Attention:

A Stochastic Model for Energy Resources Management in Smart Grids

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ABSTRACT

Renewable energy resources such as wind and solar are increasingly more important in distribution networks and microgrids as their presence keeps flourishing. They help to reduce the carbon footprint of power systems, but on the other hand, the intermittency and variability of these resources pose serious challenges to the operation of the grid. Meanwhile, more flexible loads, distributed generation, and energy storage systems are being increasingly used. Moreover, electric vehicles impose an additional strain on the uncertainty level, due to their variable demand, departure time and physical location. This paper formulates a two-stage stochastic problem for energy resource scheduling to address the challenge brought by the demand, renewable sources, electric vehicles, and market price uncertainty. The proposed method aims to minimize the expected operational cost of the energy aggregator and is based on stochastic programming. A realistic case study is presented using a real distribution network with 201-bus from Zaragoza, Spain. The results demonstrate the effectiveness and efficiency of the stochastic model when compared with a deterministic formulation and suggest that demand response can play a significant role in mitigating the uncertainty.

KEYWORDS: *demand response; electric vehicles; energy resource scheduling; smart grid; stochastic programming; uncertainty.*

Nomenclature

Indices

e	ESSs
i	DG units
l	Loads
m	Market
s	External suppliers
t	Time periods
v	EVs
z	Scenarios

Parameters

$C_{Supplier}$	External supplier cost [m.u. /kWh]
C_{LoadDR}	Load reduction cost [m.u./kWh]
$C_{Discharge}$	Discharging cost of ESSs/EVs [m.u. /kWh]
C_{DG}	Generation cost of DG unit [m.u. /kWh]
C_{NSD}	Non-supplied demand (NSD) cost of loads [m.u. /kWh]
C_{GCP}	Curtailment cost of DG units [m.u. /kWh]
MP_{Sell}	Forecast price of markets [m.u. /kWh]
π	Occurrence probability of scenarios
T	Number of time periods in the scheduling horizon
Z	Number of scenarios
Δt	Duration of period t (1 = hour)
N_i	Number of DG units
N_e	Number of ESSs
N_l	Number of loads
N_s	Number of external electricity suppliers
N_v	Number of EVs
N_m	Number of markets
$P_{DGScenario}$	Forecasted generation of non-dispatchable DG units [kW]
$P_{DGMinLimit}$	Minimum active power of dispatchable DG unit*s* [kW]
$P_{DGMaxLimit}$	Maximum active power of dispatchable DG units [kW]
$P_{SMinLimit}$	Minimum active power of suppliers [kW]
$P_{SMaxLimit}$	Maximum active power of suppliers [kW]
$P_{LoadDRMaxLimit}$	Maximum limit of active power reduction of loads [kW]
$P_{DischargeLimit}$	Maximum active discharge rate of ESSs/EVs [kW]
$P_{ChargeLimit}$	Maximum active charge rate of ESSs/EVs [kW]
$P_{MarketOfferMax}$	Maximum energy offer allowed in market*s* [kW]
$P_{MarketOfferMin}$	Minimum energy offer allowed in markets [kW]
E_{Trip}	Forecasted energy demand for EVs' trip [kWh]
E_{BatCap}	Maximum energy stored allowed by ESSs/EVs [kWh]
$E_{MinCharge}$	Minimum energy stored required in ESSs/EVs [kWh]
η_c	Charging efficiency of ESSs/EVs
η_d	Discharging efficiency of ESSs/EVs

Variables

OC_{Total}^{D+1}	Day-ahead operation cost [m.u.]
p_{DG}	Active power generation of DG unit [kW]
$p_{Supplier}$	Active power of external supplier [kW]
p_{LoadDR}	Active power reduction of loads [kW]
$p_{Discharge}$	Active power discharge of ESSs/EVs [kW]
p_{Charge}	Active power charging of ESSs/EVs [kW]
p_{NSD}	Active power of NSD of load [kW]
p_{GCP}	Generation curtailment power of DG units [kW]
p_{Sell}	Active power sold to market [kW]
E_{Stored}	Energy stored in ESS/EVs [kWh]
x_{DG}	Binary variable of state of DG units
$x_{Supplier}$	Binary variable of choosing suppliers
$x_{ESS/EV}$	Binary variable representing discharging state of ESSs/EVs
$y_{ESS/EV}$	Binary variable representing charging state of ESSs/EVs
x_{Market}	Binary variable that represents the choice of markets

Sets

Ω_{DG}^{d}	Set of dispatchable DG units
Ω_{DG}^{nd}	Set of non-dispatchable DG units

1. Introduction

The increasing number of renewable energy sources, such as wind and solar-based generation, positively contributes to the reduction of the carbon footprint of electricity generation. It also leads to independence from the fossil fuels in power generation. However, unlike the conventional generation units, renewable sources are characterized by a high level of uncertainty and variability. Another important feature of modern power systems is the increasing flexibility of customers, provided by controllable loads, i.e. non-critical loads that can be adjusted by the customer or by a third-party utility on a contractual basis to enable efficient management of the affordable resources. An example of such loads is Electric Vehicle (EV). In contrast to other types of loads, EVs can be connected to different locations, thus increasing the level of uncertainty [1]. An advanced scheduling model taking into account these factors is important. In fact, one of the top R&D needs identified by department of energy in United States is to have robust control and predictive models to deal with the stochastic behavior [2]. The motivation of establishing a stochastic modeling framework is associated with the increasing challenge of addressing the uncertainty of energy resources in smart distribution networks and microgrids [3]. These resources' share is significantly increasing and can constitute a large portion of the total generation portfolio. In this context, the entities related with the Energy Resources Management (ERM), such as energy aggregators [4], need adequate tools to tackle the increasing level of uncertainty.

The topic of energy scheduling in smart grids using stochastic methods is still in its infancy. Several works have been reported in the literature, mainly focusing on deterministic operation [5–11]. At the transmission-level, the stochastic energy management has demonstrated good results in taking into account the uncertainty associated with renewables and worst-case scenarios [12–15]. However, at the distribution and microgrid levels more advances are needed. The work presented in [1] regards a two-stage stochastic formulation to address the energy scheduling in MicroGrids (MG) with Distributed Generation (DG), EVs and Energy Storage Systems (ESS). The model solves the day-ahead energy scheduling using a linear formulation without network constraints and not considering Vehicle-To-Grid (V2G). An iterative approach is used to validate the network constraints with a power flow software returned from the master linear problem. Several scenarios were considered only for wind and solar power, while the EVs' behavior, load demand and hourly market prices are considered deterministically. In [4], an optimal bidding strategy for EV aggregator is formulated under uncertainty in day-ahead context to minimize charging costs while satisfying EVs' demand. V2G possibility of EV aggregators is not modeled in the paper. The day-ahead stochastic scheduling method presented in [13] considers the hourly forecast errors of wind energy and system load. The work is developed for a conventional generation system with wind energy, but at transmission network side. In [16], the authors develop a stochastic energy scheduling model for a local smart grid system with a single energy source and several consumers. The problem is transformed into an easier and simple optimization in order to be used in a distributed and real-time environment. The uncertainty in the fuel cell outages is considered in the optimization model developed in [17] to perform the battery scheduling of a MG. The stochastic model results indicate that a conservative yet more lucrative solution is obtained, resulting in potential savings exceeding 6%. In [18], an optimal day-ahead scheduling is formulated for a microgrid. The model proposed by the authors is a two-stage stochastic formulation to cope with the intermittent nature of the renewable energy while exploiting the thermal dynamic characteristics of the buildings. Recently, in [19], a two-stage stochastic model is proposed to address the centralized ERM in hybrid AC/DC microgrids considering DGs, ESS and EVs and uncertainty in regular and EV demand, renewable generation, and fluctuating electricity prices. However, the possibility of DR is not considered in the referred work. Furthermore, evaluated it considers a smaller grid system (38-bus) with only 8 DG units. Their work is more oriented for smaller hybrid AC/DC grids whereas our model is devised for larger smart grids and tested with a real 201-bus system. Their model is mixed integer nonlinear whereas ours is mixed integer linear to increase computational performance. The works presented in [20,21] address the day-ahead resource scheduling of a renewable-based virtual power plant. The work considers uncertainties in price, load demand and renewables but fails to consider the possibility of DR, EVs and V2G. A specific work regarding stochastic energy management using compressed air storage integrated with renewable generation is studied in [22]. In [23], authors provide a robust optimization for scheduling optimization considering uncertainties. These works [20–23] demonstrate that it is possible to mitigate system uncertainties with adequate use of energy resources, namely ESS systems. However, these works do not consider EVs and its related uncertainties, which are a relevant feature of future grids. In [24] a two-stage stochastic offering model for a VPP is presented. The model considers an intermittent source, a dispatchable and a storage unit. The VPP trades in the day-ahead and balancing markets, while the uncertainty is considered in the market price and intermittent generation. In [25], a two-stage robust optimization approach is used to deal with uncertainties in wind power and market price of a VPP participating in both day-ahead and real-time markets. Authors indicate that their approach is suitable to represent the uncertain data, but suggest stochastic programming could be used and compared as future work. In [26], a multi-stage risk-constrained stochastic complementarity approach is proposed for wind power producers to tackle uncertainties in wind, market prices, demands' bids and rivals' offers using a set of scenarios. The results reveal that the expected profit increases when a strategic position is adopted, while taking a risk-averse position decreases the expected profit by a small margin. Authors claim they use a computer with 250 GB of RAM to tackle the optimization problem. They suggest that the model may be decomposable and subject of future research. These works [24–26] are more concerned in the market interaction, namely the VPP risk and strategy than the energy resources scheduling, particularly of large-scale nature.

