Uncertainty Quantification of Wind Penetration and Integration into Smart Grid: A Survey

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***Abstract*— Quantification of uncertainty due to wind-energy production becomes more and more crucial as the penetration of wind into smart grid increases. System operators (TSOs) and planners would be interested to see how wind production varies over different look-ahead hours and estimate the probability of those variations under several uncertain conditions. As wind is a stochastic source of generation, this paper provides a state-of-the-art literature review on the uncertainties related to wind-energy dispatch.**

***Index Terms*—Uncertainty Quantification, Renewable Energy Sources, Wind, Variability.**

I. INTRODUCTION

Electric power industry is experiencing a drastic change in its economic outlook as most countries are now trying to replace fossil fuel with renewable energy sources (RES). This change is evident as many European countries are committed to make RES as their main source of power by 2020 [1]. To satisfy the increasing energy demand, there is a greater need to significantly increase the percentage contribution of RES in the power grid. Although integration of RES is beneficial to the environment in reducing greenhouse gas emissions, it comes with technological challenges for utilities. The major issue in the integration of RES is their variability and reliability problems [2]. The most widely used RES's are wind and solar. The energy production from these sources depend on several factors such as wind speed, wind direction, solar irradiance, temperature, etc., which may vary instantaneously influencing the generation. In operations and planning of power system, it is vital to know and be able to quantify the uncertainty associated with RES [3]-[5]. Wind power is both uncertain and variable, while solar power is considered less uncertain, but more variable than wind power [6]-[9]. Solar power can be predicted to a better accuracy when compared to wind. The number of uncertain variables are less in solar when compared to wind power. In this survey, the focus is on uncertainty associated with wind power generation.

Economic dispatch (ED) is a process of economically allocating generation values to a mix of generating units to satisfy the system load requirements. The allocation process is done subject to load, generation, and transmission constraints with the goal to reduce the generation costs [10]. This paper presents a literature review on the uncertainty quantification approaches in ED of an RES integrated grid. The rest of the paper is organized based on the following sections: a brief discussion about the uncertainty of wind power, uncertainty approaches in ED, followed by discussion and conclusion.

II. UNCERTAINTY OF WIND POWER

Forecasting wind power generation is challenging, as there are several unknown variables during the quantification process. For example, A. Lira et al. [10] discussed the different uncertainties such as wind-flow, equipment failure, sensor assemblies and their related inaccuracies and calibration. They proposed a probability of exceedance concept to quantify the uncertainty in calculating the total wind power. The authors calculated the net-wind energy production using a normal distribution.

A combined approach of Neural Networks (NN's) and quantile regression was discussed by H. Dehghani et al. in [11]. In this work, a multilayer NN perceptron (MLP) technique was used to predict the wind speed values and non-polynomial equations were then used to calculate the corresponding wind energy. The quantile regression is then applied to the predicted wind energy values to produce prediction-intervals as a measure of the associated uncertainties. This approach has the benefit of not requiring a probability distribution model.

An uncertainty evaluation model is proposed by C. L. Anderson et al. [12], which evaluates three types of uncertainties associated with the power distribution system; namely wind forecast variations, load changes and generators availability. This is a two-stage optimization model–the first stage processes the forecasted values of wind and demand; the second stage updates the model with realized values. They used Monte Carlo simulation to capture the uncertainties.

A bi-level optimization model was proposed by X. Fang et al. in [13] to evaluate Locational Marginal Prices (LMP) under wind variations. An ED model was then developed and LMP intervals were found using a Lagrangian function. This method has the advantage of not using the computationally extensive Monte Carlo simulation method.

In [14], M. Shaaban et al. investigated the effect of wind energy on power dispatch and used two reliability indices– loss of load probability (LOLP) and expected demand not supplied (EDNS) to quantify the associated risks. Using Monte Carlo simulation, they used a normally distributed wind speed and a multi-state wind turbine model to calculate the above risk indices. The authors have also investigated the displacement of conventional generators by renewable energy sources.

