Day-ahead stochastic scheduling model considering market transactions in smart grids

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***Abstract*— The integration of renewable generation and electric vehicles (EVs) into smart grids poses an additional challenge to the stochastic energy resource management problem due to the uncertainty related to weather forecast and EVs user-behavior. Moreover, when electricity markets are considered, market price variations cannot be disregarded. In this paper, a two-stage stochastic programming approach to schedule the day-ahead operation of energy resources in smart grids under uncertainty is presented. A realistic case study is performed using a large-scale scenario with nearly 4 million variables with the goal to minimize expected operation cost of energy aggregators. Three scenarios are analyzed to understand the effect of market transactions and external suppliers on the aggregator model. The results suggest that the market transactions can reduce expected cost, while the external supplier offers risk-free price. In addition, the performance metric shows the superiority of the stochastic approach over an equivalent deterministic model.**

***Index Terms*—Energy scheduling, smart grid, uncertainty, electric vehicles, two-stage stochastic programming.**

I. INTRODUCTION

There is a growing need in power grids for the integration of renewables, such as wind- and solar-based generation. Because these resources can mitigate the carbon footprint of electricity generation, and they highly contribute to the dream of a fossil fuel free electricity generation. The significant drawback is that renewables are characterized by a high level of uncertainty related to weather aspects. Another important consideration is the possible flexibility from the customer-side, provided by some loads, i.e., non-critical loads that can be adjusted by utilities or consumers manually or in an automated way. The Electric Vehicle (EV) is an example of a load that can provide flexibility. In contrast to other types of loads, EVs can be connected to different locations, thus increasing the level of uncertainty [1], [2]. An advanced energy scheduling model for the future smart grid taking into account these uncertainty factors is a current research priority. In fact, one of the top R&D needs identified by DOE is the need to develop robust control and predictive models to deal with stochastic and uncertainty [3]. Establishing a stochastic model is therefore crucial for addressing the variability of renewable energy resources, which can account for a large part of the total generation capacity. In this context, the energy aggregators dealing with the energy resources management (ERM) require adequate tools to improve their competitiveness.

In the literature, many works have been proposed focusing on deterministic operation for energy scheduling in smart grids [4]–[9]. However, due to the significant amount of computational resources required to provide an optimal solution, deterministic approaches typically neglect the effect of uncertainty by assuming perfect, or highly accurate, forecast of renewable generation or EVs behavior. Some other works make use of computational intelligence techniques to reduce computational burden and make the problem tractable [10]–[14]. However, when considering a high penetration of Distribution Energy Resources (DER) (i.e., large-scale problems), Computational Intelligence (CI) approaches cannot guarantee an optimal solution. Stochastic models for transmission networks have been suggested to provide good results in modeling the uncertainty related to renewables worst-case scenarios [15], [16]. The stochastic optimization has proved to be a promising method to deal with the uncertainties in the optimization problems. Several studies have been reported in the recent literature at the distribution and microgrid (MG) level. In [17] a two-stage stochastic formulation is presented to address the energy scheduling in MG, considering Distributed Generation (DG), EVs and Energy Storage Systems (ESS). The proposed model solves the day-ahead energy scheduling using a linear formulation without network constraints and not considering Vehicle-To-Grid (V2G). The proposed problem formulation minimizes the expected operational cost and power losses. Only wind and solar power uncertainty are considered, represented by a set of scenarios. The work in [1] presents an optimal bidding strategy for EVs aggregator. The problem is formulated under uncertainty in day-ahead context to minimize charging costs while satisfying EVs demand. It is essential to refer that the V2G possibility of EV aggregators is not modeled in the

