Operation and Planning of Distribution Networks with Integration of Renewable Distributed Generators Considering Uncertainties: A Review

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Abstract

Distributed generators (DGs) are a reliable solution to supply economic and reliable electricity to customers. It is the last stage in delivery of electric power which can be defined as an electric power source connected directly to the distribution network or on the customer site. It is necessary to allocate DGs optimally (size, placement and the type) to obtain commercial, technical, environmental and regulatory advantages of power systems. In this context, a comprehensive literature review of uncertainty modeling methods used for modelling uncertain parameters related to renewable DGs as well as methodologies used for the planning and operation of DGs integration into distribution network.

The authors strongly recommend this review to researchers, scientists and engineers who are working in this field of research work.

Keywords: Distributed generation; Distribution system; optimization methods; uncertainty modelling.

1. Introduction

Provision of electric energy for consumers is mostly based on having centralized generation which involves use of conventional generators. Then, the generated electricity is transmitted via a transmission line to substations where the voltage is step down before the electricity is distributed for energy consumption. However, the centralized generation is characterized by the following challenges including transmission and distribution losses, high cost of fossil fuels, and greenhouse effect (greenhouse effect is a process whereby some of the sunlight energy to the earth is been trap by the atmosphere). Therefore, the distributed generators (DGs) have been adopted to overcome these challenges. Dispersed generation, district generation, decentralized generation, embedded generation, local generation, and on site generation, are all terms that refer to DG.

In order to help understand the DG concept, there are different definitions of DG in the existing literature [1-8], which are defined from the perspective of location and/or capacity.

With respect to location, DG can be defined as electric power generation source connected directly to distribution network or on the customer side (very close to the demand) [1, 2]. Also, it means small generating units installed in strategic places of the power network close to load centres [3-5]. In perspective of capacity, DG is a large number of small size power (500 kW and 1 MW) generating unit which are distributed within the distribution network [6]. While, others defined DG as the strategic placement of small power generating units (rating from 5 kW to 25 MW) at or near customer loads [2]. In perspective of location and capacity, DG is a small unit of power (usually with rating from less than 1 kW to many tens of MW) that is not a part of a large central power network and is located close to the load [7]. Small generation units of 30 MW or less located at or near consumer centres are also referred to with the same term [8]

In general, DG is defined as an electric power source connected directly to the distribution network or on the customer site of the network [1]. From the perspective of size, Ackerman et al. [1] have classified DG into four sizes as follows: micro distributed generation (1 W to 5 kW), small distributed generation (5 kW to 5 MW), medium distributed generation (5 MW to 50 MW) and large distributed generation (50 MW to 300 MW).

Currently, DGs installation in power systems are rapidly increasing due to its ability to maximize the usage of renewable energy such as wind, solar, hydro, geothermal, biomass and ocean energy etc. [1, 9-15]. According to Borges et al, DGs can be used in an isolated way to supply the consumer's local demand or in an integrated way to supply power to the remaining of the system [3]. Optimum priority during planning should be given to location, size, and types of DG in order to maximize the benefits of DGs [11]. Optimal allocation of DGs reduces system losses and leads to improvement in the voltage profile, enhances system reliability, load ability, voltage stability, voltage security, and power quality.

DG is considered as an alternative solution to supply power for new costumers especially in the competitive electricity market [5] for the following reasons : a) Quick response time and minimal risk to investment since it is built in modules ; b) Small-size modules that can track load variation more closely; c) The government approval for utilities and land availability can be discarded due to small physical size that can be installed at load centers; d) The successive improvement of DG technologies.

In the following literature, most of the studies have been carried out to investigate optimal methodologies in order to minimize the power losses and cost of DGs. For example, the authors in [16-19] have focused on reviewing the optimization methods used in DGs planning considering objectives, decision variables, and DG type applied constraints. While, in [20, 21] the authors have reviewed uncertainty modeling approaches for DGs planning to show both the weakness and robustness of these methods.

It is clearly shown from the above description that all the published review work was restricted to consider the DGs planning. According to the author's knowledge, there is no study that covers the uncertainty and optimization methods concurrently, which is most important for any researcher in DGs planning. With the above backdrop, the novelty of this work relates to review the optimization method used in DGs placement problem in addition to uncertainties methods.

This paper is organized in the following manner. Section 2 represents the details of DG include the technologies and types, applications and benefits. Section 3 illustrates the challenges to increased penetration of DG. Section 4 discusses DG planning models including objectives, constraints, uncertainties modeling methods, reliability indices under uncertainties, market and economic operation aspects of renewable DGs under uncertainty and mathematical algorithms. Finally, a conclusion is presented in section 5.

2. Distributed generation (DG)

2.1 Technologies and types

DGs technology can be classified into three types including renewable technology (green or sustainable), non-renewable technology (traditional) and storage technology [22-26]. Renewable technology comprises wind, solar (photovoltaic (PV) and thermal), bio-mass, geo-thermal, tidal and hydro-power (small and micro). Non-renewable technology comprises micro-turbine, gas turbine, reciprocating engines and combustion turbine. Storage technology comprises batteries, supercapacitor, flywheels, compressed air energy storage (CAES) and pumped storage. Each technology has its own benefits and properties [12-27]. Furthermore, the deployment of these technologies has started to take place in the electricity market, thereby providing an alternative means of meeting the customer load demand. Figure 1 depicts the classification of DGs technologies.

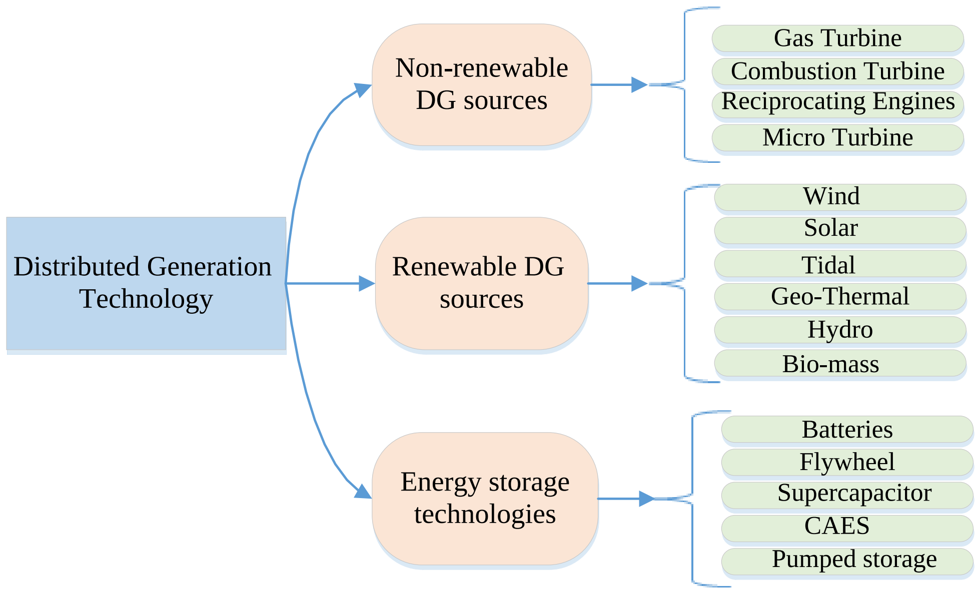

Figure 1: Distributed Generation Technologies

2.2 Applications

The types of DGs technologies that can be used in various applications according to the load requirements, includes [28, 29]:

- As stand-by sources for supplying the desired power for sensitive loads (e.g. hospitals) during grid outages.
- Standalone sources in isolated areas – rural and remote areas.
- As supply for peak loads at peak periods in order to reduce the power cost.
- To combine heat and power (CHP), also known as Cogeneration, by injecting power into the network.
- To supply part of load and support the grid by improving voltage profile, power quality and reducing the power losses.

- Grid connection to sell electric power.

2.3 Benefits

Several benefits can be attained by connecting DGs to distribution systems. These benefits are categorized into technical, economic and environmental benefit. Table 1, gives a description of these benefits according to their category [22, 28-33].

Table 1. DG benefits

Technical point of view	Economical point of view	Environmental point of view
• Integration of DG at strategic locations leads to reduced system losses. • Integration of DG provides enhanced voltage support thereby improving voltage profile. • Improved power quality. • Enhancement in system reliability and security. • Power supply autonomy of rural or isolated areas. • Increase overall electric power energy efficiency.	• Deferred investments for upgrade of facilities. • Lowering operation and maintenance cost. System productivity is enhanced due to diversification of resources. • It results to an indirect monetary benefit by reduce healthcare costs due to improved environment. • Reduced fuel costs due to increased overall efficiency. • Reduced reserve requirements and associated costs. • Lower operating costs due to peak shaving. • Reduction of investment risks.	• Reduced output emissions of pollutants. • Reduce global warming • Encourages use of renewable energy

3. Challenges

Today's DGs installations are facing multiple challenges that can be classified into four types; commercial, technical, environmental and regulatory. Overcoming of these challenges will lead to maximize the utilization of DGs[14, 17]. These challenges are better explained in Figure 2.

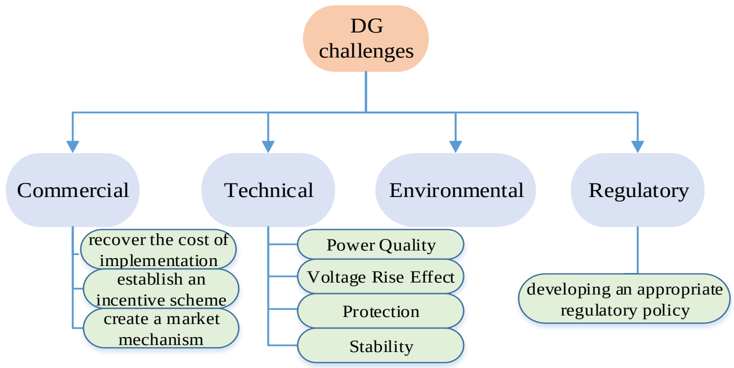

Figure 2: DG challenges

3.1 Commercial Challenges

The number of DGs can be increased by implementing active management approaches in distribution networks. New commercial arrangements need to be used in order to support the development of active distribution networks and extract the benefits associated with connecting increased amount of DGs. Generally, three approaches are possible [34]:

1- To recover the cost of implementation the active management directly through price controls mechanisms (increase the amount of recoverable capital and operate expenditure associated with active management). Recovery of cost could be achieved by increasing the charges of network usage.
2- To establish an incentive scheme that would reward the companies for connecting DGs, as has been recently developed in the United Kingdom [35]. These schemes could be funded from increasing the charges imposed on generators and/or customers such as a green levy.
3- To create a market mechanism and a commercial environment to develop active networks.

3.2 Technical Challenges

3.2.1 Power Quality

Power quality commonly takes into account two important aspects: harmonic distortion of the network voltage and transient voltage variations. DGs could decrease or increase the quality of the power factor, current and voltage received by other users of the distribution network which depends on the particular circumstances. Power quality improvement might be obtained by increasing the effect of network fault level. This is done through adding DG to the network [34].

