Energy Resource Scheduling Optimization for Smart Power Distribution Grids – Hour-Ahead Horizon

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***Abstract*—As the use of renewable energy sources grows, the energy aggregator company plays an increasingly significant role in ensuring extremely flexible supply and demand, as requested by the smart grid architecture. This study presents a model for the problem of intraday energy resource scheduling (hour-ahead). The model is solved using the CPLEX solver and is developed as mixed integer linear programming. A distribution network with 180 buses located in Portugal considering high distributed energy resources penetration is used to demonstrate the application of the proposed model. The findings indicate how forecast errors and contractual restrictions with energy storage systems and electric car charging stations affect hour-ahead scheduling costs.**

***Index Terms*—aggregator, distribution network, electric vehicles, energy resources management, energy storage systems, hour-ahead, smart grid**

I. INTRODUCTION

Recent investment in distribution-level renewable generation has been motivating decentralization, decarbonization and emergence new business models [1], [2]. Sophisticated technology, namely smart grid communications and smart meter data, needs to be in place to fully realize the potential of distributed energy resources [3]. End-users will thus be encouraged to play a significant role in the energy community and facilitate the transition to a sustainable energy system [1], [4].

In this paper we deal with energy resources management (ERM). This problem is considered to be one of the most challenging optimization in energy systems, since it is considered to be a problem of high dimensionality and with high number of restrictions [5]–[7]. In this way, platforms have been developed to study this crucial problem in intelligent network operations [8], [9].

To address some of the complexity in optimization of smart grids, computational intelligence (CI) [10] has emerged. CI studies adaptive mechanisms to determine intelligent conduct in complex systems [11]. It consists of numerous branches, such as neural networks [12], [13], evolutionary computing [14], [15], fuzzy systems [16], [17], among others. In fact, in this context CI aims to optimize the variables that control the resources under the new paradigm of smart grids [3]. On the other hand, evolutionary computing (EC) has been widely applied in the energy field [18], because of the problem's complexity, where it was suggested because of its great efficiency and scalability. It can be expressed that evolutionary computing is inspired by the different evolutionary mechanisms of the nature, where several evolutionary algorithms have been used in the solution of some optimization problems, for example, electricity markets [19], [20], demand prediction [21], [22], intervention planning [23], [24], energy resources management [5]–[7]. Despite the wide use of EC and CI techniques applied to address the challenging day-ahead problem, due to high number of variables such as distributed energy resources and electric vehicles, we adopt a mathematical deterministic approach. In fact, in this paper we attempt to model the energy resource management problem in intraday operation based on previous works in day-ahead modeling [9], [25]. The intraday problem is modeled with 15-minute resolution in a hour-ahead horizon configuration following the day-ahead results. We adopt a deterministic approach since first we attempt to obtain a reference solution for this problem, before approaching CI and EC methods. Moreover, the problem considered is modelled as MILP and the dimensionality is substantially less than the day-ahead ERM problem. Hence, given that efficient solvers for MILP are available in the market we take this approach. Uncertainty in forecasts is not considered but can be a opportunity for justifying the CI/EC approaches.

The article is organized as follows: after the introduction in Section I, in Section II, the proposed methodology is described, including the method diagram and the hour-ahead formulation. The case study for a 180-bus distribution network is provided in Section III; while the respective results are presented and discussed in IV; and finally, the conclusions of this research are fully drawn in Section V.

II. PROPOSED METHODOLOGY

A full description of the proposed methodology is offered in this section. The established model for hour-ahead energy resource management (H-ERM) is described in Subsection II-A, while Subsection II-B presents the used mathematical model.

A. Hour-Ahead Model

Fig. 1provides a graphical representation of energy resource management scheduling in an hour-head perspective. The

H-ERM model requires that an aggregator can control and operate different DERs in the network or in a specific area of the grid. The model also needs a database with all the DERs characteristics and the necessary forecasts for the next hours with a 15 minutes time slots resolution, this is, for the next four 15 minutes slots. The results from the day-ahead and the last time slot of the previous hour are also needed. Thus, as a result from the model, we have a decision in hour *h* for the energy resource scheduling of the hour *h+1* with a 15 minutes time slots resolution.

When the aggregator does not need to consider network constraints in energy resource management scheduling because the distribution system operator (DSO) is responsible for power network analyses and communicates the feasible set-point to the aggregator, the problem can be formulated as a mixed-integer linear programming (MILP) [26].