These works reveal some gaps that require additional attention. Uncertainty on wind and solar generation are usually considered, while the variability of market prices and load demand is frequently overlooked. Moreover, when formulating the energy scheduling from the viewpoint of an EV aggregator, the uncertain problem is formulated without considering the V2G possibility. Furthermore, Demand Response (DR) is not considered in most of the studied works and the case studies are relatively small in terms of optimization problem size, therefore lacking realism. This paper presents a stochastic programming approach for ERM in a smart distribution network, in the context of Smart Grids (SG) considering several forms of energy resources, including DR. The proposed model formulates the uncertainty in regular load demand, wind and photovoltaic (PV) power, EVs demand and location. In addition, the variability of market prices is considered in the model. The energy aggregator aims to minimize the expected operation cost while managing Distributed Energy Resources (DER), including DG (e.g. Wind, PV, and biomass), EV with V2G possibility, ESS, electricity supplier contracts, market transactions and DR. Thus, the proposed integrated energy management model with the several sources of uncertainty is innovative in the literature. Table 1 summarizes the features found in the studied references regarding sources of uncertainty considered and the features present in the models.

Table 1. Summary of the contributions regarding revised papers

Ref.	**Model includes**			**Sources of uncertainty**
	V2G	**DR**	**ESS**	
[1]	No	No	Yes	Only in wind and PV
[4]	No	No	No	Driving patterns and market bids
[13]	No	Yes	No	Only in wind
[16]	No	No	No	Only in energy demand
[17]	No	No	Yes	Only in the fuel cell outages
[18]	No	Yes	Yes	Load, renewable generation and electricity price
[19]	Yes	No	Yes	Load, renewable generation, EV demand and price
[20]	No	No	No	Renewable generation, load and electricity price
[21]	No	No	No	Renewable generation, load and electricity price
[22]	No	Yes	Yes	Wind/PV, load demand and market price
[23]	No	Yes	Yes	Wind/PV only
[24]	No	No	No	Wind, market bids and price rivals' offers
[25]	No	No	No	Wind and market price
[26]	No	No	Yes	Intermittent source and market price
Proposed work	**Yes**	**Yes**	**Yes**	All sources of uncertainty (Wind/PV, EVs, regular demand and market price)

Regarding previous works, the major contributions of this paper are as follows:

1) proposing a two-stage stochastic model for smart grids characterized by heterogeneous management of large-scale energy resources considering uncertainty in wind, PV, EV and market price integrated in the same model;

2) consideration of DR program in the two-stage stochastic model, and assessing its impacts when uncertainty is considered;

This paper is organized in five main sections: after this introduction, section 2 presents more details about the stochastic model approach and describes the two-stage stochastic formulation, section 3 describes the test system, while the results of the case study and the discussion are presented in section 4. Finally, section 5 presents the conclusions.

2. Stochastic Model

The energy scheduling problem is formulated in this section as a two-stage stochastic model. Theoretical background on two-stage or multi-stage stochastic programming models can be found in [27]. The idea is to make an optimal decision in the first stage, on the day-ahead energy transactions, while taking into account possible real-time operations like the wind, solar power and EVs' uncertainty, in the second stage. The objective is to minimize the expected operation costs, by reducing the risk of energy transactions for the energy aggregator. With the proposed model, it is possible to obtain the amount of electricity to be purchased from the electricity suppliers, the sale of energy to the market and the commitment of the dispatchable DG units over the next 24 hours. To achieve this, a scenario based approach is used to model the underlying uncertainty. It means that wind and solar generation or the load demand varies from one scenario to another. The first-stage decisions do not change across the scenarios in the second stage, i.e. the variables without uncertainty remain the same for every scenario.

2.1. Uncertain data

In stochastic programming problems, the stochastic processes are represented with continuous or discrete random variables. Dealing with a finite set of possible outcomes is the adopted way in decision-making problems under uncertainty, otherwise it would be impossible to solve the problem [28]. An appropriate representation of a continuous random variable using a finite set of values can be difficult. Scenarios can be generated using different techniques, including path-based methods, moment matching, internal sampling and scenario reduction [28]. Different realizations of the random variables can be represented by arcs in a scenario tree. The probability of a scenario to occur is the product of the probabilities associated with the arcs. The sum of the probabilities of the generated scenarios is equal to 1. Figure 1 presents a simple example of one scenario tree with 5 scenarios and 10 nodes. Node 6 (*n*6) corresponds to scenario 1 and its probability results from the product of nodes *n*2, *n*3.

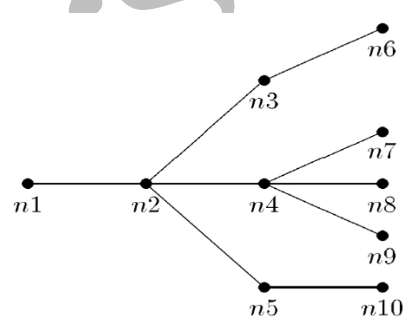


Fig.1. Scenario tree with 5 scenarios and 10 nodes [29]

In order to improve computational performance, scenario reduction is usually applied to downsize a scenario set while keeping stochastic information as intact as possible. Scenario reduction techniques start with a large set of randomly generated scenarios. The large set is reduced to a small set trying to maintain the original probability distribution function. In other words, it would be possible to measure the quality of the reduction process by comparing the optimal solution obtained with the reduced set and with the original set. If the solutions are close enough, it means that a good reduction has been obtained. Nevertheless, this comparison is only possible for small instances due to computational limitations.

The ERM problem under study involves several sources of uncertainty in the input data, namely in the load demand, market price, wind and solar generation forecasts. Moreover, the presence of EVs poses an additional source of uncertainty in the ERM problem, because trips and energy demand of EVs depend on the users' behavior, which is not easy to predict. The aggregator requires knowing the timing of the trips and the associated expected energy consumption, as well other parameters, such as battery size. This means that the drivers would need to notify the aggregator of their planned trips in advance, or eventually machine learning algorithms could be used to forecast driving needs [4].

