Stochastic Unit Commitment in Isolated Systems With Renewable Penetration Under CVaR Assessment

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***Abstract*—Isolated regions and islands are facing imported fossil-fuel dependency, higher electricity prices, and vulnerability to climate change. At the same time, they are increasing their renewable penetration and, therefore, risk for electric utilities. Integrating stochastic energy resources in noninterconnected systems may take advantage of an intelligent and optimized risk-averse unit commitment (UC) model. This paper presents a two-stage stochastic UC model with high renewable penetration including reserve requirements for the efficient management of uncertainty. In order to account for the uncertainty around the true outcomes of load, wind, and photovoltaic (PV) generation, a minimum conditional value at risk term has been included in the model formulation. A stochastic measure of the value of the stochastic solution is used to evaluate the benefits of using stochastic programming. The model considers the need for reserves dependent on the forecasting horizon and the amount of renewable generation. Active power demand, and wind and PV generations are considered as probability distribution functions. The model is applied to the Lanzarote–Fuerteventura system in the Canary Islands, Spain, and Crete, Greece.**

***Index Terms*—Conditional value at risk (CVaR), mean-risk value of the stochastic solution (MRVSS), mixed-integer linear programming, risk aversion, two-stage stochastic programming, unit commitment (UC).**

NOMENCLATURE

Indices and Sets

i	Conventional generation technology.
j	Wind generation technology.
z	Photovoltaic (PV) generation technology.
Ω^I	Set of conventional generation units.
Ω^J	Set of wind generation units.
Ω^Z	Set of PV generation units.
k	Segments for cosine approximation.
n, np	Network nodes.
$\Omega_i^n, \Omega_j^n, \Omega_z^n$	Set of technologies connected to node n.
Ω^L	Set of connection lines.
t	Time period (h).
Ω^t	Set of time periods $(0, \ldots, 24)$.
w	Scenario.
Ω^W	Set of scenarios.

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Parameters

A^+, B^+	Positive balancing linearization (%).
A^-, B^-	Negative balancing linearization (%).
c^{EPS}	Cost of PV curtailment (€/MWh).
c^{EWS}	Cost of wind curtailment (€/MWh).
$D_{n,t,w}$	Initial demand level at time t (MW).
c_i^F	Fixed commitment costs (€).
$\mathrm{RR}_{\mathrm{Ci}}$	Ramp committed capacity (%).
$\mathrm{RR}_{\mathrm{NCi}}$	Ramp noncommitted capacity (%).
c_i^V	Variable generation costs (€/MWh).
c_i^{SU}	Start-up costs for generation unit i (€).
$\mathrm{PV}_{t,w}$	PV power output per MW installed at time t and scenario w (%).
$W_{t,w}$	Wind power output per MW installed at time t and scenario w (%).
c^{NSE}	Cost of energy not served (€/MWh).
$R_{n,np}$, $X_{n,np}$	Resistance and reactance line parameters (Ω).
ξ_w	Scenario probability.
α	Per unit confidence level.
β	Weighting parameter for cost versus risk tradeoff.
$\overline{G_i}$	Installed capacity for conv. generation (MW).
$\underline{G_i}$	Minimum output for conventional generation (MW).
$\overline{\mathrm{PV}_z}$	Installed PV capacity (MW).
$\overline{\mathrm{WP}_z}$	Installed wind capacity (MW).
$u_{i,0}$	Initial commitment status for generator i.
m_k	Slope of the cosine approximation segment k.
n_k	Intercept of the cosine approximation segment k.
θ_N	Phase angle voltage of node n at time t (rad).
$\bar{\theta}$	Maximum phase angle voltage $(\pi/2, \pi/2)$.
$\overline{fl}_{n,np,t,w}$	Bound for active power flow from node n to np.

Variables

$\mathrm{bal}_{t,w}^+$	Positive balancing power at time t and scenario w (MW).

$\mathrm{bal}^{-}_{t,w}$	Negative balancing power at time t and scenario w (MW).
$\mathrm{nse}_{n,t,w}$	Energy not served at node n, time t and scenario w (MWh).
$f^{+}_{i,t,w}$	Upward output flexibility of generation technology i at time t and scenario w (MW).
$f^{-}_{i,t,w}$	Downward output flexibility of generation technology i at time t and scenario w (MW).
$g_{i,t,w}$	Active power generation of generation technology i at time t and scenario w (MW).
$\mathrm{eps}_{z,t,w}$	PV power curtailment at time t and scenario w (MW).
$\mathrm{pv}_{z,t,w}$	PV active power injected at time t and scenario w (MW).
$\mathrm{ews}_{j,t,w}$	Wind power curtailment at time t and scenario w (MW).
$\mathrm{wp}_{j,t,w}$	Wind active power injected at time t and scenario w (MW).
$\mathrm{fl}_{n,np,t,w}$	Line flow between nodes n and np at time t and scenario w (MW).
VaR	Value at risk (€).
CVaR	Conditional value at risk (€).
MRRP	Mean-risk recourse problem (€).
MREV	Mean-risk expected value (€).
MRVSS	Mean-risk value of the stochastic solution (€).
c_w	Scenario costs (€).
$z_{i,t}$	Start-up decision for generator i at time t.
$x_{i,t}$	Shut-down decision for generator i at time t.
$u_{i,t}$	Commitment status for generator i at time t.
tc	Scenario-weighted expected costs (€).
$\theta_{n,t,w}$	Phase angle in node n at time t (rad).

I. Introduction

RENEWABLE generation technologies have been promoted by policy-makers throughout the years in an effort to increase the sustainability of electric power systems. Threats experienced by isolated systems as a consequence of the increasing renewable energy sources (RES) penetration are higher than those experienced by interconnected systems, since they cannot depend on the smoothing effect of a large balancing area and interconnection flows. In addition, renewable technologies are becoming price-competitive, especially in isolated systems, where diesel and heavy fuel oil generation units dominate the generation mix. Islands will face considerable challenges in the coming future in order to meet their energy needs in a sustainable, affordable, and reliable way. The short-term operational scheduling of electric power systems has been traditionally subject to a two-level hierarchy paradigm, including unit commitment (UC) and economic dispatch (ED). Stochastic programming is an effective technique to deal with renewable generation involving uncertainty.

Variability and uncertainty are not unique to stochastic generation resources. Similar challenges are posed by aggregated electricity demand and, to a certain extent, by supply resources. Over the years, different techniques for managing the variability of demand and generation of the system through the use of reserves have been developed by grid operators. In addition, reserves have been operated for diverse purposes across multiple time scales.

Reserve commitment rules have been traditionally differentiated into contingencies and operating reserves. For standard system management, this approach has effectively and efficiently coped with operation reserve requirements. However, the increasing penetration of stochastic generation units makes the above-mentioned reserve classification unclear, thereby making the validity of current reserve commitment rules questionable [1]. Following the definition proposed in [2], operating reserves are considered as real power capability that can be given or taken to assist in generation and load balance and frequency control. Operating reserves should account for contingencies, like the sudden loss of a generator or a line, or events on a longer time scale such as net load ramps and forecasting errors. Thus, models should take into account the need for reserves dependent on the forecast horizon and nondispatchable generation share. As outlined in [3], the enforcement of reserve requirements in different scenarios serves the further purpose of building confidence for UC decisions by the operators, addressing the inherent risk of these uncertainties.

The increasing stochastic generation share in the overall generation mix calls for a review in current UC procedures, assessing their impact on costs and system performance. A more suitable approach to account for the variability and uncertainty associated to demand and nondispatchable generation technologies results from the application of stochastic programming methodologies. Stochastic programming represents a framework for modeling optimization problems considering uncertainty in the input data. Stochastic programming has proved its flexibility and usefulness in a wide range of science areas, smoothing out the random irregularities of each singular scenario.

