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Effect of Risk Aversion on Reserve Procurement With Flexible Demand Side Resources From the ISO Point of View

Nikolaos G. Paterakis, *Member, IEEE,* Agustín A. Sánchez de la Nieta, *Member, IEEE,* Anastasios G. Bakirtzis, *Fellow, IEEE,* Javier Contreras, *Fellow, IEEE,* and João P. S. Catalão, *Senior Member, IEEE*

Abstract—In this study a two-stage stochastic programming joint day-ahead energy and reserve scheduling model to address uncertainty in wind power generation is developed. Apart from the generation side, the demand side is also eligible as a reserve resource and is modeled through responsive load aggregations, as well as large industrial loads that directly participate in the scheduling procedure. The main contribution of this paper is the inclusion of a risk metric, namely the Conditional Value-at-Risk (CVaR), which renders a conceptually different resource scheduling framework. The proposed model is employed in order to analyze the behavior of energy and reserve scheduling by both generation and demand for a risk-averse Independent System Operator (ISO). To reach practical conclusions, the proposed methodology is tested on the real non-interconnected insular power system of Crete, Greece, which is characterized by a significant penetration of wind power generation.

Index Terms—Ancillary services, conditional value-at-risk (CVaR), demand response, reserves, risk management

Nomenclature

The main notation used is alphabetically listed below. Other symbols and abbreviations are defined where they first appear.

A. Sets and Indices

d index of industrial loads.
$f(F^i)$ index (set) of steps of the marginal cost function of unit i.

i index of conventional generating units.
j index of aggregated loads.
s index of wind power generation scenarios.
t index of time periods.
w index of wind farms.

B. Parameters

a_d^{max} positive integer; number of available production lines of industry d.

$C_{i,f,t}$ energy offer price/marginal cost of step f of unit i in period t (€/MWh).

$C_{x,t}^{R^{y,x}}$ availability cost of reserve of type y (U-up spinning, D- down spinning and, NS- non spinning reserve) by resource type x (G- generating units, L-aggregated loads and, I-industrial consumer) in period t (€/MWh).

$D_{d,t}^{min}$ minimum required consumption for period t of the scheduling horizon for industry d (MW).

ER_j total energy required during the scheduling horizon by aggregated load j (MWh).

$L_{j,t}^{S,max}$ maximum consumption of aggregated load j in period t (MW).

$L_{j,t}^{S,min}$ minimum consumption of aggregated load j in period t (MW).

P_d^{line} power of production line of industry d (MW).

$P_{w,t,s}^{WP}$ power output of wind farm w in scenario s in period t (MW).

$P_w^{WP,max}$ maximum power that can be scheduled by wind farm w (MW).

SDC_i shutdown cost of unit i (€).

SUC_i startup cost of unit i (€).

V_j^{ENS} cost of energy not served for load j (€/MWh).

V^S cost of wind energy spillage (€/MWh).

α confidence level (used in the calculation of $CVaR$).

β weighting factor (used in the calculation of $CVaR$).

γ_j load recovery rate of aggregated load j (% of the nominal load).

π probability of occurence of wind power generation scenario s.

C. Decision Variables

$a_{d,t}$ positive integer variable; number of production lines scheduled in period t from industry d.

$a_{d,t}^{down}$ positive integer variable; number of production lines scheduled to contribute to down reserve in period t from industry d.

$a_{d,t}^{up}$ positive integer variable; number of production lines scheduled to contribute to up reserve in period t from industry d.

$a_{d,t,s}^{down,2}$ positive integer variable; number of production lines deployed to contribute to down reserve in period t from industry d in scenario s.

$a_{d,t,s}^{up,2}$ positive integer variable; number of production lines deployed to contribute to up reserve in period t from industry d in scenario s.

$b_{i,f,t}$ power output scheduled from the f-th block of the marginal cost function/offer block of unit i in period t (MW).

$CVaR$ conditional value-at-risk (€).

$D_{d,t,s}^{C}$ actual power consumed by industry d in period t in scenario s (MW).

$D_{d,t}^{S}$ scheduled consumption by industry d in period t (MW).

$L_{j,t,s}^{C}$ power actually consumed by aggregated load j in period t in scenario s (MW).

$L_{j,t}^{S}$ scheduled demand of aggregated load j in period t (MW).

EC expected cost (€).

EC^{SI} scenario-independent component of expected cost (€).

EC_{s}^{SD} scenario-dependent component of expected cost in scenario s (€).

$ENS_{j,s}$ energy not supplied for aggregated load j in scenario s (MWh).

$P_{i,t,s}^{G}$ actual power output of unit i in period t in scenario s.

$P_{i,t}^{S}$ power output scheduled from unit i in period t (MW).

$P_{w,t}^{WP,S}$ scheduled wind power from wind farm w in period t (MW).

$R_{x,t}^{y,x}$ scheduled reserve of type y (U- up spinning, D- down spinning and, NS- non spinning reserve) by resource of type x (G- generating units, L- aggregated loads and, I- industrial consumer) in period t (MW).

$r_{i,f,t,s}^{G}$ reserve deployed by the f-th block of unit i in period t in scenario s (MW).

$r_{x,t,s}^{y,x}$ deployed reserve of type y (U- up spinning, D- down spinning and, NS- non-spinning reserve) by resource x (G- generating units, L- aggregated loads and, I- industrial consumer) in scenario s in period t (MW).

$S_{t,w,s}$ wind power spilled in scenario s from wind farm w in period t (MW).

$y_{i,t}^{1}$ binary variable; 1 if unit i is starting up in period t, else 0.

$y_{i,t,s}^{2}$ binary variable; 1 if unit i is starting up during period t in scenario s, else 0.

$z_{i,t}^{1}$ binary variable; 1 if unit i is shut down in period t, else 0.

$z_{i,t,s}^{2}$ binary variable; 1 if unit i is shut down during period t in scenario s, else 0.

η_{s} auxiliary variable related to scenario s used in the calculation of CVaR.

ξ auxiliary variable (equals VaR at optimal solution) (€).

I. INTRODUCTION

ENVIRONMENTAL and economic factors suggest that renewable energy sources (RES) are likely to represent a significant portion of the generation mix of many power systems around the world in the near future [1]. Given the fact that providing low cost electricity is essential for the economic development of a region or a whole country, the increasing scarcity and cost of conventional fuels has led many governments and international institutions to introduce policies in order to exploit regional energy sources and, therefore, to isolate the electricity production cost from geopolitical factors and transportation costs related to fuel imports. This situation is more intense in non-interconnected systems. For example, 94% of the electricity generation in the Canary Islands depended on imported fuels in 2010 [2], while Cyprus has been almost exclusively relying on the use of heavy fuel oil and diesel in electricity production [3]. As a result, exploiting local RES presents multiple advantages and could reduce market prices [4].

However, the large scale integration of the two most common and technologically mature RES, wind and solar power generation, is linked to a series of issues that need to be faced by Independent System Operators (ISO), mainly stemming from their intrinsically stochastic nature and the direct dependence of their production on the instantaneous, daily, seasonal and yearly fluctuations of wind speed and solar irradiation. The integration of high levels of non-dispatchable resources in power systems and especially in relatively small-sized, non-interconnected systems such as the insular ones, poses operational and economic challenges that need to be addressed. The magnitude of the problem depends on the penetration of RES in the production mix, while its mitigation is reflected on the flexibility of the power system. The majority of existing power systems has been designed considering the fluctuations of the demand. Nevertheless, it is questionable whether the grid can serve both varying loads and high amounts of variable generation such as wind and solar. In order to accommodate the significant uncertainty in operations, an increased amount of reserves should be maintained. Especially, regulation and load following requirements, both in terms of capacity and ramping capability, are likely to increase with the growing penetration of wind and solar generation.

