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A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms

Mahmoud Pesaran H.A[a,b,*], Phung Dang Huy[a], Vigna K. Ramachandaramurthy[a]

[a] Power Quality Research Group, Department of Electrical Power Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia

[b] Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran

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ABSTRACT

Distributed generation, with respect to its ability in utilizing the alternative resources of energy, provides a promising future for power generation in electric networks. Distributed generators contribution to power systems include improvement in energy efficiency and power quality to reliability and security. These benefits are only achievable with optimal allocation of distributed resources that considers the objective function, constraints, and employs suitable optimization algorithm. In this paper, a comprehensive review on the optimal allocation of distributed generators was carried out for different objectives, constraints, and algorithms. Current review highlights how the methods and algorithms for optimal distributed generation allocation play an important role in improving the accuracy and efficiency of the results.

1. Introduction

Unlike the traditional centralized generation, distributed generation refers to a method in which a part of the electric power is generated and delivered to customers with small generation units placed close to the end users. The distributed generation can also be addressed as dispersed generation, embedded generation, or decentralized generation. Distributed generation covers a wide range of locally installed power generation units which can be of both renewable and conventional types. Nowadays, with respect to the technical developments, enormous benefits can be achieved from Distributed Generators (DGs) in economical, technical, and environmental fields [1–3]. Those advantages could be earned by optimal selection, sizing, and placement of DGs in power systems.

There are technical and environmental restrictions in the conventional power plants' expansion. Moreover, unsecure fossil fuel market has led the electricity market towards new energy resources. In this way, there are a number of incentives for encouraging network planners to use combined heat power (CHP) resources in distribution networks. Some of the issues which can be addressed by DG integration in distributed networks are: power losses, voltage control, reliability, stability, and fault level [3–11]. Since the DG installation in power networks changes the network characteristics and the nature of the electricity market [12,13], proper legislative regulations for the electricity sector are being introduced at the same time. A comprehensive review on above matters, including the distributed power generation resources, regulation, and integration arrangement, has been carried out in Ref. [14].

Distributed Generation Allocation (DGA) can also include Distributed Generation Planning (DGP). Since the objectives, constraints, and optimization approaches are common in either DGA or DGP, most of the studies which have been reviewed in this article focused on distributed generation allocation as well as planning. According to the selected objectives and the operation constraints, the utilized method in DGA can be categorized with respect to their approaches for optimization such as normal search methods, intelligent methods, or fuzzy set based methods. An extensive review on the technical aspects of optimal distributed generation planning was done in Ref. [15]. In current study, optimal DG allocation has been reviewed and presented with focus on mathematical models and employed solutions. A brief review was also carried out on the related studies with respect to their objectives and constraints as follows:

Single or multi-objective functions are considered to maximize the benefits of DG due to the considered constraints. Normally, the real power loss [16–37] and the voltage profile [36–47] are the base objectives. Some other objectives may accompany this base objective such as reactive power minimization [48], DG capacity maximization [49–61], or economy oriented objectives [62–75]. Other than the above, multi-objectives models including various type of objectives [76–103] have also been implemented in DGA formulations. There are

* Corresponding author.
E-mail addresses: mpesaran@live.com (M. Pesaran H.A), huydvn@gmail.com (P.D. Huy), vigna@uniten.edu.my (V.K. Ramachandaramurthy).

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also studies on the influence of DG on supply system security and reliability, which clarified that these parameters could be improved by means of a proper DGA [104–110]. Technical issues of variable DGs (e.g. wind turbines) derived from time varying nature [14] and integrated in distribution networks using suitable DGA approaches are also investigated in Refs. [25,50,88,111–115]. A wide range of constraints has been selected for optimal DGA fitness functions of either single or multi objectives. These constraints can be categorized into two main classes: power systems conservation constraints and utilities capacity limitations. However, other constraints including power exchange between areas [17], voltage step [51], and short circuit level and ratio (SCL & SCR) [52] are also discussed in the literatures. The following sections discuss the objectives and constraints in DGA studies and presents the methods and algorithms for optimal DGA.

2. Selected objectives for optimal DGA

Most of the DGA studies were done with the objective of real power loss minimization. Besides that, the reactive power loss, voltage profile, the current reduction in weak lines, spinning reserve power, and network MVA capacity are also take in to account. Normally, the real power loss is selected as the base objective index and other objectives are used to form single or multi objective fitness functions for optimization. The most common combinations are explained in the following sub-sections and summarized in Fig. 1.

2.1. Power loss minimization

In this scheme, optimal location of DG units has been investigated by minimizing active power loss in the lines through DGA [16,17,33,41,42,116–121]. The formulation was done by assuming that the summation of the total injected power on all nodes could represent the network losses. The aforementioned formula for power losses has been extended according to the second order technique in Refs. [16] and [17] based on the Newton's method and genetic algorithm, respectively. In addition, in Ref. [17], the objective function has been expressed for each load level by total cost of the losses for that specific load level. Furthermore, the loadability has been improved by optimal allocation of DG units and by minimizing the total reactive power losses in Ref. [18]. In another study, the total line losses has been minimized to investigate the impact of DG on voltage stability and power transfer capacity of distribution network [19]. It has been understood that due to the injection of the active power, overall impact of DG installation is positive. Later on, the power loss has been minimized by focusing on the transmission losses to determine the installation bus and size of a type-3 DG (induction generator empowered by wind turbine) in Ref. [36]. On the other hand, the authors in Ref. [20], have expressed the total power loss as a function of the injected current to the network branches.

The majority of researches only focused on total real losses in power systems (exact losses) [21–26], while, the total energy loss and energy loss for 24 h are chosen to minimize the power losses in Refs. [27] and [28], respectively. Moreover, the total power losses has been represented by the annual energy losses in the number of studies [29–31]. The annual energy loss is minimized by optimal DGA in Ref. [29] using biomass and wind DGs in combination or as a single source. They were installed in both dispatchable and nondispatchable forms. Same objective is minimized by optimal DGA of 3 wind turbines [30]. The trend was followed by optimization of hybrid DG unit comprising solar, wind, and non-renewable DG [31]. In addition, the power losses was

