an ideal case the amount of renewable energy saved in ESS_m is equal to the amount required by household $m \in \mathcal{M}$ from the power grid: $\sum_{t=1}^{T} r_m(t) = \sum_{t=1}^{T} g_m(t)$. This ideal case cannot be accomplished all the time since it depends on the production of renewable resources at each time-slot and the ESS_m capacity.

The fourth step recalculates the ESS_m profile $s_m(t)$ and total amount of energy needed from the power grid by the community at each time-slot, $g(t)$. A complete description of the renewable integration method is given in Algorithm 1.

Algorithm 1 Renewable energy integration

Input : $C_m^{\max}$, T, $\mathbf{w}_m$, $\mathbf{u}$, $\mathbf{u}_m$;
Output : $\mathbf{g}, \mathbf{s}_m$;
Initialization : Set to zero $\mathbf{g}_m, \mathbf{s}_m, \mathbf{r}_m, \sigma$;
Step 1) Calculate $\mathbf{g}_m, \mathbf{s}_m$ using (3), (4) and μ_m in (1);
  if $g_m(t) = 0$, for all $t = 1 \ldots T$ **then** exit algorithm;
Step 2) Recalculate $\mathbf{g}_m$ using (3), $\mathbf{s}_m$ calculated in **Step 1)** and $\boldsymbol{\mu}_m = \mathbf{u}_m$;
  if $g_m(t) = 0$, for all $t = 1 \ldots T$ **then** exit algorithm;
Step 3) Save renewable resources for the RES owner:
  y=$\arg_t\{g_m(t) > 0\}_{t=1}^{T}$;
  for i=1 to size(**y**) do:
    $j = y(i); \quad \sigma = g_m(j) + s_m(j)$;
    repeat: *j=j-1*
    Calculate $\Delta_m(j)$ using (1) when $\mu(j) = u_m(j)+r_m(j)$;
      if $\Delta_m(j) > 0$
        $r_m(j) = r_m(j) + \min\{\Delta_m(j), \sigma\}$;
        $\sigma = \sigma - \min\{\Delta_m(j), \sigma\}$;
      end if
    until: $\sigma = \min\left\{\Delta_m(j), \sigma\right\}$ or *j=1*;
  end for
Step 4) Calculate final grid requirement and storage profile $\mathbf{g}, \mathbf{s}_m$ using $\mathbf{g}_m$ computed in **Step 2)** and $\boldsymbol{\mu}_m$ in (1):
  for t=1 to T do:
  $g(t) = |\min\{\sum_{m\in\mathcal{M}}[\Delta_m(t) - \sum_{k=1}^{t}(r_m(k) - g_m(k))], 0\}|$;
  $s_m(t) = \min\{\max\{\Delta_m(t) - \sum_{k=1}^{t}(r_m(k) - g_m(k)), 0\}, C_m^{\max}\}$.
  end for

IV. Load balancing with price reduction

An important incentive for the load aggregator to participate in the renewable energy trade among residential users is the need for a balanced power grid load profile. In order to obtain constant grid consumption over time for the community, we propose a GP based optimization method where the objective is given by the Cobb-Douglas production function from economics [9]. A production function can be used to model how to combine different inputs to produce certain levels of outputs. In our problem the input is given by the per-time-slot cost of electricity required from the main power grid: $\xi(t)g(t)$. The objective function of our problem is modeled as:

$$\max_{b} \prod_{t=1}^{T} b^{\alpha_t}(t), \quad (5)$$

where $\alpha_t = \frac{\sum_{j=1, j\neq t}^{T} \xi(j)\cdot g(j)}{(T-1)\sum_{t=1}^{T} \xi(t)\cdot g(t)}$ represents the elasticity parameter of the Cobb-Douglas production function. Because our goal is to obtain constant consumption from the power grid, the amount of energy actually consumed from the power grid should be different from the amount of energy required from the power grid. In order to obtain a constant grid consumption *b(t)* over time *t=1…T*, the elasticity parameters must satisfy: $\sum_{t=1}^{T} \alpha_t = 1$. Therefore, each one of these terms is inversely proportional to the cost of required energy at a certain time-slot, $\xi(t)g(t)$, scaled to the total cost of the required energy from the power grid. The set of constraints employed in our load balancing and consumption cost reduction problem are:

