Stochastic Modelling of Renewable Energy Sources from Operators' Point-of-View: A Survey

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Abstract

High penetration of renewable energy sources, especially weather-dependent sources, has increased the power systems uncertainties. For any analysis in power systems such as planning and operation, it is essential to confront the stochastic nature of these sources in order to get much more precise results. Since operators need proper strategies and methods to decline negative effects of the stochastic behavior of renewable power generators, such as total operation cost growth, this paper provides a review of different state-of-the-art approaches from the operator's viewpoint for handling the stochastic behavior of renewable sources. Hence, in this paper, three different strategies are categorized for stochastic analysis of these sources. The first strategy is mathematical modelling including stochastic dependency and independency, multi-dimensional dependence, forecast and scenarios. Afterwards, demand side management, which is one of the other approaches for dealing with these uncertainties, is investigated and different demand response programs and some methods to model them are presented. Finally, the effect of different electricity market schemes and relevant optimization methods to mitigate the variations of renewable energy sources are discussed. The study demonstrates that an operator should choose one or a combination of these three approaches based on its requirements.

Keywords: renewable energy sources; stochastic modelling; operator; demand side management.

1. Introduction

Renewable energy sources are being highly merged into the power systems. They can be found everywhere in different sizes either as a centralized huge power plant or as a distributed generation near the end-users [1]. Moreover, it is possible to apply several renewable sources as a hybrid system to meet the load requirements of a region [2]. In this case, combining these sources like wind and solar with backup units provides more reliable, environment-friendly and economic load supply in comparison with a single source. There are stand-alone renewable sources which can be operated alone without the need of global network [3],[4]; however, stand-alone renewable sources are beyond the scope of this literature. The main target of this literature is an investigation of different aspects of emerging renewable energy sources in power systems.

Many kinds of literature have studied the impact of renewable sources penetration on voltage [5], frequency [6,7], power quality [8], environment [8], power systems dynamic and stability [8,9] and power losses [10]. Before analyzing renewable energy sources in power systems especially weather-dependent sources like wind and solar, their stochastic nature should be considered in order to increase the accuracy of the results. The uncertainty of weather-dependent renewable sources has studied in some literature by different stochastic methods including possibility and probability approaches. Some literature used possibility approach which is divided into two categories including quantitative and qualitative methods [11].

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The quantitative is used for epistemic uncertainty like fuzzy power flow analysis [12,13], and the latter is for choosing the proper type of weather-dependent source for designers in planning stage [14]. In this survey, stochastic analysis of renewable energy resources in power systems operation is investigated through probability approach which includes Monte-Carlo simulation (MCS). Meanwhile, these uncertainties can be managed by some flexibilities like supply-side flexibility, e.g., capacity limits, ramping limits, minimum up/ down limits, energy storage availability, and transmission limit enhancement [15].

Moreover, Ref. [15] demonstrates the demand side flexibility for managing the sources uncertainties. In fact, renewable sources can be facilitated by demand response (DR) programs. Furthermore, impacts of stochastic nature of renewable energy sources on electricity market can be investigated for markets like day-ahead or balancing market because the market participants should make a decision in advance [15]. In fact, operators, due to their position, responsibility and duty, have to take proper measurements to address negative impacts of renewable sources uncertainties on the operation scheduling like total operation cost growth and deviations from scheduling. To this end, they have many options so that one or a combination of some of them should be selected based on their requirements and capabilities. In this paper, the most common, useful and modern strategies for operators are introduced and investigated through a comprehensive study among relative articles. Some literatures like [16] studied uncertainty modelling techniques in power systems and its classification is for general usages in power systems. We study stochastic modelling techniques from weather-dependent renewable sources in different kinds of literatures which include stochastic dependency and independency, multi-dimensional dependence, forecast, and scenarios. Afterwards, demand side management, which is one of the other approaches to deal with these uncertainties, is investigated and different demand response programs and some methods to model them are presented. Moreover, different methods of stochastic optimization in different market frameworks for dealing with uncertainties raised from stochastic renewable sources are discussed through relevant literature. This is a new classification of stochastic analysis of renewable resource among other review papers.

The article is structured in four Sections. In Section 2, methods of dealing with the stochastic behaviour of stochastic generators including solar and wind are investigated. Applying demand side flexibility to confront power generation uncertainty is described in Section 3. Section 4 expresses the role of the electricity market to mitigate the effect of renewable energy sources uncertainty. Finally, in Section 5 conclusion and possible future work are presented.

2. Stochastic Analysis of Renewable Energy Sources

For obtaining enough information in terms of renewable sources output, forecasting their output are important especially for decision makers and operational problems. According to needs of operators, different methods are applied for tackling the renewable uncertainties; therefore, in this article from a deterministic forecast to a scenario-based one are studied.

In the following, various models for forecast and stochastic modelling in both dependent, independent, and the multi-dimensional state will be investigated which is demonstrated in Fig. 1.

2.1. Stochastic Independency

Forecast and scenarios are in fact extrapolation. It means that a model is built and fitted to a set of data. The correlation between different stochastic variables may not consider, and the scenario generation or forecast is conducted, independently.

2.1.1. **Point Forecasts**

In this method, the renewable sources forecasts are generated at time t for time $t + m$, which is m time after the time t and it is a single valued either in the deterministic or stochastic framework. In deterministic one, no uncertainty is realized, and in stochastic it is just a forecast in the presence of uncertainty. In other words, since only one value will be generated in the point forecast method, the stochastic model would be implemented like a deterministic model with the difference that, in contrary with a deterministic model, uncertainty is going to be addressed in the stochastic model. In [17], point forecast of wind and solar are considered in both deterministic and stochastic approaches for comparison purposes in microgrid scheduling. In fact, the deterministic approach is a special case of stochastic approach with only one scenario. First, a day-ahead simulation is run through the forecast point of the wind and solar power output, and then, in real-time, the actual amount is replaced. The point forecast error will be compensated by energy storage systems in the microgrid.

2.1.2. **Probabilistic Forecast**

In contrast to point forecast, probabilistic one aims to get full information about what is going to occur in the future. It can be divided into some subsection.

2.1.2.1. Quantile Forecast

This method is based on quantile of the distribution function. It means, at time t a random variable is generated for time $t + m$, and then, a forecast of probability density function (PDF) or related cumulative distribution function (CDF) is issued to fit the random variable. The random variables can be generated by different methods such as Markov chain Monte Carlo methods, pseudorandom generators, Metropolis-Hastings algorithm and so on. In quantile forecast, random variable in time $t + m$ determines a quantile which tells at time t there is a special probability (nominal level) that renewable energy generation will be less than its quantile at time $t + m$ [18,19].

Moreover, it is in the form of threshold level related to probability and can be used for some operational problems. In [20], authors analysed forecast error to build a model of quantiles of forecast error in wind farms. Wind power uncertainty was modelled in [21] through linear quantile regression by formulation a cubic B-splines for obtaining the quantile with a proportion of the forecast error. Authors in [22] applied quantile forecast method for both solar and wind generator forecast which is used for deterministic power system unit commitment and comparison with the different probabilistic forecast method.

2.1.2.2. Forecast Interval

Quantile forecast method does not deliver any information about forecast uncertainty level. To this end, the forecast interval is used in [23]. Forecast interval is usually proper for robust optimization. Forecast interval has a nominal coverage rate and lower and upper bounds which define, for example, the probability that a wind farm generation is higher than a specific amount. Actually, forecast interval can cover point forecasts and quantile forecast through considering different nominal coverage rates. Therefore, full forecast distribution of stochastic variable like wind power can be obtained by this method [24].

2.1.2.3. Density Forecasts

Density forecast gives the whole information about renewable sources generation for the future. The produced PDF or CDF includes a complete description of the stochastic variable.

In [25], to tackle wind power generation uncertainty, probability density forecasting provides an expected future values of uncertainties. To this end, a new type of forecast called weather ensemble forecasting is applied, which is generated from the atmospheric model and include several scenarios for the future value of a weather variable.

The distribution of these scenarios would be used as density forecast. Moreover, statistical time series techniques like daily wind speed or solar irradiance data of generalized autoregressive conditional Heteroskedasticity (GARCH) and long-memory time series model for a generation of density forecast is used [26,27].

2.1.3. Scenario Forecast

In scenario generation method, some information about characteristics of the stochastic variable like renewable power generation is given. In a simple way, each lead time, location and renewable energy type are considered, independently. Since each forecast includes some kinds of errors and these errors can be in a relation with time and increase time by time, if the forecasts errors are not strongly correlated in time, the temporal dependence structure can be disregarded.

2.1.3.1. Analytical Methods

Analytical methods are based on convolution methods like fast Fourier transform method (FFTM), Multi-linear simulation method (MLSM) and point estimate method (PEM). In [28], FFTM is used for generation of a PDF for wind speed for some investigation about available transfer capability (ATC). MLSM is used in [29] for probabilistic load flow (PLF) of distribution system with the wind and photovoltaic (PV).

PEM is employed in [30], as a deterministic routine to find the statistical moments of output random variables. The article implements PEM to model the output power of solar and wind power generators. It is important to put some simplifications in their formulation. These simplifications are linearization, independence and normality. In linearization of the system model, the problem can be solved much easier because it permits the representation of the system outputs as a linear combination of systems inputs [11].

In independent assumption, system inputs are considered statistically independent. This assumption, in a combination of linearization, helps to compute outputs by series of convolution or application of Gram-Charlier expansion method and computation of cumulants of system outputs by system inputs based on their invariance to a linear transformation. This method is widely used for PLF [31]; however, some articles considered wind generators besides probabilistic load flow.

