An Optimization Model for the Aggregation of End-user Energy Management Systems in a Residential Setting

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Abstract: This paper proposes a model for an aggregator of energy management systems (energy box aggregator - EBAg) to operate as an intermediary between individual energy management systems (local energy boxes) and the System Operator / Energy Market capable of facilitating a "load follows supply" strategy in a Smart Grid context. The EBAg is aimed at using the flexibility provided by end-users of demand-side resources to respond to system service requirements, via contracts, involving lowering or increasing the energy consumption in each time slot. The aim is contributing to the balance between load and supply, avoiding peaks in the aggregate load diagram, and coping with the intermittency of renewable sources. For this purpose an optimization model for the EBAg has been developed, which is tackled using a genetic algorithm based approach to deal with the combinatorial characteristics of the model.

1 INTRODUCTION

The efforts to reduce greenhouse gases (GHG) emissions related to electricity generation have been leading to a fast increase in the deployment of renewable generation (European Commission, 2010). However, renewable sources present characteristics that differ from conventional energy sources. The power output is driven by environmental conditions, which are inherently variable and outside the control of generators and system operators. They cannot be reliably dispatched or perfectly forecast, and exhibit significant temporal variability. As a result, the proper integration of renewables into the electric grid presents a major challenge and new tools are required to ensure the grid reliability.

At the same time, the energy consumption in European Union (EU) households has been steadily growing due to the widespread utilization of new types of loads and the requirement of higher levels of comfort and services. The electricity consumption breakdown in EU households was recently characterized (de Almeida et al., 2001), recognizing that several 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 behaviour (Kowli et al., 2010).

As far as security of supply is concerned, the most severe problems due to 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) programs and technologies have the potential to contribute to optimize consumption and reduce peak loads, in (near) real-time. In this way, DR is an enabling strategy for the successful integration of renewable energy sources 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 (Joo et al., 2007).

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 (Livengood and Larson, 2009). Therefore, an in-house demand responsive energy management system (Local Energy Box - LEB) is required, based on fully interactive Information and Communication Technologies (ICT), to help the end-user optimizing

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the energy use without compromising comfort, achieving energy savings and satisfying constraints on the quality of the energy services provided. The LEB should also enable two-way communication, between the house and the grid in order to improve the global performance of the electric power system (Livengood and Larson, 2009); (Verschueren et al., 2010). Otherwise, in a scenario of a low price signal from the grid, all LEB 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 (EU Comission Task Force for Smart Grid). In this context, a few recent 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 (EU Comission Task Force for Smart Grid). 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 is becoming an attractive alternative (Agnetis et al., 2011).

In this context, an aggregator energy management system (Energy Box Aggregator - EBAg) is proposed, which is an intelligent mediator between the end-users (via LEB) and the grid (System Operator / Energy Market, SO/EM) allowing the coordination of a large-scale dissemination of in-house DR devices (Figure 1).

The main aim of the EBAg is to provide system service requirements, increasing the grid efficiency, ensuring the required levels of supply security, reliability and quality of service, taking into account inputs such as end-user flexibility of operation of demand-side resources and both grid and load technical constraints, thus contributing to the balance between load and supply coping with the intermittency of renewable sources and avoiding peaks in the load diagram, while minimizing overall electricity supply costs (Kowli et al., 2010).

The optimization problem faced by the EBAg consists in receiving requests from the grid to lower or increase electricity consumption and allocating these requests among clusters of LEB while satisfying technical and quality of service constraints, in order to maximize its profits. This is a combinatorial problem and an approach based on genetic algorithms (GA) has been developed, which combines features for handling discrete and continuous variables.

This paper is structured as follows. Section 2 introduces the problem formulation and the related key concepts, also referring to model and business strategy and the potential benefits for the end-user and the grid (SO/EM). Section 3 presents the optimization model and the algorithmic approach, which has been used in an experimental case study presented in section 4. The results of the simulations are briefly presented in section 5. Concluding remarks and future work are outlined in Section 6.

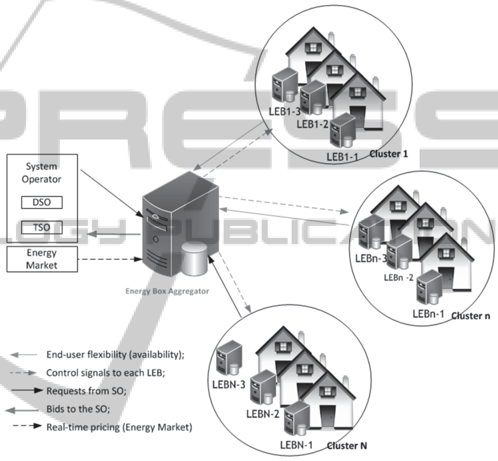

Figure 1: EBAg mediating the relation between LEB and the grid.

