Intraday Energy Resource Scheduling for Load Aggregators considering Local Market

José Almeida[1], João Soares[1], Bruno Canizes[1], Iván Razo-Zapata[2], and Zita Vale[3]

[1] GECAD Research Center, R. Dr. António Bernardino de Almeida 431, Portugal
jorga@isep.ipp.pt
[2] Mexico Autonomous Institute of Technology, Mexico City, Mexico
[3] Polytechnic of Porto, Porto, Portugal

Abstract. Demand response (DR) programs and local markets (LM) are two suitable technologies to mitigate the high penetration of distributed energy resources (DER) that is vastly increasing even during the current pandemic in the world. It is intended to improve operation by incorporating such mechanisms in the energy resource management problem while mitigating the present issues with Smart Grid (SG) technologies and optimization techniques. This paper presents an efficient intraday energy resource management starting from the day-ahead time horizon, which considers load uncertainty and implements both DR programs and LM trading to reduce the operating costs of three load aggregator in an SG. A random perturbation was used to generate the intraday scenarios from the day-ahead time horizon. A recent evolutionary algorithm HyDE-DF, is used to achieve optimization. Results show that the aggregators can manage consumption and generation resources, including DR and power balance compensation, through an implemented LM.

Keywords: aggregator, computational intelligence, demand response, energy resource management, local market, smart grid

1 Introduction

Smart grid (SG) technologies, in contrast to today's traditional electricity grid, encourage the high integration of distributed energy resources (DER). These resources bring uncertainty to the conventional grid, which can cause problems in voltage levels and frequency stability. The SG can incorporate this uncertainty by implementing energy resource management (ERM) mechanisms [1]. In this context, computational intelligence (CI) algorithms emerge, leading to better optimization of the variables that control the resources involved in the SG context [2]. Within CI, evolutionary computation (EC) stands out. It has been the target of study within power systems due to its effectiveness in solving problems with a high number of variables and constraints. As such several artificial intelligence (AI) algorithms have been applied to the ERM problem such as Particle Swarm

Optimization (PSO) and its variants [3], Differential Evolution (DE) [4], Genetic Algorithm (GA) [5], Estimation of Distribution Algorithm (EDA) [6], and many others. The literature presents multiple works on day-ahead DER scheduling [7, 8], with few that go further and do this scheduling for intraday time horizon. The work in [9] presents an optimal hour-ahead energy resource scheduling in a real university distribution network (DN). This scheduling is done by an aggregator that tries to maximize its profits. In [10], an hour-ahead home energy management system through peer-to-peer energy trading is proposed to reduce day-ahead forecast uncertainty. To improve the proposed model, the authors implement demand response (DR) mechanisms for residents to deal with household appliances and energy storage systems (ESSs). An optimal ERM of three different load aggregators is proposed in this paper. The aggregators schedule their resources for the intraday time horizon, starting from the day ahead's expected scheduling. A state-of-the-art metaheuristic is used for this optimization problem, more precisely, an evolutionary algorithm (EA) named Hybrid-Adaptive Differential Evolution with Decay Function (HyDE-DF) [11]. This algorithm was considered for this work because it has proven excellent results compared to others regarding energy management problems [12]. All the considered aggregators are located in a smart city (SC) with a 13 bus DN with an extensive penetration of electric vehicles (EVs) and renewables. The considered aggregators optimize this scheduling of resources to minimize costs. A comparison between the objective function obtained in the two considered time horizons is made in the result section. The scheduling plots are also presented for the hour (15 minute time periods) where the results obtained were the best in the total 24 hours for each aggregator. This model intends to simulate the future of distribution networks where various aggregators and/or electricity suppliers will coexist in a competitive environment. Each aggregator will seek to establish contracts with apartments, residential buildings, industry, and others for their consumption or production (prosumers), seeking to provide the best service to these customers to maximize their profits.

2 Proposed Methodology

According to the mathematical formulation, optimization model considering multiple metaheuristics, and uncertainty management, this section outlines the methodology implemented in this paper.