3.2.2 Voltage Rise Effect

Voltage rise effect can occur when connecting DGs in the network. This is the main factor that limits the amount of extra DG capacity that can be connected to rural distribution networks. Optimal power flow under equality and inequality constraints could be used to control instability of power supply, and active and reactive power variations that are caused by the voltage rise effect [36, 37].

3.2.3 Protection

The connection of DGs to the distribution systems depends on some aspects that need to be identified [34]. These aspects are:

- Protection of the generation equipment from internal faults.
- Protection of the faulted distribution network from fault currents supplied by the DGs.
- Anti-islanding or loss-of-mains protection (islanded operation of DG will be possible in future as penetration of DG increases)

3.2.4 Stability

The design of distribution network and transmission network are considering the factor of stability under the impact of different circumstances. As a result, the issue of stability was not recommended to discuss. While, it is worthy to account the stability in case of dealing with DGs, which is hardly subjected to change for bigger network security. There are two areas that need to be considered to assess the renewable DG schemes: transient (first swing stability) as well as long term dynamic stability and voltage collapse [34].

3.3 Environmental

Increase DG usage is not always beneficial for the environment [38]. This is depending on the market share of the different DGs technologies. For example, DGs technologies which consume fossil fuels like fuel cells, micro turbines have more impact on the environment than renewable energy technology like hydroelectric, wind turbines and solar cells. However, even technologies such as Wind turbine are claimed to be environmentally damaging. As such it is critical to consider each technology carefully.

3.4 Regulatory

It seems that the developing of appropriate policies is so important to support the integration of DGs into distribution networks due to the absence of clear governmental regulations [39].

4. DG Planning Models

Optimal planning of distribution networks is a process to help supplying the power to loads of feeders in the presence of DGs in order to achieve maximum potential benefits of DGs with minimum costs. Optimal DG planning depends on two factors, technical constraints and the optimization of economic targets. Technical constraints refer to equipment capacity, voltage drop, radial structure of the network, reliability indices. The optimization of economic targets includes minimization of investment and operating costs, minimization of energy imported from transmission, minimization of energy loss, and reliability costs [40].

4.1 Objectives of DG integration

The objective functions that are mainly used in DG integration are as follows [11].

- Maximization of renewable DG penetration.
- Maximization of system reliability.
- Maximization of Distributed Generation Capacity.
- Maximization of social welfare and voltage profits.
- Reduction in system losses and improvement in voltage profile.
- Minimization of investment, operational cost and total payments toward compensating for system losses.
- Minimization of line loss.

4.2 Constraints of DG Planning

There are two types of constraints, equality constraints and inequality constraints.

1. Equality constraints consist of active and reactive power balance at each bus of the system.
2. Inequality constraints consist of voltage profile limits, line thermal limit, phase angle limit, traditional active and reactive power generation limits, substation transformer capacity limit, DG active and reactive power generation limits, number of DG limit, short circuit level limit, Intertie’s delivery power limit, power factor limit, tap position limit, total line loss limit, short circuit ratio limit and voltage step limits [11, 41].

4.3 Modeling of Uncertainties in the Planning of Renewable DGs

4.3.1 Uncertain parameters

Uncertain parameters can be classified into two different groups as follows [42]:

a. Technical parameters: includes demand values, generation values, forced outage of lines and generators or metering devices.

b. Economic parameters: includes uncertainty in the fuel supply, cost of production, market prices, business taxes, labor and raw materials, economic growth, unemployment rates, gross domestic product and inflation rates.

The abovementioned uncertain parameters are shown in Fig. 3.

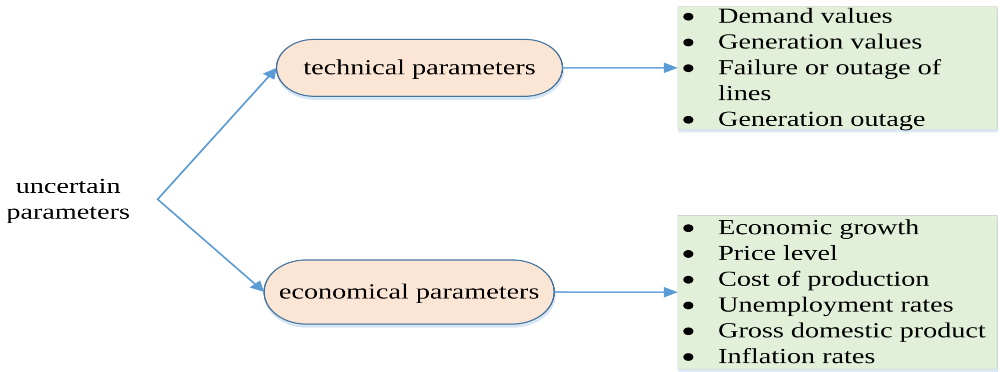

Figure 3: Uncertain parameters

4.3.2 Uncertainty Modelling Methods

There are several uncertainty handling approaches developed for dealing with the abovementioned uncertain parameters as illustrated in Fig. 4. This figure derives from ref. [20, 21] and gives a summary of the appropriate PDP (Power Distribution Problem) approaches to model uncertainty parameters. These approaches include robust optimization, interval analysis, probabilistic approach, possibilistic method, hybrid possibilistic - probabilistic approaches and information gap decision theory (IGDT) [20, 21]. The fundamental aim of these approaches is to measure the influence of uncertain input parameters on the output parameters in distribution networks. The details of these methods are described as follows:

a. Robust optimization (RO): Robust optimization approach was proposed by Soyster in 1973 [43]. In this method, the uncertainty groups are used to describe the uncertainty related to input parameters. The advantage of applying this technique is to obtain decisions that remain optimal for the worst-case investigation of the uncertain parameter within a specific group. In [44], the authors have proposed adaptive RO approach for multi-period economic dispatch under high level of wind resources penetration. Also this approach has been proposed in [45] to carry out an endogenous stress test for the spot prices as a function of the buy-and-sell portfolio of contracts and green energy generation scenarios. RO is adopted for scheduling of multi-micro grid systems considering uncertainties in variable renewable sources, forecasted load values and market prices [46]. The authors in [47] have established a RO with adjustable uncertainty budget (RO-AUB) model for coordinating reliability and economy of a large-scale hybrid wind/photovoltaic/hydro/thermal power system during uncertainty period in order to reduce the limitation while taking full advantage of clean energy and improving reliability of the system. RO method has been proposed in [48] to manage uncertainties related to electricity prices and battery demand. Also this method has been used in [49] to simulate the uncertainties associated with the load demand and the output power of the renewable DGs. In [50], RO is used to model the uncertainties associated with the electricity prices.

b. Interval analysis (IA): In 1966, Moore introduced interval analysis technique [51] assuming that the uncertain parameters are obtained values from a recognized interval. It is somewhat similar to the probabilistic modelling with a uniform PDF (probability density function). This technique finds the bounds of output variables. In [52] the probabilistic distribution-based interval arithmetic approach has been proposed to evaluate the effects of the uncertainties related to load demand. An approach based on the interval analysis has been proposed to solve the directional overcurrent relays coordination problem considering uncertainty in the network topology [53]. In [54], interval analysis techniques has been used to quantify the impact of uncertain data and to maximize the possibility of reliability improvement and/or loss reduction. The author in [55] have proposed interval analysis method for power flow solution of balanced radial distribution system.

c. Probabilistic approaches: One of the earliest work in probabilistic approach was carried out by Dantzing in 1955 [56]. This technique assumed that the PDF of input parameters variables are known. Probabilistic approaches can be classified into two groups: numerical and analytical approaches.

1. Numerical approaches

Monte Carlo Simulation (MCS) is one of the most common and accurate stochastic approach. This approach has been used in [57] to systematically sample from random processes (i.e. uncertainty in the load demands, the available capacity of conventional generation resources and the time-varying, intermittent renewable resources, with their temporal and spatial correlations, as discrete-time random processes) and emulate the side-by-side power system and transmission-constrained day-ahead market operations. In [58], MCS with the traditional Newton–Raphson method have been used to ensure the coverage of all the possible operating scenarios of the system based on the operating system boundaries and the accuracy of the solution. In [59],the problem of renewable DGs penetration in medium voltage distribution networks has been modelled with MCS which takes into account for the intrinsic variability of electric power consumption. In [60], MCS has been used to deal with the uncertainties related to load values, generated power of wind turbines and electricity market price. Also in [61], the uncertainty associated with load growth has been modelled by MCS, which delivers an estimate of the network response to a set of possible future load scenarios. The uncertainties related to intermittent generation of PVs and load demands are modelled by MCS in [62]. The authors in [63] have used combined MCS technique and optimal power flow to maximize the social welfare considering different combinations of wind speed and load demands over a year. In [64], MCS has been proposed to handle uncertainties including the stochastic output power of a plug-in electric vehicle (PEV), wind speed, solar irradiance, volatile fuel prices used by a fueled DG, and future uncertain load growth in the optimal siting and sizing of DGs. There are three types of MCS approach used for probabilistic uncertainty analysis:

Sequential Monte Carlo Simulation, Pseudo-Sequential Monte Carlo Simulation and Non Sequential Monte Carlo Simulation.

1.1 Sequential Monte Carlo Simulation (SMCS):

Sequential Monte Carlo methods, also known as particle methods, are a class of sequential simulation-based algorithms which provide a convenient and attractive approach to compute the posterior distribution [65]. In [66] SMCS has been applied to assess distribution system reliability. The authors in [67] have used SMCS in order to preserve the characteristics of the time series of the variable energy sources and the variable load. A Sequential Monte Carlo method enhanced by a temporal wind storm sampling strategy was introduced in [68] to evaluate the impacts of wind storms on power distribution. In [69], a pattern search-based optimization method was proposed in conjunction with a SMCS to optimally find the size of the hybrid system components and satisfy the reliability requirements. The authors in [70] have developed the SMCS in order to evaluate adequacy of power systems with wind farms.

1.2 Pseudo-Sequential MCS:

Leite da Silva in 1994 proposed, for the first time, Pseudo-Sequential Monte Carlo simulation which is based on the non-sequential sampling of system states and on the chronological simulation of only the sub-sequences associated with failed states [71]. In [72], a method based on the pseudo-sequential MCS technique has been proposed to evaluate the impact of high photovoltaic (PV) power penetration on customers' nodal reliability and system energy and reserve deployment. The authors in [73] have developed a new tool for the reliability assessment of the future smart distribution network (SDN) based on a Pseudo-Sequential MCS. In [74], pseudo-chronological simulation was introduced to evaluate loss of load indices, with particular emphasis on loss of load cost assessment, for composite generation and transmission systems considering time varying loads for different areas or buses.

1.3 Non-Sequential MCS:

This method known as the state sampling approach. An efficient method for composite system well-being evaluation based on non-sequential MCS is presented in [75].Also in [76], non-Sequential MCS is presented to evaluate reliability indices of composite system. In [77], a novel approach based on non-sequential MCS and pattern recognition techniques was proposed to evaluate well-being indices for a composite generation. The authors in [78], have developed an original non-sequential Monte Carlo simulation tool in order to calculate the optimal dispatch of classical generation in order to minimize polluting gases emissions in presence of wind power. Also, in [79] a calculation method of wind farms' capacity credit based on Non-Sequential MCS is presented.