2 BUSINESS MODEL AND STRATEGY

This section presents a framework for analysing the EBAg role in the electric power system and the players involved. This comprises the information that is transmitted to/from the LEB, which interfaces the end-user directly with the EBAg, and the relation of the EBAg with the grid (SO/EM).

Nowadays the only direct relation between the grid and the end-user is with the retailer company, being associated through a contract for power supply with specific tariffs (power and energy prices). In such framework end-users are not generally aware of the existence of the energy market.

The energy consumption of domestic consumers presents some flexibility and end-use loads may be broadly characterized into four categories:

- Shiftable: loads that can be used in another period of time and therefore can have their working cycle anticipated or postponed but not interrupted (e.g, dishwashers or laundry machines);

- Re-parameterizable: loads that can have their control parameters re-set (i.e., air conditioners);
- Interruptible: loads whose operation can be interrupted during a certain period of time (e.g., electric water heaters).
- Non-controllable: loads that cannot be the target of any type of demand response actions (e.g., computers, entertainment);

Based on this end-use load categorization, it is possible to exploit the load flexibility within each house. 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 the flexibility of end-use loads to be shifted, re-parameterized or interrupted in a certain period of time. The EBAg will gather this flexibility from the end-users by means of each LEB, asking them to adjust their load profile by offering a remuneration scheme specified in a contract, which is typically variable along the day with some relation with market prices.

Thereby, the EBAg is able to sell the flexibility gathered by making offers to the grid according to its requests in each time slot (i.e., increase or decrease a certain amount of load), with the aim of optimizing its own profits and offering benefits to all entities involved (increasing retail profits, decreasing consumption costs). Figure 1 and figure 2 depict the architecture adopted.

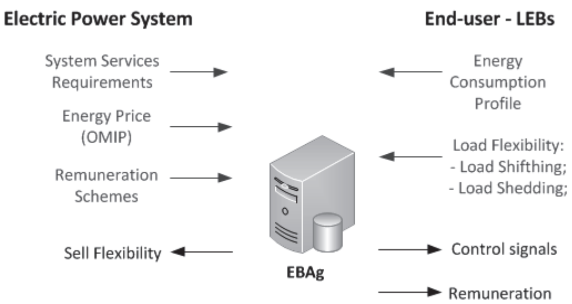

Figure 2: EBAg global architecture.

The EBAg sees its associated end-users grouped into clusters, which contain end-users with similar characteristics. The normal energy profile of the cluster, i.e. in the absence of a flexibility request, can be represented as a baseline load profile curve. The EBAg knows the baseline load profile of clusters as well as the possible load profile responses associated with each request.

The time variable remuneration schemes are known, i.e. the €/kW value paid by the grid to the EBAg and by the EBAg to the clusters. The incentive to remunerate the customer to participate in DR programs is a significant issue for the success of this type of programs (Quinn et al., 2010). An adequate EBAg business model should be designed to attract and maintain residential end-users under demand management contracts, in which end-users receive a reward to offer a certain amount of load flexibility to the EBAg. Customers sign up for programs depending on the benefits they derive in the form of upfront payments, i.e. when demand discounts and interruption payments exceed their perceived cost of interruption or consumption shifting (Fahrioglu and Alvarado, 2000).

The remuneration scheme presently implemented is based on the electricity price at OMIP (MIBEL - Iberian EM) (OMIP). The remuneration schemes are in place when the EBAg requests for consumption change are satisfied. The EBAg may be an Energy Service Company (ESCO) that buys and manages the end-user's flexible load and sells it to provide system services to the SO/EM.

Using the information gathered from the grid (SO/EM) and the individual LEB aggregated in clusters, a model to maximize the EBAg profits is developed that is then tackled using a GA approach.

3 OPTIMIZATION MODEL

The model aims at determining the best matching of the requests by the grid and the flexibility specified by the LEB. Binary variables denote whether or not the EBAg is able to gather load flexibility from the clusters and offer it to the grid, in each time slot. Continuous variables represent the corresponding amount of energy managed.