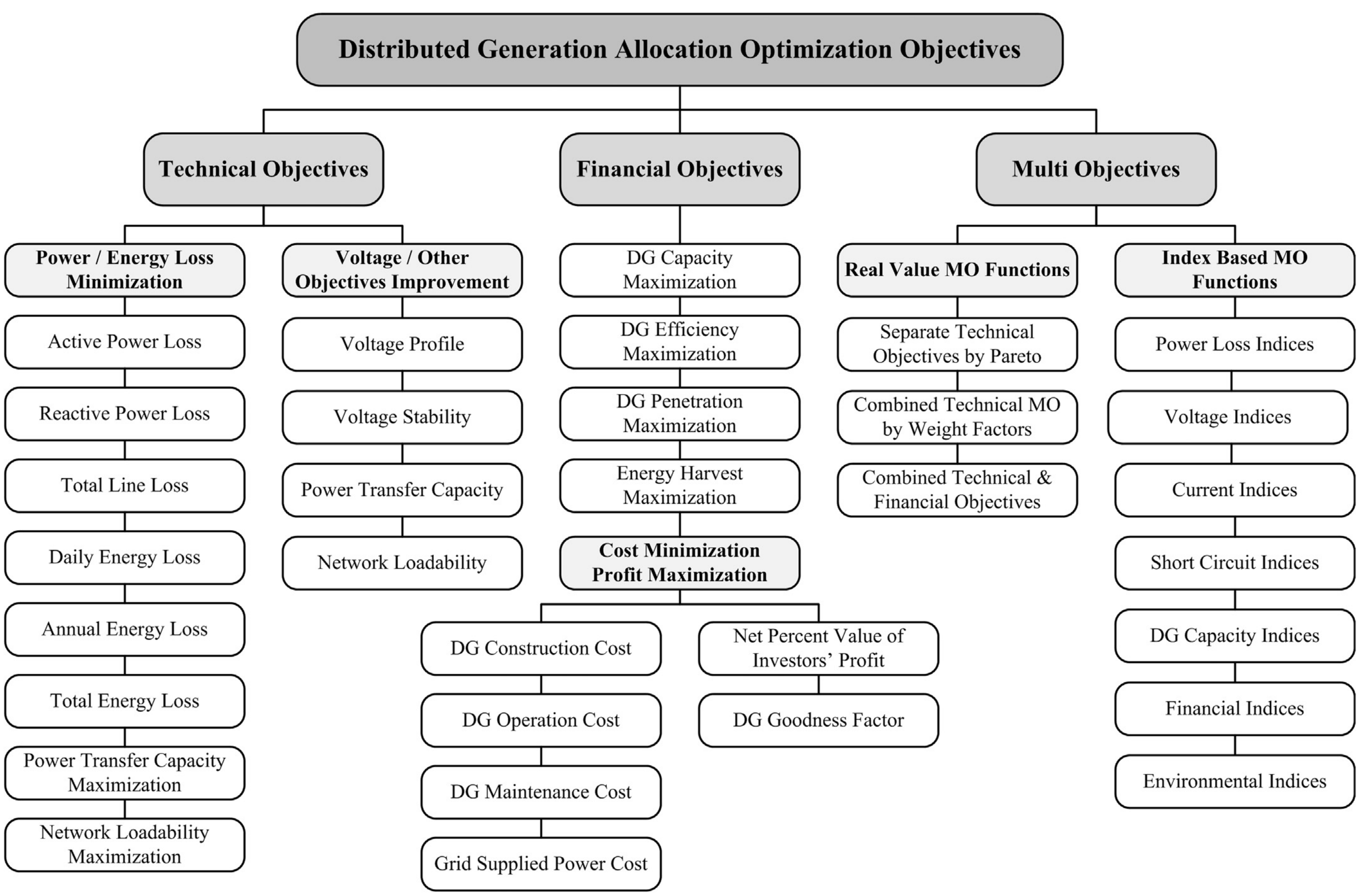

Fig. 1. Selected objectives in distributed generation allocation.

treated as the daily energy loss and minimized using a mathematical method [32].

However, line losses is one of the most important characteristics of network performance, but it is not comprehensive enough to be selected as a singular objective value to establish the objective function.

2.2. Voltage profile improvement

Among the researchers which studied optimal DGA, some purely focused on voltage profile [38,39] or voltage stability [40] improvement as the optimization objective, while most of them considered loss reduction along with the voltage profile improvement [36,37,41–47,49]. There also exist other articles that combined more objectives, e.g. reliability, stability, or nodal pricing for optimal DGA [84,104,117,122], which are discussed in the multi-objective sub-section.

Interestingly, the voltage profile has been optimized by maximizing the DG penetration level in Ref. [39]. It has been improved through the bus selection by differential evolution (DE) on standard 6-bus and 30-bus test systems, considering the sensitivities to voltage incremental (dV/dP) and line flow constraints. In addition, the DGs' optimal allocation using genetic algorithm in a portion of Tehran distribution grid is reported in Ref. [44]. They concentrated on reducing the power losses and improving the voltage profile, while similar objectives have been handled in Ref. [45] by modified artificial bee algorithm for the standard 33 bus radial distribution system. Fuzzy logic has been employed in Ref. [46] to improve above objectives with a new developed analytical method for size calculation. The proposed method was applied on a three radial networks i.e. 12, 33, 69 bus networks. Similar combination of objectives were selected for optimal placement and sizing of DG units using the genetic algorithm in Ref. [47].

2.3. Objectives with financial concerns

2.3.1. DG efficiency and energy harvest maximization

In most of the studies on DG capacity and efficiency, it has been assumed that one generator is installed on each bus. This objective has been subjected to the constraints and being selected for the DG optimal allocation in a number of studies [49–54]. Likewise, the objective has been optimized by considering the DGs as negative loads in Ref. [55]. Simultaneously, DG capacities have been optimally maximized by modeling them as the power sources with negative cost and minimizing the imported or exported energy in Refs. [56,57]. Later on, the real load curtailment and supplied power by grid have been minimized to optimize the DG size and capacity in Ref. [58]. In addition, the penetration level, as a key criterion for energy harvest, has been maximized to achieve the optimal allocation of DGs in Ref. [59], while the same objective was handled by minimizing the cost of power per kW and the cost for capacity per kWh in Ref. [60]. Maximum energy harvest per Euro of investments has been selected as an objective in Ref. [61]. The authors also take into account the maximum benefits from the existing energy resources and assets.

Similar to line losses, DG capacity maximization cannot be a single objective for optimal allocation of distributed generation units. Nevertheless, it is good to use DGs with their maximum capacity and at high efficient point, but they need to be accompanied by other objectives.

2.3.2. Cost minimization and profit maximization

The following objectives on electricity generation cost have been studied in the literatures: DG construction, operation, and maintenance costs [42,67–69]. In Ref. [67], the total investment was modeled with respect to the formulation of supply chain. They minimized aforementioned three cost objectives concurrently for different scenarios. The assumed operational cost comprised of: additional power purchase and loss compensation service. They have concluded that the electricity demand growth can be addressed under three options by the local network management corporations: 1- Purchasing the extra required electricity from the main network power plant and injecting it into the distribution network through the network junctions. 2- Buying the required power from the already existed local power producers and delivering it to their own distribution network. 3- Installing DGs in response to distribution network demand rise without constructing any new transmission or distribution lines. Afterwards, another combination of multi cost objectives has been employed in Ref. [68], while in most of the studies the operational costs are studied in detail, this research looked in to DG integration benefits in a different way. They have optimized the DGA by focusing on the reliability cost, deferred energy cost, and emission cost. The minimum and maximum functions have been optimized simultaneously but separately, and the results have been selected based on Pareto front or non-dominant solution sets. Additionally, authors have considered the solar farm costs as well and they have minimized conventional generator, solar farm, and gas emission cost along with the above base cost objectives [69].

There are some studies which have combined the income besides the cost objectives [70–72]. In this category, the objective function in Refs. [70,71] includes maximizing the profits for DG owners and minimizing the payments for Distribution Corporation (DISCO). In addition, Ameli and Bahrami et al. [71] have added a big value penalty term to the objective function in case of constraints violation. In another study, the net percent value of investor's profit has been maximized as the revenue and at the same time, the integration cost, composed of equipment cost, transportation cost, land cost, and labor cost has been minimized along with operation and maintenance cost [72]. Subsequently, the DG profit has been represented by maximum saving in system upgrade investments in Ref. [73], while the objective function was formed by the cost of annual energy loss, and the cost of interruption. Moreover, the financial objectives have been combined and treated as an index in a couple of studies [74,75]. In this regard, the ECOST reliability index (expected outage cost of the system as a whole) which was developed by Chowdhury has been implemented to optimize the location of DGs in Ref. [74]. Furthermore, the goodness factor of DG units has been considered in Ref. [75] which is formed by computing the DG units' contribution to the losses of the distribution system. The objective function has been built for DISCO owned DGs and investor owned DGs to minimize costs with respect to the DISCO owned DGs. The objective function needs to be readjusted when the investors own the DG units instead of the utility. However, the power of those generation units is absorbed by DISCO, but they do not include any dispatch tuning procedure and the modifications are only applied on utility owned DGs. In such case, the expressed formula for objective function was changed by replacing the operational costs of DGs that are owned by DISCO, with the cost of power purchased from the investor owned DG units. With respect to the fact that the described value is constant, it does not have any impact on optimization and could be neglected during cost minimization.

Normally, cost related objectives are in contrast with technical objectives, and collecting them in the form of a single value objective function is very difficult, even impossible. With respect to this fact, a suitable set of objectives can be composed as multi-objective functions. The combination of the performance related financial and technical objectives are elaborated in the next section.

2.4. Multi objective optimization

As discussed above, several single or combinatorial objectives have been used to create DGA objective function (OF). The Multi Objective (MO) scheme aims to accomplish a concession among the various objectives of an optimal DGA. The multi-objective functions create a better model of the real environment, which generally contains contradicting objectives and enable planners to select the best solution from available solutions, according to their experiences and points of view.