2.1 Intraday Model

The diagram of resource scheduling planning in the hour-ahead sense is presented in Fig. 1. The hour-ahead ERM model requires the technical data and the hour-ahead forecast data. The forecasts are made with a 15-minute time slot resolution for the following four-time slots. Also required are the results from the day-ahead. In this case, the market and dispatchable generation solutions are the day-ahead solutions that come in intraday and are fixed through the limits. Also required are solutions of the last time slot of the previous hour. For the problem at hand, the initial state of the ESSs at time h for the first time slot is equal to the solution obtained at $h-1$ in the last time slot. Therefore, a decision is made in period h for the energy resource scheduling of hour $h+1$ due to the model.

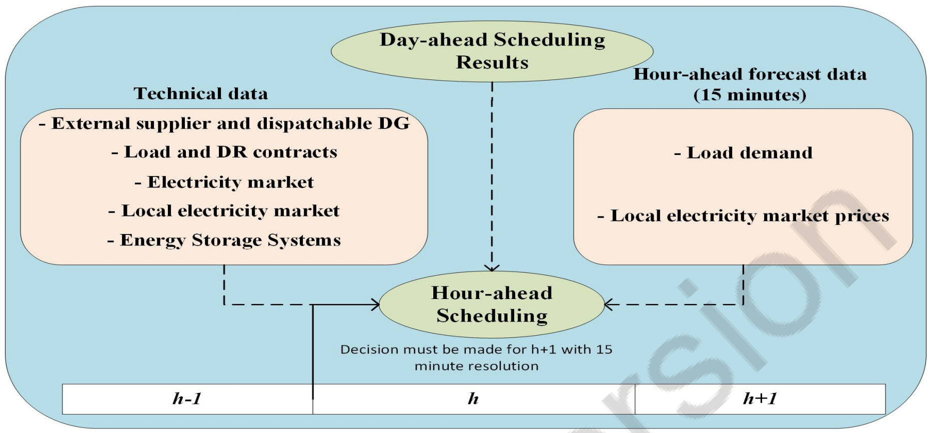

Fig. 1. Hour-ahead energy resource scheduling model.

2.2 Problem Formulaion

Within an intraday market, aggregators face an optimization problem that can be described as:

$$minimize\ Z = OC - In \tag{1}$$

Where OC represents the operational costs, and In is the income from market trading. The aggregator's operational costs and income can be presented as:

$$\begin{aligned} OC = & \textstyle\sum_{i \epsilon \Omega_{DG}^{d}} P_{DG(i,t)} \cdot C_{DG(i,t)} \\ & + \textstyle\sum_{t=1}^{T} \sum_{k=1}^{N_k} P_{ext(k,t)} \cdot C_{ext(k,t)} \\ & + \textstyle\sum_{s=1}^{N_s} \sum_{t=1}^{T} (\sum_{e=1}^{N_e} P_{ESS^-(e,t,s)} \cdot C_{ESS^-(e,t)} \\ & + \textstyle\sum_{l=1}^{N_L} P_{curt(l,t,s)} \cdot C_{curt(l,t)} \\ & + \textstyle\sum_{l=1}^{N_L} P_{imb^-(l,t,s)} \cdot C_{imb^-(l,t)}) \cdot \Delta t \cdot \pi(s) \end{aligned} \tag{2}$$

$$In = \sum_{s=1}^{N_s} \sum_{t=1}^{T} (\sum_{m=1}^{N_m} (P_{buy(m,t)} - P_{sell(m,t)}) \cdot MP_{(m,t,s)}) \cdot \Delta t \cdot \pi(s) \tag{3}$$

Where T is the number of periods (four 15-minute periods), Ω_{DG}^{d} is the set of dispatchable generation, N_k the number of external suppliers, N_s that is the total number of scenarios, N_e the number of ESSs, and N_m the number of markets. P_{DG} is the active power generation (MW), P_{ext} is the external power supplied (MW), P_{ESS^-} is the ESS power discharge (MW), P_{curt} represents the power reduction of load (MW) P_{imb^-} is the non-supplied power, P_{buy} represents the power bought from the market (MW), and P_{sell} is the power sold to the market (MW). C_{DG} is the cost of distributed generation (DG), C_{ext} is the cost of external supplier (m.u./MWh), C_{ESS^-} the discharging cost of ESS (m.u./MWh), C_{curt} is the load curtailment cost (m.u./MWh), C_{imb^-} is the non-supplied energy cost (m.u./MWh), and MP is the electricity market price (m.u./MWh). Finally, $\pi(s)$ is the scenario probability for each scenario.