Indices:

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

f - 0,1,… F. Identifies the request that the EBAg sends to cluster *c*; *f*=0 means that no request is sent by the EBAg. The EBAg congregates the flexibility offered by each cluster. A response function is associated with request *f*.

t = 1,2,…T. Identifies the time slot. A time resolution of 15 minutes is considered, thus having T=96 time slots in one day.

Coefficients:

E_t - Reward paid by the grid to the EBAg for the load flexibility provided, in each time slot *t*.

I_t - Reward paid by the EBAg to the clusters for the load flexibility provided, in each time slot *t*.

L_{ctf} - Load flexibility (kW) response function (i.e., consumption reduction) of cluster *c* in each time slot *t*, associated with request *f*.

$Lmax_{ct}$ - Maximum value of flexible load (kW) in each cluster *c*, in each time slot *t*.

$Pmin_t$ – Minimum amount of load (kW) the EBAg can offer to the grid, in time slot *t*.

R_t – Consumption reduction request from the grid (kW), in each time slot.

Decision variables:

$a_t \in \{0,1\}$. Represent the decision offers of the EBAg to the grid, in each time slot t. If $a_t = 1$ then the EBAg is able to present an offer to the grid in time slot *t*, according to the grid request R_t. Otherwise, $a_t = 0$.

P_t – Continuous variable representing the quantity of power (kW) that the EBAg is capable to offer to the grid, in each time slot *t*: $P_t > 0$ when $a_t = 1$.

$b_{ctf} \in \{0,1\}$. Represents the decision of sending an action/signal to each cluster *c* in time slot *t* responding to request *f*. If b_{ctf}=1 then the EBAg obtains the load flexibility response function L_{ctf}. Otherwise, b_{ctf}=0, $f = 0$ and the cluster is in the baseline load profile.

D_t – Continuous variable expressing the overall flexibility for all clusters *c* associated with the EBAg. It assumes only positive values since it represents a consumption reduction, in each time slot.

The objective function consists in maximizing overall EBAg profits.

$$max \sum_{t=1}^{T} P_t . E_t - \sum_{t=1}^{T} D_t . I_t$$

The first term accounts for the gains from selling the load flexibility to the grid, while the second term accounts for the cost that the EBAg has to pay to the clusters for their participation.

Subject to:

1. Only one action/signal request *f* for each cluster *c*, in each time slot *t*:

$$\sum_{f=0}^{F} b_{ctf} = 1, \forall_c, \forall_t$$

2. In each time slot, it is assumed that the load flexibility response function (L_{ctf}) has an upper bound of the maximum value of flexible load ($Lmax_{ct}$) in each cluster c. The overall load flexibility in each time period is obtained:

$$D_t = \sum_{c=1}^{C} \sum_{f=0}^{F} L_{ctf}\, b_{ctf} \ , \forall_t$$

3. The amount of power offered to the grid is bounded by a minimum offer and the overall load flexibility response gathered from all clusters, whenever the EBAg is able to present an offer to the grid (a_t=1):

$$Pmin_t\, a_t \leq P_t \leq D_t\, a_t, \forall_t$$

4. Whenever the EBAg receive a request from the grid, R_t, the offer to the grid, P_t, cannot exceed the requested flexible load in each time slot:

$$P_t \leq R_t, \forall_t$$

4 ALGORITHMIC APPROACH

A GA approach has been developed to tackle this model, namely to cope with its combinatorial nature. GAs efficiently exploit the search space using genetic operators (selection, crossover and mutation) to create new individuals (solutions) with expectedly improved performance. The evolutionary search process balances two main procedures: exploring the whole search space and exploiting the neighbourhoods of promising solutions. A GA for a particular problem has generally the following components: a representation (encoding) of potential solutions to the problem; a procedure to create an initial population of solutions, generally taking into account model constraints; a fitness function to evaluate the quality of solutions, possibly including a penalty term associated with constraint violations; genetic operators that make the solution population evolve, trying to preserve its diversity; values for the parameters (population size, probabilities of applying genetic operators, etc.).

The model and the GA approach have been implemented in Matlab. A problem-specific repairing process of infeasible solutions obtained in each generation has been designed. The size of the population is 100 individuals. Binary tournament has been used as the selection method. Elitism is considered by retaining the 3 individuals with better fitness, which go into the next generation population without being subject to the operators in order to guarantee that the best solutions are not lost. One-point crossover operators have been designed taking into account the binary/continuous nature of decision variables. These operators ensure the consistency relations to be satisfied between the corresponding sets of binary and continuous variables. Mutation is a genetic operator used to maintain diversity in the population and promote the exploration of the search space. The mutation operator is also tailored to the binary and continuous variables ensuring their mutual consistency after mutation is carried out. For binary variables a bit flip is done with a certain probability, and for continuous variables a change is made within a given interval centered in the present value using a uniform distribution. After applying the mutation operator, infeasible solutions are subject to a repairing process. The evolutionary process ends after 100 generations, which has been set after experimentation.

