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How to deal with uncertainties in electric power systems? A review

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ABSTRACT

In electric power systems, there exist many diverse uncertain parameters such as loads, electricity price, wind power generation and photovoltaic power generation. In power system studies, appropriate modeling and handling of these uncertain parameters is essential. In this paper, the sources of uncertainties in power systems are described and different uncertainty handling methods in power systems are classified and reviewed in details, mentioning the merits and demerits of each method. Based on the conducted review, some directions for future research are delineated.

1. Introduction

In electric power systems, we are facing different uncertain parameters [1–5]. Restructuring of power systems along with proliferation of renewable energy integration, not only have increased the severity of uncertainties, but also have introduced new uncertain parameters in power systems. Load forecasting errors, photovoltaic and wind power generation, charging/discharging behavior of electric vehicles, stochastic topology of power systems and forecasted electricity price are some sources of uncertainty in electric power systems. The classification of sources of uncertainty in electric power systems can be seen in Fig. 1 [2]. As this figure shows, power system uncertain parameters can be categorised into two categories; Technical parameters and economical parameters. Each category has itself been subdivided into two subcategories.

To have a realistic modeling and making better decisions in electric power systems, the uncertainties must be taken into account. The common approaches for dealing with power system uncertainties can be classified into three main categories. In the approaches of the first category, referred to as probabilistic approaches, uncertain parameters are modeled by probability density functions (PDF's) and are dealt with different probabilistic strategies such as Monte Carlo simulation (MCS), scenario-based analysis and point estimate method (PEM). In the approaches of the second category, referred to as possibilistic approaches, uncertain parameters are represented by fuzzy membership functions and dealt with fuzzy arithmetic. The third category includes hybrid probabilistic-possibilistic approaches wherein some uncertain parameters are represented by PDF's and are dealt with probabilistic strategies, while other uncertain parameters are represented by fuzzy membership functions and are dealt with possibility theory. In this paper, different uncertainty handling techniques in power systems are classified and reviewed in details. The paper can give the reader an idea how to deal with different kinds of uncertainties in electric power systems. The rest of the paper is organised as follows; in the second section, different uncertainty handling approaches in power systems are classified and reviewed in details. In the third section, an overall review of different uncertainty handling techniques in electric power systems is presented and finally, the fourth section contains conclusions.

2. Classification and review of uncertainty handling approaches in power systems

The common approaches for dealing with power system uncertainties can be classified into three main categories; namely, probabilistic approaches, possibilistic approaches and hybrid probabilistic-possibilistic approaches [2]. In this section, those approaches are described and reviewed. A classification of the common uncertainty handling techniques in electric power systems can be seen in Fig. 2.

2.1. Probabilistic approaches

Probabilistic approaches are the most commonly used approaches in handling power system uncertainties. In these approaches, uncertain parameters are modeled by probability density functions (PDF's) and

Abbreviations: PDF, Probability density function; MCS, Monte Carlo Simulation; PEM, Point estimate method; SBA, Scenario-based analysis; PV, Photovoltaic; MF, Membership function; IGDT, Information gap decision theory; DNO, Distribution network operator; DR, Demand response; UC, Unit commitment; PSO, Particle swarm optimisation; GA, Genetic algorithm; DE, Differential evolution; ABC, Artificial bee colony; PEV, Plug-in electric vehicle; GenCo, Generation company

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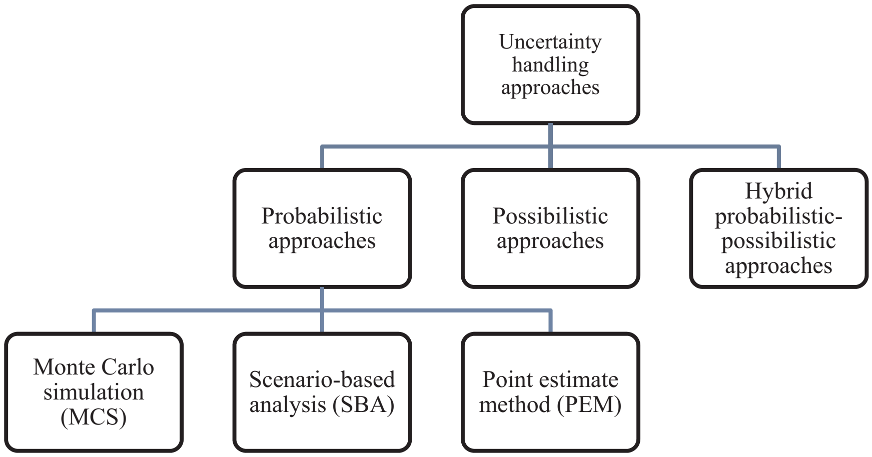

Fig. 1. Sources of uncertainty in electric power systems [2].

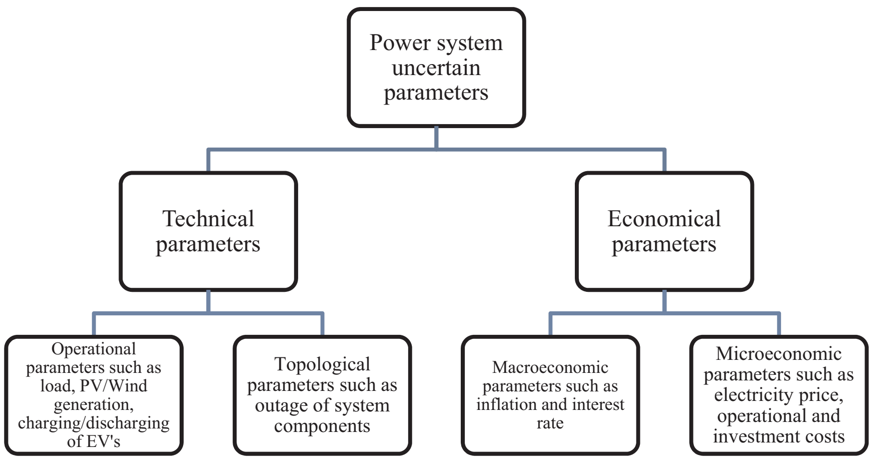

Fig. 2. Classification of uncertainty handling techniques in electric power systems.

are dealt with different probabilistic strategies such as Monte Carlo simulation (MCS), scenario-based analysis (SBA) and point estimate method (PEM). Here, first, the most common PDF's used for different uncertain parameters in power systems are introduced.