The author in [15] used Monte Carlo simulation to model the uncertainty associated with wind along with variations of elfectric prices, loads, construction and operation costs, and maintenance costs. The proposed framework generates a probabilistic distribution of net present value (NPV) of the project, which enables the users to decide on wind power investments. The method is proven to be superior to the single-point estimates. The author suggested that the proposed framework can be extended to other RES.

A method to evaluate annual energy production at a wind farm was proposed by B. Hrafnkelsson et al. in [16] using a Monte Carlo simulation approach. The proposed method has the advantage of not using a predefined distribution for the wind speed and has the advantage of using the historical wind data available at the site. They reported that the evaluated wind generation had a closer agreement with the actual energy production and was superior to the Weibull distribution based approaches.

III. Uncertainty quantification Methods used in Economic dispatch

Several uncertainty quantification approaches discuss economic dispatch with wind resources being a part of the generation mix. The applicability of these methods varies with the situation and depends on the availability of complete data sets, accuracy, and computational burden. In this section, we discuss specific methods that focus on the economic dispatch using wind energy.

A. Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a power tool used in computational physics. It is a common method used to capture and quantify the uncertainty associated with variable processes. The results are obtained through repeated random-sampling and statistical analysis. One major disadvantage of the MCS method is the larger computational time required for convergence [17]. Several literature sources exist that explain the usage of MCS to quantify the uncertainty associated with variable factors [18]-[22] and some of the research works have focused on renewable energy sources as described in the previous section [12], [14], [15] and [16].

In MCS, a statistical distribution for each input parameter along with an appropriate random number generator are used for generating random samples. For a given random data set, a distribution fitting method can be used to generate the function to represent the data. The random samples generated from the distribution represent the input value of the parameters. Statistical analyses are performed on the output parameter values to produce the required results [18].

Z. Zhao et al. [23] explored the concept of Conditional Value-at-Risk (CVaR) as an index to quantify the uncertainty associated with wind energy. The security of a wind integrated power system is represented by a risk function that is evaluated using random input sample values generated by MCS approach. The ED is modelled as a stochastic optimization problem that includes a risk factor. The optimized result for the ED is obtained using the level function method. The authors tested the validity of their method on a modified IEEE 30 bus system.

B. Quasi- Monte Carlo Simulation

B. C. Gu et al. in [24] proposed a Quasi-Monte Carlo simulation (QMC) based approach to quantify the uncertainty of wind energy in ED. Compared to conventional MCS, the QMC method has the advantage of reducing the complexity of the problem. In their approach, wind speeds are assumed to follow a strict analytical Weibull or Gaussian distribution instead of using random number generators and sampling techniques. This approach results in greater reduction in the number of scenarios to be generated and processed. The authors claim that their QMC based ED model is easier to implement and solve. The multi-objective ED problem is solved using a Group Search Optimizer with Multiple Producers (GSOMP) method. They report the superiority of their proposed method by comparing the results with conventional MCS and other deterministic approaches.

C. Chance Constrained Programming (CCP)

The Chance Constrained Programming (CCP) is a popular optimization technique for solving problems with uncertainty factors. Modeling of the problem formulation is done in such a way that probability of satisfying a constraint is above a certain level. The main idea behind the technique is that it allows constraint violation but the probability of that happening should not exceed a predefined risk value [25].

Z. Wang et al. [26] proposed an ED model with wind power uncertainty as a CCP problem. The paper considers wind uncertainty but does not take into account the uncertainty associated with load and solar power. The wind generation was assumed to follow a non-Gaussian correlated pattern represented by a Gaussian Mixture Model. The probability of chance constraints was calculated, and later transformed into deterministic values. The chance constrained ED model was modeled as a convex optimization problem to find the global optimum. The authors validated their proposed method using the IEEE 39-bus system and compared its performance with the conventional methods.

