Two-stage Stochastic Model using Benders' Decomposition for Large-scale Energy Resources Management in Smart grids

João Soares, *Member, IEEE,* Bruno Canizes,
M. Ali Fotouhi Ghazvini, Zita Vale, *Senior Member, IEEE*
GECAD - Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
Polytechnic of Porto, 4200-072, Porto, Portugal
{joaps,brmrc,mafgh,zav}@isep.ipp.pt

G. K. Venayagamoorthy, *Senior Member, IEEE*
Real-Time Power and Intelligent Systems Lab.
Clemson University, Clemson, SC 29634, USA and
School of Engineering, University of KwaZulu-Natal, Durban, South Africa
gkumar@ieee.org

***Abstract* -- The ever-increasing penetration level of renewable energy and electric vehicles threatens the operation of the power grid. Dealing with uncertainty in smart grids is critical in order to mitigate possible issues. This paper proposes a two-stage stochastic model for large-scale energy resources scheduling problem of aggregators in a smart grid. The idea is to address the challenges brought by the variability of demand, renewable energy, electric vehicles, and market price variations while minimizing the total operation cost. Benders' decomposition approach is implemented to improve the tractability of the original model and its' computational burden. A realistic case study is presented using a real distribution network in Portugal with high penetration of renewable energy and electric vehicles. The results show the effectiveness of the proposed approach when compared with a deterministic model. They also reveal that demand response and storage systems can mitigate the uncertainty.**

***Index Terms*--Benders decomposition, Energy management, Energy resources, Large-scale systems, Optimization methods, Power generation scheduling, Stochastic systems, Uncertainty**

NOMENCLATURE

Indices

b,w	Electrical buses
e	Energy storage systems (ESSs)
i	Distributed generation units (DG)
l	Loads
s	Scenarios
sp	External suppliers
t	Timeslot
v	Electric vehicles (EVs)

Parameters

C_{DG}	Generation cost of DG units [m.u./kWh]
$C_{Discharge}$	Discharging cost of ESSs/EVs [m.u./kWh]
C_{GCP}	Curtailment cost of DG units [m.u./kWh]
C_{LoadDR}	Load reduction cost [m.u./kWh]
C_{NSD}	Non-supplied demand cost [m.u./kWh]
$C_{Supplier}$	External suppliers cost [m.u./kWh]
E_{BatCap}	Capacity of ESSs/EVs batteries [kWh]
$E_{MinCharge}$	Minimum energy stored in ESSs/EVs [kWh]
MP	Market price [m.u./kWh]
N_i	Number of DG units
N_e	Number of ESSs
N_l	Number of loads
NL	Number of lines
N_s	Number of external electricity suppliers
N_v	Number of EVs
$P_{ChargeLimit}$	Maximum charge rate of ESSs/EVs [kW]
$P_{DGScenario}$	Forecasted generation of non-dispatchable DG [kW]
$P_{DGMinLimit}$	Min. active power of dispatchable DG [kW]
$P_{DGMaxLimit}$	Max. active power of dispatchable DG [kW]
$P_{DischargeLimit}$	Maximum discharge rate of ESSs/EVs [kW]
$P_{LoadDRMaxLimit}$	Maximum power reduction of loads [kW]
$P_{MarketOfferMax}$	Maximum offer allowed in market [kW]
$P_{MarketOfferMin}$	Minimum offer allowed in market [kW]
$P_{MarketBuyMax}$	Maximum buy allowed in market [kW]
$P_{MarketBuyMin}$	Minimum buy allowed in market [kW]
$P_{SMinLimit}$	Minimum active power of suppliers [kW]
$P_{SMaxLimit}$	Maximum active power of suppliers [kW]
T	Number of time periods
Z	Number of scenarios
λ^{m-1}	Lagranges from slave in *m*-1 iteration
Δt	Duration of period *t* (1 = hour)
π	Occurrence probability of scenarios
η_c	Charging efficiency of ESSs/EVs
η_d	Discharging efficiency of ESSs/EVs

Variables

E_{Stored}	Energy stored in ESS/EVs [kWh]
P_{Buy}	Active power bid in market [kW]
P_{Charge}	Active power charging of ESSs/EVs [kW]
$P_{Discharge}$	Active power discharge of ESSs/EVs [kW]
P_{DG}	Active power of dispatchable DG [kW]
P_{LoadDR}	Active power reduction of loads [kW]
P_{GCP}	Generation curtailment power of DG [kW]
P_{NSD}	Active power of NSD of load [kW]
P_{Sell}	Active power offer in market [kW]
$P_{Supplier}$	Active power of external suppliers [kW]

x_{DG} Binary variable of state of DG units
$x_{ESS/EV}$ Binary variable representing discharging state of ESSs/EVs
x_{Market} Binary variable that represents the choice of markets
$x_{Supplier}$ Binary variable of choosing suppliers
$y_{ESS/EV}$ Binary variable representing charging state of ESSs/EVs
ZA Relaxation variable in Benders slave (bus)
ZF Relaxation variable in Benders slave (lines)

Sets

Ω_{DG}^{d} Dispatchable DG units
Ω_{DG}^{nd} Non-dispatchable DG units
Ω_{DG}^{b} DG units connected to bus *b*
Ω_{E}^{b} ESSs connected to bus *b*
Ω_{L}^{b} Loads connected to bus *b*
Ω_{SP}^{b} External suppliers in bus *b*
Ω_{V}^{b} EVs connected to bus *b*

I. BACKGROUND

Renewable energy sources present a high level of variability concerning energy generation. This unpredictability should be managed efficiently by smart grid (SG) technologies to accommodate high penetration of renewable energy. Transactive energy systems can contribute to providing the flexibility required by the smart grid, e.g. controllable loads, including electric vehicles (EVs) under interoperable architectures [1], [2]. This flexibility can be provided through energy aggregators, which are meaningful for small producers under market-oriented environments [3]. To allow efficient and cost effective operation, energy aggregators require suitable energy resources management (ERM) tools to deal with the increasing number of resources and its underlying uncertainty, e.g. EVs and renewables [4], [5]. The day-ahead energy scheduling is an important part of an ERM system to obtain the expected operation cost (or profit) while providing adequate decisions one day in advance. However, the energy scheduling is quite challenging due to the inherent uncertainties and the high number of resources.

