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Robust Energy Resource Management Incorporating Risk Analysis Using Conditional Value-at-Risk

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ABSTRACT The energy resource management (ERM) problem in today's energy systems is complex and challenging due to the increasing penetration of distributed energy resources with uncertain behavior. Despite the improvement of forecasting tools, and the development of strategies to deal with this uncertainty (for instance, considering Monte Carlo simulation to generate a set of different possible scenarios), the risk associated with such variable resources cannot be neglected and deserves proper attention to guarantee the correct functioning of the entire system. This paper proposes a risk-based optimization approach for the centralized day-ahead ERM taking into account extreme events. Risk-neutral and risk-averse methodologies are implemented, where the risk-averse strategy considers the worst scenario costs through the conditional value-at-risk (*CVaR*) method. The model is formulated from the perspective of an aggregator that manages multiple technologies such as distributed generation, demand response, energy storage systems, among others. The case study analysis the aggregator's management inserted in a 13-bus distribution network in the smart grid context with high penetration of renewable energy and electric vehicles. Results show an increase of nearly 4% in the day-ahead operational costs comparing the risk-neutral to the risk-averse strategy, but a reduction of up to 14% in the worst-case scenario cost. Thus, the proposed model can provide safer and more robust solutions incorporating the CVaR tool into the day-ahead management.

INDEX TERMS Aggregator, conditional value-at-risk, energy resource management, risk-based optimization, uncertainty.

NOTATION

Binaries:

x^{DG}	State of DG units.
x^{ext}	State of external supplier units.

Indices:

e	Energy storage system (ESS) unit.
ex	Extreme scenarios.
i	Distributed generator (DG) unit.
k	External supplier unit.
l	Load unit.
m	Electricity market.
r	Consumption energy resource unit.
s	Scenarios.
t	Time period.
v	Electric vehicle (EV) unit.

Parameters:

α	Confidence level.
β	Risk aversion factor.
Δt	Period resolution (hour).
η^{c}	Charging efficiency of ESSs and EVs.

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η^{d} Discharging efficiency of ESSs and EVs.
ρ_s Scenario probability.
C^{Curt} Cost of load curtailment (m.u./MWh).
C^{DG} Cost of DG unit generation (m.u./MWh).
C^{ENS} Cost of energy not supplied (m.u./MWh).
C^{ext} Cost of external supplier unit generation (m.u./MWh).
C^{GCP} Cost of excess generation (m.u./MWh).
E^{BatCap} Battery capacity of ESSs and EVs (MWh).
E^{MinC} Minimum energy required for ESSs and EVs (MWh).
ESS^{MaxC} Maximum active charging power of ESSs (MW).
ESS^{MaxD} Maximum active discharging power of ESSs (MW).
$ESSC^{\mathrm{Disch}}$ Cost of ESS unit discharge (m.u./MWh).
EV^{MaxC} Maximum active charging power of EVs (MW).
EV^{MaxD} Maximum active discharging power of EVs (MW).
EVC^{Disch} Cost of EV unit discharge (m.u./MWh).
MP Electricity market prices (m.u./MWh).
N_k, N_i, N_e Number of external suppliers/DGs/ESSs.
N_m, N_s, N_{ex} Number of markets/scenarios/extreme scenarios.
N_v, N_l, N_r Number of EVs/loads/resources.
$P^{\mathrm{DG}_{\mathrm{min/max}}}$ Minimum and maximum active power generation of DG unit (MW).
$P^{\mathrm{DG}_{\mathrm{nd}}}$ Forecasted active power generation of non-dispatchable DG unit (MW).
$P^{\mathrm{ext}_{\mathrm{min/max}}}$ Minimum and maximum active power generation of external supplier unit (MW).
P^{load} Forecasted active power of load unit (MW).
P^{MaxB} Maximum active power bid in electricity market (MW).
P^{MaxDR} Maximum active load reduction power (MW).
P^{MaxS} Maximum active power offer in electricity market (MW).
T Number of periods.

Sets and subsets:

Ω_{DG} Set of DG units.
$\Omega_{\mathrm{DG}}^{\mathrm{d}}$ Subset of dispatchable DG units.
$\Omega_{\mathrm{DG}}^{\mathrm{nd}}$ Subset of non-dispatchable DG units.

Variables:

$CVaR_\alpha$ Conditional value-at-risk (m.u.).
E^{stored} Stored energy in ESSs and EVs (MWh).
ESS^{cost} Total discharging cost of ESS unit (m.u.).
ESS^{Power} Active power of ESS unit (MW).
EV^{cost} Total discharging cost of EV unit (m.u.).
EV^{Power} Active power of EV unit (MW).
OF Objective function costs (m.u.).
P^{Curt} Active power reduction of load unit (MW).
P^{DG} Active power generation of DG unit (MW).
P^{ENS} Active power of non-supplied demand (MW).
P^{ext} Active power generation of external supplier unit (MW).
P^{GCP} Active excess power of DG unit (MW).
P^{Market} Active power traded in the market (MW).
P_s Penalty for bound violation (m.u.).
VaR_α Value-at-risk (m.u.).
Z^{Ex} Expected cost (m.u.).
Z_s^{In} Scenario revenue (m.u.).
Z_s^{OC} Scenario operational costs (m.u.).
Z_s^{tot} Total scenario costs (m.u.).

I. INTRODUCTION

The The current evolution of energy management systems, supported by modern smart grid technologies, foresees a significant penetration of fluctuating renewable generation. The increased adoption of these types of generation helps European (and consequently worldwide) targets to counteract climate issues, expecting to achieve a 27% share of renewable generation in addition to a 40% of greenhouse gases reduction in Europe by 2030 [1].

Renewable generation, either solar or wind types, is usually weather-dependent. Therefore, their management has always associated an uncertain variability that jeopardizes the operation of the entire energy chain [2]. One solution to consider such uncertainties is to rely upon the accuracy of forecasting techniques, assuming a low degree of error (or none at all) in the predictions. Unfortunately, different works use this assumption in the mathematical formulation of the problem, oversimplifying the model to a level in which their application into real-world scenarios is not realistic [3], [4]. Other solutions search to handle technical constraints considering active control and the use of flexible devices such as energy storage systems or demand respond [5]–[8]. However, these types of solutions mitigate the uncertainties to some degree and do not consider extreme scenarios that might still occur in the day-ahead operation.

In this context, an energy management system should be both reliable and resilient, operating as expected in the case of events with a high probability of occurrence and a reasonably small effect (e.g., reliable under different faults in the power system), and prepared to deal with events that despite a low probability, have a considerable influence in the outcome of the operation (e.g., resilient to extreme events such as hurricanes, thunderstorm, etc.) [9].

Recently, energy management models are incorporating risk-based methods to handle the uncertainty associated with variable parameters. For instance, some works have included the value-at-risk (*VaR*) in their formulations, a concept widely used in economics to measure the risk of an investment [10], [11]. The *VaR* parameter is a statistical mechanism that allows measuring the losses associated with a portfolio over time with a given confidence level. In other words, the *VaR* parameter opens the possibility of finding solutions that are resilient to the occurrence of extreme scenarios (i.e., scenarios with a high variation and a low probability of occurrence) [12].

Although *VaR* is a suitable tool for risk analysis, one of its significant drawbacks lies in considering extreme scenarios that might occur beyond the established confidence level. To overcome this drawback, the concept of conditional *VaR* (*CVaR*) was introduced as an extension of *VaR*, allowing the evaluation of risk when least likely scenarios, beyond the confidence level, occur [13]. The *CVaR* provides higher security, protecting the investor against extreme scenarios at a higher cost. From the perspective of optimization, the *CVaR* transforms the problem into a Pareto optimization with two objectives: the expected return and the inherent risk of a given solution. Although *CVaR* is a concept widely associated with the economy and its aspects, some literature is adopting this strategy in the field of electric power systems, considering, for instance, the return as the aggregator costs and the risk associated with the management of renewable generation among other uncertain parameters [14]–[16].

In this work, we model the energy resource management (ERM) problem under uncertainty of renewable generation, load consumption, market prices, and electric vehicles (EVs) trips [7], [17]. The stochastic behavior of these parameters is considered through various scenarios associated with a probability of occurrence. The novelty of our approach lies in the incorporation of risk strategies into the formulation, allowing the aggregator to plan its operation considering different degrees of risk associated with diverse scenarios (risk-neutral and risk-averse considerations). The contributions of this work are as follows:

- a day-ahead ERM model considering uncertainties of renewable generation, load consumption, market prices, and EVs trips.
- incorporation of risk analysis strategies using *VaR* and *CVaR* measures in the mathematical formulation of the ERM problem to deal with the uncertainty of parameters. In this way, we aim at getting solutions that protect the aggregator against extreme scenarios creating a unique optimization model considering a large number of distributed energy resources (DER).
- implementing a solution method based on modern metaheuristic optimization to deal with the computational burden of considering diverse possible scenarios of uncertain parameters and the large number of variables considered.
- analyzing the impact of *VaR* and *CVaR* measures over a set of case studies using real power and energy systems data.

In this article, we hypothesize that the incorporation of risk parameters into the formulation results in solutions that, despite their higher cost, protect the aggregator (and, in consequence, the end-user) against possible scenarios that might endanger the entire system. The paper is organized as follows: Section II presents the literature regarding similar work to the topic of the article. In Section III the mathematical formulations regarding the risk-neutral and risk-averse methodologies are described. The ERM formulation and scenario generation are given in Section IV, and in the following section, the structure of the optimization technique used is presented. Section VI gives the case study utilized for the application of the proposed methods and shows obtained results for the risk-neutral and risk-averse strategies. Finally, Section VII draws significant conclusions from the work.

II. RELATED WORK

The incorporation of risk-based techniques in the context of electrical energy systems is usually devoted to the planning of microgrid reconfiguration to reduce utility blackouts or natural disasters or for emergency islanding mode control [13]. In recent studies, risk-based techniques are used to support the planning of hybrid energy systems considering the uncertainty arising from river streamflow [18], or in energy storage systems planning taking into consideration, the variation of wind production [19]. Also, risk-based strategies have been applied for the optimal microgrid planning considering the uncertainty of DER to reduce power loss and energy not supplied (ENS) [20].