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paper. In [16], a stochastic method is presented to solve the hourly scheduling of optimal reserves considering the hourly forecast errors of wind energy and system load. The method utilizes a two-stage stochastic programming for the day-ahead scheduling of wind energy and conventional units. The authors in [18] develop a stochastic energy scheduling model for a local smart grid system with a single energy source and several consumers. The objective is to schedule the energy consumptions to maximize the expected system utility under the given energy consumption and energy generation constraints. The work in [19] presents an optimal day-ahead multi-objective problem that aims to maximize the expected benefit of the MG in the deregulated electricity market and to minimize the operation cost. The problem is formulated as a two-stage stochastic formulation to cope with the intermittent nature of the renewable energy and the thermal characteristics of the buildings. In [20], a two-stage stochastic optimization model is presented for the unit commitment problem. The model has the objective to minimize the expected operational cost considering the wind power uncertainty. The work in [21] presents a stochastic programming framework for a multiple timescale economic dispatch problem into power systems. The model considers the uncertainties of renewable generation.

The literature review suggests that more work can be done to propose new models and motivate further research that mitigates the identified gaps. Uncertainty on wind and solar generation has been considered in some works, while the variability of market prices and load demand is more neglected. It is often common that the problem is formulated without considering the V2G capabilities in this context. Therefore, this paper presents a two-stage stochastic programming approach for energy scheduling in smart grids (SGs) considering V2G and market bidding. Similarly to previous works from the authors [22] [23], the model used in this work formulates the uncertainty in regular load demand, wind and photovoltaic (PV) power, EVs demand and location, and market price. The primary target of the aggregator consists in minimizing the expected operation cost while considering several Distributed Energy Resources (DERs), including DGs (e.g. Wind, PV, biomass), EVs with V2G possibility, ESS, electricity supplier contracts and market transactions. Different from [22], in this work, the stochastic model is extended by considering both market offers and buy bids, providing a major degree of flexibility for the aggregator. Moreover, unlike the model presented in [23], in this work we focused on the aggregator decisions by decoupling the distribution system operator (DSO) functions from the model[1]. By doing this, we keep the model more tractable compared to [23] and the model is more in line with the current trends in liberalized electricity markets where the aggregator and DSO are two independent entities.

The major contributions of this paper are as follows:

1) Considering market bidding in a two-stage stochastic model, i.e. both buy and offer bids;

2) Efficiently solving the problem with a realistic large-scale test system with nearly 4 million variables;

3) Evaluating the proposed stochastic model under three possible scenarios, namely case A (with market and supplier), case B (without market bidding) and case C (no energy supplier).

This paper is organized as follows: after this introduction, section II describes the two-stage stochastic formulation, section III describes the case study, while results and discussion are presented in Section IV. Finally, section V presents the conclusions.

II. Two-Stage Stochastic model

In this section, the ERM problem under uncertainty is formulated as a two-stage stochastic model. The stochastic model aims at finding an optimal decision for the first stage variables (i.e., market bids, energy from external suppliers and dispatchable DGs) while taking into account the uncertainty from real-time operations (i.e., renewable generation and EVs) in the second stage[2]. The objective is to minimize the expected operation costs for the aggregator and at the same time reduce the risk of energy transactions. The model provides the amount of energy to be transacted in the market (bids and offers), the electricity bought from external suppliers, and the dispatchable energy of the DG units over a period of 24 hours. The uncertainty from wind and solar generation, EVs, market price and load is modeled using a scenario based approach as in [22] [23]. This means that some scenarios (162 in this work), different from each other, for the second stage variables are generated using Monte Carlo Simulation (MCS) in an initial phase. When applying the stochastic model, the first-stage decisions do not change across the scenarios in the second stage. Fig. 1 illustrates an overview of the proposed work done.