B. Mathematical Problem Formulation

This subsection presents the optimization model used in this research work. The optimization model presents the following outputs variables: 1) Active power supplied by the external supplier [1]; 2) Active power supplied by the dispatchable distributed generators; 3) Energy bought and sale to the wholesale energy market; 4) Demand response power value; 5) Active Power not supplied; 6) Active generation curtailment power; 7) Active power charge and discharge of the energy storage systems; 8) Active power charge and discharge of the electric vehicle charging stations (CS).

The objective function *OC* (1) is minimized over the scheduling horizon *T*, and represents the estimated hour-ahead operation costs in monetary units (m.u.). The day's four 15-minute segments (i.e. one hour) are covered by the scheduling time horizon.

$$
\begin{aligned}
&Minimize \quad OC = \\
&\sum_{t=1}^{T}\left[\begin{array}{l}
\sum_{i\in\Omega_{DG}^{d}} p_{DG(i,t)}\times C_{DG(i,t)}+\\
\sum_{s=1}^{N_s} p_{Supplier_{(s,t)}}\times C_{Supplier_{(s,t)}}+\\
\sum_{i\in\Omega_{DG}^{nd}} p_{DG(i,t)}\times C_{DG(i,t)}+\\
\sum_{l=1}^{N_l}\left(p_{LoadFlexDown(l,t)}+p_{LoadFlexUp(l,t)}\right)\times\\
C_{LoadFlex(l,t)}+\\
\sum_{e=1}^{N_e} p_{Discharge_{(e,t)}}\times C_{Discharge_{(e,t)}}+\\
\sum_{v=1}^{N_v} EV_{Discharge_{(v,t)}}\times EVC_{Discharge_{(v,t)}}+\\
\sum_{l=1}^{N_l} p_{NSD(l,t)}\times C_{NSD(l,t)}+\\
\sum_{i=1}^{N_i} p_{GCP(i,t)}\times C_{GCP(i,t)}+\\
\sum_{m=1}^{N_m}\left(p_{Buy(m,t)}-p_{Sell(m,t)}\right)\cdot MP_{(m,t)}
\end{array}\right]\times\Delta t
\end{aligned}
\tag{1}
$$

where:
Ω_{DG}^{d} is the subset of dispatchable DG units; Ω_{DG}^{nd} is the subset of non-dispatchable DG units; *i* is the DG units; *s* is the external suppliers index; $p_{Supplier_{(s,t)}}$ is the active power scheduled for external supplier *s* in period *t* (MW); $C_{Supplier_{(s,t)}}$ is the costs associated to the energy supplier *s* in period *t* (m.u./MWh); N_s is the number of external suppliers; $p_{DG(i,t)}$ is the forecasted active power of non-dispatchable DG unit *i* in period *t* (MW); $C_{DG(i,t)}$ is the generation cost of DG unit *i* in period *t* (m.u./MWh); $p_{LoadFlex(l,t)}$ is the active power reduction of load *l* in period *t* (MW); $C_{LoadFlex(l,t)}$ is the demand flexibility cost of load *l* in period *t* (m.u./MWh); N_l is the number of loads; $p_{Discharge_{(e,t)}}$ is the active power discharge of energy storage system (ESS) *e* in period *t* (MW); $C_{Discharge_{(e,t)}}$ is the discharging cost of ESS *e* in period *t* (m.u./MWh); N_e is the number of ESS units; $EV_{Discharge_{(v,t)}}$ is the EV charging station *v* active discharging power in period *t* (MW); $EVC_{Discharge_{(v,t)}}$ is the EV charging station *v* discharging cost in period *t* (m.u./MWh); N_v is the number of EV charging stations; $p_{NSD(l,t)}$ is the active power of non-supplied demand of load *l* in period *t* (MW); $C_{NSD(l,t)}$ is the non-supplied demand cost of load *l* in period *t* (m.u./MWh); $p_{GCP(i,t)}$ is the generation curtailment power of DG unit *i* in period *t* (MW); $C_{GCP(i,t)}$ is the DG unit *i* curtailment cost in period *t* (m.u./MWh); N_i is the number of generation units; $p_{Buy(m,t)}$ is the active power bought in market *m* in period *t* (MW); $p_{Sell(m,t)}$ is the active power sold in market *m* in period *t* (MW); $MP_{(m,t)}$ is the market energy price (m.u./MWh); N_m is the total number of markets.