2.4.1. Singular/consolidate multi-objective functions

The multi objectives have been optimized separately in some studies. For instance, a multi-objective function with two separate parameters including the network power loss and voltage regulation have been treated by Pareto optimal front method in Refs. [76,77]. In addition, the multi-objective function has been optimized by minimizing different independent functions in Ref. [78]. Similarly, in Ref. [79], the objective function has been formulated using three different objectives: energy loss cost, voltage profile, and power quality. Unlike above, most of the studies consolidated multi objective values using proper weight factors to form a single value objective function. In this manner, daily energy loss and voltage profile have been normalized and combined using weight factors to form the objective function in Ref. [80]. Later, the daily energy loss has been replaced by the power loss and merged with the Voltage Stability Margin (VSM) [81], or Voltage Stability Factor (VSF) [82] to create the objective function. From this category, three objectives including the active power loss, short circuit current, and the bus voltage level have been considered as OF in Ref. [83]. Later, Nayeripour and Mahboubi-Moghaddam et al. [84] substituted the short circuit current from above objective function formula with the transient stability. It is worth mentioning that, the most comprehensive study on the technical aspects of DG installation advantages has been carried out in Ref. [85]. The authors have reduced the voltage and frequency deviations through a multi-objective function which comprised of: improvement in the voltage profile, increase in the spinning reserve, reduction in the power flow, and reduction in the line loss. At the same time, Sutthibun and Bhasaputra [86] have concentrated on minimizing the real power loss and the gas emission, while improving the severity index which represent the contingency of power system regarding the power generation and balance constraints. Again, the multi-objective function has been formed by summing the weighted objectives, where the weight factor values have been selected according to the importance of their related terms in the objective function calculation.

2.4.2. Index base multi-objective function

A range of technical indices has been employed to form multi-objective performance index (MOI) and investigate the DG impact on different parameters of the electric networks [87–91]. Different numbers of objective indices have been combined using proper weighting factors in each paper to carry out a single value index. For instance, the objective function in Ref. [87] consists of the active and reactive power loss indicesILP and ILQ, the voltage drop and regulation indices,IVD and IVR, the conductor current capacityIC, and three phase and single phase short circuit currents$ISC3$ and $ISC1$. In another study, the multi-objective function was made up using the same objectives except for the voltage regulation index IVR [88]. Moreover, the short circuit indices were also removed during the composition of the performance index in Ref. [89]. Other objective indices are also combined with some of the above to create multi-objective functions. In this regards, a set of objective indices including ILP, IVR, MVA capacity improvement index $IMVA$, and the environmental impact reduction index IEI have been combined to construct a single value objective function in Ref. [90], while, only ILP and Voltage Stability Margin (VSM) have been employed to form the objective function in Ref. [91].

2.4.3. Multi-objective functions including financials

In addition to aforementioned technical parameters, there are also plenty of studies that combined the financial objectives with technical objectives, including power losses, injected reactive power, reliability, and loading margin, to optimize the DG allocation. For instance, concurrent cost and loss minimization have been selected to form the objective function in Ref. [92]. At the same time, the sensitivity to line loss and price variation for each node have been employed as the operational and commercial criteria for optimal DG installation site identification in Ref. [93]. In this study, a penalty objective function, which is limited by network constraint violation, was created to minimize the total curtailed load during a single step restoration after a long time electricity interruption. Moreover, the objective function has been constructed based on the amount of load that cannot be supplied with respect to the violation of branch currents, violation of bus voltage, and transformer load limit violation in a substation. Afterwards, the network loss along with the capital, replacement, start-up, and maintenance costs have been minimized in Ref. [94], considering the renewable energy source uncertainties in a competitive energy market. Earlier, a multi aspect financial objective including DISCO investment, operating cost, payment for loss compensation, and cost of unserved power have been exercised and minimized in Ref. [95]. In this research, the objective function has been composed by minimizing the fuel cost for both DG and conventional sources together with minimizing the network line losses. In another attempt, the economic impacts of PV units in radial networks have been introduced as the objective function in Ref. [96] by combining the voltage stability and economic impact of PV integration, including profitability and loss reduction. Simultaneously, the cost of total power generation and losses together with total reactive power request has been minimized by Golshan and Arefifar [97] using a combination objective function for distribution generation planning which includes reactive sources, distributed generation capacity, and also network configuration.

A combination of cost based objective and system reliability has been employed in Refs. [98,99] for optimal DGA. While the objectives have been comprised of minimizing the basic cost objectives along with environmental penalty (emission for fossil fuel plant), and maximizing the reliability in Ref. [98], while, only three main cost objectives have been minimized in Ref. [99] by maximizing the benefits of an active power demand reduction (from grid) and reliability improvement. The maximization of the Loading Margin (LM) and DISCO profit along with the minimization of energy loss cost and investment cost have been chosen as the objectives in Ref. [100]. In further studies, an interesting approach has been selected to form a multi-objective function which consists of technical and economical factors [101]. In this study, the objective function included voltage profile improvement and increase in loading margin as technical factors. The cash inflow of DG, life cycle cost, and power loss on feeder have been selected to represent the economical aspect. In another study, four objectives which consist of total line loss, main grid energy flow, DG installation cost, and gas distribution investment (source for gas based DG) have been optimized separately to obtain 4 dimensional Pareto optimal front (trade-off front) [102]. Recently, a combination of constraint dissatisfaction, costs, and environmental emissions have established the objective function for optimal DGA [103].

In all researches, the multi-objective values have been selected for composing the objective functions or making decision on the optimal allocation using the Pareto Front method. However, only a portion of them used the weight factors to create a single-value objective function and the rest employed Pareto Front method which includes the consequences of interference due to human decision in optimal allocation procedure.

3. Constraints for optimal DGA

The constraints have been considered in a single or multi objective function optimization to ensure that the operational or design conditions are within the limits during the recognition of the best location and size of DGs. A number of power system conservation constraints and utilities capacity limitations have been considered by the researchers. The power balance, node voltage, line current, and power factor of DG are the most common power systems conservation constraints, while the short circuit current, capacity of intertie power, number of

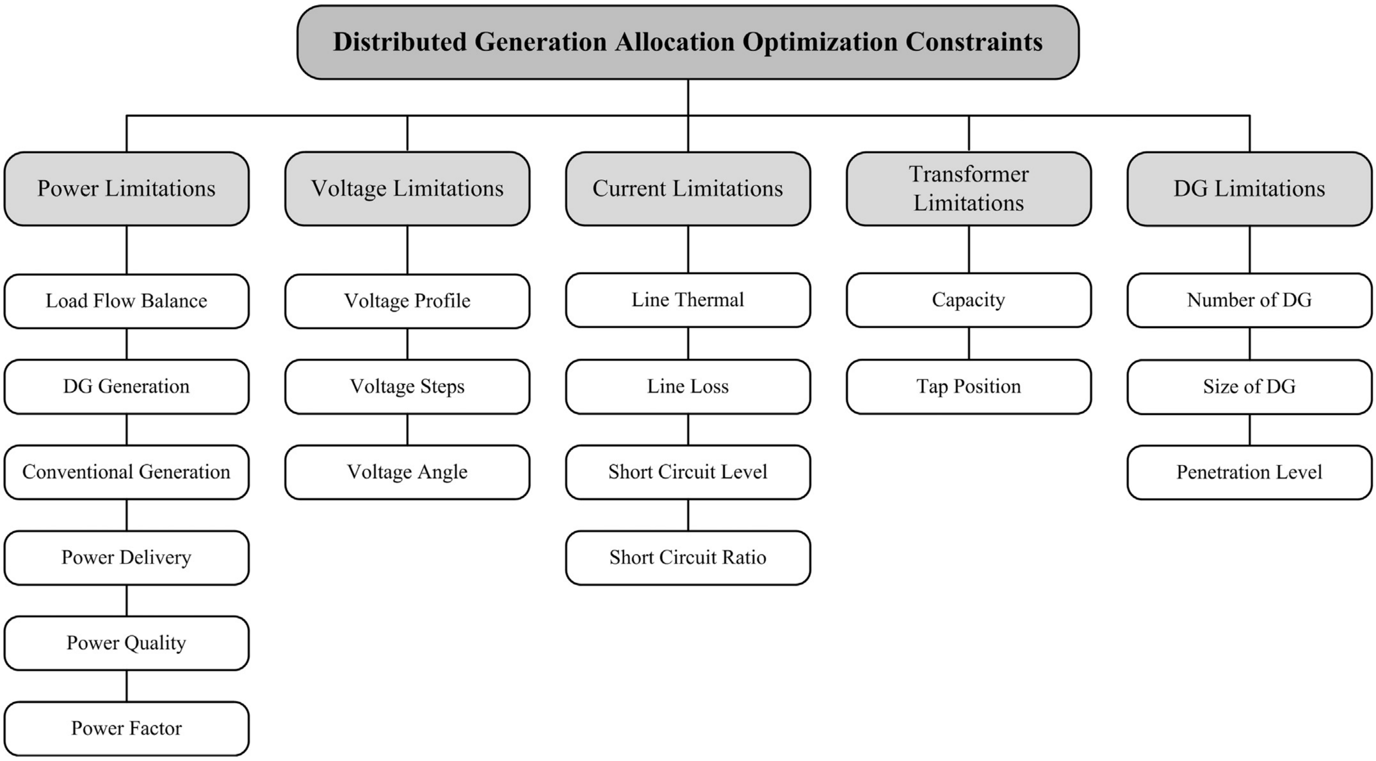

Fig. 2. Considered constraints in distributed generation allocation.