Generators providing regulation and load following reserves incur significant costs such as efficiency loss because of ramping, environmental costs because of increased emissions, increased wear and tear and, therefore, increased operating and maintenance costs, as well as opportunity costs in the energy market [5]. The increasing penetration of RES may also lead to the displacement of peaking and intermediate units, forcing base load plants to be operated in a cycling manner, an operation which does not match their technical characteristics such as long start-up, minimum up, down and decommissioning times. These problems can be eased in two ways, with the combination of several mature technologies [6]–[8] and by the participation of the demand side in providing load following reserves. Certain types of loads such as air conditioning and electric space heaters have the ability to adjust their power to changes in demand instantaneously [9], in contrast with conventional generators, the ramp rates of which are limited. Furthermore, it is argued that services provided by demand side resources could prove to be more reliable since the reliability of the response of an aggregation of a significant number of loads is greater than the one of a small number of large generators [10].

Another important issue that is primarily linked to wind generation and can be faced by using demand side resources is wind over-generation [11]. This problem appears when large amounts of wind generation are available during off-peak periods, typically at night or early in the day. In such cases, due to the fact that many markets consider wind power generators as must-run units, either the output of the conventional generation must be reduced in order to accommodate wind generation, or the excessive wind energy should be curtailed, an option that may bear high penalties, in order to maintain the balance of the system. The situation escalates when the system comprises relatively inflexible base load generators that are committed to operating near their technical minimum power output during such periods. Evidently, one solution that the deployment of demand side reserves can offer is the increase of the demand in periods in which there is excessive wind power generation. Loads that can be shifted in such a way that allows the otherwise spilled wind energy to be exploited include water pumping, irrigation, municipal treatment facilities, thermal storage in large buildings, industrial electrolysis, aluminium smelting etc. [12].

Although the problem of reserve procurement under uncertainty has been studied to some extent (a recent review may be found in [13]), to the best of the authors' knowledge, there is no study considering the effect of risk aversion on reserve procurement under the presence of flexible demand side resources from the point of view of an ISO. Aiming to contribute to the investigation of this area, a joint energy and load following reserve market clearing model based on two-stage stochastic programming that explicitly incorporates risk management, in terms of optimizing the conditional value-at-risk (CVaR) metric, is developed in this paper. The CVaR metric has been widely used in the literature to model the risk averse behavior of a decision maker. For instance, in [14] a single-period robust optimal power flow formulation which includes CVaR either in the objective function, or as a problem constraint is presented. CVaR is evaluated in terms of sampling the wind power output in order to decide on the output of the conventional generators. However, neither the procurement of reserves, nor the participation of demand side resources is related to the subject of the work presented in [14]. Also, the study in [15] utilized the CVaR metric in order to define a minimum level of reserves that should be scheduled from conventional units based on a Monte Carlo simulation. The presented optimization model itself is cast as deterministic. On the contrary, in our study CVaR is optimally evaluated as a part of two-stage stochastic optimization problem, while reserves and energy from the generation and the demand side are jointly cleared considering both the expected cost and the level of risk aversion. Finally, it is to be noted that CVaR has been utilized in studies not directly related to the unit commitment problem, such as for the optimal management of energy storage systems [16], or to derive optimal offering strategies for virtual power plants [17], [18].

The proposed model is conceptually different in comparison with other related stochastic joint energy and reserve market clearing models. More specifically, the contribution of this paper is threefold:

1) to develop a reserve valuation mechanism based on a risk-averse market clearing procedure. As a result, in this paper the levels of committed reserves are driven by the trade-off between cost and risk, while uncertainty associated with wind production is optimally managed;
2) to consider demand side resources such as large industrial consumers and load aggregations eligible for the provision of reserve services;
3) to apply the proposed methodology to a real non-interconnected power system with significant penetration of wind power generation, namely the insular power system of Crete in Greece, in order to reach practical conclusions as regards the value of introducing demand side resources to reserve provision mechanisms.

The remainder of this paper is organized as follows: Section II presents the methodology proposed to evaluate the impact of the active demand side resources. In Section III the methodology is tested on a real power system and relevant results are discussed. Finally, conclusions are drawn in Section IV.

II. MATHEMATICAL MODEL

A. Objective Function

The objective of the ISO is to minimize the total expected operational cost of the system (EC) taking into account the effect of different levels of risk aversion, by also minimizing the CVaR metric as expressed by (1). Parameter β is non-negative and defines the relative importance of the minimization of CVaR versus the minimization of EC.

EC is defined in (2). EC comprises two components: a component that is scenario independent (start-up and shut-down cost of units, energy and reserve cost of generators and demand side reserve procurement cost) as presented in (3) and, a scenario-dependent component that considers the cost of altering the commitment status of units and materializing reserves as energy. Also, two fictitious costs are considered (wind spillage cost and energy not served). The scenario dependent part is described by (4).

$$C = EC + \beta \cdot CVaR \qquad (1)$$

$$EC = EC^{SI} + \sum_s \pi_s \cdot EC_s^{SD} \qquad (2)$$

$$
\begin{aligned}
EC^{SI} = \sum_t \Bigg\{ &\sum_i \Bigg[\sum_f (C_{i,f,t} \cdot b_{i,f,t}) \\
&+ (SUC_i \cdot y_{i,t}^1 + SDC_i \cdot z_{i,t}^1) \\
&+ (C_{i,t}^{R^{D,G}} \cdot R_{i,t}^{D,G} + C_{i,t}^{R^{U,G}} \cdot R_{i,t}^{U,G} + C_{i,t}^{R^{NS,G}} \cdot R_{i,t}^{NS,G}) \Bigg] \\
&+ \sum_j (C_{j,t}^{R^{D,L}} \cdot R_{j,t}^{D,L} + C_{j,t}^{R^{U,L}} \cdot R_{j,t}^{U,L}) \\
&+ \sum_d (C_{d,t}^{R^{D,I}} \cdot R_{d,t}^{D,I} + C_{d,t}^{R^{U,I}} \cdot R_{d,t}^{U,I}) \Bigg\}
\end{aligned}
\qquad (3)
$$

$$EC_s^{SD} = \sum_t \left[\sum_i \left(\sum_f (C_{i,f,t} \cdot r_{i,f,t,s}^G) \right) \right.$$
$$SUC_i \cdot (y_{i,t,s}^2 - y_{i,t}^1) + SDC_i \cdot (z_{i,t,s}^2 - z_{i,t}^1)) \quad (4)$$
$$\left. \sum_w (V^S \cdot S_{w,t,s}) + \sum_j (V_j^{ENS} \cdot ENS_{j,s}) \right] \quad \forall s$$

Representing a random variable by its expected value is advantageous in comparison with a deterministic approach. Nevertheless, the characteristics associated with the distribution of the outcomes of the individual scenarios are disregarded. As a result, an acceptable expected cost value that may be favorable for the ISO does not necessarily mitigate the possibility of facing significant costs in several scenarios. To overcome this ambiguity, a risk measure should be incorporated in the optimization problem. A risk measure is a function that results into a real number characterizing the risk associated with the specific expected value of a random variable. 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 [19] and [20].