Even though most of the literature does not consider a risk-based methodology when it comes to the operation of energy resources (for instance, by an aggregator), the occurrence of extreme events can massively affect the management solution of network operators [21]. In fact, some papers have proposed a risk-based formulation for aggregators. For instance, in [22], a decision-making problem is presented for profit maximization of a wind generation provider and the supply of EV and demand response (DR) aggregators. In that work, the risk measuring parameter is implemented to minimize the impact of the uncertainty associated with market prices, EV, DR demand, and offers made by other wind production entities. Reference [23] provides a two-stage model for the operation of an aggregator pursuing end-users cost minimization and risk minimization for day-ahead and real-time operation. In the risk minimization stage, the aggregator can purchase energy from the wholesale market to meet the scheduled day-ahead electricity, either in the day-ahead or real-time markets (to achieve imbalance reduction). The risk-constrained stochastic power procurement problem of electrical retailers is formulated in [24] taking into consideration load and pool-market prices uncertainty. The authors propose a risk strategy to achieve equal cost in all uncertainty scenarios, making it a scenario-independent process that imposes more costs to the retailer but almost zero risk. In [25], a risk-based mechanism, using *CVaR*, is utilized in a bi-level optimization problem to evaluate the risk associated with the uncertainty of the renewable generation. Results show that by incorporating this risk mechanism, the total expected cost increases with the risk aversion but the value associated with *CVaR* decreases guaranteeing a more robust solution. Furthermore, optimal management of DER for profit maximization considering the

CVaR to evaluate the risk associated with the uncertainties of multiple DER is proposed in [26]. This work shows that the average profits decrease with the weight given to the risk aversion, whereas the *CVaR* cost increases. However, the EVs have not been considered in the model as included in this research work.

In the literature, one of the topics where risk measurement is considered is related to market participation and offers from the aggregating entities to the end-user, mainly for profit maximization. In [27], [28] the risk mechanism is implemented to deal with the uncertainties associated with EV demand, day-ahead, and balance market prices, and other offers presented by competing EV aggregators. In this case, the risk measuring parameters are used, so the EV aggregator participates in both proposed markets and provides offers to EV owners for profit maximization (resulting in cost minimization from the EV user point of view). Reference [29] proposes a decision-making model for a demand DR aggregator for profit maximization considering market bids and energy offers for customer attraction. This work contemplates the *CVaR* and *VaR* risk measurement mechanisms for regret minimization in the event of worst-case scenarios realization.

III. RISK-BASED ENERGY RESOURCE MANAGEMENT

The proposed ERM model uses a risk-based technique for the day-ahead operation. This section explains how to formulate a risk-neutral and risk-averse strategy. The risk-neutral process does not take into account risk-related characteristics. On the other hand, the risk-averse employs these characteristics to ensure a more robust solution against extreme events.

A. RISK-NEUTRAL METHODOLOGY

The risk-neutral strategy for the day-ahead ERM considers the uncertain behavior of aggregator's technologies such as renewable generation, load consumption, market prices, and EV consumption behavior. The stochastic behavior of these parameters is considered in the approach through various scenarios with an associated probability of occurrence.

The aggregator's management is formulated based on the expected scenario when the risk is not considered. The cost and the value of the objective function when a risk aversion strategy is not considered is given by the expected cost as:

$$Z_s^{\text{tot}} = Z_s^{\text{OC}} - Z_s^{\text{In}} + P_s \tag{1}$$

$$Z^{\text{Ex}} = \sum_{s=1}^{N_s} (\rho_s \times Z_s^{\text{tot}}) \tag{2}$$

where Z_s^{tot} is the total objective function (OF) value of each scenario s given by the difference between operational costs in each scenario (Z_s^{OC}), the income in each scenario (Z_s^{In}), and the penalty for bound violations (e.g., power capacity limits) of any variable (P_s). The expected OF cost is represented by Z^{Ex}, and ρ_s is the probability of the respective scenario.

B. RISK-AVERSE METHODOLOGY

A risk-aversion strategy considers the risk associated with the uncertainty of the previously mentioned technologies. In this situation, the aggregator considers the worst-case scenario when day-ahead management is performed. This situation is due to extreme scenarios with a low probability of occurrence, significantly affecting management. As a result, they present significant variations compared to the other scenarios, that is, scenarios with high consequences. For example, these scenarios can represent a high peak in market prices, load demand, a reduction, or even the absence of renewable production.

In this work, the *CVaR* is implemented as a risk measurement mechanism that will consider these extreme events to minimize their impact. *CVaR* adds to the concept of *VaR* because *VaR* can only measure risk when the expected cost Z^{Ex} does not exceed the confidence level (α) for all simulated scenarios. On the contrary, $CVaR_\alpha$ allows measuring risk for scenarios that surpass the confidence level. That is, this parameter is added to the expected cost Z_{Ex} when the value of the OF of the scenarios is higher than $Z^{\text{Ex}} + VaR_\alpha$ which gives them the notation of conditional expected cost. For the simulations involving risk-aversion, α was 95% which is a typical value for this parameter. The VaR_α, $CVaR_\alpha$, and Z^{Ex} concepts are represented in Figure 1 through the normal and cumulative probability distribution functions. Considering the cost of each scenario and for the α value already known, the VaR_α was calculated using the cumulative probability distribution function as shown in Figure 1.

As previously mentioned, $CVaR_\alpha$ is an additional cost that is added to Z^{Ex} in (1-α)% of the scenarios with the highest costs. After calculating the value of VaR_α, the $CVaR_\alpha$ is calculated using the following formulation [30]:

$$CVaR_\alpha(Z_s^{\text{tot}}) = VaR_\alpha(Z_s^{\text{tot}}) + \frac{1}{1-\alpha} \sum_{s=1}^{N_s} \rho_s \times \varphi_s \tag{3}$$

where $\varphi_s = Z_s^{\text{tot}} - Z^{\text{Ex}} - VaR_\alpha(Z_s^{\text{tot}})$ if $Z_s^{\text{tot}} \geq Z^{\text{Ex}} + VaR_\alpha(Z_s^{\text{tot}})$, and $\varphi_s = 0$ otherwise. This parameter is associated with the cost in the worst scenarios, that is, when the cost of each scenario s exceeds the expected cost with the addition of the VaR_α value. If the opposite occurs φ is given the value of zero.

Taking this parameter into account, the OF of the management problem varies according to the level of risk aversion considered as:

$$OF = Z^{\text{Ex}} + \beta \cdot CVaR_\alpha(Z_s^{\text{tot}}) \tag{4}$$

In this situation, the β parameter represents the percentage of aversion to the risk. This parameter can vary between 0 and 1 when $\beta = 0$, the OF value is only equal to the expected cost, which is considered a risk-neutral strategy. On the other hand, if $\beta = 1$, we say that the strategy has 100% aversion to risk, presenting the safest solution when it comes to the worst scenarios. As it can be seen in Eq. (4), the aggregator tries to minimize the OF value, which is a weighted sum of the ERM expected costs, and the consideration of *CVaR* through the use of β. Therefore, the consideration of the *CVaR* is proportional to the weight given by β. This consideration means that the more β increases, the more importance is given to the extreme events in the next 24 hours.

IV. PROPOSED METHODOLOGY

This section presents the proposed mathematical problem formulation of the day-ahead ERM model, as well as the scenarios generation mechanism to represent the uncertainty.

A. ENERGY RESOURCE MANAGEMENT FORMULATION

The mathematical formulation of the day-ahead ERM takes into consideration the total operation cost and the profits in each scenario s (see the first and second term of Eq. (1)). Thus, the total operational cost for each scenario s is given by:

$$Z_s^{\mathrm{OC}} = \sum_{t=1}^{T} \cdot \left[\begin{array}{c} \sum\limits_{i\in\Omega_{\mathrm{DG}}^{\mathrm{d}}} P_{(i,t)}^{\mathrm{DG}} \cdot C_{(i,t)}^{\mathrm{DG}} + \\ \sum\limits_{k=1}^{N_k} P_{(k,t)}^{\mathrm{ext}} \cdot C_{(k,t)}^{\mathrm{ext}} + \\ \sum\limits_{i\in\Omega_{\mathrm{DG}}^{\mathrm{nd}}} P_{(i,t,s)}^{\mathrm{DG}} \cdot C_{(i,t)}^{\mathrm{DG}} + \\ \sum\limits_{e=1}^{N_e} ESS_{(e,t,s)}^{\mathrm{cost}} + \sum\limits_{v=1}^{N_v} EV_{(v,t,s)}^{\mathrm{cost}} + \\ \sum\limits_{l=1}^{N_l} P_{(l,t,s)}^{\mathrm{Curt}} \cdot C_{(l,t)}^{\mathrm{Curt}} + \\ \sum\limits_{r=1}^{N_r} P_{(r,t,s)}^{\mathrm{ENS}} \cdot C_{(r,t)}^{\mathrm{ENS}} + \\ \sum\limits_{i=1}^{N_i} P_{(i,t,s)}^{\mathrm{GCP}} \cdot C_{(i,t)}^{\mathrm{GCP}} \end{array} \right] \cdot \Delta t \quad \forall s \tag{5}$$

where:

$$ESS_{(e,t,s)}^{\mathrm{cost}} = \begin{cases} ESS_{(e,t,s)}^{\mathrm{Power}} \cdot ESSC_{(e,t)}^{\mathrm{Disch}} & \mathit{if}\ ESS_{(e,t)}^{\mathrm{Power}} \le 0 \\ 0 & \mathit{otherwise} \end{cases} \tag{6}$$

$$EV_{(v,t,s)}^{\mathrm{cost}} = \begin{cases} EV_{(v,t,s)}^{\mathrm{Power}} \cdot EVC_{(v,t)}^{\mathrm{Disch}} & \mathit{if}\ EV_{(v,t)}^{\mathrm{Power}} \le 0 \\ 0 & \mathit{otherwise} \end{cases} \tag{7}$$

Notice that $ESS_{(e,t,s)}^{\mathrm{Power}}$ / $EV_{(v,t,s)}^{\mathrm{Power}}$ are continuous variables that take a negative value when discharging, and a positive value when charging. Therefore, $ESS_{(e,t,s)}^{\mathrm{cost}}$ and $EV_{(v,t,s)}^{\mathrm{cost}}$ in Eq. (5), are only taken into account when the battery system is discharging, as modeled in Eqs. (6)-(7). In other words, the aggregator needs to pay a cost for the energy used coming from these technologies. On the other hand, the cost of charging the batteries is not considered in Eq. (5) since this is a payment that the aggregator receives for supplying the demanded energy. Similarly, these payments are not considered in Eq. (8) because we only take into consideration market transactions.