DGs, maximum power production of DG, and transformer capacity are the more popular examples of utilities limitations constraints. Some of the mentioned constraints are illustrated and categorized in Fig. 2 as follows:

3.1. Active power: load-flow/generation

The total active losses and demand should be covered by total active generation from traditional generators and all DG units. Such constraint is called Active Power Balance Limit (APBL) and has been considered in most of DGA studies [18,24,26,30,33,37,39,40,43,56–58,67,69–73,77,80,81,85,89–91,93–95,97,100,102,103,116,119,120,123].

The Traditional Active Power Generation Limitations (TAPGL) have been focused in a couple of studies. In Refs. [62,66,69,72,85], the generated active power by traditional generation units is subjected to the lower and upper active power generation limits, while in Ref. [75] only the upper limit of the active power has been considered.

DGs' Active Power Generation Limitations (DGAPGL) has also been taken into account in a number of researches. The lower and upper restrictions for active generated power have been applied in Refs. [18,22,25,37,42,71,72,75,76,81,84,85,93,95,104,115,123,124] while, only the upper limit has been taken into account in Refs. [43,67,93,102].

No significant limitation has been applied to the total supplied load through DGs, however, in Refs. [48,93], the authors have restricted DG maximum installed capacity to 20% and 30% of the substation capacity, respectively.

3.2. Reactive power: load-flow/generation

The total reactive losses and demand should be covered by total reactive generation from traditional generators and all DG units. This constraint is named as Reactive Power Balance Limit (RPBL) and has been examined almost in all studies [18,24,26,30,37,39,40,43,56–58,67,69–73,77,81,89,90,93–95,100,102,103,116,119,120,123].

The Traditional Reactive Power Generation Limitations (TRPGL) is another constraint being contemplated in studies. The generated reactive power of traditional generation units has been restricted to the lower and upper reactive power generation limits [62,66,69,72], while only the upper limit of reactive generated power has been applied in Ref. [75].

The next constraint for reactive power generation is DG Reactive Power Generation Limits (DGRPGL). In Refs. [18,37,42,68,71,72,75,76,80,81,93,95,123], the reactive power of each DG has been limited to both lower and upper limits, on the other hand, only the upper limitation has been exercised in Refs. [43,67,102,125].

3.3. Voltage: profile/steps/angle

The Voltage Profile Limitations (VPLs) have been exercised in majority of DGA studies. For instance, the constraints limited the bus voltage to the voltage upper and lower limitations, for all buses [18,24,26,28,29,32,37,38,40,42,43,58,59,67–71,73,76,78,80–82,84,89,90,94–96,98,100,101,103,117,118,120,126]. On the other hand, the maximum of 5% variation has been considered for the voltage in Refs. [24,30,31,39,116,127] while, the variation limitation of 10% has been implemented in Ref. [119]. In a recently published study, the voltage constraints have been applied through the penalty factor in the OF whenever the bus voltages exceed the limitations [60].

In the case of a distributed generator outage, the voltage step should be changed immediately. Voltage Step Limitations (VSLs) have been discussed as the bus contingency voltage in Ref. [53]. In addition, the study was done by a DG disconnection scenario in a security constrained optimal power flow. This constraint has been expressed by considering the bus voltage before DG disconnection, and the voltage step and the contingency voltage at a bus after DG disconnection.

The Phase Angle Limitation (PAL) for the bus voltage has been exerted in Refs. [93,120,123]. In these studies, the angle of bus voltage, which is limited to its upper and lower bands, has been considered as the constraint.

3.4. Line: the thermal/loss constraints

The maximum capacity of a feeder is defined by considering lines thermal and stability limitations. The Line Thermal Limitations (LTL) constraint limits the feeder capacity in MVA into the maximum power which can flow through the line. This limitation was very common in optimal DGA studies [23–26,29–31,40,42,43,48,51,52,56–58,61,62,65–68,70–72,75,80,81,84,88–90,93,95,98,100,103,106,108,111,115,120,128].

In Ref. [48], the authors maximized the DG units' capacity by focusing on the Total Line Loss Limitation (TLLL) with and without DG units installation. According to this constraint, total line loss after DG installation should not exceed the total line loss before DG installation.

3.5. Transformer: capacity/tap

The total power which is supplied through a substation transformer, has been limited to its maximum capacity by the Substation Transformer Capacity Limitations (STCL) [52,56,57,61,67,93,95,-103,120].

On the other hand, the tap position of the voltage transformers (VTs) is limited to its upper and lower limitations. This restraint has been called the Tap Position Limitation (TPL) and being integrated in Refs. [97,124].

3.6. Short circuit: level/ratio

To ensure that the short circuit level for network with new configuration after DG installation does not exceed the old system short circuit protection level, a short circuit calculation has been carried out with new configuration and checked against the Short Circuit Level Limitation (SCLL) [48,52,56,57,61,83].

According to the definition, Short Circuit Ratio (SCR) is the ratio of delivered active power to each bus from DG units in (MW), with respect to the power factor, to the value of short circuit level on each bus. Hence, a small enough SCR can limit the voltage dip transients. The Short Circuit Ratio Limitation (SCRL) has been considered in Ref. [61]. Induction generator connection to network with high X/R ratio may lead to the voltage instability, if the short circuit ratio is not limited. These limitations were explained in Refs. [129,130], and it has been recommended to keep them limited to 10%.

3.7. Power: delivery/quality/power factor

The imported power through intertie power delivery link, must be less than or equal to the Intertie Power Delivery Limitation (IPDL). This constraint has been considered in Ref. [70], and the cost of the delivered power through intertie is calculated by multiplying the intertie power limit factor by the price of electricity in the market. In another study, the power delivery has been limited to the maximum of Bulk Electric System (BES) [91]. Moreover, the maximum allowable power injection on each bus has been included as a constraint for optimal DGA in Ref. [80].

The power quality limitation has been considered by restricting the Total Harmonic Distortion (THD) to a maximum allowed level [31], THD and Individual Harmonic Distortion (IHD) [59], or by including the Loss of Load Probability (LOLP) [98]. In addition, the power quality constraint has been reflected by taking the Total Demand Distortion (TDD), THD, and the Harmonic Current limitations into account in Ref. [117].

Due to assumptions, DGs with real power output and reactive power output are supposed to operate in a specified constant power factor. The Power Factor Limitation (PFL) has been integrated in Refs. [24,56,57,65,66,68,72,119].

3.8. DG: number/size/penetration level

The number of DG units should not exceed the maximum number of DGs. Such limitation is referred to as the Number of DG Limitation (NDGL) which has been examined in Refs. [29,35,70,75]. Moreover, the DG size limitation has been integrated in Refs. [24,30,90,94,103,119].

The maximum penetration of hybrid DG units in system [31], the maximum DG penetration on each bus [40], and the maximum allowable penetration of wind turbine in whole network and on each bus [30,81], have been investigated. The maximum penetration level of 30% and 150% for DG units have been considered in Ref. [116] and [96,101], respectively. In addition, a combination of the number of DGs and penetration level for wind turbines due to the system load level have been integrated into the set of constraints in Ref. [26]. While, the maximum capacity of DG has been subjected to be less than 40% of load demand in Ref. [100], the maximum of 60% of substation rating for the DG penetration level along with the number of DGs have been chosen in Ref. [73].

Some of the above mentioned constraints are in contrast with the objective values which can be employed in the objective function composition. With respect to this matter and the proposed methods for objective function calculation, commonly, in most of the studies only the power system conservation constraints along with a couple of utilities capacity limitations are being exercised for optimal DGA.