2. Analytical methods:

The basic idea of the analytical approach is to do arithmetic with probability density function (PDF) of stochastic inputs variables. The analytical methods can be classified into two groups: based on linearization and basedon PDF approximation.

2.1 Based on linearization: the first group of analytical methods are based on linearization such as

- Convolution method:

Convolution method has been used in [80] to deduce the density functions of the unknown quantities but the main problem associated with this method is that the technique demands a large amount of storage and computation time in large systems. The authors in [81] have noted this problem and tried to solve it by applying the discrete frequency domain convolution method to reduce the computational burden.

- Cumulants method:

Cumulants method was introduced to prevent the convolution operation that appears in the calculation of the PDF of a linear combination of several random variables. In [82] the cumulant method for the probabilistic optimal power flow problem was introduced and the results using the cumulant method had a substantial reduction in computational expense while maintaining a high level of accuracy compared with the results from MCS. Cumulant based stochastic reactive power planning method in distribution systems with integration of wind generators has been proposed in [83].

- Taylor series expansion:

Taylor series expansion usually is used to approximate a function. This expansion gives quantitative estimates on the error in this approximation. in [84] Taylor series expansion is proposed for power system state estimation and reliability assessment. In [85] Taylor series expansion of the Markov chain stationary distribution is introduced in order to propagate parametric uncertainty to reliability and performability indices in Markov reliability and reward models.

- First Order Second moment method (FOSMM):

FOSMM is a probabilistic method to determine the stochastic moments of a function with random input variables which allows the estimation of uncertainty in the output variable without knowing the shapes of PDFs of input variables in detail. This method has been applied in [86] in order to deal with the uncertainties that effects in the computation of transfer capability, transmission reliability margin (TRM). In [87], a new probabilistic load flow method based on the FOSMM has been proposed to solve the probabilistic load flow problems. The aim of this method is to obtain the mean and standard deviation of load flow solution distributions considering various uncertainties in system operation. The authors in [88] have presented a formulation of probabilistic optimal power flow problem using the FOSM method to model the uncertainties and correlations of the system load.

2.2 Based on PDF approximation: the second group of analytical methods are based on the PDF approximation such as:

- Point estimate method (PEM):

The point estimation method concentrates on the statistical data provided by the first few central moments of uncertain input. In [89] probabilistic power flow method based on the PEM was introduced to handle various sources of uncertainties including output of the wind power generators and load demands. In [90], PEM was used to model the uncertainties related to wind power outputs and volatile electricity prices in a competitive electricity market. In [91] PEM has been used for energy management in order to minimize the cost and increase the efficiency. In [92] two-point estimate method was proposed to model the uncertainties associated with volatile electricity price, load demand and wind speed. In [93] a new probabilistic framework based on 2m Point Estimate Method (2m PEM) has been proposed to consider the uncertainties in the optimal energy management of the Micro Grids including different renewable power sources.

- Unscented Transformation (UT):

The UT is a powerful method in assessing stochastic problems with/without correlated uncertain variables. In [94] a new method for power system's probabilistic load flow (PLF) evaluation using the UT method has been presented. In [95] UT was used to study the impact of transformer correlations in state estimation. In [96] UT was provided to calculate the mean and covariance of nonlinear functions of random variables (which represent power system measurements as nonlinear functions of the power system state).

c. Possibilistic approach: In 1965, Zadeh introduced the concept of fuzzy arithmetic [97] where the input parameters are described by using the membership functions. In [98], a fuzzy evaluation tool was proposed for analysing the effect of renewable DGs on active power losses and the ability of distribution network in load supply at presence of uncertainties. In [99] a new method according to fuzzy extension principle has been proposed to represent and propagate the possibilistic uncertainties associated with wind power in power system. In [100] a new possibilistic fuzzy model was presented for multi-objective optimal planning of distribution systems which finds multi objective solutions corresponding to the simultaneous optimization of the fuzzy economic cost, level of fuzzy reliability, and exposure (optimization of robustness) of the network. In framework of possibilistic harmonic load flow, the authors in [101] proposed an improved approach which overcomes possibilitiy of interaction between input parameters.

d. Hybrid possibilistic–probabilistic approaches: In this technique, random and possibilistic parameters are presented to handle the uncertain parameters [102, 103]. A brief explanation of these approaches is described as follows:
   - Fuzzy and Monte Carlo: The authors in [103] have used Fuzzy and Monte Carlo Simulation as a hybrid possibilistic–probabilistic evaluation tool for analysing the effect of uncertain power production of renewable DGs on active power losses of distribution networks.
   - Fuzzy – scenario based approach: The authors in [104] have presented a hybrid possibilistic–probabilistic tool to assess the impact of DG units on technical performance of distribution network with taken into account the uncertainty of electric loads, DG operation/investments .

e. Information gap decision theory (IGDT): In 1980, Yakov Ben-Haim proposed IGDT [105]. This technique does not use PDF and membership function (MF) for input parameters. However, it measures the differences between parameters and their estimation. The authors in [106] have applied IGDT in order to handle the uncertainties associated with the uncertainties related to wind speed. In [49], IGDT has been used to model the uncertainty in the load and output of the renewable DGs. In

[107], IGDT has been proposed for distribution network operator (DNO) when it is faced with different uncertainties in load demands and renewable DGs . In [108], IGDT has been proposed to address the uncertainty related to renewable DGs.

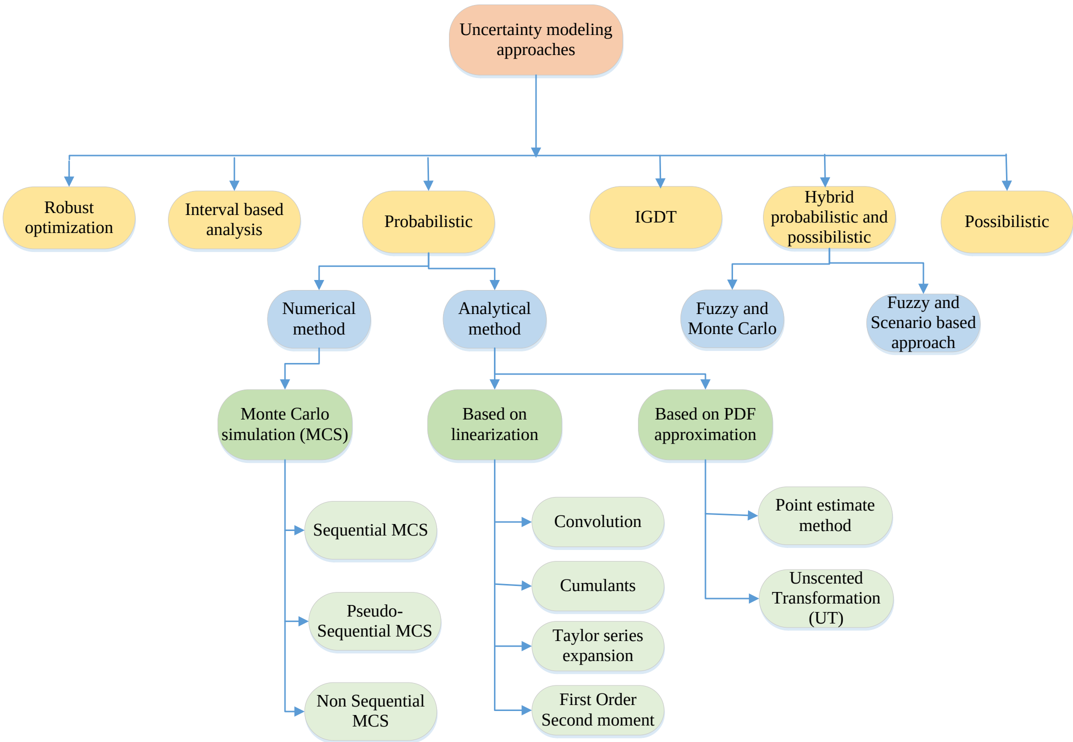

Figure 4: Uncertainty modeling approaches

A summary of uncertainty approaches used in DGs is presented in Table 2, while Table 3 depicts the advantages and disadvantages of uncertainty modeling approaches.

Table 2. Summary of uncertainty modeling

Uncertainty modeling approaches		References
Robust optimization		[44-49]
Interval analysis		[52-55]
Probabilistic approach	Sequential MCS	[66-70]
	Pseudo-Sequential MCS	[72-74]
	Non-Sequential MCS	[75-79]
	Convolution method	[80, 81]
	Cumulants	[82, 83]
	Taylor series expansion	[84, 85]
	First Order Second moment	[86-88]
	Point estimate method	[89-91]
	Unscented Transformation (UT)	[94-96]
Possibilistic		[98, 99, 109]
Hybrid probabilistic and possibilistic	Fuzzy and Monte Carlo	[103]
	Fuzzy–scenario based approach	[104]
Information gap decision theory (IGDT)		[49, 106, 107]

Table 3. Summary of Evaluation of Uncertainty modeling approaches

Uncertainty modeling approaches			Advantages	Disadvantages	References
Robust optimization			It is useful when only an interval exists	It is difficult to employ in nonlinear problems	[43-49]
Interval analysis			It is useful when just an interval exists	Cannot put the connection among intervals	[51-55]
Probabilistic (Numerical)	Sequential MCS		This method does represent chronological aspects in order that it is the most flexible strategy for assessing distribution system reliability	Sequential MCS requires a more substantial computational effort than the other approaches, and may be infeasible for some applications	[65-70, 110]
	Pseudo-Sequential MCS		It is easy to implement and faster than the conventional SMCS	The number of simulations needed increases as the degrees of freedom of the solution area increases	[71-74]
	Non-Sequential MCS		Non-Sequential MCS has high computational efficiency	cannot simulate the chronological aspects of system operation	[75-79, 111]
Probabilistic (Analytical)	Based on linearization	Convolution method	This method has greater accuracy while providing a breakthrough in computational speed	Requires a large amount of storage and time especially when there are many functions involved due to large systems.	[80, 81]
		Cumulants	The loss of accuracy associated with truncation of the order of the cumulants used	The technique demands a large amount of storage and computation time in large systems	[82, 83]
		Taylor series expansion	It allows for incredibly accurate (depending on the number of terms) estimates of common functions	Some calculations become tedious or the series doesn't converge quickly.	[84, 85]
		First Order Second moment	Allows the estimation of uncertainty in the output variable without knowing the shapes of PDFs of input variables in detail	Complicated	[86-88]
	Based on PDF approximation	Point estimate method [PEM]	It is a non-iterative, computationally efficient technique. simple and easy to implement.– There is no convergence problem	It only gives the mean and standard deviation of the uncertain output, no information about the shape of the PDF of the output is provided, gives more reliable answers for non-skewed PDFs, The accuracy would be low when the number of random variables is large	[89-91]
		Unscented Transformation (UT)	efficiency, the accuracy would not decrease when the number of random variables is large, applicable to problems with correlation among multiple uncertain input parameters and it is easy to implement	Its running time depends on number of uncertain variables and it is only applicable in problems which the input variables are described using their PDF	[94-96]
Possibilistic			It can convert linguistic information to numerical values	Complicated	[97, 109]
Hybrid probabilistic and possibilistic	Fuzzy and Monte Carlo			It is time consuming	[103]
	Fuzzy–scenario based approach		high computational efficiency	Its accuracy is low	[104]
Information gap decision theory (IGDT)			It is useful for decision in severe uncertainties	Too complicated	[49, 105-107]

