An Energy Management System Aggregator Based on an Integrated Evolutionary and Differential Evolution Approach

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Abstract. The increasing penetration of renewable generation in the electric power system has been leading to a higher complexity of grid management due to its inherent intermittency, also with impact on the volatility of electricity prices. Setting the adequate operating reserve levels is one of the main concerns of the System Operator (SO), since the integration of a large share of intermittent generation requires an increased amount of reserve that is needed to balance generation and load. At the same time, the energy consumption in households has been steadily growing, representing a significant untapped savings potential due to consumption waste and load flexibility (i.e., the possibility of time deferring the use of some loads).

An aggregator has been designed to operate as an intermediary between individual energy management systems and the SO/Energy Market, capable of facilitating a load follows supply strategy in a Smart Grid context. The aggregator is aimed at using the flexibility provided by each end-user aggregated into clusters of demand-side resources to satisfy system service requirements, involving lowering or increasing the power requested in each time slot. This contributes to the balance between load and supply and coping with the intermittency of renewable sources, thus offering an attractive alternative to supply side investments in peak and reserve generation.

For this purpose, a multi-objective optimization model has been developed to maximize the aggregator profits, taking into account revenues from the SO/Energy Market and payments to end-user clusters, and minimize the inequity between the amounts of load flexibility provided by the clusters to satisfy grid requests. An approach based on an evolutionary algorithm coupled with a differential evolution algorithm has been designed to deal with this model.

Keywords: Evolutionary algorithm · Differential evolution algorithm · Multi-objective · Energy management systems · Aggregator

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1 Introduction

The efforts to reduce greenhouse gases (GHG) emissions, foreign energy dependence and the impacts of fossil fuel price volatility have been leading to a fast increase in the deployment of electricity generation based on renewable energy sources (RES), in particular photovoltaic and wind power. RES are being deployed not only as bulk generation facilities but also as distributed local generation connected to the electricity distribution grid or to private consumption infrastructures. The generation patterns associated with RES normally do not follow the typical end-user demand profile and cannot be predicted with great accuracy. The variability of wind electricity generation has to be managed in the short-term adjusting both generation and demand [1]. In electric power systems the end-users are nowadays subject to yearly fixed tariffs without knowing the entire market conditions. The System Operator (SO) should deal with the variability of electricity generation costs and the demand requests, in order to manage the electric power system securely and safely [1, 2].

The power output of RES is driven by environmental conditions, which are inherently variable and outside the control of generators and the SO. RES cannot be reliably dispatched or perfectly forecasted, and exhibit significant temporal variability. As a result, the proper integration of RES into the electric grid presents a major challenge and new tools are required to ensure the grid reliability. The adjustment is generally done using “fast-reacting” generation (as peaking power plants or spinning reserves) to safeguard the system against unexpected events such as generation deficit, speedy load variations or a combination of both [3, 4], which involve high costs. Therefore, other methods to compensate the imbalances in the electric power system should be envisaged. Electricity can be stored during periods in which supply exceeds demand and used during the peak hours. Demand can be reduced during peak hours, by interrupting, shifting or re-parameterizing the loads [5]. A better integration of intermittent RES in the electric power system needs to accommodate these issues, namely concerning the possibilities of managing demand in a perspective of integrated energy resource management to deal with the supply volatility.

The energy consumption in European Union (EU) households has been steadily growing during the last few years due to the widespread utilization of new types of loads and the requirement of higher levels of comfort and services [4]. The electricity consumption breakdown in EU households was characterized [6], and it was verified that some end-use loads present some kind of flexibility; therefore, if properly controlled these loads can be used as a demand side resource capable of offering a responsive behavior [7, 8]. As an example, washing and drying appliances can be rescheduled to other periods (in particular those with lower electricity prices) thus flattening the demand curve, or to periods of higher energy generation based on RES, also contributing to reduce GHG emissions. Thermal loads (cooling appliances, water heating, space heating/cooling and air conditioning systems) can be interrupted during shorts periods of time, without major reductions in service quality, to avoid the most unbalanced situations between generation and consumption, thus compensating the effects of the variability of RES availability.