4. Employed optimization methods and algorithms

The employed objective and constraints in optimal distributed generation allocation have been discussed in the last two sections. In this section, the methods and techniques which are commonly used for the optimization problems are presented. The employed algorithms can be divided into two major classes which are classic and artificial intelligent algorithms. The classic algorithms cover both mathematical based methods and the basic search approaches. Moreover, due to the huge number of studies which have been done by evolutionary and nature inspired techniques, the artificial intelligent based search methods are sub-categorized into three more sections including: search methods inspired by physic and society phenomena, natural inspired algorithms, and hybrid search approaches. All of those categories are illustrated in Fig. 3.

4.1. Classic approaches

Classical approaches are mostly based on the mathematical solution of the problem. These methods are employed for DGA in a couple of studies. In this review, those algorithms are classified under the following subheadings:

4.1.1. Analytical or deterministic algorithms

The Analytical Algorithms (AA) for identifying the optimal DG installation size and site in the distribution network have done by using different approaches in reported studies [20–22,29,54,96]. In Refs. [54], the authors have minimized the objective function for optimal bus recognition by the following steps: the admittance matrix is calculated before DG installation, then recalculated after implementing DG units along with impedance and equivalent resistance matrices. In order to find the optimal bus, the objective function is evaluated for DG connection to different buses. If all bus voltages are in the voltage constraint, then the DG connection bus is the optimal bus for DG installation. Else, if some of those voltages are not in range, then the DG needs to be moved around the connecting bus to meet the voltage limitation. Otherwise, if none of the identified buses can fulfill the voltage rule, the DG size should be changed and the procedure repeats with a new DG size. Acharya and Mahat et al. [21] used loss approximation instead of accurate load flow calculation. By using this

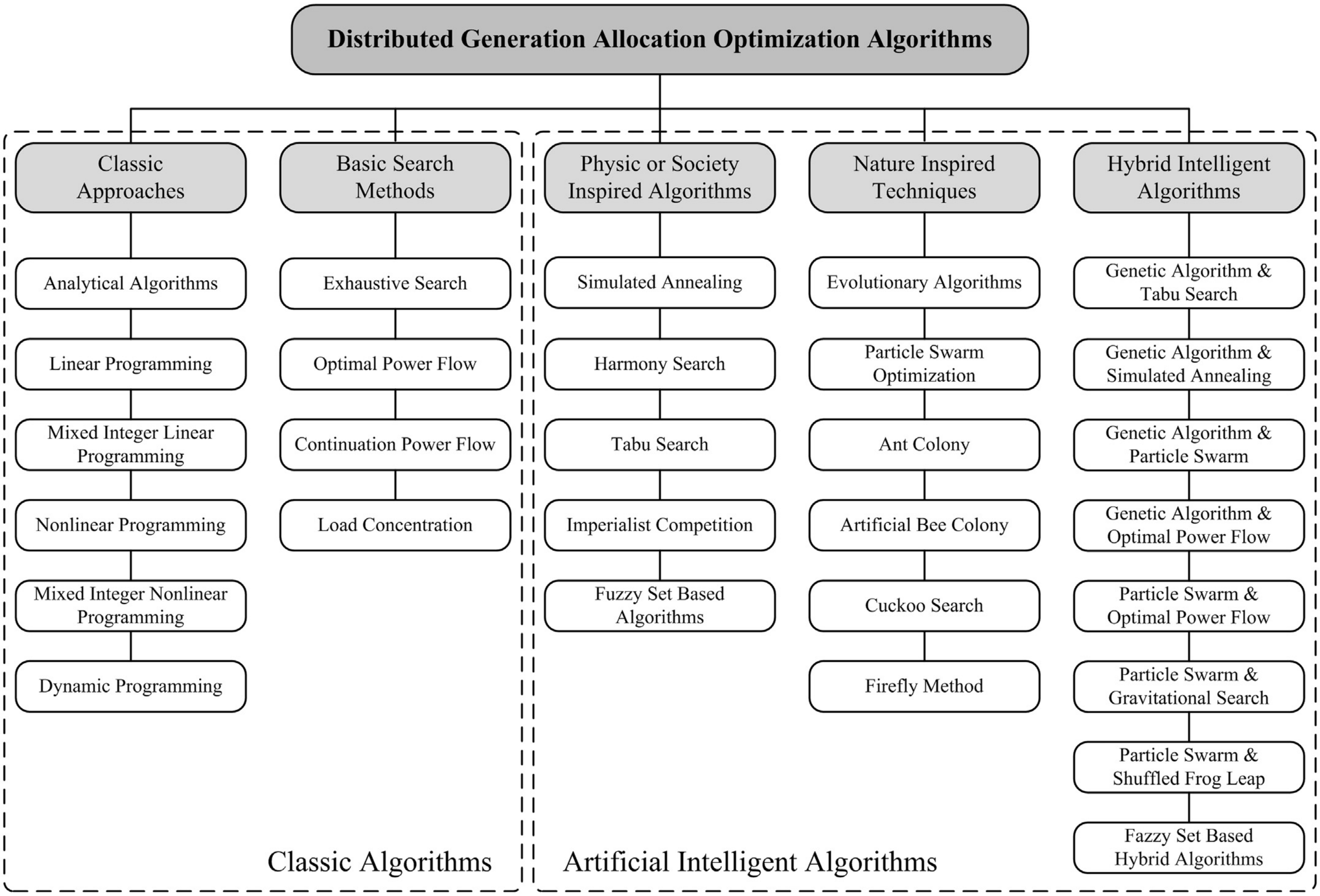

Fig. 3. Optimization algorithms for distributed generation allocation.

method, the number of load flow analysis decreased to two times only, first one is done in the base case and the second is accomplished at the end of the optimization to achieve the final results. The DG optimal size on each bus is obtained when the losses reduction is stabilized while DG power injection increase. Then, loss is approximated by installing a DG of optimal sizing on that bus and the minimum value for the approximated value of losses identifies the optimal connection bus. Finally, accurate loss is determined by load flow calculation for the selected size and site of DG. A mathematical formula has been developed in Ref. [32] to determine the best node in a feeder to connect PV, such that power from PV can flow downstream and upstream to provide power to loads but does not reach the substation. The size of PV is then determined by the number of nodes which are supplied. A value based analytic method has been employed in Ref. [74] for optimization of DG location to improve the ECOST reliability index.

One of the most popular methods for distribution load flow analysis that uses equivalent current injection have been employed in Ref. [20]. In this approach, the matrices of Branch-Current to Bus-Voltage (BCBV) and Bus-Injection to Branch-Current (BIBC) are implemented in calculations which are formed according to distribution network topology. Thus, only one load flow is required for the base case. The changes in total power losses resulted from active power injection to each bus is equated to zero, to identify the optimum size of DG. Then, DG with the optimal size is installed on buses and the bus with the minimum power losses is determined as the potential optimal location. The recognized bus will be selected as installation site if bus voltages follow the voltage limitation rules, otherwise, the next bus with minimum losses will be replaced and the voltages will be rechecked. Duong Quoc and Mithulananthan et al. [22] have improved the proposed method of Acharya and Mahat et al. [21] by developing a comprehensive formulation to recognize the optimum location and size of DGs. The active and reactive power delivery capabilities have been considered for four most popular types of DGs with respect to their terminal characteristics. These algorithms need to check every possible combination as solution, thus, they are not applicable on large size networks which have several buses and conditions for generation unit installation. Moreover, a procedure for optimal DGA of PV units on radial distribution systems has been offered in Ref. [96]. They have simulated the 37 bus and 26 bus test networks aiming to improve the voltage stability, reduce losses, and maximize the profitability by proper siting and sizing of PV units. They have considered load variation over a year and the result has shown improvement in voltage profile and power loss reduction.

The analytical expressions have been proposed to identify the optimal size and power factor of DG unit simultaneously for each location to minimize the power losses [29]. Then, the expressions have been adapted to place renewable DG units to minimize the annual energy losses in a 69-bus distribution test system with a variable demand and generation. In this study, the mathematical method which analyzes the generation variation with demand changes (dP/dL) have been utilized to find the best size and power factor for each location and comparing different locations to find the best one. The results show that the dispatchable units by themselves or in combination with nondispatchable DGs have better performances than pure nondispatchable resources. In the proposed method, the constraints are not included in the formula and only used as an indicator to stop iterations. Nevertheless, in this method, the number of iterations can be bulky, if trials keep going. Another deterministic approach has been employed in Ref. [43]. In this paper, firstly, the DG placement has been optimized by the loss sensitivity index for all bus voltages (smallest dP/dV). Then, the Lagrange function has been formulated for optimal sizing, and Modified Primal-Dual Interior Point Algorithm (MPDIPA) has been employed to speed up the optimization convergence.