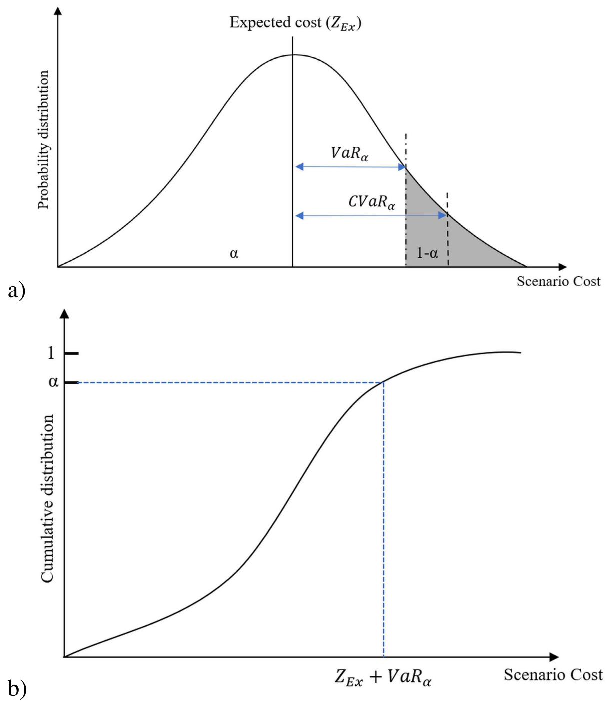


FIGURE 1. Representation of VaR_α, $CVaR_\alpha$ and Z_{Ex} through a) normal; b) cumulative distribution functions.

Regarding the profits, the aggregator achieves monetary value by participating in the market according to:

$$Z_s^{\mathrm{In}} = \sum_{t=1}^{T} \left[\sum_{m=1}^{N_m} P_{(m,t)}^{\mathrm{Market}} \cdot MP_{(m,t,s)} \right] \cdot \Delta t \quad \forall s \tag{8}$$

By combining both terms into a minimization problem, the proposed algorithm tries to minimize Eq. (5) while maximizing Eq. (8) for each scenario s. Depending on the market prices and operational costs, the aggregator trades energy as much as possible to make a profit.

The OF of the management problem is subject to different constraints as follows:

Active power balance: At each period t, the generation must be equal to the consumption for each scenario s:

$$\left[\begin{array}{c} \sum\limits_{i\in\Omega_{\mathrm{DG}}^{\mathrm{d}}} P_{(i,t)}^{\mathrm{DG}} + \sum\limits_{k=1}^{N_k} P_{(k,t)}^{\mathrm{ext}} + \\ \sum\limits_{i\in\Omega_{\mathrm{DG}}^{\mathrm{nd}}} (P_{(i,t,s)}^{\mathrm{DG}} - P_{(i,t,s)}^{\mathrm{GCP}}) + \\ \sum\limits_{l=1}^{N_l} (P_{(l,t,s)}^{\mathrm{Curt}} - P_{(l,t,s)}^{\mathrm{load}}) + \\ \sum\limits_{e=1}^{N_e} ESS_{(e,t,s)}^{\mathrm{Power}} + \sum\limits_{v=1}^{N_v} EV_{(v,t,s)}^{\mathrm{Power}} + \\ \sum\limits_{r=1}^{N_r} P_{(r,t,s)}^{\mathrm{ENS}} + \sum\limits_{m=1}^{N_m} P_{(m,t)}^{\mathrm{Market}} \end{array} \right] = 0 \quad \forall s \tag{9}$$

Active power generation: Maximum and minimum limits for active power generation at each period t is as follows:

$$P_{(i,t)}^{\mathrm{DG_{min}}} \cdot x_{(i,t)}^{\mathrm{DG}} \leq P_{(i,t)}^{\mathrm{DG}} \quad \forall i \in \Omega_{\mathrm{DG}}^{\mathrm{d}}, \ \forall t \tag{10}$$

$$P_{(i,t)}^{\mathrm{DG}} \leq P_{(i,t)}^{\mathrm{DG_{max}}} \cdot x_{(i,t)}^{\mathrm{DG}} \quad \forall i \in \Omega_{\mathrm{DG}}^{\mathrm{d}}, \ \forall t \tag{11}$$

The external supplier power generation: Maximum and minimum limits at each period t can be modeled as:

$$P_{(k,t)}^{\mathrm{ext_{min}}} \cdot x_{(k,t)}^{\mathrm{ext}} \leq P_{(k,t)}^{\mathrm{ext}} \quad \forall k, \ \forall t \tag{12}$$

$$P_{(k,t)}^{\mathrm{ext}} \leq P_{(k,t)}^{\mathrm{ext_{max}}} \cdot x_{(k,t)}^{\mathrm{ext}} \quad \forall k, \ \forall t \tag{13}$$

The non-dispatchable generation: Formulated according to each scenario s:

$$P_{(i,t,s)}^{\mathrm{DG}} = P_{(i,t)}^{\mathrm{DG_{nd}}} \cdot x_{(i,t)}^{\mathrm{DG}} \quad \forall i \in \Omega_{\mathrm{DG}}^{\mathrm{nd}}, \ \forall t \tag{14}$$

Energy storage systems: The battery balance constraint for each ESS unit is defined as follows:

$$\begin{aligned} E_{(e,t,s)}^{\mathrm{stored}} = E_{(e,t-1,s)}^{\mathrm{stored}} + \eta_{(e)}^{\mathrm{c}} \cdot ESS_{(e,t,s)}^{\mathrm{Power}} \cdot \Delta t \\ - \frac{1}{\eta_{(e)}^{\mathrm{d}}} \cdot ESS_{(e,t,s)}^{\mathrm{Power}} \cdot \Delta t \quad \forall e, \ \forall t, \ \forall s \end{aligned} \tag{15}$$

The maximum discharge and charge limits for each ESS unit can be formulated as:

$$-ESS_{(e,t)}^{\mathrm{MaxD}} \leq ESS_{(e,t,s)}^{\mathrm{Power}} \leq ESS_{(e,t)}^{\mathrm{MaxC}} \quad \forall e, \ \forall t, \ \forall s \tag{16}$$

The maximum battery capacity limit for each ESS unit can be written as:

$$E_{(e,t,s)}^{\mathrm{stored}} \leq E_{(e)}^{\mathrm{BatCap}} \quad \forall e, \ \forall t, \ \forall s \tag{17}$$

The minimum energy stored required to be guaranteed at the end of period t can be modeled as:

$$E_{(e,t,s)}^{\mathrm{stored}} \geq E_{(e,t)}^{\mathrm{MinC}} \quad \forall e, \ \forall t, \ \forall s \tag{18}$$

Electric vehicles: The constraints for the EVs are similar to the ESSs since both are storage systems. We consider the set of EVs as a collection of loads representing virtual batteries in this work. However, notice that EVs have some restrictions and requirements that ESSs have not. For instance, EVs are located in predetermined network locations and have traveling requirements associated with user preferences. These requirements are also related to the uncertainty related to EV travel behavior. While these requirements are set as an input to the problem, EVs' constraints do not change. With this consideration, the battery balance constraint of each individual EV is formulated as follows:

$$\begin{aligned} E_{(v,t,s)}^{\mathrm{stored}} = E_{(v,t-1,s)}^{\mathrm{stored}} + \eta_{(v)}^{\mathrm{c}} \cdot EV_{(v,t,s)}^{\mathrm{Power}} \cdot \Delta t \\ - \frac{1}{\eta_{(v)}^{\mathrm{d}}} \cdot EV_{(v,t,s)}^{\mathrm{Power}} \cdot \Delta t \quad \forall v, \ \forall t, \ \forall s \end{aligned} \tag{19}$$

The discharging and charging limits for each EV are represented by the following:

$$-EV_{(v,t)}^{\mathrm{MaxD}} \leq EV_{(v,t,s)}^{\mathrm{Power}} \leq EV_{(v,t)}^{\mathrm{MaxC}} \quad \forall v, \ \forall t, \ \forall s \tag{20}$$

The maximum battery capacity limit for each EV unit is given by:

$$E_{(v,t,s)}^{\mathrm{stored}} \leq E_{(v)}^{\mathrm{BatCap}} \quad \forall v, \ \forall t, \ \forall s \tag{21}$$

The minimum energy stored required to be guaranteed at the end of period t for each EV can be defined as:

$$E_{(v,t,s)}^{\mathrm{stored}} \geq E_{(v,t)}^{\mathrm{MinC}} \quad \forall v, \ \forall t, \ \forall s \tag{22}$$

Demand response: The DR model, namely direct load control where consumption is reduced by the end-user in exchange for an incentive. The maximum amount of load that can be reduced can be formulated as:

$$P_{(l,t,s)}^{\mathrm{Curt}} \leq P_{(l,t)}^{\mathrm{MaxDR}} \quad \forall l, \ \forall t, \ \forall s \tag{23}$$

Electricity market: The maximum and minimum amounts of energy that the aggregator can buy and sell in the electricity market are given by:

$$-P_{(m,t)}^{\mathrm{MaxB}} \leq P_{(m,t)}^{\mathrm{Market}} \leq P_{(m,t)}^{\mathrm{MaxS}} \quad \forall m, \ \forall t \tag{24}$$

In addition, in our formulation, if any of the restrictions in Eqs. (10)-(14), Eq. (16), Eq. (20), and Eqs. (23)-(24) is violated, a monetary penalty (1,000 m.u. in this work) is added to P_s for each variable that exceeded the specified bounds.