The uncertainty associated with nondispatchable technologies introduces risk into power systems economics and operation. Therefore, risk measuring plays a fundamental role in optimization under uncertainty, providing valuable information to decision-makers. The proposed model incorporates risk aversion by constraining the volatility of the expected cost through CVaR assessment, avoiding over-conservative solutions.

Aligned with the goal of boosting the penetration of RES in future smart grids, energy management with renewables (including UC, ED, and optimal power flow) has been extensively investigated in the last few years. This paper includes risk aversion in the UC problem for isolated systems, which, in our opinion, has not yet been adequately considered. First-stage variables are related to the UC and the start-up/shut-down variables and second-stage variables are related to production expected for the different units using scenarios.

This paper is organized as follows. First, a literature review on stochastic UC models is provided in Section II. Then, the stochastic UC model under CVaR assessment is explained in Section III. Lanzarote–Fuerteventura (LZ–FV) case study is presented in Section IV. Section V enhances the case study with the inclusion of a larger system [Crete (CR)]. Finally, the conclusion is presented in Section VI.

II. Literature Review and Contributions

A. Literature Review

Traditional UC assumes a deterministic approach when including small penetration of renewable technologies, since perfect information for demand and nondispatchable energy resources is considered [4]. However, when the increasing amount of renewable penetration is taken into consideration, the traditional practice may not be sufficient. There are two common approaches to incorporate uncertainty in the UC problem: 1) stochastic programming; and 2) reserve requirements. Ruiz *et al.* [3] compared stochastic and reserve methods and evaluated the benefits of a combined approach for the efficient management of uncertainty in UC. A two-stage stochastic programming model for committing reserves in systems with high wind power penetration is discussed in [1]. A stochastic long-term security constrained UC formulation is proposed in [5], accounting for uncertainties in the availability of generation units and transmission lines and inaccuracies in load forecasting. Lagrangian relaxation is applied to make the problem computational tractable. A short-term forward electricity market-clearing problem with stochastic security, capable of accounting for nondispatchable renewable generation, is presented in [6].

In order to analyze system operation with large renewable penetration, different authors proposed a rolling planning rescheduling when updated information becomes available. Meibom *et al.* [7] presented a mixed-integer stochastic optimization scheduling model, where schedules are updated in a rolling manner as updated information is accessible. A solution for the unified UC problem in systems with high renewable penetration grounded on an mixed integer linear programming (MILP)-based multiple time resolution UC model is presented in [8]. Pozo and Contreras [9] presented a chance-constrained method for joint energy and reserved scheduling and UC with *n*–*K* reliability constraints. Zhao and Guan [10] presented a unified stochastic and robust UC model to accommodate uncertainties.

Several risk management methods can be found in [11]–[15]. The most widely used are VaR and CVaR [16], included as constraints in the formulation of the optimization problem. Risk aversion assessment based on CVaR has been traditionally used to hedge a portfolio of financial instruments to reduce investment risks. Huang *et al.* [17] have developed a two-stage stochastic UC integrating nongeneration resources such as energy storage and demand response, using CVaR to model the risk associated with the decisions in a stochastic environment. This model compares the results of including different nongeneration resources quantifying risk-aversion in terms of loss allowance. These authors focused on the reliability parameter analysis regarding confidence levels and load-shedding allowances, not assigning a cost to this not served energy. Zhao *et al.* [18] formulated an expected value and chance constrained stochastic optimization approach for the UC problem with uncertain wind power output, where the wind utilization factor can be adjusted. A risk-based day-ahead UC model that considers the risks of the loss of load, wind curtailment, and branch overflow caused by wind power uncertainty is presented in [19].

Robust optimization (RO) has received growing attention in both research and applications over the past. The RO approach puts the random problem parameters in a predetermined uncertainty set containing the worst-case scenario instead of making assumptions on specific probability distributions. Zhao *et al.* [20] adopted the RO approach for the solution of the UC problem, aiming at the maximization of social welfare under the worst-case wind power output and demand response scenarios. An and Zeng [21] presented a risk-constrained robust UC model that derives solutions subject to different bounds on worst-case performances in different uncertainty sets.

Chen [22] proposed a dynamic programming algorithm to coordinate the wind and thermal generation scheduling problem for operating an isolated hybrid power system. Different constraints are applied to determine the maximum proportion of wind generator capacity that can be integrated into the system. Lowery and O'Malley [23] quantified the interaction among the implicit reserve carried by a rolling planning stochastic UC, deterministic reserve criteria, and the quality of information around wind forecast error for the Irish isolated system. An advanced energy management system (EMS) for isolated microgrids is presented in [24].

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As wind power penetration increases in isolated power systems, more innovative and sophisticated approaches to system operation will need to be adopted due to the intermittency and unpredictability of wind power generation. Several references have been proposed in the literature targeting the aforementioned problems. However, in our opinion, none of the existing works sufficiently stresses the relevance of isolated systems. Table I summarizes all these references whose formulation has been stated as MILP.

TABLE I
UC MODELS

Author and year	*Reference*	*Renewable*	*Demand Response*	*Reserves*	*Risk management*	*Curtailment*	*Network*	*MRVSS*
Ruiz *et al.*, 2009	[3]	No	No	Yes	No	No	No	No
Abdollahi-Mansoorkhani *et al.*, 2013	[5]	Yes	No	Yes	No	No	Yes	No
Bouffard and Galiana, 2008, Meibom *et al.*, 2011, Bakirtzis *et al.*, 2014	[6], [7], [8]	Yes	No	Yes	No	Yes	No	No
Pozo and Contreras, 2013, Zhang *et al.*, 2014	[9], [19]	Yes	No	Yes	Yes	Yes	No	No
Huang *et al.,* 2014	[17]	Yes	Yes	No	Yes	No	No	No
Zhao *et al.*, 2014	[18]	Yes	No	No	Yes	No	No	No
Zhao *et al.*, 2013	[20]	Yes	Yes	No	No	No	No	No
Chen, 2008	[22]	Yes	No	Yes	No	Yes	No	No
Current paper	-	Yes	No	Yes	Yes	Yes	Yes	Yes

B. Contributions

In the considered optimization problem, operational costs are minimized taking into account the demand balance constraint, up and down reserves, minimum and maximum generation capacities, ramping constraints, and the logic sequence for the startup and shutdown decisions. Renewable generation is continuously increasing its penetration in isolated systems, becoming more and more an issue for system operators. Additionally, reserve requirements in isolated systems used to overcome the lack of interconnection are highly influenced by renewable generation, making its assessment dependent of expected renewable generation for the considered time horizon. High renewable input might lead to problems of thermal generation reserve if not correctly managed. Additionally, wind and PV curtailment costs have been included in the cost formulation. The introduction of risk aversion in the UC formulation may lead to a coherent tradeoff between economic efficiency of the system and risk assumed. In our approach, risk aversion is incorporated by limiting the volatility of the expected cost through the CVaR. The optimal solutions based on the efficient frontier are helpful for providing decision-makers with information about the tradeoff between risk mitigation and UC costs.