In another attempt [102], a deterministic approach (DA), which has been formulated as Quadratic Objective Quadratic Constraint (QOQC) and can be solved mathematically, have been proposed. The drawbacks of the previous studies, such as the difficulty to extend to a long term planning, have been also discussed with respect to uncertain factors like weather and load growth. Likewise, an algebraic approach which can provide a quick estimation of a suitable location and minimum DG rating for a single synchronous DG has been proposed in Ref. [38] to satisfy the required minimum voltage level. In this study, a synchronous DG (renewable or non-renewable) has been planned to support network voltage only, especially when a practical long and loaded feeder has been introduced. The loads were assumed to be uniformly distributed and the optimal location has been determined based on the distance (in km) from the first substation. A suitable location with a minimum DG rating at a constant power factor is desired to ensure that the required voltage level in the network is satisfied.

The maximized DG penetration level in a distribution system, consisting of both three phases DG connection and single phase shunt capacitor installation, has been inspected in Ref. [39] by an iterative deterministic method. The location and size of both devices have been considered as the controlled variables. Firstly, the Voltage Ranking Index (VRI) has been developed to find the weakest buses for interconnection, then a DG has been connected to the bus and continued to increase its capacity by 1% as long as the voltage is still in limitations. The highest possible value is the optimal size for the first DG. Since the value is not zero, additional DG is utilized by the same procedure. All steps have been applied for the optimization of single phase shunt capacitor; the only difference is that the weakest bus is selected from the single phase buses. In Ref. [27], a formula was developed using mathematical analysis to determine the best node in a feeder to connect PV to, such that power from PV can flow downstream and upstream to provide power to loads but does not reach the substation. The size of PV is then determined according to the number of nodes that is supplied by PV to ensure the loss minimization. In Ref. [72], a mathematical analysis along with Monte Carlo Simulation (MCS) have been integrated for optimal DGA. More recently, an analytical expressions have been employed to find the size and pf for PV and Battery Energy Storage (BES) by solving the $dIMO/dP = 0$ and $dIMO/dpf = 0$ equations [91]. A comparison among several index based methods, comprising combined power loss sensitivity (for location), index vector method, and the voltage sensitivity index for optimal location and size of a single DG was provided in Ref. [41]. The benchmarks include real and reactive power loss, as well as minimum voltage in the system. The DG was operating at unity and 0.9 power factors lagging, and the authors have concluded that the lagging power factor gives larger optimal DG size and lower loss, as compared to unity value.

A two-stage model for optimal allocation of a single DG has been employed in Ref. [119]. Firstly, the DG location is optimized by sensitivity test for each bus. Then, curve-fitted technique is used for optimal sizing by plotting the power loss for several DG sizes with different power factors. The optimal size is then found by x-intersect and followed by running load flow to check the constraints. The Optimal Location Index (OLI) has been proposed to select the optimal location for DG [121]. In the suggested method, the Kalman filter has been used to reduce the computational load of size optimization.

4.1.2. Linear Programming (LP)

Linear programming algorithms have been employed in Refs. [52,61,85] to form an objective function by formulating linear equations and constraints. However, the LP method is only applicable on linear equation and constraints, but it has the ability to handle large number of various operational limitations for power system including contingency constraints. In spite of the LP methods' huge contributions to DGA, they became useless in the case of OPF calculations and are not capable of finding the exact solution for system because of inaccurate system loss evaluation.

4.1.3. Nonlinear Programming (NLP)

The first step to solve a nonlinear programming problem is choosing the direction of search for an iterative procedure. This direction for DGA can be determined by the first derivative of the power system reduced gradient equations. Nonlinear programming has been employed in many different ways. For instance in Ref. [131], a first order method which is also referred to as Generalized Reduced Gradient (GRG) has been utilized to solve OPF. In Ref. [61], nonlinear programming has been employed in its second order form to solve the second order partial derivative power flow equations by a sequential quadratic programming together with Newton's method and the constraints have also been applied using second order partial derivatives (Hessian matrix). The amount of resources at the selected nodes has been computed using the second order method to minimize the objective function of system losses in Ref. [16]. As stated in Ref. [132], NLP integration in large power systems faces two major difficulties: Firstly, depending on the search procedure starting point, different optimal points can be achieved because of the method nature which can be trapped in local optimal point. Secondly, the convergence of this method is guaranteed and it is not affected by starting point, but they can be very slow because of its zig-zaging motion over the final solution. Moreover, the minimization of DGs number in the system as one of the objectives has been carried out by NLP [81]. A high number of DGs would increase short circuit level and make it more difficult to reconfigure protection coordination. The algorithm has also resulted in the optimal location of DGs, which needs to be in the middle of the feeder and not the end bus of the radial branches when a huge number of DGs is installed. Fuzzification is employed to unify the scale of different objective and combine them with weight factors to form the objective function.

4.1.4. Mixed Integer Linear Programming (MILP)

Rider and López-Lezama et al. [70] have proposed a bi-level approach for optimal location and contract pricing of distributed generation in radial distribution systems mixed integer linear programming. They have converted a two level optimization problem into a single level optimization using duality theory. The paper looks at the optimization problem from both perspectives of distribution company and DG owners. For DG owners, the variables are contract price and DG location, while for DISCO, it is the energy that they are going to buy after running OPF. Using the duality theory, the owners' desire is set as the objective function while DISCO's perspectives are reflected in the constraints.

4.1.5. Mixed Integer Nonlinear Programming (MINLP)

In MINLP method for DGA optimization, the integer part contains the variables with 0 and 1 values representing the existence of DG units on the buses. A mixed integer nonlinear programming method has been utilized to formulate a comprehensive optimization objective function for DG optimal siting and sizing in Refs. [67,93], and a General Algebraic Modeling System (GAMS) with the use of Sparse Nonlinear Optimizer (SNOPT) by integer decision variables containing 0 and 1 have been implemented in the model formulation [133]. However, the method has some improvements in comparison to the NLP methods, but the difficulties for those methods still exist. The most important objectives in this study were: i- Determination of best installation area for DG according to operational and economical aspects (the nodal price of real power and sensitivity index of power loss). ii- Finding the optimum location and number of DGs for installing inside the selected zone with a MINLP algorithm. iii- Calculating the demand variation impact.

In another attempt, a probabilistic planning method has been used to determine the optimal shares of different hybrid renewable DG units consist of wind, solar, and biomass modules [111]. The method is subjected to minimize the annual energy losses within the constraints' limitations. The MINLP has been applied to formulate the problem respecting the renewable DG sources uncertainties and load profile hourly variations. The Voltage Stability Margin (VSM) has been improved and loading has been maximized by integrating DGs into the power system. In this regards, the impact of location and size of DGs on these two values have been studied in Ref. [40]. Most suitable candidate buses for the optimal location of DG have been found by voltage sensitivity indexes, then the sizes have been recognized by MINLP. The load and generation variations have been considered using IEEE-RTS as well as Beta and Weibull probability distribution functions.

4.1.6. Dynamic Programming (DP)

Basic Dynamic Programming aims to solve the problems in which the optimal decisions should be made sequentially. The method has been introduced by Richard Bellman in the 1940s. The word dynamic represents the time varying nature of a problem, which is solved by optimal programming method. The method is considered as a programming method as well as mathematical optimization. He refined his proposed method from 1952 to 1956 by redefining the large decision making problems in the form of inner smaller recursive optimization problems [134–136]. The procedure of breaking the complicated problem down into simpler nested ones may result in sub-problems which share the decision spans and have dependent optimal result to other sub-problems. It is where the recursive aspect of method helps and does the optimization in sequential manner; this technique is normally referred as optimal substructure.

The Dynamic Programming Optimization (DPO) has been utilized in Ref. [99] to find the location and size of multiple DGs in the distribution system. Both benefits and costs of installing and operating DGs have been included in the objective function. The problem is divided into stages, with the number of stages equal to the number of candidate notes. The decision for a current situation takes into account the information of previous behavior of system from the previous stage. Backward procedure has been employed, in which the algorithm starts from the last node in the system. It stops when all DGs have been allocated for all nodes. Three load scenarios have been used, however, no especial constraint has been considered as well as the variation of generation which has not been covered. In Ref. [116], DP has been employed to optimize the size of multiple DGs, in which the location has been determined. The algorithm is based on three states of power for each bus and the paths connecting these states among the given buses. These paths have been evaluated using power flow utilizing the Gauss Seidel method and the path which gives the minimum loss has been chosen for the next step. DG penetration level limit is included in the constraints. However, generation and loads are still assumed to have fixed values.