Adopting advanced energy management models that consider uncertainty factors are critical for successful implementation of SGs. The United States Department of Energy (DOE) has identified predictive models to deal with stochastic behavior and uncertainty as a top R&D priority [6].

The day-ahead problem tackled by this paper is a combinatorial problem of large-scale nature when many distributed energy resources (DERs) are considered. Due to nonlinearity features of the problem, it is usually classified as mixed integer nonlinear programming (MINLP). MINLP techniques require significant computer resources. The computation time needed for solving these types of problems is not compatible with the time limitations of short-term energy scheduling [7].

To overcome the computational burden issue, some approaches have been proposed in previous research. The work developed in [8] adopts Benders' decomposition approach to solve a multi-objective model in day-ahead context. The authors were able to reduce the complexity of the original MINLP scheduling problem compared to a previous formulation proposed in [7]. However, it was found later in [9], that the slave problem formulated as an hourly distribution power flow in [8] leads to sub-optimal solutions, due to temporal dependencies in distributed energy resources. Therefore, the work in [9] proposes a multi-period model to obtain better results. Furthermore, the work in [8] seems limited in the sense that it does not consider demand response (DR), renewable generation such as wind or PV, and energy storage systems (ESS), which are increasingly important in SGs. Although the proposed works have contributed to reducing the original problem complexity, uncertainty factors have not been considered in the mentioned works [7]–[9] and many others presented in the literature [10]–[15].

Energy scheduling models that incorporate stochasticity have been studied in the literature. In [16], a dispatch scheduling approach is proposed for a wind farm using ESSs. The results indicate that the ESS can be used to perform a joint production schedule and address the forecasting errors during the real-time operation. Stochastic energy management with compressed air storage integrated with renewable generation has demonstrated to be effective in [17]. The models developed in [18], [19] focus on aggregator's market strategies and the risks associated with their portfolio optimization problems. The authors suggest that the model may be decomposable and subject of future research [19]. In [20], a stochastic model is proposed to address the ERM in hybrid AC/DC microgrids considering DERs and uncertainty in EV demand, renewable generation, and electricity price. However, DR is not considered in the work above and it only considers a small power system (38-bus) with 8 DG units. The model is adequate for small hybrid AC/DC grids whereas the proposed model in this paper is targeted to deal with larger grids. In [21], authors present a stochastic day-ahead scheduling to address carbon emission, generation fuel costs and uncertainties in microgrid operation. The work does not incorporate network constraints and the experiments are based on a small 3 generator system. The work presented in [22] tackles the ERM problem of a renewable-based virtual power plant. These models consider the uncertainty in electricity prices and renewables, but the consideration of resources such as DR, EVs, and V2G capacity have been overlooked. The use of energy resources (e.g. ESS) can mitigate system uncertainties as demonstrated in [4], [16], [17], [22], [23]. Nevertheless, these works do not consider EVs and related uncertainties, which are expected to grow considerably in next decade. Other works consider the EV uncertainty [20], [24] but do not incorporate grid constraints. When the grid is included in the stochastic models, it is either decoupled or only suited for a small grid system with few scheduling units. In this paper, the proposed model attempts to overcome this issue by using a stochastic Benders' decomposition, which allows to include network constraints, a high number of DERs, EVs and several sources of uncertainty in the same model without requiring external validation, while still allowing scalability and good results.

The present research paper takes into account the lessons learned from [9], where Benders' decomposition is proposed to address energy resources scheduling considering several kinds of DERs and network constraints. In the current research, a two-stage stochastic model research is developed to incorporate the ability to handle uncertainty factors, which were not tackled in [9]. The Benders' decomposition scheme is applied to the two-stage stochastic model to reduce the computational burden of the large-scale problem. In addition, several modifications to the original optimization model have been undertaken to allow the method to handle several representative scenarios efficiently. A realistic case study using a real 180-bus grid from Portugal with high penetration of DERs is used to demonstrate the application of the method.

This paper is structured as follows: Section II represents the problem formulations; Section III presents the case study used in this work, while Section IV presents the results and respective discussion. Finally, the last section presents the main conclusions of the paper.

II. Problem Formulation

In this section, the two-stage stochastic formulations are represented after introducing the approach used for uncertainty modeling.

A. Uncertainty representation

The aggregator in this model faces several sources of uncertainty, namely the forecast errors of EV fleet characteristics, hourly load demands and the generation profile of the renewable sources [25]. The uncertainties related with these inputs are taken into account in the model and the scheduling problem is developed as a stochastic scenario-based optimization model. The uncertainties associated with the EV fleet characteristics is caused by the random driving pattern of the EV drivers and their uncertain behavior [25].

In this form of problems, where a set of scenarios needs to be handled, the main issue is to generate a set of realizations for the random variable, which can adequately represent the probabilistic characteristics of the data [26]. The initial set of scenarios is a large data set generated by the Monte Carlo Simulation (MCS) technique for representing power system uncertainties. The MCS parameters are the probability distribution functions of the forecast errors, which obtained from the historical data [26][27]. In order to include the forecast error, an additional term which can be positive or negative is added to the forecasted profile ($x^{forecasted}$)

$$x^{s}(t) = x^{forecasted}(t) + x^{error,s}(t), \qquad \forall t, \forall s. \tag{1}$$

The error term ($x^{error,s}$) is a zero-mean noise with standard deviation σ [26], [28]. Scenarios are represented with x^s. In this model, the forecast errors for the uncertain inputs are all represented by normal distribution functions.