- Load

Ideally, due to the forecasting errors, in power system planning and operation studies, the loads should not be assumed as certain deterministic parameters. Instead, they are commonly modeled as a Gaussian PDF whose mean is equal to the forecasted value. In most cases, a fraction of forecasted load value is taken as the standard deviation of PDF [6,7].

$$PDF(S) = \frac{1}{\sqrt{2\pi\sigma}} exp\left[-\frac{(S-\mu)^2}{2\sigma^2}\right] \tag{1}$$

Where S denotes apparent power of load, σ and μ respectively represent mean (forecasted) and standard deviation of apparent power.

In Fig. 3, the typical PDF of a load with mean of 100 kW and standard deviation of 5 kW has been depicted.

- Wind power generation

The generated power of a wind turbine mainly depends on the wind speed [6,8–15]. The wind speed of a wind turbine is commonly modeled as a Weibull PDF which is characterised by the following equation [6,16,17].

$$PDF(v) = \left(\frac{K}{C}\right).\left(\frac{v}{C}\right)^{K-1} exp\left(-\left(\frac{v}{C}\right)^{K}\right) \tag{2}$$

Where K and C respectively denote shape factor and scale factor of Weibull function.

The generated power of a wind turbine is a function of wind speed that characterised by the equation below.

$$P(v) = \begin{cases} 0 & v \le v_{in}^c \ \ or \ \ v \ge v_{out}^c \\ \frac{v - v_{in}^c}{v_{rated}^c - v_{in}^c} & v_{in}^c \le v \le v_{rated}^c \\ P_r & else \end{cases} \tag{3}$$

Where v_{in}^c and v_{out}^c respectively represent cut in speed and cut out speed of wind turbine in m/s, v_{rated}^c denotes turbine's rated speed and P_r denotes rated power of wind turbine [6].

In Fig. 4, the PDF of wind speed has been depicted and in Fig. 5, output power of a wind turbine versus wind speed has been illustrated. In these figures, the following parameters have been used. $K = 1.75$, $v_{in}^c = 3m/s$, $v_{out}^c = 25m/s$, $v_{rated}^c = 13m/s$, $C = 8.78$ and $P_r = 0.5kW$.

- Photovoltaic power generation

The generated power of a PV generator mainly depends on solar irradiation [6,18–21]. Solar irradiation is commonly characterised by Beta distribution function as follows [6].

$$PDF(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha).\Gamma(\beta)}.\ s^{\alpha-1}.\ (1-s)^{\beta-1} & if \ \ 0 \le s \le 1 \\ 0 & otherwise \end{cases} \tag{4}$$

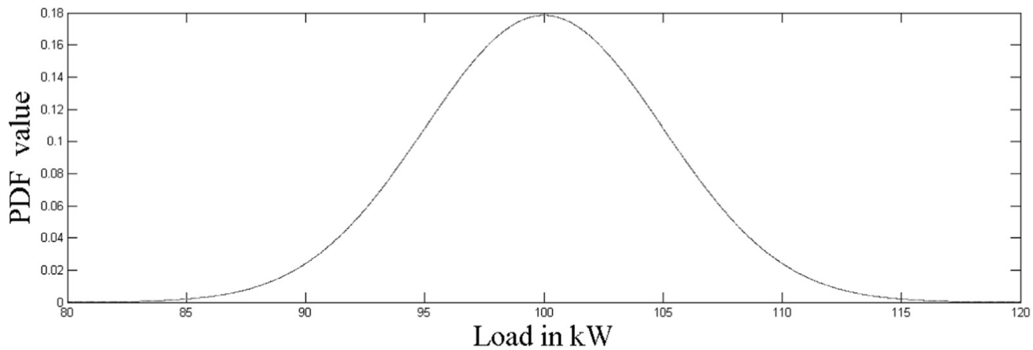

Fig. 3. Typical PDF of a load in power system.

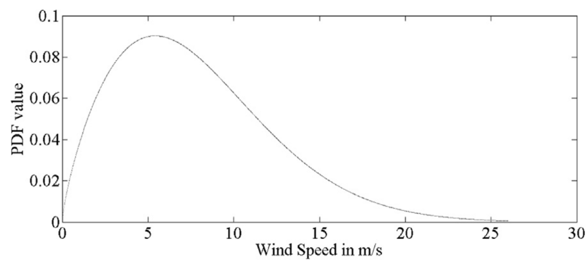

Fig. 4. Typical PDF of wind speed.

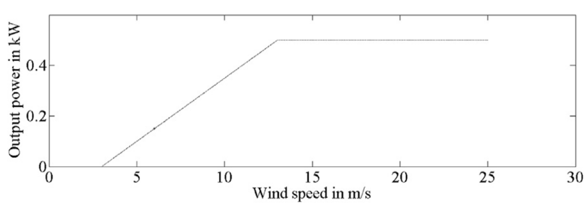

Fig. 5. Output power of a wind turbine versus wind speed.

Where s represents solar irradiation in kW/m^2 , α and β are parameters of Beta distribution. Fig. 6 shows the PDF of a typical PV generator while the parameters of Beta distribution has been set as $\alpha = 6.38$ and $\beta = 3.43$.

- Electricity price

Electricity price is another uncertain parameter in power systems [22]. It may be modeled as a Gaussian PDF whose mean is equal to the forecasted price [23]. In some cases, a fraction of forecasted price value is taken as the standard deviation of PDF.

$$PDF(p) = \frac{1}{\sqrt{2\pi\sigma_p}} exp\left[-\frac{(p-\mu_p)^2}{2\sigma_p{}^2}\right] \tag{5}$$

Where p denotes electricity price, μ_p and σ_p respectively represent mean (forecasted) and standard deviation of electricity price.

