A Multi-Objective Optimization Approach to Risk-Constrained Energy and Reserve Procurement Using Demand Response

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Abstract—**Large-scale integration of wind generation in power systems increases the need for reserve procurement in order to accommodate its highly uncertain nature, a fact that may overshadow its environmental and economic benefits. In this study, a joint energy and reserve day-ahead market structure based on two-stage stochastic programming is presented. The developed model incorporates explicitly the participation of demand side resources in the provision of load following reserves. Since a load that incurs a demand reduction may need to recover this energy in other periods, different types of the load recovery effect are modeled. Furthermore, in order to evaluate the risk associated with the decisions of the system operator and to assess the effect of procuring and compensating load reductions, the conditional value-at-risk (CVaR) metric is employed. To solve the resulting multi-objective optimization problem, a new approach based on an improved variant of the epsilon-constraint method is adopted. This study demonstrates that the proposed approach to risk management presents conceptual advantages over the commonly used weighted sum method.**

Index Terms—**augmented epsilon-constraint method; conditional value-at-risk; day-ahead market; demand side reserves; load recovery; risk management; stochastic optimization; wind power.**

I. Nomenclature

The main notation used throughout the paper is alphabetically listed in Tables I-III. Other symbols and abbreviations are defined where they first appear.

II. Introduction

A. Motivation and Background

LARGE-scale integration of renewable energy sources (RES) in power systems plays a central role in ambitious programs initiated by leading countries around the world, such as the regional greenhouse gas emission control schemes in the U.S. and the 20/20/20 targets in the European Union [1].

TABLE I
SETS AND INDICES

b	Index of transmission lines.
f	Index of steps of bidding curves of generating units.
i	Index of conventional units.
j	Index of demand.
n	Index of nodes.
s	Index of scenarios.
t	Index of time intervals.
w	Index of wind farms.
$B(n,nn)$	Set of transmission lines.
B_b^n	Set of sending nodes of transmission lines.
B_b^{nn}	Set of receiving nodes of transmission lines.
J^0	Set of inelastic loads.
J^1	Set of demand response providers of type 1.
J^2	Set of demand response providers of type 2.
N_n^x	Set of resources of type $x \in \{i, w, j\}$ connected to node n.

TABLE II
PARAMETERS

$B_{b,n}$	Absolute value of the imaginary part of the transmission line b admittance (p.u.).
$B_{i,f,t}^G$	Size of the f-th block of the bidding curve of unit i in period t (MW).
$C_{i,f,t}^G$	Marginal cost of the f-th block of the bidding curve of unit i in period t (€/MWh).
$C_{i,t}^{G,U}$	Offer cost of up spinning reserve from unit i in period t (€/MWh).
$C_{i,t}^{G,D}$	Offer cost of down spinning reserve from unit i in period t (€/MWh).
$C_{j,t}^{DRP,U}$	Offer cost of load reduction scheduling from demand j in period t (€/MWh).
$c_{j,t}^{DRP,U}$	Cost of load reduction deployment from demand j in period t (€/MWh).
$D_{j,t}$	Nominal load of demand j in period t (MW).
f_b^{max}	Maximum capacity of transmission line b (MW).
N_j^{in}	Maximum allowed number of interruptions of demand j.
P_i^{max}	Maximum power output of unit i (MW).
P_i^{min}	Minimum power output of unit i (MW).
$P_w^{W,max}$	Capacity of wind farm w (MW).
p	Maximum participation of demand side resources (%).
$R_j^{DRP,U,m}$	Minimum load reduction of demand j (MW).
RD_i	Ramp down rate of unit i (MW/min).
RD_j^{DRP}	Load pick-up rate of demand j (MW/min).
RU_i	Ramp up rate of unit i (MW/min).
RU_j^{DRP}	Load drop rate of demand j (MW/min).
SDC_i	Shut-down cost of unit i (€).
SUC_i	Start-up cost of unit i (€).
T_j^{rec}	Duration of the load recovery period (h).
T^S	Spinning reserve delivery time (min).
V_j^{ENS}	Cost of energy not served/not recovered for demand j (€/MWh).
V^S	Wind energy spillage cost (€/MWh).
$WP_{w,t,s}$	Random variable — power output of wind farm w in period t in scenario s (MW).
a	Confidence level used in the calculation of CVaR$_\alpha$.
γ_j	Load recovery rate with respect to load reduction of demand j (%).
ΔT	Duration of time interval (min).
$\xi_{j,t}^D$	Maximum downward modification rate of demand j in period t (%).
$\xi_{j,t}^U$	Maximum upward modification rate of demand j in period t (%).
π_s	Probability of scenario s.

TABLE III
DECISION VARIABLES

$CVaR_a$	Conditional Value-at-Risk at a confidence level α (€).
$D_{j,t,s}^{A}$	Actual consumption of demand j in period t in scenario s (MW).
$ENR_{j,s}$	Energy of demand j not recovered in scenario s (MWh).
$f_{b,t,s}$	Power flow through transmission line b in period t in scenario s (MW).
$L_{j,t,s}^{shed}$	Load shed from demand j in period t in scenario s (MW).
$P_{i,t,s}^{G}$	Actual output of unit i in period t in scenario s (MW).
$P_{i,t}^{sch}$	Output scheduled from unit i in period t (MW).
$P_{i,f,t}^{sg}$	Output scheduled from the f-th segment of unit i in period t (MW).
$P_{w,t}^{W,sch}$	Wind power scheduled from wind farm w in period t (MW).
$R_{j,t}^{DRP,D}$	Load recovery scheduled from demand j in period t (MW).
$R_{j,t}^{DRP,U}$	Load reduction scheduled from demand j in period t (MW).
$R_{i,t}^{G,D}$	Down spinning reserve scheduled from unit i in period t (MW).
$R_{i,t}^{G,U}$	Up spinning reserve scheduled from unit i in period t (MW).
$r_{j,t,s}^{DRP,d}$	Load recovery of demand j in period t in scenario s (MW).
$r_{j,t,s}^{DRP,u}$	Load reduction of demand j in period t in scenario s (MW).
$r_{i,t,f,s}^{G}$	Reserve deployed from the f-th block of unit i in period t in scenario s (MW).
$r_{i,t,s}^{G,d}$	Deployed down spinning reserve from unit i in period t in scenario s (MW).
$r_{i,t,s}^{G,u}$	Deployed up spinning reserve from unit i in period t in scenario s (MW).
$S_{w,t,s}$	Available wind generation spilled from wind farm w in period t in scenario s (MW).
ξ	Value-at-Risk (€).
$u_{i,t}$	Binary variable-1 if unit i is committed in period t.
$u_{j,t,s}^{DRP,d}$	Binary variable- 1 if demand j is recovering in period t in scenario s.
$u_{j,t,s}^{DRP,u}$	Binary variable- 1 if demand j is curtailed in period t in scenario s.
$y_{i,t}$	Binary variable- 1 if unit i is starting up in period t.
$z_{i,t}$	Binary variable- 1 if unit i is starting up in period t.
$\delta_{n,t,s}$	Voltage angle at node n in period t in scenario s (rad).
η_s	Auxiliary variable used in the calculation of CVaR (€).
$\mu_{j,t,s}$	Auxiliary variable used to linearize load recovery (MW).

Among the different RES options, wind capacity is expected to increase significantly in the future [2, 3]. Despite the potential environmental benefits that arise from the widespread adoption of wind power generation, its uncertain nature may jeopardize the security of the power system and pose new challenges to system operators (SO) [4]-[7].

In order to accommodate the wind power volatility, apart from the traditionally required ancillary services (i.e. regulation, contingency reserve etc.), increased additional amount of load following reserves must be generally procured to match the total production and consumption [8]. Interestingly empirical facts from some particular markets, such as the German energy market, concur that on some occasions the integration of RES can be supported by alternative means. In fact, since 2008, the capacity of RES in Germany has grown from 27 GW to 78 GW, yet over the same period, the amount of balancing reserves procured by the Transmission System Operators (TSO) was reduced by 15%. Hirth and Ziegenhagen [9] highlighted this issue which is known as the "German Paradox", providing also several candidate factors that could have overcompensated the expansion of renewables: improved forecasting tools, reduced frequency of power plant outages, more cost-aware behavior of TSOs, cooperation of TSOs in reserve sizing and improved intraday market liquidity. Recently Ocker and Ehrhart [10] argued that there are two main reasons that can explain this "paradox". First, the introduction of a common balancing market between the four German TSOs in the period 2009-2010 and the foundation of the International Grid Control Cooperation (IGCC) in 2011 led to a significant reduction in reserve procurement in Germany, induced by the augmentation of the balancing area. Second, market design adaptations which allowed more flexible wind trading closer to real-time have improved the liquidity of the intraday market. Based on this evidence Ocker and Ehrhart suggested that the increasing penetration of renewables can be managed without necessarily increasing the amount of operational reserves by implementing such national and international measures. Nevertheless, this would require the harmonization of European balancing power markets which are currently characterized by large discrepancy in market design and renewable energy integration [11]. In addition to that, the liquidity of the different intraday markets varies significantly across Europe. For instance, in contrast with the relatively liquid German intra-day energy market, the amount of energy traded in the Nordic intraday market accounts only for about 1% of the total consumption [12]. Finally, on many occasions it is not possible to augment the balancing area due to geographical restrictions. This is the case for non-interconnected power systems such as the ones in islands in which the magnitude of the problems related to the integration of RES depends on their penetration level in the production mix, while their mitigation is reflected by the flexibility of the power system [13].