The proposed objective function is constrained by the following:

Power balance The problem's active power balance constraint in each time t is as follows:

$$\begin{aligned} &\textstyle\sum_{i\epsilon\Omega_{DG}^d} P_{DG(i,t)} + \sum_{k=1}^{N_k} P_{ext(k,t)} \\ &+ \textstyle\sum_{l=1}^{N_L}(P_{imb^-(l,t,s)} + P_{curt(l,t,s)} \\ &-P_{load(l,t,s)}) + \textstyle\sum_{e=1}^{N_e}(P_{ESS^-(e,t,s)} - P_{ESS^+(e,t,s)}) \\ &- \textstyle\sum_{m=1}^{N_m}(P_{buy(m,t)} - P_{sell(m,t)}) = 0 \qquad \forall t, s \end{aligned} \tag{4}$$

Dispatchable generation and external suppliers In each cycle t, the maximum and minimum limits for the external supplier and DG units can be written as follows:

$$P_{DGmin(i,t)} \cdot x_{DG(i,t)} \leq P_{DG(i,t)} \qquad \forall t, i\epsilon\Omega_{DG}^d \tag{5}$$

$$P_{DG(i,t)} \leq P_{DGmax(i,t)} \cdot x_{DG(i,t)} \qquad \forall t, i\epsilon\Omega_{DG}^d \tag{6}$$

$$P_{minlimit(k,t)} \cdot x_{supplier(k,t)} \leq P_{ext(k,t)} \qquad \forall t, k \tag{7}$$

$$P_{ext(k,t)} \leq P_{maxlimit(k,t)} \cdot x_{supplier(k,t)} \qquad \forall t, k \tag{8}$$

Where $P_{DGmin(i,t)}$ is the minimum power generation of controllable DG unit i in period t (MW); $P_{DGmax(i,t)}$ is the maximum active power generation of controllable DG unit i in period t (MW) $P_{minlimit(k,t)}$ is the minimum active power of external supplier k in period t (MW); $P_{maxlimit(k,t)}$ is the maximum active power of external supplier k in period t (MW), and $x_{DG(i,t)}$, and $x_{supplier(k,t)}$ are the binary variables corresponding to the status of the DG units, and external suppliers (connected/not connected).

Eenergy storage systems Each ESS's battery balance constraint is defined as follows:

$$\begin{aligned} E_{stored(e,t,s)} = &E_{stored(e,t-1,s)} + \eta_{c(e)} \cdot P_{ESS^+(e,t,s)} \cdot \Delta t \\ &- \tfrac{1}{\eta_{d(e)}} \cdot P_{ESS^-(e,t,s)} \cdot \Delta t \qquad \forall e, t, s \end{aligned} \tag{9}$$

Where $E_{stored(e,t,s)}$ is the energy stored in ESS e in period t for scenario s (MWh), $\eta_{c(e)}$ is the charge efficiency of ESS e (%), $\eta_{d(e)}$ is the discharge efficiency of ESS e (%).

The following are the overall discharge and charge limits for each ESS:

$$P_{ESS^-(e,t,s)} \leq P_{dischargelimit(e,t)} \qquad \forall e, t \tag{10}$$

$$P_{ESS^+(e,t,s)} \leq P_{chargelimit(e,t)} \qquad \forall e, t \tag{11}$$

Where $P_{dischargelimit(e,t)}$ is the maximum discharge rate of ESS e in period t (MW), and $P_{chargelimit(e,t)}$ is the maximum charge rate of ESS e in period t (MW).

Every ESS has a maximum battery capacity limit as well as a minimum energy stored requirement at the end of each cycle t, which can be written as:

$$E_{stored(e,t,s)} \leq E_{BatCap(e)} \qquad \forall e, t, s \tag{12}$$

$$E_{stored(e,t,s)} \geq E_{MinChr(e,t)} \qquad \forall e, t, s \tag{13}$$

Where $E_{BatCap(e)}$ is maximum of energy that each battery e can take (MWh), and $E_{MinChr(e,t)}$ is the minimum energy stored required by e in period t (MWh).