The lack of realistic historical data is a barrier to actually build accurate case studies. Hence, most of the time, forecasts and associated errors are assumed based on previous experiences, trying to simulate real-world behavior. The stochastic model is used assuming that a correct set of scenarios can be generated considering future availability of such historical data. In fact, scenario generation is a broad topic that is beyond the scope of this paper. Nevertheless, in the current literature, some authors have presented possible approaches that can be implemented in scenario generation tools in control centers for the ERM. In [1], Monte Carlo Simulation (MCS) is used to capture the uncertainty of the wind power forecast. A scenario reduction technique is used to reduce the number of scenarios generated. Furthermore, they assume that solar scenarios forecast errors follow a normal distribution. The authors finally consider 10 independent scenarios for the wind generation and another 10 scenarios for the solar generation, which results in 100 scenarios with an equal probability of 0.01. A traffic simulation is used in [4] to observe arrival, departure times and energy consumption for each vehicle. The authors model the arrival, departure time and trip consumption as stochastic variables using exemplary distributions. By using these distributions, it is possible to generate different realizations of the driving pattern for each individual vehicle. Authors in [30] use the statistical nonparametric bootstrap method as an alternative to MCS to account for the EVs charging temporal uncertainties.

2.2.Implementation requirements

The proposed model is one-step forward towards an effective energy management of the future smart grid. The optimization can be implemented in real-world cases once the main pillars of smart grid are developed, i.e., technology, policy and standards. It is assumed that the infrastructure has the following characteristics:

1) the smart distribution grid and microgrids are independent entities that are able to manage its assets, local DERs and energy supply;
2) the advanced metering infrastructure is in place with communication capability to allow the broadcast of the electricity market prices for the next 24 hours;
3) the control center can communicate with the local controllers of DERs and is equipped with an energy management system, in which the proposed model can be implemented;
4) the energy management system runs the two-stage stochastic optimization routine every 24 hours and has forecasting and scenario generation tools required to run the model;
5) in the considered model the energy aggregator does not buy energy to the market, instead it buys from external supplier with fixed contract price;
6) Generation curves and hot/cold start-up constraints of the small dispatchable generation units are not considered in the present model.

2.3. Objective function

The objective function $E\left(OC_{Total}^{D+1}\right)$, which represents the expected day-ahead operation costs in monetary units (m.u.), is minimized over the scheduling horizon T (1). The scheduling horizon covers the 24 hours of the next day. The first stage variables correspond to the dispatchable DG units, suppliers and market bids. Second stage variables are clearly identified in the formulation when the z index is present in the variables' subscript.

$$\text{Minimize } E\left(OC_{Total}^{D+1}\right)=$$

$$\sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum\limits_{i\in\Omega_{DG}^{d}} p_{DG(i,t)}\cdot C_{DG(i,t)}+\\ \sum\limits_{s=1}^{N_s} p_{Supplier(s,t)}\cdot C_{Supplier(s,t)}\end{array}\right)\cdot\Delta t\right]+\sum_{z=1}^{Z}\sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum\limits_{i\in\Omega_{DG}^{nd}} p_{DG(i,t,z)}\cdot C_{DG(i,t)}+\\ \sum\limits_{l=1}^{N_l} p_{LoadDR(l,t,z)}\cdot C_{LoadDR(l,t)}+\\ \sum\limits_{e=1}^{N_e} p_{Discharge(e,t,z)}\cdot C_{Discharge(e,t)}+\\ \sum\limits_{v=1}^{N_v} p_{Discharge(v,t,z)}\cdot C_{Discharge(v,t)}+\\ \sum\limits_{l=1}^{N_l} p_{NSD(l,t,z)}\cdot C_{NSD(l,t)}+\\ \sum\limits_{i=1}^{N_i} p_{GCP(i,t,z)}\cdot C_{GCP(i,t)}\end{array}\right)\cdot\pi(z)\cdot\Delta t\right]- \tag{1}$$

$$\sum_{z=1}^{Z}\sum_{t=1}^{T}\left[\sum_{m=1}^{N_m} p_{Sell(m,t)}\cdot MP_{Sell(m,t,z)}\cdot\pi(z)\cdot\Delta t\right]$$

2.4. Stochastic model constraints

The constraints incorporate the multi-period equations for EV charging and discharging rates, battery capacity and balance considering predicted demand and location, technical limits of ESSs, balance and capacity in each period, dispatchable DG capacity and supplier's limits. In addition, the DR is considered in the constraints, namely the maximum amount of power reduction of each load. It is important to note that some of the constraints spread across all scenarios, like the energy balance equation. However, there are few constraints that are not dependent on the variation of the scenarios, e.g. the limits of the dispatchable generation.

1) Energy balance

The balance constraint (2) is included in the proposed model. The amount of generated energy should equal the amount of consumed energy at every instant *t*. In the proposed model, balance equation (2) is a multi-period, multi-scenario equation as the balance must be satisfied not only for each period *t* but also within the different scenarios *z*. Compared with the deterministic counterpart, the stochastic model has a much higher number of energy balance constraints. The equation terms include the dispatchable DG generation, the acquisition of energy with external suppliers, the non-dispatchable DG forecast, the load demand (subtracting the scheduled demand response or the "non-desirable" not supplied demand), the EVs charge and discharge, and the storage charge and discharge. Finally, the market sale is added to the balance. The result of this equation as represented should be zero. The stochastic balance constraint will validate if the first stage variables can match the load balance among the different scenarios *z* as follows:

$$\begin{aligned}
&\sum_{i\in\Omega_{DG}^{d}} p_{DG(i,t)} + \sum_{s=1}^{N_s} p_{Supplier(s,t)} + \sum_{i\in\Omega_{DG}^{nd}} \left(p_{DG(i,t,z)} - p_{GCP(i,t,z)}\right) + \\
&\sum_{l=1}^{N_l} \left(p_{NSD(l,t,z)} + p_{Load\,DR(l,t,z)} - p_{Load(l,t,z)}\right) + \sum_{v=1}^{N_v} \left(p_{Discharge(v,t,z)} - p_{Charge(v,t,z)}\right) + \\
&\sum_{e=1}^{N_e} \left(p_{Discharge(e,t,z)} - p_{Charge(e,t,z)}\right) - \sum_{m=1}^{N_m} p_{Sell(m,t)} = 0 \qquad \forall t, z
\end{aligned} \tag{2}$$

2) DG units and external supplier

A binary variable is used to represent the commitment status of dispatchable DG units. A value of 1 means that the unit is connected. Maximum and minimum limits for active power in each period *t* can be formulated as:

$$x_{DG(i,t)} \cdot P_{DGMinLimit(i,t)} \leq p_{DG(i,t)} \leq x_{DG(i,t)} \cdot P_{DGMaxLimit(i,t)} \qquad \forall t, \forall i \in \Omega_{DG}^{d} \tag{3}$$

$$p_{DG(i,t,z)} = P_{DGScenario(i,t,z)} \qquad \forall t, \forall i \in \Omega_{DG}^{nd}, \forall z \tag{4}$$

The upstream supplier maximum limit in each period t regarding active power can be formulated as:

$$x_{\text{Supplier}(s,t)} \cdot P_{SMinLimit(s,t)} \leq p_{Supplier(s,t)} \leq x_{\text{Supplier}(s,t)} \cdot P_{SMaxLimit(s,t)} \qquad \forall t, \forall s \tag{5}$$