The objective function (1) is subject to the power balance (which defines that the amount of generated power should be equal to the amount of consumed power at every instant *t*); Limits on power generation and external supply in each period *t*; Maximum battery balance for each ESS, maximum and minimum discharge limit for each ESS, ESS charge and discharge cannot be simultaneous (two binary variables guarantee this condition for each ESS), maximum and minimum charge limit for each ESS, maximum battery capacity limit for each ESS, and minimum stored energy to be guaranteed at the end of period *t*; Electric Vehicles Charging Stations constraints (in this research work the EVs are dealt as virtual batteries where represent an EV parking lot or charging station located in a given network point (bus).), namely, the charge and discharge cannot happen at the same time (for each EV parking lot or charging station *v*, two binary variables ensure this), the battery

[1]External suppliers are producers connected outside the distribution network.

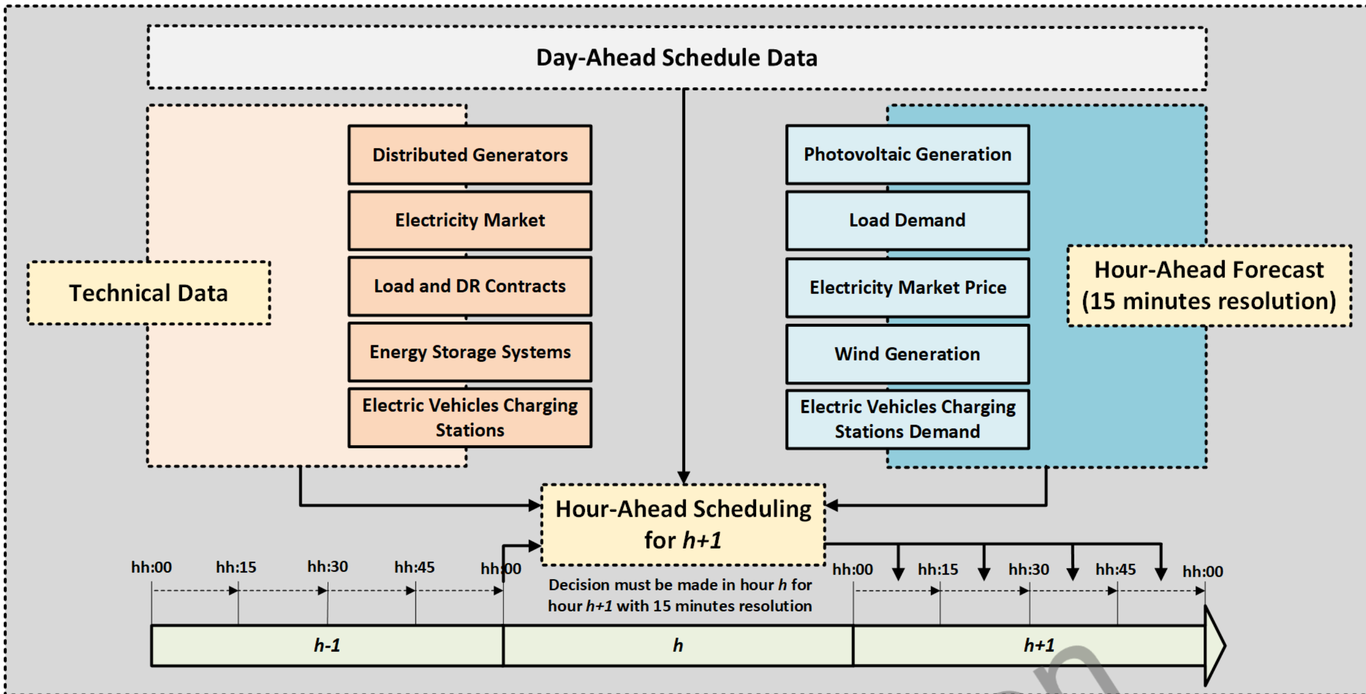

Fig. 1: Proposed model diagram.

power balance for each charging station, the charging station charge and discharge limit varies according to the number of EVs in each bus (charging station) on a given period t, the discharge limits for each charging station v, the charge limits for each virtual battery v, the maximum capacity limit for each charging station; Demand Power Flexibility (by using direct load control, in which the consumer receives an incentive if their load is reduced or incremented), namely, the maximum amount that each load l can be reduced or incremented in each period t; Market offers and bids for electricity are based on values agreed in the day-ahead wholesale market for each hour. In other words, each 15 minutes time slot of an hour, assume the same value negotiated the day-ahead); Non-Supplied Demand constraints (the non-supplied demand power cannot be higher than the load forecasted demand l in each period t); Power of generation curtailment (the generation curtailment power of non-dispatchable DG units cannot be higher than the forecasted amount of generation).