4.2. Basic search methods

Basic search methods were the inspiring sources for various studies on optimal DGA. Most highlighted studies using basic search methods for DGA are being discussed under the following main categories:

4.2.1. Exhaustive Search (ES)

Exhaustive Search, which is also known as brute force, direct search or generate and test, is a thorough test of target function with all possible input values. For discrete problems such as what exist in DGA, this method could be used. However, it is not an efficient solution method, but the results are always reliable because of all possibility checking [137]. A comparison between exhaustive search method and genetic algorithm has also been accomplished in Ref. [138]. The exhaustive search method could be considered as the simplest meta-heuristic method. It can ensure that the most accurate solutions will be found, if there is any. The main reason of proposing the exhaustive search as an approach for an optimal generation positioning is its simplicity and accuracy [139]. In Ref. [140], a multi-variable method has been suggested for finding the optimal installation point and size of distributed generation units by implementation of the exhaustive search. The optimization has been applied on network total active and reactive losses together with voltage variation. However, as the candidates' number raises, the possible solution number increases rapidly. Therefore, the suggested algorithm is only applicable for small number of candidates due to its costly computations. The direct search has been used in Ref. [127] to optimize the location, size, and number of DG units by focusing on voltage profile as a single objective value.

Afterwards, the ES has been employed for optimal placement of 1WM solar farm in a distribution network on the basis of daily power consumption and production fluctuation in Ref. [28]. The study was done on 30 bus network by placing the PV farm on all nodes one by one and for each node, the power flow has been carried out for every hour with respect to the PV farm generation and demand curves. If the constraint of voltage failed at any hour, PV is moved to the next node till the constraint is satisfied. The total power loss for 24 h is calculated by summing all of the power losses, formulated using line parameters, at each hour for the nodes which fulfill the voltage constraint. The node with minimum power loss determined the optimal placement of PV farm. Another study in this field investigated the clustering based approach and a 2 stages exhaustive search to determine the optimal location and size of the multiple DGs [80]. The first few buses with similar Load Sensitivity Factor (LSF) and bus voltage were grouped together to select a subset of candidate with high value of LSF and low voltage for hybrid DG location comprising PV, CHP, and micro hydro generators. Then, the internal stage uses exhaustive search to select the best combination of DG sizes among all of the possible choices, utilizing normal load flow. The variation of generation and load is considered with one hour steps for a day. The optimization targets are: to minimize daily energy loss and improve voltage profile and they have ensured no basic constraints of power system were violated. Furthermore, the steady state Voltage Stability Index (VSI) has been examined to choose the location of DG unit in Ref. [117] (nodes with minimum index), then Direct Search with load flow has been integrated to find the optimal size. The step size of 0.1 MW has been selected as DG power increment up to 2WM. For each step, 5000 samples of radiation and temperature have been used to calculate the average loss. Hernandez et al. [101] also handled a couple of contradicted economical and technical objectives by employing a combination of direct search and Pareto front method.

4.2.2. Optimal Power Flow (OPF)

The optimal power flow algorithm, which is another basic search method, has been utilized for optimal DGA in many research studies [30,51,53,55–57,62,65,66,75]. In Ref. [55], maximum DG capacity and system available headroom have been identified by considering voltage and thermal constraints through the implementation of optimal power flow under "reverse load-ability" method. In Ref. [62], demand bids have also been considered in addition to the generation bids in a traditional optimal power flow approach to minimize cost. In this method, Locational Marginal Price (LMP) is applied as Lagrangian multiplier in OPF power balance equation. The primary nodal prices, demand, and generation dispatch are calculated by OPF aiming for social welfare maximization. Then, the DG locations are identified using the achieved nodal prices, hence, by changing dispatch scenario the demand is supplied at a lower price. Algarni and Bhattacharya [75] have integrated GD units' goodness factor directly into the distribution system model. DG units' incremental contribution to power losses (both active and reactive) has been implemented as Incremental Loss Indices (ILI) in OPF framework. Besides, OPF has been employed to allocate the generation capacity focusing on the power system tolerance to the fault levels [56,57,66]. In similar manner, the work in Ref. [51], has been done by integrating voltage step constraints in to the OPF algorithm to identify the DG accommodation capacity of network. In [53], the authors have used a one by one line outage contingency solution in OPF to recognize the maximum generation under the security limitations. Likewise, OPF approach has been implemented to indicate the maximum capacity of a network, which is incorporating with variable DGs [50]. Due to the huge load of iterative calculation in this method, the method is normally applied on radial distribution networks.

The DGA optimization problem was formulated by mixed integer nonlinear programming (MINLP) under GAMS software environment and solved by OPF in Ref. [30]. In this study, the authors have proposed a probabilistic planning technique, in which a combination of probabilistic generation and load model has been developed. The optimal allocations of 3 wind turbines have been found on a rural distribution system, giving minimum annual energy loss and ensuring no violation in power system constraints. The wind speed probability is modeled utilizing Rayleigh probability density function (pdf) and loads variation is modeled by IEEE-RTS system.

4.2.3. Continuation Power Flow (CPF)

Analysis of power flow continuation and search for the bus with the most sensitivity to voltage collapse has been done in Ref. [19] to determine the optimal place for DG installation. The continuous power flow algorithm is used for determination of maximum loading or most sensitive bus to voltage collapse. Then, one DG with a specified capacity is installed on the recognized bus as the most sensitive bus, then, the power flow program is iteratively being executed till the satisfactory estimation for objective function is achieved. In this algorithm, the size of DG is not recognizable and only the location of installation is identified.

4.2.4. Load Concentration (LC)

Lee and Park [33] were the first to implement the LC method for optimal DGA on the IEEE 30 bus benchmark network. They have found the optimal location by identifying load-concentration-buses in the network and the number of DGs, which were equal to the number of these buses (each bus represents one load area in the system). Four load concentration buses have been identified based on the load values and the configuration of the system. Then, these buses were selected as the optimal locations for DG connection, while their optimal sizes were determined by Kalman filter algorithm. Initial estimated value of each DG size is equal to the sum of all the loads in the area of the bus. The results showed the reduction in network power loss, which is the single objective of this study. In another attempt, a systematic method to optimize the location and size of multiple DGs based on load centroid concept (based on equivalent aggregated load) and direct search has been proposed in Ref. [77]. All loads have been summed up at first to get the equivalent load. Then, the equivalent load was placed on each bus, one at a time, while all of the other loads were disconnected. The node with the best OF value after load flow has been selected as the installation bus for the first DG with a predefined size. By repeating the procedure, the site of the remaining DGs is being recognized, until the total power exported from the installed DGs reaches the optimal DG penetration. This optimal DG penetration is determined between 2–100% of equivalent load, by searching for the best OF. The authors believe that heuristic methods like GA and PSO or analytical methods have their own drawbacks, such as sub-optimal value, divergence (heuristic) or hard to extend (analytic). The test systems include both radial and mesh system.

4.3. Physic or society inspired algorithms

To cope with uncertainties and local optimum points in DGA problems, the intelligence search algorithms have been integrated as heuristic solvers. There are also studies which combined these algorithms with conventional optimization techniques or fuzzy set based algorithms to solve DGA problem. A numerous number of researches have been carried out in recent years, which concentrate on the implementation of meta-heuristic methods for solving DGA problems.

4.3.1. Simulated Annealing (SA)

In Simulated Annealing, the problem of optimization is modeled as an annealing process. In this approach a probability function is being used for rejecting or accepting new solutions, to avoid being trapped in local optimal points. The algorithm has been proposed in Ref. [141] for the first time. This method's usage has been rising since its introduction because of its simplicity in implementation and reliable outcomes [123]. The algorithm includes initialization, perturbation, cooling schedule, and acceptance probability procedures. In this algorithm, the temperature initialization and cooling play the key roles in achieving good results. In Ref. [86] the SA has been selected to minimize losses, emission, and contingency by optimal siting and sizing of DG units. The main weaknesses of this algorithm are its dependence on initial values and cooling parameters setting.