The scenario tree concept can clearly illustrate how the discrete outcome for each stochastic input can be combined to construct the larger set of scenarios. A scenario tree consists nodes that represent the states of the random variable at particular time points, branches to show different realizations of the variable and the root which shows the beginning point where the first stage decisions are made [26]. Fig. 1 shows the scenario tree model for the proposed scenario-based stochastic programming model [26]. x_n^s refers to the n^{th} random variable. Variables can have different natures. For instance, x_1^s may represent load demand and x_2^s can denote market prices. The number of the nodes at the second stage is equal to the total number of scenarios. The occurrence probability of each scenario is equal to the product of the branches' probabilities [26].

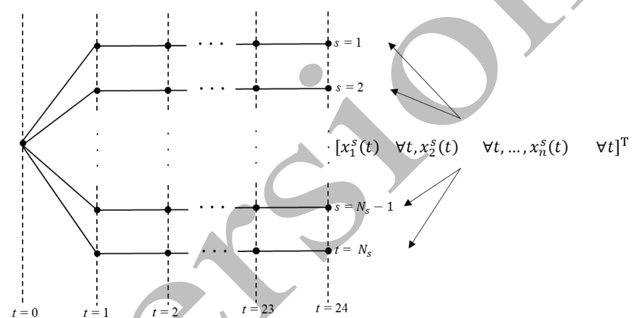

Fig. 1. Scenario tree representation

Including all the generated scenarios in the optimization problem results in a large-scale optimization problem [26]. Generally, there should be a tradeoff between model accuracy and computation speed [25], [29]. In order to handle the computational tractability of the problem, the standard scenario reduction techniques developed in [30] is used. These scenario reduction algorithms exclude the scenarios with low probabilities and combines those that are close to each other in terms of statistic metrics [30]. They determine a scenario subset of the prescribed cardinality and probability which is closest to the initial distribution in terms of a probability metric [27]. The main purpose of scenario reduction is to reduce the size of the problem. The number of variables and equations are reduced after applying these algorithms. Consequently, the solutions can be found more efficiently, without losing the main statistical characteristics of the initial dataset [31]. However, the potential cost of applying these approaches is introducing imprecision in the final solution [29]. The reduction algorithms proposed in [30] consists of algorithms with different computational performance and accuracy, namely fast backward method, fast backward/forward method and fast backward/backward method. The selection of the algorithms depends on the problem size and the expected solution accuracy [27], [30]. For instance, the best computational performance with the worst accuracy can be provided by the fast backward method for large scenario tress. Furthermore, the forward method provides best accuracy and highest computational time. Thus, it is usually used where the size of reduced subset is small [27].

The main decision variables are the optimal day-ahead market transactions and the generation scheduling of the controllable sources (first stage). They are made taking into account possible deviations in the operation, like wind and solar power and EVs (second stage). The first-stage decisions do not change across the scenarios in the second stage. In other words, the decisions to be made one day in advance remain unchanged.

The two-stage stochastic model is decomposed into two smaller problems, the master problem and the slave problem. The Benders' decomposition approach is used for decomposition to make the model computationally tractable, as discussed in subsection B.

B. Two-stage stochastic model

The outputs of this optimization model are the decision variables regarding the purchases from the external suppliers, optimal bids to the wholesale market and the dispatch of the controllable DG units. The total expected operation cost for the day-ahead operation, *D+1*, is represented by (2), corresponding to the first-stage operation costs (OC^1) and second-stage operation costs (OC^2) and market transactions (*MT*). Theoretical background on stochastic programming models can be found in [32].

$$\text{Minimize} \quad E\left(OC_{Total}^{D+1}\right) = OC^1 + E\left(OC^2 + MT\right) \tag{2}$$

The expected operation cost in the first stage, OC^1, is represented by (3), which includes the cost of controllable DG units and external suppliers' electricity acquisition:

$$OC^1 = \sum_{t=1}^{T} \left[\left(\begin{array}{l} \sum_{I \in \Omega_{DG}^{d}} p_{DG(i,t)} \cdot C_{DG(i,t)} + \\ \sum_{sp=1}^{N_{sp}} p_{Supplier(sp,t)} \cdot C_{Supplier(sp,t)} \end{array} \right) \cdot \Delta t \right] \tag{3}$$

The expected operation cost in the second stage, OC^2, is represented by (4), which includes the cost of non-dispatchable DG units, demand response, ESS/EVs discharge, non-supplied demand (NSD) and generation curtailment power (GCP).

$$E\left(OC^2\right) = \sum_{s=1}^{S} \sum_{t=1}^{T} \left[\left(\begin{array}{l} \sum_{i \in \Omega_{DG}^{nd}} p_{DG(i,t,s)} \cdot C_{DG(i,t)} + \\ \sum_{l=1}^{N_l} p_{LoadDR(l,t,s)} \cdot C_{LoadDR(l,t)} + \\ \sum_{e=1}^{N_e} p_{Discharge(e,t,s)} \cdot C_{Discharge(e,t)} + \\ \sum_{v=1}^{N_v} p_{Discharge(v,t,s)} \cdot C_{Discharge(v,t)} + \\ \sum_{l=1}^{N_l} p_{NSD(l,t,s)} \cdot C_{NSD(l,t)} + \\ \sum_{i=1}^{N_i} p_{GCP(i,t,s)} \cdot C_{GCP(i,t)} \end{array} \right) \cdot \pi(s) \cdot \Delta t \right] \tag{4}$$

The expected cost of the market transactions are represented as:

$$E\left(MT\right) = \sum_{s=1}^{S} \sum_{t=1}^{T} \left[\left(p_{Buy(t)} \cdot MP_{(t,s)} - p_{Sell(t)} \cdot MP_{(t,s)} \right) \cdot \pi(s) \cdot \Delta t \right] \tag{5}$$

The "here and now" variables, which are known as first stage variable, are p_{Buy}, p_{Sell}, p_{DG}, and $p_{Supplier}$. They are determined before the actual uncertainty is revealed.