Several other literatures exist which use the concept of chance constrained programming to model the uncertainty associated with RES, such as the work by Y. Wang et al. [25], in which they use CCP along with goal programming to model wind uncertainty in the Unit Commitment (UC) problem. The CCP along with Genetic algorithm was used by Q. Li et al. [22] to model the ED with RES uncertainty. The model controls the curtailment of variable loads and RES generation to balance the uncertainty.

D. Point Estimation Methods

Point estimation involves finding a single value to represent a population. It is an approximation method applied to a sample data and the accuracy of the value obtained depends upon the population size and the method used. Even though the traditional methods like Monte Carlo methods can be applied to a data set to provide reliable results; in some cases, the associated computational burden can be excessive [27].

Y. Tan et al. [28] proposed a stochastic economic dispatch model with renewable energy generation using two-point estimate method. The authors investigated an optimal resource allocation problem in a microgrid. They used an efficient two-point estimate method to model the uncertainty and an improved particle swarm optimization algorithm to find the optimal solution of the ED problem.

The concept of point estimation was also used in other resource allocation problems like UC and optimal power flow. C. S. Saunders [27] modelled a probabilistic optimal power flow of a grid with integrated wind energy. The point estimation method was used to model the stochastic characteristic of the wind energy. The authors report that the proposed method is effective, accurate, and compared to the traditional MCS creates a less computational burden. Another unique point estimation method was proposed by H. Haiteng et al. [29]. The proposed method used a Nataf transformation and Gauss-Hermite integration method. Their model converts the power flow with uncertain power generation into a response function with random variables. The authors validate the improved accuracy and run-time of the new method by comparing it with the traditional point estimation method. Two-point estimate method was used by S. M. Mohseni-Bonab et al. [30] to model load uncertainty in optimal reactive power dispatch problem. The proposed method was verified using the IEEE 14 and 30 bus systems. The efficiency of their method was found to be superior to deterministic and Monte Carlo simulation approaches.

E. Interval Analysis

Interval analysis or interval arithmetic is an approach in which bounds are placed on errors or measurements. Instead of representing a measurement by a single value, it is represented by using a range of values. Point forecasts with a single forecasted value in each time period are not enough to represent the uncertainty or error in the forecasted values. However, prediction intervals represent a quantity using three components: an upper bound, lower bound and a confidence level. Prediction intervals are powerful statistics to represent the uncertainty associated with single point forecasts [34].

T. Ding et al. [35] utilized interval numbers to model the uncertainty associated with wind energy in a security constrained economic dispatch problem. It is modelled as an optimal interval, and the values of upper and lower bounds are obtained using a bi-level programming model. They assert the effectiveness of the proposed method by applying it to the IEEE 118 bus system.

A mixed-integer linear programming (MILP) model of a security constrained ED model was developed by T. Ding et al. in [36] to minimize the curtailment cost in a wind power integrated system. The curtailment is used to prevent the Security Constrained Economic Dispatch (SCED) from becoming infeasible in the event of wind power variations. The authors model the wind uncertainty as an interval number.

The concept was also used in UC problems. A Prediction Interval (PI) based technique was introduced by H. Quan et al. in [34] to represent the uncertainty associated with wind power forecasting. The uncertainty quantification was performed using a Neural Network based prediction interval. A particle swarm optimization (PSO) based lower-upper bound estimation was used to compute the PIs. Instead of representing the wind uncertainty by a single PI, multiple PIs are used in this model. The UC model was solved using Genetic Algorithm. The robustness of the proposed stochastic model was verified against a deterministic model.

F. Game Theory

Game theory is an important mathematical tool used by mathematicians, economists, social engineers, politicians and sociologists for decades due to its capability in solving decision making problems consisting of multiple objectives and entities. It can also handle complex action sequences and can help the user to understand the interaction between individuals in decision making under uncertain and competitive environments. In a game theoretical problem, each entity tries to get the best pay off from its interaction with other players [37].