Now, after introducing common probability density functions of various uncertain power system parameters, different well-known probabilistic uncertainty handling techniques are described and reviewed.

2.1.1. Monte Carlo simulation

Monte Carlo simulation (MCS) is a very common method for handling power system uncertain parameters. Assume that input-output relation of a power system is represented by the following function.

$$y = f(X, Z) \tag{6}$$

Where X represents the set of uncertain input parameters, such as loads, generated power of wind generators and PV generators, electricity price, decisions of distributed generator (DG) owners, Z represents the set of decision variables such as location of DG units and y represents the output of the system such as power loss, reliability metric, net present value.

In MCS, while the termination criterion is not met, with fixed value of Z, samples of X are generated using PDF's, then the corresponding y values are calculated using input-output relationship. The, the output variable y is represented by a Gaussian PDF whose mean and standard deviation are given by calculating mean and standard deviation of these y values. Therefore, in MCS, the PDF of output variable is found using PDF's of input parameters [6].

Assume that an optimisation problem with an objective function, represented by (6), with some uncertain decision variables is going to be solved by a metaheuristic optimisation algorithm. As an example, assume that the location of DG units in a distribution system is going to be found in a way that power loss is minimised, while the uncertainty of loads are taken into account. In this example, X represents loads with

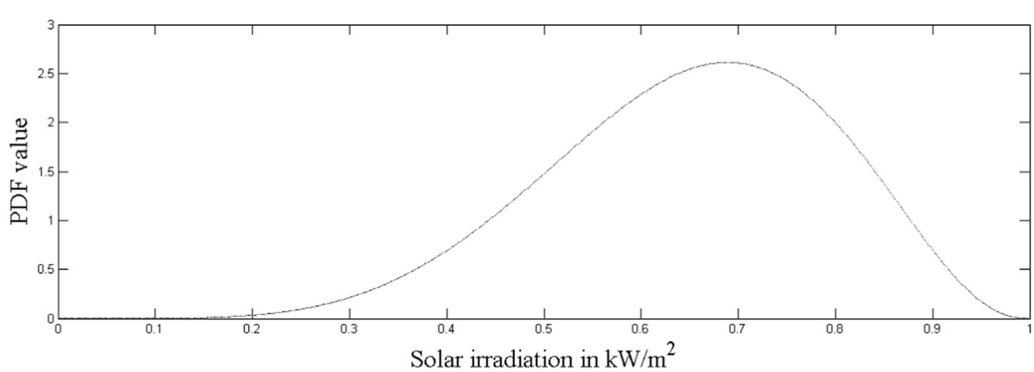

Fig. 6. PDF of a typical PV generator.

known PDF's, Z represents the location of DG units that must be found in optimisation process and y represents power loss of the system. In MCS, for each individual (search agent), with fixed value of Z, different samples of decision variables are generated using PDF's and the objective value is calculated for each one. Then, the mean of objective values is considered as the merit of that individual. In this case, different individuals are evaluated at different iterations and when the termination criterion is met, the best individual is selected as optimal solution. The pseudocode of MCS can be seen below. In this pseudocode, n denotes the number of MCS trials, *me* and *std* respectively represent mean and standard deviation of the Gaussian PDF of y.

For i = 1: n
Generate sample $X_{e,i}$ using PDF of uncertain decision variables.
Calculate $y_{e,i} = f(X_{e,i}, Z)$
End for

$$me = \frac{\sum_{i=1}^{n} y_{e,i}}{n}$$

$$std = \sqrt{\frac{\sum_{i=1}^{i=n} (y_{e,i} - me)^2}{n}}$$

The more the number of trials is, the more accurate results is achieved, although the computational time increases. It should be noted here that by increasing the number of uncertain parameters, the required trials of MCS is increased. Overall, the simplicity is the most important advantage of using MCS for dealing with uncertain parameters, although it is a computationally expensive technique.

In [24], MCS has been used for handling uncertainties of loads and electricity price in multi-stage expansion planning of distribution networks. Both loads and electricity price have been modeled using Gaussian PDF. In the coordinated multi-stage expansion planning of distribution network and DG's, the installation year, location and capacity of new substations, lines and substations have been determined by particle swarm optimisation (PSO), while the total cost of distribution network has been taken as objective function. The proposed methodology has been validated on a 9-bus distribution network and a real-world distribution network.

In [25], MCS has been used for dealing with uncertainties of loads, output power of plug-in electric vehicles, wind and PV generated power in optimal allocation of DG's. Gaussian PDF has been used for output power of plug-in EV and load values. It is assumed that at peak hours, the PEV injects power to the grid, while at off-peak hours it absorbs power from grid. On the other hand, Weibull PDF has been used for both wind speed and solar irradiation. Optimal size and location of DG units has been found by GA. The optimisation problem has been formulated as a chance-constrained problem with the following chance constraint.

$$prob(I_i - I_{i,max} \leq 0) \geq \gamma \quad (i = 1, 2, ...) \tag{7}$$

Where I_i and $I_{i,max}$ respectively represent current and maximum allowable current of i th branch and γ is the desired confidence level.

The described constraint holds the probability of overload in each branch at a level higher than or equal to γ.

In [26], MCS has been used for handling uncertainties of wind power, loads and vehicle to grid (V2G) power in economic load dispatch problem. Loads and V2G power have been modeled by Gaussian PDF and wind speed has been represented by Rayleigh PDF which is a special case of Weibull distribution whose shape factor is equal to 2. Interior point strategy has been integrated into PSO and the developed optimisation algorithm has been applied to economic dispatch problem in IEEE 118 bus power system. The results indicate the outperformance of hybrid interior point-PSO over differential evolution (DE), genetic algorithm (GA) and a PSO variant.