1) Network grid constraints

The DC power flow constraints are considered in the optimization model (6). The usage of a DC model is justified because in many countries, like in Portugal, the distribution networks have voltage regulators and capacitors banks carefully positioned along the grid in order to keep the voltage and reactive power between the desire limits. Thus, in this case the complete model would only make the method more complex and computationally intractable. Usually, the voltage stability is placed at the HV/MV substation level. However, in the Portuguese case the MV/LV transformers also have voltage regulators. When *b*=1 in (6), the term $\left(p_{Sell(t)} - p_{Buy(t)}\right)$ is subtracted to the left part of the equation. It is assumed that the upstream grid is connected to the distribution network at *b*=1.

$$\begin{array}{l} \sum_{i \in \Omega_{DG}^{b}} \left(p_{DG(i,t)} - p_{GCP(i,t)}\right) + \sum_{sp \in \Omega_{SP}^{b}} p_{Supplier(sp,t)} + \\ \sum_{l \in \Omega_{L}^{b}} \left(p_{NSD(l,t,s)} + p_{Load\,DR(l,t,s)} - p_{Load(l,t,s)}\right) + \\ \sum_{e \in \Omega_{E}^{b}} \left(p_{Discharge(e,t,s)} - p_{Charge(e,t,s)}\right) + \\ \sum_{v \in \Omega_{V}^{b}} \left(p_{Discharge(v,t,s)} - p_{Charge(v,t,s)}\right) - \\ \sum_{b,w=1}^{NL} \left(p_{(b,w,t,s)} - p_{(w,b,t,s)}\right) = 0 \qquad \forall b,t,s \end{array} \tag{6}$$

The maximum admissible line flow is expressed by (7).

$$p_{(b,w,t,s)} \le p_{(b,w)}^{Max} \quad \forall t,s \tag{7}$$

2) Controllable DG units and the external supplier

x_{DG} is a binary decision variable, which is 1 when the controllable DG unit is determined to be online. Maximum and minimum limits for active power in each period *t* are formulated as:

$$p_{DG(i,t)} \ge x_{DG(i,t)} \cdot P_{DGMinLimit(i,t)} \qquad \forall t, \forall i \in \Omega_{DG}^{d} \tag{8}$$

$$p_{DG(i,t)} \le x_{DG(i,t)} \cdot P_{DGMaxLimit(i,t)} \qquad \forall t, \forall i \in \Omega_{DG}^{d} \tag{9}$$

The upstream supplier limits in each period *t* regarding active power can be formulated as:

$$p_{Supplier(sp,t)} \ge x_{\text{Supplier}(sp,t)} \cdot P_{SMinLimit(sp,t)} \qquad \forall t, \forall sp \tag{10}$$

$$p_{Supplier(sp,t)} \le x_{\text{Supplier}(sp,t)} \cdot P_{SMaxLimit(sp,t)} \qquad \forall t, \forall sp \tag{11}$$

3) Energy storage systems constraints

The charging and discharging status of the ESSs are respectively represented by x_{ESS} and y_{ESS}. Charging and discharging cannot occur simultaneously:

$$x_{ESS(e,t,s)} + y_{ESS(e,t,s)} \le 1 \qquad \forall t, \forall e, \forall s \tag{12}$$

The state of charge of the ESS is characterized as follows:

$$E_{Stored(e,t,z)} = E_{Stored(e,t-1,s)} + \eta_{c(e)} \cdot p_{Charge(e,t,s)} \cdot \Delta t - \frac{1}{\eta_{d(e)}} \cdot p_{Discharge(e,t,s)} \cdot \Delta t \qquad \forall t, \forall e, \forall s \tag{13}$$

The maximum discharge limit for each ESS is represented by:

$$p_{Discharge(e,t,s)} \leq P_{DischargeLimit(e,t)} \cdot x_{ESS(e,t,s)} \qquad \forall t, \forall e, \forall s \tag{14}$$

The maximum charge limit for each ESS is represented by:

$$p_{Charge(e,t,s)} \leq P_{ChargeLimit(e,t)} \cdot y_{ESS(e,t,s)} \qquad \forall t, \forall e, \forall s \tag{15}$$

The maximum battery capacity limit for each ESS is represented by:

$$E_{Stored(e,t,s)} \leq E_{BatCap(e)} \qquad \forall t, \forall e, \forall s \tag{16}$$

Minimum stored energy to be guaranteed at the end of period t is represented by:

$$E_{Stored(e,t,s)} \geq E_{MinCharge(e,t)} \qquad \forall t, \forall e, \forall s \tag{17}$$

4) *Electric vehicles constraints*

The EVs are treated as virtual batteries in the proposed model. A virtual battery can represent a parking lot or a set of EVs located in a given network point, which can be estimated in advance. The considered technical constraints are very similar to the set of formulations provided for the ESSs. However, EVs related constraints are distinguished from ESS because some parameters present source of uncertainty due to EVs randomness behavior.