B. SCENARIO GENERATION

In the considered model, the aggregator needs to deal with uncertainty coming from numerous resources, e.g., random driving patterns of EV users and charging behavior, variations in market prices, uncontrollable renewable generation, etc. Since the exact outcome of these resources is nearly hard or impossible to predict (due to the randomness of these variables), the success of the decision-making process cannot be completely guaranteed. Therefore, the proposed method considers the uncertainties associated with the mentioned resources by using a scenario-based optimization technique.

To this end, Monte Carlo Simulation (MCS) method is utilized to obtain a sizeable random sampling of the possible numerical results. This situation means that simulations are repeated numerous times to determine the heuristic probability. MCS builds a viable product model for any variable with uncertainty using a probability distribution (the normal distribution function for simplicity in this work). After that, the results are recalculated with a range of values between the determined minimum and maximum. The scenarios x^s can be represented using the sum of a forecasted mean value and errors obtained from historical data as given by [17]:

$$x_s = x^{\mathrm{forecasted}}(t) + x^{\mathrm{error},s}(t) \tag{25}$$

where $x^{\mathrm{forecasted}}(t)$ is the mean forecasted value in each instant t, which can have a negative or positive value, $x^{\mathrm{error},s}(t)$ is the term associated with the error involving each scenario s with a normal distribution function with a zero-mean noise, and standard deviation σ ($\mathcal{N}(0, \sigma)$).

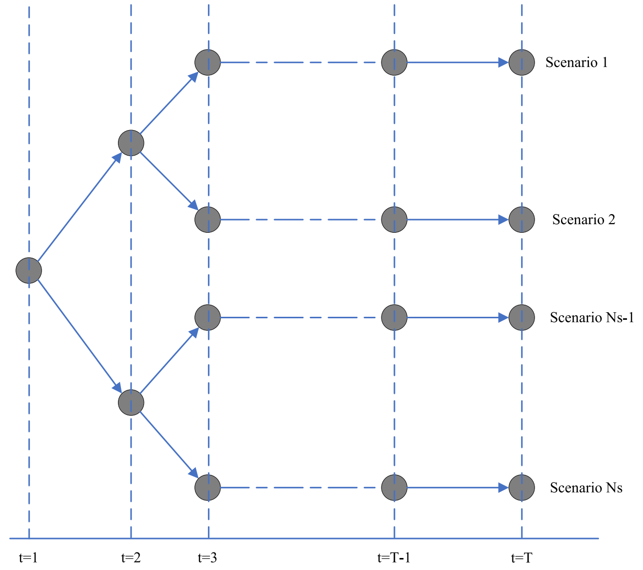


FIGURE 2. Scenario tree.

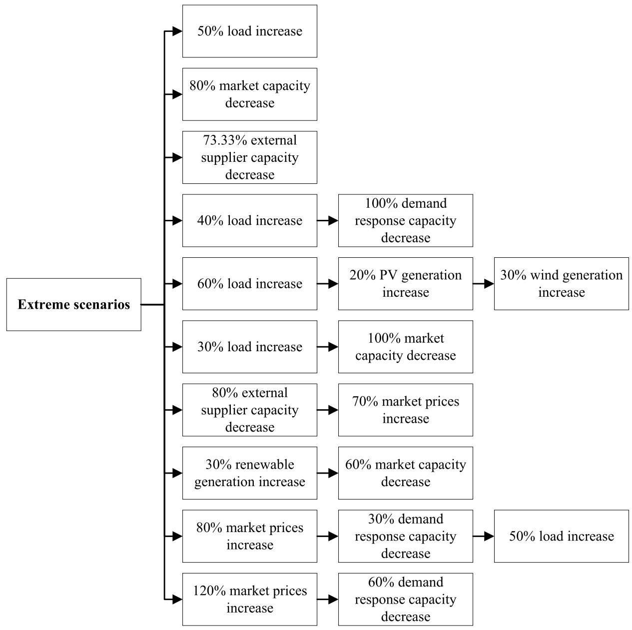


FIGURE 3. Extreme scenarios generated.

Figure 2 shows an example of a scenario tree where each circle represents a node which gives the state of a random variable at a certain time t, and each branch represents the specific scenario s. Many scenarios are initially created, resulting in a large-scale problem. The larger the number of scenarios is, the more accurate the model is. However, there is a trade-off between computational time and memory requirements despite higher accuracy (i.e., the larger the set of scenarios is, the more time and memory are required).

A scenario reduction strategy is employed to deal with the problem's tractability [31]. To do so, similar scenarios are grouped while scenarios with a low chance of occurrence are excluded. As a result, a scenario subset is produced near the initial distribution in terms of a probability measure. The essential purpose of scenario reduction is to reduce the size of the large-scale problem. Furthermore, the number of variables and constraints is reduced by applying these strategies. Also, the processing time significantly decreases, allowing faster discovery of suitable solutions while preserving the original data set statistical properties. The computing effort is likewise lowered, requiring less system memory. Notice that, despite maintaining the statistical properties of the original data set, it is impossible to avoid some imprecision in the final solutions as a product of this reduction.

This article also considers the possibility of scenarios with low probability but a more drastic impact on the operation. To this end, ten random extreme scenarios were produced from the database for the risk-based strategy, modeling natural settings for extreme events as shown in Figure 3. In the first extreme scenario, a 50% increase in load during the day was modeled. In the second extreme scenario, we set a drop of 80% in buy/sell market capacity throughout the day. In the third scenario, the external supplier's maximum generation capacity was cut to 8 MW in hours 1 to 7 and 23 to 24 to represent, for instance, the damage to distribution lines that can significantly impact the power capacity coming from an external supplier. The fourth scenario was designed to evaluate DR absence due to, for instance, a breakdown of the communication system between aggregator and end-user. Thus, the DR was set to zero throughout the day, and demand increased by 40% from hours 16 to 22. In the fifth scenario, we consider a simulation in which the aggregator might be at risk, combining a 60% increase in load, a 20% increase in wind output at different times of the day, and a 30% increase in PV production. In the sixth extreme scenario, a 30% load increase was projected from hours 13 to 20, and no market capacity for trading was considered from hours 1 to 12 and 22 to 24. For the seventh scenario, the external supplier capacity was again constrained, plus a consideration of market price increments at different times. In the eighth scenario, we set the market capacity to 4 MW and a 30% increase in renewable generation. In the ninth scenario, we put a load increase of 50%, a 30% drop in DR capacity, and an 80% increase in market prices throughout the day. Finally, the tenth risk scenario considered a 120% rise in market prices from the hours 17 to 22 and a 60% loss of DR capability from hour 9 to hour 19.

The total probability of the extreme scenarios was equal to 0.5%. By doing this, the probability of the remaining scenarios needed to be altered to match a total of 100% of probability. In order to do this, we modify the probability of scenarios as:

$$S_{s-ex} = \frac{1 - \sum_{s=1}^{N_s} \rho_s}{N_s - N_{ex}} \tag{26}$$

where S_{s-ex} represents the probability added to the rest of the scenarios, excluding the extreme scenarios.

V. OPTIMIZATION TECHNIQUE

For the optimization of the risk-based day-ahead ERM problem, a metaheuristic proposed in [32] was implemented. This section describes the algorithm optimization process, the solution representation used by the metaheuristic, and the fitness evaluation when considering the risk strategies.

A. ALGORITHM PROCEDURE

The Cellular Univariate Marginal Distribution Algorithm with Normal-Cauchy Distribution (CUMDANCauchy) (Algorithm 1) is an evolutionary algorithm (EA) that searches for novel solutions using the Normal and Cauchy distributions.

Initially, the algorithm starts by setting the control parameters needed for the optimization (step 1). Such parameters include the number of parent individuals (p) selected from the initial population size (NP), the number of individuals chosen from the parent solution (s), and the maximum number of iterations (*iterMax*). After NP initial solutions are randomly generated between specified variable bounds (step 2), the fitness evaluation of these solutions is made, obtaining the OF cost of each individual (step 3). Next, the resulting fitness values are sorted in decreasing order, obtaining a rank for each solution depending on their position (step 4). Then, some solutions are selected according to the number of parents specified by the parameter p (step 5), and the best parent individual is saved as the best global solution found (step 6). After this, the algorithm enters into an iterative process for a given number of iterations (step 8).

The first step in this iterative process estimates the parent individuals according to the Normal and Cauchy distributions (step 9). Then, based on the learning process of the estimated distribution, a new population of NP individuals is generated for (step 11), updating the variables according to boundary constraints (step 12). s individuals are selected from this new population and saved as auxiliary solutions (step 13). The best individual from these auxiliary results is also saved (step 15), and a comparison is made between this individual and the global best individual (step 16), keeping the minimum as the new global best solution (step 17). Finally, The best solution is updated (step 18), and the iterative process starts again.

This final process of comparison between x_{sbest} and $x_{\text{globalbest}}$ is an upgrade from the CUMDANCauchy algorithm, which results in the new CUMDANCauchy++ algorithm [33], an algorithm created especially to deal with the uncertainty present in the ERM problem, which highly placed in a competition on evolutionary computation in the energy domain [34].