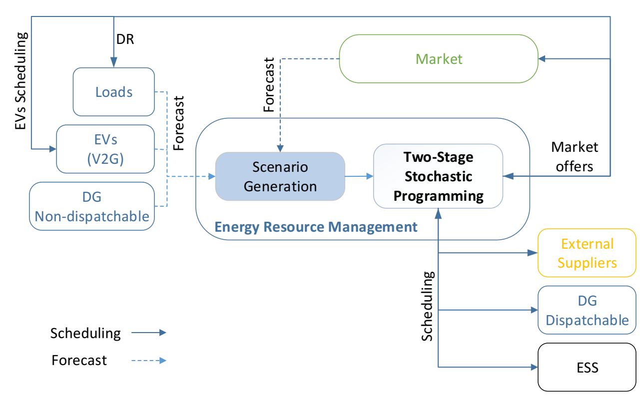

Figure 1. Overview of the methodology

A. Scenarios generation

The first part of a stochastic programming approach is to identify the uncertain variables (inputs) and how to model their uncertainty using a probabilistic distribution. In this sense, the considered ERM problem involves several

[1] In [23], the stochastic model considers network constraints to assist DSO functions. As a result, decomposition techniques such as Benders' decomposition, are required to reduce computational burden and make the problem tractable.

[2] Theoretical background on two-stage stochastic programming models can be found in [26], [30].

uncertainties in the problem data, namely in the load demand, wind and solar generation forecasts, EVs demand and market price. The energy demand of EVs depends on certain driving patterns, which are not easy to predict. The aggregator requires knowing the driving patterns, including the timing of trips and expected energy consumption [1].

In this paper, MCS [17] is used to generate the scenarios for wind solar, load and market prices, namely by considering normal distribution functions and adopting commonly standard deviation errors. For the EVs, EVeSSi [24] is used to generate different samples of driving patterns using departure times and locations as stochastic variables. After sampling and selecting representative scenarios using similarity features, a scenario tree is used to obtain a total set of possible scenarios.

B. Model assumptions

The proposed model requires certain infrastructure to operate in a smart grid context. The following assumptions are considered in this work: the energy aggregator is an independent entity that is able to manage its assets (i.e., local DERs and energy supply); smart metering equipment is in place for communication into the grid (i.e., enabling the announcement of energy market prices); the aggregator is equipped with an energy management system, in which the proposed model can be implemented; the system has forecasting and scenario generation tools required to run the two-stage stochastic optimization every 24 hours before the market bidding .

C. Mathematical model

The objective function *E(OC)* minimizes the expected operation costs over the scheduling horizon *T*, i.e. next 24 hours similarly to [22]. In addition, we have included the possibility of market bidding in this paper, namely both selling and buy as described by:

$$\text{Minimize} \quad E\left(OC_{Total}^{D+1}\right)=$$
$$\sum_{t=1}^{T}\left[\left(\sum_{I\in\Omega_{DG}^{d}} P_{DG(I,t)}\cdot c_{DG(I,t)}+\sum_{S=1}^{N_S} P_{Supplier(S,t)}\cdot c_{Supplier(S,t)}+\right)\right]+$$
$$\sum_{z=1}^{Z}\sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum_{I\in\Omega_{DG}^{nd}} P_{DG(I,t,z)}\cdot c_{DG(I,t)}+\\ \sum_{E=1}^{N_E} P_{Discharge(E,t,z)}\cdot c_{Discharge(E,t)}+\\ \sum_{V=1}^{N_V} P_{Discharge(V,t,z)}\cdot c_{Discharge(V,t)}+\\ \sum_{L=1}^{N_L} P_{NSD(L,t,z)}\cdot c_{NSD(L,t)}+\\ \sum_{I=1}^{N_{DG}} P_{GCP(I,t,z)}\cdot c_{GCP(I,t)}+\\ P_{Buy(t)}\cdot\lambda_{SpotMarket(t,z)}-P_{Sell(t)}\cdot\lambda_{SpotMarket(t,z)}\end{array}\right)\cdot\pi(z)\right] \tag{1}$$

The first stage variables correspond to the dispatchable DG units, suppliers and market bidding (bids and offers). The sets are described by: Ω_{DG}^{d} is a set of dispatchable DG units; Ω_{DG}^{nd} is a set of non-dispatchable DG units. The indices are represented by: E is an index of ESSs; I is an index of DG units; L is an index of loads; S is an index of external suppliers; t is an index of time periods; V is an index of time EVs; z is an index of scenario z.