5 CASE STUDY

Experiments have been carried out, based on real consumption data gathered through audits. These data provided a realistic basis to the specification of clusters, energy prices, baseline load profile, load flexibility response functions, bounds for load flexibility offered by each cluster, and bounds for the offers the EBAg can make to the grid.

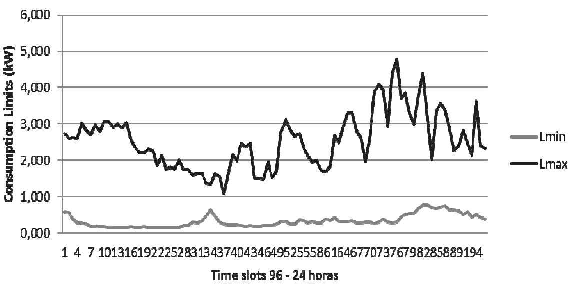

Figure 3: Maximum and minimum consumption of a cluster, in each time slot.

The data for these experiments have been obtained from a sample of 30 users of the Cloogy technology (CLOOGY), which is an energy management solution that allows monitoring and controlling energy consumptions in households. The energy consumption was monitored during one year, January 2012 to January 2013, with a time resolution of 15 minutes. An inquiry has then been made in order to create the house energy profile of each end-user (baseline load profile).

Clusters have been defined based on specific features of each house, namely geographical distribution, contracted power, number of inhabitants in the house, number and type of appliances and house typology (see table 1).

The experiments herein reported have been made with a reduced data set in order to moderate the computational effort. Each cluster is composed of 100 users (using the average of 30 end-users actually audited taking into account their consumption profile). Table 1 displays the daily consumption (kWh), the average power, the maximum power and the minimum power in each time slot for each cluster.

Table 1: Examples of clusters.

Clusters	Typology	Dweller	Consump. (kWh)	Ave. (kW)	Max. (kW)	Min. (kW)
C1	T0-T1	1-2	10,09	0,42	1,15	0,14
C2	T1-T2	2-3	12,22	0,51	1,21	0,25
C3	T2-T3	3-4	16,34	0,68	1,3	0,48
C4	+ T4	+4	33,45	1,4	3,1	0,18

The electrical signature of shiftable loads has been monitored for different machine (laundry and dishwashing) models and programs. These electrical signatures have been used to derive the load flexibility response functions associated with each cluster.

The evolution of the GA can be seen in figure 4, where the upper line displays the evolution of the best solution in the population, and the lower line displays the average performance of the population.

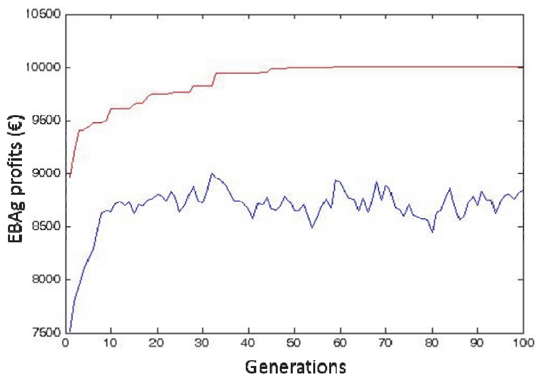

Figure 4: Representation of the GA performance, with 100 generations.

In general, after 60 generations the best solution is achieved. The best solution obtained gives an objective function value (EBAg profit) of 10.007€/day.

The load flexibility offered by each cluster to the EBAg is illustrated in Figure 5, and Figure 6 represents the load diagram of the cluster before (baseline load profile) and after (flexible load diagram) the AG execution.

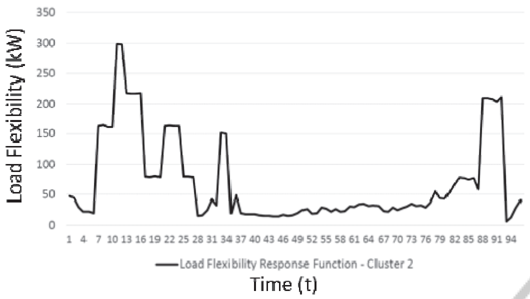

Figure 5: Representation of amount of load flexibility response function, in each time slot, provided by each cluster (example of Cluster 2).