3) Energy storage systems

The constraints for the ESS (batteries) are described below. The ESS charge and discharge cannot be simultaneous. Therefore, two binary variables guarantee this condition for each ESS:

$$x_{ESS(e,t,z)} + y_{ESS(e,t,z)} \leq 1 \qquad \forall t, \forall e, \forall z \tag{6}$$

The battery balance for each ESS can be formulated as:

$$\begin{aligned} E_{Stored(e,t,z)} &= E_{Stored(e,t-1,z)} + \\ \eta_{c(e)} \cdot p_{Charge(e,t,z)} \cdot \Delta t &- \frac{1}{\eta_{d(e)}} \cdot p_{Discharge(e,t,z)} \cdot \Delta t \qquad \forall t, \forall e, \forall z \end{aligned} \tag{7}$$

The maximum discharge limit for each ESS can be represented by:

$$p_{Discharge(e,t,z)} \leq P_{DischargeLimit(e,t,z)} \cdot x_{ESS(e,t,z)} \qquad \forall t, \forall e, \forall z \tag{8}$$

The maximum charge limit for each ESS can be represented by:

$$p_{Charge(e,t,z)} \leq P_{ChargeLimit(e,t,z)} \cdot y_{ESS(e,t,z)} \qquad \forall t, \forall e, \forall z \tag{9}$$

The maximum battery capacity limit for each ESS can be represented by:

$$E_{Stored(e,t,z)} \leq E_{BatCap(e)} \qquad \forall t, \forall e, \forall z \tag{10}$$

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

$$E_{Stored(e,t,z)} \geq E_{MinCharge(e,t,z)} \quad \forall t, \forall e, \forall z \tag{11}$$

4) Electric vehicles

The charge and discharge of each EV is not simultaneous. Two binary variables are needed for each vehicle that can be represented by:

$$x_{EV(v,t,z)} + y_{EV(v,t,z)} \leq 1 \qquad \forall t, \forall v, \forall z \tag{12}$$

Battery balance for each EV. The energy consumption for period t travel has to be considered jointly with the energy remaining from the previous period and the charge/discharge occurred in the period:

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

When connected to the grid the vehicle cannot discharge to the grid more than the admissible rate. The discharge limit for each EV considering battery discharge rate can be formulated as:

$$p_{Discharge(v,t,z)} \leq P_{DischargeLimit(v,t,z)} \cdot x_{EV(v,t,z)} \qquad \forall t, \forall v, \forall z \tag{14}$$

When connected to the grid the vehicle cannot charge more than the admissible safety rate. The charge limit for each EV considering battery charge rate can be formulated as:

$$p_{Charge(v,t,z)} \leq P_{ChargeLimit(v,t,z)} \cdot y_{EV(v,t,z)} \qquad \forall t, \forall v, \forall z \tag{15}$$

The maximum battery capacity limit for each EV can be represented by:

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

Another important aspect is the minimum stored energy to be guaranteed at the end of period t. This can be seen as a reserve energy (fixed by the EVs' users or estimated by the operator) that can be used for a regular travel or an unexpected travel in each period t:

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

5) Demand response

Equation (18) formulates a DR model, namely direct load control, in which the consumer receives an incentive if their load is reduced. The maximum amount that each load l can be reduced in each period t in scenario z , can be formulated as:

$$p_{LoadDR(l,t,z)} \leq P_{LoadDRMaxLimit(l,t)} \qquad \forall t, \forall l, \forall z \tag{18}$$

6) Market

The stochastic model is compatible with the possibility to make offers in several markets, for instance in the wholesale market and/or the local energy markets [31]. The energy aggregator may desire to keep its market offers within certain limits or a given market may have a minimum required amount to access. Therefore, the market offers are constrained by (19) and (20), namely maximum and minimum offer:

$$p_{Sell(m,t)} \leq P_{MarketOfferMax(m,t)} \cdot x_{Market(m,t)} \qquad \forall t, \forall m \tag{19}$$

$$p_{Sell(m,t)} \geq P_{MarketOfferMin(m,t)} \cdot x_{Market(m,t)} \qquad \forall t, \forall m \tag{20}$$

2.5.Solution Algorithm

The formulated problem is a Mixed Integer Linear Programming (MILP), due to the presence of both continuous and integer variables and linear constraints. The MILP is implemented in TOMLAB, which is an advanced optimization toolbox for MATLAB [32], using CPLEX solver.

Several quality metrics can be used to appraise the interest of using stochastic programming models and to evaluate the value of having accurate forecasting procedures to obtain the most likely scenarios. The Expected value of Perfect Information (EVPI), described by (21), represents the quantity that the decision maker would need to pay to obtain perfect information about the future. z^{S*} is optimal objective function of the two-stage stochastic programming problem, and z^{P*} is the optimal objective function of the same problem when the nonanticipativity of decisions is relaxed. In this problem, which is known as the *wait-and-see* problem, all variables are defined as scenario-dependent [28].

$$\mathrm{EVPI} = z^{S*} - z^{P*} \tag{21}$$

The Value of Stochastic Solution (VSS) measures the economic advantage of using the stochastic programming approach over a deterministic problem (22). In order to obtain z^{D*}, the first step is to replace the uncertain parameters in the original two-stage problem with their expected values. After solving this deterministic problem, the first stage decision variables of the original problem are replaced with the optimal values obtained in the previous step. A new stochastic programming is obtained, and $z^{\mathrm{D}*}$ is the optimal objective function of this modified problem [28].

$$\mathrm{VSS} = z^{\mathrm{D}*} - z^{\mathrm{S}*} \tag{22}$$

3. Test System

The proposed methodology is tested using a case study implemented on a real distribution network with 201 buses. This network is part of the distribution grid in Zaragoza, Spain. Figure 2 depicts the single-line diagram of the 201-bus 11 kV distribution network [33]. Given the original network one optimal reconfiguration was obtained with the considered DGs, storage units and EVs. In this case study, the production and consumption values are modified to meet the expectations for year 2030. A high penetration of DG units was considered, corresponding to about 70% of the installed capacity, according to what is expected in 2030 [34]. Regarding DG, the photovoltaic installed capacity represents about 30%, wind represents 22 %, small hydro represents 11%, biomass represents 4% and the cogeneration represents 33%. Moreover, an approximate number of 1300 EVs was estimated to connect to this part of the distribution grid during a typical day, taking into account the expected rate of EVs' penetration (14%), in the fleet size of Spain for 2030 [35]. The mentioned penetration rate is the recommended value, according to [35], in order to understand the effects of mass integration of EVs in the different applications. The charging and discharging efficiency considered for EVs and ESS is 90% and the minimum state of charge in the end of day should be at least 30% (imposed by hard constraint (16)).

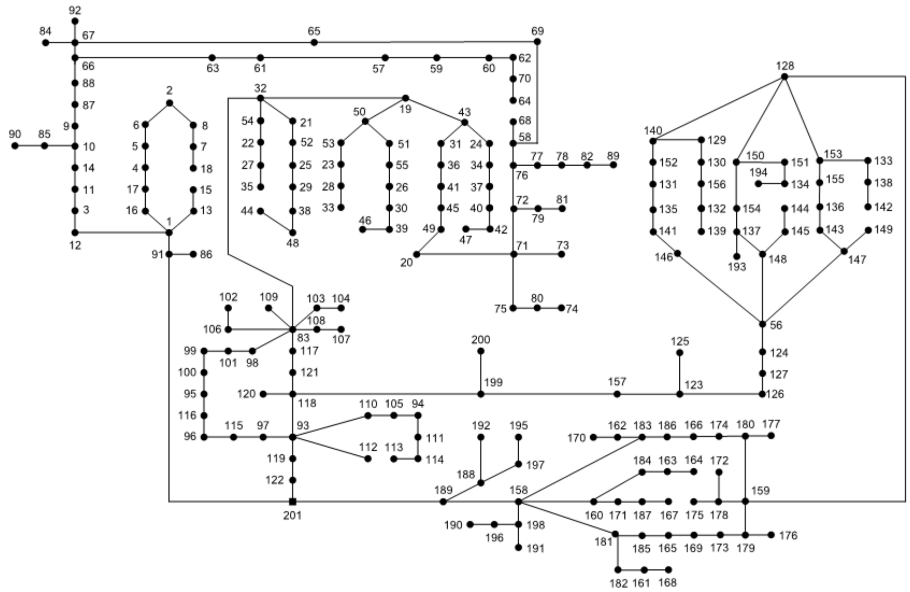


Fig.2. 201-bus MV network used in the case study (adapted from [33])