Until recently, the required reserve services have been almost exclusively procured by the generation side. However, several types of demand side resources are technically capable of providing ancillary services and especially, the recently proposed flexibility reserve which responds to large and unexpected wind and solar ramp events [14]. The utilization of demand side resources to provide flexibility reserves alleviates the adverse environmental, technical and economic impacts of regulating the highly volatile wind power generation using fast-response conventional generators. However, one of the main barriers to introducing demand response (DR) in the operational practice is its justification as a valuable system addition in comparison with other technologies. Strbac [15] argues that the value of DR lies both in system operation and development. The operational status of the system and the flexibility of the generation mix are important criteria to assess the value of DR. In systems that are stressed, i.e. that operate close to their capacity limits and have a relatively inflexible base load generation, the contribution of DR to integrate greater amounts of RES generation could be significant.

Many SOs, especially in the U.S., have taken steps towards integrating demand side resources by initiating market-based programs that allow the participation of demand response providers (DRP) [1]. A DRP may be an individual load (i.e. a large consumer) or an aggregation of loads that are technically qualified (in terms of response time, minimum level of curtailment etc.) to participate in a specific DR program. DRPs are allowed to bid on load curtailments. If the bids are accepted, the DRPs are paid for committing to be on standby. In case the load curtailments are indeed required during the actual operation of the power system, the participants are notified by the SO and are paid for the energy reduction they provide. More details regarding existing demand side participation programs in the U.S. markets may be found in [16]. However, despite the fact that the implementation of various demand side participation programs in the U.S. has proven beneficial in many aspects, demand response (DR) is currently available only in a few European countries [17].

The integration of demand side resources into electricity markets has also drawn the attention of the technical literature. Several studies investigate the participation of demand side resources in the procurement of energy and reserve services. Seminal studies [18]-[20] have developed pool based market structures considering the participation of demand side resources into the energy and reserve markets. However, these models are deterministic. The economic effect of price responsive demand on energy only markets was investigated in [21] and [22]. A more detailed deterministic model of demand side participation in the day-ahead energy market was presented in [23]. There are also studies that evaluate the contribution of demand side resources to contingency and load following reserves [24]-[27]. Nevertheless, these studies do not consider the effect of wind power penetration on reserve procurement.

The exploitation of demand side resources to support the integration of RES, especially wind power, has been studied in [28]-[31]. However, these studies do not investigate the effect of DR on the risks associated with the operational cost of the system. Risk-aware stochastic programming based decision making has been widely applied to portfolio optimization. Recently, risk-constrained optimal offering strategies for microgrid aggregators [32], wind power producers [33, 34] and virtual power plants [35] have been proposed, considering also the participation of DR in the mitigation of the risk associated with the distribution of profits. Nevertheless, although stochastic programming has been also applied to market clearing and unit commitment formulations [36], investigating the risk that is embedded in the decisions of the SO under the presence of renewables' related uncertainty, the potential benefits of DR and pinpointing potential limiting factors is a topic that has not been studied extensively in the relevant literature. For instance, in [37] a stochastic programming model was presented in which demand side resources may provide load following and contingency reserves, disregarding the risk associated with the decisions of the SO. Also, in [1] and [2], demand side resources were employed to facilitate the integration of wind power, employing deterministic reserve criteria. In [38] a stochastic load model of an industrial consumer participating in load following reserves procurement under high wind power penetration was presented. However, this study also neglected the quantification of the risk in the decision making of the SO.

Finally, although, several risk-constrained unit commitment formulations have also been proposed in the literature, most of them focus on the operational risk, i.e., security of the load supply and uncertainty [39]-[43], while only a few are investigating the economic risk the SO is exposed to in terms of solving a probabilistic optimal power flow problem that incorporates variance and semi-variance as risk metrics [44], [45].

B. Contribution and Organization of the Paper

Determining the optimal levels of reserves in order to allow for the SO to respond to the deviations of wind power production with respect to the amount cleared in the day-ahead market is a technically and economically challenging task. When accounting for the uncertainty in the wind power production in order to schedule the optimal levels of reserves using stochastic programming, the volumes are optimal with respect to the expectation of operational costs, while other characteristics of the distribution of the system costs are disregarded, exposing the SO to financial risks. For this reason, in this study, a risk-aware joint energy and reserve day-ahead market structure based on two-stage

stochastic programming is developed. The SO that is responsible for the clearing of the market may utilize generation and demand side resources in order to procure load following reserves in order to accommodate the uncertain wind production.

Risk-management is applicable when decision making is subject to uncertainty. As it has already been mentioned the notion of risk-aversion is common in studies that deal with investments and the trading strategy of market participants. This may be attributed to the fact that risk has a direct influence on the profitability of an investment or the economic effectiveness of a market participant. However, the perception of the risks that a SO has to take mostly focuses on the technical management of the grid (e.g., energy not served, etc.) and the fact that economic inefficiencies can, at least to some extent, be socialized. In fact considering the reliability of the power system while clearing a joint energy and reserve market introduces a notion of risk in the daily decision making of the SO, while reserves are the technical instrument that is used to face such risk. Although it is not so common, studies that consider the financial risk faced by the SO due to wind power generation uncertainty can be also found in the literature [44], [45].

The main contributions of this work are summarized in the following:

- The risk-averse behavior of the SO in terms of the operational costs of the system is considered. The formulation presented in this study is conceptually different from other risk-constrained unit commitment-based market clearing approaches in the sense that the focus is mainly on the economic risks due to the uncertainty in wind power production.

- Unlike the majority of the relevant studies in the literature where risk management is enforced by means of optimizing a composite objective function where each objective (e.g., cost/profit and risk metric) is accounted for with a weighting factor, a multi-objective optimization approach based on an improved implementation of the epsilon-constraint method, namely the augmented epsilon-constraint method (AUGMECON) is proposed in this study. Simulation results indicate a richer mapping of the Pareto frontier.

- The contribution of DRPs to reserve procurement is taken into account. A generic load recovery effect model is developed in order to preserve the internal energy balance of the demand side resources participating in reserve provision, with the aim of investigating its impact on the deployment of demand side resources, expected cost and risk. The proposed methodology is applied on the insular power system of Crete, Greece, in order to extract realistic quantitative results.

The remainder of the paper is organized as follows: in Section III the optimization model is developed. Then, in Section IV the proposed solution technique is presented. Numerical results are presented and discussed in Section V. Finally, conclusions are drawn in Section VI.

III. OPTIMIZATION MODEL

In this section the mathematical model of the joint energy and reserve day-ahead market based on two-stage stochastic programming from the point of view of a risk-averse SO is presented. The aim is to determine the optimal energy and reserve volumes while guaranteeing that reserves are sufficient to tackle the plausible realizations of the uncertain wind power production

which is modelled in terms of a finite set of scenarios. Three sets of constraints can be discerned. The first stage constraints involve variables that do not depend on any specific scenario (here-and-now decisions), while the second stage constraints describe relationships pertaining only decision variables that depend on scenario realizations (wait-and-see decisions). In other words, the second stage variables represent the reaction of the SO to each plausible realization of uncertainty. Finally, the linking constraints connect the day-ahead market decisions with each specific scenario realization by involving both scenario dependent and independent variables. It is to be noted that reserve providers are compensated both for committing to be on stand-by and for the actual deployment of reserves.

This approach aims to guarantee that within the considered set of scenarios, energy and reserve volumes are optimally determined. In practice it is possible that the realization of uncertainty will not match exactly any of the realizations that are explicitly considered in the scenario set. Nevertheless, the reserve levels are sufficient to respond to at least any wind power generation realization that is higher than the minimum amount of wind power that is being explicitly considered in the scenario set. To optimally determine the individual response of each reserve provider in real-time a rolling decision making approach can deployed [46]. The output of the generators must be fixed to the energy output level cleared in the day-ahead market, while the available reserves from each provider are also fixed to the cleared reserve volumes. Then, a sequence of optimization problems has to be solved by the SO at each real-time interval to define the exact contribution of each provider on the basis of their reserve deployment costs. Note that since intertemporal constraints have been taken into account during the determination of the reserve levels, they do not need to be accounted for in real-time. Formulating the problem of optimally dispatching the scheduled reserves in real-time is out of the scope of our study.

The only source of uncertainty considered is related to the production of the wind farms since uncertainty associated with the response of the demand side resources may be neglected, based on practical evidence [14] that indicate reliable performance of DRPs. In addition to that, in cases where the DRP is either an aggregator of small-scale flexible loads or a large industrial consumer participating directly in the day-ahead market, it can be assumed – on the basis of the development of regulatory framework that promotes the non-discriminatory participation of resources in electricity markets, e.g. the Articles 15.4 and 15.8 of the Energy Efficiency Directive of the European Commission [47] – that they are also balance responsible parties. This means that guaranteeing the delivery of the service for which they are committed is not the responsibility of the SO.