In this study, the CVaR metric [21] is used because it presents three important advantages: 1) it can be incorporated in the optimization problem using a linear formulation, 2) in contrast with the popular value-at-risk (VaR) metric, it quantifies "fat tails" in the probability distributions and, 3) it is a coherent risk measure.

For a given $\alpha \in (0,1)$ the VaR is equal to the minimum cost ξ that will not be exceeded with probability α. It should be noted that ξ is the variable representing the value of the risk measure and not a pre-fixed parameter. Mathematically, VaR is defined by (5).

$$VaR_a = \min\{\xi : P(EC^{SI} + EC_s^{SD} \le \xi) \ge \alpha\} \quad (5)$$

Utilizing VaR as a risk metric may not be fully descriptive of the characteristics of the distribution of system operational costs, especially in case the latter is fat-tailed. In practice this means that although VaR acts as a cutoff value, the cost in scenarios that exceed this value may be substantial. On the other hand, utilizing CVaR as a risk metric eases this concern. CVaR 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). If all scenarios are equiprobable, then CVaR is equivalent to the expected cost of the $a \times 100\%$ worst scenarios. Evidently, smaller values of the CVaR are more desirable from the perspective of a risk-averse ISO. The mathematical definition of CVaR is given in (6).

$$CVaR_a = \min\{\xi + \frac{1}{1-\alpha} \mathbf{E} \left[\max\{EC^{SI} + EC_s^{SD} - \xi, 0\} \right] \}$$
$$(6)$$

In this study, the optimization problem that needs to be solved by the ISO is cast as a mixed-integer linear program (MILP). As a result, the non-linear equation (5) that defines

the CVaR metric is replaced by the linear constraints (7)-(9). In (7) η_s is defined as a non-negative auxiliary variable which according to (8) represents the difference between the cost in each particular scenario and variable $\xi(\xi^* \equiv VaR)$. If the difference is positive for some scenario s, then this is a scenario the cost of which exceeds VaR and it holds that $\eta_s > 0$ else, it holds that $\eta_s = 0$. Finally, (9) is used to account for the expected value of $\max\{EC^{SI} + EC_s^{SD} - \xi, 0\}$ with respect to the $(1 - \alpha)$-quantile. These values are then superimposed to the value of VaR so that the CVaR is appropriately associated with the cost distribution.

$$\eta_s \ge 0 \; \forall s \quad (7)$$

$$EC^{SI} + EC_s^{SD} - \xi \le \eta_s \; \forall s \quad (8)$$

$$CVaR = \xi + \frac{1}{1-\alpha} \sum_s \pi_s \cdot \eta_s \quad (9)$$

B. First Stage Constraints

This section presents the first stage constraints of the optimization problem. These constraints involve only decision variables that do not depend on any specific scenario (here-and-now decisions) and represent the day-ahead market decisions.

1) Scheduled Wind Farm Production: Typically the wind power generation scheduled in the day-ahead market is considered equal to its forecast value. However, in this study it is considered that the ISO schedules the optimal amount of wind according to the techno-economic optimization within the limits imposed by (10). The upper limit stands for the installed capacity of the wind farm.

$$0 \le P_{w,t}^{WP,S} \le P_w^{WP,max} \; \forall w, t \quad (10)$$

2) Aggregated Load Scheduling: Constraint (11) stands for load scheduling. The load may also be scheduled to provide down reserves (12) that stand for a load increase and up reserves (13) that stand for a load decrease. Finally, (14) is an energy requirement constraint which states that, during the day, at least γ_j of the nominal demand of load j has to be satisfied. If a load is inelastic, then the two limits of (11) coincide with $L_{j,t}^S$.

$$L_{j,t}^{S,min} \le L_{j,t}^S \le L_{j,t}^{S,max} \; \forall j, t \quad (11)$$

$$0 \le R_{j,t}^{D,L} \le L_{j,t}^S - L_{j,t}^{S,min} \; \forall j, t \quad (12)$$

$$0 \le R_{j,t}^{U,L} \le L_{j,t}^{S,max} - L_{j,t}^S \; \forall j, t \quad (13)$$

$$\sum_t L_{j,t}^S \ge \gamma_j \cdot ER_j \; \forall j \quad (14)$$

3) Industrial Consumer Scheduling: The industrial load model is portrayed in Fig. 1. Constraint (15) enforces the fact that the hourly power demand of the industry comprises
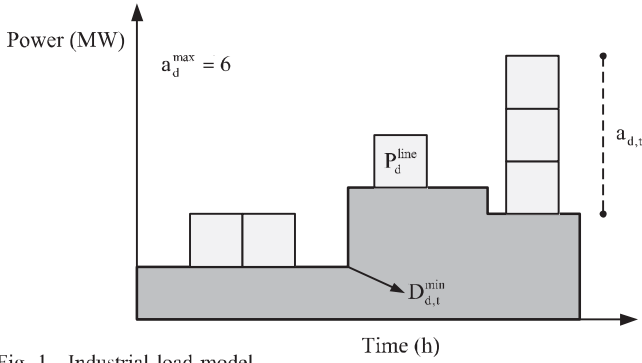
Fig. 1. Industrial load model.

an inelastic part and the power of a number of production lines that may be allocated during a period. For the sake of simplicity, it is considered that all the lines have the same power rating and that no interrelation exists between their operation and functionality. This constrains the present industrial consumer model applicability to certain types of industrial processes that can operate discretely and without operating time limits or other restrictions. Alternatively, it represents the time allocation of the total energy required by a single process. The number of production lines that can be allocated in a single period is constrained by (16) and it cannot surpass the total number of production lines available for flexible demand allocation. The energy requirement of the industrial consumer is enforced by (17). This constraint ensures that the industry does not incur any economic loss due to participating in the provision of system services. It is to be noted that since production lines represent blocks of energy that may be optimally scheduled, the term $a_d^{max} \cdot P_d^{line}$ stands for the total amount of energy required by the flexible processes of the industry that need to be completed within the horizon.

$$D_{d,t}^S = D_{d,t}^{min} + a_{d,t} \cdot P_d^{line} \;\; \forall d, t \qquad (15)$$

$$0 \le a_{d,t} \le a_d^{max} \;\; \forall d, t \qquad (16)$$

$$\sum_t D_{d,t}^S = \sum_t D_{d,t}^{min} + a_d^{max} \cdot P_d^{line} \;\; \forall d \qquad (17)$$

The industry can provide up or/and down reserves in a discrete manner by switching on or off one or more production lines during one or more scheduling periods, as described in (18)-(21).

$$R_{d,t}^{U,I} = a_{d,t}^{up} \cdot P_d^{line} \;\; \forall d, t \qquad (18)$$

$$0 \le a_{d,t}^{up} \le a_{d,t} \;\; \forall d, t \qquad (19)$$

$$R_{d,t}^{D,I} = a_{d,t}^{down} \cdot P_d^{line} \;\; \forall d, t \qquad (20)$$

$$0 \le a_{d,t}^{down} \le a_d^{max} - a_{d,t} \;\; \forall d, t \qquad (21)$$

A more complete modeling of the industrial consumer that

covers several types of dispatchable industrial processes may be found in [22].