In [27], uncertainties of different charging schemes of PHEV's have been modeled by different PDF's and the effect of charging scheme on energy management of microgrids have been investigated [28]. Uncontrolled charging scheme has been modeled by a rectangular PDF from 9.00 P.M. to 12.00 P.M., while controlled charging scheme has been modeled by a rectangular PDF from 6.00 P.M. to 7.00 P.M. Eventually, smart charging scheme has been modeled by a Gaussian PDF. The vehicle daily mileage has been represented by log-normal PDF. Optimal scheduling problem for different DG units, including PV, wind, mircroturbine, fuel cell and battery has been formulated for minimisation of total cost of microgrid. Symbiotic organisms search algorithm has been used for optimisation, which outperformed GA, conventional PSO and some other PSO variants. The simulation results testified that the charging scheme significantly affects the cost of microgrid.

In [29], in transmission expansion planning (TEP) problem, MCS have been used for dealing with the uncertainty of loads. Load uncertainty has been modeled by Gaussian PDF. Optimal location, installation date and number of new transmission lines have been found in a way that the planning cost including loss of load cost is minimised. Shuffled frog leaping algorithm (SFLA) has been used for optimisation and has been validated by comparing with PSO and GA. Only, two major loads of the test system have been considered uncertain and the results of stochastic TEP and deterministic TEP have been compared. In [30], MCS has been used for dealing with uncertainties of outage of generating units and transmission lines, uncertainties of wind power generation and demands in unit commitment problem. The UC problem has been formulated as a mixed-integer linear programming problem and has been solved by mixed-integer linear programming (MILP) technique.

In [31], MCS has been used for handling uncertainties in transmission expansion planning, while the uncertainties of loads and wind power have been taken into account. Costs, reliability and social welfare have been included in objective function and PSO has been used for optimisation. The simulation results indicate the outperformance of PSO over GA in TEP problem for the used test systems. The effect of uncertainties on TEP results has been investigated. It must be noted here that, other than the above-mentioned works, in [32–44], MCS has been used for dealing with different kinds of power system uncertainties.

2.1.2. Scenario-based analysis

Scenario-based analysis (SBA) is another common strategy for dealing with uncertain parameters. In this approach, the PDF curve of uncertain parameter is subdivided into a number of regions. Then, using PDF, the probability of falling uncertain variable within each region is calculated. Each region corresponds to a scenario and we assume that we have scenarios $i = 1, 2, ..., i, ..., K$ with probabilities $P_1, P_2, ..., P_i, ..., P_k$. The average of lower and upper bounds of region i, denoted as X_i, is considered as the value of uncertain parameter in that region. Then the expected value of output variable y is calculated as follows:

$$y = \sum_{i=1}^{K} P_i X_i \tag{8}$$

It must be noted here that higher number of scenarios increases the accuracy of the achieved results at expense of higher computational burden.

In [45], the uncertainties of wind speed and solar irradiation have been respectively represented by Weibull and Beta distribution functions and scenario-based analysis have been used for handling those uncertain parameters. In such an uncertain environment, optimal location and size of wind and PV generators have been found in a way that power loss and voltage stability index are optimised. PSO has been used for optimisation. In [46], scenario-based analysis has been used for dealing with uncertainties in unit commitment problem. The uncertainties of loads, PV generation, wind generation and PEV power have been modeled by discrete PDF's. Unit commitment has been done in presence of wind and PV resources and PEV's, while PSO has been used for minimisation of costs and emissions. In [47], scenario-based analysis has been used for dealing with uncertainties of wind and PV power in optimal scheduling of DG units. Wind speed has been modeled by Rayleigh PDF and solar irradiation has been modeled by Beta distribution. Three scenarios have been defined for each uncertain parameter, i.e. wind speed and solar irradiation.

In [48], scenario-based analysis has been used for dealing with the uncertainty of real-time prices in price-based demand response program. Risk-based optimal scheduling of home appliances including electric water heaters has been done for 5-min time slots. A minimum and a maximum limit for hot water tank volume have been pre-specified. Electric water heater is considered as a shiftable and interruptible appliance if the hot water tank volume is within the specified range, while it is considered as a non-interruptible and non-shiftable appliance if the hot water tank volume violates the specified range. Optimal scheduling problem has been formulated as a mixed integer nonlinear programming problem, whose objective is a weighted sum of the expected bill payment and risk. The comfort of the residential consumers has been considered as the constraints of the problem.

In [49], Scenario-based analysis (SBA) has been used for dealing with the uncertainties in unit commitment problem of microgrids including dispatachable, PV and wind generating units. In UC, energy and reserve scheduling has been done and a minimum total spinning reserve has specified for the microgrid. The uncertainties of load and renewable power generation have been considered. For a microgrid with one PV generator and one wind unit, based on normal PDF's for forecasting errors, 75 different scenarios have been created. A specified occurrence probability is assigned to each scenario. In order to alleviate the effect of uncertainties in loads and renewable power generation, the required spinning reserve of the microgrid has been increased. The results show that when the uncertainties are taken into account, the total operational cost of the microgrid increases. This is due to the fact that because of the uncertainty, the required spinning reserve increases which results in the increase of the operational cost of the microgrid. The results also indicate the increase of the operational cost by increase in the severity of the uncertainties. However, in this research, the uncertainty of market price has not been taken into account.

In [50], scenario-based analysis has been used for dealing with the uncertainties in unit commitment problem of microgrids with different renewable and non-renewable generating units and storage units. The uncertainties of loads, PV and wind generation and market price have been considered. Different scenarios have been generated and in order to reduce the computational burden, a scenario reduction strategy has been used. Indeed, in the scenario reduction, 20 scenarios have been selected out of 2000 scenarios. The wind speed has been modeled by Weibull PDF, while PV power generation, market price and load have been modeled by normal PDF's. Unit commitment results with and without considering the uncertainties have been compared.