In the proposed formulation the SO strives to optimize simultaneously both the expected cost and the associated financial risk. As a result, the proposed two-stage stochastic programming model is in fact a multi-objective problem that needs to be solved by means of employing a suitable methodology as described in Section IV. An overview of the proposed methodology is portrayed in Fig. 1.

A. Objective Functions

A.1. Expected Cost

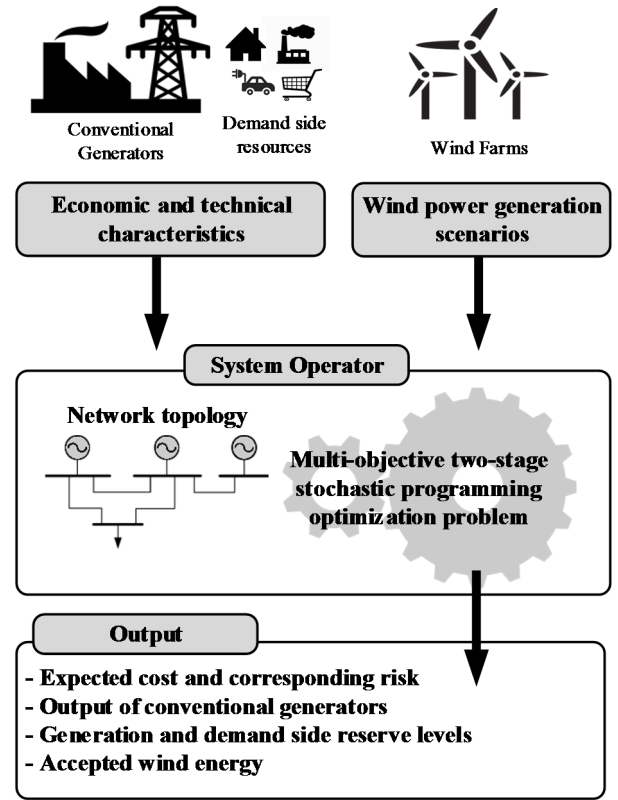The objective of the SO is to minimize the total expected cost of energy and reserve procurement.

Fig. 1. Overview of the proposed methodology.

The expected cost (EC) comprises a scenario independent (EC^{SI}) and a scenario dependent (EC_s^{SD}) component which are expounded in (2) and (3) respectively. In (2) the energy procurement cost, the start-up and shut-down costs of generating units, as well as the generation and demand side reserve procurement costs are taken into account. The cost that emerges from altering the output of generating units to deploy reserves, the cost of deploying reserves from DRPs, the penalty of involuntary load shedding, the wind spillage cost, as well as the cost of energy not recovered after the deployment of a DRP load reduction are considered in (3).

$$EC = EC^{SI} + \sum_s \pi_s \cdot EC_s^{SD} \tag{1}$$

$$EC^{SI} = \sum_t \left[\sum_i \left(\sum_f (C_{i,f,t}^G \cdot P_{i,f,t}^{sg}) \right. \right.$$
$$+ (SUC_i \cdot y_{i,t} + SDC_i \cdot z_{i,t})$$
$$\left. \left. + (C_{i,t}^{G,U} \cdot R_{i,t}^{G,U} + C_{i,t}^{G,D} \cdot R_{i,t}^{G,D}) \right) + \sum_j (C_{j,t}^{DRP,U} \cdot R_{j,t}^{DRP,U}) \right] \tag{2}$$

$$EC_s^{SD} = \sum_t \left[\sum_i \sum_f (C_{i,f,t}^G \cdot r_{i,t,f,s}^G) \right.$$
$$+ \sum_j \left(c_{j,t}^{DRP,U} \cdot r_{j,t,s}^{DRP,u} + V_j^{ENS} \cdot L_{j,t,s}^{shed} \right) + \sum_w (V^S \cdot S_{w,t,s}) \right] \tag{3}$$
$$+ \sum_j (V_j^{ENS} \cdot ENR_{j,s}) \ \forall s$$

A.2. Conditional Value-at-Risk

Although attempting to minimize the expected cost of the operation of the system is advantageous in comparison with a deterministic approach in which a perfect forecast for the wind power generation is considered, the characteristics associated with the distribution of the outcomes of the individual scenarios are disregarded. As a result, an acceptable expected cost value may correspond to a cost distribution in which the probability of facing significant costs in several scenarios is high. To overcome this ambiguity, a notion of risk should be incorporated in the optimization problem. A risk measure is a scalar function characterizing the risk associated with the obtained expected cost.

There are various perceptions of risk and therefore, several different risk measures may be used. Extensive discussion on how to incorporate different risk measures in stochastic programming formulations is performed in [48]. The risk measure employed in this study is the Conditional Value-at-Risk (CVaR) metric [49] since it presents three important advantages: 1) it is a coherent risk measure, 2) in contrast with the popular Value-at-Risk (VaR) metric, it quantifies "fat tails" in the cost distribution and, 3) it is compatible with a linear formulation.

For a given confidence level $\alpha \in (0,1)$ the VaR_α is equal to the minimum value ξ for which the probability of obtaining a cost less than ξ is higher than α. It should be noted that ξ is a variable representing the value of the risk metric and not a pre-fixed parameter. VaR_α is defined by (4).

$$VaR_\alpha = \min\{\xi: P(s|EC^{SI} + EC_s^{SD} \leq \xi) \geq \alpha\} \qquad (4)$$

$CVaR_\alpha$ is defined as the expected value of the cost of the scenarios with cost higher than the $(1-\alpha)$-quantile of the cost distribution (VaR_α). The mathematical definition of $CVaR_\alpha$ is given in (5).

$$CVaR_\alpha = \min\{\xi + \frac{1}{1-\alpha}\sum_s [\pi_s \cdot \max\{EC^{SI} + EC_s^{SD} - \xi, 0\}]\} \qquad (5)$$

Risk aversion may be enforced by considering (6) as an objective function (see Section IV) and (7)-(8) as constraints of the optimization problem. Constraint (7) states that the risk metric is considered with respect to the expected cost of each scenario. Finally, (8) states that the auxiliary variable is nonnegative. It should be noted that the continuous auxiliary variable η_s equals to the maximum of $EC^{SI} + EC_s^{SD} - \xi$ and 0 according to (5).

$$CVaR_\alpha = \xi + \frac{1}{1-\alpha} \cdot \sum_s \pi_s \cdot \eta_s \qquad (6)$$

$$EC^{SI} + EC_s^{SD} - \xi \leq \eta_s \ \forall s \qquad (7)$$

$$\eta_s \geq 0 \ \forall s \qquad (8)$$

In this study it is considered that wind producers are exempt from the participation in the market and the wind energy that is accepted in the day-ahead market is determined by the SO. For instance this might be imposed by policies that consider RES generation as must-take. At any rate, costly reserve services have to be procured from conventional generating units on a market basis in order to satisfy this requirement in real-time, a fact that increases the financial risk that the SO is exposed to. It is to be noted that in markets in which wind producers are considered as Balance Responsible Parties, they bear the financial obligation of

covering the imbalances that they cause through appropriate market mechanisms. In fact this defines the scope of this work since in such cases risk management should be rather included in the decision making of the wind producers rather than of the SO [33]-[35]. Nevertheless, the proposed day-ahead market model is still be applicable when SO operators have the balancing responsibility of a number of relatively small or subsidized RES producers [50].

B. Constraints

B.1. First Stage Constraints

B.1.1. Generating Units

The bidding curves of the generators are approximated using a monotonically ascending step-wise linear marginal function as in [37]. This is enforced by (9) and (10). The output of a generating unit is constrained between a minimum and maximum value considering also the scheduled down and up spinning reserves by (11) and (12), respectively. The ramping constraints are taken into account by (13) and (14). Furthermore, the scheduled up and down reserves are limited by (15)-(16). Minimum up and down time constraints and unit commitment constraints are also taken into account as in [25].

$$P_{i,t}^{sch} = \sum_f P_{i,f,t}^{sg} \ \forall i,t \qquad (9)$$

$$0 \leq P_{i,f,t}^{sg} \leq B_{i,f,t}^G \ \forall i,f,t \qquad (10)$$

$$P_{i,t}^{sch} - R_{i,t}^{G,D} \geq P_i^{min} \cdot u_{i,t} \ \forall i,t \qquad (11)$$

$$P_{i,t}^{sch} + R_{i,t}^{G,U} \leq P_i^{max} \cdot u_{i,t} \ \forall i,t \qquad (12)$$

$$P_{i,t}^{sch} - P_{i,t-1}^{sch} \leq RU_i \cdot \Delta T \ \forall i,t \qquad (13)$$

$$P_{i,t-1}^{sch} - P_{i,t}^{sch} \leq RD_i \cdot \Delta T \ \forall i,t \qquad (14)$$

$$0 \leq R_{i,t}^{G,D} \leq RD_i \cdot T^S \cdot u_{i,t} \ \forall i,t \qquad (15)$$

$$0 \leq R_{i,t}^{G,U} \leq RU_i \cdot T^S \cdot u_{i,t} \ \forall i,t \qquad (16)$$

B.1.2. Wind Power Production

Constraint (17) limits the wind power production that may be scheduled. In this study, it is considered that the minimum scheduled wind production is zero and the maximum limit coincides with the installed capacity of the wind farm.