The on-going transformations of the electric power system, namely concerning the exploitation of distributed generation and the evolution towards the smart grid, simultaneously require and facilitate a load follows supply strategy to cope with the penetration of RES and ensure an adequate level of power reserve [5]. Avoiding peak loads while maintaining the balance between the load and supply diagrams is increasingly important in order to reduce the need for additional generation capacity as a backup for volatile supply and face disturbances occurring in the network [5].

As far as security of supply is concerned, the most severe problems due to the power intermittence occur in peak load hours, since most system resources are already in use and a sudden reduction of power generation can have critical consequences on the system reliability. Thus, instead of acting on the supply side, Demand Response (DR)[1] programs and technologies have the potential to contribute to optimize consumption and reduce peak loads, in (near) real-time, allowing the participation of end-users in the electricity market. In this way, DR is an enabling strategy for the successful integration of RES in the electric system, in a perspective of integrated energy resource management, involving controlling flexible loads according to (price and/or emergency) signals from the grid and end-users' preferences. In addition, DR can become a new source of revenue for entities that "aggregate" this load flexibility.

In a smart grid context, it is expected that the traditional end-user will become a *prosumer* (i.e., simultaneously producer and consumer) and dynamic (time-differentiated) electricity tariffs will be offered [2]. In order to implement DR programs the household needs to have local energy management systems (EMS) based on fully interactive Information and Communication Technologies (ICT), to help the end-user optimizing the energy use without compromising comfort, achieving energy savings and satisfying constraints on the quality of the energy services provided, enabling the two-way communication between the house and the grid in order to improve the global performance of the electric power system [2, 3]. Otherwise, in a scenario of a low price signal from the grid, all EMS devices would attempt to achieve benefits for the end-user engaging in similar actions (e.g., by shedding the same type of loads), eventually taking no notice of the instability that could impair the operation of the system, since the true impact of household consumption arises when it is summed up over a large number of houses [4].

In this context, a few studies have addressed the combination of demand and supply sides to implement DR programs for the provision of system services, i.e. the balancing services that are provided by system operators for ensuring reliable system operations [7]. These services have been traditionally provided by generators, which are capable of adjusting their output rapidly in response to unanticipated imbalances between supply and demand. In the smart grid context, the provision of these services by aggregating electricity consumers using DR programs may become an attractive alternative [8].

This role can be performed by an aggregator energy management system (Energy Box Aggregator - EBAg), which is an intelligent decision-making mediator between the end-user (local energy box - LEB) and the grid (SO/Energy Market) allowing the

[1] According to the Federal Energy Regulatory Commission Demand Response may be defined as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."

coordination of a large-scale dissemination of in-house DR devices (Fig. 1). The EBAg is aimed at using the demand-side flexibility provided by clusters of end-users to provide system service requirements, involving lowering or increasing the power requested in each time slot of a planning horizon. This contributes to balancing load and supply, avoiding peaks in the load diagram, and coping with the intermittency of RES, thus increasing the overall grid efficiency by offering an attractive alternative to supply side investments on peak and reserve generation [8].

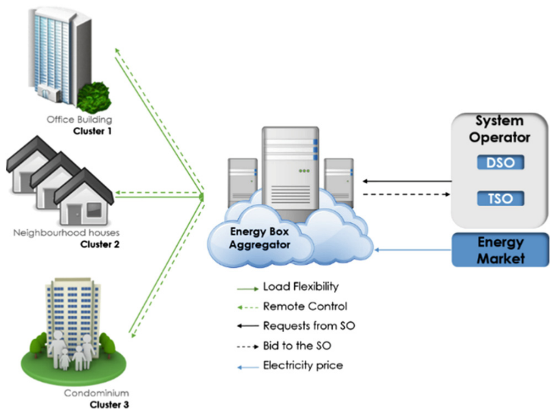

Fig. 1. EBAg global architecture

The purpose of this paper is to present an approach based on an evolutionary algorithm (EA) coupled with a differential evolution algorithm (DEA) to deal with a multi-objective optimization (MOO) model, as seen by the EBAg, considering the maximization of the EBAg profits, taking into account revenues from the SO/Energy Market, payments to end-user clusters and additional penalties, and the minimization of the inequity among clusters, i.e., the maximum relative difference between the load flexibility provided by the clusters and the one used by the EBAg, as a surrogate for fairness in the usage of end-user load flexibility.