In [51], during the optimal scheduling of appliances in smart home microgrids for demand response programs, the uncertainties of PV generation, wind generation and EV availability have been modeled by probability density functions and are dealt with scenario-based analysis approach. The home appliances participating in demand response program includes diverse appliances such as EV, HVAC and EWH. The wind speed has been modeled by Weibull distribution, solar irradiation has been modeled by Beta distribution and EV's arrival time, departure time and state of charge has been modeled by truncated Gaussian distribution. Roulette Wheel Mechanism has been used for scenario generation. Considering the mentioned uncertainties, optimal scheduling of appliances has been determined in order to minimise bill payment and response fatigue index.

In [23], SBA and MCS have been used for dealing with uncertainties during simultaneous planning of PHEV charging stations and wind generators. It is assumed that charging/discharging program of PHEV's are smartly controlled by distribution system manager (DSM) and DG's are assumed to be owned by private sector. While DSM and DG owner (DGO) have conflicting objectives, a benefit sharing scenario has been used for dealing with this issue. Uncertainty of loads, electricity price and presence percentage of PHEV's in charging station have been modeled by Gaussian PDF's and have been handled by MCS. Wind speed has been modeled by Weibull PDF and has also been handled by MCS. On the other hand, initial state of charge of PHEV's has been modeled by Gaussian PDF and has been dealt by SBA. Benefits of charging/discharging programs, benefit of reliability improvement and benefit of power loss reduction, all have been included in the objective function [52] and NSGA2 has been used for optimising the objective function and generating pareto fronts. Some other applications of SBA in handling power system uncertainties can be found in [53,54].

2.1.3. Point estimate method

Point estimate method (PEM) has been frequently used for dealing with uncertain parameters in electric power systems. It works based on the moments of uncertain input parameters and characterises output variable as a Gaussian PDF. In the case where we have m uncertain parameters, it works as follows [55].

1. Set $E(Y) = 0$, $E(Y^2) = 0$, $k = 1$
2. The locations and probabilities of concentrations $\varepsilon_{k,i}$ and $P_{k,i}$ are calculated as below.

$$\varepsilon_{k,i} = \frac{M_3(X_k)}{2\sigma_{X_k}^3} + (-1)^{i+1}\sqrt{n+0.5\left(\frac{M_3(X_k)}{\sigma_{X_k}^3}\right)^2}$$

$$P_{k,i} = (-1)^i \frac{\varepsilon_{k,3-i}}{2n\sqrt{n+0.5\left(\frac{M_3(X_k)}{\sigma_{X_k}^3}\right)^2}}$$

   Where $M_3(X_k)$ represents the third moment of X_k .
3. Calculate the concentration points $X_{k,i}$ as below.

   $X_{k,i} = \mu_{X_k} + \varepsilon_{k,i}\sigma_{X_k}$ *for* $i = 1, 2.$

   Where μ_{X_k} and σ_{X_k} respectively represent mean and standard deviation of X_k .
   Then, calculate f for both $X_{k,i}$ as

   $X = [X_1, X_2, \ldots, X_{k,i}, \ldots, X_n](i = 1, 2)$

   Where n represents the number of uncertain variables and f is the function that relates output and inputs.
4. Calculate $E(Y)$ and $E(Y^2)$ by the following equations.

$$E(Y) = E(Y) + \sum_{i=1}^{2} P_{k,i} f(X_1, X_2, \ldots, X_{k,i}, \ldots, X_n)$$

$$E(Y^2) = E(Y^2) + \sum_{i=1}^{2} P_{k,i} f^2(X_1, X_2, \ldots, X_{k,i}, \ldots, X_n)$$

5. $k = k + 1$ if $k \geq n$ continue, otherwise go to step 2.
6. Mean and standard deviation of output is calculated by the equations below.

$$\mu_y = E(Y)$$

$$\sigma_y = \sqrt{E(Y^2) - E^2(Y)}$$

As it is evident from the described performance of PEM, it needs only $2n$ function evaluations, when n represents the number of uncertain parameters. Therefore, it is considered a computationally inexpensive method.

In [6], an unsymmetrical two-point estimate method has been used for dealing with uncertainties of loads, PV generators and wind generators in distribution networks. The loads have been modeled using Gaussian PDF, the wind speed has been modeled using Weibull PDF and solar irradiation has been modeled by beta distribution function. The power loss of the network and the power imported from upstream grid have been taken as outputs of the system and their PDF's have been found. For evaluating the performance of the proposed unsymmetrical two-point estimate method, MCS has been done and used as a basis for comparison. The results on a 9-bus distribution system and a real-world 574-bus distribution network shows that the proposed unsymmetrical two-point estimate method offers low computational time and outperforms symmetrical two-point estimate method, Gram-Charlier method and Hypercube sampling method. In [56], two-point estimate method has been used for dealing with uncertainties in optimal scheduling of solar and wind generators, fossil-fueled generators and storage devices, considering the uncertainties of wind speed, solar irradiation and loads. Both wind speed and solar irradiation have been modeled by Weibull distribution function. GA has been used for optimising the objective function, while interior point method and MCS have been used for validation of the proposed methodology. Some other applications of point-estimate method can be found in [57–65].

2.2. Possibilistic approaches

The idea of Possibilistic uncertainty modeling was introduced by Zadeh [66]. In this approach, the input uncertain parameters are represented by appropriate fuzzy membership functions. Then, α-cut method is used to find membership function of output variable, using membership function of input variables. After applying α-cut method and finding membership function of output variable, a defuzzification strategy is used to defuzzify the output and give out a crisp output value. Centroid method is a commonly used defuzzification strategy.

In [67], possibilistic method was used for dealing with uncertainties in environmental-economic dispatch in a microgrid with diverse generating units. The uncertainty of electricity price was modeled as a triangular fuzzy membership function and Net present value, including environmental objective and different economic-based objectives, was used as objective function. Quadratic programming and PSO were used for optimising objective function. In [68], possibilistic approach was used for handling uncertainties during the configuration and DG allocation in distribution networks. The uncertainty of loads has been modeled by triangular fuzzy membership functions. Operational costs, power loss, emissions and voltage stability index were included in objective function and a multi-objective big bang-big crunch optimisation algorithm was used for optimisation, while fuzzy decision making was used for finding the compromised solution. The results on two distribution networks indicated the outperformance of used optimisation algorithm over NSGA2, multi-objective PSO and multi-objective ABC. Another application of Possibilistic approach in handling power system uncertainties may be found in [69].