Algorithm 1 Cellular Univariate Marginal Distribution Algorithm With Normal-Cauchy Distribution

```
1:  Initialize control parameters p, s,NP, iterMax
2:  Generate initial population (NP) randomly
3:  Evaluate fitness of NP individuals
4:  Sort obtained solutions
5:  Select p individuals from sorted solution
6:  Save best individual from p solutions as x_globalbest
7:  t ← 1
8:  while t ≤ iterMax do
9:      Estimate Normal(μ, σ) × Cauchy(μ, σ) of p individuals
10:     for all NP do
11:         Sample new NP individuals according to the estimated distribution
12:         Verify boundary constraints
13:         Apply selection of s individuals and update population
14:     end for
15:     Save best individual from s solution as x_sbest
16:     if x_sbest < x_globalbest then
17:         x_globalbest = x_sbest
18:         Update solution
19:     end if
20:     t ← t + 1
21: end while
```

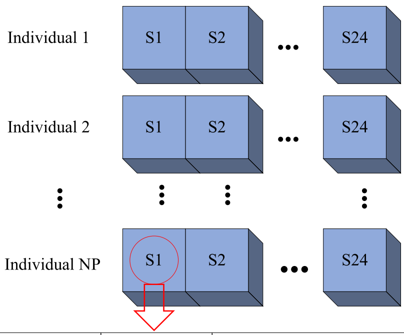
B. SOLUTION ENCODING

The solution structure is an essential feature of metaheuristics for expressing a given solution (e.g., an individual in DE [35], a particle in PSO [36], or a genotype in GA [37]). Because we're dealing with an EA, the solution to the metaheuristic is determined by the individuals (solutions) involved.

The metaheuristic's initial solution is created randomly between the maximum and minimum values set for each variable. The vector representation of the generated population for the day-ahead is shown in Figure 4. Each individual is composed of a group of sequentially repeated variables per period (S1, S2, …, S24). The variables in each group are defined by the technologies present in the DN. All variables are of continuous type varying according to the specified bounds, except for the state of the generators, which is represented by a binary state; that is, it can only be 0 or 1. This variable when its 0 means that the generator is not connected to the grid, and 1 when it is.

The first group of variables generated is the active power generation which includes renewable production. The non-dispatchable generation cannot be controlled due to solar and wind factors, respectively. Even though the variables associated with this type of generation are demonstrated in the solution vector, it is essential to note that these variables have an unchangeable value that depends on the uncertainty scenario, so the bounds of these variables are limited to the maximum production value.

EV and ESS solutions are set to vary from the maximum active power discharge to the maximum active power charge, assuming the discharging as a negative variable (generation) and the charging as a positive variable (consumption). The DR is only assumed as a load reduction, but a load increase



Variable name	Type	Bounds	Dimension
Generators active power	Continuous	[minPower,maxPower]	21
Generators state	Binary	0,1	21
EVs charge/discharge	Continuous	[-maxDischarge,maxCharge]	2,000
Load reduction	Continuous	[0,maxReduce]	25
ESSs charge/discharge	Continuous	[-maxDiscahrge,maxCharge]	2
Market	Continuous	[-maxBuy,maxSell]	1
			2,070

FIGURE 4. Encoding of metaheuristic solutions.

program could also be considered. Hence, the DR variable varies from 0 to the maximum active power reduction. When it comes to market variables, it is assumed that the negative value is the power bought in the market, and the positive variable value is the power sold.

In this case, the metaheuristic does not consider binary variables for ESSs, EVs, and the marketplace because it would increase problem complexity with a considerable rise in the number of variables. To avoid this situation, as presented in Figure 4 the metaheuristic generates a value between the specified limits for each period. This situation means that the solution for each instance can only be negative (discharge) or positive (charge) and not both simultaneously, guaranteeing that the technologies do not charge/discharge simultaneously. The same approach is used for the marketplace. For each period, the offer/bid values are given by a continuous variable that can only be positive or negative and not both. In [7], [17] similar formulations are made to the proposed work but considering deterministic methods where binary variables are considered for the state of charge/discharge of ESSs and EVs and power bought/sold in the electricity market.

The considered ERM has 49,680 variables per individual given by 2,070 variables per period, with 21 variables composing the generators' active power and state. A total of 2,000 EVs were also considered with 25 load types, 2 ESSs, and 1 market.

C. FITNESS EVALUATION

Regarding the optimization process of the risk-based methodology, Figure 5 shows the fitness function that the chosen metaheuristic evaluates for cost minimization. Initially, the database with the formulated scenarios is passed as an argument to the function, containing the scenarios with extreme events. The value of the variable that controls risk aversion is also initialized. It is only set to 0 and 1, but a variation could be applied in this situation. Next, each scenario is evaluated according to the equations in Section IV-A. This evaluation is done to obtain each scenario cost, which is saved to calculate the expected cost as in Eq. (2).

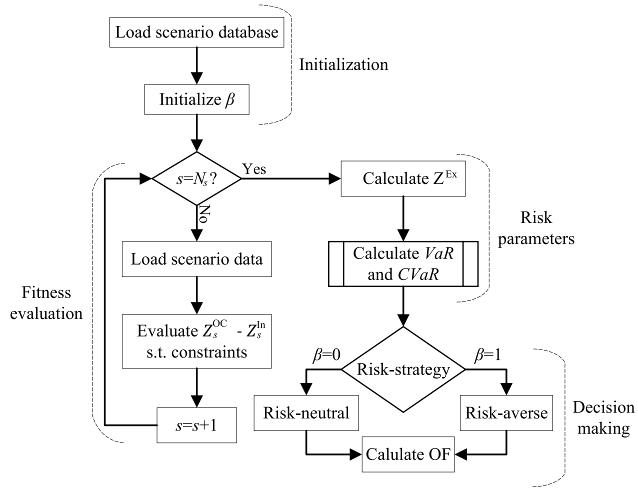


FIGURE 5. Flowchart of fitness function for risk-based strategies.

The expected cost, the cost of each scenario, and the probabilities of each scenario are used to calculate VaR_α and $CVaR_\alpha$ values according to the formulation in Section III-B. After the parameters that measure risk have been calculated, the aggregator enters a decision process according to the risk aversion factor. Through the value of the OF, the aggregator chooses the best strategy.

The metaheuristic does this evaluation to minimize the value of the OF in a given number of iterations, so when the β is zero, the metaheuristic will only minimize the expected cost. When β is 1, the metaheuristic minimizes the expected cost as well as the $CVaR_\alpha$.

The value of *CVaR* in the optimization process decreases as the value of the risk-aversion factor increases like it is formulated in Eq. (4). Since we are in the presence of a minimization problem, as we increase β, the heuristic will try to decrease the *CVaR* to the extent that it does not massively affect the OF. In the final step of the flowchart in Figure 5, the aggregator decides which β to use. Meaning by choosing β as zero, the aggregator is more prone to risk in its solution, not caring about the occurrence of extreme events. By choosing β as one, he becomes less susceptible to the risk in its solution, adopting a safer and more robust solution against extreme events.

VI. RESULTS AND DISCUSSION

This section contains the case study details adopted in this research paper. It also presents the numerical results obtained for the risk-neutral and risk-averse methods regarding the aggregators' costs and energy management results.

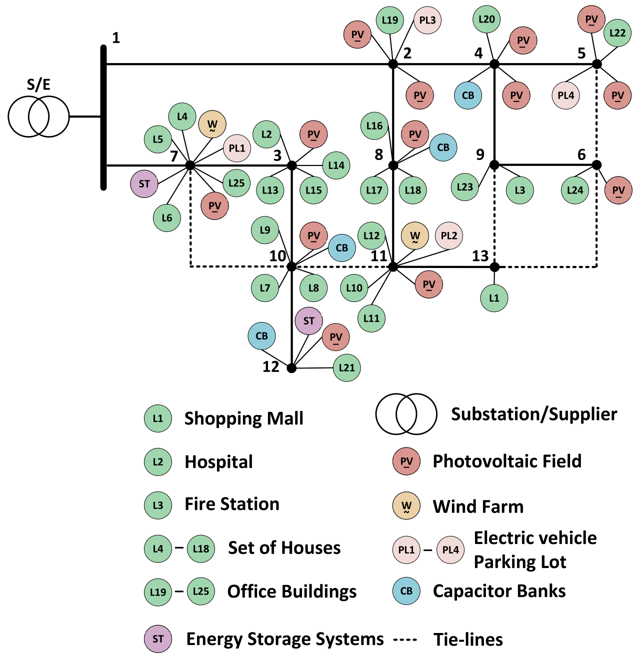


FIGURE 6. Line-diagram of the 13-bus DN [38].

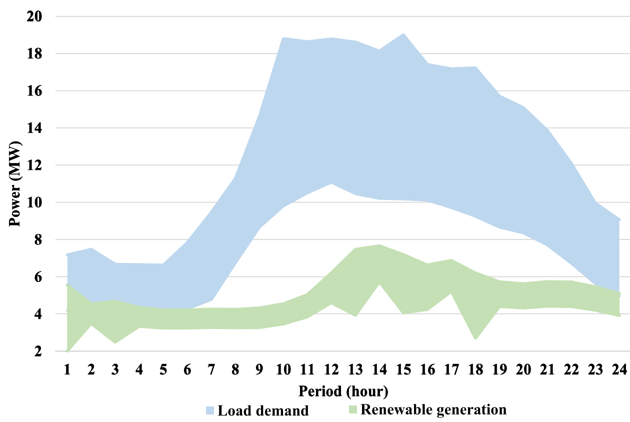


FIGURE 7. Scenario range for day-ahead load demand, and renewable generation.

A. CASE STUDY

A medium voltage (MV) distribution network (DN) of a smart city (SC) located in the BISITE laboratory in Salamanca, Spain, was chosen for this case study [38]. This DN features one 30 MVA substation in bus 1, 15 DG units (2 wind farms and 13 PV parks), and four 1 MVAr capacitor banks (which in this problem are not considered since we are not taking into account reactive power). When it comes to consumption, this DN has 25 different loads composed of residential and office buildings and some buildings that provide a service (hospital, fire station, and shopping mall). The SC has seven charging stations allowing EVs to charge their batteries, including four 7.2kW slow charging stations and 50kW fast-charging stations. The single-line diagram presented in Figure 6 of the 13-bus 30-kV DN shows the single-line diagram as well as the loads, generation, and equipment attached to each node. This case study takes into account the high penetration of EVs and renewables.