$$0 \leq P_{w,t}^{W,sch} \leq P_w^{W,max} \ \forall w,t \qquad (17)$$

B.1.3. Demand Response Providers

In this study, it is considered that DRPs may participate in upward reserve scheduling by rendering a portion of their demand available to be curtailed under suitable incentives. Furthermore, the fact that the demand which is curtailed during a given interval may have to be recovered in other periods allows the DRPs to contribute to downward reserves through appropriate coordination of the curtailment and the recovery periods. In order to participate in the reserve market, the SO may require several parameters to be submitted by the DRPs together with the demand reduction and recovery costs such as: maximum demand modification rate, rate of energy recovery, load pick-up/drop rate, minimum demand curtailment, load recovery duration and maximum number of curtailments per day. Constraints (18)-(20) enforce the reserve scheduling from the DRPs.

$$0 \leq R_{j,t}^{DRP,U} \leq \min\left(\xi_{j,t}^{U} \cdot D_{j,t}, RU_j^{DRP} \cdot T^S\right) \forall j \notin J^0, t \quad (18)$$

$$0 \leq R_{j,t}^{DRP,D} \leq \min\left(\xi_{j,t}^{D} \cdot D_{j,t}, RD_j^{DRP} \cdot T^S\right) \forall j \notin J^0, t \quad (19)$$

$$\sum_{j \notin J^0} R_{j,t}^{DRP,U} \leq \frac{p}{1-p} \cdot \sum_{i} R_{i,t}^{G,U} \quad \forall t \quad (20)$$

Specifically, (18) states that the upward reserve scheduled by a DRP is constrained either by the maximum upward demand modification rate or by the load drop rate. Similarly, the downward reserve as a result of scheduled load recovery is constrained either by the maximum downward demand modification rate or by the load pick-up rate (19).

Despite the fact that the utilization of demand side resources is generally promoted, a SO may impose limits on their contribution to reserves. This market rule is taken into account by (20) that states that the contribution of DRPs into upward reserves during a given period cannot exceed p% of the total scheduled upward reserves during that period. For instance, the Midcontinent Independent System Operator (MISO) adopted a limit of 30% (in the summer of 2012) on spinning reserve capacity procurement from DRPs in order to reduce the dependence on demand side resources for critical ancillary services until the performance of these resources is proven [51]. The reasons why a SO may enforce such constraints on the procurement of services from DRPs can be manifold. For instance, progressive evaluation of the effect of procuring reserves from the demand side on the market and the capacity factor of conventional generation that has been traditionally providing these services might be desirable. As a result, the reliability of response is not necessarily the major reason for imposing such limitations. The reason why constraint (20) is enforced in the mathematical formulation is to highlight the fact that valuating the participation of DRPs in reserve provision under such conditions might underestimate positive externalities such as financial risk mitigation for the SO.

B.1.4. Power Balance

Equation (21) enforces market power balance. It is common in the literature and also in real power systems not to enforce the network constraints in the first stage [8]. Nonetheless, any market scheme can be implemented within the proposed formulation.

$$\sum_{i} P_{i,t}^{sch} + \sum_{w} P_{w,t}^{W,sch} = \sum_{j} D_{j,t} \quad \forall t \quad (21)$$

B.2. Second Stage Constraints

B.2.1. Generating Units

Constraints (22)-(24) enforce the minimum and maximum power output as well as the ramp up and ramp down limits for the actual generation in each individual scenario.

$$P_i^{min} \cdot u_{i,t} \leq P_{i,t,s}^G \leq P_i^{max} \cdot u_{i,t} \ \forall i, t, s \quad (22)$$

$$P_{i,t,s}^G - P_{i,t-1,s}^G \leq RU_i \cdot \Delta T \ \forall i, t, s \quad (23)$$

$$P_{i,t-1,s}^G - P_{i,t,s}^G \leq RD_i \cdot \Delta T \ \forall i, t, s \quad (24)$$

B.2.2. Wind Spillage and Load Shedding

Constraints (25) and (26) state that the system operator may opt for spilling available wind production or partially shed inelastic load in order to satisfy the system constraints. Naturally, this is the last option of the operator since using such measures bears significant penalties.

$$0 \leq S_{w,t,s} \leq WP_{w,t,s} \ \forall w, t, s \quad (25)$$

$$0 \leq L_{j,t,s}^{shed} \leq D_{j,t} \ \forall j \in J^0, t, s \quad (26)$$

B.2.3. Demand Response Providers

1) Reserve Deployment

Constraints (27)-(29) enforce the requirement that a DRP cannot reduce and increase its consumption simultaneously. Also, the left hand side of (27) states that a load reduction should be over a minimum amount of curtailment. Furthermore, (30) imposes a maximum limit to the load reductions that may be procured by a DRP over a given scheduling horizon.

$$u_{j,t,s}^{DRP,u} \cdot R_j^{DRP,U,m} \leq r_{j,t,s}^{DRP,u} \leq RU_j^{DRP} \cdot T^S \cdot u_{j,t,s}^{DRP,u} \ \forall j, t, s \quad (27)$$

$$0 \leq r_{j,t,s}^{DRP,d} \leq RU_j^{DRP} \cdot T^S \cdot u_{j,t,s}^{DRP,d} \ \forall j, t, s \quad (28)$$

$$u_{j,t,s}^{DRP,u} + u_{j,t,s}^{DRP,d} \leq 1 \ \forall j, t, s \quad (29)$$

$$\sum_{t} u_{j,t,s}^{DRP,u} \leq N_j^{in} \ \forall j, s \quad (30)$$

2) Energy Recovery

Practical and economic reasons suggest that the provision of reserves by DRPs should not be viewed as a mere increase or decrease in their load. Electrical energy is used in order to facilitate the activities of a certain sector (i.e., residential, commercial, or industrial), the primary activity of which is not the participation in the electricity market. Thus, technical and social constraints imply that the curtailed energy will have to be provided to the consumers before or after the interruption occurs. Alternatively, in economic terms, if the internal load energy balance is not conserved, then the value that the DRPs assign to electrical energy is not consistent [21]. In certain cases, depending on the dynamics of a load that incurs an interruption, more energy than the amount that has been curtailed has to be provided [24]. The aforementioned facts suggest that DRP reserve provision is to be viewed as a redistribution of the demand over time and therefore the energy recovery should be appropriately modeled. In this paper, two different types of load recovery are considered. The first type (type 1) refers to a DRP that represents loads capable of storing (e.g. using batteries, air compressors, products [22] etc.) or foregoing energy and therefore, the energy recovery is rather flexible. This type of load recovery is modeled by (31).

$$\sum_{t} r_{j,t,s}^{DRP,d} + ENR_{j,s} \geq \gamma_j \cdot \sum_{t} r_{j,t,s}^{DRP,u} \ \forall j \in J^1, s \quad (31)$$

The system operator may procure load reduction from a DRP of type 1, on the condition that the energy is recovered before or after the reduction occurs. Note that if $0 \leq \gamma_j < 1$ a portion of energy is not necessarily recovered.

The second type (type 2) describes a DRP with the strict requirement to recover the reduced energy within T_j^{rec} intervals starting directly after a reduction occurs, while another interruption cannot be sustained before this period is over (e.g., air-conditioning load). The first requirement is fulfilled by the nonlinear constraint (32), the use of which is further motivated in Appendix I. Additionally, in order to preserve the mixed-integer linear programming (MILP) formulation, a reformulation of this constraint is presented in Appendix II. The second requirement is enforced by (33). This constraint states that in a period t a DRP is

in the recovery phase $\left(u_{j,t,s}^{DRP,d} = 1\right)$ if a curtailment has taken place $(u_{j,t,s}^{DRP,u} = 1)$ up to T_j^{rec} period in the past. As a result, another curtailment cannot occur because of (27) and (29). In the special case in which $T_j^{rec} = 1$, constraint (32) may be substituted by the simpler constraint (34). Finally, (35) states that during the first scheduling interval, load recovery is not possible.

$$u_{j,t,s}^{DRP,u} \cdot \sum_{\tau=t+1}^{t+T_j^{rec}} r_{j,\tau,s}^{DRP,d} = \gamma_j \cdot r_{j,t,s}^{DRP,u} \ \forall j \in J^2, t, s \tag{32}$$

$$u_{j,t,s}^{DRP,d} = \sum_{\tau=t-T_j^{rec}}^{t-1} u_{j,\tau,s}^{DRP,u} \ \forall j \in J^2, t, s \tag{33}$$

$$r_{j,t+1,s}^{DRP,d} = \gamma_j \cdot r_{j,t,s}^{DRP,u} \ \forall j \in J^2, t, s, if \ T_j^{rec} = 1 \tag{34}$$

$$u_{j,t,s}^{DRP,d} = 0 \ if \ t = 1, \forall j \in J^2, s \tag{35}$$

The constraints that are used to model reserve deployment and load recovery in this study are generic. Other constraints such as minimum and maximum duration of an interruption, load recovery sequence etc. are out of the scope of this paper.