Demand response The DR model incorporated in this problem was a direct load control method given by:

$$P_{curt(l,t,s)} \leq P_{DRmaxlimit(l,t)} \qquad \forall l, t, s \tag{14}$$

Where $P_{DRmaxlimit(l,t)}$ is the maximum amount reduction of load l in period t (MW).

Electricity market The following equations can be used to express market offers (sell) and bidding (buy) in both wholesale (WS), and LM constraints:

$$P_{sell(m,t)} \leq P_{offermax(m,t)} \cdot x_{offer(m,t)} \qquad \forall m, t \tag{15}$$

$$P_{sell(m,t)} \geq P_{offermin(m,t)} \cdot x_{offer(m,t)} \qquad \forall m, t \tag{16}$$

$$P_{buy(m,t)} \geq P_{buymin(m,t)} \cdot x_{buy(m,t)} \qquad \forall m, t \tag{17}$$

$$P_{buy(m,t)} \geq P_{buymin(m,t)} \cdot x_{buy(m,t)} \qquad \forall m, t \tag{18}$$

The market cannot simultaneously sell and buy energy, so $x_{offer(m,t)}$, and $x_{buy(m,t)}$ are two binary variables where:

$$x_{offer(m,t)} + x_{buy(m,t)} \leq 1 \qquad \forall m, t \tag{19}$$

Some decision variables are not considered in the intraday context because their value was already decided in the day-ahead time horizon as explained in Section 2.

3 Case Study

The proposed hour-ahead intraday case study starts from the day-ahead. The methodology presented is then applied to a medium voltage 13 bus DN located at the University of Salamanca, Spain, more precisely at the BISISTE laboratory.

Different types of loads (in total 25) compose this DN, such as multiple residential buildings, offices, hospitals, fire stations, and shopping malls. A 30MVA substation is also present in the DN located at bus 1. A total of three aggregators were modeled for this case study, each with separate aggregate clients such as: Aggregator 1: Hospital, fire station and shopping mall; Aggregator 2: 15 Residential buildings; Aggregator 3: 7 Office buildings.

Through GAMS/SCENRED [4] 5000 scenarios were created for the uncertainty and later reduced to 150 scenarios for the day-ahead scheduling. Using these generated scenarios, the procedure described in Section 2, in the scenario generation part, was applied to create 150 new intraday scenarios from the scenario with the highest probability in the day-ahead to inject into the presented hour-ahead model.

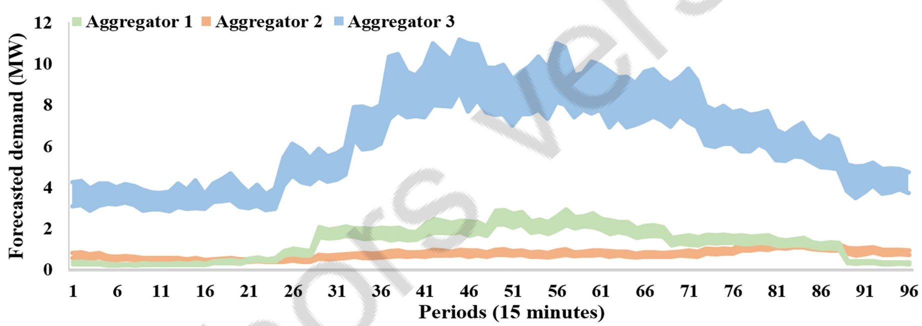

Fig. 2. Total demand forecasted for each aggregator in the intraday time horizon.

The DN data filtering according to the resources associated with each was performed for the described aggregators, considering these new 150 scenarios. Figure 2 shows the total demand predicted for each of the three aggregators resulting from the observed methodology. It can be seen that aggregator 3 is the one with the highest predicted load in comparison. Figure 3 it is possible to observe the prices that are considered in the intraday markets for the resource optimization of these aggregators. The external supplier and WS market prices are fixed and do not vary compared to the LM that changes its prices in the range shown in Figure 3. Since the LM is usually more expensive than the WS market due to being closer to retail, a percentage of 50% was considered for the price difference between these two markets. The capacity considered for the LM is 50% that of the WS market.