For example, in [32], authors used a combination of cumulants and Gram-Charlier expansion to calculate (PLF) containing large-scale wind power. In normality assumption, inputs are presumed to be normally distributed. This assumption let to apply linear correlation for the dependence structure among random variables [11]. Some literature mention that analytical methods

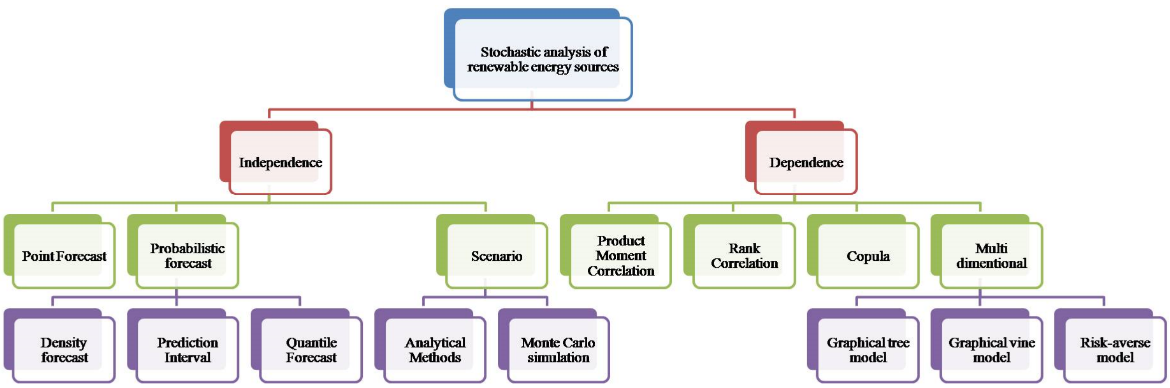

Fig. 1. Various methods of stochastic analysis of renewable energy sources.

need a fewer number of the simulation than Monte-Carlo simulation (MCS) method [33].

2.1.3.2. Monte-Carlo Simulation

MCS methods are the most accurate and straight-forward method; however, it needs remarkable computational efforts [33]. For the wind or PV generation, a PDF should be assigned for every time period. In the most articles, Weibull PDF is considered as the best function for modelling the stochastic behaviour of wind power generation [34–37]. Beta PDF is generally dedicated for the stochastic attitude of solar power generation [38,39].

With determining the proper PDF, related PDF for every time period is generated through the expected or forecasted value of the wind or solar power generation. A large number of scenarios can be generated by fitting random variables to the PDFs with equal probability. The procedure is repeated for a number of iterations.

Some methods like Latin hypercube sampling (LHS) [40], sample-splitting approach (SPA) [41] and fission and roulette(F&R) method [42], are used to decrease the computation burden of MCS. Therefore, in each scenario, there are *t* time period (based on the horizon time) random wind or PV generation based on forecasted generation [43].

2.2. Stochastic Dependence

Some simplifications like independency between random variables and considering all PDF as Normal distribution would not get the accurate results and are full of fallacies. Therefore, it is essential to consider stochastic dependence between system inputs especially from output aggregation of multiple renewable generation inputs. The difference dependence structures yield different distributions around the same central point [11].

In this sense, it is required to find a way to measure the dependence between random variables. In [11], this correlation between two stochastic power generators is considered. The most common method is the product moment correlation (PMC) or linear/Pearson correlation which for the dual case is as follows:

$$\rho(X,Y)=\frac{E(XY)-E(X)E(Y)}{\sigma(X)\sigma(X)}=\frac{E[(X-\mu(X))(Y-\mu(Y))]}{\sigma(X)\sigma(X)}=\frac{Cov(X,Y)}{\sigma(X)\sigma(X)} \tag{1}$$

where X and Y are random variables with finite expectations of $E(X)$ and $E(Y)$, and finite variance $\sigma^2(X)$ and $\sigma^2(Y)$. If there are N pairs of samples from variables, it calculates the population product moment correlation as follows:

$$\rho_{x,y}=\frac{\sum_{i=1}^{N}(x_i-\bar{X})(y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{X})^2}\sqrt{\sum_{i=1}^{N}(y_i-\bar{Y})^2}} \tag{2}$$

where:

$$\bar{X}=\frac{1}{N}\sum_{i=1}^{N}(x_i) \tag{3}$$

$$\bar{Y}=\frac{1}{N}\sum_{i=1}^{N}(y_i) \tag{4}$$

Some of the results of equations (2), (3), (4) in some particular condition are as follows:

- If X, Y are independent, then: $\rho(X,Y)=0$
- If X, Y are linear dependent, i.e., $X=aY+b$, then: $\rho(X,Y)=1$.

If the problem is not in the normal domain just in linear condition, it provides completely stochastic dependence; however, in non-linear states, it may cause some misleading. In other words, for two wind power generation, it cannot be introduced linearly because the distribution function is Weibull and the distribution is not linear. Therefore, it leads to introduce rank correlation [44].

In rank correlation, instead of measuring the correlation between the real amounts of random variables, the samples are ranked from lowest to highest, and then, the product moment correlation for responsive ranks is measured. In other words, the value of each sample is replaced by the value of its rank among other samples and product moment correlation is calculated using the ranks.

By using CDF to random variables, marginal distributions are transformed to rank. For example, authors in [45] transferred random variables of wind speeds, solar irradiance to a rank domain by using CDF transformation and stochastic dependence was examined. Moreover, for considering multivariate stochastic dependence, diagonal band copula, which will introduce later in this part, was applied. In fact, through this method, dependence structure from marginal is decoupled, and the information of dependency between random variables is maintained in these ranks.

Moreover, for multivariate distribution function Copulas are a function to couple them to their single dimensional margins [46–48]. As can be seen in Fig. 2, it has different types including Sklar's theorem [49], Frechet-Hoeffding bounds, Gaussian Copulas, Normal Copula, Elliptical Copulas, Archimedean Copulas and Diagonal band Copula [45]. In [50], an integration of PV and wind turbines in a distribution network were studied using Archimedean copulas.

2.3. Multidimensional Dependence

Multidimensional dependence model has to be modelled based on available information. In this sense, joint normal transform (JNT) is suitable for a stochastic system with adequate information [51], which is an extension model of the normal copula. According to this model system correlation matrix is build.

Therefore, in multidimensional dependence method, the matrix should be semi-definite, which without it, it can be a problem for this method. To solve this problem, it is required to fill the matrix with positive semi-definiteness amounts and convert the matrix into a consistent one. In the case of lack of enough information and increasing the uncertainty or dimension, some methods like graphical model trees and vines [46] should be applied based on available information.

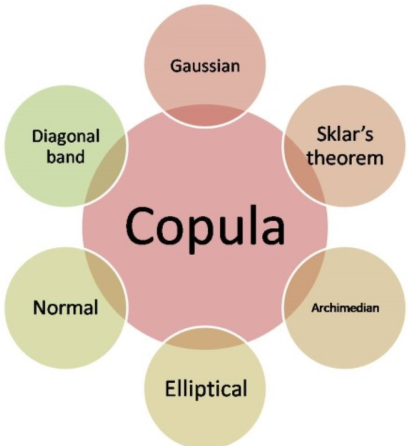

Fig. 2. Different types of Copula methods.

Another way for modelling high-dimensional Gaussian distributions is to simplify the multidimensional dependency model by a risk-averse model reduction technique [52–54]. It means that instead of making dependence between all random variables, risk-averse model is divided into groups which are called stochastic plants.

In Table 1, a summation of different mentioned methods for modelling stochastic nature of weather-dependent renewables in different articles are classified based on publication year. As can be seen, due to the accuracy of MCS and also since MCS gives more complete information about stochastic behavoir of the variables, the trend of using MCS is being boosted.

Table 1. Taxonomy of different methods for modelling renewables uncertainties

year	**Point forecast**	**Quantile forecast**	**Forecast interval**	**Density forecast**	**Scenario forecast (analytical methods)**			**Monte-Carlo simulation**		**Product moment correlation**	**Rank correlation**	**Copula**	**Multi-dimensional dependency**
					FFTM	**MLSM**	**PEM**	**wind**	**solar**				
2016								[16]	[16]				[53]
2015		[22]			[28]			[37,39]	[38,39]			[45]	[51]
2014	[17]					[29]							[52]
2013			[23]										
2012				[26]			[30]					[49]	
2011		[21]											[54]
2010			[24]									[50]	
2009				[25,27]				[34]					[46]
2008		[19]						[35]					
2007										[11]			
2006		[20]									[44]		

3. Uncertainty Tackling by Demand Side Flexibility

Demand side can participate to system flexibility to confront uncertainties raised from weather-dependent renewable sources. To this end, some measurements can be taken like shifting energy from high demand to low demand periods and lowering peak demand [15]. Growing of the communication facilities, advanced metering infrastructure (AMI) and internet-of-things (IoT), the potential of using demand flexibility integrated by renewable energy sources is going to be higher [55,56].

The advantages of using DR include the ability to balance fluctuations in renewable generation, facilitate higher penetration of renewable sources on power systems, an increase in economic efficiency through the implementation of real-time pricing, and a reduction in generation capacity requirement, which are studied in [57]. However, there are some challenges faced DR including lack of experience and consequently need to employ huge assumption for modelling and evaluation sources. If a DR program is implemented successfully, an acceptable effect of DR in electricity price reduction can be revealed [58]. The existence of renewable energy sources can cause a reduction in electricity prices especially when wind production comes as an extra production to the system with zero marginal price and when there is a high CO2 tax for thermal generators in the market [59,60]. Therefore, one of the other advantages of DR in these conditions and in pricing area is hedging cost reduction. As it will discuss in the next part, DR program has different types of implementation which according to the proposed usage can be applied, properly.

For compensation, the shortage power of weather-dependent renewable sources due to their inaccurate forecast, one of the DR programs is applied. One approach is providing direct control of customer; however, it is less acceptable for customers. According to [61], one of the best ways to get customers flexible is running a real-time pricing of electricity. It means that price-based elastic and load-shifting responses should be made. Moreover, authors have mentioned that using price-based elastic during low-wind events, peak demand in the UK may be reduced, significantly.

3.1. Various Demand Response Modelling

In this section, first the regular classification of DR programs is introduced, and then, some assumptions and models implemented by the literature in smart grids are discussed.

3.1.1. Demand Response Programs

There are some different DR programs which regarding the special utilization can be applied. Literature has classified DR programs in different ways; however, the most suitable and common ones are described in [56,62–65] where DR programs were classified into two categories including dispatchable and non-dispatchable, as can be seen in Fig. 3.

In dispatchable DR programs, customers participate voluntarily in a special scheme for controlling customers appliances by operators [66]. For example, the operator can directly control the appliances like air conditioners during peak periods. Two methods in this category, including direct load control (DLC) and interruptible/curtailable service (I/C), are being used since long time ago [56]. In these aforementioned methods, operators make an incentive for reducing or curtailing the consumption of customer who has either contract (I/C method) or no contract (DLC) [64]. In emergency DR program (EDRP), customers need to respond only during the emergency period of time and operator pay customers in those time period. In the capacity market program (CMP), some customers offer a specific amount of load reduction in advance when the grid is in needs [65].