The charge and discharge cannot be simultaneous. Therefore, two binary variables guarantee this condition for each virtual battery v:

$$x_{EV(v,t,s)} + y_{EV(v,t,s)} \leq 1 \qquad \forall t, \forall v, \forall s \tag{18}$$

The battery balance for each virtual battery v is:

$$E_{Stored(v,t,z)} = E_{Stored(v,t-1,s)} + \eta_{c(e \ll v)} \cdot p_{Charge(v,t,s)} \cdot \Delta t - \frac{1}{\eta_{d(v)}} \cdot p_{Discharge(v,t,s)} \cdot \Delta t \qquad \forall t, \forall v, \forall s \tag{19}$$

The virtual battery charge and discharge limit varies for each scenario s, as well as its capacity. This depends on the number of EVs in each bus on a given period t. The maximum discharge limit for each virtual battery v is represented by:

$$p_{Discharge(v,t,s)} \leq P_{DischargeLimit(v,t,s)} \cdot x_{EV(v,t,s)} \qquad \forall t, \forall v, \forall s \tag{20}$$

The maximum charge limit for each virtual battery v is represented by:

$$p_{Charge(v,t,s)} \leq P_{ChargeLimit(v,t,s)} \cdot y_{EV(v,t,s)} \qquad \forall t, \forall v, \forall s \tag{21}$$

The maximum battery capacity limit for each virtual battery v is represented by:

$$E_{Stored(v,t,s)} \leq E_{BatCap(v,s)} \qquad \forall t, \forall v, \forall s \tag{22}$$

The minimum stored energy to be guaranteed at the end of period t is stochastic and is represented by:

$$E_{Stored(v,t,s)} \geq E_{MinCharge(v,t,s)} \qquad \forall t, \forall v, \forall s \tag{23}$$

5) *Demand response constraints*

Equation (24) formulates a DR load model, namely the direct load control. The maximum amount that each load l can be reduced in each period t in scenario s is formulated as:

$$p_{LoadDR(l,t,s)} \leq P_{LoadDRMaxLimit(l,t)} \qquad \forall t, \forall l, \forall s \tag{24}$$

6) *Electricity market constraints*

The stochastic energy scheduling model is compatible with the possibility to make bids (buy or sell) to a wholesale market [33]. The energy aggregator may limit the bids within certain bounds. In certain electricity markets, there is a minimum required amount to access.

The market offers are constrained by (25) and (26), namely maximum and minimum offer:

$$p_{Sell(t)} \leq P_{MarketOfferMax(t)} \cdot x_{MarketSell(t)} \qquad \forall t \tag{25}$$

$$p_{Sell(t)} \geq P_{MarketOfferMin(t)} \cdot x_{MarketSell(t)} \qquad \forall t \tag{26}$$

The market bids (buy) are constrained by (27) and (28), namely by maximum and minimum amount:

$$p_{Buy(t)} \leq P_{MarketBuyMax(t)} \cdot x_{MarketBuy(t)} \qquad \forall t \tag{27}$$

$$p_{Buy(t)} \geq P_{MarketBuyMin(t)} \cdot x_{MarketBuy(t)} \qquad \forall t \tag{28}$$

The market transactions in each period are unique:

$$x_{MarketBuy(t)} + x_{MarketSell(t)} \leq 1 \qquad \forall t \tag{29}$$

7) *Non-supplied demand constraint*

The NSD cannot be higher than the forecasted demand in scenario s:

$$p_{ENS(l,t,s)} \leq p_{Load(l,t,s)} - p_{LoadDR(l,t,s)} \qquad \forall t, \forall l, \forall s \tag{30}$$

8) *Generation curtailment power*

The generation curtailment power of non-dispatchable DG units cannot be higher than the predicted amount of generation:

$$p_{GCP(i,t,s)} \leq P_{DGScenario(i,t,s)} \qquad \forall t, \forall i \in \Omega_{DG}^{nd}, \forall s \tag{31}$$

C. *Benders' decomposition approach*

J. F. Benders [34] presented in 1962 a decomposition methodology to solve mixed integer problems. This method is based on the principle of the main problem decomposition into sub-problems. Benders decomposition method uses duality theory [35] in linear and nonlinear mathematical programming to divide a problem whose resolution is difficult in sub-problems. These sub-problems consider specific variables that are solved iteratively until the optimal solution is obtained [34]. The Benders' decomposition approach usually converges in one iteration when the master problem is feasible or close to be feasible, i.e. adjusting some continuous variables in slave problem to become feasible.

Benders decomposition technique is adequate to solve large-scale problems like the ERM problem. The problem can be divided into a master problem and one or more slave problems. The master problem is usually classified as a linear or mixed integer problem including fewer technical constraints. The slave problems are linear or nonlinear and attempt to validate if the solution of the master problem is technically feasible. In this level, the network technical constraints are considered (lines flow (put here the variables) and also the thermal line limits (equations (6) and (7))).