[4] https://www.gams.com/latest/docs/T_SCENRED.html

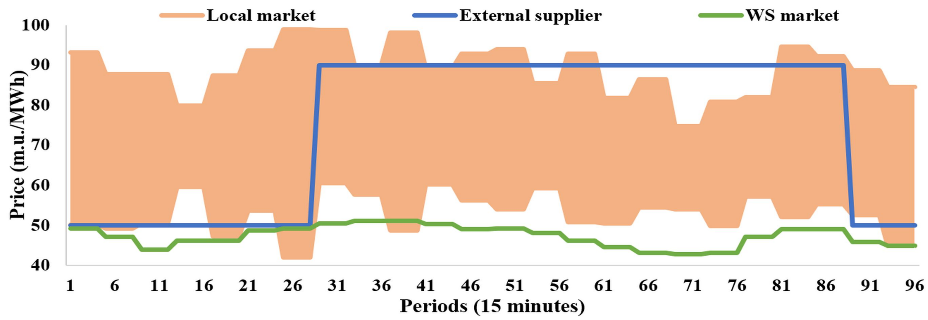

Fig. 3. External supplier, and market prices in the intraday time horizon.

It was also considered 2 ESSs with charging and discharging costs of 110 m.u./MWh and 90 m.u./MWh, respectively, with the maximum charging and discharging limits of 0.25MW. The DR model, based on direct load control, has a load reduction limit that corresponds to 30% of the load forecast and a fixed associated cost of 100 m.u./MWh.

HyDE-DF was used for this optimization problem. The first parameter that is set is population size (NP) with ten individuals. The preceding parameter is the number of iterations with 500 iterations. The following parameters are the probability of crossover (Cr) and the scaling factor (F), respectively set to 0.5 and 0.3. In MATLAB 2018a, all the simulations performed were implemented on a device with a 4 core AMD Ryzen 5 3600 processor with 3.6GHz running Windows 10 with 16 GB of RAM.

4 Results and Discussion

This section presents the obtained results obtained when applying the proposed mathematical formulation to each aggregators case study shown in Section 3.

Table 1 presents the results obtained in terms of the average and standard deviation objective function values for resource scheduling for each aggregator considered, for both day-ahead and intraday, time horizons in the total of 5 runs simulated. Increase in costs from the day ahead to the intraday in the first aggregator occurs and decreases for the remaining. Here the goal is to minimize this increase or decrease. The aggregator that best achieved this goal through the variation seen in the table was aggregator 2, with the lowest variation of about -0.13%.

Figure 4 shows the resource scheduling for aggregator 1 when it got the best value in the objective function. This value was about 10.81 m.u. in hour two of the simulation. Through the figure, it is understood that both consumption and generation values are shallow where the energy bought in the day-ahead market is the majority of the total generation which is more than enough to satisfy the demand. In this case, this aggregator's surplus energy is sold in the LM, as Figure 4b shows.

Table 1. Day-ahead and intraday average objective function values obtained and deviation percentage.

Aggregators	Day-ahead		Intraday		Increase (%)
	Avg. Cost (m.u.)	Std. Cost (m.u.)	Avg. Cost (m.u.)	Std. Cost (m.u.)	
1	1492.34	21.90	1516.14	1.48	1.57
2	935.20	8.05	933.96	1.64	-0.13
3	7648.08	77.57	7461.27	6.40	-2.50

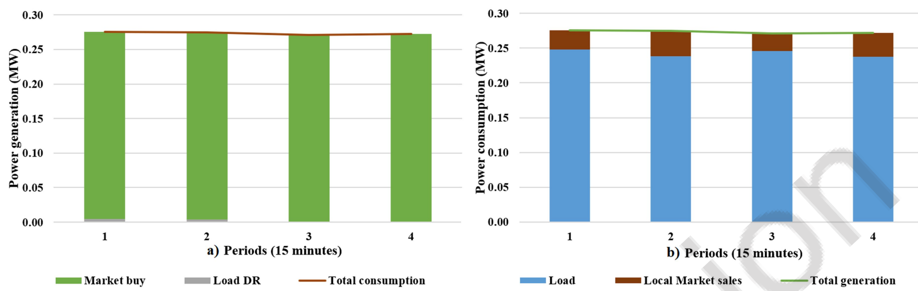

Fig. 4. Hour-ahead scheduling results for aggregator 1 regarding a) power generation; b) power consumption.