In this case study, the energy aggregator is able to manage 118 DG units, the energy bought from external supplier, 6 storage units, 1300 EVs[1], and 89 aggregated consumers with DR programs. It is assumed that the aggregator manages the customers in the area, using the proposed stochastic model, with the aim to minimize the expected operation costs. The scenario-based approach requires to have scenarios that catch the representative uncertainty in the data. Due to computational limitations, a simplified load balance and few representative scenarios are considered for each uncertain type of data, namely wind and solar energy production, as well as the EVs' travels and market prices. In this work, EVeSSi [36] was used to generate different samples of driving patterns using departure times, and locations as stochastic variables. Therefore, varying trip duration and energy consumption was obtained in each sample. Then, 3 representative samples of the obtained trips' realizations were chosen to be used in the scenario-based approach. For wind, solar

[1] 1300 EVs are aggregated in 100 equivalent units to reduce computational burden.

generation, and regular demand, 3 representative scenarios were generated based on the initial forecast available as well as the corresponding average error. These scenarios can be seen in Figures 3 and 4. The techniques learned from [37,38] have been used to generate these scenarios, namely MCS and clustering to track similarity features and reduce burden to 3 representative scenarios. The 3 representative EV scenarios can be seen in Figure 5.

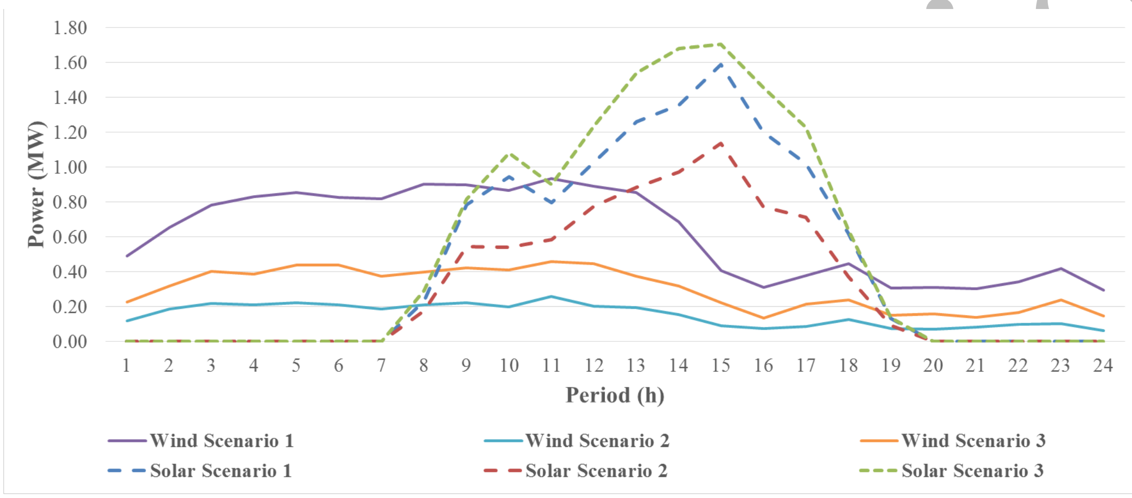


Fig.3. Wind and solar scenarios

In the case of the market price 2 different scenarios are considered as can be seen in Figure 6. In addition, only one market *m* was considered in this case study, namely the day-ahead market. Finally, equiprobable scenarios were built, using a scenario tree to obtain a set of 162 possible scenarios, i.e. combining each of the representative scenarios.