4.3.3 Reliability indices under uncertainty

Power system reliability is one of the most important issues in the power system planning and operation. It can be divided into two parts, adequacy and security. Chowdhury et al in [112] have presented a reliability model for determining the DG equivalence to a distribution facility for using in distribution system planning studies in the new competitive environment. This model has been extended based on the Distribution Reliability (DISREL) program in order to include: System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), Customer Average Interruption Frequency Index (CAIFI), Average Service Availability Index (ASAI), Average Service Unavailability Index (ASUI), EUE (in kWh per year) , and expected outage cost in dollars ($). In [113-118] several reliability indices and their corresponding costs are calculated in order to quantitatively measure system reliability and its economic impact. In [119] SAIFI and SAIDI have been calculated as a part of solving the multistage planning problem of a distribution network. In [120], SAIFI, SAIDI, ASAI are calculated in order to quantitatively measure system reliability and its economic impact. Reference [121] has addressed the incorporation of uncertainty and reliability indices (SAIFI, SAIDI, ASAI, Expected energy not supplied (EENS)) in the joint expansion planning of distribution network assets and renewable DGs. The authors in [122] have applied a genetic algorithm based on a probabilistic load flow and used different scenarios to model the uncertainty in load demand and wind power generation. Also, reliability was assessed in two stages, namely fault location and fault repair. In [123] the uncertainty associated with the output wind power generation , load types and load variability have been modeled as a multi-state variable by a probability density function. Genetic algorithm was used in order to allow assessing reliability by the calculation of nodal interruption costs based on Monte Carlo simulation. In [124], SAIFI, SAIDI and CAIDI to evaluate the reliability of distribution networks in the presence of wind power are calculated by using the Monte Carlo simulation method. The authors in [125], have evaluated the reliability performance of distribution systems considering uncertainties in both generation and load demands. Reference [126] has presented analytical approach for the reliability modeling of large wind farms. In [127], the fuzzy numbers approach for reliability calculation of electrical energy indices was proposed. In [128], Monte-Carlo simulation approach to distribution/transmission reliability evaluation assuming loads defined by fuzzy numbers has been introduced. In [129], a fuzzy operation technique for load duration curve modeling in order to evaluate reliability indices of composite power systems based on probability and fuzzy set methods has been presented. In [130], a possibilistic approach using fuzzy set has been introduced to calculate the possibilistic reliability indices (loss-of-load expectation) according to the degree of uncertainty. In [131], a genetic algorithm guided by fuzzy numbers to evaluate the distribution system EENS index has been introduced. In [132], according to the randomness of output power of renewable DGs and the time series characteristic of load, a reliability evaluation model based on sequential Monte Carlo simulation for distribution system has been proposed. In [133] a reliability model has been presented to study the impacts of demand response programs on short-term reliability assessment of wind integrated distribution systems.

4.3.4 Market and economic operation aspects of renewable DGs under uncertainty

Planning and operation of power system has become much more complicated with integration of renewable energy resources and has brought great challenges to its economy and regulation [134]. The uncertainties related to future load growth, output power of renewable DGs, demand response and prices are some of the challenges. These challenges created new field for developing new methodologies for the system operation in the presence of controllable loads. The primary objective of proactive customers is to reduce their electricity payments to increase savings, hence they tend to rely on price-based schemes for managing local generation and load resources. In [135], an interior point method has been used to solve the optimal power flow problem with a multi-objective optimization problem for maximizing both social benefit and the distance to maximum loading conditions. In [136], load and price uncertainties within a distribution electricity market environment have been discussed. In [137] uncertainty in future load estimation as well as renewable DG power production have been introduced by probabilistic approaches. In [138] the uncertainties related to load demand and renewable generation have been modelled by using fuzzy-based method. Demand side management is a set of techniques, and strategies that carry out by the grid operators in order to influence and modify the users' energy consumptions [139]. The authors in [140] proposed a combined MCS and optimal power flow to maximize the social welfare with integrating demand response scheme considering different combinations of wind generation and load demand over a year. A stochastic modeling for electric capacity expansion planning under uncertainty in demand has been presented in [141]. In [142] Monte Carlo simulation methods has been used for modeling the uncertainties associated with load demand and renewable sources power production. In[143], the genetic algorithm and the market-based optimal power flow has been proposed to jointly maximize the net present value related to the investment made by WTs' developers and the social welfare within a distribution market environment. In [144] a market-based optimal power flow has been used for optimally allocating wind turbines in order to maximise social welfare considering different combinations of load demand and wind generation. Stochastic programming approach Proposed in [145] for reactive power scheduling of a micro-grid considering the uncertainty of wind power. The authors in [146] have used Monte Carlo simulation method and market-based optimal power flow to maximize the social welfare with integration of demand side management scheme considering different combinations of wind generation and load demand over a year. In [147], in order to model the random nature of load demand and wind forecast errors, a scenario-based stochastic programming framework has been presented. In [148] Monte Carlo simulation method has been used to determine a probabilistic hourly/seasonal model for wind and solar based DGs, and the system demand. To solve the problem of uncertainties of renewable DG output and load, multi-scenario technique has been adopted in [149]. In [150] price uncertainty has been modeled through robust optimization technique using duality properties and exact linear equivalences. In [151] Price uncertainty has been modeled by a simple linear programming algorithm which can be easily integrated in the energy management system of a household or a small business. The authors in [152] have proposed a probabilistic method for active distribution networks planning with integration of demand response. Optimal demand response and energy storage system scheduling for distribution losses payments minimization under electricity price uncertainty has been presented in [50]. In [153], a method for evaluating investments in decentralized renewable distribution network considering price volatility has been presented. In [154], a Monte Carlo simulation-based approach has been proposed for distribution network planning to capture the uncertainties related to the price volatility of renewable DG.

4.4 Mathematical Algorithm and Solution Techniques for DG planning (DGP)

Due to the increasing penetration of DGs in distribution network, the location and sizing of DGs in distribution network planning is becoming increasingly important. Various optimization methods employed in DGP to solve different DG problems (optimal location and/or sizing). Briefly, these methods can be divided into three main sets:

1. Conventional methods are also called classical or non-heuristic methods. It includes linear programming (LP), non-linear programming (NLP), mixed integer non-linear programming (MINLP), dynamic programming (DP), optimal power flow-based Approach (OPFA), direct approach (DA), ordinal optimization (OO), analytical approach (AA) and continuous power flow(CPF).
2. Intelligent search-based methods are also called heuristic methods. It includes simulated annealing (SA), evolutionary algorithms (EAs), tabu search (TS), particle swarm optimization (PSO) ant colony system algorithm (ACSA), artificial bee colony (ABC), artificial immune system (AIS), bacterial foraging optimization algorithm (BFOA), bat algorithm (BA), imperialist competitive algorithm (ICA), cuckoo search algorithm (CSA), intelligent water Drop (IWP) algorithm and fuzzy set theory (FST).
3. The prospective methods include firefly algorithm (FA), shuffled frog leaping algorithm (SFLA), and big bang-big (BB-BC) algorithm.

4.4.1 Conventional methods (Non-Heuristic)

A) Linear programming (LP)

Linear programming (LP) is defined as a mathematical technique used for optimization of linear objective functions and linear constraints [155]. In [156, 157] LP was employed to solve optimal DG placement (ODGP) problem to achieve maximum DG penetration. Also Abou El-Ela et al. [158] used LP to investigate of varying ratings and locations of DG for losses minimizing in order to maximize DG benefits.

B) Nonlinear programming (NLP)

The nonlinear programming (NLP) refers to fact that the computation in this method is based on the derivatives. Solving a nonlinear programming problem could be done by first choosing a search direction in an iterative procedure which is specified by the first partial derivatives of the equation (the reduced gradient). This method is referred to as first-order method and includes the generalized reduced gradient method [159]. The second order methods such as successive quadratic programming [160] and Newton Raphson method [161] require the counting of the second order partial derivatives of the power-flow equations and other constraints. Rau and Yih-Heui [162] have employed a second order algorithm to compute the capacity of DGs in selected nodes to obtain optimum quantities and maximized benefits of DGs. In [163], the Newton Raphson method was introduced to find optimal size and optimal placement of DGs in order to obtain the optimization of both cost and loss. Also the study focused on optimization of weighting factors which balance the cost and the loss factors.

C) Mixed-integer nonlinear programming (MINLP)

MINLP was used to solve DGP problem with integer variables with values (0 or 1) to represent if a new DG should be installed [164]. The proposed model in [165] integrated comprehensive optimization model and planner’s experience to achieve optimal sizing and location of DGs. This model is formulated as MINLP in General Algebraic Modeling System (GAMS) using binary decision variables with an objective function for minimizing the total system cost. In [166] the optimal planning problem is formulated as MINLP, with an objective function for minimizing the energy losses and for optimally allocating with wind DGs in the distribution network. Atwa et al. [167] have used different types of renewable DGs such as wind and solar in order to minimize the annual power losses considering network constraints. In [168], the authors have employed a MINLP method to find the optimal size and site for the different types of DGs by considering the electricity market price volatility. Also, MINLP was used to determine the optimal placement and number of DGs in hybrid electricity market [169]. The optimal problem for location and sizing of DG is formulated by using MINLP, with an objective of improving the voltage stability margin considering the probabilistic nature of the renewable energy resources and the load [170]. In [171], multi-period OPF used in order to improve the hosting capacity of distribution systems by applying both static and dynamic reconfiguration considering active network management (ANM) schemes. In [172], MINLP is proposed to solve DGP planning problem in order to minimize the total operational cost.

D) Dynamic programming (DP)

Dynamic programming (DP) algorithm is an approach that guaranties optimal solution of multi-stage decision problems [173, 174]. Celli et al. [173] have used DP for planning active distribution network with DGs in order to reduce the capital expenditures (CAPEX) and operational expenditures (OPEX). In addition, real-world examples are provided to illustrate the effectiveness of DP for active distribution networks. In [174] DP is used to solve multi-period planning problem with such as minimization of investment and interruption costs and losses. In [175], DP is proposed to determine the optimal feeder routes and branch conductor sizes with simultaneous optimization of cost and reliability. Khalesi et al. [176] have used DP to solve multi-objective optimization problem in order to determine the optimal site of DGs in the distribution network to minimize power losses and improve both the voltage profile and reliability.