Figure 5 presents the scheduling of resources for aggregator 2, following the same reasoning used for aggregator 1. The best cost value obtained for this aggregator was about 24.40 m.u. and was observed at hour four. It can be seen in Figure 5a that the energy bought in the day-ahead market together with DR was not enough to satisfy the load in periods 1 and 3, so this aggregator had to purchase power in the LM. For periods 2, and 3 this aggregator has to sell the energy excess in the LM (Figure 5b).

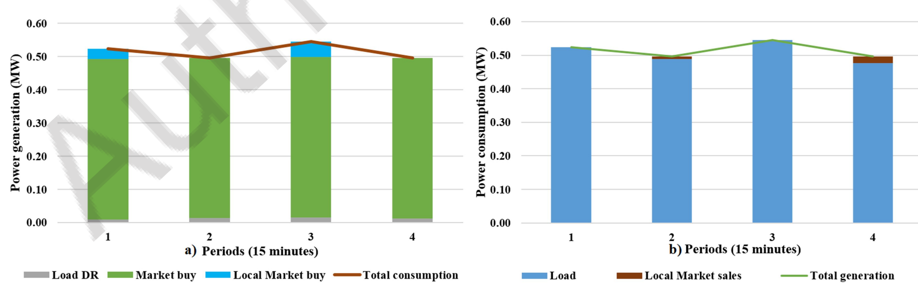

Fig. 5. Hour-ahead scheduling results for aggregator 2 regarding a) power generation; b) power consumption.

Following the same analysis as the previous two aggregators, it can be said that aggregator 3 presented a cost of 172.03 m.u. obtained in hour six of the simulation. Analyzing Figure 6a, one can observe that the production is almost entirely from the external supplier origin closed in the day-ahead time-horizon, with some DR and ESS discharge which creates an excess of energy in all periods. Because the market sales and load are not enough to assure the power balance equation, the aggregator needs to sell this surplus, so the constraints are met.

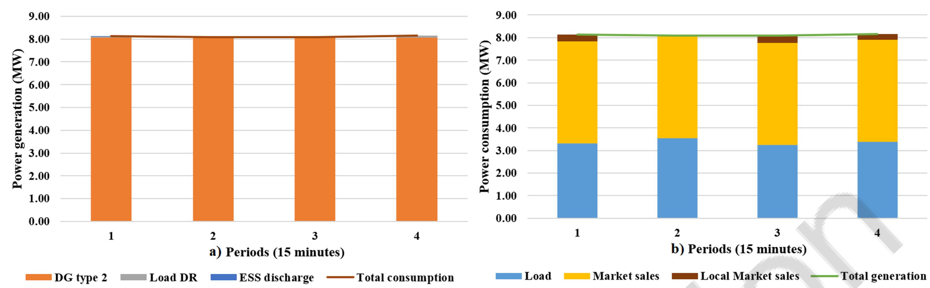

Fig. 6. Hour-ahead scheduling results for aggregator 3 regarding a) power generation; b) power consumption.

5 Conclusions

This paper presented an optimal model for the intraday resource management in a DN for three different load aggregators considering a direct load control model for the DR and LM transactions to compensate the power balance.

Each aggregator can run the developed tool, starting from the solution obtained in the day ahead. By running this tool, the aggregator is left with the hour-by-hour scheduling results in 15-minute periods for the total 24 hours, taking into account the uncertainty associated with hour-ahead scheduling resources and the decision process. The second and third aggregators showed a decrease in costs in the intraday, which is not expected in this situation. Still, it should be noted that a heuristic was used for this optimization, which does not guarantee an optimal solution, as well as LM prices, can influence these values. One can conclude that the results presented are promising given that the variations in scaling from day-ahead to intraday were minor, especially aggregator 2 with almost 0 variation.

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