The parameters are described by: $\pi(z)$ is the probability of scenario z (%); $C_{CGP(I,t)}$ is the curtailment cost of DG unit I in period t (m.u.); $C_{DG(I,t)}$ is the generation cost of DG unit I in period t (m.u.); $C_{Discharge(E,t)}$ is the discharging cost of ESS E in period t (m.u.); $C_{Discharge(V,t)}$ is the discharging cost of EV V in period t (m.u.); $C_{NSD(L,t)}$ is the non-supplied demand (NSD) cost of load L in period t (m.u.); $\lambda_{SpotMarket(t,z)}$ is the expected spot price in period t scenario z (m.u.); N_{DG} is the number of DG units; N_E is the number of ESSs; N_L is the number of loads; N_M is the number of markets; N_S is the number of external electricity suppliers; N_V is the number of EVs; T is the number of periods; Z is the number of scenarios. The variables are described by: $E\left(OC_{Total}^{D+1}\right)$ is the expected total operation cost for day-ahead (*m.u.*); $P_{Buy(t)}/P_{Sell(t)}$ is the offered amount of energy (buy/sell) to spot market in period t (kW); $P_{CGP(I,t,z)}$ is the generation curtailment power of DG unit I in period t in scenario z (kW); $P_{DG(I,t,z)}$ is the active power generation of DG unit I in period t in scenario z (kW); $P_{Discharge(E,t,z)}$ is the active power discharge of ESS E in period t in scenario z (kW); $P_{Discharge(V,t,z)}$ is the active power discharge of EV V in period t in scenario z (kW); $P_{NSD(L,t,z)}$ is the active power of NSD of load L in period t in scenario z (kW)*;*

Moreover, Eq. (1) is also subject to constraints concerning DER technical limits such as EV/ESS charging and discharging rates, capacity, balance, and location in each period, as well as dispatchable DG capacity and external supplier's limits. It is worth noting that some constraints are involved in all the considered scenarios. More details about the constraints of the model can be found in [22][23].

The market constraints (to sell/buy energy) are developed below. The constraints regarding market sales are represented by (2) and (3), namely maximum and minimum energy to sell ($P_{MarketSellMax}$ and $P_{MarketSellMin}$). $P_{Sell(t)}$ is a variable representing the quantity of energy to sell in period t. $X_{MarketSell(t)}$ is a binary variable indicating if the sale offer is selected in period t.

$$P_{Sell(t)} \le P_{MarketSellMax(t)}\cdot x_{MarketSell(t)} \qquad \forall t \tag{2}$$

$$P_{Sell(t)} \ge P_{MarketSellMin(t)}\cdot x_{MarketSell(t)} \qquad \forall t \tag{3}$$

Similarly, the market purchases constraints are represented by (4) and (5), namely by maximum and minimum amount allowed to buy by the aggregator:

$$P_{Buy(t)} \le P_{MarketBuyMax(t)}\cdot x_{MarketBuyt(t)} \qquad \forall t \tag{4}$$

$$p_{Buy(t)} \ge P_{MarketBuyMin(t)}\cdot x_{MarketBuy(t)} \qquad \forall t \tag{5}$$

Eq. (6) represents the decision of bids and asks, which are not concurrent:

$$x_{MarketBuy(t)}+x_{MarketSell(t)} \le 1 \qquad \forall t \tag{6}$$

D. E aluation metrics in t o stage stochastic programming

The mathematical model was formulated as a Mixed Integer Linear programming (MILP) problem (i.e., the problem includes continuous and integer variables and linear constraints) and can be solved used specialized software such as TOMLAB [25].