This paper is structured as follows: Sect. 2 presents the MOO model formulation for the EBAg problem; Sect. 3 describes the algorithmic approach and the case study; Sect. 4 illustrates the results and discusses them, and Sect. 5 presents the main conclusions.

2 A MOO Model for the EBAg

The aim of this section is to define a framework for the EBAg role in the electric power system. This comprises the information that is transmitted from an LEB to the EBAg, and the relationships between the LEB and the grid (SO and energy market).

The large-scale deployment of LEB imposes an essential challenge concerning the coordination of grid and end-user objectives. I.e., requests from the grid should be weighed against end-user flexibility to shift or shed loads. In this way, the EBAg will gather flexibility from its end-users by means of each LEB, asking them to adjust their daily load profile, using a remuneration scheme specified in a contract with end-users associated in clusters. A critical issue is the incentive paid to the end-users to participate in these demand management programs and provide load operation in a cost effective way.

Thereby, the EBAg is able to sell the flexibility gathered, presenting offers to the grid, according to its requests, in the form of ancillary services, with the aim of offering benefits to all entities involved (increase retail profits, decrease consumption costs). The EBAg may receive signals from the SO, and take appropriate actions to avoid violation of network operational constraints. In case of abnormal operating conditions, the SO can request load increasing or decreasing, in each time slot, to the EBAg. The interaction with the SO may be also important for solving congestions in the distribution network.

2.1 Model Formulation

The MOO model as seen by the EBAg consists in: - maximizing its profits, taking into account the revenues of selling the load flexibility obtained from the end-user clusters to the grid and the rewards given to the clusters as well as the penalties paid to the grid for not meeting the flexibility requested and to the clusters for the amount of flexibility not used; - and minimizing inequity among clusters, i.e., minimizing the maximum relative difference between the load flexibility provided by the clusters and the one used by the EBAg, as a surrogate for fairness in the usage of end-user load flexibility.

Indices

c 1, 2, …C - cluster, where C is the number of clusters associated with the EBAg. Each cluster gathers a set of end-users (LEB).

t 1, 2, …T - time slot, considering a time resolution of 15 min (T = 96 time slots in one day).

Coefficients

I_t^+ Reward paid by the grid to the EBAg for the flexibility provided (load shedding, i.e. power decrease), in each time slot t.

I_t^- Reward paid by the grid to the EBAg for the flexibility provided (load increase), in each time slot t.

E_t^+ Reward paid by the EBAg to the clusters (equal for all clusters) for the flexibility used (load shedding, i.e. power decrease), in each time slot t.

E_t^- Reward paid by the EBAg to the clusters (equal for all clusters) for the flexibility used (load increase), in each time slot t.

F_t^+ Penalty paid by the EBAg to the grid for not complying with the contracted flexibility (load shedding, i.e. power decrease), in each time slot t.

F_t^- Penalty paid by the EBAg to the grid for not complying with the contracted flexibility (load increase), in each time slot t.

C_{ct}^+ Penalty paid by the EBAg to the cluster c for the amount of flexibility not used (load shedding, i.e. power decrease), in each time slot t.

C_{ct}^{-} Penalty paid by the EBAg to the cluster c for the amount of flexibility not used (load increase), in each time slot t.

R_t^{+} Power reduction (load shedding) request by the grid to the EBAg in each time slot t.

R_t^{-} Power increase request by the grid to the EBAg in each time slot t.

$Dmax_{ct}^{+}$ Maximum value of power the cluster c can offer to the EBAg (decrease) in each time slot t.

$Dmax_{ct}^{-}$ Maximum value of power the cluster c can offer to the EBAg (increase) in each time slot t.

∂_c^{+} Minimum fraction of $Dmax_{ct}^{+}$ that cluster c may offer to decrease power (positive flexibility margin).

∂_c^{-} Minimum fraction of $Dmax_{ct}^{-}$ that cluster c may offer to increase power (negative flexibility margin).

D_{ct}^{+} Amount of power that cluster c offers to decrease (load shedding) in time slot t, accounting for a range of variation in the cluster response.