Due to the big size and the quite complex nature of stochastic programs in comparison to deterministic ones, it is interesting and important to quantify the advantage of using stochastic optimization over solving a series of deterministic optimization programs fixing the value of random parameters in each one of them. The value of the stochastic solution (VSS) is a widely used measure designed to indicate the adequacy of modeling randomness using a risk-neutral two-stage stochastic programming model. However, this measure cannot be directly used with the proposed risk-averse two-stage stochastic programming model. VSS is based on expected values and, so, is useful to evaluate risk-neutral stochastic programming models. Noyan [25] proposed a new indicator for VSS in order to quantify the effect of involving risk in a two-stage stochastic programming model. The MRVSS represents the possible gain from solving the stochastic model that incorporates the mean-risk function for the random outcome of interest in the model formulation. Contribution of this paper is the introduction of the MRVSS indicating the improvement in the solution quality in terms of the specified risk preference by solving the risk-averse model instead of solving the expected value problem. Applying MRVSS allows the comparison of the results with the traditional UC problem.

Summarizing the above described arguments, the main contributions of this paper are as follows.

1) Formulation of an MILP model that includes a CVaR assessment to account for the impact of uncertainty and risk aversion in UC decisions in isolated systems with high renewable penetration. Such compact modeling contributes to improving the calculation efficiency of the risk-constrained UC model.
2) The proposed formulation introduces wind and PV curtailment costs in the model formulation to adequately measure the risk tradeoff. Network constraints have been included in the model. Additionally, reserve requirements in isolated systems have been formulated as dependent on overall demand and penetration of renewable technologies.
3) A further contribution of the proposed methodology is the assessment of MRVSS quantifying the improvement of the solution obtained. MRVSS indicates the improvement in the solution quality compared to the deterministic solution. Solution algorithms have been developed for the proposed model with CVaR and introducing new stochastic measures on the VSS.

III. PROBLEM FORMULATION

This paper adds CVaR constraints to the traditional two-stage stochastic UC model formulation to quantify the risk assumed during the commitment and dispatch procedure against uncertainties [11]. CVaR assessment is able to quantify the risk potential beyond VaR and represents an appropriate approach to integrate the inherent risk management problem in the commitment and dispatch procedures. By definition, with respect to a specified probability level α, VaR of a portfolio is the lowest dispatch cost such that, with probability α, the dispatch cost will not exceed a considered amount, whereas the CVaR is the conditional expectation of dispatch cost above that amount (Fig. 1). As a function of the decision variables, CVaR is convex and, therefore, can be efficiently controlled/optimized using convex or linear programming.

For a given $\alpha(0, 1)$, VaR represents the lowest dispatch cost, ensuring that the probability of obtaining a total dispatch cost

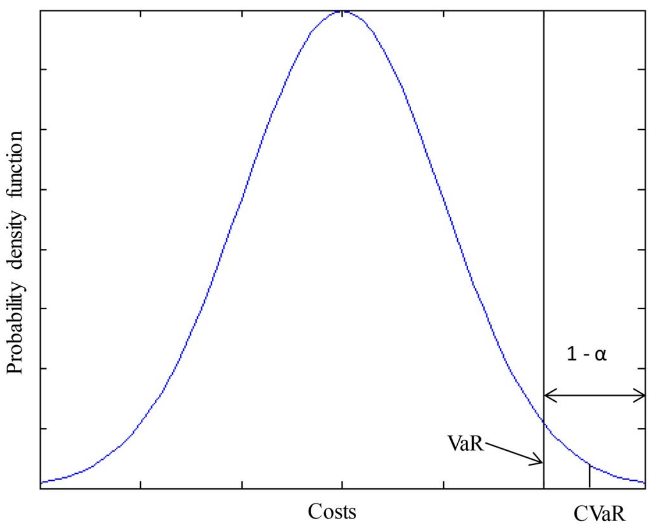

Fig. 1. VaR and CVaR illustration.

higher than this value is lower than $(1-\alpha)$. According to [16], the discontinuous distribution of VaR may lead to failures in optimization problems. Additionally, the VaR risk measure is nonsensitive to extreme risks, providing a risk limit. On the contrary, CVaR points out the tail mean and provides an estimate of the weighted costs. Based on this claim, CVaR is a coherent risk aversion measure for stochastic optimization problems, such as the one presented here. In addition, CVaR results in a convex function with respect to the considered portfolio positions, allowing the construction of efficient optimizing problems.

Given the previous modeling assumptions (neglecting of ohmic losses and CVaR approach), the two-stage stochastic UC model with nondispatchable and variable wind and PV power generation sources is presented below

$$\min((1-\beta)*tc)+\beta*\mathrm{CVaR}) \tag{1}$$

$$\text{subject to:} \quad \mathrm{CVaR}=\mathrm{VaR}+\frac{1}{1-\alpha}\sum_{w}\xi_w*\eta_w \tag{2}$$

$$c_w-\eta_w-\mathrm{VaR}\leq 0 \tag{3}$$

$$\eta_w\geq 0 \tag{4}$$

$$\begin{aligned} c_w=&\sum_{\forall i\in\Omega^I}\left(\sum_t\left(c_i^{\mathrm{SU}}*z_{i,t}+c_i^F*u_{i,t}\right)\right)\\ &+\sum_{\forall i\in\Omega^I}\left(\sum_t\left(c_i^V*g_{i,t,w}\right)\right)\\ &+\sum_{\forall z\in\Omega^Z}\sum_t\left(c^{\mathrm{EPS}}*\mathrm{eps}_{z,t,w}\right)\\ &+\sum_{\forall j\in\Omega^J}\sum_t\left(c^{\mathrm{EWS}}*\mathrm{ews}_{j,t,w}\right)\\ &+\sum_t\sum_n\left(c^{\mathrm{NSE}}*\mathrm{nse}_{n,t,w}\right) \end{aligned} \tag{5}$$

$$tc=\sum_w(\xi_w*c_w) \tag{6}$$

$$\begin{aligned} &\sum_{\forall i\Omega_i^n}g_{i,t,w}+\sum_{\forall j\Omega_j^n}wp_{j,t,w}\\ &+\sum_{\forall z\Omega_z^n}\mathrm{pv}_{z,t,w}+\sum_{\forall n,np\in\Omega^L}\mathrm{fl}_{n,np,t,w}\\ &=D_{n,t,w}-\mathrm{nse}_{n,t,w}\forall n\Omega^n \end{aligned} \tag{7}$$

$$\mathrm{fl}_{n,np,t,w}=\frac{\left(\theta_{n,t,w}-\theta_{np,t,w}\right)}{X_{n,np}} \tag{8}$$

$$\theta_{n,t,w}-\theta_{np,t,w}\leq X_{n,np}*\overline{\mathrm{fl}}_{n,np,t,w} \tag{9}$$

$$\theta_{n,t,w}-\theta_{np,t,w}\geq -X_{n,np}*\overline{\mathrm{fl}}_{n,np,t,w} \tag{10}$$

$$f_{i,t+1,w}^{+}\leq \mathrm{RR}_{Ci}*g_{i,t,w}+\mathrm{RR}_{\mathrm{NC}i}*\overline{G_i}*(1-u_{i,t}) \tag{11}$$

$$f_{i,t+1,w}^{-}\leq \mathrm{RR}_{Ci}*g_{i,t,w} \tag{12}$$

$$f_{i,t+1,w}^{+}\leq \overline{G_i}-g_{i,t,w} \tag{13}$$

$$f_{i,t+1,w}^{+}\leq g_{i,t,w} \tag{14}$$

$$g_{i,t+1,w}\leq g_{i,t,w}+f_{i,t+1,w}^{+} \tag{15}$$

$$g_{i,t+1,w}\geq g_{i,t,w}-f_{i,t+1,w}^{-} \tag{16}$$

$$\mathrm{bal}_{t,w}^{+}=A^{+}*\sum_n D_{n,t,w}+B^{+}*\left(\sum_z\mathrm{pv}_{z,t,w}+\sum_j\mathrm{wp}_{j,t,w}\right) \tag{17}$$