B.2.4. DC Power Flow

The network constraints are considered for the actual operation of the power system, using a DC power flow representation. The power balance at each node is enforced by (36), while the flow through a branch is defined by (37) and (38). Note that voltage angle must be fixed at the reference node.

$$\sum_{i \in N_n^i} P_{i,t,s}^G + \sum_{w \in N_n^w} \left(WP_{w,t,s} - S_{w,t,s}\right) + \sum_{n \in B_b^{nn}} f_{b,t,s}$$
$$- \sum_{n \in B_b^n} f_{b,t,s} = \sum_{j \in N_n^j} \left(D_{j,t,s}^A - L_{d,t,s}^{shed}\right) \ \forall \ b, n, t, s \tag{36}$$

$$f_{b,t,s} = B_{b,n} \cdot \left(\delta_{n,t,s} - \delta_{nn,t,s}\right)$$
$$\forall b, (n, nn) \in B(n, nn), t, s \tag{37}$$

$$-f_b^{max} \leq f_{b,t,s} \leq f_b^{max} \ \forall b, t, s \tag{38}$$

B.3. Linking Constraints

B.3.1. Generating Units

Constraints (39)-(41) link the scheduled power output with the actual power generation and the scheduled reserve capacity with the deployed reserves, respectively. Moreover, constraints (42)-(44) decompose the deployed reserves into the blocks of energy.

$$P_{i,t,s}^G = P_{i,t}^{sch} + r_{i,t,s}^{G,u} - r_{i,t,s}^{G,d} \ \forall i, t, s \tag{39}$$

$$0 \leq r_{i,t,s}^{G,u} \leq R_{i,t}^{G,U} \ \forall i, t, s \tag{40}$$

$$0 \leq r_{i,t,s}^{G,d} \leq R_{i,t}^{G,D} \ \forall i, t, s \tag{41}$$

$$r_{i,t,s}^{G,u} - r_{i,t,s}^{G,d} = \sum_f r_{i,t,f,s}^G \ \forall i, t, s \tag{42}$$

$$r_{i,t,f,s}^G \leq B_{i,f,t}^G - P_{i,f,t}^{sg} \ \forall i, f, t, s \tag{43}$$

$$r_{i,t,f,s}^G \geq -P_{i,f,t}^{sg} \ \forall i, f, t, s \tag{44}$$

B.3.2. Demand Response Providers

Constraints (45)-(47) are similar to (39)-(41) that hold for the generating units.

$$D_{j,t,s}^A = D_{j,t} - r_{j,t,s}^{DRP,u} + r_{j,t,s}^{DRP,d} \ \forall j, t, s \tag{45}$$

$$0 \leq r_{j,t,s}^{DRP,u} \leq R_{j,t}^{DRP,U} \ \forall j, t, s \tag{46}$$

$$0 \leq r_{j,t,s}^{DRP,d} \leq R_{j,t}^{DRP,D} \ \forall j, t, s \tag{47}$$

IV. SOLUTION TECHNIQUE

In Section III it was rendered evident that both the objective functions (1) and (6) that represent the expected cost and the $CVaR_\alpha$ metric value are to be minimized, subject to constraints (2)-(3) and (7)-(47). Essentially, this is a multi-objective optimization problem (MOOP) with conflicting objectives, which implies that the set of Pareto efficient solutions is sought. In this section the classical approach (weighted sum method) to solve the MOOP is firstly discussed and its drawbacks are highlighted. Subsequently, the application of a variant of the epsilon-constraint method, namely the AUGMECON method to address the risk management problem of this study is presented.

Meta-heuristics based MOOP solution algorithms are generally considered to present computational advantages, especially in the case of large-scale optimization problems with unfavorable mathematical properties [52], [53]. However, they return an approximation of the Pareto frontier (pseudo-optimal Pareto solutions). On the contrary, AUGMECON is an exact (deterministic) solution technique that is capable of mapping the actual Pareto front for multi-objective MILP problems. Furthermore, AUGMECON has been proved to be statistically more computationally efficient in comparison with the widely-applied Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for combinatorial problems such as the radial distribution system reconfiguration problem [54]. More specifically, due to the dependence of the solutions on the initialization of the algorithm, many independent runs have to be performed that may be characterized by significantly variable computational time.

A. Classical Approach

The classical approach suggests transforming the MOOP into a single objective optimization problem by constructing a composite objective function [55] as in (48).

$$\text{Minimize} (1 - \beta) \cdot EC + \beta \cdot \text{CVaR}_\alpha$$
$$\text{s.t. } (2) - (3) \text{ and } (7) - (47) \tag{48}$$

The parameter $\beta \in [0,1]$ is a weighting factor that implements the trade-off between the expected cost and risk aversion. By varying the parameter β different solutions are obtained and the efficient frontier of expected cost versus risk is constructed. This approach is straightforward and easy to implement and therefore, has been widely adopted in the technical literature in different power systems problems in which risk needs to be considered. However, it presents several technical disadvantages [55]: 1) this method is only usable for convex efficient sets, 2) a uniformly distributed set of weights does not guarantee a uniformly distributed set of efficient solutions and as a result, the mapping of the Pareto efficient set may be insufficient, and 3) the weighted sum method suffers from the fact that there may be different combinations of weights that result into the same efficient solution. In practical terms, many more iterations would be needed in order to discover a given number of unique efficient optimal solutions.

B. Proposed Approach

The aforementioned problems of the weighted sum method may be addressed by another well-known MOOP solution method, namely the epsilon-constraint method, in which one of the objective functions is optimized using the other objective functions as constraints, as shown in (49).

$$\text{Minimize } EC$$
$$\text{s.t. } CVaR_\alpha \leq \bar{e} \qquad (49)$$
$$(2) - (3) \text{ and } (7) - (47)$$

By parametrical variation in the right hand side of the constrained objective function in (49) the efficient solutions of the problem are obtained. This approach is advantageous since it addresses the pitfalls of the weighting method. However, the main implication associated with the application of this method is that the parameter vector $\bar{e}$ must lie in the range of the objective functions, else the efficiency of the returned solutions is not guaranteed and the method may return weakly efficient solutions, instead. AUGMECON is a variant of the epsilon-constraint method that retains its advantages and addresses its disadvantages. Specifically, the ranges of the objective functions are calculated using lexicographic optimization, the efficiency of the returned solutions is proven and the use of acceleration techniques enhances the computational efficiency of the method. These conceptual advantages qualify AUGMECON as an acceptable exact technique to incorporate risk management into a stochastic optimization problem. A detailed presentation of the method can be found in [56]. The application of AUGMECON can be decomposed into three distinct steps: use of lexicographic optimization to define the ranges of the objective functions, definition of the parameter vector and solution of the optimization sub-problems.

B.1. Lexicographic construction of the pay-off table

The calculation of the range of the objective functions is not trivial. The common approach is to calculate the ranges using the pay-off table that contains the results of the individual optimization of the objective functions. Without loss of generality, considering two objective functions to be minimized, although the minimum value of the objective functions is easily obtained, the maximum value is not easily identified. In case of the maximum value is approximated by the maximum value of the corresponding column, these values may not represent efficient points. This problem is confronted with the use of lexicographic optimization that defines reservation values, i.e. upper limits for the objective functions. In this case, the values of the pay-off table Lex (50) are calculated by solving the optimization problems (51)-(54).

$$Lex = \begin{bmatrix} Lex_{1,1} & Lex_{1,2} \\ Lex_{2,1} & Lex_{2,2} \end{bmatrix} \qquad (50)$$

$$Lex_{1,1} = EC^* : \left(\begin{matrix} \text{Minimize EC} \\ \text{s.t. } (2) - (3) \text{ and } (9) - (47) \end{matrix} \right) \qquad (51)$$

$$Lex_{2,2} = CVaR_\alpha^* : \left(\begin{matrix} \text{Minimize } CVaR_\alpha \\ \text{s.t. } (2) - (3) \text{ and } (7) - (47) \end{matrix} \right) \qquad (52)$$

$$Lex_{1,2} = CVaR_\alpha^* : \left(\begin{matrix} \text{Minimize } CVaR_\alpha \\ \text{s.t. } (2) - (3), (7) - (47) \text{ and} \\ EC = Lex_{1,1} \end{matrix} \right) \qquad (53)$$

$$Lex_{2,1} = EC^* : \left(\begin{matrix} \text{Minimize } EC \\ \text{s.t. } (2) - (3), (7) - (47) \text{ and} \\ Lex_{2,2} = CVaR_\alpha \end{matrix} \right) \qquad (54)$$

B.2. Definition of the constraint parameter vector

The decision maker needs to specify a number P of grid points $e_p \in \bar{e}$ over which the Pareto efficient frontier is evaluated. The number of points defines the detail in which the efficient frontier is represented. The values of p evenly distributed points are calculated using (55).

$$e_p = e_{p-1} + \frac{Lex_{1,2} - Lex_{2,2}}{P}, p > 1$$
$$e_p = Lex_{2,2}, p = 1 \qquad (55)$$

B.3. Optimization problem

To guarantee that the solutions produced at each iteration are indeed efficient, the inequalities constraining the second objective in the original epsilon-constraint method (49) must be binding. Thus, a transformation of the inequality constraint of the original method to equality is used to force the method produce only efficient solutions. The equivalent optimization problem is presented in (56) in which $\varepsilon \to 0$ and σ is a non-negative slack variable. By parametrically varying e_p in the vector defined by (55), the efficient frontier of EC versus $CVaR_\alpha$ is constructed.