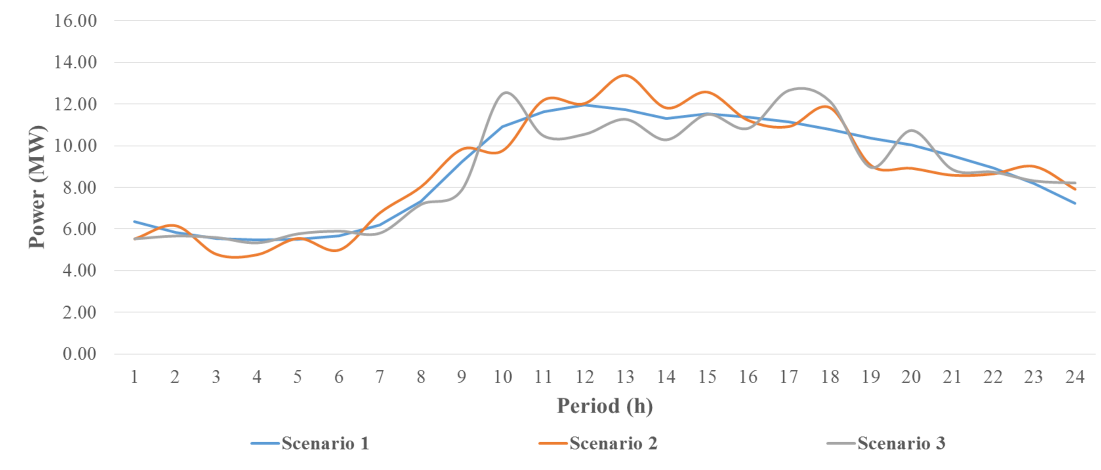


Fig.4. Regular load demand scenarios

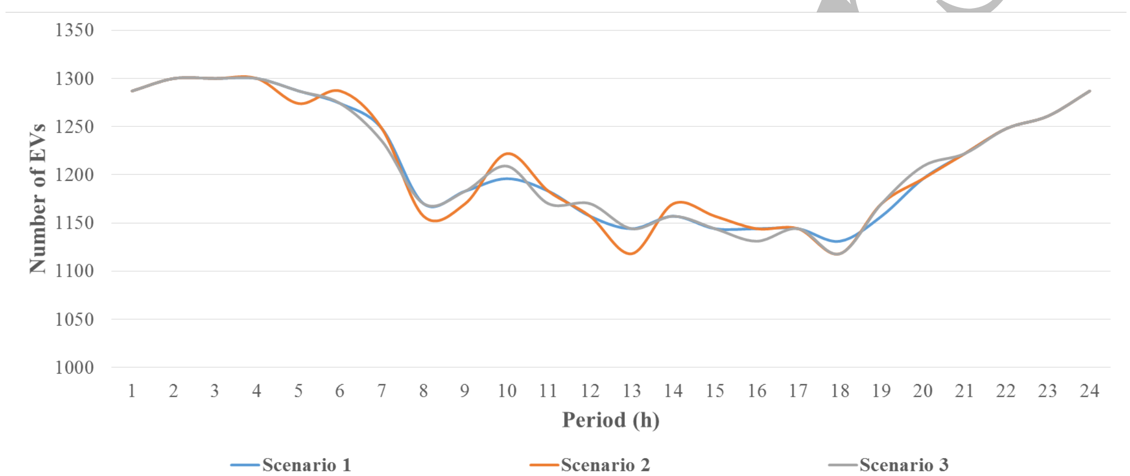


Fig.5. Electric vehicles scenarios: number of grid-connected EVs

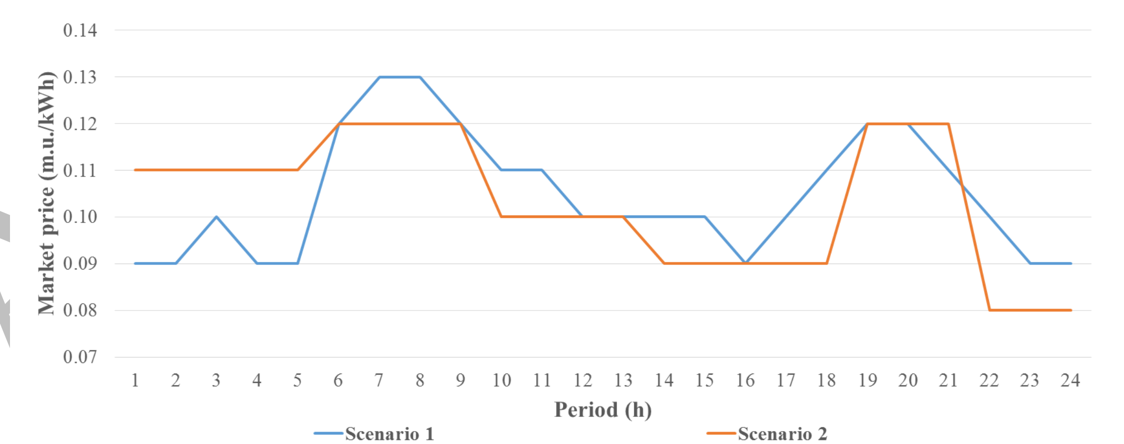


Fig.6. Market prices scenarios

Table 2 shows the energy resources data and prices. The information of price is depicted in monetary units per MWh (m.u./MWh).

Table 2. 201-bus grid scenario characterization

Energy resources		Prices (m.u./MWh) min – max	Capacity (MW) min – max	Forecast (MW) min-max	Units #
Biomass		150 – 150	0.00 – 0.52		1
CHP		100 – 120	0.00 – 4.00		4
Small Hydro		130 – 130	0.12 – 0.35		1
Photovoltaic		200 – 200		0.00 – 1.70	82
Wind		120 – 120		0.07 – 0.94	30
External Supplier		90 – 200	0.00 – 7.30		1
Storage	Charge	120 – 120	0.00 – 1.50		6
	Discharge	180 – 180	0.00 – 1.50		
Electric Vehicle	Charge	130 – 130	0.00 – 6.94		1300
	Discharge	190 – 190	0.00 – 6.16		
Demand Response	Reduce program	110 – 170	0.33 – 0.89		89
Load		90 – 150		4.77 – 13.88	168
Market		80 – 130	0.00 – 4.00		1

The prices in Table 2 have been designed according to [39]. The capacity column is the aggregated minimum/maximum availability of a given resource during the considered day in MW. Analogous the forecast column is the aggregated minimum/maximum predicted amount of a given resource or load during the considered day in MW. The aggregator has several contracts with different energy resources and consumption sources. The DG and ESS units are not owned by the aggregator in this case. The aggregator incurs in a cost when buying energy from the different energy resources at the contracted price and receives an income when selling energy.

Two different cases have been considered to compare the performance of the two-stage stochastic programming under different situations. Case 1 considers DR availability, while case 2 does not. The results discussion of these cases are described in the next section.

4. Results and Discussion

The proposed two-stage stochastic model is applied to the described case study in section 3, namely the 2 cases regarding DR availability. The dimension of the optimization problem is 3,802,992 variables (of which 824,424 integer) with 1,594,740 constraints (162 scenarios). The work was developed in MATLAB R2014a 64 bits using a computer with one Intel Xeon E5-1650 processor and 12 GB of RAM running Windows 8.1.

Figures 7 and 8 present the stochastic resource scheduling for cases 1 and 2, respectively. The scheduled generation (first stage decisions) concerning the external suppliers is respectively 138.27 MWh and 147.22 MWh for cases 1 and 2 (dark blue in the figure). The dispatchable generation scheduled is respectively 79.30 MWh and 81.08 MWh for cases 1 and 2. The uncertain dispatched amount, only certain in real-time (includes EVs, ESS and DR) is provided by the optimization and shown as blue-grey semi-transparent bars for each period, while the certain amount is a solid bar. As shown in the figures, the uncertainty is higher during daylight periods, namely between periods 9 and 20. This is due to the higher uncertainty in renewable generation, particularly in solar power.

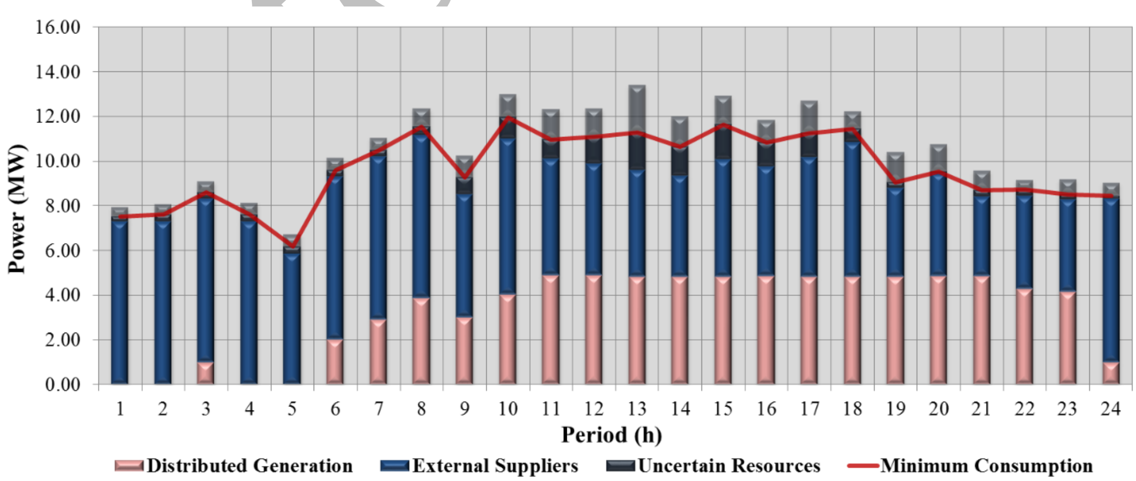


Fig.7. Stochastic energy resource scheduling for case 1 (with DR)

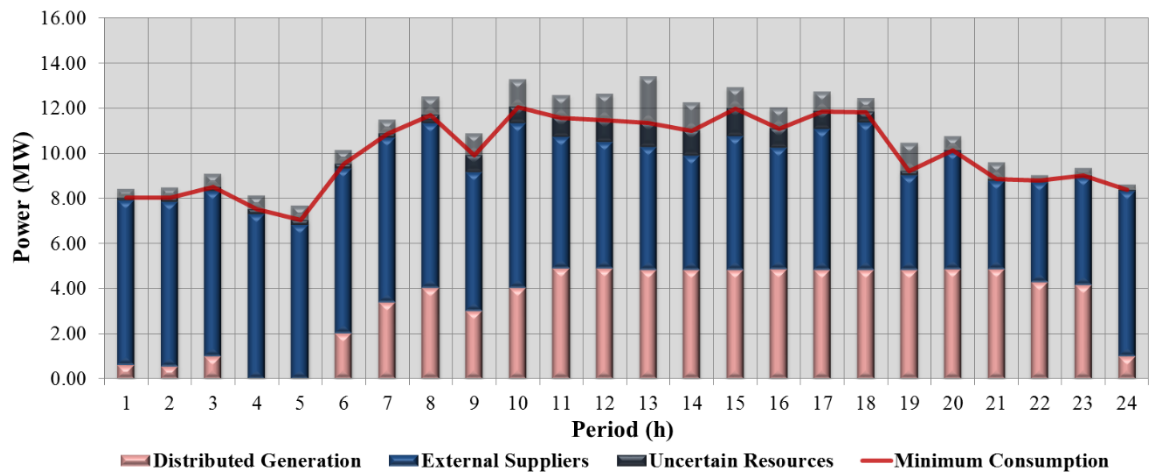


Fig.8. Stochastic energy resource scheduling for case 2 (no DR)

Figures 9 and 10 present the stochastic consumption scheduling for cases 1 and 2, respectively. The optimal values for the market purchases (in light blue) are same for all scenarios, namely 18.11 MWh and 14.82 MWh for cases 1 and 2, respectively. In case 2, there is a small possibility that NSD occurs in some scenarios (up to 0.53 MWh in period 13), depending on the available renewable energy production. This value could be higher in a traditional deterministic approach, which is not desirable.