$$\mathrm{bal}_{t,w}^{-}=A^{-}*\sum_n D_{n,t,w}+B^{-}*\left(\sum_z\mathrm{pv}_{z,t,w}+\sum_j\mathrm{wp}_{j,t,w}\right) \tag{18}$$

$$\sum_i g_{i,t+1,w}+\mathrm{bal}_{t-1,w}^{+}\leq\sum_i g_{i,t,w}+\sum_i f_{i,t+1,w}^{+} \tag{19}$$

$$\sum_i g_{i,t+1,w}+\mathrm{bal}_{t+1,w}^{+}\leq\sum_i g_{i,t,w}+\sum_i f_{i,t+1,w}^{-} \tag{20}$$

$$0\leq g_{i,t,w}\leq u_{i,t}*\overline{G_i} \tag{21}$$

$$\mathrm{pv}_{z,t,w}=\mathrm{PV}_{z,t,w}*\overline{\mathrm{PV}_z}-\mathrm{eps}_{z,t,w} \tag{22}$$

$$\mathrm{wp}_{j,t,w}=W_{j,t,w}*\overline{W_j}-\mathrm{ews}_{j,t,w} \tag{23}$$

$$u_{i,t+1}=u_{i,t}+z_{i,t+1}-x_{i,t+1} \tag{24}$$

$$g_{i,t,w}+f_{i,t,w}^{+}\leq u_{i,t}*\overline{G_i} \tag{25}$$

$$\begin{aligned} &g_{i,t,w}-f_{i,t,w}^{-}\geq u_{i,t}*\underline{G_i}\\ &\forall t\in\Omega^t, w\in\Omega^w, i\in\Omega_i^n, j\in\Omega_j^n, z\in\Omega_z^n, (n,np)\in\Omega^l. \end{aligned} \tag{26}$$

The overall objective function of (1) aims at minimizing system costs accounting for risk aversion through the β parameter. CVaR in (2) is calculated based on scenario-dependent costs, in order to obtain an adequate Gaussian distribution and is a coherent risk measure, since it can be expressed using a linear formulation. In (3), variable c_w represents the expected costs in scenario w and η_w is an auxiliary variable whose value is equal to zero if scenario w has a total cost lower than VaR. Note that η_w is lower than the difference between VaR and the corresponding costs for any other scenario. The inclusion of the weighted correction factor β underlines the balance between risk and expected costs. The value of β varies from 0 to 1. The scenario-based costs and the weighted-average costs are calculated in (5) and (6), respectively.

Here-and-now decisions considered in the two-stage stochastic programming model correspond to UC, determining the operational status of generation units. Wait-and-see variables correspond to the dispatch problem, where optimal values for generation output and nonserved energy are defined, considering the available resources defined in the here-and-now problem.

The objective function is subject to simplified transmission network constraints (7)–(10). Constraint (7) corresponds to the active power balance. This equation states that, for every period and node, all the power generated at a certain node plus the net power flowing into the node through the lines connected to it (the flow could be negative, which would represent an outflow instead of an inflow) has to be equal to the power demanded in the node minus the nonserved energy at the node. The variable for the energy not served is actually a slack variable that represents the energy that cannot be covered by the generators and is strongly penalized in the total costs formulation. Constraint (8) calculates the power flowing through each line for every period. This is determined by the difference in the angle phases of the two nodes forming the line divided by the reactance of the line.

Constraints (9) and (10) define the limits for the phase angles of the nodes. Ramping rates of the generation units have been introduced in the model in (11) and (12) for both committed and noncommitted units. The available flexibility for each generation unit is constrained by (13)–(16). Additionally, balancing requirements account for both positive and negative reserves. Flexibility requirements are defined as a function of the instantaneous renewable penetration and demand volume, respectively (17) and (18). Fulfillment of upward and downward reserve requirements is guaranteed in (19) and (20). Conventional generation, and wind and PV generations have been considered as variables limited by (21)–(23). Wind and PV curtailments are considered in order to reduce hourly injections when over-generation is detected, as shown in (22) and (23). UC decisions for generators are considered global variables for all scenarios (24). Constraints (25) and (26) guarantee a feasible dispatch for a single generator including required reserve margin.

The metric applied to evaluate the improvement in the solution by solving the risk-averse model instead of solving the expected value problem is the aforementioned MRVSS. MRVSS (29) represents the possible gain from solving the stochastic model incorporating a mean-risk function. MRRP (27) is the mean-risk stochastic function obtained from the model (1)–(26). MREV (28) is the solution obtained when the first-stage decisions $\bar{u}(\bar{w})$ are made based on the weighted average forecast

$$\mathrm{MRRP} = \min_{u \in U}\{(1-\beta) * E[f(u,w)] + \beta * \mathrm{CVaR}[f(u,w)]\} \tag{27}$$

$$\mathrm{MREV} = (1-\beta) * E\big[f(\bar{u}(\bar{w}),w)\big] + \beta * \mathrm{CVaR}\big[f(\bar{u}(\bar{w}),w)\big] \tag{28}$$

$$\mathrm{MRVSS} = \mathrm{MREV} - \mathrm{MRRP}. \tag{29}$$

TABLE II
LZ-FV NETWORK DATA

from (n)	*to (np)*	$R_{n,np}$ (Ω)	$X_{n,np}$ (Ω)
1	2	0.3093	1.1021
2	3	0.4269	1.5290
3	1	0.9365	0.6055
3	4	3.7810	1.7685
4	5	1.2502	3.7200
5	6	2.9621	0.9801
5	7	0.8581	4.0032
7	8	0.6926	3.2409

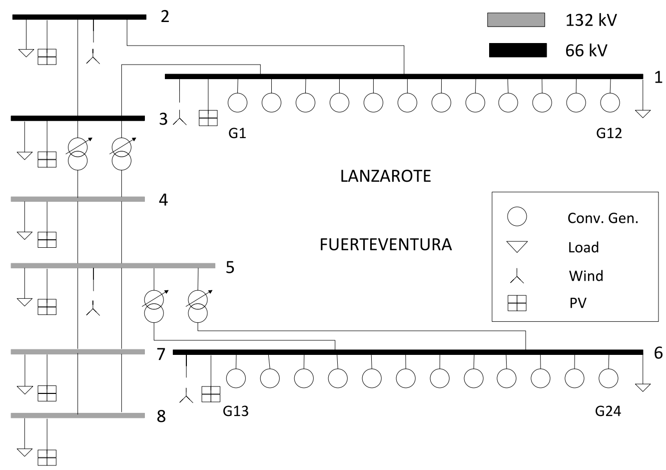

Fig. 2. LZ–FV 8-node transmission network.

IV. LANZAROTE-FUERTEVENTURA CASE STUDY

A. System Description

The electric power system of LZ–FV has a generation mix based on diesel and gas plants, with a continuously increasing renewable penetration. The analyzed LZ–FV system has two thermal power plants with 24 units, all owned by ENDESA generation with a total installed capacity of 346.5 MW: 187.2 MW in Punta Grande (node 1, LZ) and 159.3 MW in Las Salinas (node 6, FV). In addition, there are two wind farms across the island of LZ with a total installed capacity of about 8.8 MW and three wind farms across the island of FV with a total installed capacity of about 18.2 MW. Finally, there is a large number PV systems, with a current total installed capacity of about 9.9 MW. In this paper, different penetration scenarios for 2020 have been considered, increasing renewable penetration from the installed power (Table II). Actual installed renewable share represents 10% of the installed capacity and considered scenarios account for 10%, 20%, 30%, and 40% of installed capacity (from now on Factors 1–4, respectively). The system consists of an eight-bus radial transmission network (Fig. 2) with a nominal voltage magnitude of 66 kV and base power of 100 MVA. The slack node considered in the proposed model is at node 1.