4) Power Balance: Equation (22) enforces the day-ahead market power balance. Any other market scheme can be naturally modelled within the proposed formulation.

$$\sum_i P_{i,t}^S + \sum_w P_{w,t}^{WP,S} = \sum_j L_{j,t}^S + \sum_d D_{d,t}^S \;\; \forall t \qquad (22)$$

5) Other Constraints: Apart from the constraints presented, a series of operational constraints pertaining to the conventional generating units are enforced in this study: generator minimum up and down times, unit commitment logic constraints, generator ramp-up and ramp-down limits and reserve scheduling constraints that consider the maximum and minimum power output of a generator as well as the ramping requirements for the provision of reserves. These constraints may be found in [22], while in [23] these constraints are generalized in order to utilize different time scales.

C. Second Stage Constraints

The second stage of the problem represents the operation of the power system given the occurrence of a specific scenario and involves variables and constraints dependent on each scenario (wait-and-see decisions).

1) Wind Spillage: A portion of available wind production may be spilled if it is necessary to facilitate the operation of the power system. This is enforced by (23).

$$0 \le S_{w,t,s} \le P_{w,t,s}^{WP} \;\; \forall w, t, s \qquad (23)$$

2) Demand Side Constraints: Energy requirement constraints are enforced for demand side resources. The actual energy consumed at each specific scenario for the load aggregations should be greater than the total nominal demand reduced by the load recovery rate. It is possible that a portion of the energy that should be supplied to the loads of an aggregation is not reimbursed as expressed by (24), and, thus, it is involuntarily curtailed at a high cost. Also, constraint (17) related to the energy demand of the industrial consumer is enforced for every scenario through (25).

$$\sum_t L_{j,t,s}^C \ge \gamma_j \cdot ER_j - ENS_{j,s} \;\; \forall j \qquad (24)$$

$$\sum_t D_{d,t,s}^C = \sum_t D_{d,t}^S \;\; \forall d. s \qquad (25)$$

3) Other Constraints: Additionally, in the second stage of the problem, operational constraints of the conventional units are enforced for each scenario, while the day-ahead market power balance constraint is substituted by network constraints using a DC power flow approximation as in [24].

D. Linking Constraints

This set of constraints couples the day-ahead scheduling and the operation of the power system in any given wind power generation scenario occurrence. It enforces the fact that reserves in the actual operation of the power system are no

longer a stand-by capacity, but they are materialized as energy instead.

The decomposition of generator power outputs is determined by (26).

$$P_{i,t,s}^G = P_{i,t}^S + r_{i,t,s}^{U,G} + r_{i,t,s}^{NS,G} - r_{i,t,s}^{D,G} \ \forall i,t,s \qquad (26)$$

Other necessary constraints to link the first and second stage decisions for the generation may be found in [22].

The decomposition of the aggregated demand consumption, as well as the relevant reserve determination is enforced by (27)-(29).

$$L_{j,t,}^C = L_{j,t}^S - r_{j,t,s}^{U,L} + r_{j,t,s}^{D,L} \ \forall j,t,s \qquad (27)$$

$$0 \le r_{j,t,s}^{U,L} \le R_{j,t}^{U,L} \ \forall j,t,s \qquad (28)$$

$$0 \le r_{j,t,s}^{D,L} \le R_{j,t}^{D,L} \ \forall j,t,s \qquad (29)$$

In a similar fashion, constraints (30)-(36) hold for the industrial consumer.

$$D_{d,t,s}^C = D_{d,t}^S + r_{d,t,s}^{D,I} - r_{d,t,s}^{U,I} \ \forall d,t,s \qquad (30)$$

$$0 \le r_{d,t,s}^{U,I} \le R_{d,t}^{U,I} \ \forall d,t,s \qquad (31)$$

$$r_{d,t,s}^{U,I} = a_{d,t,s}^{up,2} \cdot P_d^{line} \ \forall d,t,s \qquad (32)$$

$$0 \le a_{d,t,s}^{up,2} \le a_{d,t}^{up} \ \forall d,t,s \qquad (33)$$

$$0 \le r_{d,t,s}^{D,I} \le R_{d,t}^{D,I} \ \forall d,t,s \qquad (34)$$

$$r_{d,t,s}^{D,I} = a_{d,t,s}^{down,2} \cdot P_d^{line} \ \forall d,t,s \qquad (35)$$

$$0 \le a_{d,t,s}^{down,2} \le a_{d,t}^{down} \ \forall d,t,s \qquad (36)$$

Apart from the aforementioned linking constraints, additional constraints must be enforced for generating units that are not capable of providing non-spinning reserves or for must-run units.

III. TESTS AND RESULTS

A. System Description

The proposed methodology is tested on the insular power system of Crete for a typical day with a peak-load equal to 626.2 MW (Fig. 2). The HV system of the island consists of 19 buses and 24 branches [25]. 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 installed capacity 186 MW. Technical and economic data of the generation system are illustrated in Table I [26]. Generator reserve prices are considered equal to 25% of the most expensive block of the marginal energy cost function
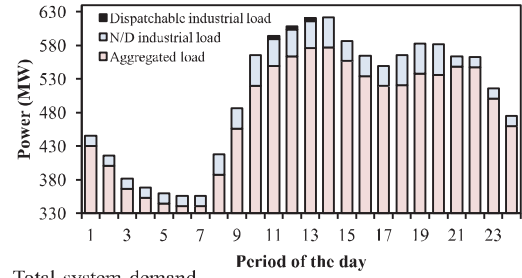

Fig. 2. Total system demand.

TABLE I
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
Total	-	25	747	-
Wind	-	31	186	-

assigned to each generator, similar to [24]. It is noted that only spinning up and down load-following reserves are assumed to be scheduled by the ISO. 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 ISO to make corrective actions in the unit commitment process in real time. Demand side participation is still at an initial stage across Greece and, as a result, the input data used for the demand side are conceptual. It is assumed that demand side services are incentivized by the regulatory authorities (e.g. through discount rates in energy bills) and, thus, not priced during scheduling. Involuntary load shedding is allowed as a last resort at a very high cost (€1000/MWh). Note that a day-ahead market does not exist in Crete, but a cost-based scheduling is performed instead. The proposed methodology is naturally consistent with such policies.

B. Scenario Generation

The scenario generation technique is based on forecasting using time series models [27] utilizing the ECOTOOL MATLAB toolbox [28]. Historical data regarding the total production of the wind farms located in the island of Crete are collected from the database of the SiNGULAR project [29] for the years 2011 and 2012. The wind farms have an installed capacity of 186 MW. Scenarios are created for the randomly selected day 4/9/2012. The generic form of the ARIMA model is represented by (37).

$$\psi_t = c + \frac{1}{(1-B)^{d_0}(1-B^{s_1})^{d_1} \ldots (1-B^{s_k})^{d_k}} \\ \frac{\theta_{q_0}(B)}{\phi_{p_0}(B)} \frac{\theta_{q_1}(B^{s_1})}{\phi_{p_1}(B^{s_1})} \ldots \frac{\theta_{q_k}(B^{s_k})}{\phi_{p_k}(B^{s_k})} \epsilon_t \qquad (37)$$

where ψ_t stands for the observed time series; ϵ_t is the residual term; $s_j, (j = 0,1,\ldots,k)$ are a set of seasonal periods, with $s_0 = 1$; $(1-B^{s_j})^{d_j}, (j = 0,1,\ldots,k)$ are the

$k+1$ differencing operators necessary to reduce the time series to mean stationarity; $\theta_{q_j}(B^{s_j})$ and $\phi_{q_j}(B^{s_j})$, $(j = 0, 1, \ldots, k)$ are invertible and stationary polynomials in the backshift operator $B : B^l = y_{t-l}$ of the type $\theta_{q_j}(B^{s_j}) = (1 + \theta_1 B^{s_j} + \theta_2 B^{2s_j} + \ldots + \theta_{q_j} B^{q_j s_j})$; c is a constant.