The master problem consists in finding the optimal solution without technical validation of the grid constraints, namely the lines flow and their thermal limits. A simple balance equation is considered instead in the master, i.e. generation and consumption must match in each period. In the master problem, the binary variables are considered. The objective function of the master problem can be formulated as (32). In the case that any infeasibilities are found, one variable is added to the master problem, namely α, which is designated by Benders' cuts.

$$\text{Minimize} \quad E(OC_{Total}^{D+1}) + \alpha \tag{32}$$

The Benders' cut is added in each iteration m if any infeasibility is found in the slave problem. It is represented as:

$$\begin{aligned}
&\alpha^* \geq Z_{up}^{m-1} + \\
&\sum_{t=1}^{T}\sum_{sp}^{N_{sp}} \lambda_{Supplier(s,t)}^{m-1} \cdot (x_{Supplier(sp,t)}^{m} - x_{Supplier(sp,t)}^{m-1}) + \\
&\sum_{t=1}^{T}\sum_{i\in\Omega_{DG}^{d}} \lambda_{DG(i,t)}^{m-1} \cdot (x_{DG(i,t)}^{m} - x_{DG(i,t)}^{m-1}) + \\
&\sum_{t=1}^{T}\sum_{e=1}^{N_e} \lambda_{ESS_dsc(e,t,s)}^{m-1} \cdot (x_{ESS(e,t,s)}^{m} - x_{ESS(e,t,s)}^{m-1}) + \\
&\sum_{t=1}^{T}\sum_{e=1}^{N_e} \lambda_{ESS_chg(e,t,s)}^{m-1} \cdot (y_{ESS(e,t,s)}^{m} - y_{ESS(e,t,s)}^{m-1}) + \\
&\sum_{t=1}^{T}\sum_{v=1}^{N_v} \lambda_{EV_dsc(v,t,s)}^{m-1} \cdot (x_{EV(v,t,s)}^{m} - x_{EV(v,t,s)}^{m-1}) + \\
&\sum_{t=1}^{T}\sum_{v=1}^{N_v} \lambda_{EV_chg(v,t,s)}^{m-1} \cdot (y_{EV(v,t,s)}^{m} - y_{EV(v,t,s)}^{m-1})
\end{aligned} \tag{33}$$

The objective function of the slave problem is represented by (34), where the operation cost (1) and the relaxation variables ZA and ZF are minimized.

$$\text{Minimize} \quad E(OC_{Total}^{D+1}) + \sum_{t=1}^{T}\sum_{b=1}^{N_b} ZA_{(b,t)} + \sum_{t=1}^{T}\sum_{h=1}^{N_h} ZF_{(h,t)} \tag{34}$$

Slack variables ZA (for power balance – first Kirchhoff law) and ZF (thermal line capacity) can take any value to make the optimization problem feasible. The value of these variables represents how much some constraints are being violated. The slave sub-problem cannot change the binary variables but is free to explore the continuous variables in order to satisfy the several constraints, while minimizing the objective function and the value of the slack variables.

The slave problem (35) represents the power flow balance. When b=1, the term $\left(p_{Sell(t)} - p_{Buy(t)}\right)$ is subtracted to the left part of the equation.

$$\begin{aligned}
&\sum_{i\in\Omega_{DG}^{b}} \left(p_{DG(i,t)} - p_{GCP(i,t)}\right) + \sum_{sp\in\Omega_{sp}^{b}} p_{Supplier(sp,t)} + \\
&\sum_{l\in\Omega_{L}^{b}} (p_{NSD(l,t)} + p_{Load\,DR(l,t)} - p_{Load(l,t)}) + \\
&\sum_{v\in\Omega_{V}^{b}} (p_{Discharge(v,t)} - p_{Charge(v,t)}) + \\
&\sum_{e\in\Omega_{E}^{b}} (p_{Discharge(e,t)} - p_{Charge(e,t)}) - \\
&\sum_{b,w=1}^{NL} (p_{(b,w,t)} - p_{(w,b,t)}) + ZA_{(b,t)} = 0 \quad \forall b,t
\end{aligned} \tag{35}$$

In, addition the line power flow is relaxed by ZF if congestion is verified as shown in (36):

$$p_{(b,w,t)} + ZF_{(b,w,t)} \leq p_{(b,w)}^{Max} \quad \forall t \tag{36}$$

D. Evaluation metrics

The benefits of the stochastic programming are evaluated through well-known indices, such as the expected value of perfect information (EVPI) and the value of stochastic solution (VSS) [35]. The EVPI represents the amount that the decision maker is not able to gain due to the presence of imperfect information, e.g. forecasts. It is useful to evaluate how the uncertainty factors affect the evaluated optimal problem. On the other hand, the VSS represents the advantage of using stochastic programming over a deterministic approach [35]. EVPI for minimization problems can be represented by (37). The stochastic solution, represented by Z^{S*} is calculated by the stochastic programming approach and represents the total expected cost (1). Z^{P*} represents the wait-and-see solution (WSS). The WSS can be obtained by using the deterministic approach for each scenario. Then, WSS is computed by multiplying the individually obtained cost by each scenario probability.

$$\text{EVPI} = z^{S*} - z^{P*} \tag{37}$$

The VSS for minimization problems is represented as follows:

$$\text{VSS} = z^{D*} - z^{S*} \tag{38}$$

where Z^{D*} is the optimal value of the modified stochastic problem. It is a deterministic version of the original problem with an average scenario. The optimal decision variables of the original stochastic problem are considered as input in the modified problem.

III. Case Study

In this section, a case study is presented to demonstrate how the proposed methodology is applied. A real distribution network from Portugal with 180 buses, 30kV and one substation [9] adapted to a future scenario is used in this paper. The network presents 90 load points, 5 parking lots for EVs, 116 DGs, one external supplier and 7 ESSs. The parking lots are distributed per 5 buses (3, 69, 96, 107 and 161). A subset of the original data was used from previous work [9], in which the EVs have been aggregated by bus, namely the aforementioned electrical buses. The external supplier is located at bus 1 corresponding to the substation location. DR with DLC contracts is considered in the case study. DLC cost considered is 0.02 m.u./kWh. The discharge prices of the EVs and ESSs are respectively 0.18 m.u./kWh and 0.01 m.u./kWh. The ESSs' initial energy level is considered zero. The considered wholesale market price forecast is presented in Fig. 2. The uncertainty of the market price forecast[1] is also illustrated in the figure. The prices and the capacities of DGs are based on the projections presented in [36]. Wind and solar power forecast, as well as the demand forecast are presented in Fig. 3.