E) Optimal Power Flow-based Approach (OPFA)

OPFA has been developed to increase the capacity of DG and identify available headroom on the system within the imposed thermal and voltage constraints [177]. Dent et al. [36] have used OPF based method considering security constraints to optimally accommodate DGs in the network. In [178], an OPF used to find the optimal capacity and placement of DGs in order to minimize the operational cost. Also in this work, Locational Marginal Price (LMP) is determined as the Lagrangian Multiplier of the power balance equation in OPF. The authors in [179] have proposed OPF to minimize the energy cost taking into account the goodness factor of each DG on the distribution system. The aim of [180, 181] is to find optimal location and size of new DGs considering the fault level constraints (FLCs) in the OPF problem. The authors in [182, 183] have proposed a multi-period AC OPF to evaluate the optimal size of new DGs which are able to be connected to a distribution network when active network management (ANM) control strategies are in operation. In [184] an OPF is used to analyze the feasibility of DG integration strategies taking into account the uncertainty of DG's output power in the study of different integration concepts, including network losses, voltage profile and line capacity.

F) Direct approach (DA)

Direct approach (DA) is introduced in [185] to reduce the inherent difficulties toward the solution and provides optimum solution at the same time in order to solve the ODGP problem. In [186] DA is applied for optimal planning by focusing on the minimum cost and higher power reliability in radial distribution systems. In [187]

DA was proposed to find the optimal size of fixed and switched capacitors in order to minimize the power losses and maximize the savings in a radial distribution system.

G) Ordinal Optimization (OO)

Ordinal optimization (OO) approach presented in [188] to find optimal site and size of DGs with discrete and continuous variables in order to minimize the losses and maximize the capacity of DGs. In [189], OO approach is applied to find the best solution for planning of distribution network with integration of electric vehicles (EVs). Zou et al. in [190] have proposed OO to obtain the optimal solution for ODGP considering the uncertainties related to renewable DGs and capability curve of them to improve the voltage profile, voltage stability and reduce the active power losses.

H) Analytical Approaches (AA)

Wang et al. [191] have applied analytical approaches to determine the optimal location of DGs in radial distribution systems in order to minimize the power losses. AA are not iterative algorithms in order that there is no convergence problems involved, therefore, the results could be obtained very quickly. In [192, 193] both the optimal sizing and siting of DGs are determined by an analytical method to minimize the total power losses. In [194] an analytical method proposed to obtain the optimal combination of different DG types in a distribution system such as size, location and operating point in order to minimize the losses. This method applies in two test systems with different configurations by establishing a comparison with the exact optimal solution obtained from the exhaustive optimal power flow (OPF) algorithm. In [15, 195, 196], analytical expressions are proposed to find an optimal size and power factor of DGs to minimize the power losses in a primary distribution network.

I) Continuation Power Flow (CPF)

Continuation power flow (CPF) method was presented in [197] to determine the optimal placement of DGs in a distribution network in order to improve the voltage profile, reduce the power losses, increase the power transfer capacity and maximize the loading and voltage stability. Hemdan and Kurrat have used CPF to analyze the systems to optimally allocate DGs in distribution systems in order to meet increasing demand, obtaining more benefits from DGs, decreasing the losses and improving the voltage profile [198].

Summary of literature review for GDP using conventional techniques can be shown in Table 4.

Table 4. Summary of literature review for GDP using conventional techniques

Conventional methods	References	Objective function	Contribution	Uncertain parameter	Mathematical modeling of Uncertainty
linear programming (LP)	Keane & O'Malley (2005) [156]	Maximum capacity	The optimal DG placement is solved using LP and take advantage of the interdependence of the buses with respect to the system constraints.		Not modelled
	Keane & Malley (2007) [157]	Maximize profit	LP is used to find the optimal model that maximizes the quantity of energy that may be reaped from a given area by taking into account its available energy resources.		Not modelled
	Abou El-Ela et al. (2010) [158]	Improve voltage and reduce line loss	LP is used for (1) demonstrating the influence of DG sitting and sizing to maximize the benefit of DG and (2) confirming the optimization results obtained by genetic algorithm (GA).		Not modelled
Nonlinear programming (NLP)	Rau & Wan (1994) [162]	Minimize real power loss	Second order algorithm was proposed to compute the amount of resources in selected nodes.		Not modelled
	Ghosh et al. (2010) [163]	Minimize both cost and power loss	Newton Raphson method was used to find the optimal sitting and sizing in DG by focusing on optimization of weighting factor, which balances the cost and the loss factors.		Not modelled
Mixed-integer nonlinear programming (MINLP)	El-Khattam et al. (2005) [165]	Minimize investment and operating costs	Optimal DG model is implemented as an economical alternative option in integrated model for solving the DGP problem.	Load demand growth	Scenario-based approach
	Atwa, et al. (2010) [167]	Minimizing the energy losses	MINLP proposed a probabilistic-based planning technique for determining optimal site with different types of DG.	Load demand and renewable DG	Scenario-based approach
	Kumar & GAO (2010) [169]	Minimization of total fuel cost and minimization line losses in the network	Hybrid electricity market of optimal Location and number of DG is presented by MINLP approach.		Not modelled
	Porkar et al. (2011) [168]	Minimize cost and maximize total system benefit	Optimal site, size, and different types of DG considering electricity market price fluctuation introduce by using MINLP method.		Not modelled
	Atwa, & El-Saadany (2011) [166]	Minimize annual energy loss	A probabilistic-based planning technique for optimum capacity and location of wind DG in distribution systems is formulated as an MINLP.	Combined generation –load model	Scenario-based approach
	Al Abri et al. (2013) [170]	Improve the voltage stability margin	Optimal sitting and sizing of DGs is formulated by using MINLP method.	load and renewable DG generation	Scenario-based approach
	Franco et al. (2014)[172]	Minimize operation and investigation cost	MINLP is proposed to solve long term expansion planning and offers low computation time.		Not modelled
	Capitanescu et al. (2015) [171]	Increase the hosting capacity of DG	ODGP problem is formulated as a MILP of multi-period optimal power flow to consider thermal and voltage constraints by centralized ANM schemes.		Not modelled
Dynamic programming (DP)	Celli et al. (2007) [173]	minimizes the capital and operational expenditures (CAPEX&OPEX)	DP is used to introduce optimal multiyear development plan of active distribution networks.		Not modeled
	Popović, et al. (2010) [174]	Minimize cost of investment loss and reliability	DP is used to improve the quality of multi-period solutions in DG.		Not modeled
	Khalesi et al. (2011)	Minimize loss and enhance	DP is used to solve multi-objective function of optimal		Not modeled

	[176]	reliability improvement and voltage profile.	locations in DG network by taking into account the time-varying loads.		
	Ganguly et al. (2013) [175]	Minimization of investment and operational costs and maximization of reliability	DP has been applied to solve distribution system expansion planning problem, considering two variables decision feeder routes and branch conductor sizes.		Not modelled
Optimal Power Flow-based Approach (OPFA)	Vovos, & Bialek (2005) [180]	Maximize profit	OPF is developed to convert FLCs to simple nonlinear inequality constraints.		Not modeled
	Vovos, et al. (2005) [181]	Maximize profit	OPFA find optimal capacity by taking into account fault level constraints imposed by protection equipment such as switchgear.		Not modelled
	Harrison & Wallace (2005) [177]	Maximize DG capacity.	OPFA has proposed to maximize the capacity of DG and identifies available headroom on the system.		Not modelled
	Gautam, & Mithulananthan (2007) [178]	Maximization social welfare and profit	OPF techniques is used to find the optimal capacity and placement of DGs		Not modeled
	Algarni and Bhattacharya (2009) [179]	Minimize energy costs	OPF method is used to minimize the distribution energy costs in Disco power system tacking into account goodness factor of DGs.		Not modelled
	Dent et al. (2010) [36]	Maximize DG capacity	OPF based method is used to determine the capacity of system to accommodate DGs. The results show voltage step limit can be more restrictive of DG capacity than a voltage level limit.		Not modelled
	Ochoa et al. (2010) [182]	Maximize DG capacity	Multi–period AC optimal power flow is proposed to find the optimal size of DGs when ANM control strategies are in operation.		Not modeled
	Ochoa& Harrison (2011) [183]	Minimizes energy losses	Multi-period AC -OPF is used to determine the optimal site of renewable DGs.	Load demand and renewable DGs	Scenario-based approach
	Karatepe et al. (2015) [184]	Minimize losses and improve voltage profile	OPFA including the output power uncertainties in DGs is proposed to investigate the comparison between single-and multiple-DG concepts.	output power of renewable DGs	Scenario-based approach
Direct approach (DA)	Samui et al. (2012) [185]	Minimize the total annual cost	DA is used to solve ODGP problem depending on tracking and calculating the cost for radial paths.		Not modelled
	Samui et al. (2012) [186]	Minimization planning cost.	DA is higher effective in optimal feeder routing considering role of reliability and planning cost of radial distribution system.		Not modeled
	Raju et al. (2012) [187]	Improve the voltage profile and maximize the net saving	DA is used to find the optimal location and size for capacitors in a radial power distribution system.		Not modeled
Ordinal optimization (OO)	Jabr, R. A., & Pal, B. C. (2009) [188]	minimize losses and maximize capacity of DG	Specific approaches have been chosen for the application of OO for the optimal placement and sizing of DGs.		Not modelled
	Zou, K et al. (2012) [190]	Reduce power losses	ODGP model considering the uncertainties and DG reactive capability has been developed by using OO.		Not modeled
	Lin et al. (2014)[189]	Minimize cost	OO is applied for planning of distribution network problems with electric vehicle (EV) charging stations.		Not modelled
Analytical approaches (AA)	Wang & Nehrir (2004) [191]	Minimize power losses of the system	Analytical methods are determined for optimal placement in DG in radial network system.		Not modelled
	Gozel et al. (2005) [193]	Minimize total power losses and feeder losses	The optimal size and placement of DG in a radial feeder are determined by analytical method.		Not modelled

	Acharya & Mithulananthan (2006) [196]	Minimize total losses	AA is used to calculate the optimal size and placement of a single DG.		Not modelled
	Gözel and Hocaoglu 2009 [15]	Minimize power losses	Employ loss sensitivity factor and based on the equivalent current injection to solve ODGP in radial system.		Not modelled
	Hung et al. (2010) [195]	Minimize losses	AA is used to find the optimal size of DGs that have the capability to deliver both real and reactive power.		Not modelled
	Elsaiah et al. (2014) [192]	Reduce total losses	An analytical method is introduced to solve the optimal location and size problem of DGs.		Not modelled
	Mahmoud et al. (2015) [194]	Loss minimization	Analytical method is employed to obtain the optimal combination of different DG types.		Not modelled
Continuation power flow (CPF)	Hedayati et al. (2008) [197]	Improve voltage profile and reduce power losses	placement of DG is based on the analysis of power flow continuation and determination of most sensitive buses to voltage collapse		Not modelled
	Hemdan, N. G., & Kurrat, M. (2011) [198]	Maximize load ability and voltage limit	CPF is proposed to solve ODGP problem.		Not modelled

4.4.2 Intelligent Searches (Heuristic Methods)

The heuristic methods based on intelligent searches have been implemented in the DG problem to treat with local minimum problems and uncertainties.