Prior to forecasting, the historical time series is transformed using logarithmic transformation in order to stabilize the variance across time. To generate wind power generation scenarios, several ARIMA models are fit to the observed time series. The rationale followed is that forecasting is performed for the 24 h of a specific day by considering different ranges of historical data. More specifically, starting from a forecast using the historical data of the first past week, a day is added to the time series and the forecasting is repeated, while a new ARIMA model is fit when adding a whole new week to the data range. For example, a particular ARIMA model is estimated both when performing a forecast based on the 7 previous days and the 14 previous days; however, the forecasts that are also considering the 8 to 13 previous days are performed using the ARIMA model that was fit for the 7-day forecast. For example, the particular ARIMA fit to the historical time series spanning from 28/8/2012-3/9/2012 is presented in (38).

$$\log \psi_t = c + \frac{1}{(1-B)(1-B^{24})}$$
$$\frac{(1-\theta_1 B^1 - \theta_2 B^2 - \theta_3 B^3 - \theta_4 B^4 - \theta_5 B^5 - \theta_9 B^9 \ldots}{(1-\phi_1 B^1 - \phi_2 B^2 - \phi_3 B^3 - \phi_4 B^4 - \phi_5 B^5 \ldots}$$
$$\frac{\ldots - \theta_{13} B^{13} - \theta_{14} B^{14})}{\ldots - \phi_6 B^6)}$$
$$\frac{(1-\theta_{17} B^{17} - \theta_{18} B^{18} - \theta_{24} B^{24} - \theta_{31} B^{31} - \theta_{48} B^{48})}{(1-\phi_{12} B^{12} - \phi_{13} B^{13} - \phi_{14} B^{14} - \phi_{17} B^{17})}$$
$$\frac{1}{(1-\phi_{24} B^{24})} \epsilon_t$$

$$(38)$$

Following this procedure and by progressively considering historical data spanning from 20/6/2012 to 3/9/2012 an initial pool of 70 equiprobable scenarios is constructed . The components of each model are selected based on the inspection of the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The residuals ϵ_t of each particular ARIMA model should follow a Gaussian distribution with zero mean and constant variance (white noise). A variant of the scenario generation technique employed in this paper was also used in [30]. It is to be noted that the requirement ϵ_t to be white noise is imposed by the fact that otherwise, characteristics of the time series would not be captured by the ARIMA model, and is not related to the addition of white noise on forecasts in order to produce scenarios such as in [26] or [31]

The computational performance of the stochastic programming models strongly depends on the size of the scenario set. In this respect, a scenario reduction technique based on the k-means clustering algorithm [32] is applied in order to reduce the number of scenarios by substituting the initial scenario set by an approximate representative set of 30 non-equiprobable scenarios with the characteristics presented in Fig. 3. It is also to be noted that the use of other scenario generation
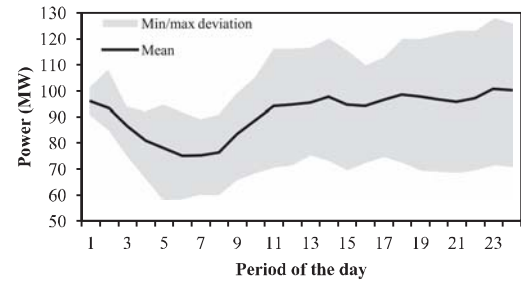

Fig. 3. Characteristics of wind power generation scenarios.

and reduction techniques, despite the numerical differences, does not affect the structure of the optimization problem and therefore, the observations presented in Section III-C should be general.

C. Simulation Results and Discussion

1) Case study: In order to evaluate the performance of the proposed model, several simulations are conducted. It is to be noted that the wind spillage cost is set to a sufficiently high value (€1000/MWh) in order to avoid wind power curtailment. In this way the case study reveals the benefits of deploying demand side resources under the requirement of fully accommodating the available wind power production. The confidence level in all the test cases is considered 90%.

In the first test case, different amounts of aggregated load flexibility are considered for varying levels of risk aversion (i.e. different values of β). It is considered that at least 90% load recovery is demanded by the loads. The load is allowed to deviate from its nominal hourly demand by 0%, 1%, 2%, and 5%, and 10%. In this manner, an approximation of the efficient frontier related to the total expected cost and the CVaR is obtained and the relevant results regarding the characteristics of the cost distribution are presented in Table II. The following are noticed:

1) Without enforcing a risk-averse behavior (i.e., when $\beta = 0$), it may be noticed that both the total expected cost and the respective standard deviation, as well as the range between the most expensive scenario and the scenario with the lowest cost, decrease as the load flexibility increases. This evidence suggests that the aggregated load is not only a means of reducing the total expected cost but also inherently reduces risk (both by reducing the value of CVaR and standard deviation).

2) For the same level of risk aversion (i.e., the value of β) the total expected cost, the standard deviation, the range of the cost and the value of CVaR decrease as the amount of load flexibility increases.

In Fig. 4 the cumulative distribution function (CDF) of the cost in individual scenarios for different levels of aggregated load flexibility and a risk aversion level expressed by $\beta = 10$ is displayed. It may be noticed that as the flexibility of the aggregated load increases, the CDF shifts to the left while the cost of the individual scenarios compacts around the total expected cost, implying a reduction in the cost of all individual

TABLE II
CHARACTERISTICS OF THE COST DISTRIBUTION FOR DIFFERENT
AMOUNTS OF AGGREGATED LOAD FLEXIBILITY

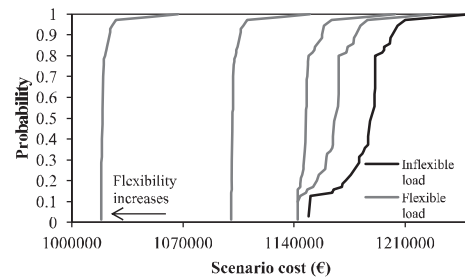|	β	CVAR (€)	Expected cost (€)	Standard deviation (€)	Range (€)
Flexibility 0%	0	1252524	1183572	22995	108593
	0.05	1218883	1183572	22953	108451
	1	1218148	1183937	22122	105753
	2	1217743	1184533	21629	104082
	5	1217367	1185482	21042	101803
	10	1217360	1185517	21012	101704
Flexibility 1%	0	1229213	1162879	20448	93387
	0.05	1195747	1162881	20370	93079
	1	1194555	1163443	19054	88441
	2	1194022	1164209	18388	86255
	5	1193607	1165186	17891	84471
	10	1193595	1165270	17848	84283
Flexibility 2%	0	1209136	1145096	18406	81391
	0.05	1175547	1145095	18178	80324
	1	1172565	1146559	15120	68548
	2	1171363	1148317	13791	63667
	5	1170781	1149690	13118	61229
	10	1170781	1149691	13118	61229
Flexibility 5%	0	1157720	1094839	17959	79184
	0.05	1124794	1094848	17800	78461
	1	1121055	1096828	14143	63692
	2	1118908	1099988	12009	55124
	5	1118190	1101624	11197	52182
	10	1117891	1103296	10466	49379
Flexibility 10%	0	1075002	1012627	17832	78596
	0.05	1042222	1012634	17612	77560
	1	1038570	1014582	14008	63048
	2	1036377	1017831	11779	54114
	5	1035550	1019715	10820	50673
	10	1035303	1021109	10216	48356

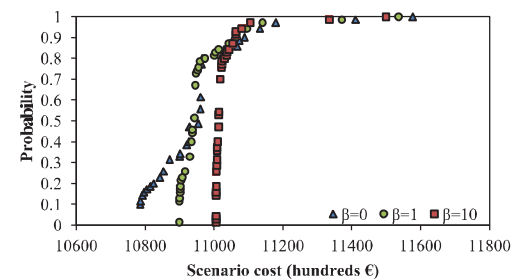Fig. 4. CDF of cost in different scenarios for different levels of aggregated load flexibility and $\beta = 10$.