D_{ct}^{-} Amount of power that cluster c offers to increase in time slot t, accounting for a range of variation in the cluster response.

$$D_{ct}^{+} = rand\left(\partial_c^{+}, 1\right) Dmax_{ct}^{+}$$

$$D_{ct}^{-} = rand\left(\partial_c^{-}, 1\right) Dmax_{ct}^{-}$$

In this way D_{ct}^{+} and D_{ct}^{-} account for the uncertainty associated to the flexibility effectively provided by end-user clusters.

Decision variables

P_t^{+} Amount of power (kW) that the EBAg is capable to offer to the grid, in each time slot t, corresponding to load shedding (power decrease).

P_t^{-} Amount of power (kW) that the EBAg is capable to offer to the grid, in each time slot t, corresponding to power increase. $P_t^{+} \,.\, P_t^{-} = 0$.

L_{ct}^{+} Amount of power that the EBAg uses from cluster c to decrease (load shedding) in time slot t.

L_{ct}^{-} Amount of power that the EBAg uses from cluster c to increase in time slot t. $L_{ct}^{+} \,.\, L_{ct}^{-} = 0$.

Objective functions

Maximizing the EBAg profits, taking into account the revenues of selling the load flexibility obtained from the end-user clusters to the grid and the rewards given to the clusters as well as the penalties paid to the grid for not meeting the flexibility requested and to the clusters for the amount of flexibility made available and not used:

$$\max z_1 = \sum_t I_t^{+} P_t^{+} + \sum_t I_t^{-} P_t^{-} - \sum_t \sum_c E_t^{+} L_{ct}^{+} - \sum_t \sum_c E_t^{-} L_{ct}^{-} - \sum_t F_t^{+}\left(R_t^{+} - P_t^{+}\right)$$
$$- \sum_t F_t^{-}\left(R_t^{-} - P_t^{-}\right) - \sum_t \sum_c C_t^{+}(D_{ct}^{+} - L_{ct}^{+}) - \sum_t \sum_c C_t^{-}(D_{ct}^{-} - L_{ct}^{-})$$

Minimizing inequity among clusters, i.e., minimizing the maximum relative difference between the load flexibility provided by the clusters and the one used by the EBAg:

$$\min z_2 = \max_c \sum_t (L_{ct} - D_{ct})/D_{ct}$$

<u>Constraints</u>

The amount of power that the EBAg uses from cluster c to decrease/increase cannot be higher than the amount of power to decrease/increase offered by cluster c in time slot t:

$$L_{ct}^{+} \leq D_{ct}^{+}, \textit{ for all } c, t$$
$$L_{ct}^{-} \leq D_{ct}^{-}, \textit{ for all } c, t$$

The amount of power that the EBAg offers to the grid to decrease/increase cannot be higher than the amount of power required to decrease/increase in time slot t:

$$0 \leq P_t^{+} \leq R_t^{+}, \textit{ for all } t$$
$$0 \leq P_t^{-} \leq R_t^{-}, \textit{ for all } t$$

The amount of power that the EBAg offers to the grid to decrease/increase cannot be higher than the total amount of power used to decrease/increase that is offered by the clusters in time slot t:

$$0 \leq P_t^{+} \leq \sum_c L_{ct}^{+}, \textit{ for all } t$$

$$0 \leq P_t^{-} \leq \sum_c L_{ct}^{-}, \textit{ for all } t$$

3 Algorithmic Approach

The algorithmic approach should be able to deal with the main characteristics of the problem, specifically its combinatorial nature. According to the authors' previous experience on load scheduling in residential energy management systems and the problem characteristics, namely concerning the types of decision variables, EA and DEA were selected as the most adequate approaches. The aim herein is computing non-dominated fronts displaying a good spread along and expected convergence to the true Pareto-optimal front (which is unknown), which could enable to study the trade-offs between the two competing objective functions (maximizing the EBAg profits and minimizing the inequity among clusters).

The solution encoding in both approaches consists in an array of continuous variable, corresponding to decision variables P_t^{+}, P_t^{-}, L_{ct}^{+}, L_{ct}^{-} in the model.