2.3. Hybrid probabilistic-possibilistic approaches

In some cases, some uncertain parameters have known PDF's, while other uncertain parameters are modeled as fuzzy membership functions. In such cases, "hybrid probabilistic-possibilistic approaches" are used for handling uncertainties, in a way that some uncertain parameters are handled probabilistically and some other uncertain parameters are handled possibilistically. In these approaches, commonly, either fuzzy arithmetic along with MCS [70] or fuzzy arithmetic along with scenario-based analysis is used [71].

In [71], a hybrid probabilistic-possibilistic approach has been used to investigate the impact of DG's on the performance of distribution systems, considering the uncertainties of loads, uncertainties of renewable DG generation and uncertainties of DG owners/operators' decisions. It is assumed that in the considered deregulated electricity market, due to unbundling rules, the distribution network operator (DNO) is not allowed to own DG units and therefore cannot determine the location and size of DG units. Loads and generated power of wind turbines have been modeled probabilistically, since their historical data and PDF is available, however, the operating/investment decisions of DG owners has been modeled possibilistically due to lack of historical data. Since, the installed capacity of both renewable and non-renewable DG units are decided by DG owners, their installed capacity has been modeled as the following fuzzy trapezoidal membership function.

$$\widetilde{Cap}_{i,t} = (a_{min}, a_L, a_U, a_{max}).\ Cap_{i,t} \tag{9}$$

Where a_{min}, a_L, a_U and a_{max} are four points of the formed trapezoid, and $Cap_{i,t}$ is the forecasted installed DG capacity at bus i and year t.

The apparent power of non-renewable DG's, such as gas turbines are decided by DG owners/operators. Therefore, they have also been modeled possibilistically as a fuzzy trapezoidal membership function. Loads have been modeled by a fuzzy trapezoidal membership function. Assuming that the forecasted value of load's apparent power at bus i and year t is $S_{i,t}^D$ and the annual demand growth rate is ε_D, the apparent power of bus i in year t has been modeled as the following fuzzy trapezoidal membership function.

$$\tilde{S}_{i,t}^D = \left(1-D_u,\ 1-\frac{D_u}{2},\ 1+\frac{D_u}{2},\ 1+D_u\right).\quad S_{i,t}^D(1+\varepsilon_D)^2 \tag{10}$$

Where D_u denotes the uncertainty factor of load.

Fuzzification, α-cut method and defuzzification have been used for handling possibilistic uncertain parameters. Wind speed has been modeled probabilistically, using Rayleigh distribution function. A voltage risk factor has been defined which reflects both the probability of over/under voltages and their severity. For dealing with probabilistic uncertain parameters, scenario-based analysis has been used. It subdivides the whole area of PDF curve into a couple of regions, called as states, and finds the probability of occurrence of each state. Then, the expected value of output is calculated using (8). The impact of DG location, installation year and penetration level on voltage risk factor and power loss has been investigated. Moreover, a comparison between scenario-based analysis (SBA) and Monte Carlo simulation (MCS) has been done. It indicates that SBA offers results close to those of MCS, but with a very lower computational burden. Even, in a large-scale system, SBA is computationally inexpensive. Some other applications of hybrid probabilistic-possibilistic approaches may be found in [72,73].

2.4. Other uncertainty handling approaches in power systems

Besides the three main categories of uncertainty handling approaches, there exists some other methods that are used for handling power system uncertainties. These methods are normally used when the uncertain parameters cannot be represented either as PDF's or as fuzzy membership functions (due to lack of sufficient information or historical data). Interval analysis is one of these approaches, wherein the ranges of output variable(s) is found based on the known ranges of input variables [74–78]. In [79], interval analysis has been used for dealing with power system uncertainties, while reliability of system is maximised using system reconfiguration.

Information gap decision theory (IGDT), proposed by Ben-Haim [80], is another technique for dealing with uncertainties and has been frequently applied for dealing with power system uncertainties. IGDT is a technique that is typically used for dealing with problems including severe uncertainties, where the PDF, MF or interval of uncertain parameters is unknown. Indeed, it does not need PDF or MF of uncertain parameters or their interval [81,82]. Assume that the following optimisation problem must be solved.

$$y = f(X, Z)$$

St. (11)

$$G(X, Z) \leq 0$$

$$H(X, Z) = 0$$

Where X represents the uncertain input parameters and Z represents decision variables.

First, (11) is solved assuming that the forecasted input uncertain parameters $\bar{X}$ are accurate and have zero error. The found optimal y is denoted by $\bar{y}$. This means that if the input parameters are equal to their forecasted values, then $\bar{y}$ would be the optimal objective value. There are two IGDT-based models; risk-averse model and risk-seeking (opportunistic) model.

In risk-averse IGDT model, if the values of uncertain input parameters are unknown, IGDT tries to find a solution which is robust against forecasting errors (the variations of uncertain input parameters). In risk-averse IGDT model, the robustness is defined as the immunity of the satisfaction of a predefined constraint [2]. Risk-averse IGDT model tries to always keep the objective below a predefined threshold l_c, no matter how the uncertain input parameters move far from their forecasted (nominal) values. In risk-averse IGDT model, the optimisation problem in (11) is firstly converted into (12).

$$f(X, Z) \leq l_c$$

$$l_c = \delta\bar{y}$$

$$\delta = (1+\varepsilon)$$

St. (12)

$$G(X, Z) \leq 0$$

$$H(X, Z) = 0$$

Where ε is the degree that decision maker tolerates the deterioration of the objective [2].