Fig. 5. CDF of cost in different scenarios for 5% aggregated load flexibility and $\beta = 0, 1, 10$.

scenarios. More specifically, a reduction of 53% in the range of the costs is noticed for $\beta = 10$ with respect to $\beta = 0$).

The CDF of cost in individual scenarios for a given level of flexibility of the aggregated load (5%) and for different levels of risk aversion is depicted in Fig. 5. As regards the impact of different values of β on the distribution of scenario costs two observations may be made: 1) the cost of the most expensive scenario is reduced with the increase in the level of risk-aversion and, 2) the spread of the individual costs is mitigated. Since the only source of uncertainty considered in this study is wind power production, the key to understanding the behavior of the model under different risk aversion levels lies in the economic impacts of wind power generation in the given model. Due to the fact that wind producers are not considered competitive agents, the injection of free energy into the system leads to a reduced energy cost in day-ahead scheduling. However, the volatility of wind power generation enforces the scheduling of a sufficient amount of reserves. If reserves are only scheduled by the generation side, there is an impact both on the energy cost (by altering the generator set points) and the scheduled reserves cost.

In Fig. 6 the scheduled reserve cost for different levels of risk aversion and aggregated load flexibility is portrayed. It is evident that as the value of β increases, the cost of the scheduled reserves decreases for all cases. Furthermore, the presence of flexible demand side resources alleviates the need for scheduling load following reserves on the generation side

and, therefore, a significant cost reduction is noticed as the amount of available flexibility increases.

In the second test case the dispatchable portion of the industrial load (a total of 15 MWh) is considered and is rendered available to be managed by the ISO into 30 discrete energy blocks of 0.5 MWh, each for different levels of risk aversion (i.e., different values of β). The efficient frontiers for both cases, inflexible load and the investigated case, are depicted in Fig. 7, respectively. Note that the effect of the dispatchable industrial load as an energy and reserve service provider is similar to the case of the flexible aggregated load. For the same level of risk aversion, both the total expected cost and the corresponding value of CVaR are reduced in comparison with the case of an inflexible load (the Pareto frontier shifts downwards and to the left). The findings are justified in the same fashion as described for the case of flexible aggregated load.

2) Value of demand response (DR): The economic compensation of DR participation in the energy market is an issue that needs to be addressed and is linked to a controversial discussion [33]. One argument is that DR providers should be compensated on a non-discriminatory basis at the full market price, such as in ISO New England and New York ISO. On the other hand, the decision not to purchase energy is not equivalent to supplying energy. The loads that participate in wholesale markets would receive dual benefits, being paid at the market price for their service and achieving retail bill savings because of their reduced consumption. In order to promote a more efficient DR compensation from the point of view of the ISO, in MISO and PJM the participation of demand side resources is compensated at the full market price minus the retail rate [34]. Nevertheless, DR providers
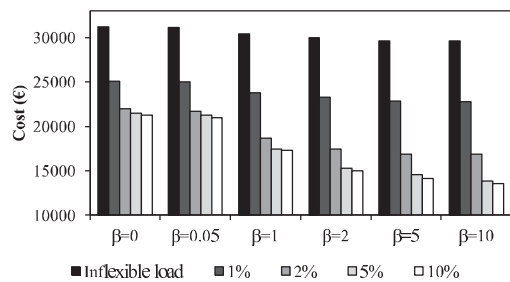
Fig. 6. Behavior of the scheduled reserve cost for different levels of risk aversion and aggregated load flexibility.

argue that DR creates positive externalities such as economic and environmental benefits and thus, they should be granted payments higher than the market prices. In this study, the reserve services that are procured from the demand side are not priced within the described market framework in compliance with the current operational practice in the insular power system of Crete that does not explicitly consider the contribution of demand side resources. This assumption is valid considering existing programs that provide alternative incentives in order to engage consumers. For instance, in Australia the "PeakSmart AC" program allocates fixed rewards depending on the cooling capacity of the air conditioners of the end-users and air conditioner units replacement for residential consumers and businesses [35].

In order to establish pricing schemes for the participation of the demand side resources in the future, the economic benefits (e.g., reduction in reserve cost and expected cost) and the potential externalities (e.g., risk mitigation) should be evaluated. To provide insight into the benefits of the demand side participation in the presented case studies, let us consider the case of the aggregated load with a 2% flexibility. The changes in EC, CVaR and day-ahead wind integration with respect to the case of a purely inelastic load and per MWh of utilized load flexibility are collected in Table III. It can be noticed that value is added to the system as regards the mitigation of the expected cost and the CVaR, while the integration of wind energy is facilitated. Taking into account the added value of demand side participation, as it is revealed by this case study, the relatively high incentives that are given to DR providers in order to recover the investments required in order to be qualified as system resources (e.g., 200-400 $/kWh in the Automated DR program of Pacific Gas&Electric Company [36]) may be justified.

3) Computational statistics: The proposed model has been implemented in GAMS software and the MILP optimization problem described in Section II has been directly solved using CPLEX 12. All tests are performed using a workstation employing two 12-core processors at 3.10 GHz and 192 GB of RAM, running a 64-bit version of MS Windows. The computational time varies among the different test cases presented. The average CPU time is approximately 2.5 minutes and does not exceed 4 minutes per single run in the computationally worst case (when dispatchable industrial load is considered) which has 482073 equations, 1542824 continuous

variables and 229687 discrete variables. Although the size of the problem is relatively large, the use of a typical multi-core processor system resulted in acceptably low solution times in all the examined cases. Taking into account that simulations were performed on a real power system, it may be argued that for power systems of a similar scale there is not an evident need for decomposition techniques to be applied.

The two-stage stochastic programming model structure was based on a node-variable formulation which implies that decision variables are associated with each stage of the problem. This is a compact formulation which is suitable for the direct solution of the problem. However, increasing the number of the considered scenarios may significantly increase the size of the problem at hand. In such a case, the proposed model may be reformulated relying on a scenario-variable approach. Although more variables and constraints would be needed to derive an equivalent problem formulation, a structure that might be exploited using decomposition techniques emerges. By relaxing the non-anticipativity constraints the optimization problem may be treated as a problem with complicating constraints which can be solved decomposed per scenario [37] using, for example, the Augmented Lagrangian Relaxation method [38].

IV. CONCLUSION

In this study a two-stage stochastic programming based day-ahead joint energy and reserve scheduling model under the presence of significant wind power generation penetration was presented. The risk-averse behavior of the ISO was modeled through the consideration of the CVaR metric. The formulation considered the generation side, as well as two types of demand side resources, that were able to provide load following reserves: aggregated loads which can alter their consumption in a continuous fashion and industrial consumers that can schedule a portion of their demand in order to alleviate system stress and provide reserves in a discrete manner. Simulations performed for the case of the insular power system of Crete, Greece allowed drawing useful insights into the integration of demand side resources.