The EA is based on NSGA-II [9], presenting the following main features:

– Population size = 30 individuals.
– Random generation of initial population.
– Crossover operator: two algorithm versions have been developed with crossover (with probability of 0.2) and without crossover. The crossover operator "respects" the model decision variables expressed in the individual representation, in the sense that each variable (physical) information is never "broken".
– The mutation operator (with a probability of 0.2) works in each decision variable composing the individuals by randomly increasing/decreasing the amount of power within a given range.
– Stop condition: 10,000 generations.

The main features of the DEA are:

– Mutation variant of DE: DE/rand/2/bin, since it consistently presented the best performance in comparison with other permutation strategies of the base vector.

The parameters were tuned after extensive experimentation. Sets of 30 independent runs were carried out for each approach. The main features of the solutions then obtained were:

– The EA consistently provided good extreme (i.e., individual optima to each objective function) solutions but displaying only a few solutions in the non-dominated front. The EA was able to rapidly finding good solutions for both objective functions, namely regarding the profit objective function. The front then evolved in an intermittent manner with groups of (slightly) dominated solutions being outperformed by generally a single non-dominated solution. Then the final non-dominated front was well spread (in the sense of good individual optimal solutions) but irregularly covered (few solutions in the front).
– The DEA provided a well spread and covered non-dominated front in a significant number of runs, but with individual optimal solutions less good than in the EA case. The evolution of the front was quite regular. However, in a non-negligible number of runs the front was of low quality because no positive values of the profit objective function could be obtained.

The analysis of this behaviour of the algorithms in different instances of the problem led to the conclusion that once solutions with positive values for the profit objective function were attained, the DEA then smoothly evolved to a well-covered and well-spread front. Since this goal was easily achieved by the EA, which in turn computed better individual optimal values for the objective functions thus expanding the front, then both approaches were combined. The EA is used in a first phase to compute good extreme values and a few solutions scattered along the front with already satisfactory values for both objective functions, and in a second phase the DEA is used to further expand and fill up the front.

The hyper-volume indicator has been used throughout this algorithm refinement process to assess and compare the quality of the fronts obtained in the computational experiments.

3.1 Case Study

Experiments have been carried out based on real data gathered throughout one year, January 2013 to January 2014, of continuous (24/7) monitoring of electrical consumption with a time resolution of 15 min (*t*). These data provided a realistic basis for the specification of clusters, energy prices, baseline load profiles and load flexibility offered by each cluster. In the end-user side, 8 types of clients were defined based on their electricity consumption profile, which were aggregated into clusters according to their consumption average and load factor (ratio average load/peak load in a specified time period). For example, cluster 1 gathers the end-users with 0–5 % load factor and cluster 20 the clients with 95–100 % load factor.

The data for these experiments have been obtained from a sample of 9,000 daily load profiles of different Cloogy technology (www.cloogy.pt) users. Cloogy is an energy management solution that allows monitoring and controlling energy consumption in households, buildings and small industries.

The profile of the cluster in the absence of any flexibility request can be represented as a baseline load profile diagram (Fig. 2). The EBAg should know how each cluster responds to every admissible request signal sent to it.

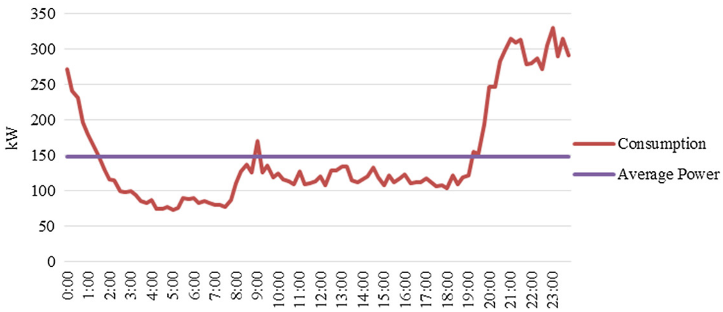

Fig. 2. Load diagram of cluster 2: load factor between 5 % – 10 %, peak power 330 kW.

The flexibility margin indicated by each cluster reflects its availability to decrease/increase load in a given time slot, with respect to the baseline consumption. This "positive" and "negative" flexibility margins are displayed in Table 1.