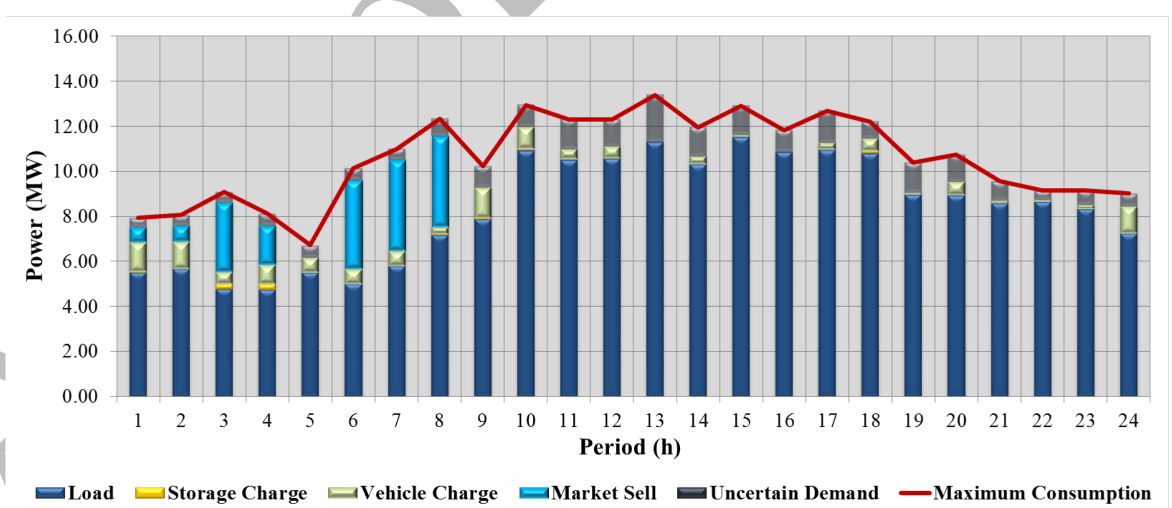


Fig.9. Stochastic consumption scheduling for case 1 (with DR)

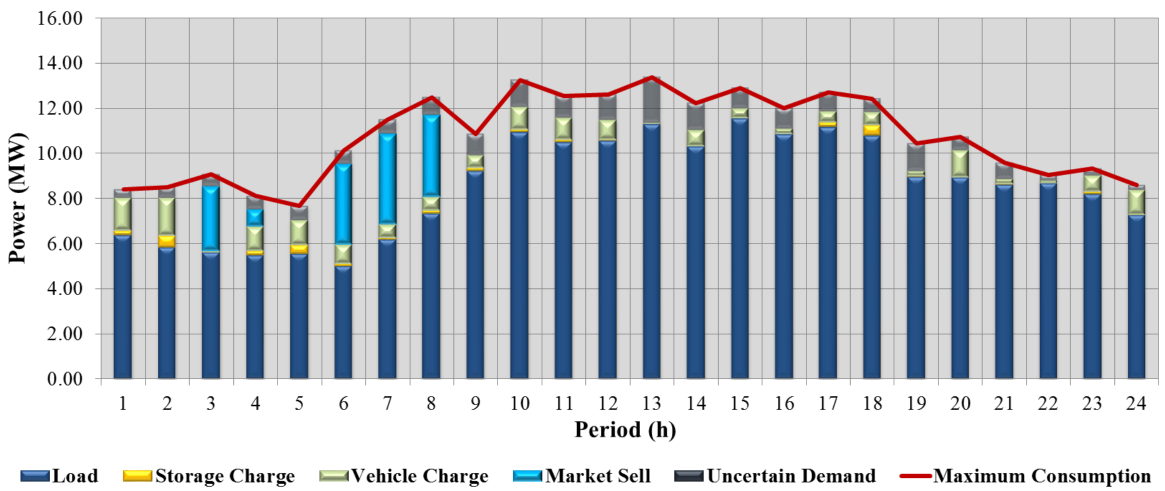


Fig.10. Stochastic consumption scheduling for case 2 (no DR)

Figures 11 and 12 present the stochastic energy resources for cases 1 and 2, respectively. It can be seen that there is a reasonable uncertainty in the variable renewable generation. This can lead to the use of DR in some scenarios. In case 2 there is no DR possibility, which can impact the use of ESS and EVs discharge (see Figure 12) when compared with case 1. In fact, this depends on the scenario, which means that the values can vary between the depicted minimum and maximum in the figures.

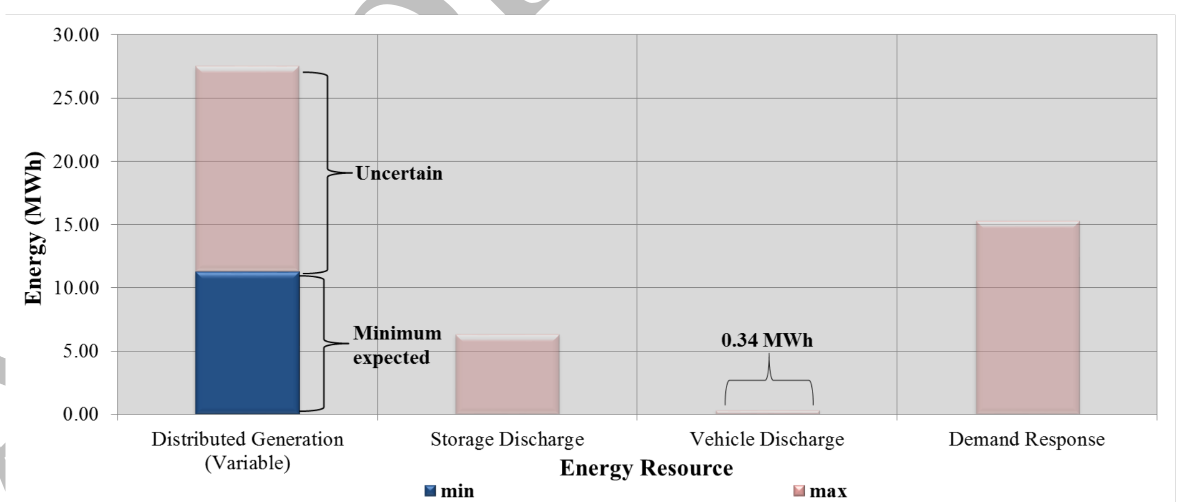


Fig.11. Stochastic scheduling of energy resources for case 1 (with DR)