In demand bidding (DB) method, customers bid amount of load reduction in the wholesale market. In other words, customers identify how much load would like to curtail at a posted prices [62]. An ancillary service DR works as a reserve source. The customer can bid load curtailment in Independent System Operator (ISO) as an operating reserve, and if accepted, ISO pays customers for committing to be standby. In case that costumers capacity is needed, ISO calls them with spot market price [62]. Calling demand response even in spot price has economic justification for ISOs. Total operation cost will be dropped due to the fact that no forced load curtailment will occur, which is much more costly, and there will be less need to occupy generators capacity as reserve. Although ISO will pay for DR with spot market price, it will be convenient for customers and increase the network reliability. Moreover, DR implementation will prevent constructing new power plants to supply loads

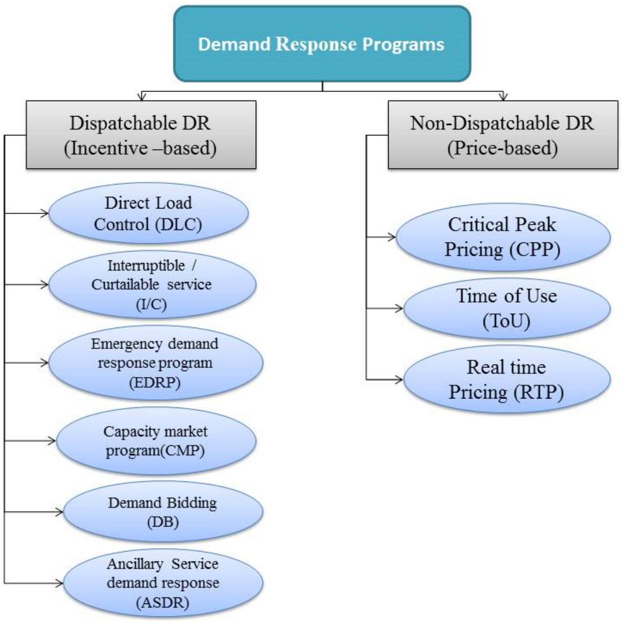

Fig. 3. Demand response programs categories.

Non-dispatchable DR programs, which can be called price-based programs, are based on dynamic pricing rates which their main intention is shaving demand profile. One of such methods is the critical peak pricing (CPP) which generally is implemented in contingencies with real-time prices [67]. Another one is the real time pricing (RTP) where participants are informed about prices on day-ahead [68]. In other words, the prices change continuously during the day. In time-of-use (ToU) method, two or more daily periods are established to show peak hours and off-peak hours to charge a higher rate during peak hours [62].

Table 2 demonstrates a classification of different DR programs and the literatures that have employed each one along with the certain contribution which the literature has been offered for the specific DR program.

Table 2. Taxonomy of Different DR programs

Reference	Demand response programs								Contribution
	DLC	I/C	EDRP	CMP	ASDR	CPP	ToU	RTP	
[69]	√		√						Distributed DLC for large-scale residential DR by two-layer communication-based control
[70]		√		√					Modelling by price elasticity of demand and customer benefit function with considering penalty for consumers
[71]	√					√			A new linear mathematical model for implementation an emission-based UC program
[72]			√						With considering dynamic elasticity factor, price responsiveness are realized
[73]								√	Optimizing the negotiation among customers and retailers through considering power-purchase of customers energy in a RTP DR
[74]					√				Competitive transactions among expensive spinning reserve of thermal units and demand side reserve source for satisfying power balance constraints
[75]							√		Defining the optimum ToU tariff rates in face of high penetration of Renewables to encourage customers for participation in ToU program.

3.1.2. Demand Response Conditions

For the implementation of DR programs, due to lack of enough experience, some assumptions should be considered in modelling approaches. Therefore, advantages of DR models highly depend on this assumption and it needs to be evaluated yet. Some models and assumption are introduced in the following sub-sections.

3.1.2.1. Demand Behaviour

It is expected that demand behaves in a rational way especially economically. To this end, it is common to consider a value as an elasticity of demand which is selected at random with a few considerations for the physical features and limitation of demands.

In order to model the load behaviour with more precision, instead of considering the single elasticity value, which can only reflect the increase or decrease of consumption, the usage of an elasticity matrix to incorporate both self and cross-elasticity [76] is desired. Cross-elasticity is for shifting demand to another time because of change in prices at that time.

For example, the author in [77] considers the wind generation in a period of time less than what was expected, and the prices get higher. Therefore, demand responds to the higher prices at that time (self-elasticity) and the shifts to the lower prices time period (cross-elasticity).

3.1.2.2. Negative Supplier

Another modelling approach is merging DR into unit-commitment. Individual loads can be aggregated to consider as some large units to participate in the market. In this approach, DR is modelled to negative generation with minimum and maximum consumption constraints and ramp rate limitations. The load can be reduced or shed according to the uncertainties in the network based on unit commitment decision.

For example in [78], authors showed the DR as a reserve in two-stage stochastic unit commitment in order to confront, somehow, the uncertainties in microgrids like wind and solar power generation. In this model, DR bidding is divided into several levels and stepwise related price. In [79], DR has been scheduled as ancillary service in a power network by considering contingencies in a two-stage stochastic programming. However, the DR bidding curve is like a supplier price curve (e.g., Fig. 4) because it is treating as a negative supplier, and when more demand is chosen in this program, more will the cost prices. In fact, when demand response is assumed as a supplier commodity, a supply curve for demand response price would be required. In other words, the more load quantity is considered for demand response, the higher price should be paid by the operator to the customer. For example, in some programs like load curtailment, load shifting as well as ancillary service demand response are like Fig. 4.

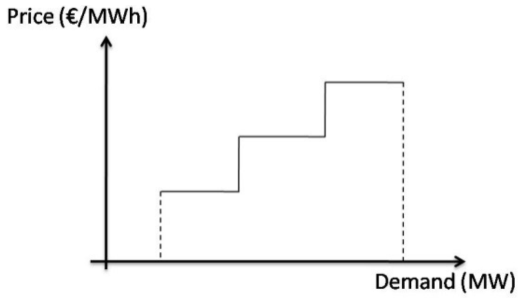

Fig. 4. Demand response bid curve as negative supplier

3.1.2.3. Demand Bidding

Load demand can participate in the market, actively through price bidding. In other words, loaders bid their desired prices in the market. To this end, some of the loaders are considered as fixed loads which are price-takers and would be settled in market-clearing price. Moreover, other loaders are considered as flexible loads which can be dispatched based on the responsive load-prices which would decrease with increasing the load quantity (such as Fig. 5). In other words, since in this model the customers offer their consumption, a demand curve like in Fig. 5 for price bidding would be required. It means that, the more load quantity is demanded for consumption by the customer, the fewer prices will be allocated for that quantity. Therefore, after ISO's decision about customers bidding, some loads are scheduled and others are not, which means a volume of loads would not be served as a DR program. This would be called flexibility in demand side, and demand response is a part of demand scheduling. These flexible loads are subject to several constraints including, minimum up/down time limits, load ramp up/down rate, allowable bound of curtailment, either hourly or daily [80].

Minimum up-time denotes the successive hours that a load must be supplied while restoring. Minimum down-time defines the sequential number of hours that a load would be shed after curtailing process. Load ramp-up represents the load ramping capability of restoring and load ramp-down implies the load ramping ability to curtail. In fact, this rate reflects the consumption change of flexible loads [81].

Allowable bound for load curtailment divides into two parts: minimum hourly curtailment and maximum daily curtailment [82]. The minimum hourly load curtailment can be caused by physical load limitation or system operator where the lower load cannot participate in the market as a responsive load. Maximum daily curtailment denotes a reasonable restriction for total curtail in the time horizon [83].

3.1.2.4. Demand Response Aggregation

In order to help customers to qualify their forecasts for DR programs, some entities are introduced as DR aggregator, which are independent of the system operator. DR aggregator can be a distribution system operator, a load serving entity or a financial entity [84]. In the model of [84], DR aggregators are in contact with system operator and customers to perform a better DRP [85]. DR aggregators are responsible for receiving the customers' bids for DR and sending it to wholesale electricity market [86]. To this end, DR aggregators evaluate the customers' potential to dedicate the special DR quantity and price based on physical or operational constraints. Moreover, to decline the number of DR contracts, aggregators gather similar customers in terms of DR strategy and prices.

There are some different physical load reduction strategies including load curtailment (LC), load shifting (LS) and load recovery (LRC) which can be performed by DR aggregators [87]. In LC, customers decline their load and do not shift their consumption to another period of time, by turning off the television, lights, computers or air conditioners without any alternative time for consumption.

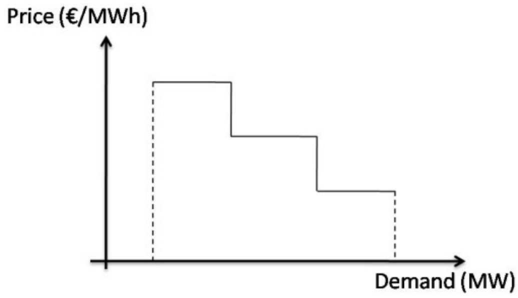

Fig. 5. Demand response bid curve for demand bidding.

In LS, a load reduction and shifting consumption to other time period are performed. In LRC, the process is the same of LS, but the exact alternative time for consumption is defined. In LS strategy, the shifted consumption can be whenever is required [88].

3.1.2.5. Demand Response Price Modelling

In cooperation of demand and retailers, most of the times, retailers present a fixed price to customers to participate in a DR program which does not include any incentive for the customer to modify their consumption [84]. In order to provide more flexible loads, demands can be controlled through price signals.

The ToU pricing is an alternative approach to get rid of fixed-price tariffs. This scheme, which has been already applying in different countries, not only the electricity prices are higher during peak hours than off-peak hours, but also some incentives are made for consumption during night hours rather than day hours by lower prices [15].

In [89], a ToU approach has been scheduled by particle swarm optimization (PSO) for manufacturing customers in the presence of renewables, and the effect of ToU pricing profile is studied.

Authors of [90], and [62] provided a framework for implementation of ToU according to load elasticity concept. ToU program is a static pricing scheme. It means that prices for peak hours, off-peak and valley times are fixed for a long time. Hence, it is not able to follow renewable sources fluctuation.