To obtain the amount of flexibility for each cluster throughout the planning period this flexibility margin is applied to its load profile (Fig. 2). For instance, when the cluster load factor is 45 % and the consumption is higher than the average consumption it is possible to have load shedding (i.e., decrease in the load) up to 12.5 % (positive flexibility), and when the consumption is lower than the average consumption it is possible to have an increase of up to 10 % (negative flexibility). The load flexibility obtained based on the analysis previously elaborated is shown in Fig. 3.

Table 1. Positive and negative flexibility margins based on aggregate load factor

Aggregate load factor	Positive flexibility	Negative flexibility
0–10 %	2.5 %	0.0 %
10–20 %	5.0 %	2.5 %
	…………….	
40–50 %	12.5 %	10.0 %
	…………….	
80–90 %	2.5 %	5.0 %
90–100 %	0.0 %	2.5 %

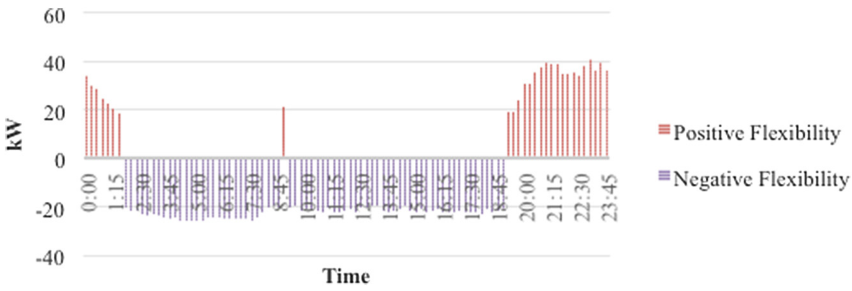

Fig. 3. Positive and negative flexibility of cluster 2

The revenues received by the EBAg from the grid and rewards given by the EBAg to the clusters are based on the electricity tariffs, considering significant variations in frequency and amplitude along the day in some way mimicking the wholesale electricity market.

4 Results and Discussion

The Pareto front is displayed in Fig. 4, which has been obtained coupling the EA with the DEA. The individual optimal solutions (maximizing EBAg profits and minimizing inequity) and three other compromise solutions are displayed in red. EA swiftly obtained very good solutions individually optimizing each objective function, thus extending the front, although with few solutions, and then DEA further improved those solutions and populated the front.

In the solution that maximizes the EBAg profits, 3127 kWh of flexibility were provided by load shedding with a remnant of 204 kWh that could not be offered due to cluster unavailability, leading to a profit of 654.3 € and 0.17 for the inequity indicator. In the solution that minimizes inequity among clusters, 2644 kWh of flexibility were provided by load shedding in clusters with a remnant not provided of 1357 kWh, leading to a profit of 557.9 € and 0.09 for the inequity indicator. The solution in the middle of the Pareto front could offer a flexibility of 2952 kWh, with a remnant 1357

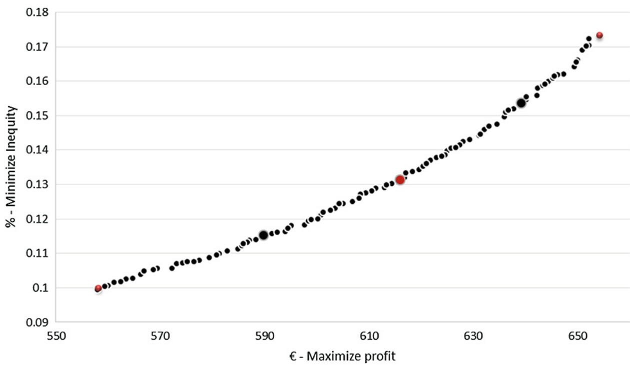

Fig. 4. Pareto front.