III. Case Study

This study will consider the results from the day-ahead obtained from work proposed by Soares, et al. [25]. Thus, to demonstrate the application of the proposed methodology it is used a real distribution network with 180 buses, 30kV and one substation [25], [27] was used to demonstrate the application of the proposed methodology. The original data was modified to include a high penetration of distributed generators units, corresponding to around 70% of the total installed capacity power. From those, 70%, around 40% are from PV, 35% from wind and 15% from biomass. Also, it is considered an aggregator capable of managing 116 DG units, the energy purchased from external supplier/market, energy sold to the market, 7 energy storage systems units, 90 loads points aggregated by bus, and 5 EV charging stations (parking lots) located in buses 3, 69, 96, 107 and 161. Furthermore, the loads are with demand flexibility programs (DFP), namely with a direct load control (DLC). The external supplier, corresponding to the substation location, is located in bus 1. The costs associated with DLC contracts are 0.02 m.u./kWh, where m.u. represents the monetary unit. The prices for EV charging stations and ESSs are 0.18 m.u./kWh and 0.01 m.u./kWh, respectively. The data and prices of the considered network's energy resources are depicted in Table I. Since the work [25] gives the results as a set of 150 scenarios (the work use a stochastic model with two stages) a weighted average of the results of those scenarios were used as input in the H-ERM proposed model. However, the weighted average scenario is not optimal and can lead to a small difference in the objective function value of day-ahead compared with the one where the 150 scenarios are used.

Table II presents the considered case studies used to show how the energy resources scheduling in the intra-day (hour-ahead) time horizon can affect the aggregator costs. The "X", represents that the corresponding option is considered in the executed study. Six levels of disturbance in load demand forecast ("Demand disturbance") varying between -15% and +15% and Six levels of disturbance in non-dispatchable RES forecast ("Non-dispatchable RES disturbance") also varying between -15% and +15% are considered. These disturbances are applied to the data (demand and Non-dispatchable RES forecast) obtained in day-ahead to represent a possible vari-

TABLE I: Energy resources information of 180 bus distribution network.

Energy resources		Prices (m.u./MWh)	Capacity (MW)	Forecast (MW)	Units
		min–max	min–max	min-max	
Biomass		130–130	0.02–6.23		17
Photovoltaic		150–150		0.00–0.36	44
Wind		90–90		0.00–0.69	55
External Supplier		100–160	0.05–5.00		1
Energy storage systems	Charge	0–0	0.00–1.20		7
	Discharge	10–10	0.00–1.20		
EV parking lots	Charge	130–130	0.31–1.01		5
	Discharge	180–180	0.31–1.00		
Demand Response	Reduce program	20–20	0.00–5.64		90
Load		160–160		0.56–14.09	90
Market buy and sell		45–84	0.00–2.00		1

ation of that data in the intra-day time horizon. Moreover, for both cases are considered two additional constraints for ESS and EV Charging Stations, meaning that the aggregator cannot change more than 10% and 5% of the day-ahead forecast data in the intra-day on those components. These constraints represent, for instance, a contract between the resources owners and the aggregator. The possibility of free change in the intra-day horizon of the ESS and EV Charging Stations is tested (ignoring the day-ahead forecast data for ESS and EV Charging Stations).

TABLE II: Case studies identification.

Case	Constrained	Non-Constrained	Demand uncertainty (%)	Non-dispatchable RES uncertainty (%)
	ESS=10% and CS=5%		0, 5, 10, 15 -5, -10, -15	0, 5, 10, 15 -5, -10, -15
1	X		X	
2		X	X	
3	X			X
4		X		X

The day-ahead forecast for power demand and non-dispatchable RES, namely wind power and PV, can be found in Fig. 2. In what concerns the wholesale market electricity price forecast and external supplier electricity price, the values are presented in Fig. 3. Fig. 4 shows the capacity day-ahead forecast for the 5 charging stations considered in the present study.