Real-time dynamic pricing is used to adapt a rapid variation of renewables, which in higher renewable production hours leads to lower market price, and vice versa [91]. These methods need to apply faster and simple response because it should be conducted near to real-time frameworks. Therefore, some pre-defined requirement should be addressed including:

- Bidirectional communication infrastructure to send and receive data like consumption state and price signal;
- Intelligent appliances to schedule the optimum consumption based on the price signal and sending pre-defined consumption to entities for adjusting the price;
- Simple controlling and optimization solvers to get the results near to real-time.

In [92], authors has proposed a model to maximize customer utility or minimizing energy cost of a household or a small business through their energy management system (EMS). In fact, based on real-time pricing scheme, an optimization model has been provided to adjust hourly load level into hourly electricity price.

Optimal real-time prices have been obtained by a few message exchanges over a communication network in [93]. To this end, a two-stage problem has been solved to maximize the quality of consumption and minimize electricity bill from user's point-of-view and maximize the profit from retailer's viewpoint.

Authors in [94] have proposed a control scheme for adjusting set-points of some high consumption appliances in households according to real-time electricity retail price and threshold price that customers set to minimize the bill. Real-time retailing-prices releases every 15 minutes and the accordingly load can be shifted from peak-hours.

Moreover, in [95] was presented a locational real-time tariff scheme to cope with time and location variability of renewables which cannot be reflected through residential tariff scheme. Real-time pricing for industrial customers, to grow the proportion of wind power generation, has been performed in [96]. The real-time pricing tariff for customers includes half-hourly wholesale market, price and fixed supplier mark-up, which largely consists of system marginal price.

Likewise, an optimization approach for obtaining real-time prices, on behalf of DR aggregator has been presented by [97], where DR aggregator serves deferrable loads by renewables, and in the case of any shortage, it can decide whether to curtail the load or procure from the wholesale based on dynamic real-time price scheduling.

4. Electricity market role for mitigation of the stochastic nature of RESs

In the electric power industry, there are two methods of trading electricity. On one hand, the first one is long-term trading which is a bilateral contract and performs through future markets. On the other hand, the second one is short-term trading which is an electricity pool. This market structure is demonstrated in Fig. 6. In bilateral contracts, a buyer and a seller make a forward contract that involves the trading of a specified amount of energy. Essentially, bilateral contracts are agreements between two parts outside the organized market [98]. Regarding the electricity pool, it can be divided in two trading arrangements, day-ahead market, intraday market and balancing market. They are operated in a similar way, as described later; however, the difference is in time of which they take place. The day-ahead market takes place one day before the delivery of energy, the intraday market is scheduled some hours before energy delivery, and the balancing market takes place a few minutes before the energy delivery. So, the electricity pool allows short-term trading and consists of by several buyers and sellers which are market participants. The market is cleared by a market operator, generally in an auction. Basically, the producers present their offers and consumers submit their consumption bids. Then, the system operator combines these offers and bids to construct aggregate curves of supply and demand. The intersection of these curves corresponds to the market clearing price. Therefore, those suppliers who have submitted their offers below market clearing price and the consumers who have submitted their consumption bids above market clearing price are scheduled [99].

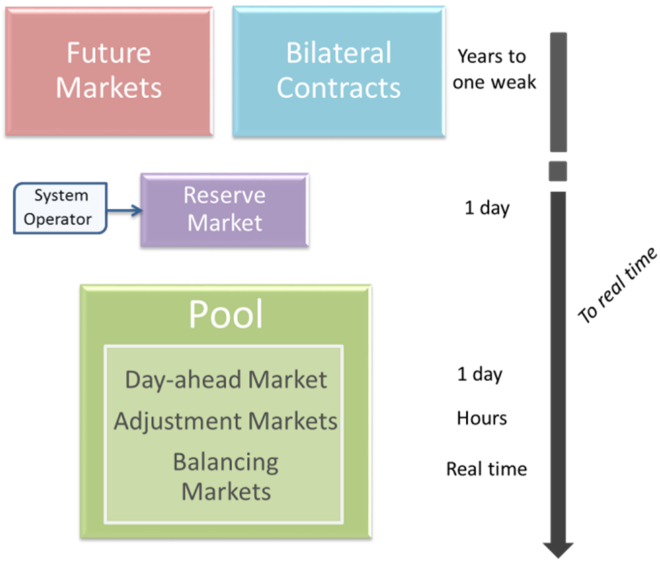

Fig. 6. Market Structures

The increase of renewable energy sources (RES) in today's markets has caused some problems that can be solved through the markets structures. Due to meteorological origins of stochastic RES, all of those sources are influenced by the weather. The wind generation depends largely on wind speed and less on air density; moreover, irradiance and temperature influence on the solar production. This meteorological influence on the generation of renewable sources makes this production uncertain and hard to predict [99]. In contrast to conventional units, production of RES is characterized by non-dispatchability, and for this reason, forecasts are needed in order to schedule the units. In addition, RES has priority over conventional units why its marginal cost is low.

Due to the high penetration of RES allied to deregulation of the electricity industry and for increasing the system reliability, a transition from traditional deterministic approaches to stochastic approaches is being widely performed.

Deterministic problems can only be used when the situation for the next day is definite. Stochastic programming models are capable of determining the energy and reserve dispatch for the day-ahead market. These models are capable of handling renewable sources, demand variations and the failures of power system components. Thus, stochastic production is normally dispatched in a point forecast of its output distribution. These approaches use optimization models, such as Unit Commitment (UC) to facilitate the decision-making process of scheduling and dispatching electric power generation resources [100,101].

To guarantee UC solutions, some requirements such as security, reliability and reverse along with their constraints should be taken into account [100].

In this context, some of the potential market solutions for RES variation are analysed for the day-ahead market, intraday market, balancing market, and demand response exchange market (DRX). The DRX is a relatively new and separate market for trading demand response in a deregulated power system which is a powerful mean to cope with problems raised from renewables uncertainty.

4.1. Day-ahead market

The day-ahead market takes place one day before the energy delivery, usually close to noon. In this market, one of the important commodities which are traded is a reserve that guarantees the balance at any time. System operator needs a reserve to cope with uncertainties in power systems.

Some approaches are presented later to show how RES can be integrated into the market industry [102]: two-stage[103], chance-constrained [104], a combination of two-stage and chance constrained [43], multi-stage [105,106] and robust programming [101].

4.1.1. Two-stage

In a two-stage approach, decisions can be made in two different categories, day-ahead market and real-time decisions. According to references like [107], a stochastic security constrained unit commitment (SCUC) model has been presented to clear the energy and reserve market considering the uncertainty of renewables and/or loads, contingencies. High penetration of wind generators brings new challenges to the system operator and may increase the operational costs. The main objective of this approach is to minimize these costs. This approach consists of two parts; the first part is related to the decisions made in the day-ahead market, such as the cost of start-up, shut-down, generation, and spinning reserve. The second part represents the real-time costs of activating the reserve, wind curtailment and shedding loads. It is also considered the uncertainty of wind production through wind scenarios [108]. Reference [103] is an example of a two-stage approach to facilitate wind integration through network reconfiguration. In some papers like [103] and [109], benders decomposition is employed to decompose the problem into two parts due to a high number of variables as a consequence of scenarios and line status [110]. Therefore, dispatch in real time should be carried out to minimize operational costs. Reference [111] has applied hourly forecast errors of wind energy and loads to schedule the optimal reserve. In fact, a stochastic two-stage programming for solving an SCUC and getting the scheduling of wind energy along with conventional units with N-1 contingencies. In addition to the method used in the previous paper, value at risk has been put in [112] to consider wind power forecasting error.

4.1.2. Chance Constrained

There is another method to solve stochastic day-ahead scheduling problem in electricity markets is introduced for satisfying the stochastic and the reliability criteria in power systems. This approach is based on chance constrained, and it considers random outages of system components and the errors originating from renewable sources and load variations. To accommodate these errors from renewable sources, enough spinning reserve should be considered in the day-ahead scheduling.

The proposed model follows some topics: for more accuracy in forecasting, renewable energy would be dispatchable in real time markets. In the case of a contingency, the system security would be jeopardized if the system is not able to change rapidly to a stationary state. The chance constraints in [104] are the hourly reserve requirements and line constraints. These constraints can be converted to deterministic equivalents, and a standard solution technique is applied. The renewable generation forecast error is presented as a normal distribution.

Briefly, the major steps of the method are:

Step 1: Identification and elimination of inactive line flow constraints for the case base and contingencies.

Step 2: Solution of master UC problem solved by a mix integer linear programming (MILP) based method. The master UC problem is divided in hourly UC and economic dispatch (ED).

Step 3: Base case evaluation, where the network security evaluation for the base case is performed by the ED obtained from step 2. If some line violation occurs, the network security evaluation is run. The step 2 and 3 are repeated until there is no violation in the base case.

Step 4: Contingency evaluation, it is calculated the hourly maximum flow for each line in each contingency, after obtaining the UC in case 3. The steps 2, 3 and 4 are repeated until there is no more violation in base case and contingencies.

The authors in [43] present another method to deal with wind power forecasting errors for keeping the reliability of the system in case of any fluctuations in wind power output. This method is mostly for taking the most advantage of wind power. Therefore, they merge two-stage programming with chance-constrained to solve a UC in an uncertainty environment. Chance constrained is applied to formulate the problem in order to guarantee that a significant part of wind power will be used in each hour. The first stage of the two-stage approach is related to traditional unit commitment problem with transmission constraints, and the total amount of wind power should be delivered. In turn, the second stage represents the penalty cost due to wind power. As the wind power usage was guaranteed by the chance constrained, if wind power output is higher than scheduled wind power, the excess can be curtailed without penalty. In contrast, if the wind power output is lower than the scheduled one, penalization for the shortage of energy will occur.

Therefore, this model can help to increase the usage of wind power and the chance constrained allows guaranteeing a maximum usage of wind power with the lowest possible curtailment.

4.1.3. Robust Programming

Robust Programming represents another solution to deal with uncertainty, but unlike stochastic approaches, this method does not require scenarios. In addition, contrary to stochastic programming where minimizes the total expected cost, in robust programming the minimization of the worst-case cost regarding all possible outcomes is expected [100]. Robust approaches have been studied considering uncertainties such as wind power [106], wind power with demand response [83] and also wind power with pumped storage hydro [113].