Two metrics are used to measure the benefits of the stochastic programming solution proposed in this work.

1) The expected value of perfect information (EVPI) indicates how much the perfect forecast (if it was possible) would cost to the aggregator and is defined by:

$$\mathrm{EVPI}_{\min} = z^{S*} - z^{P*} \quad (7)$$

where

Z^P wait-and-see solution (m.u.)

Z^S cost of stochastic solution (m.u.)

A high value of EVPI will stress the importance of considering uncertainty since it indicates that there exists a higher risk of variability in the expected objective values when perfect information is not available.

2) The value of the stochastic solution (VSS) represents the advantage of adopting the proposed stochastic approach over a deterministic one, and it is defined as:

$$\mathrm{VSS}_{\min} = z^{D*} - z^{S*} \quad (8)$$

where

Z^{D*} cost of the modified stochastic problem (m.u.)

VSS also can be seen as a measure of the benefit obtained from modeling random variables with stochastic scenarios and avoiding to replace them with average values [26].

III. Case Study

A case study consisting in a part of a real distribution network with 201 buses in Zaragoza, Spain (taken from [22]) is used to test the two-stage stochastic model proposed in this work. Energy production and consumption follow expected values for the year 2030. For instance, it is considered a high penetration of DG units (around 70% of the installed capacity) according to predictions for the year 2030 [27]. Besides, CO_2 emissions are expected to reduce up to 68% by 2030 compared to 1990 levels [28].

The case study also considers that the energy aggregator, by using the proposed stochastic model, can manage all its resources consisting of 118 DG units, 1 external supplier, 6 ESS units, 1300 EVs, and 89 aggregated consumers with DR capability. Regarding uncertainty in renewables, EVs, demand, and market prices, 162 scenarios have been generated using MCS as in [17], [22]. Table I summarize the available resources and information for the aggregator. The information of prices in monetary units per kWh (m.u./kWh), and the availability in MW, were set up as in [29]. The capacity limit of the external supplier is 7.3 MW in each period and the price, known in advance, varies between 0.09 m.u /kWh and 0.20 m.u./kWh. The spot market has a forecast price between 0.08 and 0.13 m.u./kWh according to the scenarios generation. We assumed that the aggregator can bid any amount to this market.

TABLE I. Energy Resource Data

Energy resources		Availability (MW) min – max	Prices (m.u./kWh) min – max	Units
Biomass (dispatchable)		0 – 0.52	0.15-0.15	1
CHP (dispatchable)		0 – 4.00	0.10-0.12	4
Small Hydro (dispatch.)		0.12 – 0.35	0.13-0.13	1
Photovoltaic (forecast)		0 – 1.70	0.20-0.20	82
Wind (forecast)		0.07– 0.94	0.12-0.12	30
External Supplier		**0 – 7.30**	**0.09-0.20**	1
Storage (ESS)	Charge	0 –1.50	0.12-0.12	6
	Discharge	0 – 1.50	0.18-0.18	
Electric Vehicle	Charge	0 – 6.94	0.13-0.13	1300
	Discharge	0 – 6.16	0.19-0.19	(100)
Load (forecast)		4.77 – 13.88	0.09-0.15	168
Market		**Unknown**	**0.08 – 0.13**	-

Fig. 2 depicts the price of external electricity supplier and the spot price in the market in an hourly period. The spot price is shown in orange (and light orange area) indicating the range of price variation as obtained in scenario generation.

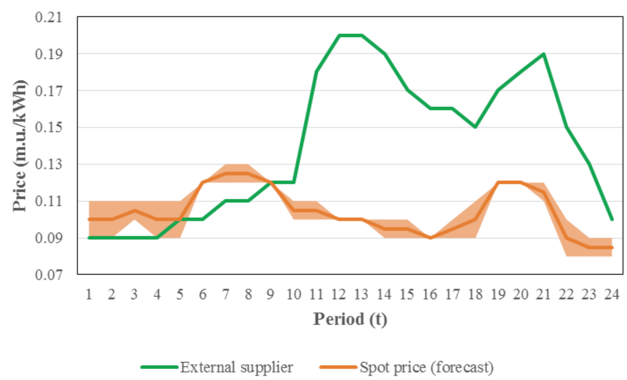

Figure 2. External supplier and spot price (forecast) during the 24 periods.