$$b(t) \geq \max\left\{g(t) - C^{\max} - \textstyle\sum_{m\in\mathcal{M}} s_m(t), 0\right\}; \quad (6)$$

$$b(t) \leq C^{\max} + g(t); \quad (7)$$

$$e(t) = e(t-1) + b(t) - g(t); \quad (8)$$

$$0 \leq e(t) \leq C^{\max} - \textstyle\sum_{m\in\mathcal{M}} s_m(t); \quad (9)$$

$$\textstyle\sum_{t=1}^{T} \xi(t)b(t) \leq \sum_{t=1}^{T} \xi(t)g(t); \quad (10)$$

$$\textstyle\sum_{t=1}^{T} b(t) = \sum_{t=1}^{T} g(t); \quad (11)$$

where (6) - (9) are computed for all *t=1,…, T*.

Inequations (6) and (7) define the power grid consumption constraints. The per-time-slot grid consumption is lower limited by the amount of electricity required by the community from the power grid at that time-slot and that cannot be satisfied by the amount of grid energy stored in the ESS (6). The maximum amount of energy from the grid that exists in storage at a certain time slot is: $C^{\max} - \sum_{m\in\mathcal{M}} s_m(t)$. Inequation (7) states that the energy consumed at each time period cannot be greater than the capacity of the storage plus the energy required from the power grid at that time-slot. In (8) and (9) the constraints for the grid energy saved in storage at each time-slot are presented. Equation (8) indicates the grid electricity amount saved in storage at each time-slot, *e(t)*. This value is calculated based on the electricity amount existing in storage from the previous slot, *e(t-1)*, the amount actually consumed from the grid at that time-slot, *b(t)*, and the required grid energy, *g(t)*. Equation (9) states that the grid energy stored at each time-slot is lower-limited by zero and upper-limited by the total ESS capacity, not needed for storing the renewable energy. Equation (10) shows the cost reduction constraint. We also want to take advantage of the fluctuations of electricity prices and obtain a consumption profile with a lower cost than that of the actual energy requested from the power grid. In (11) it is shown that the total balanced energy that shall be consumed from the power grid over the period T must be equal to the total energy required from the power grid.

Because the objective function of our problem is of monomial type, we shall formulate our optimization problem as a GP [11]. The constraints described above are in a linear form. In order to transform these constraints in GP form they must be written as posynomial or monomial inequations. Constraints (6) and (7) may be rewritten as:

$$b(t)^{-1}[\max\{g(t) - C^{\max} - \textstyle\sum_{m\in\mathcal{M}} s_m(t), 0\}] \leq 1; \quad (12)$$

$$b(t)[C^{\max} + g(t)]^{-1} \leq 1. \quad (13)$$

For the energy storage constraints we substitute (8) in (9) and obtain: $0 \leq e(t-1) + b(t) - g(t) \leq C^{\max} - \sum_{m\in\mathcal{M}} s_m(t)$. The amounts of energy stored from previous time-slots are computed as: $e(i-1) = e(i-2) + b(i-1) - g(i-1)$, for $i = 2, \ldots, t$. Then, by setting the initial amount of stored energy to zero, *e(0)=0*, we obtain: $0 \leq \sum_{i=1}^{t}(b(i) - g(i)) \leq C^{\max} - \sum_{m\in\mathcal{M}} s_m(t)$, for all $t = 1, \ldots, T$. Rewriting the upper inequality in terms of balanced consumption we obtain the following upper limiting constraint for the storage:

$$[\textstyle\sum_{i=1}^{t} b(i)][C^{\max} - \sum_{m\in\mathcal{M}} s_m(t) + \sum_{i=1}^{t} g(i)]^{-1} \leq 1. \quad (14)$$