The model comprises 8 buses, 24 conventional generators connected to the 66 kV network, and different renewable generation technologies connected to both 66 and 132 kV

TABLE III
RENEWABLE TECHNOLOGY GENERATION IN LZ–FV

Gen.	*InstCap [MW]*	*Connection Node*	*Gen.*	*InstCap [MW]*	*Connection Node*
PV 1	1.423	1	PV 8	0.612	8
PV 2	1.632	2	Wind 1	7.65	1
PV 3	0.306	3	Wind 2	1.125	2
PV 4	0.408	4	Wind 3	1.7	5
PV 5	0.311	5	Wind 4	1.125	8
PV 6	3.774	6	Wind 5	1.539	8
PV 7	1.445	7			

TABLE IV
CONVENTIONAL TECHNOLOGY GENERATION
COSTS IN LZ (PUNTA GRANDE)

Tech.	**Generation Costs**				
	InstCap [MW]	*Start-up Costs [€]*	*FixCosts [€]*	*VarCosts [€/MWh]*	*Pmin. [MW]*
LZ-Diesel 1	6.49	527	96.801	180.235	4.2
LZ-Diesel 2	6.49	527	96.801	180.235	4.2
LZ-Diesel 3	6.49	527	96.801	180.235	4.2
LZ-Diesel 4	12.85	1494	71.083	145.041	8.7
LZ-Diesel 5	12.85	1494	71.083	145.041	8.7
LZ-Diesel 6	20.51	2287	109.11	145.051	14.09
LZ-Diesel 7	17.2	1529	119.27	156.439	11.8
LZ-Diesel 8	17.2	1529	119.27	156.439	11.8
LZ-Gas 1	19.6	2468	253.61	292.051	6.79
LZ-Gas 2	32.34	2468	252.91	245.011	6.79
LZ-Diesel 9	17.6	1529	119.29	156.575	11.8
LZ-Diesel 10	17.6	1529	119.29	156.575	11.8

transmission networks. Table II shows the network specifications of the considered test system.

Connection nodes and installed capacities of renewable technologies are described in Table III. A curtailment cost for renewable power of €100/MWh has been included in the model, inspired by the negative prices observed in different energy markets.

The mean annual energy consumption of LZ–FV is almost 1.4 TWh and the peak load demand escalates to 240 MW during summer, owing to tourism. Tables IV and V give an overview of the actual conventional generation mix of the LZ–FV, including installed capacity, minimum power, and fixed and variable costs.

In the UC problem, the decision-maker faces the uncertainty associated with demand, wind, and PV generations. Demand, wind, and PV generations are considered in this paper as random functions depending on the time period t. Forecast errors are simulated with increasing variance mimicking the increasing forecast uncertainty for an increasing time horizon. Therefore, demand, wind, and PV forecast functions are described by Normal distributions with zero-mean normally distributed errors for each time period. A Monte Carlo simulation is used to generate 5 scenarios for each single uncertainty driver, accounting for 125 scenarios. Considering a sufficiently large number of time series, it is possible to represent uncertainty around the true outcomes of load, wind, and PV generation. The maximum deviations for demand, PV, and wind forecasts are set in the model at 5%, 25%, and 25% in the worst case ($t = 24$). Wind and PV power costs are assumed to be null. For simplicity reasons, ramping rates have been set to 80%, which is a normal assumption considering diesel generators. Flexibility requirements dependent on renewable penetration and demand have been set to 15%, in line with normal operation in isolated systems. The considered costs for not served energy (€750/MWh, €1000/MWh, and €1250/MWh) are consistent with those applied to different energy markets, being several times higher than the average marginal cost.

TABLE V
CONVENTIONAL TECHNOLOGY GENERATION
COSTS IN FV (LAS SALINAS)

Tech.	**Generation Costs**				
	InstCap [MW]	*Start-up Costs [€]*	*FixCosts [€]*	*VarCosts [€/MWh]*	*Pmin. [MW]*
FV-Diesel 1	3.82	270	53.022	174.018	2.4
FV-Diesel 2	3.82	270	53.022	174.018	2.4
FV-Diesel 3	4.11	440	96.829	180.507	2.8
FV-Diesel 4	6.21	227	96.859	180.805	4.2
FV-Diesel 5	6.21	527	96.859	180.805	4.2
FV-Diesel 6	20.51	2287	109.11	145.510	14.09
FV-Gas 1	21.85	2468	253.48	283.135	6.79
FV-Gas 2	29.4	2255	253.01	251.703	9.69
FV-Diesel 7	17.2	1529	119.27	156.439	11.8
FV-Mob.Gas1	11.74	2255	254.39	343.795	2.93
FV-Diesel 8	17.2	1529	119.27	156.439	11.8
FV-Diesel 9	17.2	1529	119.27	156.439	11.8

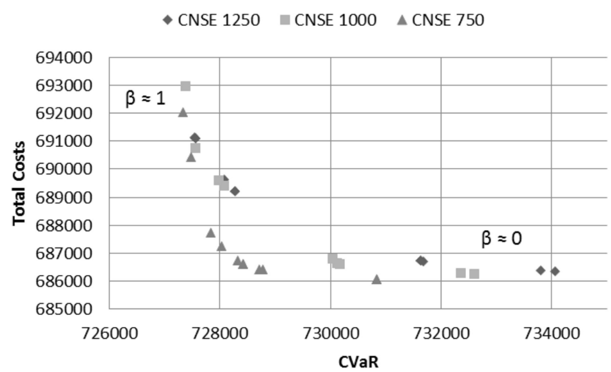

Fig. 3. Total costs versus CVaR: efficient frontier ($\alpha = 0.99$; Factor 4).

B. Results

Figs. 3–5 represent CVaR variation versus total UC costs for $\alpha = 0.99$ with different values for energy not served and renewable penetration factors: Factors 4, 3, and 2, respectively). Note that, as risk aversion increases, so does the overall dispatch cost. The total costs are considered as the weighted average of the costs for each scenario. Numerical values for Fig. 3 are provided in Table VI. Solving the problem for different values of β and not supplied energy costs allows for the representation of the efficient frontier.

There are 11 points arising from the solution of the minimization problem described in (1)–(26) by modifying parameter β. This parameter models the tradeoff between the expected

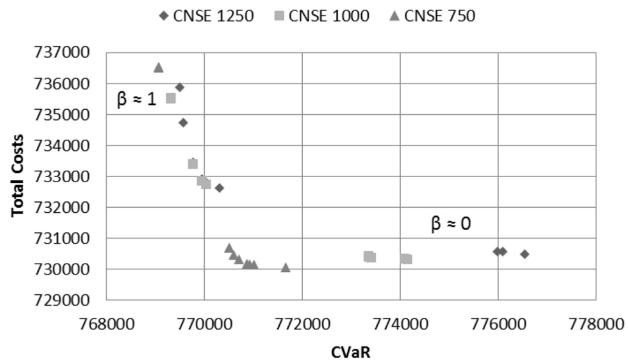

Fig. 4. Total costs versus CVaR: efficient frontier ($\alpha = 0.99$; Factor 3).

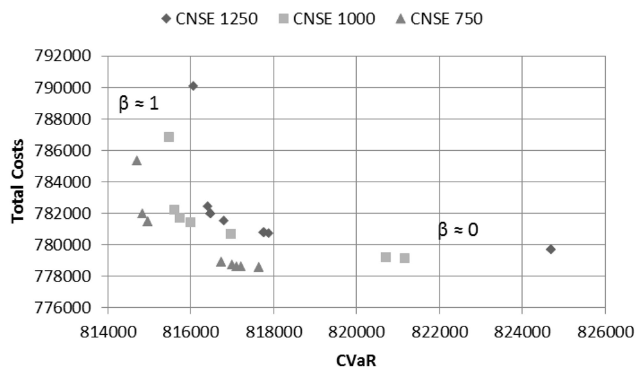

Fig. 5. Total costs versus CVaR: efficient frontier ($\alpha = 0.99$; Factor 2).