We have considered three different cases to compare the performance of the two-stage stochastic programming.

Case A – Considers the possibility of bidding to the spot market (both buy and offer) and buy energy from an external supplier and other DGs with a fixed price term previously agreed.

Case B – The spot market is not considered as in case A.

Case C – The external supplier is not available as in A.

IV. Results and Discussion

The two-stage stochastic model is tested in the three cases as already described in section III. The dimension of the optimization problem is around 3.8 million variables.

Fig. 3 presents the obtained results regarding market bids and offers for case A and C. Case B is not present in this picture because the market is not considered. The positive values are market offers and the negative identify the buy bids. It can be seen that only case A present market offers in periods 1-4 and 6-8, i.e., a total amount of 20 MWh. The total amount of market bids (buy) in case A is 161 MWh while in case C it is 191 MWh. In fact, the resulting bids (buy) in case A and C are the same in the corresponding periods. In case B it is 0 MWh.

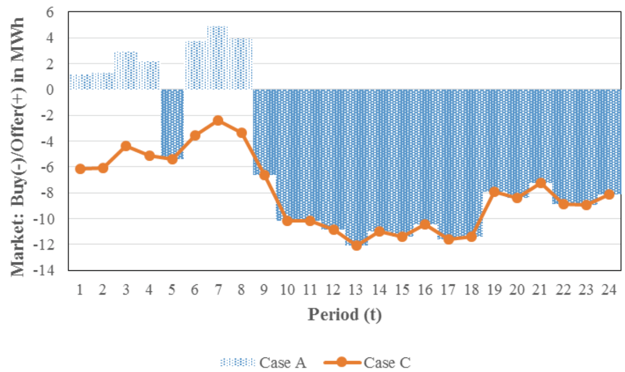

Figure 3. Market results for case A and C

Fig. 4 presents the obtained results regarding the external supplier for case A and B, where this resource is considered.

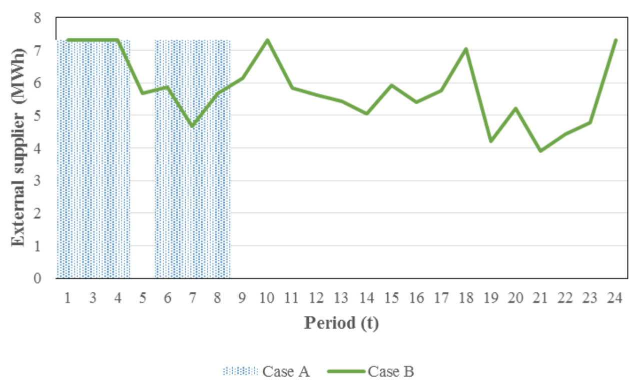

Figure 4. External supplier result for case A and case B

In case A, only periods 1-4,6-8 are scheduled. It coincides with the periods of the market offers (see Fig. 1) while the remaining periods the energy supply is assured by the market. The total amount scheduled in case A is 51 MWh and in case B, 140 MWh. In case C, it is 0 MWh.

Table II illustrates the results obtained with the developed tool. The performance of the stochastic model is compared with the deterministic model via the indices illustrated in Section II. The case that presents the lowest expected operation cost is case A. The results suggest that worst situation (case B) occurs when it is not possible to buy energy from the electricity market. In this case, the expected operation cost is expected to rise 22% in comparison with case A. The VSS demonstrates that the stochastic model performs better than the deterministic model, i.e. 17-18%. In fact, case A presents the highest value regarding percentage (18%), suggesting that the stochastic approach is even more important when considering the market bidding. The average execution time measured from the proposed model is around 4 minutes.