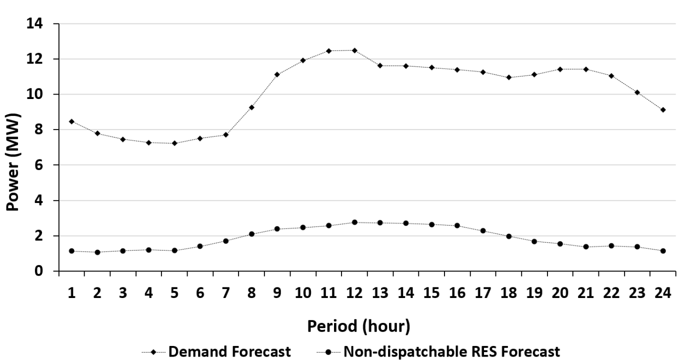

Fig. 2: Power demand and non-dispatchable renewable energy sources day-ahead forecast.

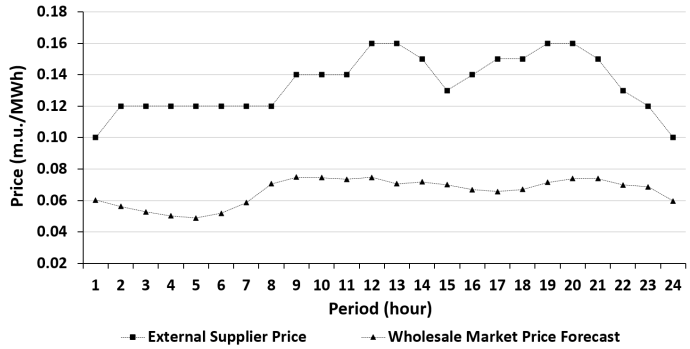

Fig. 3: External supplier price and wholesale market price forecast.

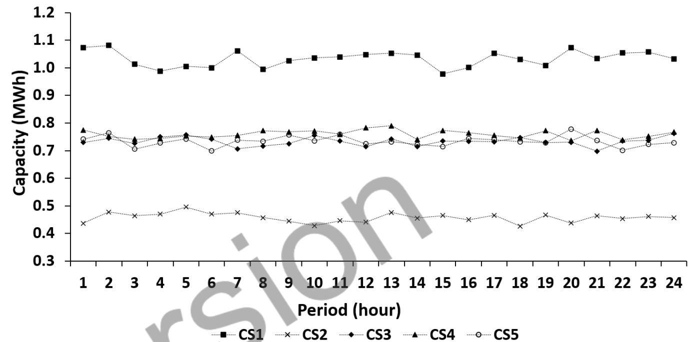

Fig. 4: Day-ahead forecast for charging stations capacity.

IV. Results and discussion

The case study described in the previous section was used to test the proposed methodology presented in II. This research was carried out using a machine with a single Intel Xeon E5-2620 v2 processor with 16 GB of RAM running Windows 10 Pro using the MATLAB R2016a and TOMLAB [2] 8.1 64 bits with CPLEX [3] solver. The model comprised 193 constraints and 2821 variables, with 96 being integer variables, for each hour period (four 15-minute time slots). For each hour period, the average execution time is 0.041 seconds, which is consistent with the time-frame for hour-ahead energy resource management scheduling. The MATLAB memory profiler tool was used to examine the computer system resource impact analysis with a memory test. Peak memory reached a maximum of 1420kB, which is entirely suitable with today's systems.

As the main analysis, it is made a comparison between objective function, taking into account the identified studies in Table II. Moreover, a comparison with the day-ahead objective function result from [25] is also made. Ideally, when there are no forecast disturbances (0% bars in Fig. 5), i.e., differences between the day-ahead and hour-ahead forecast values, the H-ERM model results should be the same as the ones obtained from the day-ahead model. However, as can be

[2] https://tomopt.com/tomlab/
[3] https://tomopt.com/tomlab/products/cplex/

seen in Fig. 5, exists a small difference of 0.47% (day-ahead objective function value is 28.38 m.u.) which can be explained by the data of the day-ahead model used in the H-ERM model (as it said in section II it was used a weighted average of the day-ahead results as input in the H-ERM, which is not optimal and can lead to a small difference). Such differences also exist in the other three cases (see Fig. 6, Fig. 7, and Fig. 8). As shown in Fig. 5 and Fig. 6, the differences between H-ERM and day-ahead objective function results tend, as expected, to increase with the error forecast increasing. It is also verified that the differences are higher with positive load demand forecast errors, namely because the aggregator needs to apply more demand response actions and use more energy stored in the ESSs.