TABLE VI
RISK VERSUS GENERATION COSTS (CNSE: COST OF NON SUPPLIED ENERGY = €1250/MWh)

α	*β*	*Total Cost [€]*	*VaR [€]*	*CVaR [€]*	*MRVSS [€]*
0.99	≈ 0	686360.4	730841.7	734055.0	57293.7
0.99	0.1	686385.7	730838.4	733807.4	61433.0
0.99	0.2	686700.9	728767.0	731679.7	66230.9
0.99	0.3	686721.8	728714.0	731626.7	71100.8
0.99	0.4	686721.8	728323.8	731626.7	75976.8
0.99	0.5	689213.4	728421.7	728266.2	81287.4
0.99	0.6	689224.7	728421.7	728266.3	86744.1
0.99	0.7	689611.9	728032.5	728071.5	92226.7
0.99	0.8	691102.5	727837.8	727551.3	97865.4
0.99	0.9	691144.5	727477.6	727545.5	103588.1
0.99	≈ 1	691101.5	727328.2	727554.6	108733.3

costs and the costs variability (measured in terms of CVaR). The first point is obtained solving the problem with a near-zero β parameter. The point represents the minimum dispatch cost but at the maximum CVaR ($\beta \approx 0$). As per (1), numerical results for $\beta \approx 0$ are equivalent to the stochastic UC problem without CVaR.

The results attained considering nonserved energy costs of €1250/MWh and 40% of renewable penetration in the overall energy mix are analyzed in further detail. As expected, the optimal solution attained for $\beta = 0$ achieves the highest value in terms of CVaR. Considering that β increases from 0 to 0.5, the expected cost increases from €686360.4 to €689213.4 (0.42%), while CVaR decreases from €734055.0 to €728266.2 (0.79%). This result presents

TABLE VII
RISK VERSUS GENERATION COSTS (CNSE = €1250/MWh)

α	*β*	*Total Cost [€]*	*VaR [€]*	*CVaR [€]*	*MRVSS [€]*
0.95	≈ 0	686359.4	725229.7	732355.2	57311.6
0.95	0.1	686385.8	725229.7	732102.5	61602.9
0.95	0.2	686644.9	723135.3	730216.1	66567.2
0.95	0.3	686721.9	723199.3	729941.2	71604.7
0.95	0.4	686722.9	723199.3	729937.0	76649.8
0.95	0.5	686721.9	723275.0	729941.2	81692.7
0.95	0.6	689452.8	723275.0	727687.1	86996.9
0.95	0.7	689452.8	723080.6	727687.1	92539.4
0.95	0.8	689666.3	723284.9	727590.1	98116.9
0.95	0.9	690680.0	722491.3	727378.5	103779.6
0.95	≈ 1	690680.0	722483.5	727378.5	108906.1

an adequate tradeoff between dispatch costs and risk, since an increase in the expected costs can be used to efficiently reduce the risk of cost variability. Furthermore, it can be observed that a higher risk exposure ($\beta > 0.5$) does not provide an additional benefit neither in terms of CVaR nor total dispatch costs. The MRVSS column represents the possible gain from solving the stochastic model incorporating the mean-risk function. MRVSS is high in general due to the high not served energy cost, increasing with higher levels of risk-aversion.

Numerical results for CVaR and total dispatch costs associated to $\alpha = 0.95$ and 40% of renewable penetration in the overall energy mix are provided in Table VII. Comparing the results obtained in Tables VI and VII, it can be observed that, as the confidence level α decreases, so do the values for CVaR and overall system costs.

The values attained for MRVSS represent the gain from solving the stochastic model that incorporates the mean-risk function for the random outcome of interest in the model formulation. In the proposed framework, there are two risk parameters represented by α and β. Analyzing the results obtained in Tables VI and VII, it can be observed how the higher the risk in the UC problem, the higher the possible gain from solving the stochastic problem. Note that the high values of MRVSS would indicate the significant improvement in the solution quality in terms of the specified risk preference by solving the risk-averse model instead of solving the expected value problem. Additionally, the value of the MRVSS decreases when the confidence level α increases. The results for the tradeoff between risk mitigation and overall UC costs are shown in Fig. 6. Increasing renewable penetration results in a better performance of the proposed methodology, achieving higher risk mitigation at a lower cost. The highest reduction is obtained for 20% renewable penetration, reaching a 1% CVaR reduction with a total cost increase of 0.35%.

The impact of renewable penetration in the overall UC costs is represented in Fig. 7. Additionally, an efficient frontier for each penetration level is included in the picture. Since renewable generation costs have been neglected, incorporating renewable technologies reduces UC costs.

Fig. 8 represents CVaR variation versus UC costs for different confidence levels and similar nonserved energy costs.

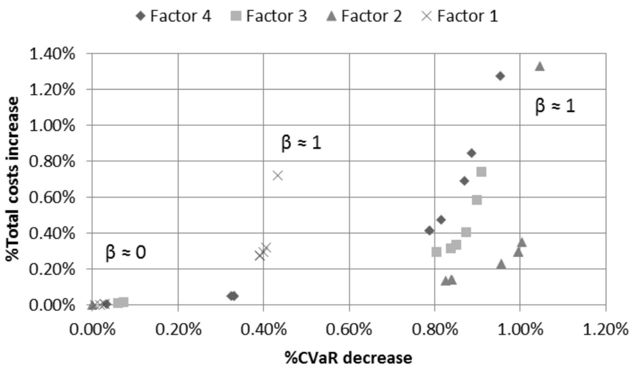

Fig. 6. Tradeoff between risk mitigation and total costs ($\alpha = 0.99$).

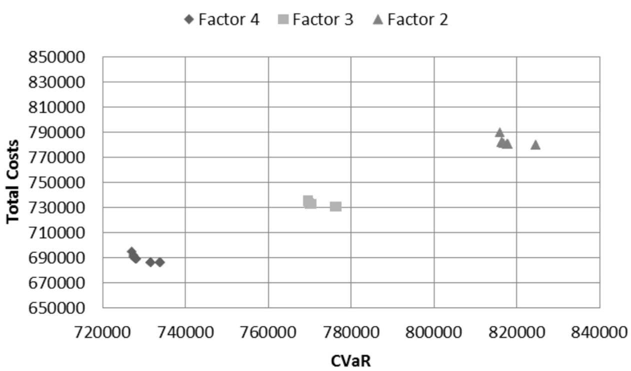

Fig. 7. Impact of renewable penetration on UC costs.

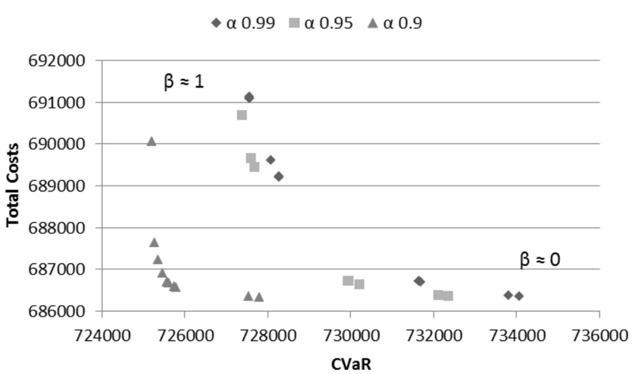

Fig. 8. Efficient frontier for different α levels (CNSE = €1250/MWh).