$$\text{Minimize } EC + \varepsilon \cdot \sigma$$
$$\text{s.t. } CVaR_\alpha + \sigma = e_p \qquad (56)$$
$$(2) - (3), (7) - (47) \text{ and } \sigma \geq 0$$

V. NUMERICAL RESULTS

A. Input Data

The proposed methodology is tested on the insular power system of Crete for a representative day with 626.2 MW peak load. The HV system of the island consists of 19 buses and 24 branches [57]. The generation mix of the island includes 25 thermal units in 3 power stations across the island exclusively utilizing diesel and heavy fuel oil. Furthermore, there are 31 wind-farms across the island with a total installed capacity of 186 MW. Technical and economic data of the generation system are illustrated in Table IV [58]. The generator reserve prices are considered equal to 25% of the most expensive block of the marginal energy bidding function of each generator, as in [8]. It is noted that only spinning up and down load following reserves are assumed to be scheduled by the SO. This simplification is justified by the fact that the generation mix of the island consists of several fast-start internal combustion engine (ICE) and open cycle gas turbine (OCGT) units, allowing for the SO to take corrective actions in real-time. To account for the stochasticity in wind power generation, an initial set of 70 scenarios is generated by performing 70 forecasts using ARIMA for a randomly selected day using the ECOTOOL Matlab toolbox [59] and historical data from the island of Crete, Greece [60]. More specifically, forecasting is performed for the 24 h of a specific day by considering different ranges of historical data when fitting the

model. Starting from a forecast using the historical data of the first week in the past, a day is progressively added to the historical time series to obtain a new forecast, while a new ARIMA model is fit when adding a whole new week to the data range. To maintain the tractability of the problem, a scenario reduction technique based on k-means clustering is to derive a reduced set of 20 non-equiprobable scenarios depicted in Fig. 2. More extensive studies on generating and reducing scenarios, as well as investigating the impact of the number of scenarios on the quality of the optimization problem solution for this particular power system can be found in [58] and [61].

The DRPs are considered to have a load pick-up/drop rate equal to 10 MW/min and can provide reserves at a capacity cost of 5 €/MWh and an exercise cost of 10 €/MWh [24], unless it is stated otherwise. The value of lost load and energy not recovered is set to 1000 €/MWh. The wind spillage cost is neglected in order to avoid introducing bias in the results. The confidence level for the evaluation of $CVaR$ is considered equal to 0.99, except for the cases in which it is differently declared.

B. Results and Discussion

B.1. Types of Load Recovery

Firstly, the deployment of the response of DRPs for the two different types of load recovery is illustrated. At a bus that stands for 15% of the total system load, a DRP is considered to render available up to 10% of its nominal load for reserve procurement.

A load recovery rate of 90% is considered. For the case that the DRP is of type 1 (Fig. 3) the number of interruptions is not limited, while for the case that the DRP is of type 2 (Fig. 4), only one interruption is allowed and the load recovery must be completed within two periods. In both cases the load curtailment occurs in periods in which the wind power that is available in a specific scenario is lower than the wind power that is scheduled day-ahead, so that the energy deficit is counterbalanced. The load recovery periods are coordinated in such a way that they coincide with periods of excessive wind power production. Especially, in Fig. 3 it may be noticed that during periods 6-7 and 23-24 significant amounts of energy are recovered in order to limit the curtailment of available wind power.

The contribution of DRPs to reducing the cost of operating the system is a function of several interlaced factors including the amount of wind spillage, the load reduction due to relaxed energy recovery requirements and, especially, the amount of reserves that are procured by the demand side. More specifically, the energy cost is affected by the load reduction over the scheduling horizon as a consequence of partial load recovery and improved wind power integration, which are in turn affected by the amount of deployed reserve. For the results of Fig. 3 the expected cost of energy is 1.07% lower than the baseline case, while the expected reserve procurement cost is reduced by 29.93%. The same changes in the components of the expected cost are 0.72% and 37.37%, respectively, in the case in which 100% of the load that is deployed by the SO needs to be recovered.

TABLE IV
GENERATION MIX OF THE SYSTEM

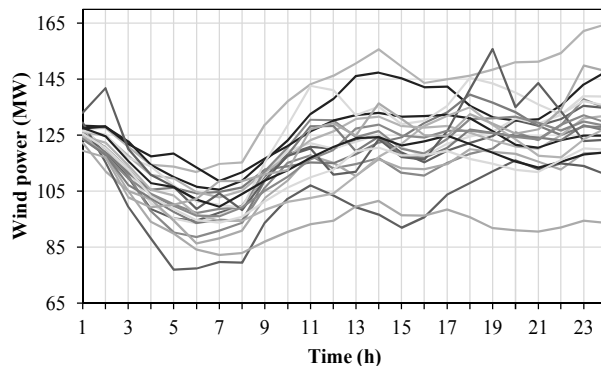| Technology	Fuel	Number of units	Capacity [MW]	Marginal Cost Range [€/MWh]
ICE	Heavy fuel oil	6	142	69.96 – 163.45
Steam	Heavy fuel oil	7	196	76.89 – 166.08
CCGT	Diesel oil	1	110	147.75
OCGT	Diesel oil	11	299	124.21 – 284.73
Wind	-	31	186	-

Fig. 2. The reduced set of scenarios used in the simulations.
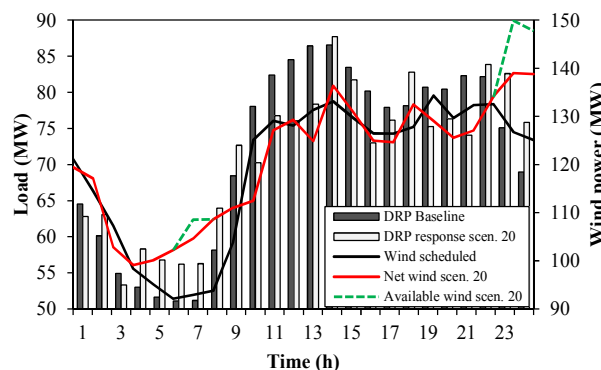

Fig. 3. Example of load recovery of type 1 (scenario 20).
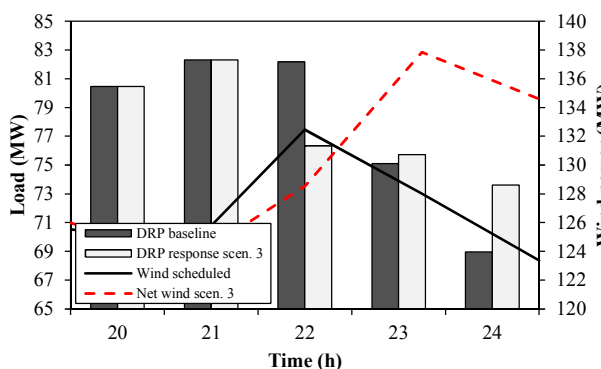

Fig. 4. Example of load recovery of type 2 (scenario 3).

B.2. Comparison Between the Classical and the Proposed Approach for Mapping the Pareto Efficient Frontier

Although establishing a direct comparison between the classical and the proposed approach is challenging, the technical advantages of the proposed method as regards the consideration of risk management can be revealed by attempting to map the same set of Pareto efficient solutions, neglecting the effect of the DRPs without loss of generality. To generate the same number of solutions, a set of 21 evenly spaced values of $\beta \in [0,1]$ is used, while 20 evenly spaced grid points are used for the application of the proposed approach. The obtained frontiers are presented in Fig. 5. The following may be noticed:

- The sets of efficient solutions discovered by the two methods (except for the solution for $\beta = 1$ and solution B) are incomparable since the methods result in two different mappings of the same Pareto frontier.
- For $\beta = 0$ the solution returned by the classical approach coincides with the extreme solution A returned using AUGMECON. However, solution B dominates the solution

obtained for $\beta = 1$ since solution B is characterized by less EC for the same value of $CVaR$. In other words, for $\beta = 1$ the returned solution is weakly efficient, i.e. for the same value of $CVaR$, a solution with a better (lower) value of EC is returned by AUGMECON. This is an expected result since the classical approach guarantees the efficiency of the returns solutions, only as long as the weights are strictly positive [55].

- Although evenly spaced values are used for both β and e_p, AUGMECON results in a more even mapping of the Pareto frontier, returning a unique solution at each iteration. On the other hand, the application of the classical approach results in the same solution for $\beta = 0.75, ..., 0.95$. Also, it can be noticed that a range of 37729 € in terms of EC and 13496 € in terms of $CVaR$ is left unmapped by the classical approach because the Pareto frontier between the solutions obtained by $\beta = 0.70$ and $\beta = 0.75$ is linear. The solutions obtained by the classical approach correspond to a tangent point in the objective space and thus only the two extreme solutions can be discovered for any $\beta \in [0.70, 0.75]$.