A) Simulated Annealing (SA)

In 1983, SA was introduced by Kirkpatrick et al. [199] as a process to simulate the optimization problem as an annealing process in order to find global optimal solutions. This approach has the ability of escaping local minima by incorporating a probability function in accepting or rejecting new solutions. Authors in [200] have used SA as an optimization tool to determine the optimum location and size of DG in order to minimize multi-objective function including the active power losses, emission and contingency. Also in [201] SA is employed to find optimal location and sizing of DGs to minimize the total losses and improve voltage profile in large radial distribution system. Nahman et al. [202] have applied SA to find optimal solution for the planning of radial distribution network in order to minimize the total cost.

B) Evolutionary Algorithms (EAs)

The flexibility of evolutionary algorithms (EAs) leads to widely employ these algorithms for solving power system operation and planning problems. These algorithms are a population based optimization process and converge to the global optimum solution with probability of one by a finite number of evolutionary steps performed on a finite group of reasonable solutions [203, 204]. EAs are type of artificial intelligence methods for optimization based on natural selection, such as mutation, recombination, crossover, reproduction and selection operators on the population of individuals to perform the search. Also it is a subset of evolutionary computation, which includes Evolutionary Programming (EP), Evolutionary Strategy (ES) and Genetic Algorithm (GA). EP, ES and GA share many similarities [203, 205]. The authors in [10, 206] have used GA to focus on the optimal placement and size of DGs with objective function to maximize the benefits related to DG and minimize the power losses. GA and an improved Hereford ranch Algorithm HRA (variant of GA) are implemented in [207] to determine the optimal sizing of DGs. In [208], GA and HRA are used to find optimal location and size of DGs in a distribution network. In [209], GA is utilized to find optimal re-closer positions when DGs are deployed in a securely optimal manner. Also in [210], GA is used to solve ODGP problem with different load models in order to minimize the power losses. In [138], DG allocation strategy for radial distribution networks under uncertainties related to load and generation using adaptive GA has been introduced and the uncertainties of load and generation are modeled using fuzzy-based approach. El-Ela et al. [158] have proposed GA to determine the optimal location and capacity of DG with multi-system constraints to achieve a single or multi-objectives.

In [211], GA based method is employed to find optimal types, locations and sizes of DGs taking into account the benefits and costs of DG. Furthermore, Borges et al. [3] have proposed GA technique to find optimal placement and size of DGs to maximize the benefit/cost ratio of DG. In [212-214] the authors have combined GA and OPF to find the best sites and capacities available for connecting a large number of DGs in the network. Also, the combination of these methods is being as an efficient solution to minimize the overall cost. GA and ant colony optimization (ACO) together with imperialist competitive algorithm (ICA) are proposed to solve the feeder reconfiguration problem in DGs and focus on positive effectiveness of DGs in loss reduction and voltage profile improvement [215]. In [216] a multi-objective programming method based on the non-dominated sorting genetic algorithm (NSGA) is introduced to find maximum sets of distributed wind power generation in order to minimize the power losses and short-circuit levels. In [217] NSGA-II and the market-based optimal power flow has been proposed to minimize the total energy losses and maximize the net present value associated with the wind power investment over a planning horizon. Ahmadi et al [218] have used the NSGA-II algorithm for optimal site and size of DGs in the network in order to minimize the total cost and line losses and improve voltage profile. Carrano et al. [61] have used NSGA-II with four local search strategies to solve the power distribution network design problem taking into account three relevant aspects: monetary cost, reliability and ability to deal with different scenarios of load growth. Also uncertainties related to load demands are modelled by a Monte Carlo simulation (MCS) in order to produce an estimate of the network response into the set of possible future load. Wang & Gao in [219] have used a non-revisiting genetic algorithm (NRGA), GA and binary space partitioning (BSP) to reduce power losses.

C) Tabu Search (TS)

In 1986, Glover and Hansen have developed the first TS algorithm to solve the optimization issues [204]. This approach is an effective solution to achieve optimization within a reasonably short time. Golshan et al. [220] have applied TS method to determine the optimal locations and sizes of DGs in a distribution network along with tap positions of voltage regulators (VRs) and network configuration. The objective function of this method is to minimize the cost of power losses. Also Nara et al. [221] have implemented TS method to find how much distribution loss can be reduced if DGs are optimally allocated at the demand side of the system. Maciel and Padilha-Feltrin have proposed a multi-objective Tabu Search (MOTS) method to find the Pareto optimal set. This study shows the comparison between MOTS and NSGA-II and confirmed that the MOTS method has a less advantage than the NSGA-II especially in more complex analysis where time requirements become critical [222].

D) Particle Swarm Optimization (PSO)

In 1995, Eberhart & Kennedy have proposed Particle Swarm Optimization (PSO) for the first time [223]. The original objective of their research inspired by social behavior bird flocking or fish schooling. Different variants of the PSO algorithm were applied to different areas of electric systems problems, but the most standard one is the global version of PSO (Gbest) model [224, 225]. Krueasuk & Ongsakul have used PSO method to determine optimal sizes and locations of multi-DGs [226]. The main goal of this study is to minimize the total power losses in the network. Beromi et al. [227] have suggested a PSO method to solve optimal DG size to improve voltage profile, minimize losses and reduce total harmonic distortion (THD) in addition to dealing with both the costs and site. Also [228] PSO approach is presented for optimal operation management of distribution networks with DGs. The authors in [229] have combined PSO and market-based OPF to choose the optimal size and number of wind turbines (WTs) in order to maximize net present value (NPV) within a distribution market environment. In addition, Raj et al. [230] and Wong et al. [12] have employed PSO to identify the optimum generation capacity and location of DG and provide maximum power quality. In [231], Multi-Objective Particle Swarm Optimization (MOPSO) is used to determine optimal size of the DG considering multi objective criteria to simultaneously minimize the power losses and improve voltage profile. In [232], PSO has been used for short term planning of DGs to minimize the total operational cost, power losses and voltage stability index. In [233, 234], multi-objective PSO method is proposed to find optimal size and location of DGs considering load uncertainty in distribution networks. Decimal coded quantum particle swarm optimization (DQPSO) in [235] is used to solve the feeder reconfiguration problem with different model of DGs in order to minimize the active power losses. The authors in [89], proposed a new method based on adaptive particle swarm optimization (APSO) for investigating the multi-objective stochastic distribution feeder reconfiguration problem. Also in this paper, various sources of uncertainties including output of the wind power generators and load demands are handled through an effective probabilistic power flow method based on point estimation method (PEM) scheme.

E) Ant Colony System Algorithm (ACSA).

In 1990s, Dorigo et al. [236] introduced Ant Colony Optimization (ACO) as a new technique for solving combinatorial optimization problems. It is inspired from ants' movement to find food. ACO is derived from ant system (AS) algorithm which has the best performance in engineering applications [237-240]. In [241], ACO is used as to determine optimal location and size of DGs to minimize investment and operational costs of the system considering DGs as constant power sources. Authors in [242] have used ant colony system algorithm (ACSA) to seek out the optimal re-closer and DG placement for radial distribution network by using the composite reliability index as the objective function in the optimization procedure. Kaur et al. [243] have used ACSA to solve capacitor allocation problem in radial distribution systems to minimize the total cost of losses. In [244], multi-objective reconfiguration problem which considers the active power losses minimization and the energy not supplied index which is solved by a modified ACO.

F) Artificial Bee Colony (ABC)

ABC algorithm was introduced by Dervis Karaboga in 2005 [245]. This method inspired by intelligent behavior of honey bees' swarm to find the nectar [245]. ABC approach is applied in [246] to solve distribution network expansion planning to obtain the optimum value of reinforcements and to find a suitable commitment schedule for the installation of new DGs. In [247], the authors have used ABC algorithm for DG planning problem in order to reduce the power losses and to improve the voltage profile in the radial distribution systems. Also, in [248], optimal DG location and size problem has been solved by ABC algorithm in order to minimize the power losses and enhance the voltage stability level. ABC have been used in [249] to find the optimal location and size of DGs with two control parameters (colony size and maximum iteration number) to be tuned.

G) Artificial Immune System (AIS)

Artificial immune algorithm (AIS) is used in [250] to generate a set of nearly-optimal solutions under load-evolution conditions (including the load for each node, and a unique expected mean energy tax). The authors in [251] have used AIS to solve DG placement problem in order to minimize the power losses taking into account the bus voltage and line current limits. In [252], AIS is used to solve the DG planning problem considering uncertainty in the load demands in distribution networks.

H) Bacterial Foraging Optimization Algorithm (BFOA

In 2002, Passino invented Bacterial Foraging Optimization algorithm (BFOA). This algorithm tried to model the single and set behavior of E. Coli bacteria (kind of bacteria that live in intestines in order to find a simple path for faster convergence [253]. In [254], BFOA is used to solve the optimal radial feeder routing in the distribution systems planning problem. Devi and Geethanjali, [255] have modified the performance of the BFO algorithm (MBFO) in order to find the optimal placement and sizing of DGs in a distribution system to reduce the total power losses and to improve the voltage profile of the distribution system. The result showed that MBFOA is more efficient in finding the minimum cost in less computational time than BFOA. . In [256], BFOA was applied to find the optimal size of capacitor banks in order to minimize the power losses by taking into account loss sensitivity factor (LSF) and voltage stability index (VSI). BFOA is presented to find the optimal size and location of multiple DGs in order to minimize the network losses, operational costs and improve the voltage stability of a radial distribution system [257].

I) Bat Algorithm (BA)

Bat Algorithm (BA) was presented by Yang in 2010 as a base on the echolocation behavior of bats [258]. Yammani et al. [259] have used BA to find the optimal location and sizing of DGs to minimize the network losses and improve the voltage profile. In [30], BA is used to determine optimal location of capacitors in radial distribution system in order to minimize the power losses and maximize the revenue. In [260], BA was used to obtain the optimal placement, size and the number of DGs in radial distribution network. In [261], BA and loss sensitivity factor (LSF) are respectively used to find the optimal size of the capacitor banks and find the optimal site of the capacitor.

J) Imperialist Competitive Algorithm (ICA)

ICA is a new approach inspired by imperialists competition and the first using was in 2007 by Atashpaz and Lucas [262]. In [263] ICA is used to find the optimal placement and size of DGs to minimize the network power losses. Moradi et.al [264] have used ICA to find optimal sitting and sizing of DGs and capacitor banks in a distribution network. The objective is to reduce the power losses, increase voltage stability index and improve the system voltage profile. In [265], the optimization problem of DGs at any load level is solved by using ICA in order to reduce the power losses and enhance the voltage stability.