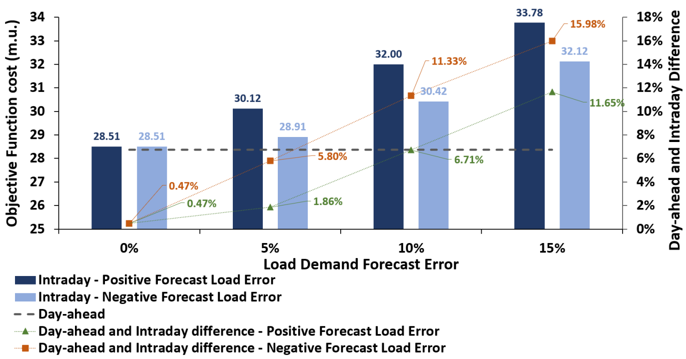

Fig. 5: Objective functions results (differences between the day-ahead and hour-ahead forecast values) for Case 1.

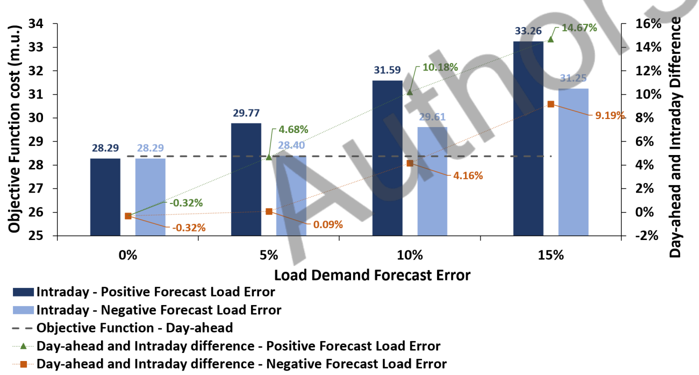

Fig. 6: Objective functions results (differences between the day-ahead and hour-ahead forecast values) for Case 2.

Fig. 7 and Fig. 8 present the objective function values for day-ahead and hour-ahead as well as the differences between them when it is considered disturbances in the non-dispatchable renewable generation. It is possible to see through these figures that there were no significant impacts on the hour-ahead objective function values when compared with day-ahead. This happens, because the ESSs and demand flexibility mitigates the disturbances impacts.

Another important aspect to note is present in case 3, and 4 (Fig. 7 and Fig. 7) when occurs 5% positive of forecast error. As can be seen in these cases, the difference between the day-ahead and hour-ahead objective function values is lower than the one where is not considered disturbance (0%). This means that the solution of H-ERM considering 5% positive error for non-dispatchable renewable generation is much closer to the optimal solution obtained in the day-ahead with 150 scenarios. This is a better scenario (in terms of the objective function) compared to the weighted average scenario.

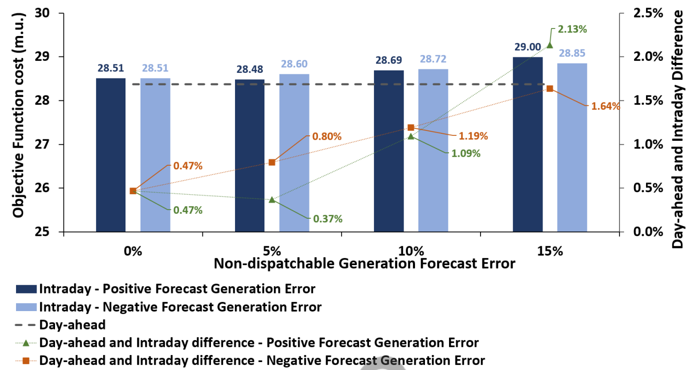

Fig. 7: Objective functions results (differences between the day-ahead and hour-ahead forecast values) for Case 3.