Various scenarios were created to deal with the uncertainty of the technology under consideration. It is assumed a normal distribution to model the error but with a standard deviation variation. The maximum standard deviation values for the load consumption and electricity market prices are 15% and 10%, respectively. The minimum values for standard deviation are 8% and 6%, correspondingly. Randomized values adopting the Gaussian/normal distribution are created for the forecast scenarios. The error for the PV generation forecast varies between 0 and 20%, and the wind production forecast error varies between 20% and 35% [39]. The MCS approach is used to produce 5000 scenarios, then reduced to 150 scenarios using a fast backward-forward procedure in GAMS/SCENRED as described in subsection IV-B.

An EV travel behavior simulator tool proposed in [40] was used to model EV uncertainty. Different classes of vehicles are used with two different types of EVs: battery EV and plug-in hybrid EV with the characteristics presented in [39]. This simulator allows us to obtain data regarding each EV's trips, such as maximum charge and discharge rate, minimum charging required so the EV can make its trip in the next hour(s), and several other parameters that serve as input for the optimization.

Variations in load demand and renewable generation can be observed in Figure 7, which shows the range of scenarios for the total load demand and renewable generation ranging between the minimum and maximum values. From period 10 to 20, a considerable variation in load limits can be seen, with the highest load value being 19.01 MW in period 15. When it comes to renewable generation variation, the extreme scenarios have little impact on the minimum and maximum values because the range is smaller when compared to load demand.

Regarding the considered costs in this scenario, Figure 8 presents the forecasted wholesale market prices and the external supplier prices. A significant variation can be seen regarding the market prices due to the multiple extreme scenarios that consider an increase in market costs. Here the maximum value of 116.22 m.u. can be seen in period 20, where the minimum value is 38.14 m.u., a difference of 78.09 m.u., which is considerable. The external supplier is contracted without uncertainty in cost, and the value is set to 50 m.u. in off-peak hours and 90 m.u. in peak hours.

The aggregator must manage its respective resources, power bought from the external supplier, and energy bought/sold in the marketplaces to satisfy the consumption. Two ESSs units were also considered in the situation. Table 1 presents the energy resources data associated with the aggregator for the day-ahead formulation. The minimum and maximum values assumed for the prices of the resources, capacity, forecasted values from the renewables and loads, and the number of units corresponding to each resource are indicated.

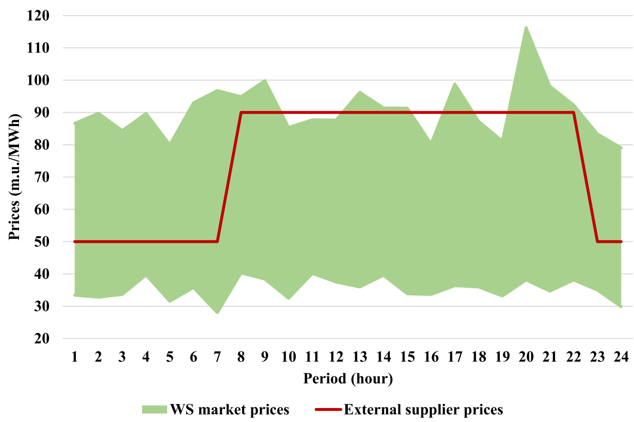


FIGURE 8. Day-ahead external supplier, and forecasted market prices.

TABLE 1. Energy resources information for the day-ahead.

Energy resources		Prices (m.u./MWh) min–max	Capacity (MW) min–max	Forecast (MW) min-max	Units
Photovoltaic		150–150		0.00–1.06	13
Wind		130–130		0.00–3.75	2
External Supplier		50–90	0.00–30.00		1
Storage	Charge	110–110	0.00–1.25		2
	Discharge	90–90	0.00–1.25		
EVs	Charge	0–0	0.01–0.13		2000
	Discharge	90–90	0.01–0.09		
Demand Response	Reduce program	100–100	0.00–1.21		25
Load		0–0		0.01–2.93	25
Market buy and sell		27.99–116.22	0.00–10.00		1

CUMDANCauchy++ was the metaheuristic used for this optimization problem due to its already demonstrated outstanding performance in ERM problems [33]. The first parameter that is set is NP with 20 individuals. We studied the sensibility of the NP parameter in [39] for the day-ahead, and we concluded that the overall best value for this parameter in the proposed algorithm was 20. The number of iterations ($iterMax$) is set up with 250 iterations corresponding to 5,000 objective function evaluations. The following parameters are p and s set to 16 and 2, respectively. All simulations were run in MATLAB 2018a on a device with a 4 core AMD Ryzen 5 3500U processor running at 2.1GHz, Windows 10 Pro, and 16 GB of RAM.

B. CASE 1 - RISK-NEUTRAL OPTIMIZATION

In the risk-neutral methodology, the aggregator schedules the energy resources for the day-ahead based on expected cost, i.e., it considers the scenarios with the highest probability of occurrence. Table 2 shows the values in each hour of the cost components and revenue obtained by the day-ahead optimization when β is zero. In this situation, the highest generation cost was verified in hour 12 due to the high load demand at this period (see Figure 9). Interestingly, the aggregator can obtain a profit at this hour due to the excess of energy bought from the external supplier and sold at a higher price in the market. In hours 2, 5, and 6, the optimization presents a penalization for ENS and a market profit. This situation is quite interesting because it reflects

TABLE 2. Cost components, and revenue obtained per hour in the risk-neutral optimization.

Hour	Costs (m.u.) Generation	Costs (m.u.) Market Bid	Costs (m.u.) ENS	Revenue (m.u.) Market offer
1	538.19	0.00	0.00	0.88
2	1,000.83	0.00	8.47	468.77
3	483.25	0.00	0.00	0.10
4	490.00	0.00	0.00	0.00
5	990.93	0.00	9.76	462.47
6	1,019.48	0.00	12.78	486.67
7	573.41	0.00	0.00	0.00
8	426.33	243.97	0.00	0.00
9	436.45	351.05	0.00	0.00
10	1,228.47	0.00	0.00	0.00
11	526.68	443.67	0.00	0.00
12	1,529.06	0.00	0.00	75.97
13	779.93	348.22	0.00	0.00
14	815.47	296.79	0.00	0.00
15	760.92	301.24	0.00	0.00
16	720.43	292.87	0.00	0.00
17	717.53	272.29	0.00	0.00
18	622.39	274.51	0.00	0.00
19	579.23	247.38	0.00	0.00
20	1,054.19	0.00	0.00	0.00
21	980.98	0.00	0.00	0.00
22	878.65	0.00	0.00	0.00
23	546.15	99.16	0.00	0.00
24	584.13	0.00	0.00	0.00

the aggregator's preference to buy energy from the external supplier and sell it in the market to profit (primarily due to the significant increase in market prices in some scenarios). In this situation, the aggregator is not interested in the penalty assigned to the ENS or using the ESSs and EVs to meet the power balance constraint.

In the risk-neutral case, the total operational costs of the aggregator are 21,485.23 m.u., where the cost components corresponding to the ENS, the generation, and the market bid are equal to 31.02 m.u., 18,283.07 m.u., and 3,171.15 m.u., respectively, which translates to the total day-ahead investment as seen in Table 4. In this case, the OF value when adding the $CVaR_{0.95}$ value is 29,701.23 m.u., and the worst scenario cost is 84,232.70 m.u. because this optimization only minimizes the expected cost (20,006.37 m.u.), as can be seen in Figure 10. Here the metaheuristic is mainly concerned with the scenarios where the probability is higher in contrast to the risk-averse optimization method.

Figure 9 depicts the risk-neutral day-ahead energy management outcomes. In this case, the total supplied energy was 241.58 MWh, while the total consumed energy was 241.59 MWh, resulting in 10.34 kWh of ENS. The generation side includes 100.52 MWh of renewable power, 73.42 MWh of external supplier output, and 67.63 MWh of market bids. 196.93 MWh of load demand, 13.08 MWh of EV charging, and 31.57 MWh of market offers account for the consumption. The ENS happens in three of the 24 optimization periods, which is not optimal for the aggregator due to the extreme scenarios examined. The aggregator did not have a way to buy the energy needed to satisfy the load in this circumstance due to load increase, market capacity decreased, and DR capacity decreased.

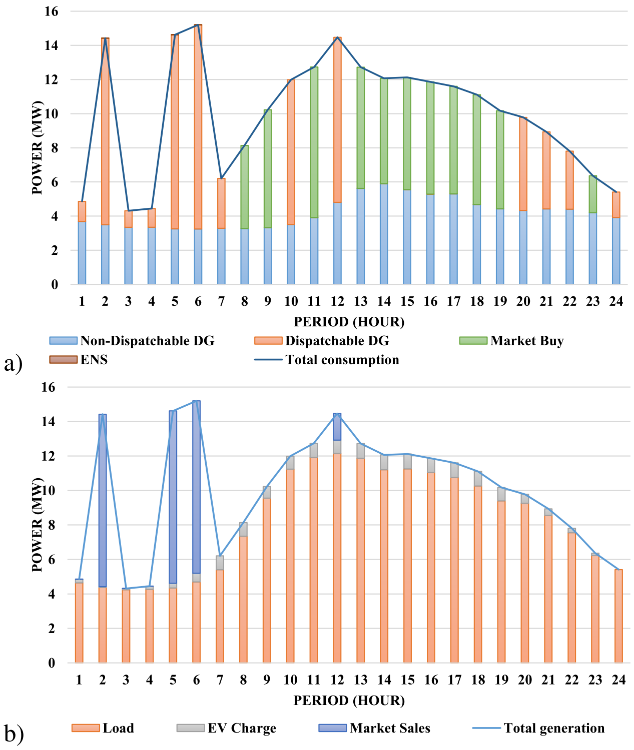


FIGURE 9. Day-ahead management results for the risk-neutral strategy regarding power a) generation; b) consumption.

C. CASE 2 - RISK-AVERSE OPTIMIZATION

When considering the risk-averse optimization in the decision-making process, a risk measurement parameter is added to the OF, so the worst scenarios cost is considered. This situation means that minimizing the OF the aggregator minimizes the expected cost and the cost associated with the extreme events. As Table 3 shows, the aggregator only obtains a small profit compared to the previous model. The highest generation cost occurs in period 21 (1,818.26 m.u.). This price is higher than in the risk-neutral strategy because the aggregator tries to protect himself against this extreme event by investing more, as shown by the ENS, which is lower. The aggregator only has to pay in the first period compared to the risk-neutral strategy in which the aggregator pays in three different periods. We also verify fewer periods where the aggregator has market revenue. In the risk-averse approach, the aggregator mostly tries to satisfy the demand without taking extra risks by going to the market to make offers.