The lower limiting constraint of the storage can be written in terms of balanced grid consumption as: $\sum_{i=1}^{t} g(i) + \sum_{i=1}^{t-1} b(i) \leq b(t)$, for all $t = 1, \ldots, T$. By substituting the left-hand side of this inequality with (14), we obtain the lower limiting value:

$$[\max\{g(t) - C^{\max} - \textstyle\sum_{m\in\mathcal{M}} s_m(t-1), 0\}] b(t)^{-1} \leq 1. \quad (15)$$

Finally constraints (10) and (11) can be rewritten as:

$$[\textstyle\sum_{t=1}^{T} \xi(t) b(t)][\sum_{t=1}^{T} \xi(t) g(t)]^{-1} \leq 1; \quad (16)$$

$$[\textstyle\sum_{t=1}^{T} b(t)][\sum_{t=1}^{T} g(t)]^{-1} \leq 1. \quad (17)$$

The solution of the optimization problem can be obtained through standard interior point algorithms [11].

V. Simulation Examples

In this section we present numerical results that demonstrate the performance of the proposed method. For simulations we assumed the case of a smart grid community composed of *M=4* residences owning RES and ESS and *P=6* other residential households that are sole energy consumers. The time framework is considered to be *T=24* hours, divided into hourly time-slots. The pricing data used in the simulations is actual pricing data of May 2013, taken from the Finland Nord Pool Spot database [12]. We simulated the renewable energy production profiles according to the model presented in [13] using true hourly temperature, air pressure and wind speed data from the Finnish Meteorological Institute database for May 2013 [14]. The 24 hours energy demands of the households were simulated with the load modeling framework proposed in [15]. We considered households of two to five inhabitants. For solving the load balancing optimization problem we used the CVX package for convex optimization [16].

The results of the proposed demand response strategy are illustrated in Fig.1. Fig.1(a)-(f) shows the simulation results for May 17th. We considered ESS_m capacities of $C_m^{\max} = \{5kWh, 8kWh, 5kWh, 8kWh\}$. Fig.1(a) presents the cumulated 24 hours wind energy production of all residences owning RES. Fig.1(b) shows the total 24h energy demand profile of the community, while Fig.1(c) shows the per-time-slot amounts of energy needed by the community from the power grid, **g**, as calculated by the renewable integration method. Fig.1(d) depicts the amounts of total renewable energy sold by the RES owners to the rest of the residences in the community. The cumulated ESS profile of the community is presented in Fig.1(e). Here we can observe the total amounts of renewable energy saved for fulfilling the energy requirements of the RES owners, the amounts of renewable energy that are stored and then sold and the amounts of grid energy that are stored for load balancing and cost reduction purposes. The community's balanced grid consumption profile is shown in Fig.1(f). Part of this energy is instantly consumed and the rest is saved in storage as shown also in Fig.1(e). The efficiency of the proposed load balancing method depends on the available ESS capacity. To measure the efficiency of the proposed load balancing method we calculated the PAR for different $C^{\max}$ values. In Fig.1(g) we can see the variation of the PAR as a function of the total ESS capacity in the community. The PAR values improve as the capacity increases, obtaining PAR values of 1.04 for $C^{\max} \geq$ 22kWh. Fig.1(h) shows the PAR values of the grid energy requirements in comparison to those of the balanced grid consumption for each day of May 2013. In the majority of the cases we obtained highly balanced grid consumption with PAR values very close to 1. The PAR was reduced on average by 52%. Fig.1(i) shows the daily cumulated electricity cost savings for the