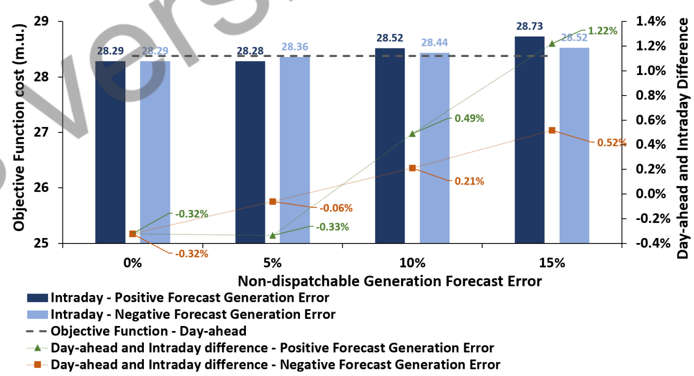

Fig. 8: Objective functions results (differences between the day-ahead and hour-ahead forecast values) for Case 4.

Fig. 9 show the differences between the constrained ESS and EVs from day-ahead results and not constrained (see Table II). The objective function differences are more evident when the demand forecast error is verified, namely in the negative forecast error. This means that the demand flexibility (increase demand) are more used to compensate the power surplus of the non-dispatchable renewable generation which are no stored in the ESS (since the ESSs variation are limited to 10% of the day-ahead value).

V. Conclusions

This work proposed a model to solve the challenging problem of aggregators' large-scale energy resource scheduling problem in a smart grid considering the hour-ahead time horizon. With the obtained results, it was possible to verify the forecast errors' influence and the contractual constraints

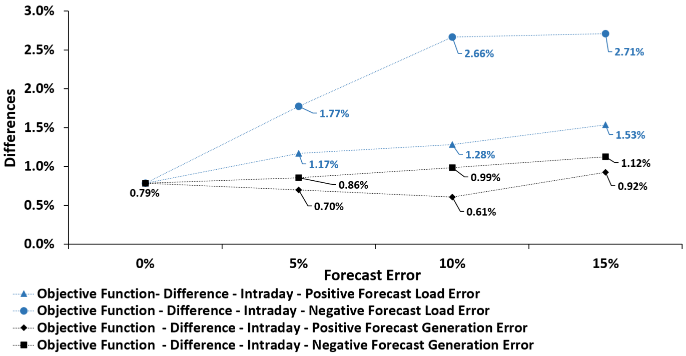

Fig. 9: ESS and CS constrained to day-ahead values *vs* ESS and CS not constrained to day-ahead values.

with ESSs and EV charging stations can cause in the hour-ahead scheduling costs. Seeing the Case 1 and case 2, namely with a forecast error of 15%, the results present strong differences between the day-ahead and hour-ahead horizon. These differences achieve more than 15% (negative error forecast) in case 1 and around 14% (positive error forecast) in case 2. The results suggest the need for adequate tools for energy resource scheduling problems to deal with the uncertainties. As future work, a two-stage stochastic optimization is being implemented within a competitive environment by considering several aggregators and a model for distribution system operator and aggregators coordination.

ACKNOWLEDGMENT

This research has received funding from FEDER funds through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020) and National Funds through the FCT Portuguese Foundation for Science and Technology, under Projects PTDC/EEI-EEE/28983/2017 (CENERGETIC), CEECIND/02814/2017 (Joao Soares grant), and UIDB/000760/2020.

REFERENCES

[1] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local energy markets: Paving the path towards fully transactive energy systems," *IEEE Transactions on Power Systems*, 2018.

[2] M. A. F. Ghazvini, S. Ramos, J. Soares, R. Castro, and Z. Vale, "Liberalization and customer behavior in the portuguese residential retail electricity market," *Utilities Policy*, vol. 59, p. 100919, 2019.

[3] J. Soares, T. Pinto, F. Lezama, and H. Morais, "Survey on complex optimization and simulation for the new power systems paradigm," *Complexity*, vol. 2018, 2018.

[4] Í. Munné-Collado, E. Bullich-Massagué, M. Aragüés-Peñalba, and P. Olivella-Rosell, "Local and micro power markets," *Micro and Local Power Markets*, pp. 37–96, 2019.

[5] D. Dabhi and K. Pandya, "Uncertain scenario based microgrid optimization via hybrid levy particle swarm variable neighborhood search optimization (hl_ps_vnso)," *IEEE Access*, vol. 8, pp. 108782–108797, 2020.

[6] J. Garcia-Guarin, D. Rodriguez, D. Alvarez, S. Rivera, C. Cortes, A. Guzman, A. Bretas, J. R. Aguero, and N. Bretas, "Smart microgrids operation considering a variable neighborhood search: the differential evolutionary particle swarm optimization algorithm," *Energies*, vol. 12, no. 16, p. 3149, 2019.