In [101], a problem to determinate the day-ahead market dispatch in an electricity market is developed with considering stochastic generation sources. A robust optimization model is presented to minimize the system cost for the worst case realization of the uncertain production. In this case, the uncertainty is represented by sets of polyhedral prevenient from historical data.

The major steps of this approach are briefly presented:

Step 1: To determinate the day-ahead energy and reserve dispatch a robust optimization is applied. The system operator finds the amount of required reserve and the optimal dispatch for the day-ahead market.

Step 2: It is proposed a reformulation of the inner *max-min* problem to determine the uncertainty and alternative solutions which can adjust polyhedral sets for a precise solution. The *max-min* determines the worst case realization through maximization problem, and the recourses cost is minimized in the minimization problem.

Step 3: The results from robust approach are compared to deterministic and stochastic programming.

4.1.4. Multi-stage

Contrary to two-stage approach, multi-stage treats towards uncertainty more than one time. Hence, multi-stage models capture the dynamics of unfolding uncertainties over time, and the decisions can be adjusted dynamically [114,115]. In some papers such as [100], [116], scenario trees are used to facilitate the formulation of this kind of models. In these approaches, the information can be updated hourly or multi-hourly and facilitate the decisions-maker's adjustments according to current states of the system and future uncertainties. Therefore, the relation between decisions making and the uncertainties becomes closer and precise.

Reference [117] presents a dynamic multi-stage model to operate isolated hybrid wind-diesel power system. A dynamic programming has been applied to deal with future uncertainties in the system.

4.2. Intraday market (adjustment market)

Weather forecast always includes errors and uncertainties. In fact, the closer we are in target hour, the more precise weather forecast we have. Through this concept, the intraday market has been introduced between day-ahead and real-time [118]. Since it is closer to real-time, revising the operation decisions with updated weather data would be applicable which helps to mitigate the uncertainty of the wind and solar power [119,120]. The intraday market is shorter than day-ahead and can be divided into several sections i.e. two, three or more for each day. Some literature has investigated the benefits of the intraday market to mitigate the weather-dependent renewable sources. Authors in [121] assessed the benefits of the intraday market compared with the day-ahead market in a competitive environment based on some criteria such as expected reserve, expected load shedding and expected wind power spillage. According to their methodology, at the end of each intraday gate closure, the program is cleared and rerun by updated forecast information. Each rerun provides operation schedules and prices for remaining hours of horizon time which are binding for the very next intraday market and non-binding for other remaining intraday markets. Outputs of this intraday market are energy, reserve and price for the very next intraday market and expected energy, expected reserve and expected price for other next intraday markets. In [122], authors believe that intraday market is a more expensive method to balance forecast errors than the day-ahead market due to the shorter response time. However balancing market is on average more expensive one, so the intraday market is more acceptable.

4.3. Balancing market

The balancing market corresponds to the last minute energy adjustments. A non-dispatchable producer has to participate in this market to cover the deviations from the production pattern settled in the pool. In this market, it is ensured that the balance between generation and demand is settled through corrections of energy imbalances. These imbalances can be positive or negative. A positive deviation occurs when the production is higher or the consumption is lower than scheduling. A negative deviation happens, when the production is lower or consumption is higher than scheduling. Consequently, the producers must sell the excess energy or buy deficit energy based on imbalance price. For obtaining prices of selling and buying an auction is made.

In the case of a positive imbalance (excess of energy), producers only repurchase their excess in a price lower than the day-ahead clearing price. So, the market participants who sold their energy in balancing market obtain a profit lower than if they sold all their production on the day-ahead market. In contrast, if the system imbalance is negative (deficit of generation), required energy will be at a price higher than the day-ahead market. Balancing market should be considered as the last mechanism to provide energy balance [99].

In [103], in order to show the impact of wind uncertainty on real-time scheduling, three different cases were studied. In the first case, the real time wind production is equal to the expected value. Therefore, it is not necessary to have a spinning reserve or loads shedding; therefore; what is scheduled in the day-ahead market is still the same in real time. In the second case, the expected value is higher than the real-time wind generation. Here, to cover the excessive amount of wind generation it is necessary to allocate down-spinning reserve. To decrease the power flow in lines, load shedding and wind curtailment are two possible solutions. Since load shedding is the most expensive option, wind curtailment is chosen. The third case is when wind generation is lower than the expected value. Consequently, the up-spinning reserve is required and other solutions such as load shedding or bringing new units online should be considered. As assumed earlier, load shedding is an expensive solution, so the second option is the most economic. In [123], microgrid aggregator concept has been introduced in a balancing market bidding to depress the effect of RES uncertainty. All in all, the operation costs are higher in the third case. A summary expression of the above three markets is demonstrated in fig. 7

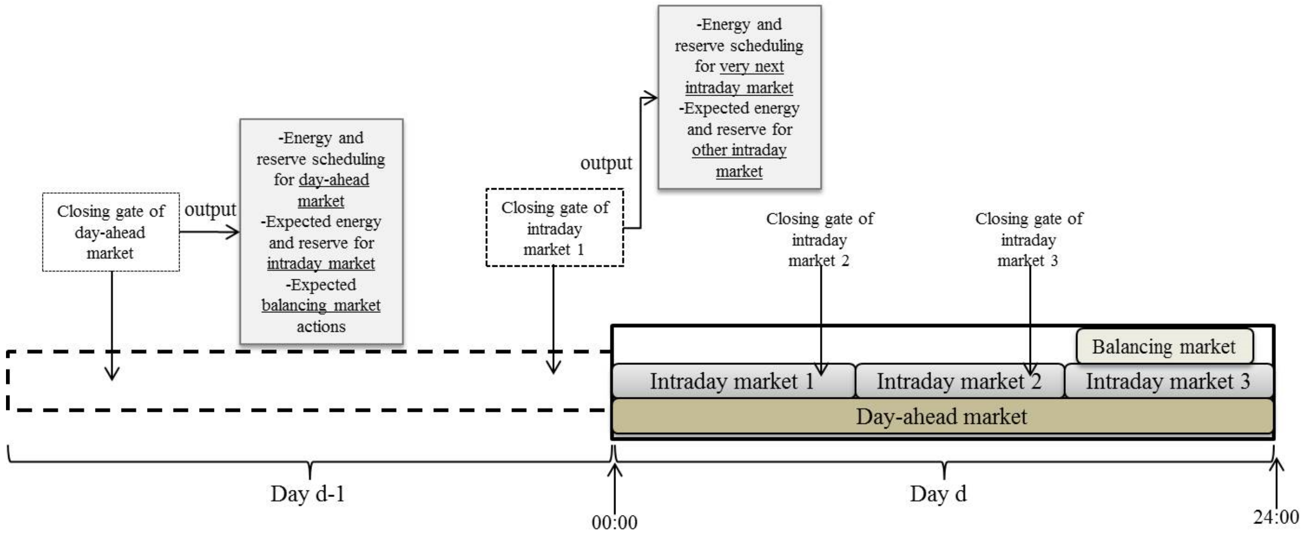

Fig. 7. The framework of short-term electricity market

4.4. Demand response exchange (DRX) market

In the DRX concept, DR is treated as a market with an exchange among buyers including transmission companies (Transcos), distribution companies (Discos) and retailers and sellers including energy service companies (ESCos) [124]. The ESCos include load serving entities (LSEs), Distribution system operators (DSOs) and Demand response providers (DRPs). The structure of DRX market is demonstrated in Fig. 8. Buyers target for participating in DRX is to provide security and reliability for their network. ESCos as Sellers are responsible for registering, aggregating, scheduling, managing and clearing the DR. They do not have the capability for controlling and commanding to customers and manipulating retail prices like retailers; however, both of them are dealing with customers. Supplying DR is performed by reducing the customer consumption. Therefore, in addition to the above key participants in this market, customers are other participants as DR producers [125]. DRX includes competition in a way that sellers lose the opportunity when they propose a payment far above true cost. Similarly, when buyers want to pay less than true price of DR, they cannot purchase this DR that is better to allocate other buyers who want to pay enough for this DR [124,126].

There are two models for the DRX including bilateral and pool-based. In the bilateral model, DR exchange is directly carried out among sellers and buyers for a specific price and amount of DR. Although a regulatory like DRX operator (DRXO) follows the contract whether they obey the market policies. On the other side, in the pool-based model, a central market is introduced for settlement and coordination by DRXO. In fact, the DR capacity is collected by DRXO in a framework which all sellers and buyers have to access this framework [124,126,127].

In [128], authors proposed a pool-based DRX model for managing the renewables variability. In this model, DRX is inside the stochastic day-ahead market run by ISO. In this procedure, first, a stochastic day-ahead scheduling is performed with considering forecast errors of renewable renewables and other uncertainties like random outages of components. Applying the output of day-ahead scheduling which is the expected locational marginal price (LMPs), the DRX is run and cleared successively.

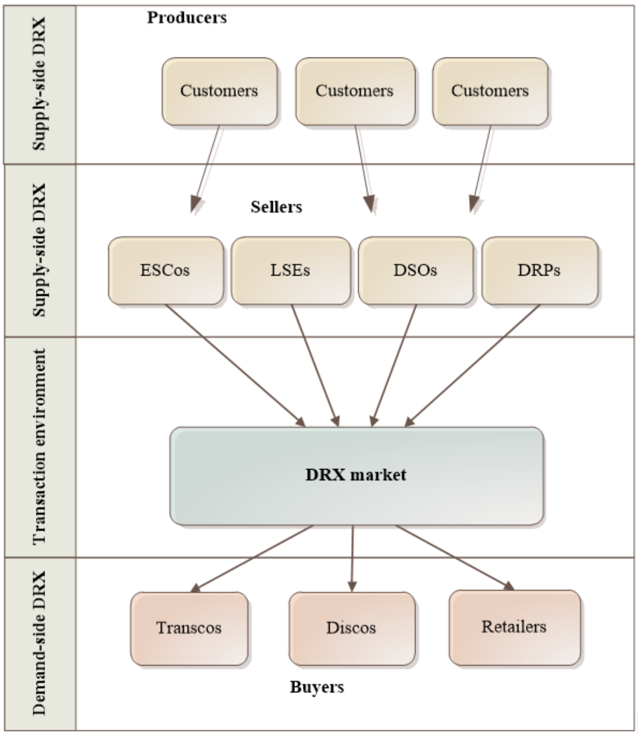

Fig. 8. DRX market framework

In Table 3 a classification of reviewed literatures related to electricity market is presented. Accordingly, different literatures are categorized based on the utilized markets.