The most important observations may be summarized as follows:

- due to its technical and economic characteristics, demand side participation in reserve provision, either in the form of large industrial consumers or of load aggregations, has the inherent capability of inducing a reduction in risk, even in the case in which the ISO is risk-neutral;
- the ISO has to make a decision as regards the joint energy and reserve market clearing from a more favorable efficient frontier as the amount of available flexibilty increases;
- it is revealed that the mechanism through which the ISO can manage the risk is mainly affected by the trade-off of integrating wind energy in the day-ahead market (energy cost) versus the amount of reserves that need to be scheduled (reserve cost);
- The relatively high incentives that are provided for load participation by different ISO may be justifiable, since
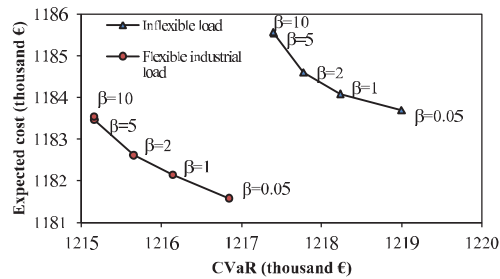
Fig. 7. Comparison of efficient frontiers for the cases in which the total system load is inflexible and for the case of a dispatchable industrial load.

TABLE III
CHANGES IN EC, CVAR AND WIND INTEGRATION FOR AGGREGATED
LOAD FLEXIBILITY 2% PER MWH OF LOAD USED

β	0	0.05	1	2	5	10
Change in EC (€/MWh)	167.7	167.7	162.9	157.8	156	156.1
Change in CVaR (€/MWh)	189.1	188.9	198.7	202.1	203	203
Day-ahead wind integration (MWh/MWh)	0.96	0.94	0.87	0.76	0.66	0.65

the participation of demand side resources, apart from contributing to cost reduction, under all circumstances created positive externalities such as reducing the risk embedded in the decisions of the ISO and increasing the wind power generation penetration in the day-ahead market.

The presented simulations have indicated that the cost savings and the risk mitigation capability of the demand side resources participation may be affected by the load recovery effect. Further investigation of the effect of the load recovery requirements of the flexible loads will be the subject of future studies to be conducted by the authors.

REFERENCES

[1] J. P. S. Catalão (ed.), Smart and sustainable power systems: operations, planning, and economics of insular electricity grids. Boca Raton: CRC Press, 2015.

[2] J. Schallenberg-Rodríguez, "Photovoltaic techno-economical potential on roofs in regions and islands: the case of the Canary Islands. Method-ological review and methodology proposal," Renewable and Sustainable Energy Reviews, vol. 20, pp. 219 – 239, 2013.

[3] P. A. Fokaides and A. Kylili, "Towards grid parity in insular energy systems: the case of photovoltaics (PV) in Cyprus," Energy Policy, vol. 65, pp. 223 – 228, 2014.

[4] A. A. Sánchez de la Nieta, J. Contreras, J. I. Muñoz, and M. O'Malley, "Modeling the impact of a wind power producer as a price-maker," IEEE Transactions on Power Systems, vol. 29, no. 6, pp. 2723–2732, 2014.

[5] B. Kirby and M. Milligan, "Capacity requirements to support inter-balancing area wind delivery," National Renewable Energy Laboratory, Golden, CO, Tech. Rep., 2009.

[6] A. A. Sánchez de la Nieta, J. Contreras, and J. I. Muñoz, "Optimal Coordinated Wind-Hydro Bidding Strategies in Day-Ahead Markets," IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 798–809, 2013.

[7] A. A. Sánchez de la Nieta, J. Contreras, J. I. Muñoz, and J. P. S. Catalão, "Optimal wind reversible hydro offering strategies for midterm planning," IEEE Transactions on Sustainable Energy, no. 99, pp. 1–11, 2015.

[8] A. A. Sánchez de la Nieta, J. Contreras, and J. P. S. Catalão, "Impact of the future water value on wind-reversible hydro offering strategies in electricity markets," Energy Conversion and Management, vol. 105, pp. 313–327, 2015.

[9] I. Stadler, "Power grid balancing of energy systems with high renewable energy penetration by demand response," Utilities Policy, vol. 16, no. 2, pp. 90 – 98, 2008.

[10] B. J. Kirby, "Load response fundamentally matches power system reliability requirements," in IEEE Power Engineering Society General Meeting, June 2007, pp. 1–6.

[11] P. Hanser, K. Madjarov, W. Katzenstein, and J. Chang, "Chapter 10 - riding the wave: using demand response for integrating intermittent resources," in Smart Grid, F. P. Sioshansi, Ed. Boston: Academic Press, 2012, pp. 235 – 256.

[12] M. Milligan and B. Kirby. Utilizing load response for wind and solar integration and power system reliability. [Online]. Available: http://www.nrel.gov/docs/fy10osti/48247.pdf

[13] Q. Zheng, J. Wang, and A. Liu, "Stochastic optimization for unit commitment -A review," IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 1913–1924, July 2015.

[14] Y. Zhang and G. B. Giannakis, "Robust optimal power flow with wind integration using conditional value-at-risk," IEEE International Conference on Smart Grid Communications (SmartGridComm, pp. 654–659, 2013.

[15] H. Chen, Y. Kong, G. Li, and L. Bai, "Conditional value-at-risk-based optimal spinning reserve for wind integrated power system," International Transactions on Electrical Energy Systems, vol. 26, no. 8, pp. 1799–1809, 2016.

[16] S. Moazeni, W. B. Powell, and A. H. Hajimiragha, "Mean-conditional value-at-risk optimal energy storage operation in the presence of trans-action costs," IEEE Transactions on Power Systems, vol. 30, no. 3, pp. 1222–1232, May 2015.

[17] J. Aghaei, M. Barani, M. Shafie-khah, A. A. Sánchez de la Nieta, and J. P. S. Catalão, "Risk-constrained offering strategy for aggregated hybrid power plant including wind power producer and demand response provider," IEEE Transactions on Sustainable Energy, vol. 7, no. 2, pp. 513–525, April 2016.

[18] E. G. Kardakos, C. K. Simoglou, and A. G. Bakirtzis, "Optimal offering strategy of a virtual power plant: A stochastic bi-level approach," IEEE Transactions on Smart Grid, vol. 7, no. 2, pp. 794–806, March 2016.

[19] F. Neise, Risk management in stochastic integer programming. With ap-plication to dispersed power generation. Heidelberg: Vieweg+Teubner, 2008.

[20] A. J. Conejo, M. Carrion, and J. M. Morales, Decision making under uncertainty in electricity markets. New York: Springer, 2010.

[21] R. Rockafellar and S. Uryasev, "Conditional value-at-risk for general loss distributions," Journal of Banking & Finance, vol. 26, no. 7, pp. 1443 – 1471, 2002.

[22] N. G. Paterakis, O. Erdinç, A. G. Bakirtzis, and J. P. S. Catalão, "Load-following reserves procurement considering flexible demand-side resources under high wind power penetration," IEEE Transactions on Power Systems, vol. 30, no. 3, pp. 1337–1350, May 2015.