K) Cuckoo Search Algorithm (CSA)

CSA is a new approach developed by Yang and Deb in 2009 to solve the optimization problems [266]. This algorithm is inspired from the obligate brood parasitism behavior of certain species of cuckoos by laying their eggs in the nests of other birds of other species. Nguyen et al. [267] have proposed CSA to find the optimum placement and size of DGs to minimize the power losses and voltage stability deviation index. Also, in [268], CSA is used for optimal DG placement to reduce the power losses and improve voltage profile of the distribution power system. In [269], COA is used to reduce the power losses and improve the voltage profile for two types of DGs: biomass and solar-thermal. The authors in [270] have applied CSA to obtain optimal location and size of DGs in distribution network to minimize the active power losses and improve the voltage profile by maintaining the fault level and line load within an acceptable limit.

L) Intelligent Water Drop (IWP) Algorithm

Intelligent water drop (IWD) was firstly proposed as a new approach to find the global optimum solutions by Shah-Hosseini in 2007. This algorithm inspired from the river procedure to find an optimal path to flow from source to destination [271]. In [272], IWP algorithm is used to find the optimal sizing of DGs in radial distribution networks in order to minimize the losses and to improve the voltage profile. In [273] (IWD) is proposed to find the optimal size and site of DGs in micro grids to minimize network power losses, improve voltage regulation and increase the voltage stability.

M) Fuzzy Set Theory (FST)

Fuzzy set theory (FST) was introduced in 1965 by Zadeh [97] as formal tools to deal with data that have non-statistical uncertainties. A fuzzy variable is modeled by a membership function which operates over the range of real numbers zero or one. Momoh et al. [274] have confirmed that FST is widely used in power system planning. In [275] fuzzy-GA is used to solve optimal DG placement problem by transforming the objective function and constraint into multi-objective function with fuzzy set. In [276], FST is used for the modeling of the load and electricity price uncertainties in the system and solved by NSGA-II in order to minimize the operational cost, technical and economic risks. The authors in [277] have applied two-stage algorithm to solve ODGP problem with voltage and line loading constraints in order to minimize the system losses. In the first stage, fuzzy approach is used to optimal DG locations while in the second stage, PSO is used to find the size of the DGs. Also In [278], Fuzzy Logic is used to find the optimal capacitor locations and BA is applied to determine size of optimal capacitors in order to reduce the power losses.

Table 5 presents a summary of literature review for optimal DGs placement problem using intelligent techniques.

4.4.3 The Prospective Methods

The main perspective revealed methods are presented as follows:

A) Firefly Algorithm (FA):

This algorithm was first introduced in 2009 by Yang [279] for solving nonlinear multidimensional optimization problems. FA is inspired from the natural behavior of the fireflies; a firefly of the maximum brightness has the largest ability to attract other fireflies regardless to their sex. References [280, 281] have used FA to find the optimal site and size of multiple DGs on a balanced radial feeder for power loss minimization. Othman et al. [282] have modified the traditional FA in order to be able to deal with the practically constrained optimization problems. This new algorithm has many advantages such as, simple concepts, easy implementation and higher stability mechanism compare with traditional FA [282].

B) Shuffled Frog Leaping Algorithm (SFLA):

This method is formed by mimetic evolution of a group of frogs when searching for an area, where the maximum amount of food available [283]. Optimal site and size of DGs considering system loss minimization and voltage profile improvement as objective functions solved by SFLA [283].

C) Big Bang-Big Crunch (BB-BC) Algorithm:

This algorithm was first introduced in 2006 by Erol and Eksin [284] as a new optimization method. This algorithm relies on one of the theories of the evolution of the universe which is named the Big Bang and Big Crunch (BB-BC) Theory. In [285], BB-BC algorithm is used to solve distribution network reconfiguration and optimal power allocation of DGs in order to minimize the total active power losses, maximize the voltage stability index, minimize the total cost, and minimize the total emission produce by DGs and the grid.

Table 5. Summary of literature review for OGDP problem using intelligent techniques

Intelligent searches		References	Objective function	Contribution	Uncertainty issue	Mathematical modeling Uncertainty
Simulated Annealing (SA)		Nahman, J. M., & Peric, D. M. (2008) [202]	Minimize investment cost and loss cost	Optimal planning problem of radial distribution is solved by apply SA combination with a steepest descent approach.		Not modeled
		Sutthibun & Bhasaputra (2010) [200]	Minimize power loss and emission	Multi-objective optimal DG placement problem is solved by SA.		Not modeled
		Injeti, S. K., & Kumar, N. P. (2013) [201]	Minimize the network power losses and improve the voltage stability.	SA is proposed to evaluate the optimal siting and sizing of DGs with unspecified power factor distribution network.		Not modeled
Evolutionary Algorithms (EAs)	HRA	Kim et al. (1998) [207]	Minimize power losses	Conventional GA and HRA are introduced for solving optimal sizing problem in DGs.		Not modeled
		Gandomkar et al. (2005) [208]	Minimizes the power losses	Simple GA and HRA are applied to introduce optimal site and size Of DGs.		Not modeled
	GA	Silvestri et al. (1999)[206]	Maximization of the benefit related to DG	Optimal sitting and sizing problem of DG solved by a GA.		Not modeled
		Teng, et al. (2002)[211]	Maximize benefit /cost ratio of DG	GA proposed to find best balance between the costs and benefits of DG placement with optimal types, locations and sizes in distribution feeders.		Not modeled
		Ganguly, S. and D. Samajpati (2015) [138]	minimizing the network power loss and maximum node voltage deviation	GA used to present a DG allocation strategy for radial distribution networks under uncertainties of load and generation.	Load, DG	fuzzy-based approach
		Popović et al. (2005)[209]	Improve voltage profile and reduce losses	GA is designed to find optimal re-closer positions when DGs are connected in a securely optimal manner.		Not modeled
		Borges & Falcao (2006)[3]	Minimize the power loss and maximize benefit / cost ratio	Used GA to introduce and solve optimal DGP problem model with reliability.		Not modeled
		Harrison et al. (2007) [213]	Maximize DG capacity,	Combined GA and OPF to solve ODGP problem.		Not modeled
		Harrison et al. (2008) [212]	Maximize profit	Hybrid method employing GA and OPF to apply optimal placement and size a predefined number of DGs.		Not modeled
		Singh & Verma (2009) [210]	Minimize real power loss	ODGP model with different load models solved by GA.		Not modeled
		El-Ela et al. (2010) [158]	Improve the voltage profile, increase the spinning reserve, and reduce the losses.	GA used to propose the optimal location and size of DG with multi-system constraints to achieve a single or multi-objectives.		Not modeled
		Talaat & Al-Ammar (2011) [10]	Minimum losses of the distribution system	Optimal penetration level, and optimal locations and sizes of DGs have been investigated using three GA.		Not modeled
		Falaghi et al. (2011) [214]	Minimize cost	GA and OPF approaches are employed as the solution tool to solve ODGP problem.		Not modeled
		Mirhoseini, et al. (2014) [215]	Minimize real power losses and improve voltage profile	GA and ACO together with ICA are proposed to solve the feeder reconfiguration problem in DGs.		Not modeled
	(NSGA)	Ochoa et al. (2008) [216]	Minimize power losses and short-circuit levels.	NSGA is applied in order to find configurations that maximize the integration of distributed wind power generation.	Demand and generation	Scenario-based approach
		Ahmadi et al. (2008) [218]	Minimize total cost, minimize line	NSGA-II algorithm used to find optimal location and		Not modeled

			losses and improve voltage profile	size of DGs.		
		Siano, P. and G. Mokryani (2015) [217]	maximize the net present value associated with the WT investment over a planning horizon	NSGA and the market-based OPF have proposed to find the optimal numbers and sizes of WTs.	Load demand and renewable generation	Scenario-based approach
		Carrano et al. (2014) [61]	Minimize cost	ODGP problem solved by (NSGA-II) with taking account monetary cost, reliability and load growth uncertainties.	Load demand	Scenario-based approach
	(NRGA)	Wang & Gao (2013) [219]	Reduce losses	NRGA, GA and BSP are used to solve distribution network optimization problem for loss reduction.		No modelling
Tabu Search (TS)		Nara et al. (2001) [221]	Reduce distribution power loss	ODGP are solved by TS method for the case of uniformly distributed loads with unity power factor.		Not modeled
		Golshan & Arefifar (2006)[220]	Minimize cost of power and losses and reactive power capacity.	DGP problem is solved by using TS method, the amount of DGs and reactive power sources RPSs are counted in selected buses.		Not modeled
		Maciel& Padilha-Feltrin, (2009) [222]	Optimal solutions set	Apply a Multi-objective TS to find the Pareto optimal solutions set, it is a better performance comparing to the NSGA-II method.		Not modeled
Particle Swarm Optimization (PSO)		Krueasuk & Ongsakul, (2006)[226]	Minimize the total real power losses	ODGP of multi-DGs determine by PSO.		Not modeled
		Niknam (2006) [228]	Summation of electrical energy generated by DGs and substation bus	The optimal operation problem solved by PSO and presents a better performance in comparison with GA.		Not modeled
		Beromi et al. (2008) [227]	Improve voltage profile, reduce loss and reduce THD	ODGP considering load flow and harmonic calculations for decision-making is applied by PSO.		Not modeled
		Raj et al. (2008) [230]	Reduces line losses, improve voltage profile and improves power quality	Find optimal value of the DG capacity by using PSO method.		Not modeled
		Wong et al. (2010) [12]	Reduces total power losses	PSO and Newton-Raphson load flow method are proposed to determine the optimal location and size of the DG.		Not modeled
		Jain et al. (2011) [231]	Minimizing power loss and improve voltage profile	Multi Objective PSO method proposed to determine the optimal size of the DG.		Not modeled
		Siano, P., & Mokryani, G. (2013) [229]	Minimizing energy costs and power losses	PSO and market-based OPF are used to choose the optimal size and number of WTs in the system with considering security constraints and inter-temporal effects.		Not modeled
		Aghaei et al. (2014) [232]	Reduce overall cost ,power losses and voltage stability index	PSO used to solve short time planning problem of DG.		Not modeled
		Zeinalzadeh et al. (2015) [234]	Minimize the cost	Multi objective PSO method is used to find optimal location and capacity of DGs and shunt capacitor banks with considering load uncertainty in the system.	Load demand	Fuzzy-based approach
		Jamian et al. (2015) [233]	Minimize the cost	ODGP problem is solved by using rank evolutionary PSO method.		Not modeled
		Guan et al. (2015) [235]	Minimizing real power loss	DQPSO used to solve the feeder reconfiguration problem with different model of DGs.	Renewable DG	Monte-Carlo simulation
		Malekpour, et al. (2013) [89]	Reduces total power losses and Minimize cost of power	A new method based on adaptive particle swarm optimization (APSO) is offered for investigating the	Renewable DG	Point estimation method (PEM) –based