Table 3. Taxonomy of different markets and relevant literatures

Reference	Day-ahead market				Intraday market	Balancing market	DRX market
	Two-stage	Multistage	Robust programming	Chance constrained			
[128]	√						√
[103]	√					√	
[123]					√	√	
[121]		√			√	√	
[117]		√					
[101]			√				
[43]	√			√			
[108]	√					√	

5. Conclusions

In this paper, some different approaches to tackling the stochastic nature of renewable energy sources, especially weather-dependent ones, have been investigated. Mathematical methods for forecasting scenarios in both dependent mode and independent mode were studied. Moreover, since another efficient approach to confront renewable sources uncertainty is demand side management, different kinds of DR programs and some modelling methods have been studied in this article. In addition, by the liberalization of the electricity market, it is possible to cope with the problems raised from the inherent stochastic features of the wind and solar generators. The role of various market schemes and optimization approaches to optimize reserve for mitigation of these uncertainties has been studied. Accordingly, there are many methods for the operator to cope with the uncertainty of weather-dependent renewables. Therefore, the operator can schedule the supplied energy more precisely and with less total cost. The outputs of the analytical methods have been employed by the operator either in one of the market schemes or in one of the DRPs. A multidimensional dependency model enables the operator to deal with several stochastic variables like wind generation and solar generation simultaneously and in a dynamic method, which leads to accurate results. Therefore, studying and applying this model more than ever can be used to solve some restrictions related to modelling uncertainties in energy scheduling. Since the target of this study is short-term scheduling, the most popular and common approach in this term is applying MCS to generate possible scenarios in a day-ahead market by two-stage programming. Nevertheless, a multi-segment market, which includes several markets (i.e. day-ahead, intraday, balancing market) together, is used to minimize the effect of forecast errors on scheduling. Meanwhile, since the novel DRX market is a combination of DR and market, it has a great potential to get developed and extended in an uncertainty environment, especially with a mixture of other short-term markets. DRX still faces a lack of enough experience in both practical and theoretical viewpoints. Providing proper policies and the definition of its different aspects can be a future research work. Moreover, this study can be extended for long-term energy scheduling in a future work.

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References

[1] Luna-Rubio R, Trejo-Perea M, Vargas-Vázquez D, Ríos-Moreno GJ. Optimal sizing of renewable hybrids energy systems: A review of methodologies. Sol Energy 2012;86:1077–88. doi:10.1016/j.solener.2011.10.016.

[2] Erdinc O, Uzunoglu M. Optimum design of hybrid renewable energy systems: Overview of different approaches. Renew Sustain Energy Rev 2012;16:1412–25. doi:10.1016/j.rser.2011.11.011.

[3] Chauhan A, Saini RP. A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control. Renew Sustain Energy Rev 2014;38:99–120. doi:10.1016/j.rser.2014.05.079.

[4] Mohammed YS, Mustafa MW, Bashir N. Hybrid renewable energy systems for off-grid electric power: Review of substantial issues. Renew Sustain Energy Rev 2014;35:527–39. doi:10.1016/j.rser.2014.04.022.

[5] Chen Z, Blaabjerg F. Wind farm—A power source in future power systems. Renew Sustain Energy Rev 2009;13:1288–300. doi:10.1016/j.rser.2008.09.010.

[6] Pandey SK, Mohanty SR, Kishor N. A literature survey on load–frequency control for conventional and distribution generation power systems. Renew Sustain Energy Rev 2013;25:318–34. doi:10.1016/j.rser.2013.04.029.

[7] Parmar KPS, Majhi S, Kothari DP. Load frequency control of a realistic power system with multi-source power generation. Int J Electr Power Energy Syst 2012;42:426–33. doi:10.1016/j.ijepes.2012.04.040.
[8] Georgilakis PS. Technical challenges associated with the integration of wind power into power systems. Renew Sustain Energy Rev 2008;12:852–63. doi:10.1016/j.rser.2006.10.007.
[9] Ulbig A, Borsche TS, Andersson G. Impact of Low Rotational Inertia on Power System Stability and Operation. IFAC Proc Vol 2014;47:7290–7. doi:10.3182/20140824-6-ZA-1003.02615.
[10] Soroudi A, Ehsan M. A possibilistic–probabilistic tool for evaluating the impact of stochastic renewable and controllable power generation on energy losses in distribution networks—A case study. Renew Sustain Energy Rev 2011;15:794–800. doi:10.1016/j.rser.2010.09.035.
[11] Papaefthymiou G. Integration of stochastic generation in power systems. Technische Universiteit Delft, 2007.
[12] Li Y, Zio E. Uncertainty analysis of the adequacy assessment model of a distributed generation system. Renew Energy 2012;41:235–44. doi:10.1016/j.renene.2011.10.025.
[13] Saraiva JT, Fonseca N, Matos MA. Fuzzy power flow-an AC model addressing correlated data. 2004 Int. Conf. Probabilistic Methods Appl. Power Syst., 2004, p. 519–24.
[14] Li YF, Huang GH, Li YP, Xu Y, Chen WT. Regional-scale electric power system planning under uncertainty—A multistage interval-stochastic integer linear programming approach. Energy Policy 2010;38:475–90. doi:10.1016/j.enpol.2009.09.038.
[15] Morales JM, Conejo AJ, Madsen H, Pinson P, Zugno M. Integrating Renewables in Electricity Markets. vol. 205. Boston, MA: Springer US; 2014.
[16] Aien M, Hajebrahimi A, Fotuhi-Firuzabad M. A comprehensive review on uncertainty modeling techniques in power system studies. Renew Sustain Energy Rev 2016;57:1077–89. doi:10.1016/j.rser.2015.12.070.
[17] Su W, Wang J, Roh J. Stochastic Energy Scheduling in Microgrids With Intermittent Renewable Energy Resources. IEEE Trans Smart Grid 2014;5:1876–83. doi:10.1109/TSG.2013.2280645.
[18] Bremnes JB. Probabilistic wind power forecasts using local quantile regression. Wind Energy 2004;7:47–54. doi:10.1002/we.107.
[19] Costa A, Crespo A, Navarro J, Lizcano G, Madsen H, Feitosa E. A review on the young history of the wind power short-term prediction. Renew Sustain Energy Rev 2008;12:1725–44. doi:10.1016/j.rser.2007.01.015.
[20] Using quantile regression to extend an existing wind power forecasting system with probabilistic forecasts - Nielsen_et_al-2006-Wind_Energy.pdf n.d. http://henrikmadsen.org/wp-content/uploads/2016/02/Nielsen_et_al-2006-Wind_Energy.pdf (accessed January 20, 2017).
[21] Wang J, Botterud A, Bessa R, Keko H, Carvalho L, Issicaba D, et al. Wind power forecasting uncertainty and unit commitment. Appl Energy 2011;88:4014–23. doi:10.1016/j.apenergy.2011.04.011.
[22] Quan H, Srinivasan D, Khambadkone AM, Khosravi A. A computational framework for uncertainty integration in stochastic unit commitment with intermittent renewable energy sources. Appl Energy 2015;152:71–82. doi:10.1016/j.apenergy.2015.04.103.
[23] Pinson P. Wind Energy: Forecasting Challenges for Its Operational Management. Stat Sci 2013;28:564–85. doi:10.1214/13-STS445.
[24] Pinson P, Kariniotakis G. Conditional Prediction Intervals of Wind Power Generation. IEEE Trans Power Syst 2010;25:1845–56. doi:10.1109/TPWRS.2010.2045774.
[25] Taylor JW, McSharry PE, Buizza R. Wind Power Density Forecasting Using Ensemble Predictions and Time Series Models. IEEE Trans Energy Convers 2009;24:775–82. doi:10.1109/TEC.2009.2025431.
[26] Jeon J, Taylor JW. Using conditional kernel density estimation for wind power density forecasting. J Am Stat Assoc 2012;107:66–79.
[27] Bacher P, Madsen H, Nielsen HA. Online short-term solar power forecasting. Sol Energy 2009;83:1772–83. doi:10.1016/j.solener.2009.05.016.
[28] Du P, Li W, Ke X, Lu N, Ciniglio OA, Colburn M, et al. Probabilistic-Based Available Transfer Capability Assessment Considering Existing and Future Wind Generation Resources. IEEE Trans Sustain Energy 2015;6:1263–71. doi:10.1109/TSTE.2015.2425354.
[29] Carpinelli G, Caramia P, Varilone P. Multi-linear Monte Carlo simulation method for probabilistic load flow of distribution systems with wind and photovoltaic generation systems. Renew Energy 2015;76:283–95. doi:10.1016/j.renene.2014.11.028.

[30] Niknam T, Golestaneh F, Malekpour A. Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm. Energy 2012;43:427–37. doi:10.1016/j.energy.2012.03.064.

[31] Zhang P, Lee ST. Probabilistic Load Flow Computation Using the Method of Combined Cumulants and Gram-Charlier Expansion. IEEE Trans Power Syst 2004;19:676–82. doi:10.1109/TPWRS.2003.818743.

[32] Yuan Y, Zhou J, Ju P, Feuchtwang J. Probabilistic load flow computation of a power system containing wind farms using the method of combined cumulants and Gram–Charlier expansion. IET Renew Power Gener 2011;5:448. doi:10.1049/iet-rpg.2010.0218.

[33] Su C-L. Probabilistic Load-Flow Computation Using Point Estimate Method. IEEE Trans Power Syst 2005;20:1843–51. doi:10.1109/TPWRS.2005.857921.

[34] Yu Z, Tuzuner A. Fractional weibull wind speed modeling for wind power production estimation. 2009 IEEE Power Energy Soc. Gen. Meet., 2009, p. 1–7. doi:10.1109/PES.2009.5275785.

[35] Hetzer J, Yu DC, Bhattarai K. An Economic Dispatch Model Incorporating Wind Power. IEEE Trans Energy Convers 2008;23:603–11. doi:10.1109/TEC.2007.914171.

[36] Celik AN. A statistical analysis of wind power density based on the Weibull and Rayleigh models at the southern region of Turkey. Renew Energy 2004;29:593–604. doi:10.1016/j.renene.2003.07.002.