Different applications of game theory in power system area are explained in [37]. The authors report the use of game theory in power system applications such as in power markets, power system planning, power system dispatch, power system control, micro-grids and distributed generation, demand response, power system security, and power system evolution. The paper also describes the use of game theory to solve robust optimization problems using the concept of zero-sum game. Here, one player tries to maximize the profit while the other tries strategies to minimize opponent's profit.

M. Zhang et al. [38] proposed a robust economic dispatch model based on Stackelberg game theory considering wind uncertainty. The ED is modelled as a leader-follower structure with the leader level trying to maximize the usage of predicted wind power output and the follower level trying to minimize the total generation cost. The bi-level programming problem is modified into a single level using Karush-Kuhn-Tucker (KKT) conditions and it is then solved as a non-linear optimization problem.

A non-cooperative game based ED model with Distributed Energy Resources (DER) was introduced by M. Marzband et al. [39]. The electricity market in [39] is modelled as a non-cooperative game of n players, where each player tries to improve its profit through distributed decision making. The game theory based method of Nikaido–Isoda function and Relaxation algorithm are used to solve the model. A game theoretical approach to solve the ED problem was explored by N. Yildira et al. [40]. The optimal operating points of generators are found using the concept of Nash equilibrium. They asserted the superiority of their proposed method by comparing it with Lagrangian function and genetic algorithm.

G. Fuzzy Systems

Fuzzy sets are a concept introduced by Zadeh as a means to model the uncertainty associated with engineering problems. Fuzzy logic typically represents the uncertainties associated with vagueness or conflicts in a process, which are not usually represented by a probabilistic framework [41]. In [42], the author described different applications of fuzzy sets in power systems such as in decision-making, optimization, controllers, etc.

The uncertainty associated with wind prediction was modelled using fuzzy set concept by R. H. Liang et al. [43]. Membership functions, which represent a degree of truth, are used to model the forecast error. The generation dispatch model is solved by genetic algorithm and the authors asserted that the proposed method is effective in obtaining an optimal solution when imprecisions are considered.

The concept of fuzzy logic was explored by B. Venkatesh et al. [44] to represent the risk associated with the integration of wind energy into power systems. A UC problem was modelled using mix-integer linear programming (MILP) along with fuzzy set theory. The fuzzy logic was also used to model a PID controller incorporating wind uncertainty by M. Gheydi et al. [45].

H. Robust Optimization

Optimization problems containing uncertain data can also be handled by a special class of optimization technique called Robust Optimization (RO). The objective functions and constraints are modelled as uncertainty sets in this optimization framework. It does not assume a probability distribution for the input data set, but assumes that the data belong to an uncertainty set. The uncertainty parameters are predetermined in the uncertainty set which makes it easier to model than a probability distribution or membership function. The uncertainty set helps to include even the worst-case variation in datasets. The optimization is done in a controlled manner against the worst-case scenario. It is a data-driven approach which can be scaled easily for larger systems. The computational tractability of RO problems containing uncertain data, makes this method a popular optimization tool [46].

C. Peng et al. [47] proposed a robust optimization based technique for a large-scale RES integrated power system. To overcome the conservative aspects of the conventional robust optimization methods, the authors introduced a concept of uncertainty budget. A flexible RO method with adjustable uncertainty budget was modeled to achieve an ideal compromise between cost and reliability of the power system. The authors of [47] claim that the proposed model results in lesser economic risks compared to a deterministic approach, even though there is a slight increase in the generation dispatch cost.