[7] F. Lezama, E. M. de Cote, L. E. Sucar, J. Soares, and Z. Vale, "Evolutionary framework for multi-dimensional signaling method applied to energy dispatch problems in smart grids," in *International Conference on Intelligent System Application to Power Systems*, pp. 1–6, 2017.

[8] F. Lezama, J. Soares, and Z. Vale, "A platform for testing the performance of metaheuristics solving the energy resource management problem in smart grids," *Energy Informatics*, vol. 1, no. 1, p. 35, 2018.

[9] F. Lezama, J. Soares, Z. Vale, J. Rueda, S. Rivera, and I. Elrich, "2017 ieee competition on modern heuristic optimizers for smart grid operation: Testbeds and results," *Swarm and evolutionary computation*, vol. 44, pp. 420–427, 2019.

[10] A. P. Engelbrecht, *Computational intelligence: an introduction*. John Wiley & Sons, 2007.

[11] L. N. Castro, L. N. De Castro, and J. Timmis, *Artificial immune systems: a new computational intelligence approach*. Springer Science & Business Media, 2002.

[12] L. O. Chua and L. Yang, "Cellular neural networks: Theory," *IEEE Transactions on circuits and systems*, vol. 35, no. 10, pp. 1257–1272, 1988.

[13] B. Yegnanarayana, *Artificial neural networks*. PHI Learning, 2009.

[14] A. E. Eiben and J. E. Smith, *Introduction to evolutionary computing*. Springer, 2015.

[15] A. Darwish, A. E. Hassanien, and S. Das, "A survey of swarm and evolutionary computing approaches for deep learning," *Artificial Intelligence Review*, vol. 53, no. 3, pp. 1767–1812, 2020.

[16] M. Sugeno, K. Asai, and T. Terano, "Fuzzy systems theory and its applications," *Tokyo Institute of Technology*, 1992.

[17] J. M. Mendel, "Uncertain rule-based fuzzy systems," in *Introduction and new directions*, p. 684, Springer, 2017.

[18] F. Lezama, R. Faia, P. Faria, and Z. Vale, "Demand response of residential houses equipped with pv-battery systems: An application study using evolutionary algorithms," *Energies*, vol. 13, no. 10, p. 2466, 2020.

[19] F. Zaman, S. M. Elsayed, T. Ray, and R. A. Sarkerr, "Evolutionary algorithms for finding nash equilibria in electricity markets," *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 4, pp. 536–549, 2017.

[20] T. Pinto and Z. A. Vale, "Aid-em: Adaptive decision support for electricity markets negotiations.," in *IJCAI*, pp. 6563–6565, 2019.

[21] M. Bhattacharya, A. Abraham, and B. Nath, "A linear genetic programming approach for modelling electricity demand prediction in victoria," in *Hybrid Information Systems*, pp. 379–393, Springer, 2002.

[22] P. Doganis, A. Alexandridis, P. Patrinos, and H. Sarimveis, "Time series sales forecasting for short shelf-life food products based on artificial neural networks and evolutionary computing," *Journal of Food Engineering*, vol. 75, no. 2, pp. 196–204, 2006.

[23] K. Dutta and S. Sarthak, "Architectural space planning using evolutionary computing approaches: a review," *Artificial Intelligence Review*, vol. 36, no. 4, p. 311, 2011.

[24] V. Oduguwa, A. Tiwari, and R. Roy, "Evolutionary computing in manufacturing industry: an overview of recent applications," *Applied Soft Computing*, vol. 5, no. 3, pp. 281–299, 2005.

[25] J. Soares, B. Canizes, M. A. F. Ghazvini, Z. Vale, and G. K. Venayagamoorthy, "Two-stage stochastic model using benders' decomposition for large-scale energy resource management in smart grids," *IEEE Transactions on Industry Applications*, vol. 53, no. 6, pp. 5905–5914, 2017.

[26] X. Han, H. W. Bindner, J. Mehmedalic, and D. V. Tackie, "Hybrid control scheme for distributed energy resource management in a market context," in *2015 IEEE Power & Energy Society General Meeting*, pp. 1–5, IEEE, 2015.

[27] B. Canizes, J. Soares, F. Lezama, C. Silva, Z. Vale, and J. M. Corchado, "Optimal expansion planning considering storage investment and seasonal effect of demand and renewable generation," *Renewable Energy*, vol. 138, pp. 937–954, 2019.