[37] Azad AK, Rasul MG, Alam MM, Uddin SMA, Mondal SK. Analysis of Wind Energy Conversion System Using Weibull Distribution. Procedia Eng 2014;90:725–32. doi:10.1016/j.proeng.2014.11.803.

[38] Velamuri S, Sreejith S. Economic dispatch and cost analysis on a Power system network interconnected with Solar Farm. Int J Renew Energy Res IJRER 2015;5:1098–1105.

[39] Abdulkarim A, Abdelkader SM, John Morrow D. Statistical Analyses of Wind and Solar Energy Resources for the Development of Hybrid Microgrid. In: Oral A., Bahsi Oral Z., Ozer M, editors. 2nd Int. Congr. Energy Effic. Energy Relat. Mater. ENEFM2014, Cham: Springer International Publishing; 2015, p. 9–14.

[40] Yu H, Chung CY, Wong KP, Lee HW, Zhang JH. Probabilistic Load Flow Evaluation With Hybrid Latin Hypercube Sampling and Cholesky Decomposition. IEEE Trans Power Syst 2009;24:661–7. doi:10.1109/TPWRS.2009.2016589.

[41] Janssen H. Monte-Carlo based uncertainty analysis: Sampling efficiency and sampling convergence. Reliab Eng Syst Saf 2013;109:123–32. doi:10.1016/j.ress.2012.08.003.

[42] Zhaohong B, Xifan W. Studies on variance reduction technique of Monte Carlo simulation in composite system reliability evaluation. Electr Power Syst Res 2002;63:59–64. doi:10.1016/S0378-7796(02)00089-5.

[43] Wang Q, Guan Y, Wang J. A Chance-Constrained Two-Stage Stochastic Program for Unit Commitment With Uncertain Wind Power Output. IEEE Trans Power Syst 2012;27:206–15. doi:10.1109/TPWRS.2011.2159522.

[44] Papaefthymiou G, Schavemaker PH, van der Sluis L, Kling WL, Kurowicka D, Cooke RM. Integration of stochastic generation in power systems. Int J Electr Power Energy Syst 2006;28:655–67. doi:10.1016/j.ijepes.2006.03.004.

[45] Othman MM, Abdelaziz AY, Hegazi YG, El-Khattam W. Approach for modelling stochastically dependent renewable energy-based generators using diagonal band copula. IET Renew Power Gener 2015;9:809–20. doi:10.1049/iet-rpg.2014.0205.

[46] Papaefthymiou G, Kurowicka D. Using Copulas for Modeling Stochastic Dependence in Power System Uncertainty Analysis. IEEE Trans Power Syst 2009;24:40–9. doi:10.1109/TPWRS.2008.2004728.

[47] Nelsen RB. An introduction to copulas. 2nd ed. New York: Springer; 2006.

[48] D. Kurowicka, R. M. Cooke. Uncertainty Analysis With High Di mensional Dependence Modelling. New York: Wiley; 2006.

[49] Hagspiel S, Papaemannouil A, Schmid M, Andersson G. Copula-based modeling of stochastic wind power in Europe and implications for the Swiss power grid. Appl Energy 2012;96:33–44. doi:10.1016/j.apenergy.2011.10.039.

[50] Valizadeh Haghi H, Tavakoli Bina M, Golkar MA, Moghaddas-Tafreshi SM. Using Copulas for analysis of large datasets in renewable distributed generation: PV and wind power integration in Iran. Renew Energy 2010;35:1991–2000. doi:10.1016/j.renene.2010.01.031.

[51] Le Z, Haihong B, Guohua C. Using an Improved Joint Normal Transform Method for Modeling Stochastic Dependence in Power System. Open Electr Electron Eng J 2015;9:380–385.

[52] Rahimiyan M. A statistical cognitive model to assess impact of spatially correlated wind production on market behaviors. Appl Energy 2014;122:62–72. doi:10.1016/j.apenergy.2014.02.004.

[53] Bruno S, Ahmed S, Shapiro A, Street A. Risk neutral and risk averse approaches to multistage renewable investment planning under uncertainty. Eur J Oper Res 2016;250:979–89. doi:10.1016/j.ejor.2015.10.013.

[54] Pousinho HMI, Mendes VMF, Catalão JPS. A risk-averse optimization model for trading wind energy in a market environment under uncertainty. Energy 2011;36:4935–42. doi:10.1016/j.energy.2011.05.037.
[55] Strbac G. Demand side management: Benefits and challenges. Energy Policy 2008;36:4419–26. doi:10.1016/j.enpol.2008.09.030.
[56] Shariatzadeh F, Mandal P, Srivastava AK. Demand response for sustainable energy systems: A review, application and implementation strategy. Renew Sustain Energy Rev 2015;45:343–50. doi:10.1016/j.rser.2015.01.062.
[57] O′Connell N, Pinson P, Madsen H, O′Malley M. Benefits and challenges of electrical demand response: A critical review. Renew Sustain Energy Rev 2014;39:686–99. doi:10.1016/j.rser.2014.07.098.
[58] Torriti J, Hassan MG, Leach M. Demand response experience in Europe: Policies, programmes and implementation. Energy 2010;35:1575–83. doi:10.1016/j.energy.2009.05.021.
[59] Holttinen H, Vogstad K-O, Botterud A, Hirvonen R. Effects of large scale wind production on the Nordic electricity market. Eur. Wind Energy Conf., Copenhagen, Denmark: 2001.
[60] Moghaddam MP, Ghadikolayi ET, Mohamadian M. A new method for pricing of wind power in short-term power markets. 16th Power Syst. Comput. Conf. PSCC, Glasgow: 2008.
[61] Roscoe AJ, Ault G. Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response. IET Renew Power Gener 2010;4:369–82. doi:10.1049/iet-rpg.2009.0212.
[62] Aalami HA, Moghaddam MP, Yousefi GR. Modeling and prioritizing demand response programs in power markets. Electr Power Syst Res 2010;80:426–35. doi:10.1016/j.epsr.2009.10.007.
[63] Moghaddam MP, Abdollahi A, Rashidinejad M. Flexible demand response programs modeling in competitive electricity markets. Appl Energy 2011;88:3257–69. doi:10.1016/j.apenergy.2011.02.039.
[64] Albadi MH, El-Saadany EF. A summary of demand response in electricity markets. Electr Power Syst Res 2008;78:1989–96. doi:10.1016/j.epsr.2008.04.002.
[65] Palensky P, Dietrich D. Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. IEEE Trans Ind Inform 2011;7:381–8. doi:10.1109/TII.2011.2158841.
[66] Aghaei J, Alizadeh M-I. Demand response in smart electricity grids equipped with renewable energy sources: A review. Renew Sustain Energy Rev 2013;18:64–72. doi:10.1016/j.rser.2012.09.019.
[67] Wang J, Biviji MA, Wang WM. Lessons learned from smart grid enabled pricing programs. 2011 IEEE Power Energy Conf. Ill., 2011, p. 1–7. doi:10.1109/PECI.2011.5740488.
[68] Edward J, Policy P. Assessment of customer response to real time pricing. New Jersey: Edward J, Bloustein School of Planning and Public Policy qqae State University of New Jersey; 2005.
[69] Chen C, Wang J, Kishore S. A Distributed Direct Load Control Approach for Large-Scale Residential Demand Response. IEEE Trans Power Syst 2014;29:2219–28. doi:10.1109/TPWRS.2014.2307474.
[70] Aalami HA, Moghaddam MP, Yousefi GR. Demand response modeling considering Interruptible/Curtailable loads and capacity market programs. Appl Energy 2010;87:243–50. doi:10.1016/j.apenergy.2009.05.041.
[71] Alizadeh M-I, Aghaei J. Critical peak pricing with load control demand response program in unit commitment problem. IET Gener Transm Distrib 2013;7:681–90. doi:10.1049/iet-gtd.2012.0739.
[72] Aghaei J, Alizadeh M-I, Siano P, Heidari A. Contribution of emergency demand response programs in power system reliability. Energy 2016;103:688–96. doi:10.1016/j.energy.2016.03.031.
[73] Lujano-Rojas JM, Monteiro C, Dufo-López R, Bernal-Agustín JL. Optimum residential load management strategy for real time pricing (RTP) demand response programs. Energy Policy 2012;45:671–9. doi:10.1016/j.enpol.2012.03.019.
[74] Aghaei J, Alizadeh M-I. Robust n–k contingency constrained unit commitment with ancillary service demand response program. IET Gener Transm Distrib 2014;8:1928–36. doi:10.1049/iet-gtd.2014.0052.
[75] Heydarian-Forushani E, Golshan MEH, Shafie-khah M. Flexible security-constrained scheduling of wind power enabling time of use pricing scheme. Energy 2015;90:1887–900. doi:10.1016/j.energy.2015.07.014.
[76] Madaeni SH, Sioshansi R. The impacts of stochastic programming and demand response on wind integration. Energy Syst 2013;4:109–24. doi:10.1007/s12667-012-0068-7.
[77] Sioshansi R. Evaluating the Impacts of Real-Time Pricing on the Cost and Value of Wind Generation. IEEE Trans Power Syst 2010;25:741–8. doi:10.1109/TPWRS.2009.2032552.
[78] Talari S, Yazdaninejad M, Haghifam M-R. Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads. IET Gener Transm Amp Distrib 2015;9:1498–509. doi:10.1049/iet-gtd.2014.0040.
[79] Parvania M, Fotuhi-Firuzabad M. Demand Response Scheduling by Stochastic SCUC. IEEE Trans Smart Grid 2010;1:89–98. doi:10.1109/TSG.2010.2046430.