5000 initial scenarios are generated and reduced to 150 scenarios using GAMS/SCENRED. As shown in Fig. 3, the wind and solar power generation forecast for period 12 varies between 2.59 MW and 3.01 MW, based on the generated scenarios. The maximum standard deviation values for the considered uncertainty variables (demand, electricity market price, parking lots capacities, parking lots charge and discharge) are 15%, 10%, 35%, 35% and 35% respectively. The minimum values are respectively 8%, 6%, 20%, 20%, 20%.

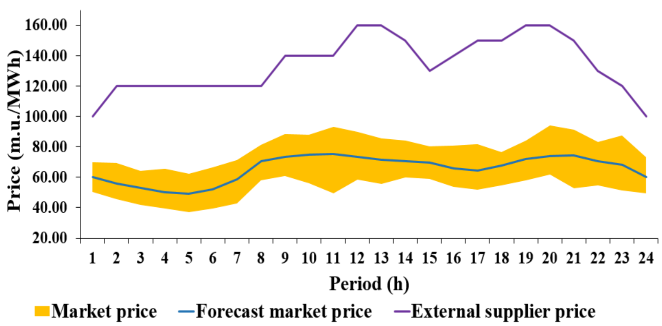

Fig. 2. External supplier price and forecast of wholesale market price

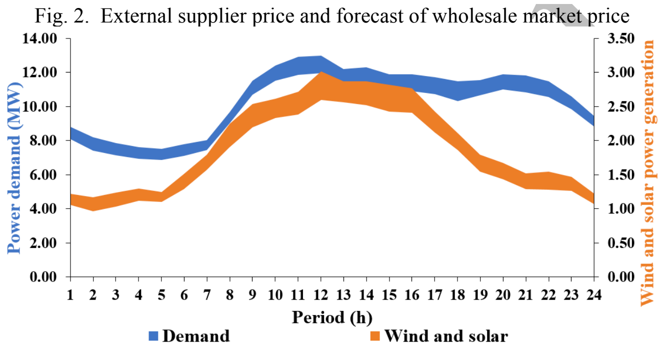

Fig. 3. Wind, solar and demand forecast

Fig. 4 depicts the box plot for the EVs battery capacity uncertainty in period 18. For instance, at parking lot 1, located at bus 3, it is possible to see a considerable uncertainty, varying between 0.05MW and a little more than 0.45MW. Around 50% of the values are located between 0.20MW and around 0.30MW, corresponding to the interquartile range. 25% of the values varying between 0.05MW and 0.20MW are located in the first quartile (Q1). Values between 0.05MW and 0.30MW (75% of the values) are in the third quartile (Q3).

The energy resources data and prices are shown in Table I. The market amount is set to 2 MW in to limit the exposure of the energy aggregator to higher levels of uncertainty.

The following four case studies are presented to show the impact of using storage and DR in the ERM, regarding the mitigation of uncertainty: A – ESS and DR are considered; B – ESS and DR are not considered; C – ESS is considered and DR is not; D – DR is considered ESS is not.

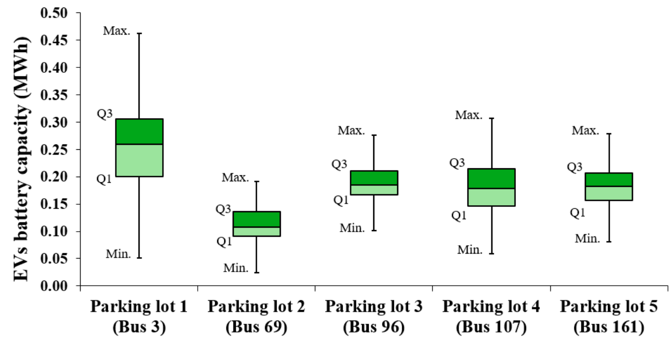

Fig. 4. Uncertainty of EVs battery capacity for period 18

The proposed research work was developed in MATLAB R2014b and TOMLAB 8.1 64 bits with CPLEX solver (version 12.5) using a computer with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro.

TABLE I
CHARACTERIZATION OF 180-BUS DISTRIBUTION NETWORK

Energy resources		Prices (m.u./MWh) min–max	Capacity (MW) min–max	Forecast (MW) min-max	Units
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
Storage	Charge	0–0	0.00–1.20		7
	Discharge	10–10	0.00–1.20		
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

IV. RESULTS AND DISCUSSION

The proposed two-stage stochastic model is applied to solve the ERM problem in the case studies. The optimization problem with 150 scenarios deals with 1,239,721 variables, of which 86,832 are integer variables and 215,188 constraints.

Table II presents the peak memory and the execution time for stochastic Benders' decomposition. The execution times are compatible for the available timeframe in the decision-making process. Each case presents an execution time less than an hour. To evaluate the impact on computer system resources, a memory test was made. The used tool for this test was MATLAB memory profiler. This command report the peak memory for each function used in the methodology developed code. As shown in Table II, higher peak memory was verified in case A. Even the peak memory doesn't exceed 1GB in this case. So, the proposed research work is compatible with a wide range of available computers in the market.

[1] The electricity market price has been obtained in http://www.omie.es

TABLE II.
PEAK MEMORY AND EXECUTION TIME FOR EACH CASE

Case	Peak memory (MB)	Execution time (seconds)
A	960	3,351
B	687	2,154
C	895	2,676
D	890	2,618

Fig. 5 and 6 respectively present the biomass and external supplier generation power for the four considered cases. Regarding biomass generation, the most considerable changes are during the periods 1-2, 8-9 and 23-24. Regarding the external supplier, the changes are verified for the cases without ESSs (i.e., B and D). The change is a reduction of the generated power in some periods of the day, because the ESS is not charged in these cases.