From a risk-neutral to a risk-averse approach, there is a 787.66 m.u. increase in investment, owing primarily to the generating cost as Table 4 shows. In an extreme occurrence, the aggregator protects itself by increasing its investment in energy production. The expenses of ENS are lowered by around 70% from the risk-neutral to the risk-averse technique in this scenario, which is a major improvement because the ENS price evaluated in this methodology is 3,000 m.u./MWh, which is a very high price. In this case the OF value ($Z^{Ex} + CVaR_{0.95}$) is equal to 25,576.73 m.u., a decrease of 4,124.50 m.u corresponding to 13.89% from the previous case (29,701.23 m.u.) even though the expected cost increased 1,322.65 m.u. from the previous mechanism. That is, the risk-based strategy implemented improved the results obtained in the cost of the extreme events, mainly in

TABLE 3. Cost components, and revenue obtained per hour in the risk-averse optimization.

Hour	Costs (m.u.)			Revenue (m.u.)
	Generation	Market Bid	ENS	Market offer
1	1,037.28	0.00	9.23	488.61
2	454.62	43.40	0.00	0.00
3	434.77	43.06	0.00	0.10
4	435.12	50.63	0.00	0.00
5	491.01	0.00	0.00	0.00
6	421.84	95.11	0.00	0.00
7	427.31	143.54	0.00	0.00
8	864.45	0.00	0.00	0.00
9	1,057.67	0.00	0.00	0.00
10	1,228.47	0.00	0.00	0.00
11	1,320.27	0.00	0.00	0.00
12	1,201.78	102.44	0.00	0.00
13	1,113.66	166.44	0.00	0.00
14	815.47	296.79	0.00	0.00
15	777.85	292.74	0.00	0.00
16	720.62	292.79	0.00	0.00
17	717.53	272.29	0.00	0.00
18	622.39	274.51	0.00	0.00
19	1,119.59	0.00	0.00	11.15
20	1,054.19	0.00	0.00	0.00
21	1,818.26	0.00	0.00	457.03
22	779.98	53.95	0.00	0.00
23	546.18	99.14	0.00	0.00
24	509.69	66.86	0.00	0.00

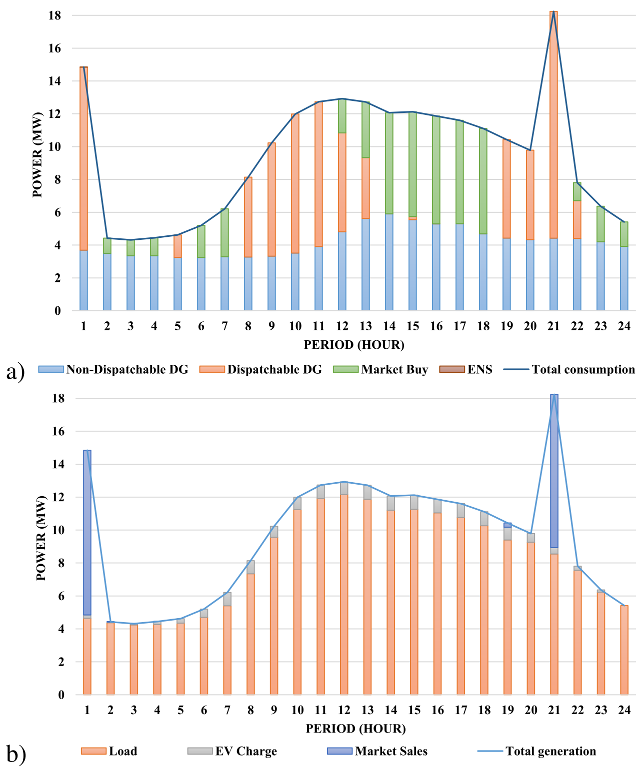


FIGURE 10. Day-ahead management results for the risk-averse strategy regarding power a) generation; b) consumption.

TABLE 4. Overall intraday objective function results and optimization time by the tested metaheuristics.

Cost components	Risk-neutral (m.u.)	Risk-averse (m.u.)
Day-ahead investment (operational costs)	21,485.23	22,272.89
ENS costs	31.02	9.23
Generation costs	18,283.07	19,970.01
Market bid costs	3,171.15	2,293.66
Market offer revenue	1,494.86	956.88
Penalties	16.00	13.00
Total expected cost	20,006.37	21,329.02
$Z_{ex} + CVaR_{0.95}$	29,701.23	25,576.73
Worst scenario	84,232.70	40,571.52

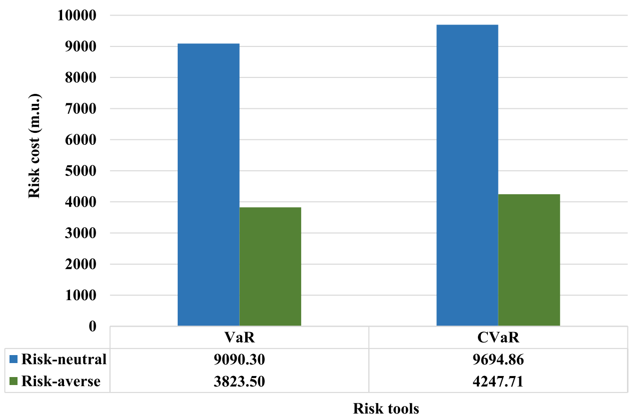


FIGURE 11. ***VaR*, and *CVaR* values for the risk-neutral and risk-averse models.**

the worst scenario (scenario 22) with a 51.83% reduction as Figure 10 shows. From the figure, it is possible to observe that the extreme scenarios considered have mostly higher costs. It is also worth noticing that in some extreme scenarios generated, such as scenarios 57 and 108, the cost increase was minimal compared to the remaining. These two scenarios correspond to the seventh and tenth extreme scenarios created in which both include an increase in market prices: the first includes an external supplier capacity reduction and the second a DR limit reduction (subSection IV-B). Also, in this situation, the metaheuristic majorly focused on reducing the worst scenario cost due to its significant impact on the solution.

The day ahead management results for the risk-averse strategy ($\beta = 1$) are shown in Figure 10. The total energy consumed was 229.58 MWh with only 3.08 kWh of ENS, a reduction of 70% from the previous case. This situation of ENS was only verified in period one, whereas in risk-neutral optimization, the ENS occurred in periods 2, 5, and 6. When it comes to the generation, 100.52 MWh of renewable energy was obtained. A total of 79.11 MWh of external supplier generation was acquired, an increase from the risk-neutral strategy, reflecting the rise in generation costs shown in Table 4. A total of 49.94 MWh of market bid energy was verified on the generation side. The load demand and EV charging energy values remained equal to the risk-neutral method. The energy value of the market offer was equal to 19.57 MWh, a smaller value than what was registered in the risk-neutral.

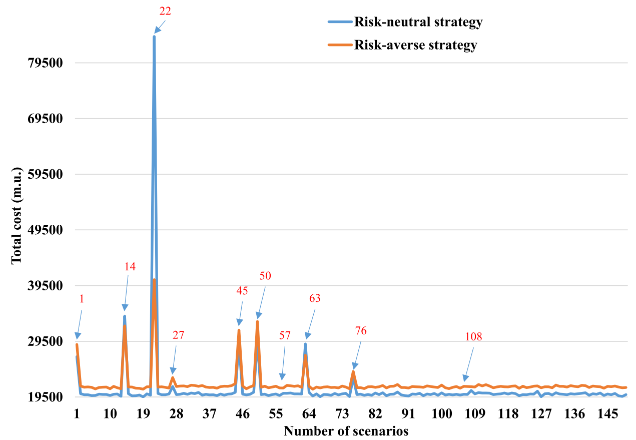


FIGURE 12. Total scenario cost for risk-neutral and risk-averse approaches.

Figure 11 shows the values of the risk instruments employed (i.e., *VaR* and *CVaR*) for the risk-neutral and risk-averse models. An increase in *VaR* to *CVaR* values (as shown in the figure) was expected to obtain a safer solution against worst events. In this regard, a rise of 604.56 m.u. from the *VaR* to the *CVaR* value was verified using the risk-neutral strategy, compared to an increase of 424.21 m.u. in the risk-averse approach. It is also possible to observe that going from the risk-neutral to the risk-averse strategy, the *VaR* value decreases 57.94%, and the *CVaR* decreases 56.19%.

VII. CONCLUSION

This paper proposed aggregators' optimal day-ahead ERM considering the mathematical formulation of risk-neutral and risk-averse strategies. The ERM model considers the uncertainty and stochastic behavior of load, EV demand, renewable generation, and market prices. We implemented an MCS model to generate a set of scenarios to deal with this uncertainty. The problem was solved using a pretty new metaheuristic, the CUMDANCauchy++. This algorithm was improved from previous work to deal with uncertainty, which showed excellent results in ERM problems.

The ERM problem considers the *CVaR* mechanism, which analyses the cost for the worst scenarios. The aggregators' ERM for the next day is made based on the OF cost in the occurrence of extreme events. So in this situation, the aggregator decides if he wants to accept the risk or if he wants to mitigate the risk, thus investing more when it comes to the operational costs. The results suggest that the risk mechanism allows obtaining a better and more robust solution even with the 4% increase in operational costs and the 6.2% increase in expected costs. This situation occurs by reducing the risk measuring parameters (*VaR* and consequently *CVaR*) and the worst-case scenario cost. In other words, by opting for this solution, the aggregator reduces its risk if the worst scenarios happen, with a 13.89% reduction in price in the OF.

The proposed methodology could be implemented in intraday management. Even though we are closer to real-time and the uncertainty diminishes, extreme events can still occur, provoking a significant impact on the management solution. This methodology could also be applied in a more competitive environment with multiple aggregators in the DN trying to provide the best service for the end-user for profit maximization or cost minimization.