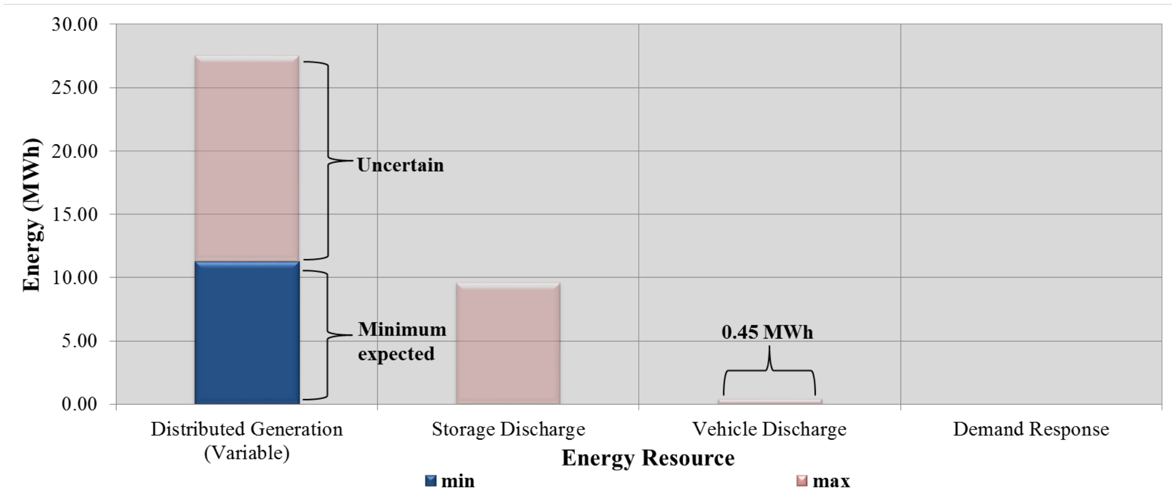


Fig.12. Stochastic scheduling of energy resources for case 2 (no DR)

Table 3 summarizes the obtained results in both cases for 162 and 81 scenarios (without market uncertainty). When DR is not available (case 2), the VSS, EVPI, and the expected total operation cost of the stochastic solution is higher. VSS reduces with DR up to just 2-3% of the expected costs. Without implementing DR programs, there is less flexibility from loads as it not possible to use it to mitigate generation imbalances. In this case, the cost is much higher with a deterministic approach in both 162/81 scenarios and the proposed model reduces the expected cost up to 17-19%. The higher EVPI in case 2 also indicates that the importance of the uncertainty ahead is higher. There is a small percentage difference regarding VSS and EVPI with or without market uncertainty. However, the expected operation cost (z^{S^*}) is higher with market uncertainty due to the imperfect information about future market price. Regarding the computational performance, execution times seem adequate for the decision maker, but due to the high number of variables, high memory use is expected (about 10 GB in case 2). The scenario without market uncertainty is considerably lighter in terms of computational burden, i.e. execution time is almost one third and memory use about half. This may suggest that memory use grows linearly with the number of scenarios. The indicated memory is the maximum peak during execution and usually lasts for a brief moment before stabilizing in lower values. For a higher number of scenarios, a server with 64GB or 128GB is advisable.

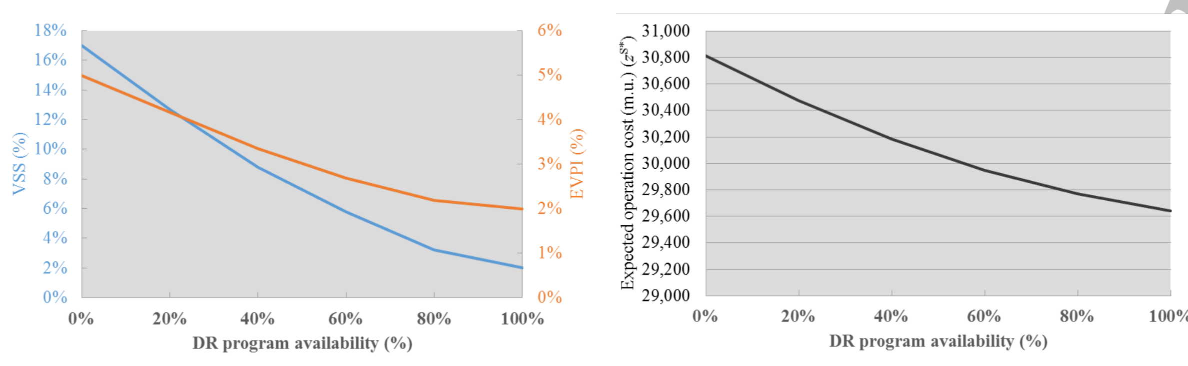
The results of VSS in general shows that stochastic modeling is more essential when the aggregator is not employing DR programs, because the gain obtained is higher. Additionally, EVPI reveals that having perfect information is more essential for the aggregator when they are not employing DR programs.

Table 3. Advantage of stochastic programming approach

Indicator	162 scenarios		81 scenarios (no market uncertainty)	
	Case 1 (with DR)	Case 2 (without DR)	Case 1 (with DR)	Case 2 (without DR)
VSS (m.u.)	607 (*2%*)	6259 (*17%*)	967 (*3%*)	6959 (*19%*)
EVPI (m.u.)	549 (*2%*)	1587 (*5%*)	503 (*2%*)	1340 (4%)
z^{S*} (m.u.)	29,639	30,814	29,174	30,147
z^{P*} (m.u.)	29,091	29,227	28,672	28,807
z^{D*} (m.u.)	30,246	37,073	30,141	37,106
Memory** (GB)	9.5	9.4	5.7	5.7
Execution time (s)	247	237	93	84

**Peak memory monitored using Windows resource monitor. Values may vary with system configuration and solvers.

Finally, a sensitivity analysis for the scenario with market uncertainty (162 scenarios) has been made to evaluate VSS and EVPI metrics under different DR availability. To simulate different DR availability, the limit represented by (18) has been modified from 0% to 100% using increments of 20%, then VSS and EVPI were calculated. Figure 13 shows VSS and EVPI percentages when DR availability was gradually incremented (a) and the reduction of the expected operation cost (b). Indeed, 100% availability corresponds to case 1 and 0% corresponds to case 2 already presented in this section. The VSS and EVPI percentage reduction is most noticeable in the 0-60% range, i.e. VSS declines from 17% to 6% while EVPI declines from 5% to 2.7%. Afterwards, the reduction is more gentle, but sill reducing to 2% for both VSS and EVPI with 100% DR availability. The reduction means that the advantage of the stochastic programming when DR is present is less noticeable but still positive. Another interpretation is that the results suggest that increasing DR availability further mitigate the impact of the uncertainty in the operation costs, by using DR resource as a way to balance the uncertainty effects.



a) b)

Fig.13. Sensitivity analysis regarding varying levels of DR availability (0% to 100%)

5. Conclusions

Wind and solar are increasingly being adopted in distribution networks. While it is true that they contribute to reduce the carbon footprint of power systems, it is also inevitable that they complicate planning and operation activities. This is mainly caused by the intermittency nature of these resources. Moreover, EVs impose an additional strain on the uncertainty level, because of their variable demand, departure time and physical location. Nevertheless, high flexible loads, DG and ESS can mitigate these issues. Energy aggregators can help by optimizing the available resources and anticipating to the several uncertainties.

This paper presented a new stochastic model with several uncertainty sources, including load demand variability, intermittency of wind and PV generation, EVs stochastic demand and location and market price in the same model. The results reveal that the stochastic programming can be used as an efficient approach to deal with the uncertainty in ERM. In the tested cases, the method appears to be more advantageous, compared to deterministic counterpart, particularly in situations with higher risks for the aggregator's operation, such as limited flexibility, i.e. no DR. Indeed, the case study revealed that DR allowed to reduce the impact of uncertainties, namely achieving reductions of 4% in operation costs, 90% in VSS and 65% in EVPI indicators considering market price uncertainty. The VSS and EVPI reductions observed in the presented cases and the sensitivity analysis suggests that the sources of uncertainty have less impact on the expected operation costs, when DR is present.

Acknowledgements

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