B.3. Factors That Limit the Contribution of DRPs to Cost Reduction and Risk Mitigation

In order to reveal different factors that would limit the capability of the demand side to reduce the expected cost and mitigate the associated risk when participating in reserve procurement, a number of factors are investigated. For these simulations, 47% of the total system load is considered to be managed by DRPs of type 1 at different buses, rendering available up to 10% of the demand for reserve procurement.

Based on the results presented in Fig. 7 as the risk aversion level increases, the SO is willing to spill more wind in order to avoid procuring costly reserves (solution 1 corresponds to the minimum level of risk aversion). Thus, relying on resources that can both provide less costly reserves to handle wind power uncertainty in comparison with the generating units and to reduce the overall demand leads in decreased expect cost, due to reduced day-ahead energy cost, and risk, because of less costly reserve scheduling and higher wind power integration. Due to the fact that the trade-offs between risk and expected cost are affected by the cost of procuring reserves, the impact of the participation of demand side resources on improving the decision making of the SO is directly related to the cost of scheduling and deploying reserves, as indicated by Fig. 8. Reducing the cost of demand side resources results in more favorable Pareto frontiers for the SO for the same level of load recovery rate of 90%.
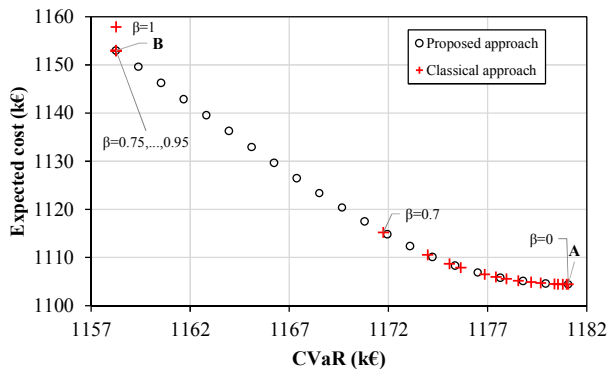

Fig. 5. Comparison of the sets of efficient solutions obtained using the classical and the proposed approach.
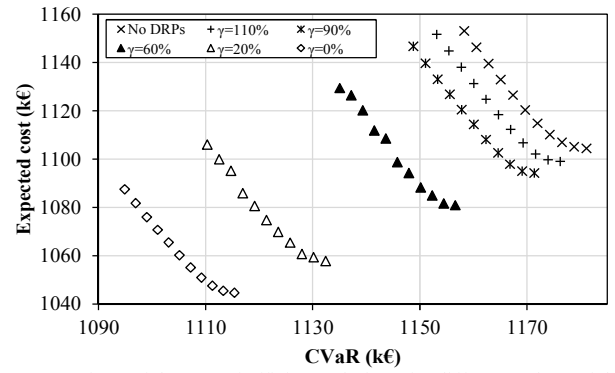

Fig. 6. Comparison of the sets of efficient solutions for different values of the load recovery rate.
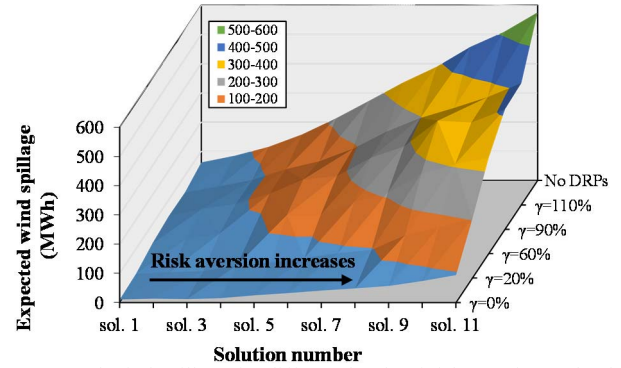

Fig. 7. Expected wind spillage for different levels of risk aversion and values of the load recovery rate (sol. 1- sol. 11 correspond to the AUGMECON solution numbering on an ascending order of risk aversion level).
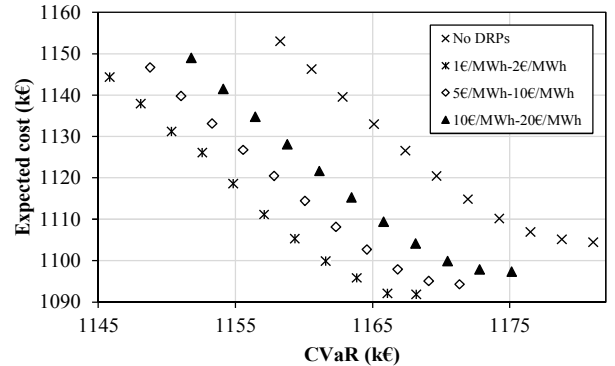

Fig. 8. Comparison of the sets of efficient solutions for different DRP reserve scheduling and deployment costs.

B.4. Effect of Confidence Level

The confidence level α is an indication of the degree of conservatism by which the value of CVaR is evaluated by the decision maker. In the aforementioned simulations the confidence level was considered equal to 0.99. In order to investigate the influence of the selection of parameter α on the performance of the system, additional simulations are performed considering that α takes values in the set $[0.90, 0.95, 0.99]$. The characteristics of the DRPs are the same with those considered in Section B.3.

The cumulative distribution functions (CDFs) of cost in individual scenarios for $\alpha = 0.90$ and $\alpha = 0.99$ together with the values of EC, VaR and $CVaR$ are displayed in Fig. 9. The CDFs correspond to the third AUGMECON solution on ascending order of risk aversion level (sol. 3). It may be noticed that for a lower value of the confidence level both the values of the EC and the $CVaR$ are reduced. However, the standard deviation of the cost is increased by 12.4%. This is a consequence of considering a larger

number of scenarios for the calculation of $CVaR$ as the confidence level decreases. Another important observation is that the CDF that was obtained by optimizing $CVaR_{0.99}$ presents a value of $CVaR_{0.9}$ that is lower by 0.23% in comparison with the CDF that was obtained by optimizing $CVaR_{0.9}$. The opposite is observed when $CVaR_{0.99}$ is evaluated on a CDF that was obtained by optimizing $CVaR_{0.90}$.

In practice, the degree of conservatism affects the trade-off between wind spillage and cost of scheduled reserves. The expected available wind generation spillage is portrayed in a common diagram with the cost of scheduling reserves in Fig. 10 for the three different values of the confidence level and different degrees of risk aversion that are evaluated. It is rendered evident that for lower confidence levels the amount of expected wind spillage increase is reduced for increasing levels of risk aversion. The contrary holds for the scheduled reserve costs.

B.5. Impact of Limitation on the Contribution of DRPs in Reserve Provision

Finally, the effect of potential rules that limit the participation of demand side resources in reserve provision is investigated. In Fig. 11 the efficient frontiers for the cases in which the total amount of upward demand side reserves (90% load recovery rate) are limited to 10%, 20% and 30% of the total amount of upward reserves are comparatively presented for a confidence level 0.99.

It is noticed that the presence of rules that limit the participation of DRPs causes a shift of the efficient frontiers towards the efficient frontier that corresponds to the case in which the contribution of DRPs is neglected. Obtaining a more advantageous Pareto frontier may be viewed as a positive effect of the participation of DRPs on the operation of the power system.
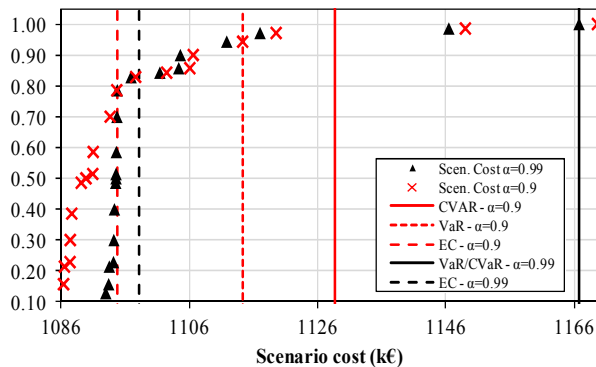

Fig. 9. Cumulative distribution functions (CDFs) of cost in individual scenarios for $\alpha = 0.9$ and $a = 0.99$ for sol. 3.
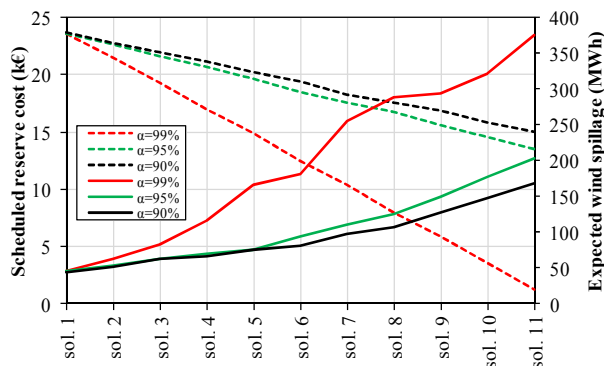

Fig. 10. Expected wind spillage (solid lines) and cost of scheduled reserves (dashed lines) for different degrees of risk aversion and confidence levels.
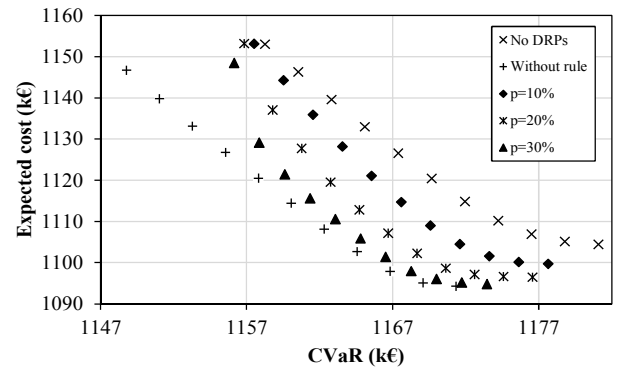

Fig. 11. Comparison of the sets of efficient solutions for different limits to DRP contribution to reserves.