In IGDT, α as the uncertainty horizon of X is defined as below [82].

$$X \in U(\alpha, \bar{X}) \tag{13}$$

$$U(\alpha, \bar{X}) = \left\{X \left| \left|\frac{X - \bar{X}}{\bar{X}}\right| \leq \alpha \right.\right\}$$

The robustness of a decision Z with the minimum satisfaction level l_c is defined as the maximum value of α at which the decision maker is sure that all the constraints are met. The resulted optimisation problem is formulated as (14) [83].

$$\begin{aligned}
&Max\alpha(l_c, Z)\\
&\forall\ X \in U(\alpha, \bar{X})\\
&f(X, Z) \leq l_c\\
&l_c = \delta\bar{y}\\
&G(X, Z) \leq 0\\
&H(X, Z) = 0
\end{aligned} \tag{14}$$

The objective function in (14) is referred to as robustness function. It means that in IGDT, the decision variables are found in a way that the robustness with respect to uncertain variables is maximised, while the minimum satisfaction level is met.

On the other hand, in risk-seeking (opportunistic) IGDT model, a target performance l_w is defined as below.

$$l_w = \gamma\bar{y}$$

Where γ is a coefficient higher than unity. Then, the opportunity function is constructed as below.

$$\begin{aligned}
&Min\ \alpha(l_w, Z)\\
&\exists\ X \in U(\alpha, \bar{X})\\
&f(X, Z) \geq l_w\\
&G(X, Z) \leq 0\\
&H(X, Z) = 0
\end{aligned} \tag{15}$$

Indeed, risk-seeking IGDT model gives the least required deviation in uncertain input parameters that achieving at least l_w for objective is possible [84].

In [84], both risk-averse and risk-seeking IGDT models have been used to find optimal generating power of GenCos in order to maximise their profit, while the uncertainties of pool market price and outage of generating units have been considered. The effect of the minimum satisfaction level (critical profit) and robustness parameter on the optimal schedule of generating units have been investigated. An after-the-fact analysis was done and showed that in the cases where the market prices were overestimated, the robust formulation resulted in higher profits, while for underestimated price forecasts, the opportunistic formulation led to higher profits. It was also confirmed that introducing robustness and risk into the operation scheduling comes at a cost.

In [85], risk-averse IGDT has been used to find the share of different sources for distribution system operator (DNO) in supplying future demand. The three possible sources for DNO are bilateral contracts, pool market and DG's inside the distribution network. Indeed, the shares of mentioned sources form three decision variables of the optimisation problem, while the objective is minimisation of total costs of DNO. The capacity of DG's (the decision of DG owners), the pool market price and demands are the considered uncertainties. First, the optimisation problem has been solved for the forecasted values and then the uncertainty horizons guaranteeing different tolerances have been found.

In [86], similar to [84], risk-averse and risk-seeking IGDT models have been used to find optimal generating power of GenCos in order to maximise their profit, while the uncertainties of pool market price has been considered. In [87], similar to [84], but considering demand response programs, IGDT models have been used to find optimal generating power of GenCos.

In [88], IGDT has been used for optimal bidding of a thermal generating unit in day-ahead electricity market, considering the uncertainty of market price. In risk-averse IGDT model, optimal bidding has been found for different time intervals in a way that the profit of generating unit is kept above a predefined threshold. On the other hand, in risk-seeking IGDT model, optimal bidding has been found for different time intervals in a way that there exists the possibility of achieving a target profit by favorable deviations of market price. In [89], IGDT model has been used in optimal power flow (OPF) for HVDC-incorporated power systems, considering the uncertainty of wind power. The generated power and voltage of generating units are found by both risk-averse and risk-seeking IGDT models. In [90], IGDT has been used in transmission expansion planning (TEP) of power systems, considering the uncertainty of capital costs and demand.

In [91], both risk-averse and risk-seeking IGDT models have been used for congestion management in power systems, considering the uncertainty of wind power generations. Demand response (DR) programs have been included. The DR schedule and reactive power of wind generators at different time intervals are found in a way that the power congestion is minimised. In [92], both risk-averse and risk-seeking IGDT models have been used to find the share that a retailer buys its electricity from different sources including forward contracts, pool market and internal DG's. The selling price of retailer is the forth decision variable. The uncertainty of pool market price has been considered, however the uncertainty of forward contract price and the uncertainty of clients' response to the retailer's price have not been taken into account.

In [93], the risk-averse IGDT model has been used to find the scheduling of a wind power generator in order to maximise its profit.

Table 1
Main features of some research works on uncertainty handling in power systems.