TABLE II. ADVANTAGE OF STOCHASTIC PROGAMMING: METRICS

Metric	Case A (market and supplier)	Case B (no market)	Case C (no supplier)
Expected cost (m.u.)	24,230	30,970	24,920
VSS (m.u.)	5185 (18%)	6203 (17%)	5154 (17%)
EVPI (m.u.)	1115	1527	1078

V. CONCLUSIONS

The present paper introduced a stochastic model that considers several sources of uncertainty, namely wind and solar generation, EVs and load demand as well the market prices. The model included the possibility of energy transactions in the market (offer and buy).

The proposed case study enabled to evaluate the effectiveness of the stochastic model using a set of three different cases. The results suggest that considering market transactions can significantly reduce the expected operation cost, but evidently exposing the energy aggregator to higher risk. The benefit of the two-stage stochastic programming over the deterministic counterpart is demonstrated by VSS, which is around 17-18%, better depending on the case. The results also suggest that market transactions further justify the use of a stochastic model, due to an increased level of uncertainty, i.e., in the market price.

Future work is highly recommended on this subject. For instance, considering a higher number of scenarios (>500) which may represent higher fidelity of the uncertainty sources. We believe that VSS may be even more significant than the results presented in this work.

REFERENCES

[1] M. Gonzalez Vaya and G. Andersson, "Optimal Bidding Strategy of a Plug-In Electric Vehicle Aggregator in Day-Ahead Electricity Markets Under Uncertainty," *IEEE Trans. Po er Syst.*, vol. 30, no. 5, pp. 2375–2385, Sep. 2015.

[2] A. A. Eajal, M. F. Shaaban, K. Ponnambalam, and E. F. El-Saadany, "Stochastic Centralized Dispatch Scheme for AC/DC Hybrid Smart Distribution Systems," *IEEE Trans. Sustain. Energy*, pp. 1–14, 2016.

[3] D. T. Ton and W.-T. P. Wang, "A more resilient grid: The U.S. Department of Energy joins with stakeholders in an R&D plan," *IEEE Po er Energy Mag.*, vol. 13, no. 3, pp. 26–34, 2015.

[4] A. Zakariazadeh, S. Jadid, and P. Siano, "Multi-objective scheduling of electric vehicles in smart distribution system," *Energy Con ers. Manag.*, vol. 79, pp. 43–53, Mar. 2014.

[5] A. Chaouachi, R. M. Kamel, R. Andoulsi, and K. Nagasaka, "Multiobjective Intelligent Energy Management for a Microgrid," *IEEE Trans. Ind. Electron.*, vol. 60, no. 4, pp. 1688–1699, Apr. 2013.

[6] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *IET ene . Po er Gener.*, vol. 5, no. 3, p. 258, 2011.

[7] J. Wang, C. Liu, D. Ton, Y. Zhou, J. Kim, and A. Vyas, "Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power," *Energy Policy*, vol. 39, no. 7, pp. 4016–4021, 2011.

[8] J. Soares, H. Morais, T. Sousa, Z. Vale, and P. Faria, "Day-Ahead Resource Scheduling Including Demand Response for Electric