Table I. Literatures that discuss both wind uncertainty and economic dispatch

Uncertainty Methods	**Ref**	**Year**	**Uncertainty Measure**	**Characteristics**
Monte Carlo Simulation	[22]	2016	Weibull distribution	+ Probabilistic results + Sensitivity and scenario analysis - Distribution assumptions - Larger computational time
Quasi-Monte Carlo Simulation	[24]	2016	Weibull distribution	+ Reduced complexity over the MCS + Reduced number of scenarios + Improved computational time over the MCS
Chance constraint programming	[26]	2017	Gaussian Mixture model	+ Allows constraint violation to a certain limit + Robust solutions - Often difficult to solve
Two-point estimation method	[28]	2015	Random variable	+ Closed-form function not required + Computation time - Uncorrelated stochastic variables are required
Interval analysis	[35] [36]	2014 2015	Interval number	+ Provides a range of values + More tractable
Game theory	[38]	2015	Prediction interval	+ Strategic decision making + Nash equilibrium - Large player games can get complicated
Non –cooperative Game theory	[39]	2016	Weibull distribution	+ Can model highly competitive energy markets + Easier to solve
Fuzzy optimization	[43]	2007	Membership function	+ Multi-objective optimization capability + Can handle disparate & contradicting objectives
Robust optimization	[47] [48]	2016 2016	Uncertainty set	+ Independent on prior knowledge + Need not assume a probability distribution + The uncertain bounds are easier to construct - Results are often too conservative
	[50]	2015	Dynamic uncertainty sets	
Active Robust optimization	[49]	2016	Uncertainty set	+ Combines Robust and Dynamic optimization + Spatial and temporal correlated uncertainties

H. Zhang et al. [48] utilized the RO method for a wind integrated economic dispatch model. A robust optimization method with uncertainty budget is utilized in the dynamic economic problem to convert it from a non-deterministic to a deterministic model. The authors used an adjustable uncertainty budget for their RO based approach. The wind forecast error is assumed to follow a normal distribution and it was tested under different uncertainty levels. The resulting deterministic process is then solved using a quadratic-programming approach. The efficiency and performance of the method was verified using two test systems.

A unique optimization method that combines robust optimization and dynamic optimization called Active Robust Optimization (ARO) was proposed by X. Wang et al. in [49]. The model considers the uncertainty parameters associated with wind and demand prices. The uncertainty set construction based on a novel auto-regressive and moving-average based method was also introduced. The performance of the proposed method was evaluated using a modified IEEE 30 and 118 test systems.

A novel framework to handle significant wind energy in a multi-period economic dispatch was developed by Á. Lorca et al. [50]. A concept of dynamic uncertainty set is explored. The proposed model combines RO with statistical prediction tools in their simulation framework.

A short summary on the quantification approaches, wind model and the solution methodology used by different researches to solve the ED problem considering wind uncertainty is given in Table I.

IV. DISCUSSIONS

In addition to the above described methods, there are recent literatures that use several other approaches to quantify the uncertainty in power systems. Some of them use techniques such as Cumulant method, Component Analysis technique, Karhunen-Loeve expansion, Polynomial Chaos expansions, etc.

Y. Yang [51] represented the correlation between uncertainty and wind power outputs using the principal component analysis (PCA). The technique can be used to transform a set of inter-related variables into a set of principal components, which will make it easier to handle uncertain variables. C. Safta et al. [52] explore the potential of using Karhunen-Loeve expansion and Polynomial Chaos expansions instead of Monte Carlo simulation, which they state to be superior to other methods in representing uncertainty. M. Fan et al. in [53] modeled the uncertainty associated with solar power generation using the Cumulant method.

The potential of hybrid methods are not yet fully developed to quantify the uncertainty associated with wind energy. Although uncertain, the wind energy is still a favored power source among the RES's. This survey enforces the idea that there is a lot of scope for further research in quantifying uncertainty that may combine one or more hybrid techniques discussed in this survey.

V. CONCLUSION

The paper presented a literature review pertaining to uncertainty quantification in power system integrated with wind energy sources. As there is more regulatory push for electric utilities to increase their penetration of wind sources, there is an immediate need to develop more accurate quantification and predictions of wind energy production. We believe this paper can act as a resource to researchers within academia and analysts in utilities to develop new methods on wind uncertainty quantitation.

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