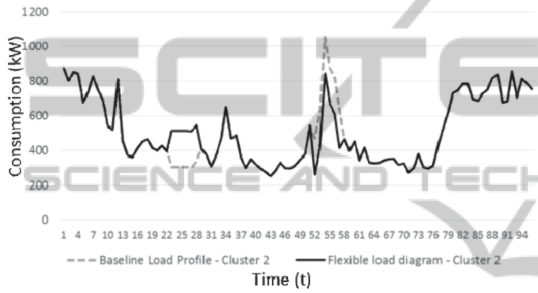

Figure 6: Representation of the baseline load profile and the flexible load diagram of the Cluster 2.

The global load flexibility provided by all clusters to the EBAg (Dt) is displayed in Figure 7.

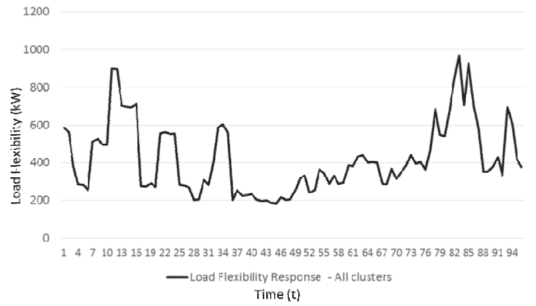

Figure 7: Representation of the amount of load flexibility offered by all clusters.

6 CONCLUSIONS

This paper presents the conceptual and operational framework of a model for a new entity - EBAg, that uses the load flexibility provided by each end-user (via LEBs), responding to the grid requests to facilitate a load follows supply strategy in a Smart Grid context, 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 that contribute to improve the system operation.

The optimization model from the EBAg perspective presents combinatorial characteristics and an approach based on GAs is proposed to deal with it. Work is underway to deal with the dynamic nature of the problem, uncertainty associated with several parameters, and multiple objectives (economic, quality of service, fairness).

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REFERENCES

European Commission, “Energy 2020: A Strategy for Competitive, Sustainable and Secure Energy”, *SEC (2010)* 1346, Brussels, 2010.

de Almeida, A., Fonseca, P., Schlomann, B., Feilberg, N., (2001). Characterization of the Household Electricity Consumption in the EU, Potential Energy Savings and Specific Policy Recommendations. *Energy & Buildings*, Vol. 43, Issue 8, pag. 1884-1894.

Kowli, A., Negrete-Pincetic, M., Gross, G., (2010). A successful implementation with the Smart Grid: Demand response resources, *Power and Energy Society General Meeting 2010*, Minneapolis (USA).

Livengood, D. and Larson, R., (2009). The Energy Box: Locally Automated Optimal Control of Residential Electricity Usage, *Service Science*. 1 1-16.

Verschueren, T., Haerick, W., Mets, K., Develder, C., De Turck, F., Pollet, T., (2010). Architectures for smart end-user services in the power grid, *Network Operations and Management Symposium Workshops 2010 IEEE/IFIP*, vol., no., pp.316-322.

EU Comission Task Force for Smart Grid (2010). Expert Group 1: Functionalities of smart grids and smart meters, December 2010, Brussels.

Joo, J. Y., Yoon, S. H. T., and Choi, J. W., (2007). Option Valuation Applied to Implementing Demand Response via Critical Peak Pricing, *IEEE Power Engineering Society General Meeting*, 24-28.

Quinn, C., Zimmerle, D., Bradley, T. H., (2010). The effect of communication architecture on the availability, reliability, and economics of plug-in hybrid electric vehicle-to-grid ancillary services, *Journal of Power Sources*; 195: 1500-1509.

Fahrioglu, M., Alvarado, F. L., (2000) "Designing incentive compatible contracts for effective demand management, *Power Systems, IEEE Transactions on*, vol.15, no.4, pp.1255,1260, Nov 2000.

Agnetis, A., Dellino, G., Pascale, G., Innocenti, G., Pranzo, M., Vicino, A., (2011) Optimization models for end-user flexibility aggregation in smart grids: the ADDRESS approach, *2011 IEEE 1st International Workshop on Smart Grid Modeling and Simulation (SGMS)*.

http://www.cloogy.pt/pt/

http://www.omip.pt/