To quantitatively assess the impact of such constraints each efficient frontier can be represented by its centroid, i.e., a fictitious point that can be found by averaging the coordinates of all the points it comprises. Subsequently the distance between the centroid of the efficient frontier corresponding to the case in which DRPs are not considered as a system resource and each of the efficient frontiers for different values of p depicted in Fig. 11 can be calculated as a performance metric. Evidently, greater distances correspond to more desirable efficient frontiers. For instance, the efficient frontier for the case in which participation of DRPs is not limited is 2.5 times greater in comparison with the efficient frontier for $p = 10$ %. This is an indication that the presence of imposing restrictions on the dependence on DRPs for procuring reserves may significantly hinder the potential benefits of DR.

C. Computational Statistics

The proposed methodology was implemented in GAMS 24.8 and the optimization problems were solved using CPLEX 12. All the simulations were performed using a workstation with two Intel Xeon processors clocking at 2.60 GHz and 128GB of RAM memory, running a 64 bit version of Windows.

In order to demonstrate the tractability of the proposed multi-objective problem formulation, the size of each optimization sub-problem and indicative computational statistics are presented. A modified system based on the actual power system of Crete that was described in Section V.A. is obtained by replicating the power system and considering an interconnection of limited capacity between the two new areas. The modified system consists of 50 conventional generating units, 22 aggregated wind-farms, 38 buses and 49 transmission lines.

The following cases are considered:
- Case A: Power system of Crete as described in Section V.A. without considering the effect of the DRPs.
- Case B: Power system of Crete as described in Section V.A. considering the effect of the DRPs (90% load recovery).
- Case C: Modified power system of Crete without considering the effect of the DRPs.
- Case D: Modified power system of Crete considering the effect of the DRPs (90% load recovery).

The relevant results are compiled in Table V. The results indicate that a direct solution of the proposed optimization problem formulation is computationally tractable for real-life power systems.

TABLE V
COMPUTATIONAL STATISTICS

	Case A	Case B	Case C	Case D
Number of continuous variables	511679	541799	1023813	1084052
Number of integer variables	2788	7588	5576	15176
Number of constraints	174917	189757	351226	380905
Pay-off table construction time (s)	114	162	536	823
Sub-problem solution time (s)	31	36	110	343

VI. CONCLUSIONS

In this study, a risk-aware joint energy and reserve market structure, incorporating demand side resources was presented. The mathematical model is based on two-stage stochastic programming in order to capture the uncertain nature of significant wind power penetration, while the risk-averse behavior of the SO with respect to the expected operational costs was considered using a novel multi-objective optimization approach, based on the AUGMECON method. Furthermore, the load recovery effect was explicitly taken into account by developing generic models. Simulations performed for the case of the insular power system of Crete, Greece, allowed drawing useful insights regarding the advantages from applying the proposed methodology to risk management and the factors that affect the beneficial contributions from demand side resources participation in reserve procurement. The most important observations may be summarized as follows:

- The application of the AUGMECON method resulted in a richer mapping of the Pareto frontier in comparison with the approximation obtained using the classical weighted sum approach.
- The risk mitigation from the participation of DRPs in reserve provision is sensitive to the load recovery requirements and the costs related to the deployment of demand side reserves.
- The mechanism through which the SO can control the risk embedded in its decisions is the amount of wind that is integrated in the system by procuring the necessary reserves. A more elastic demand side leads to higher exploitation of wind energy at any level of risk-aversion.
- The existence of rules that limit the amount of reserves that may be scheduled by DRPs may underestimate their contribution, as well as positive externalities such as risk mitigation.

APPENDIX I
LOAD RECOVERY OF TYPE 2

In Reference [24] load recovery is modeled using a constraint that is essentially equivalent to (32) when omitting the multiplication of the left hand side with the binary variable. Although such a constraint seems straightforward, in fact it can be easily proven that it is valid only for the case in which $T_j^{rec} = 1$.

Let us assume that in period τ of scenario s an amount of up reserve is deployed from DRP j ($r_{j,\tau,s}^{DRP,u} > 0$) and that it must be recovered in the next $T_j^{rec} > 1$ periods. Without loss of generality, assume also that $\gamma_j = 1$. Then, in period τ, $r_{j,\tau,s}^{DRP,u} = r_{j,(\tau+1),s}^{DRP,d} + \cdots + r_{j,\tau',s}^{DRP,d} + \cdots + r_{j,(\tau+T_j^{rec}),s}^{DRP,d}$. If $r_{j,\tau',s}^{DRP,d} > 0, \tau' > \tau + 1$, then the constraint $r_{j,(\tau+1),s}^{DRP,u} = r_{j,(\tau+2),s}^{DRP,d} + \cdots + r_{j,\tau',s}^{DRP,d} + \cdots + r_{j,(\tau+T_j^{rec}+1),s}^{DRP,d}$, that must also hold, is violated due to the fact that $r_{j,(\tau+1),s}^{DRP,u}, \dots, r_{j,(\tau+T_j^{rec}),s}^{DRP,u} = 0$ since in the recovery period another

curtailment is not possible as stated by (33), unless $r_{j,\tau',s}^{DRP,d} = 0, \forall \tau' > \tau + 1$. This implies that either $T_j^{rec} = 1$ or alternatively, feasibility is achieved by recovering all the curtailed load in the first period following the interruption.

To overcome this limitation, the nonlinear constraint (32) is introduced. Constraints (29) and (33) assert that if $u_{j,\tau,s}^{DRP,u} = 1$, then $u_{j,\tau+1,s}^{DRP,u}, \dots, u_{j,\tau',s}^{DRP,u}, \dots, u_{j,(\tau+T_j^{rec}),s}^{DRP,u} = 0$. As a result, $r_{j,\tau,s}^{DRP,u} = \left(r_{j,(\tau+1),s}^{DRP,d} + \cdots + r_{j,\tau',s}^{DRP,d} + \cdots + r_{j,(\tau+T_j^{rec}),s}^{DRP,d} \right) \cdot 1$ and $r_{j,(\tau+1),s}^{DRP,u} = \left(r_{j,(\tau+2),s}^{DRP,d} + \cdots + r_{j,\tau',s}^{DRP,d} + \cdots + r_{j,(\tau+T_j^{rec}+1),s}^{DRP,d} \right) \cdot 0$ are feasible for $r_{j,\tau',s}^{DRP,d} > 0, \forall \tau' > \tau + 1$.

APPENDIX II
MIXED-INTEGER LINEAR REFORMULATION OF (32)

Constraint (32) can be substituted by the set of linear constraints (A.1.)-(A.5.) in order to preserve the MILP formulation.

$$\mu_{j,t,s} \leq RD_j^{DRP} \cdot T^S \cdot T_j^{rec} \cdot u_{j,t,s}^{DRP,u} \; \forall j,t,s \qquad (A.1.)$$

$$\mu_{j,t,s} \geq \sum_{\tau=t+1}^{t+T_j^{rec}} r_{j,\tau,s}^{DRP,d} - \left(1 - u_{j,t,s}^{DRP,u}\right) \cdot RD_j^{DRP} \cdot T^S \cdot T_j^{rec} \qquad (A.2.)$$
$$\forall j,t,s$$

$$\mu_{j,t,s} \leq \sum_{\tau=t+1}^{t+T_j^{rec}} r_{j,\tau,s}^{DRP,d} \; \forall j,t,s \qquad (A.3.)$$

$$\mu_{j,t,s} = \gamma_j \cdot r_{j,t,s}^{DRP,u} \; \forall j,t,s \qquad (A.4.)$$

$$\mu_{j,t,s} \geq 0 \; \forall j,t,s \qquad (A.5.)$$

To achieve the linearization of (32), first the nonnegative auxiliary variable $\mu_{j,t,s}$ which replaces $u_{j,t,s}^{DRP,u} \cdot \sum_{\tau=t+1}^{t+T_j^{rec}} r_{j,\tau,s}^{DRP,d}$ must be bounded. A suitable upper bound is the maximum technically achievable amount of energy that may be recovered during the recovery period that is constrained by the load pickup rate ($RD_j^{DRP} \cdot T^S \cdot T_j^{rec}$). Note that if in period t a curtailment occurs, then $u_{j,t,s}^{DRP,u} = 1$ and from (A.2.)-(A.3.) it is deduced that $\mu_{j,t,s} = \sum_{\tau=t+1}^{t+T_j^{rec}} r_{j,\tau,s}^{DRP,d}$. Alternatively, if no curtailment occurs, then $u_{j,t,s}^{DRP,u} = 0$. In this case (A.1.) and (A.5.) imply that $\mu_{j,t,s} = 0$.

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