REFERENCES

[1] B. Knopf, P. Nahmmacher, and E. Schmid, "The European renewable energy target for 2030—An impact assessment of the electricity sector," *Energy Policy*, vol. 85, pp. 50–60, Oct. 2015.
[2] G. Mavromatidis, K. Orehounig, and J. Carmeliet, "A review of uncertainty characterisation approaches for the optimal design of distributed energy systems," *Renew. Sustain. Energy Rev.*, vol. 88, pp. 258–277, May 2018.
[3] T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares, "Intelligent energy resource management considering vehicle-to-grid: A simulated annealing approach," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 535–542, Mar. 2012.
[4] F. Lezama, L. E. Sucar, E. M. de Cote, J. Soares, and Z. Vale, "Differential evolution strategies for large-scale energy resource management in smart grids," in *Proc. Genet. Evol. Comput. Conf. Companion*, Jul. 2017, pp. 1279–1286.
[5] Y. M. Ding, S. H. Hong, and X. H. Li, "A demand response energy management scheme for industrial facilities in smart grid," *IEEE Trans. Ind. Informat.*, vol. 10, no. 4, pp. 2257–2269, Nov. 2014.
[6] R. H. Byrne, T. A. Nguyen, D. A. Copp, B. R. Chalamala, and I. Gyuk, "Energy management and optimization methods for grid energy storage systems," *IEEE Access*, vol. 6, pp. 13231–13260, 2017.
[7] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local energy markets: Paving the path toward fully transactive energy systems," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4081–4088, Sep. 2019.
[8] J. Soares, M. A. F. Ghazvini, N. Borges, and Z. Vale, "A stochastic model for energy resources management considering demand response in smart grids," *Electr. Power Syst. Res.*, vol. 143, pp. 599–610, Feb. 2017.
[9] M. Tavakoli, F. Shokridehaki, M. F. Akorede, M. Marzband, I. Vechiu, and E. Pouresmaeil, "CVaR-based energy management scheme for optimal resilience and operational cost in commercial building microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 100, pp. 1–9, Sep. 2018.
[10] W. Mensi, S. J. H. Shahzad, S. Hammoudeh, R. Zeitun, and M. U. Rehman, "Diversification potential of Asian frontier, BRIC emerging and major developed stock markets: A wavelet-based value at risk approach," *Emerg. Markets Rev.*, vol. 32, pp. 130–147, Sep. 2017.
[11] A. M. Andries and E. Galasan, "Measuring financial contagion and spillover effects with a state-dependent sensitivity value-at-risk model," *Risks*, vol. 8, no. 1, p. 5, Jan. 2020.
[12] J. Chen, "On exactitude in financial regulation: Value-at-risk, expected shortfall, and expectiles," *Risks*, vol. 6, no. 2, p. 61, Jun. 2018.
[13] X. Cao, J. Wang, J. Wang, and B. Zeng, "A risk-averse conic model for networked microgrids planning with reconfiguration and reorganizations," *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 696–709, Jan. 2020.
[14] A. Narayan and K. Ponnambalam, "Risk-averse stochastic programming approach for microgrid planning under uncertainty," *Renew. Energy*, vol. 101, pp. 399–408, Feb. 2017.
[15] M. Roustai, M. Rayati, A. Sheikhi, and A. Ranjbar, "A scenario-based optimization of smart energy hub operation in a stochastic environment using conditional-value-at-risk," *Sustain. Cities Soc.*, vol. 39, pp. 309–316, May 2018.
[16] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-Khah, and P. Siano, "Optimal bidding of profit-seeking virtual associations of smart prosumers considering peer to peer energy sharing strategy," *Int. J. Electr. Power Energy Syst.*, vol. 132, Nov. 2021, Art. no. 107175.
[17] J. Soares, B. Canizes, M. A. F. Ghazvini, Z. Vale, and G. K. Venayagamoorthy, "Two-stage stochastic model using benders' decomposition for large-scale energy resource management in smart grids," *IEEE Trans. Ind. Appl.*, vol. 53, no. 6, pp. 5905–5914, Nov. 2017.
[18] Ö. Çavuş, A. S. Kocaman, and Ö. Yılmaz, "A risk-averse approach for the planning of a hybrid energy system with conventional hydropower," *Comput. Oper. Res.*, vol. 126, Feb. 2021, Art. no. 105092.
[19] H. Saber, M. Moeini-Aghtaie, M. Ehsan, and M. Fotuhi-Firuzabad, "A scenario-based planning framework for energy storage systems with the main goal of mitigating wind curtailment issue," *Int. J. Electr. Power Energy Syst.*, vol. 104, pp. 414–422, Jan. 2019.
[20] F. S. Gazijahani and J. Salehi, "Optimal bilevel model for stochastic risk-based planning of microgrids under uncertainty," *IEEE Trans. Ind. Informat.*, vol. 14, no. 7, pp. 3054–3064, Jul. 2018.
[21] D. N. Trakas, M. Panteli, N. D. Hatziargyriou, and P. Mancarella, "Spatial risk analysis of power systems resilience during extreme events: Spatial risk analysis of power systems resilience," *Risk Anal.*, vol. 39, no. 1, pp. 195–211, Jan. 2019.
[22] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-Khah, and J. P. S. Catalão, "A bi-level risk-constrained offering strategy of a wind power producer considering demand side resources," *Int. J. Electr. Power Energy Syst.*, vol. 104, pp. 562–574, Jan. 2019.
[23] B. S. K. Patnam and N. M. Pindoriya, "Centralized stochastic energy management framework of an aggregator in active distribution network," *IEEE Trans. Ind. Informat.*, vol. 15, no. 3, pp. 1350–1360, Mar. 2019.
[24] L. Guo, T. Sriyakul, S. Nojavan, and K. Jermsittiparsert, "Risk-based traded demand response between consumers' aggregator and retailer using downside risk constraints technique," *IEEE Access*, vol. 8, pp. 90957–90968, 2020.
[25] P. Sheikhahmadi and S. Bahramara, "The participation of a renewable energy-based aggregator in real-time market: A bi-level approach," *J. Cleaner Prod.*, vol. 276, Dec. 2020, Art. no. 123149.
[26] P. Beraldi, A. Violi, G. Carrozzino, and M. E. Bruni, "A stochastic programming approach for the optimal management of aggregated distributed energy resources," *Comput. Oper. Res.*, vol. 96, pp. 200–212, Aug. 2018.
[27] H. Rashidizadeh-Kermani, H. Najafi, A. Anvari-Moghaddam, and J. Guerrero, "Optimal decision-making strategy of an electric vehicle aggregator in short-term electricity markets," *Energies*, vol. 11, no. 9, p. 2413, Sep. 2018.
[28] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, H. Najafi, A. Anvari-Moghaddam, and J. Guerrero, "A stochastic bi-level scheduling approach for the participation of EV aggregators in competitive electricity markets," *Appl. Sci.*, vol. 7, no. 10, p. 1100, Oct. 2017.
[29] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-Khah, and P. Siano, "A regret-based stochastic bi-level framework for scheduling of DR aggregator under uncertainties," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3171–3184, Jul. 2020.
[30] M. Esmaeeli, A. Kazemi, H. Shayanfar, G. Chicco, and P. Siano, "Risk-based planning of the distribution network structure considering uncertainties in demand and cost of energy," *Energy*, vol. 119, pp. 578–587, Jan. 2017.
[31] N. Growe-Kuska, H. Heitsch, and W. Romisch, "Scenario reduction and scenario tree construction for power management problems," in *Proc. IEEE Bologna Power Tech Conf.*, vol. 3, Bologna, Italy, Jun. 2003, pp. 152–158.
[32] Y. Martínez-López, A. Y. Rodríguez-González, J. M. Quintana, A. Moya, B. Morgado, and M. B. Mayedo, "CUMDANCauchy-C1: A cellular EDA designed to solve the energy resource management problem under uncertainty," in *Proc. Genet. Evol. Comput. Conf. Companion*, Prague, Czech Republic, Jul. 2019, pp. 13–14.
[33] Y. Martínez-López, A. Y. Rodríguez-González, J. M. Quintana, M. B. Mayedo, A. Moya, and O. M. Santiago, "Applying some EDAs and hybrid variants to the ERM problem under uncertainty," in *Proc. Genet. Evol. Comput. Conf. Companion*, Cancún Mexico, Jul. 2020, pp. 1–2.
[34] J. Soares, F. Lezama, B. Canizes, and Z. Vale, "WCCI/GECCO 2020 competition evolutionary computation in uncertain environments: A smart grid application," GECAD, Porto, Portugal, Dec. 2019, pp. 1–21.
[35] R. Storn and K. Price, "Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces," *J. Global Optim.*, vol. 11, pp. 341–359, 1997.
[36] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. Int. Conf. Neural Netw. (ICNN)*, vol. 4, Perth, WA, Australia, 1995, pp. 1942–1948.
[37] O. Kramer, *Genetic Algorithm Essentials* (Studies in Computational Intelligence), vol. 679. Cham, Switzerland: Springer, 2017.
[38] B. Canizes, J. Soares, Z. Vale, and J. M. Corchado, "Optimal distribution grid operation using DLMP-based pricing for electric vehicle charging infrastructure in a smart city," *Energies*, vol. 12, no. 4, 2019.
[39] J. Almeida, J. Soares, B. Canizes, F. Lezama, M. A. Ghazvini Fotouhi, and Z. Vale, "Evolutionary algorithms for energy scheduling under uncertainty considering multiple aggregators," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Kraków, Poland, Jun. 2021, pp. 225–232.
[40] J. Soares, B. Canizes, C. Lobo, Z. Vale, and H. Morais, "Electric vehicle scenario simulator tool for smart grid operators," *Energies*, vol. 5, no. 6, pp. 1881–1899, Jun. 2012.

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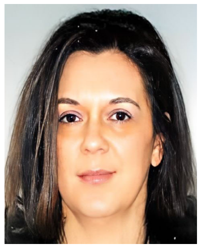

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