Ref	Considered uncertain parameters	PDF/MF used for each uncertain parameter	Uncertainty handling method	Category of uncertainty handling method	Remarks
[6]	Load, wind speed, solar irradiation	Gaussian for load, Weibull for wind speed and Beta for PV's solar irradiation	Unsymmetrical two-point estimate method	Probabilistic	The unsymmetrical two-point estimate method outperforms symmetrical two-point estimate method, Gram-Charlier method and Hypercube sampling method.
[56]	Load, wind speed, solar irradiation	Gaussian for load, Weibull for wind speed and solar irradiation	two-point estimate method	Probabilistic	Optimal scheduling of generating units has been done in an uncertain environment. MCS have been used for validation of the proposed PEM.
[31]	Load, wind speed	Gaussian for load, Weibull for wind speed	MCS	probabilistic	Transmission expansion planning has been done for optimising reliability, costs and social welfare. PSO has been used for optimisation.
[29]	Load	Gaussian PDF for load	MCS	Probabilistic	In transmission expansion planning, considering load uncertainties, planning cost including loss of load cost is minimised. Shuffled frog leaping algorithm has been used for optimisation.
[24]	Load, electricity price	Gaussian	MCS	Probabilistic	Expansion planning of distribution network has been done, considering uncertainties of load and electricity price. It has been assumed that the location and capacity of DG's can be decided by DNO.
[25]	Output power of plug-in EV, load, wind speed, solar irradiation	Gaussian PDF for output power of PEV's and load, Weibull PDF for wind speed and solar irradiation	MCS	Probabilistic	Optimal size and location of DG units have been identified in an uncertain environment.
[45]	Wind speed, solar irradiation	Weibull PDF for wind speed, beta distribution for solar irradiation	Scenario-based analysis	Probabilistic	Optimal location and size of wind and PV units have been found, considering their uncertainties. Power loss and voltage stability index have been used as objective functions.
[23]	loads, electricity price and presence percentage of PHEV's in charging station, wind speed, initial state of charge of PHEV	Gaussian PDF's for loads, electricity price, presence percentage of PHEV's, initial state of charge of PHEV's, Weibull PDF for wind speed.	Both MCS and SBA have been used.	Probabilistic	Uncertainty of loads, wind speed, electricity price and presence percentage of PHEV's in charging station have been handled by MCS. Uncertainty of initial state of charge of PHEV's has been dealt by SBA.
[67]	Electricity price	Triangular fuzzy MF	possibilistic	Possibilistic	Considering the uncertainty of electricity price, an environmental-economic dispatch in a microgrid with different generating units has been done.
[68]	Load	Triangular fuzzy MF	possibilistic	Possibilistic	Considering the uncertainty of loads, reconfiguration and DG allocation has been done.
[46]	Load, PV generation, wind generation, power of PEV	Discrete PDF's for uncertain variables	Scenario-based analysis	probabilistic	Unit commitment has been done in presence of renewable energy resources and PEV's, considering their uncertainties.
[26]	Load, wind speed, output power of V2G	Gaussian PDF for load, output power of V2G, Rayleigh PDF for wind speed	MCS	probabilistic	In an uncertain environment, optimal economic dispatch of electric vehicles and wind generators has been done by hybrid of interior point method and PSO.
[27]	Wind, PV, output power of PHEV's	Rectangular PDF for uncontrolled and controlled PHEV charging, Gaussian PDF for smart PHEV charging. The PDF of solar irradiation and wind speed has not been mentioned.	MCS	probabilistic	The effect of charging scheme on energy management of microgrid has been investigated. The simulation results testify that the charging scheme significantly affects the cost of microgrid.
[47]	Wind, PV	Rayleigh PDF for wind speed, beta distribution for solar irradiation	SBA	probabilistic	Optimal scheduling of PV, wind and biomass units has been done considering uncertainties of wind and PV.
[71]	Load, installed capacity of DG units, apparent power of DG's, wind power	Rayleigh PDF for wind speed, fuzzy trapezoidal MF for loads, installed capacity of DG units and apparent power of DG's.	Hybrid probabilistic- Possibilistic approach. SBA has been used for probabilistic analysis.	Hybrid probabilistic-possibilistic	The effects of DG's uncertainties and load uncertainties on performance of distribution systems have been investigated.

The uncertainties of day-ahead market price and wind power generation have been taken into account. In [94], both risk-averse and risk-seeking IGDT models have been used for solving unit commitment problem in power systems, including wind power generators and demand response programs. The uncertainty of wind power generation has been considered. In [95], information gap decision theory (IGDT) has been used for dealing with uncertainties in unit commitment problem of microgrids considering time of use demand response program. The uncertainties of loads, PV and wind generation have been considered.

Robust optimisation is another technique, used for dealing with uncertainties [96,97] and uses uncertainty sets for characterizing uncertainty of input parameters. It has been applied for dealing with power system uncertainties [98,99]. In [98], robust optimisation has been used for dealing with the uncertainties of wind power generation and demand response in unit commitment problem. Considering these uncertainties, UC has been formulated as an optimisation problem that is solved by Benders decomposition. The proposed robust UC model is designed for the reliability unit commitment (RUC) phase in the daily market operation. The RUC phase is done by the ISO after the clearance of the day-ahead energy market [98]. In [99], robust optimisation has been used for dealing with uncertainties of demands in power system expansion planning problem.

Table 1 has tabulated main features of some research works on uncertainty handling in power systems.

3. Overall review on uncertainty handling research works and some directions for future research

After reviewing the existing research works on uncertainty handling in electric power systems, the following points must be considered.

- Overall, MCS and SBA are the simplest methods for handling uncertainties. They are simpler than PEM and Possibilistic methods. However, they are computationally expensive. Assume that for a problem with n uncertain parameters, k samples are generated for each uncertain parameter. Then, in MCS and SBA, k^n function evaluations are required, while in PEM, only $2n$ function evaluations is required. As an example, for 5 uncertain parameters and 20 samples for each uncertain parameter, in MCS and SBA 3,200,000 function evaluations are required, while in PEM, only 10 function evaluations is needed.
- Developing novel probabilistic uncertainty handling methods with more accuracy and lower computational burden is recommended for future research.
- In practice, in most cases, there exists correlation among different uncertain power system parameters, however, only a few research works have taken the correlation among them into account [100]. Considering the correlation among different uncertain power system parameters in a realistic way is recommended for future research.
- A comprehensive comparison of the performance of different uncertainty handling methods, in terms of the accuracy and computational burden, in handling power system uncertainties, is recommended for future research.
- In most of the research works in power systems, uncertainties are not taken into account and uncertain parameters are treated as certain deterministic parameters. In order to have a realistic modeling, different uncertainties of power systems must be taken into account, so that realistic results are achieved in power system studies.

4. Conclusions

In this paper, the diverse sources of uncertainties in power systems have been mentioned and different uncertainty handling methods have been classified and reviewed in details, mentioning the advantages and disadvantages of each method. Uncertainty handling methods have been classified into three main categories; i.e. probabilistic methods wherein the uncertain parameters are characterised by probability density functions and include methods such as Monte Carlo Simulation, scenario-based analysis and point estimate method. Possibilistic methods wherein the uncertain parameters are characterised by fuzzy membership functions (MF's) and hybrid probabilistic-possibilistic methods, wherein some uncertain parameters are characterised by PDF's and dealt with probabilistic methods, while some other uncertain parameters are characterised by MF's and dealt with possibilistic method. The findings of this review indicate that although a great deal of research effort has already been put for uncertainty handling in electric power systems, there is still room for improvement, so some directions for future research has been suggested.

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