Note that, as the confidence levels increase, the efficient frontier shifts to higher CVaR values, since a higher confidence level reduces the number of dismissed scenarios. For all cases, the efficient frontier is represented by a strictly increasing monotone curve, as described in the literature.

Each model solution, depending on the weighting parameter β and the nonserved energy costs, provides the optimal commitment and dispatch solution for the considered scenarios. The UC solution listed in Tables VIII and IX represents the final commitment solution for the stochastic UC problem with 40% of renewable penetration in the overall energy mix associated to $\alpha = 0.99$ for different values of parameter β (0 and 0.5). The management of LZ-Gas 2, LZ-Diesel 9, FV-Diesel 2, FV-Diesel 3, FV-Diesel-4, FV-Diesel 5, FV-Gas 1, FV-Gas 2, and FV-Diesel 8 varies depending on the considered tradeoff between UC costs and risk mitigation.

Simulations have been implemented on a Dell PowerEdge R910X64 with four Intel Xeon E7520 processors at 8 GHz and 32 GB of RAM using CPLEX 12 [23] under GAMS 24.2 [24].

TABLE VIII
UC ($\alpha = 0.99$, $\beta \approx 0.0$, AND CNSE = €1250/MWh)

Unit	*Hour (1-24)*
LZ-Diesel 1	000000001111111111111111
LZ-Diesel 2	000000001111111111111111
LZ-Diesel 3	000000001111111111111111
LZ-Diesel 4	111111111111111111111111
LZ-Diesel 5	111111111111111111111111
LZ-Diesel 6	111111111111111111111111
LZ-Diesel 7	111111111111111111111111
LZ-Diesel 8	111111111111111111111111
LZ-Gas 2	000000000111111111111111
LZ-Diesel 9	000000011111111111111111
LZ-Diesel 10	111111111111111111111111
FV-Diesel 1	000000011111111111111111
FV-Diesel 2	000000011111111111111111
FV-Diesel 3	000000000011111111111111
FV-Diesel 4	000000001111111111111111
FV-Diesel 5	000000001111111111111111
FV-Diesel 6	111111111111111111111111
FV-Gas 2	000000000000111111110000
FV-Diesel 7	111111111111111111111111
FV-Diesel 8	111111111111111111111111
FV-Diesel 9	111111111111111111111111

TABLE IX
UC ($\alpha = 0.99$, $\beta = 0.5$, AND CNSE = €1250/MWh)

Unit	*Hour (1-24)*
LZ-Diesel 1	000000001111111111111111
LZ-Diesel 2	000000001111111111111111
LZ-Diesel 3	000000001111111111111111
LZ-Diesel 4	111111111111111111111111
LZ-Diesel 5	111111111111111111111111
LZ-Diesel 6	111111111111111111111111
LZ-Diesel 7	111111111111111111111111
LZ-Diesel 8	111111111111111111111111
LZ-Gas 2	000000000111111111111111
LZ-Diesel 9	111111111111111111111111
LZ-Diesel 10	111111111111111111111111
FV-Diesel 1	000000011111111111111111
FV-Diesel 2	000000001111111111111111
FV-Diesel 3	000000000001111111111111
FV-Diesel 4	000000001111111111111110
FV-Diesel 5	000000001111111111111110
FV-Diesel 6	111111111111111111111111
FV-Gas 1	000000000000000001000000
FV-Gas 2	000000000000111111111110
FV-Diesel 7	111111111111111111111111
FV-Diesel 8	000000011111111111111111
FV-Diesel 9	111111111111111111111111

TABLE X
CR NETWORK DATA

from (n)	*to (np)*	$R_{n,np}$ (Ω)	$X_{n,np}$ (Ω)
1	2	2.309	9.442
2	3	0.98	4.007
3	4	1.924	7.866
3	6	5.304	21.689
5	6	1.543	6.308
4	9	8.201	33.536
6	9	4.709	19.255
7	13	4.668	10.509
9	8	4.452	10.023
8	7	2.872	6.466
9	10	0.477	1.95
9	12	1.933	7.904
9	14	3.932	16.079
9	11	0.738	3.019
10	12	1.456	5.954
11	12	1.408	5.758
12	19	11.693	47.814
13	16	10.782	24.274
14	15	2.897	11.847
15	16	2.09	8.547
16	19	3.742	15.302
16	17	6.935	15.614
17	18	1.15	2.589
18	19	2.335	9.549

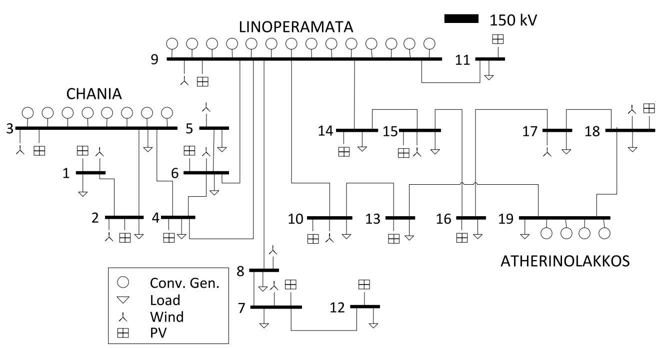

Fig. 9. CR transmission power system.

CPLEX requires around 2000 s for the 11 iterations required for parameter β, ranging from 0.01 to 0.99. CPU time does not depend on the value of parameter β.

V. CRETE CASE STUDY

A. System Description

In this section, the proposed model has been enhanced including the CR's Island power system, which is the largest isolated power system in Greece and one of the biggest in Europe. The electric power system of CR has a generation mix based on diesel and gas plants, with a continuously increasing renewable penetration. Conventional generation is located in Chania (Cha, node 3), Linoperamata (Lin, node 9), and Atherinolakkos (Ath, node 19), accounting for a total of 740 MW (Table X). CR exhibits the highest solar radiation in Europe and in many locations the average wind speed exceeds 7 m/s. Wind and PV systems have been installed all across the island, accounting for 185.6 and 94.2 MW, respectively (Table XI). The actual installed renewable share

TABLE XI
RENEWABLE TECHNOLOGY GENERATION IN CR

Gen.	*InstCap [MW]*	*Connection Node*	*Gen.*	*InstCap [MW]*	*Connection Node*
PV 1	3.39	1	PV 16	7.09	16
PV 2	3.39	2	PV 18	9.29	18
PV 3	7.1	3	Wind 1	18.2	1
PV 4	1.6	4	Wind 2	10.8	2
PV 6	16.62	6	Wind 5	7.2	5
PV 7	15.25	7	Wind 6	7.2	6
PV 9	0.35	9	Wind 7	17.4	7
PV 10	3.42	10	Wind 8	14.45	8
PV 11	1.06	11	Wind 9	3.6	9
PV 12	7.65	12	Wind 10	5.95	10
PV 13	10.47	13	Wind 15	11.9	15
PV 14	2.32	14	Wind 16	32.9	16
PV 15	5.17	15	Wind 18	56.2	18