[23] N. G. Paterakis, O. Erdinç, A. G. Bakirtzis, and J. P. S. Catalão, "Qualification and quantification of reserves in power systems under high wind generation penetration considering demand response," IEEE Transactions on Sustainable Energy, vol. 6, no. 1, pp. 88–103, 2015.

[24] J. M. Morales, A. J. Conejo, and J. Perez-Ruiz, "Economic valuation of reserves in power systems with high penetration of wind power," IEEE Transactions on Power Systems, vol. 24, no. 2, pp. 900–910, May 2009.

[25] E. S. Karapidakis, Y. A. Katsigiannis, P. S. Georgilakis, and E. Thalassi-nakis, "Generation expansion planning of Crete power system for high penetration of renewable energy sources," Materials Science Forum, vol. 670, pp. 407–414, December 2010.

[26] C. K. Simoglou, E. G. Kardakos, E. A. Bakirtzis, D. I. Chatzigiannis, S. I. Vagropoulos, A. V. Ntomaris, P. N. Biskas, A. Gigantidou, E. J. Thalassinakis, A. G. Bakirtzis, and J. P. S. Catalão, "An advanced model for the efficient and reliable short-term operation of insular electricity networks with high renewable energy sources penetration," Renewable and Sustainable Energy Reviews, vol. 38, pp. 415 – 427, 2014.

[27] G. E. Box, G. M. Jenkins, and G. C. Reinsel, Time Series Analysis: forecasting and control. John Wiley & Sons, 2013.

[28] D. J. Pedregal, J. Contreras, and A. A. Sánchez de la Nieta, "ECOTOOL: a general MATLAB forecasting toolbox with applications to electricity markets," in Handbook of Networks in Power Systems I. Springer, 2012.

[29] SiNGULAR EU FP7 Project. [Online]. Available: http://www.singular-fp7.eu/

[30] V. Guerrero-Mestre, A. A. Sánchez de la Nieta, J. Contreras, and J. P. S. Catalão, "Optimal bidding of a group of wind farms in day-ahead markets through an external agent," IEEE Transactions on Power Systems, vol. 31, no. 4, pp. 2688–2700, July 2016.

[31] S. I. Vagropoulos, E. G. Kardakos, C. K. Simoglou, A. G. Bakirtzis, and J. P. S. Catalão, "Ann-based scenario generation methodology for stochastic variables of electric power systems," *Electric Power Systems Research*, vol. 134, pp. 9 – 18, 2016.

[32] P. Beraldi and M. E. Bruni, "A clustering approach for scenario tree reduction: an application to a stochastic programming portfolio optimization problem," *TOP*, vol. 22, no. 3, pp. 934–949, 2014.

[33] E. Cutter, C. Woo, F. Kahrl, and A. Taylor, "Maximizing the value of responsive load," *The Electricity Journal*, vol. 25, no. 7, pp. 6 – 16, 2012.

[34] S. Newell and A. Hajos, "Demand response in the Midwest ISO: an evaluation of wholesale market design," The Brattle Group, Tech. Rep., 2010.

[35] Energex Company - Positive Feedback for Households and Business. [Online]. Available: https://www.energex.com.au/residential-and-business/positive-payback

[36] Pacific Gas&Electric company (PG&E) - demand response. [Online]. Available: http://www.pge.com/en/mybusiness/save/energymanagement/index.page

[37] A. Papavasiliou, S. S. Oren, and R. P. O'Neill, "Reserve requirements for wind power integration: A scenario-based stochastic programming framework," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2197–2206, Nov 2011.

[38] C. Beltran and F. J. Heredia, "Unit commitment by augmented lagrangian relaxation: Testing two decomposition approaches," *Journal of Optimization Theory and Applications*, vol. 112, no. 2, pp. 295–314, 2002.

Javier Contreras (SM'05- F'15) received the B.S. degree in electrical engineering from the University of Zaragoza, Zaragoza, Spain, in 1989, the M.Sc. degree from the University of Southern California, Los Angeles, in 1992, and the Ph.D. degree from the University of California, Berkeley, in 1997.

He is currently Full Professor at the University of Castilla-La Mancha, Ciudad Real, Spain. His research interests include power systems planning, operations and economics, and electricity markets.

Nikolaos G. Paterakis (S'14-M'15) received the Dipl. Eng. degree from the Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece in 2013 and the Ph.D. degree from the University of Beira Interior, Covilhã, Portugal in 2015, working under the EU FP7 funded Project "SiNGULAR". Since October 2015 he has been a Post-doctoral fellow with the Department of Electrical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands.

His research interests include power systems operation and planning, renewable energy integration, ancillary services, demand response and smart grid applications.

Agustín A. Sánchez de la Nieta (M'15) received the B.S. and Ph.D. degrees in industrial engineering from the University of Castilla-La Mancha, Ciudad Real, Spain, in 2008 and 2013, respectively.

He is currently a Post-doctoral fellow in UBI and INESC-ID and Researcher in European project "SiNGULAR", FP7, in University of Beira Interior, Portugal. His research interests include power systems planning and economics, electricity markets, forecasting, and risk management for renewable energy sources.

Anastasios G. Bakirtzis (S'77-M'79-SM'95-F'15) received the Dipl. Eng. Degree from the Department of Electrical Engineering, National Technical University, Athens, Greece, in 1979 and the M.S.E.E. and Ph.D. degrees from Georgia Institute of Technology, Atlanta, in 1981 and 1984, respectively. Since 1986 he has been with the Electrical Engineering Department, Aristotle University of Thessaloniki, Greece, where he is currently Professor. His research interests are in power system operation, planning and economics.

João P. S. Catalão (M'04-SM'12) received the M.Sc. degree from the Instituto Superior Técnico (IST), Lisbon, Portugal, in 2003, and the Ph.D. degree and Habilitation for Full Professor ("Agregacão") from the University of Beira Interior (UBI), Covilhã, Portugal, in 2007 and 2013, respectively. Currently, he is a Professor at the Faculty of Engineering of the University of Porto (FEUP), Porto, Portugal, and Researcher at INESC-ID - Lisbon, and C-MAST/UBI. He was the Primary Coordinator of the EU-funded FP7 project SiNGULAR ("Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration"), a 5.2 million euro project involving 11 industry partners. He has authored or coauthored more than 400 publications, including, among others, 130 journal papers, 250 conference proceedings papers and 20 book chapters, with an h-index of 25 (according to Google Scholar), having supervised more than 35 post-docs, Ph.D. and M.Sc. students. He is the Editor of the books entitled Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling (Boca Raton, FL, USA: CRC Press, 2012) and Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids (Boca Raton, FL, USA: CRC Press, 2015). His research interests include power system operations and planning, hydro and thermal scheduling, wind and price forecasting, distributed renewable generation, demand response and smart grids. Prof. CatalÃčo is an Editor of the IEEE TRANSACTIONS ON SMART GRID, an Editor of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, and an Associate Editor of the IET Renewable Power Generation. He was the Guest Editor-in-Chief for the Special Section on "Real-Time Demand Response" of the IEEE TRANSACTIONS ON SMART GRID, published in December 2012, and the Guest Editor-in-Chief for the Special Section on "Reserve and Flexibility for Handling Variability and Uncertainty of Renewable Generation" of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, to be published in April 2016. He was the recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities and the 2012 Scientific Award UTL/Santander Totta. Also, he has won 4 Best Paper Awards at IEEE Conferences.