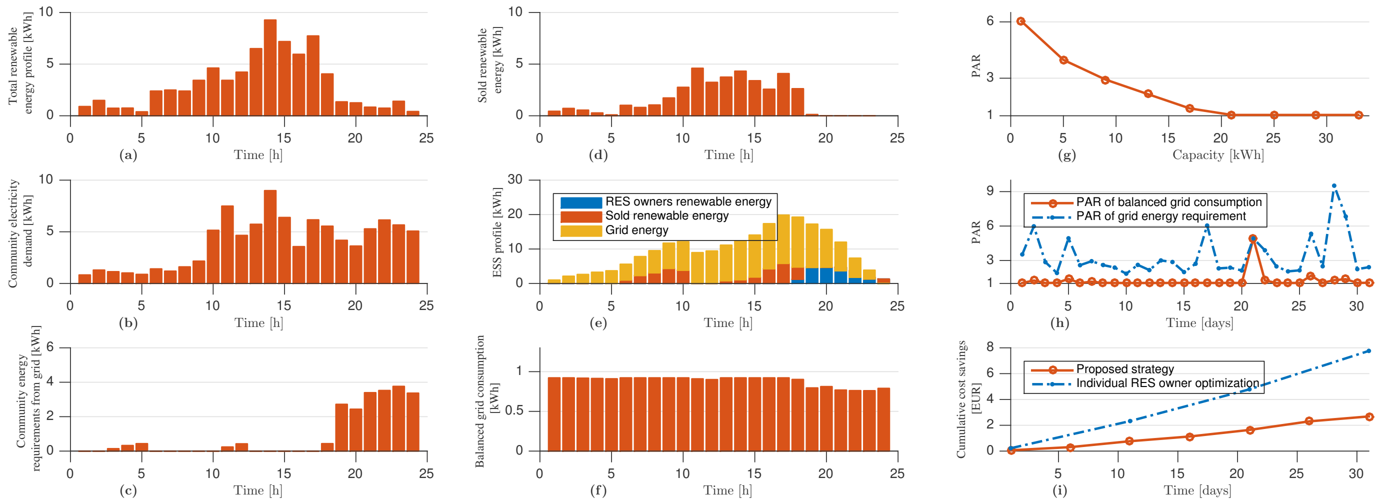

Fig. 1: Renewable energy integration, load balancing and cost reduction. (a): the community's 24-hour wind energy production profile. (b): the total energy demand of the community. (c): the profile of the required grid energy. (d): the total amount of renewable energy sold per time-slot.(e): the community's total ESS profile including wind energy and grid energy stored for load balancing purpose. (f): the balanced grid consumption profile.(g): the variation of the PAR as a function of $C^{\max}$. For $C^{\max}$ above 22kWh the PAR values are 1.04. (h): the PAR values of the grid demand and of the balanced consumption for 31 days. (i): the cumulated cost savings over 31 days.

community for May 2013. First plot shows the daily cumulated cost savings obtained when using the proposed energy trade strategy together with the load balancing with cost reduction optimization. The 31-day grid energy cost before the load balancing optimization was: $\sum_{t=1}^{T} \xi(t)g(t)$=70.4 €, while after performing the load balancing optimization the cost was $\sum_{t=1}^{T} \xi(t)b(t)$=67.5 €. The cost reduction obtained through the load balancing optimization is about 4%. The second plot shows the cost savings of the proposed energy trading method in comparison with the case when the RES owners would use their ESS to perform individual cost reduction and not sell the excess renewable resources. In this case we denote by $b_m^*(t)$ the grid energy needed by each RES owner. The community's cost for energy purchased from the grid would be $\sum_{t=1}^{T}[\sum_{m\in\mathcal{M}} \xi(t)b_m^*(t) + \sum_{p\in\mathcal{P}} \xi(t)u_p(t)]$=75.5 €. The proposed energy trading method reduces this cost by 10.5%.

VI. Conclusion

In this paper we proposed a novel demand response strategy for energy management within a smart-grid community of households. Some households in the community own RES and ESS and sell their excess renewable energy to the residences that need energy. The proposed strategy comprises an off-line algorithm that schedules the renewable energy integration. The algorithm facilitates fast consumption of renewable resources and offers a way to fairly trade the renewable energy. The method also comprises a GP based optimization method that uses the ESS for balancing the grid energy needed by the community and for reducing the grid consumption cost. Simulation results showed that the proposed method balances the load by reducing the PAR values by 52%. The energy trading method may provide a cost reduction of about 10% for the gird energy bought by the community, while the load balancing optimization may provide a cost reduction of 4%.

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