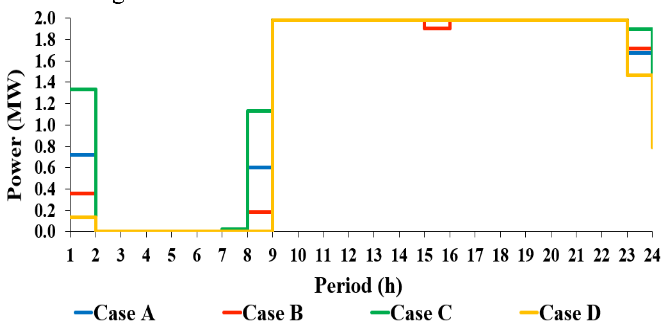

Fig. 5. Biomass generated power for the considered cases

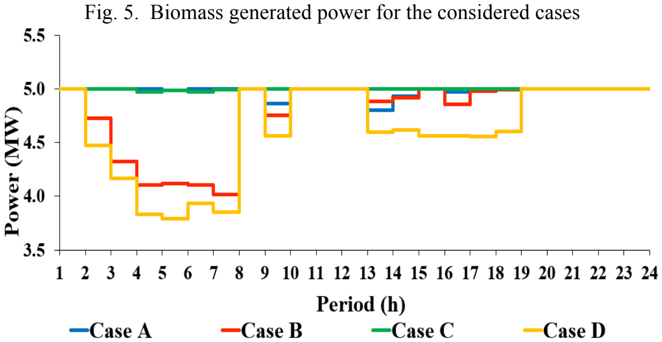

Fig. 6. External supplier generated power for the considered cases

The values of the quality indices are shown in Fig. 7. The cost for stochastic and deterministic models are also shown in this figure. It is possible to see that the lower cost is verified when ESS and DR are available. The case without both resources have higher costs for both stochastic (47,208 m.u.) and deterministic (48,668 m.u.) models. For cases C and D, the costs for stochastic model are similar, but in the deterministic model the costs are 8.85% higher when the ESS is not available. Results also suggest that ESS contributes to avoid a higher cost when the deterministic model is used (case C). In case D, the DR resource is not as effective as ESS in case C. The comparison between cases C and D is a good proof of the previous statement, where the VSS is higher in case D (11.75%) which means that without ESS the stochastic model is more important to achieve lower expected costs mitigating the uncertainty.

Fig. 8 depicts the results of the stochastic scheduling of energy resources for cases A and B. Regarding the wind and solar, the quantified uncertainty is 6.4MWh (cases A and B). This quantity represents the most probable variable amount. In case A, the ESS and parking lots discharge and DR presents an uncertainty of 11.29MWh, 1.24MWh and 7.81MWh respectively. The minimum expected values are 0.47MWh for ESS discharge and zero for the other two resources. For case B, the uncertainty of parking lot discharge is 2.8MWh and the minimum expected value is zero. In this case study, it was verified that the market results do not change. The market bid result is 2 MW during each period, which corresponds to the maximum amount that it can bid in the market (imposed in this case study).

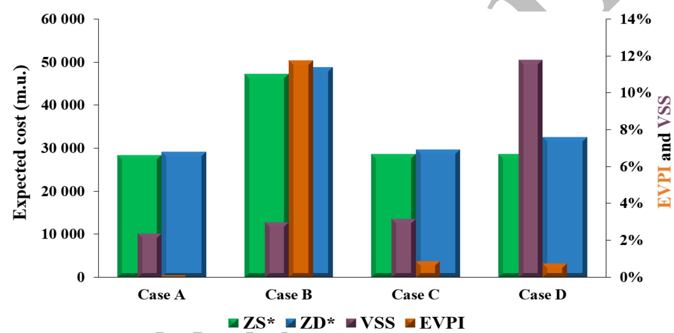

Fig. 7. EVPI and VSS for the considered cases

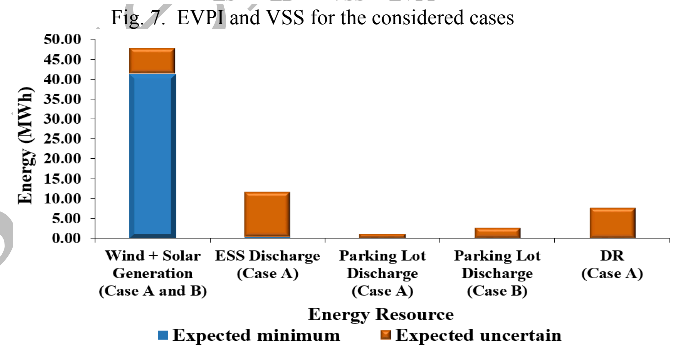

Fig. 8. Stochastic scheduling of energy resources for the case A and B)

V. CONCLUSIONS

A two-stage stochastic model using Benders' decomposition was proposed to solve the challenging problem of considering several sources of uncertainty in an integrated model and with network validation. The network constraints are validated for each scenario in the Benders' slave problem. The results indicate that the problem complexity can be reduced if the EVs are adequately aggregated instead of decentralized control. Therefore, it is possible to increase the scalability of the model and consider several uncertainty sources. The results also reveal that the increasing levels of uncertainty can be mitigated either with ESS or DR. In fact, the costs have been decreased by around 40% when ESS and DR have been both considered in the case study. In this particular case, the ESS also reduced the impact of uncertainty more effectively than DR.

Future work should address how the nonlinearities can be tackled in the proposed stochastic model. New research may be based on hybrid versions of decomposition approaches, such as Dantzig-Wolfe or even evolutionary algorithms.

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