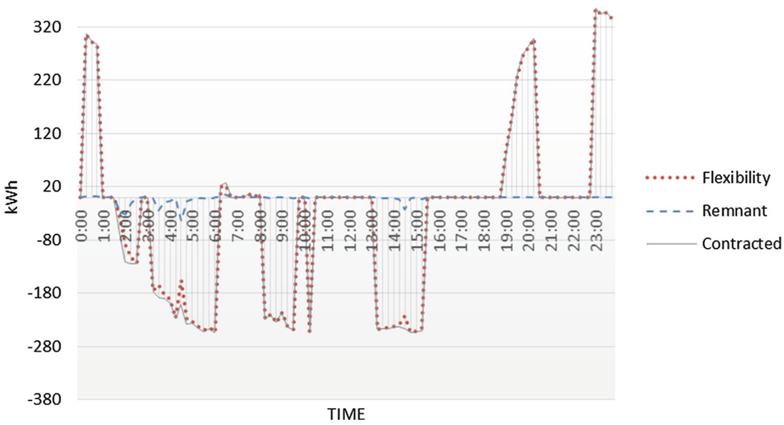

Fig. 5. Physical representation of the solution maximizing EBAg profits.

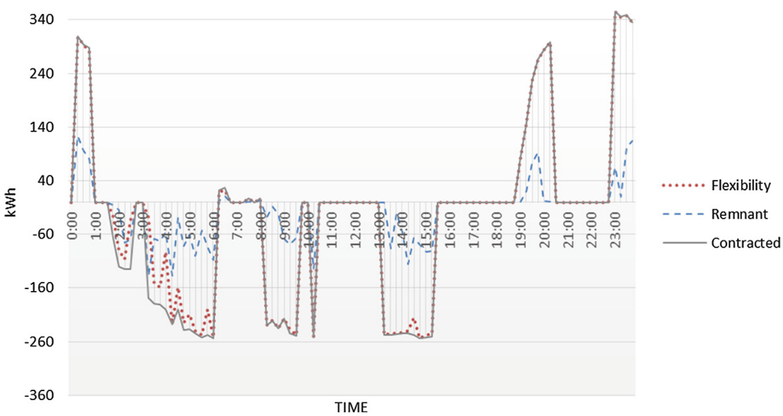

Fig. 6. Physical representation of the solution minimizing inequity.

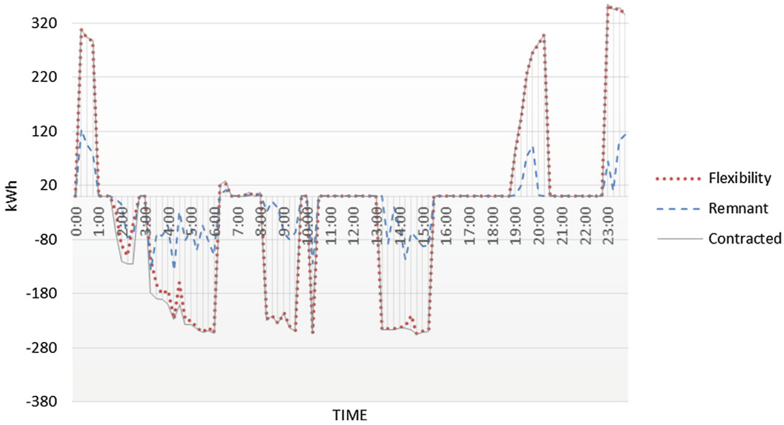

Fig. 7. Physical representation of the "middle" solution.

kWh not provided, achieving a profit of 615.9 € and 0.13 for the inequity indicator. Figures 5, 6, and 7 display the physical representation (load flexibility provided by the clusters to satisfy SO requests) of the solutions that maximize the EBAg profits, minimize the inequity among clusters, and the "middle" solution.

5 Conclusions

This paper presented a MOO model for an aggregator of local energy management systems, which uses the load flexibility provided by each end-user to respond to the grid requests and facilitate a load follows supply strategy in a Smart Grid setting, with potential benefits for all participants involved. The role of the EBAg is twofold: it makes the most of demand responsive loads according to in-house load flexibility and it provides system services contributing to improve the system operation.

The optimization model from the aggregator perspective presents multi-objective evaluation aspects (economic, quality of service, fairness) of the merits of potential solutions. An approach based on an evolutionary algorithm coupled with a differential evolution algorithm displayed an improved performance to obtain a well spread and populated Pareto front.

Future work will deal with the dynamic nature of the problem and uncertainty associated with input information of different nature.

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