TABLE XII
CONVENTIONAL TECHNOLOGY GENERATION IN CR

Tech.	**Generation Costs**				
	InstCap [MW]	*Start-up Costs [€]*	*FixCosts [€]*	*VarCosts [€/MWh]*	*Pmin. [MW]*
Lin 1, Lin 2	13.5	900	25.94	150.62	7.5
Lin 3	24	900	25.94	138.27	16
Lin 4, Lin 5	23.5	1350	18.08	126.32	17
Lin 6	13	1350	25.83	418.84	3
Lin 7	14	1350	25.83	408.72	3
Lin 8	43	425	130.12	189.49	8
Lin 9	14	425	120.82	318.92	3
Lin 10	28	1020	39.44	289.78	5
Lin11-Lin14	10.5	425	70.04	84.77	5
Cha 1	12	1020	37.86	486.70	3
Cha 2	18	324	10.86	405.07	3
Cha 3	28	324	10.86	363.68	12
Cha 4, Cha 5	52	324	10.86	289.94	23
Cha 6	28	324	10.86	289.78	12
Cha 7	55	85	188.54	234.33	23
Cha 8	55	425	86.76	234.33	23
Ath 1, Ath 2	46	595	93.54	106.55	28
Ath 3, Ath 4	48	595	40.58	88.63	33

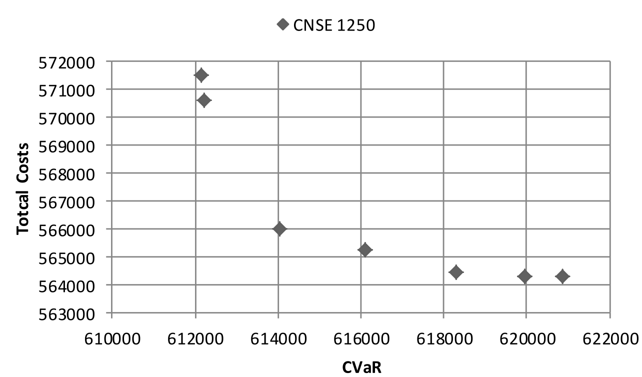

Fig. 10. Total costs versus CVaR: efficient frontier ($\alpha = 0.95$).

TABLE XIII
RISK VERSUS GENERATION COSTS (CNSE = €1250/MWh)

α	*β*	*Total Cost [€]*	*VaR [€]*	*CVaR [€]*	*MRVSS [€]*
0.95	≈ 0	564299.6	618541.5	620882.5	46845.4
0.95	0.1	564309.0	617767.6	619954.7	51813.1
0.95	0.2	564309.0	617767.6	619954.7	55554.7
0.95	0.3	564442.4	616112.7	618295.5	58877.5
0.95	0.4	564442.4	616112.7	618295.5	64805.1
0.95	0.5	565269.0	613995.3	616095.5	71786.1
0.95	0.6	565269.0	613995.3	616095.5	71589.6
0.95	0.7	565269.0	613995.3	616095.5	77527.9
0.95	0.8	566014.5	611936.4	614030.4	84401.4
0.95	0.9	570631.5	610718.2	612210.0	84346.6
0.95	≈ 1	571533.3	610064.9	612154.7	91072.0

TABLE XIV
UC ($\alpha = 0.95$, $\beta \approx 0.0$, AND CNSE = €1250/MWh)

Unit	*Hour (1-24)*
Lin 1	111111111111111111111110
Lin 2	111111111111111111111110
Lin 3	111111111111111111111110
Lin 4	111111111111111111111110
Lin 5	111111111111111111110000
Lin 6	000000000000000000000000
Lin 7	000000000000000000000000
Lin 8	111111111111111111110000
Lin 9	000000000000000000000000
Lin 10	000000000000000000000000
Lin 11	111111111111111111111111
Lin 12	111111111111111111111111
Lin 13	111111111111111111111111
Lin 14	111111111111111111111111
Cha 1	000000000000000000000000
Cha 2	011111111111111111111111
Cha 3	000000000000000000000000
Cha 4	000000000000000001111000
Cha 5	111111111111111111111111
Cha 6	111111111111111111111111
Cha 7	011111111111111111111111
Cha 8	011111111111111111111000
Ath 1	011111111111111111111000
Ath 2	000000000000011111111000
Ath 3	111111111111111111111111
Ath 4	111111111111111111111111

represents 27.5% of the installed capacity. The system consists of a 19-bus meshed transmission network (Fig. 9) with a nominal voltage magnitude of 150 kV and base power of 100 MVA.

The slack node considered in the proposed model is at node 9. Table X shows the network specifications of the considered test system. As for the previous case, a curtailment cost for renewable power of €100/MWh has been included in the model for both wind and PV generations.

Wind and PV installed capacities and the corresponding connection nodes are presented in Table XI.

During the last years, electricity consumption in CR has remained steady between 2.8 and 2.65 TWh. Table XII gives

TABLE XV
UC ($\alpha = 0.95$, $\beta \approx 1$, AND CNSE = €1250/MWh)

Unit	*Hour (1-24)*
Lin 1	111111111111111111111110
Lin 2	111111111111111111111110
Lin 3	111111111111111111111100
Lin 4	111111111111111111110000
Lin 5	111111111111111111110000
Lin 6	000000000000000000000000
Lin 7	000000000000000000000000
Lin 8	111111111111111111110000
Lin 9	000000000000000000000000
Lin 10	000000000000000000000000
Lin 11	111111111111111111111111
Lin 12	111111111111111111111111
Lin 13	111111111111111111111111
Lin 14	111111111111111111111111
Cha 1	000000000000000000000000
Cha 2	000000000000000000000000
Cha 3	011111111111111111111111
Cha 4	000000000000000000010000
Cha 5	000000000000000000000000
Cha 6	000000000000000000000000
Cha 7	000000000000000000000000
Cha 8	000000000000000000000000
Ath 1	000000000000000000000000
Ath 2	000000000000000000000000
Ath 3	111111111111111111111111
Ath 4	111111111111111111111111

an overview of the actual conventional generation mix of the CR system, including installed capacity, minimum power, and fixed and variable costs.

B. Results

Fig. 10 and Tables XIII–XV present the test results obtained for the CR transmission system. The impact of renewable penetration has been already discussed in the previous case study, and, therefore, an increased penetration has not been considered for the Greek case. For the same reason, a sensitivity analysis of the cost of nonserved energy with different confidence levels has not been included. The solution of the model for different values of β allows for the representation of the efficient frontier (Fig. 10). Numerical results for CVaR and total dispatch costs associated to $\alpha = 0.95$ are provided in Table XII.

Tables XIV and XV represent the final UC solution for the stochastic UC problem associated to $\alpha = 0.95$ for different values of parameter β (0 and 1). As in the previous case, the assets management significantly varies depending on the considered tradeoff between UC costs and risk mitigation. The management of Lin 3, Lin 4, Cha 2, Cha 3, Cha 4, Cha 5, Cha 6, Cha 7, Cha 8, Ath 1, and Ath 2 varies depending on the considered tradeoff between UC costs and risk mitigation.

CPLEX requires around 6000 s for the 11 iterations required for parameter β, ranging from 0.01 to 0.99. CPU time does not depend on the value of parameter β.

VI. Conclusion

Stochasticity and the intermittency of RES cannot be fully integrated in traditional UC schemes. The effects of this situation are increasingly becoming an issue for grid operators, due to the public and political pressure to increase the penetration of renewable generation technologies. Threats experienced by isolated systems caused by increasing renewable penetration are higher than for nonisolated systems, since they cannot take advantage of the smoothing effect of a larger balancing area and interconnections. This paper explores the impact of uncertainty and risk aversion on UC decisions in isolated systems with high renewable penetration. The proposed optimal solutions based on the efficient frontier are helpful for decision-makers, providing valuable information of the tradeoff between risk mitigation and overall UC costs. Considering different confidence levels, the proposed framework is able to quantify the risk created by forecasting uncertainties while minimizing the overall system costs. A decision-maker can, therefore, make reasonable decisions based on adequate solutions measuring risk. MRVSS is used to evaluate the economic benefit by solving the stochastic model incorporating a mean-risk function.

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