Vehicles," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 596–605, Mar. 2013.
[9] T. Sousa, T. Pinto, H. Morais, Z. Vale, and Ieee, "Intelligent Electric Vehicle Heuristic for Energy Resource Management using Simulated Annealing," in *rd Ieee Pes Inno ati e Smart Grid Technologies Europe*, 2012.
[10] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1244–1252, 2012.
[11] L. Hernandez *et al.*, "A Survey on Electric Power Demand Forecasting: Future Trends in Smart Grids, Microgrids and Smart Buildings," *IEEE Commun. Sur . Tutorials*, vol. 16, no. 3, pp. 1460–1495, 2014.
[12] F. Lezama, J. Soares, E. Munoz de Cote, L. E. Sucar, and Z. Vale, "Differential Evolution Strategies for Large-Scale Energy Resource Management in Smart Grids," in *GECCO Genetic and E olutionary Computation Con erence Companion Proceedings*, 2017.
[13] F. Lezama, J. Palominos, A. Y. Rodriguez-Gonzalez, A. Farinelli, and E. Munoz de Cote, "Agent-Based Microgrid Scheduling: An ICT Perspective," *Mo . Net orks Appl.*, May 2017.
[14] S. Y. Abujarad, M. W. Mustafa, and J. J. Jamian, "Recent approaches of unit commitment in the presence of intermittent renewable energy resources: A review," *ene a le and Sustaina le Energy e ie s*, vol. 70. pp. 215–223, 2017.
[15] R. Jiang, J. Wang, and Y. Guan, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Trans. Po er Syst.*, vol. 27, no. 2, pp. 800–810, 2012.
[16] C. Sahin, M. Shahidehpour, and I. Erkmen, "Allocation of hourly reserve versus demand response for security-constrained scheduling of stochastic wind energy," *IEEE Trans. Sustain. Energy*, vol. 4, no. 1, pp. 219–228, 2013.
[17] W. Su, J. Wang, and J. Roh, "Stochastic Energy Scheduling in Microgrids With Intermittent Renewable Energy Resources," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1876–1883, Jul. 2014.
[18] Chen Gong, Xiaodong Wang, Weiqiang Xu, and A. Tajer, "Distributed Real-Time Energy Scheduling in Smart Grid: Stochastic Model and Fast Optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1476–1489, Sep. 2013.
[19] D. T. Nguyen and L. B. Le, "Optimal Bidding Strategy for Microgrids Considering Renewable Energy and Building Thermal Dynamics," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1608–1620, Jul. 2014.
[20] X. Wang, Z. Hu, M. Zhang, and M. Hu, "Two-stage stochastic optimization for unit commitment considering wind power based on scenario analysis," in *Electricity Distri ution (CICED), China International Con erence on*, 2016, pp. 1–5.
[21] H. Gangammanavar, S. Sen, and V. M. Zavala, "Stochastic optimization of sub-hourly economic dispatch with wind energy," *IEEE Trans. Po er Syst.*, vol. 31, no. 2, pp. 949–959, 2016.
[22] J. Soares, M. A. F. Ghazvini, N. Borges, and Z. Vale, "A Stochastic Model for Energy Resources Management in Smart Grids," *Electr. Po er Syst. es.*, 2016.
[23] J. Soares, B. Canizes, M. A. Fotouhi Gazvhini, Z. Vale, and G. K. Venayagamoorthy, "Two-stage Stochastic Model using Benders' Decomposition for Large-scale Energy Resources Management in Smart grids," *IEEE Trans. Ind. Appl.*, pp. 1–1, 2017.
[24] J. Soares, B. Canizes, C. Lobo, Z. Vale, and H. Morais, "Electric Vehicle Scenario Simulator Tool for Smart Grid Operators," *Energies*, vol. 5, no. 12, pp. 1881–1899, Jun. 2012.
[25] TOMLAB, "TOMLAB optimization," 2016. .
[26] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making nder ncertainty in Electricity Markets*, vol. 153. Boston, MA: Springer US, 2010.
[27] A. Zervos, C. Lins, and J. Muth, *E thinking a % rene a le energy ision or the European nion*. EREC, 2010.
[28] C. Hewicker, M. Hogan, and A. Mogren, "Power Perspectives 2030: On the road to a Decarbonised Power Sector," techreport, 2011.
[29] "Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2015," 2015.
[30] J. R. Birge and F. Louveaux, *Introduction to stochastic programming*. Springer Science & Business Media, 2011.