			multi-objective stochastic distribution feeder reconfiguration (SDFR) problem.		approach
Ant Colony Optimization (ACO).	Teng & Liu (2003) [239]	Minimize the cost	ACO is used to solve the optimum switch relocation problem.		Not modeled
	Gómez et al. (2004) [238]	Minimize the investment and operation costs	ACO is proposed to solve planning problem of distribution systems.		Not modeled
	Vlachogiannis et al. (2005) [240]	Minimize real power losses	ACO approach is applied to the solution of the constrained load flow (CLF) problem as a combinatorial optimization problem.		Not modeled
	Falaghi & Haghifam (2007) [241]	Minimizing the DG operation and investment cost	ACO used as the optimization tool to solve optimal location and size problems in DG.		Not modeled
	Wang, L., & Singh, C. (2008) [242]	Minimizing a composite reliability index and minimizing the customer interruption costs	ACO is proposed to seek out the optimal re-closer and DG placement.		Not modeled
	Kaur, D., & Sharma, J. (2013) [243]	Minimize the total cost	Multi-period optimization problem solved by ACO.		Not modeled
	Mirhoseini et al. (2015) [244]	Minimizes both real power losses and energy not supplied index	Multi-objective reconfiguration problem consider the real power losses and the energy not supplied index was discussion together by a modified ACO.		Not modeled
Artificial Bee Colony (ABC)	Padma Lalitha et al. (2010) [247]	Maximum loss reduction	ABC algorithm and Fuzzy are used to find the optimal DG locations and sizes in the system.		Not modeled
	Abu-Mouti et al. (2011) [249]	Minimize the total real power loss	ABC used find the optimal site, size and power factor of DGs.		Not modeled
	El-Zonkoly (2013) [246]	Minimizing cost	ABC is applied to solve dynamic expansion planning problem of DGs through discuss unit commitment (UC) mathematical model and a multistage expansion planning strategy.		Not modeled
	N. Mohandas et al. (2015) [248]	Improve voltage profile	Optimal DG location and size problems have been solved by ABC algorithm.		Not modeled
Artificial Immune System (AIS)	Carrano et al. (2007) [250]	Minimizing cost	Immune algorithm (IA) used to generate a set of nearly-optimal under a set of load-evolution conditions.	Load demand	Monte-Carlo simulation
	Aghaebrahimi et al. (2009) [251]	Minimize power losses	AIS is used to solve DG placement problem in power network.		Not modeled
	Souza et al. (2011) [252]	Minimize total costs	AIS used to solve the DGP problem by taking account the effect of uncertainty in electric distribution networks.	Load demand	Monte Carlo simulation
Bacterial Foraging	Singh et al. (2012) [254]	Minimizing cost	Bacterial foraging introduce to provide a rapidly solutions with a best probability in order to obtain a global optimal solution of the distribution planning problem.		Not modeled
	Devi, S., & Geethanjali, M. (2014) [255]	Reduce the total loss and improve the voltage profile	MBFO is proposed to improve the convergence characteristics of BFO algorithm to solve optimal problems of radial distribution systems.		Not modeled
	Kowsalya, M. (2014) [257]	Minimize network power losses	BFOA is proposed to solve the various optimization problems at different load levels.		Not modeled
	Devabalaji et al. (2015) [256]	Minimize power losses	BFOA was used to fine optimal size of capacitor bank with taking account both LSF and VSI.		Not modeled

Bat Algorithm	Yammani et al. (2013) [259]	Minimize system loss and improve voltage profile	BA used to find the optimal location and sizing of the DGs.	Load demand	Scenario-based approach
	Injeti et al. (2015) [30]	Loss minimization	Optimal Location problem of capacitors in radial DGs is solved by BA and Cuckoo Search (CS).		Not modeled
	Candelo-Becerra et al. (2015) [260]	Minimizing power losses	BA was used to obtain optimal solution of DGs problem in radial distribution network.	Renewable DG	Scenario-based approach
	Devabalaji et al. (2015) [261].	Reduce the total power loss	BAT Algorithm used to find optimal size of the capacitor banks and LSF used to pre- find the optimal site of the capacitor placement.		Not modeled
Imperialist Competitive Algorithm (ICA)	Mahari et al. (2012) [263]	Minimizing the total system active power losses	ICA used to find optimal location and size of DGs.		Not modeled
	Moradi et al. (2014) [264].	Reduce power loss , increase voltage stability index and improving system voltage profile	ICA employed to solve the ODGP problem of DG and capacitor banks in the distribution network.		Not modeled
	Poornazaryan et al. (2016) [265].	Reduce power losses and enhance voltage stability.	Optimal location and size of DG unit are obtained by proposed ICA with considering load variations.	Load demand	Scenario-based approach
Cuckoo Search Algorithm (CSA)	Fard et al. (2012) [269].	Reduce the losses and improve the voltage profile	CSA introduce to solve ODGP problem for different types of DG in the network.	Load demand	Monte Carlo method
	Moravej et al. (2013) [268].	Minimize real power losses and improve voltage profile	Optimal location and size problem is solved by employing CSA.		Not modeled
	Buaklee et al. (2013) [270].	Loss reduction and improve voltage profile	CSA is proposed to find optimal site and size of DGs by considering the fault level constraints.		Not modeled
	Nguyen et al. (2016) [267]	Minimize total power loss and enhance voltage stability.	CSA employ to solve optimal location and size problems in DGs network.		Not modeled
Intelligent Water Drop (IWP) Algorithm	Prabha et al. (2015) [272].	Minimize the losses	IWD used to find optimal sizing and the loss sensitivity factor (LSF) for the installation of DGs in the radial distribution network.		Not modeled
	Moradi et al. (2016) [273]	Minimize network power losses, improve voltage regulation and increase the voltage stability.	IWD method with GA is proposed to find size and site of DG in micro grids.		Not modeled
Fuzzy Set Theory (FST)	Kim et al. (2002) [275]	Reduce power loss costs	Fuzzy-GA method used to solve the ODGP problem by transforming the objective function and constraints it to multi-objective function with fuzzy sets		Not modeled
	Haghifam et al. (2008) [276]	Minimization of total cost , technical and economic risk	Load and electricity price uncertainties in the system are modelled using fuzzy numbers and solve by non-dominant sorting genetic algorithm (NSGA-II).	Load demand	Fuzzy numbers
	Lalitha et al. (2010) [277]	Reduce power losses and improve the voltage profile	Fuzzy and PSO algorithm including voltage and line loading constraints proposed to find the optimal DG locations and sizes.		Not modeled
	Reddy, V. U., & Manoj, A. (2012) [278]	Reduce power losses	BA used to determine the size of optimal capacitors in DGs.		Not modeled

The above table shows that the trend of using the intelligent methods has been gradually increased to find the optimum solution in DGs placement problem. In addition, the scientists have recently applied two or three methods as a combination to obtain a new strategies in order to solve the optimization of DGP problem efficiently, such as [12, 207, 208, 212-215, 219, 247, 273, 275-277].

Tables 6 and 7 show the summary of the conventional and intelligent methods characteristics.

Table 6. Advantages and disadvantages of conventional methods

Conventional methods	References	Advantages	Disadvantages
Linear programming (LP)	[156-158]	Easy to implement, and it accommodates large variety of power system operating constraints	Used just when the objective function is linear.
Nonlinear programming (NLP)	[162, 163]	Simple and Efficient.	Long time to run.
Mixed-integer nonlinear programming (MINLP)	[165-172, 286]	It is fast, robust, efficient and deal with very large scale DGP problems.	It may insert errors due to the linearization of the nonlinear characteristics of DGP.
Dynamic programming (DP)	[173-176, 286]	Efficient and easy.	Not suitable for large-scale DGP problems
Optimal Power Flow-based Approach (OPFA)	[36, 177-184]	Easy, simple and efficiency in computational time	The results may not be optimal when the problem is highly complex and Hard to understand and implement
Direct approach	[185-187]	Robust, very efficient and suitable for large-scale distribution systems	Not deals with the radial network structure.
Ordinal optimization (OO)	[188-190]	It is deal with non-deterministic polynomial (NP) complete problems such as DG planning with discrete and continuous variables.	Need long time.
Analytical approaches (AA)	[15, 191-196]	Simple, easy implementation and efficiency in computational time.	Only obtains approximate solution.
Continuation power flow (CPP)	[197, 198]	Faster, Very efficient, robust, qualified to treat different level penetration of DG.	May not find the optimal solution.

Table 7. Summary of Evaluation Intelligent Methods

Intelligent methods	References	Advantages	Disadvantages
Simulated Annealing (SA)	[200-202]	Ease of implementation, get best solutions and robust.	It requires excessive computation time.
Evolutionary Algorithms (EAs)	[206-208]	Simple, speedy processing time , efficient and accurate results, very useful for complex problems	Used a larger population size, repeated fitness function evaluation for large and complex problems may be time consuming.
Tabu Search (TS)	[220, 221]	It is an efficient to achieve near -optimal solution within a reasonably short duration.	Need considerable parameters to be define
Particle Swarm Optimization (PSO)	[12, 226-232, 287, 288]	It is easy to implement Insensitive to scaling of design variables, Simple implementation, easily parallelized for concurrent processing, derivative free, Very few algorithm parameters, and very efficient global search algorithm.	Need to solid mathematical background.
Ant Colony System Algorithm (ACSA).	[238-244]	Easy to understand and code Rapid discovery of good solutions	Theoretical analysis is difficult
Artificial bee colony (ABC)	[245-249, 289, 290]	Very simple, robust, efficient algorithm, fast-converging, capable of handling complex optimization problems and it does not require external parameters.	The performance of this method may be influenced depending on the constraint handling method used
Artificial immune system (AIS)	[250-252]	Effective, can find and maintain set of suboptimal solutions simultaneously with the existing better solution.	Complex system
Bacterial foraging	[254-257]	Efficiency to find result in less computational time	It requires the tuning of great number of parameters.
Biologically inspired algorithm (Bat Algorithm)	[30, 259-261, 278]	Efficient and Accurate.	The convergence rate is very much influenced by adjustment parameters.

Imperialist Competitive Algorithm (ICA)	[263-265].	effective, fast, and capable of handling complex nonlinear mix-integer optimization problems in DGs.	harder to code fewer literature example
Cuckoo Search Algorithm (CSA)	[266, 268-270]	It is more generic and robust, efficient, easy to code, less parameters setting.	Slow convergence.
Intelligent Water Drop (IWP) Algorithm	[271, 272]	fast, efficient, easy to implement and need less iteration to find good results	fewer literature example
Fuzzy Set Theory (FST)	[275-277]	Easy to comprehend, and suitable to model uncertainties to find better solution	fewer literature example

5. Conclusion

Distributed generators (DGs) are reliable solution to provide power which accommodate the load increase and relieve network overload in addition to offer technical and economic benefit.

This paper reviews a number of studies which already been carried out to develop an efficient and robust optimization algorithms to solve DGs placement problem (size, site and the type). The sequence of this study has considered a comprehensive review of uncertainty modeling in power system and application of these methods in DGs planning and operation problems. Also, the conventional, intelligent and perspective approaches used for the DGs problem are specifically reviewed. Then, the comparison between these methods has been shown to locate the advantage and disadvantage.

This work is specialized by incorporating the reviewing of the methods which recently used as solution of DGs placement problem and characterized as simple concepts, easy implementation and higher stability mechanism.

The recent review depicts that the intelligent methods are mostly used to obtain an optimum solution of DGs placement problem. Also shows the new ways of combining more than one method to gain the proposed optimum solution.

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