[80] Wu H, Shahidehpour M, Khodayar ME. Hourly Demand Response in Day-Ahead Scheduling Considering Generating Unit Ramping Cost. IEEE Trans Power Syst 2013;28:2446–54. doi:10.1109/TPWRS.2013.2254728.
[81] Nguyen DT, Le LB. Risk-Constrained Profit Maximization for Microgrid Aggregators With Demand Response. IEEE Trans Smart Grid 2015;6:135–46. doi:10.1109/TSG.2014.2346024.
[82] Su CL, Kirschen D. Quantifying the Effect of Demand Response on Electricity Markets. IEEE Trans Power Syst 2009;24:1199–207. doi:10.1109/TPWRS.2009.2023259.
[83] Zhao L, Zeng B. Robust unit commitment problem with demand response and wind energy. 2012 IEEE Power Energy Soc. Gen. Meet., 2012, p. 1–8. doi:10.1109/PESGM.2012.6344860.
[84] Siano P. Demand response and smart grids—A survey. Renew Sustain Energy Rev 2014;30:461–78. doi:10.1016/j.rser.2013.10.022.
[85] Heleno M, Matos MA, Lopes JAP. A bottom-up approach to leverage the participation of residential aggregators in reserve services markets. Electr Power Syst Res 2016;136:425–33. doi:10.1016/j.epsr.2016.03.025.
[86] Shafie-khah M, Fitiwi DZ, Catalão JPS, Heydarian-Forushani E, Golshan MEH. Simultaneous participation of Demand Response aggregators in ancillary services and Demand Response eXchange markets. 2016 IEEEPES Transm. Distrib. Conf. Expo. T D, 2016, p. 1–5. doi:10.1109/TDC.2016.7519950.
[87] Parvania M, Fotuhi-Firuzabad M, Shahidehpour M. Optimal Demand Response Aggregation in Wholesale Electricity Markets. IEEE Trans Smart Grid 2013;4:1957–65. doi:10.1109/TSG.2013.2257894.
[88] Parvania M, Fotuhi-Firuzabad M, Shahidehpour M. ISO's Optimal Strategies for Scheduling the Hourly Demand Response in Day-Ahead Markets. IEEE Trans Power Syst 2014;29:2636–45. doi:10.1109/TPWRS.2014.2316832.
[89] Wang Y, Li L. Time-of-use based electricity demand response for sustainable manufacturing systems. Energy 2013;63:233–44. doi:10.1016/j.energy.2013.10.011.
[90] Aalami H, Yousefi GR, Moghadam MP. Demand Response model considering EDRP and TOU programs. 2008 IEEEPES Transm. Distrib. Conf. Expo., 2008, p. 1–6. doi:10.1109/TDC.2008.4517059.
[91] Borenstein S, Jaske M, Rosenfeld A. Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets. Cent Study Energy Mark 2002.
[92] Conejo AJ, Morales JM, Baringo L. Real-Time Demand Response Model. IEEE Trans Smart Grid 2010;1:236–42. doi:10.1109/TSG.2010.2078843.
[93] Qian LP, Zhang YJA, Huang J, Wu Y. Demand Response Management via Real-Time Electricity Price Control in Smart Grids. IEEE J Sel Areas Commun 2013;31:1268–80. doi:10.1109/JSAC.2013.130710.
[94] Yoon JH, Baldick R, Novoselac A. Dynamic Demand Response Controller Based on Real-Time Retail Price for Residential Buildings. IEEE Trans Smart Grid 2014;5:121–9. doi:10.1109/TSG.2013.2264970.
[95] Dupont B, De Jonghe C, Olmos L, Belmans R. Demand response with locational dynamic pricing to support the integration of renewables. Energy Policy 2014;67:344–54. doi:10.1016/j.enpol.2013.12.058.
[96] Finn P, Fitzpatrick C. Demand side management of industrial electricity consumption: Promoting the use of renewable energy through real-time pricing. Appl Energy 2014;113:11–21. doi:10.1016/j.apenergy.2013.07.003.
[97] Papavasiliou A, Oren SS. Large-Scale Integration of Deferrable Demand and Renewable Energy Sources. IEEE Trans Power Syst 2014;29:489–99. doi:10.1109/TPWRS.2013.2238644.
[98] Bitar EY, Rajagopal R, Khargonekar PP, Poolla K, Varaiya P. Bringing Wind Energy to Market. IEEE Trans Power Syst 2012;27:1225–35. doi:10.1109/TPWRS.2012.2183395.
[99] Conejo AJ, Carrión M, Morales JM. Decision Making Under Uncertainty in Electricity Markets. vol. 153. Boston, MA: Springer US; 2010.
[100] Zheng QP, Wang J, Liu AL. Stochastic Optimization for Unit Commitment #x2014;A Review. IEEE Trans Power Syst 2015;30:1913–24. doi:10.1109/TPWRS.2014.2355204.
[101] Zugno M, Conejo AJ. A robust optimization approach to energy and reserve dispatch in electricity markets. Eur J Oper Res 2015;247:659–71. doi:10.1016/j.ejor.2015.05.081.
[102] Birge JR, Louveaux F. Introduction to Stochastic Programming. Springer Science & Business Media; 2011.
[103] Nasrolahpour E, Ghasemi H. A stochastic security constrained unit commitment model for reconfigurable networks with high wind power penetration. Electr Power Syst Res 2015;121:341–50. doi:10.1016/j.epsr.2014.10.014.
[104] Wu H, Shahidehpour M, Li Z, Tian W. Chance-Constrained Day-Ahead Scheduling in Stochastic Power System Operation. IEEE Trans Power Syst 2014;29:1583–91. doi:10.1109/TPWRS.2013.2296438.
[105] Zhao C, Wang J, Watson JP, Guan Y. Multi-Stage Robust Unit Commitment Considering Wind and Demand Response Uncertainties. IEEE Trans Power Syst 2013;28:2708–17. doi:10.1109/TPWRS.2013.2244231.

[106] Jiang R, Wang J, Zhang M, Guan Y. Two-Stage Minimax Regret Robust Unit Commitment. IEEE Trans Power Syst 2013;28:2271–82. doi:10.1109/TPWRS.2013.2250530.
[107] Dai H, Zhang N, Su W. A Literature Review of Stochastic Programming and Unit Commitment. J Power Energy Eng 2015;3:206–14. doi:10.4236/jpee.2015.34029.
[108] Beraldi P, Conforti D, Violi A. A two-stage stochastic programming model for electric energy producers. Comput Oper Res 2008;35:3360–70. doi:10.1016/j.cor.2007.03.008.
[109] Papavasiliou A, Oren SS. A comparative study of stochastic unit commitment and security-constrained unit commitment using high performance computing. 2013 Eur. Control Conf. ECC, 2013, p. 2507–12.
[110] Ruszczyński A. Decomposition methods in stochastic programming. Math Program 1997;79:333–53. doi:10.1007/BF02614323.
[111] Sahin C, Shahidehpour M, Erkmen I. Allocation of Hourly Reserve Versus Demand Response for Security-Constrained Scheduling of Stochastic Wind Energy. IEEE Trans Sustain Energy 2013;4:219–28. doi:10.1109/TSTE.2012.2213849.
[112] Stochastic analysis of wind energy uncertainty impact on ISO risk-taking in joint energy and reserve markets using conditional value at risk. J Renew Sustain Energy 2016;8:53101. doi:10.1063/1.4962413.
[113] Jiang R, Wang J, Guan Y. Robust Unit Commitment With Wind Power and Pumped Storage Hydro. IEEE Trans Power Syst 2012;27:800–10. doi:10.1109/TPWRS.2011.2169817.
[114] Growe-Kuska N, Heitsch H, Romisch W. Scenario reduction and scenario tree construction for power management problems. 2003 IEEE Bologna Power Tech Conf. Proc., vol. 3, 2003, p. 7 pp. Vol.3-pp. doi:10.1109/PTC.2003.1304379.
[115] Triki C, Beraldi P, Gross G. Optimal capacity allocation in multi-auction electricity markets under uncertainty. Comput Oper Res 2005;32:201–17. doi:10.1016/S0305-0548(03)00211-9.
[116] Meibom P, Barth R, Brand H, Weber C. Wind power integration studies using a multi-stage stochastic electricity system model. 2007 IEEE Power Eng. Soc. Gen. Meet., 2007, p. 1–4. doi:10.1109/PES.2007.385950.
[117] Hu Y, Morales JM, Pineda S, Sánchez MJ, Solana P. Dynamic multi-stage dispatch of isolated wind–diesel power systems. Energy Convers Manag 2015;103:605–15. doi:10.1016/j.enconman.2015.06.070.
[118] Weber C. Adequate intraday market design to enable the integration of wind energy into the European power systems. Energy Policy 2010;38:3155–63. doi:10.1016/j.enpol.2009.07.040.
[119] Borggrefe F, Neuhoff K. Balancing and Intraday Market Design: Options for Wind Integration. DIW Berlin, German Institute for Economic Research; 2011.
[120] Mathieu JL, Kamgarpour M, Lygeros J, Andersson G, Callaway DS. Arbitraging Intraday Wholesale Energy Market Prices With Aggregations of Thermostatic Loads. IEEE Trans Power Syst 2015;30:763–72. doi:10.1109/TPWRS.2014.2335158.
[121] Jafari AM, Zareipour H, Schellenberg A, Amjady N. The Value of Intra-Day Markets in Power Systems With High Wind Power Penetration. IEEE Trans Power Syst 2014;29:1121–32. doi:10.1109/TPWRS.2013.2288308.
[122] Kiviluoma J, Meibom P, Tuohy A, Troy N, Milligan M, Lange B, et al. Short-Term Energy Balancing With Increasing Levels of Wind Energy. IEEE Trans Sustain Energy 2012;3:769–76. doi:10.1109/TSTE.2012.2209210.
[123] Pei W, Du Y, Deng W, Sheng K, Xiao H, Qu H. Optimal Bidding Strategy and Intramarket Mechanism of Microgrid Aggregator in Real-Time Balancing Market. IEEE Trans Ind Inform 2016;12:587–96. doi:10.1109/TII.2016.2522641.
[124] Nguyen DT. Demand response exchange in a deregulated environment. University of Tasmania, 2012.
[125] Nguyen DT, Negnevitsky M, de Groot M. Walrasian Market Clearing for Demand Response Exchange. IEEE Trans Power Syst 2012;27:535–44. doi:10.1109/TPWRS.2011.2161497.
[126] Nguyen T, Negnevitsky M, Groot M de. Pool-based Demand Response Exchange: Concept and modeling. 2011 IEEE Power Energy Soc. Gen. Meet., 2011, p. 1–1. doi:10.1109/PES.2011.6039051.
[127] Arasteh HR, Moghaddam MP, Sheikh-el-Eslami MK. Bidding strategy in demand response exchange market. Electr. Power Distrib. Netw. EPDC 2012 Proc. 17th Conf. On, IEEE; 2012, p. 1–5.
[128] Wu H, Shahidehpour M, Alabdulwahab A, Abusorrah A. Demand Response Exchange in the Stochastic Day-Ahead Scheduling With Variable Renewable Generation. IEEE Trans Sustain Energy 2015;6:516–25. doi:10.1109/TSTE.2015.2390639.