4.3.2. Harmony Search (HS)

The basic Harmony Search algorithm has been proposed by Zong Woo Geem in 2001 [142]. The algorithm is inspired by music harmony as a combination of sounds considered pleasing from an aesthetic point of view. The basic optimization algorithm tries to find the fantastic harmony representing global optimum using aesthetic standards as the objective function which estimates the value of variables by simulating the pitches of instruments in the course of successive practices. Harmony search is being carried out through four main steps and procedures comprising: 1- Initialize a Harmony Memory (HM). 2- Improvise a new harmony from HM. 3- If the new harmony is better than minimum harmony in HM, including the new harmony in HM, and excluding the minimum harmony from HM. 4- If stopping criteria are not satisfied, go to Step 2.

Nekooei and Farsangi et al. [76] have proposed a multiple-objective planning framework, in which they have developed a method called IMOHS, an improved multi-objective version of normal harmony search based on the Novel Global Harmony Search (NGHS). Optimal values of the location and sizes of multiple DGs have been found based on Pareto front, which gives several optimal solutions for the two objectives of voltage profile and network loss. The results have been compared with the popular methods like GA and PSO when the multi-objective functions have been applied with weight factors, or NSGA-II where the two Pareto fronts have been plotted and compared. They have considered general type DGs with fixed lagging power factor of 0.8 to be installed on 33 and 69 buses radial test systems with non-variable load and generation.

4.3.3. Tabu Search (TS)

The Tabu Search algorithm was first proposed in 1986 by Glover and McMillan [143], based on human memory performance, to solve planning and arrangement of optimization problems. It can find optimal or suboptimal efficient solution for combinatorial problems in a reasonable time, through a procedure which does not need much iteration. It also has the ability of passing the local optimal solutions. The optimization procedure includes moves, neighborhood, tabu list, aspiration, intensification, and diversification sub-procedures. In the proposed algorithm, various types of memory consisting, short, intermediateand long term memories have been considered. Network configuration and tap positions of Voltage Regulators (VRs) as well as the installation location, size, and operation of Distribution

Generation Resources (DGRs) and Reactive Power Sources (RPSs) have been identified in Ref. [97] by using TS as planning algorithm. The constraints violating selections are considered in tabu list to avoid future forbidden selection. Nara and Hayashi et al. [35] have introduced the coordination/decomposition technique and implemented the proposed approach along with TS for optimal DGA respecting the total loss minimization. In the suggested method, the size identification has been excluded in allocation procedure for the sake of simplicity. The disadvantage of this method is that the regression model needs to be solved by any change in the initial weight factor values to calculate the mean squared error.

4.3.4. Imperialist Competitive Method (ICM)

The Imperialist Competitive Method as a global search method was inspired by socio-policy and proposed in 2007 [144]. Like other intelligent search methods, ICM uses an initial random population with feasible values which are representing countries. The initial population is evaluated and the best fitting countries are selected as the imperialist countries and the remaining are assigned as the colonies for these imperialists. On the second step after initial population evaluation, the colonies are distributed among the imperialists according to the imperialist countries normalized power using cost parameter for each imperialist member. Using this way, the empires are being constructed and on the next steps the colonies tries to get closer to their empire. This helps to determine the total power of empire and then the empires can compete on the basis of their total power. The competition will result in stronger empires power gain and the weaker empires power loss which may finally lead to weak empires destruction. Finally, the optimal solution will be handed out by colonies movement and weaker empires collapse.

The ICM has been employed for DGA by distribution network total real power loss minimization in Ref. [145], while Soroudi and Ehsan [146] have integrated ICM in DGA considering a combination of technical and economic objectives, they have used the reduction of total active loss and network investigation deferment as the objective functions to maximize the distribution network operators benefits. The ICM was implemented in Ref. [147], for recognition of size and site of DG units for a distribution network containing the sensitive loads working in islanded mode. The distribution network was sectionized in this paper and each section includes both DG and sensitive loads considering load density to reduce the enclose buses in a section. This resulted in reasonable sizes for generation units for all sections and reduction in network losses while increasing the reliability of islanding mode for sensitive loads. The implementation time for this algorithm is long compared to other algorithms; however, due to the various step sizes, the time can be reasonable.

4.3.5. Fuzzy Set Based Algorithms (FS)

Fuzzy Set theory, as a tool for analyzing uncertain systems and their soft modeling, was introduced in 1965 by Zadeh [148] and then it was enormously used in power system analysis [149]. A value between zero and one is assigned to a set as the degree of membership, using a membership function, to model a fuzzy variable. In DGA, the used parameters and data come from various sources and have a very wide range of different accuracies. For example, in spite of high uncertainty in distribution network load it is considered specified in approximately all methods. Moreover, some level of variance can be experienced in the case of DG cost, electricity market price, and peak power shaving. These uncertainties may result in uncertain decision-making environment because of insufficient information, which in turn, causes the calculations with average values validity to be unverifiable. Based on the above said reasons, the fuzzy set method plays an important role in DGA planning with uncertain data as input data and multi normally conflicted goals as objectives.

Both objective function and constraints were handled by fuzzy sets in Refs. [23,128,150,151]. Lalitha and Reddy et al. [23] have achieved the DG Suitability Index (DGSI) by modeling the Power Loss Index (PLI) and nodal voltage using fuzzy set method. In Ref. [128], a multi-objective model composed of technical risk, economic risk, and monetary cost indices were modeled by a fuzzy set theory. A fuzzy set has been employed along with GA and goal programming to form a multi-objective function in Ref. [150]. In Ref. [151], the authors develop their own Adaptive Interactive Decision Making System (AIDMS) based on the Bellman-Zadeh method to solve a multi-objective resource allocation problem. The objective function comprises of power loss cost as an objective and DGs number or size together with voltage deviation as constraints. On top of that, the load uncertainties were modeled by a fuzzy set with respect to the load and voltage constraints [152–154]. It is worth to indicate that, fuzzy set method enables the researchers to implement the effect of power system parameter uncertainty into the system model and hands out a less compromised solution while reducing the needed iteration time [95]. In conclusion, fuzzy set theory offers alternatives for DG size and location selection to the distributed generation planners, however, the main disadvantage of the fuzzy based methods is that there is no correction step or factor and a wrong classification of variables may result in complete incorrect answers. Fuzzy expert system with the input of voltage profile and power losses (from load flow running without DG) has been used to determine the optimal location of DG. Then, the size is determined by dP_L/dP_i=0 and finally, the load flow was carried out again to check the constraint of voltage.

4.4. Nature Inspired Techniques

In the following sections, a couple of natural inspired methods are being covered and discussed such as: Ant Colony System (ACS), Bee Colony Optimization (BCO), Cuckoo Search Optimization (CSO), and Firefly Optimization (FFO). Moreover, there are several studies on Hybrid Intelligent Algorithms which will be covered in the following sections:

4.4.1. Evolutionary Algorithms (EAs)

In Evolutionary Algorithms approach, unlike the conventional optimization algorithms, the cost function and constraints do not need to be differentiated. According to the [139], EAs are the optimization algorithms which are based on populations and result in the global optimal solution in a finite evolutionary steps, considering a finite set of potential answers. EAs such as Evolutionary Strategy (ES), Evolutionary Programming (EP), and Genetic Algorithm (GA) are referred to as artificial intelligence algorithms in which natural selection processes such as reproduction, recombination, crossover, and mutation are playing the main roles. In reproduction process, the best solution of the population is regenerated up to the finite number and substitutes the worst solutions during selection application. Recombination mixes the parts of a candidate solution randomly to form a new solution. Crossover operand selects a swapping point for two strings and exchanges the elements after the selected position in those two strings. In mutation, the population members are randomly selected and some random elements are varied in them. The evolutionary programming algorithm was introduced in Ref. [139] for the first time and has been utilized for power planning in Ref. [155]. EAs after some simplifications and improvements, which were applied on the proposed method, was employed in DGA. Single and multi-objective functions are integrated in this approach by considering different constraints. However, the result's accuracy and the convergence of these methods are the points of concern. In Ref. [26], the authors have used EP to solve the optimization problem of locating multiple DGs, in a distribution network. To reduce the computational burden, loss sensitivity is firstly analyzed on the buses to select a set of candidate buses. Then, the fitness function consist of the energy loss over the studied period was minimized, while a penalty factor was implemented whenever the constraints of voltage and line loadings are violated. The load uncertainty and generation variance have also been considered and modeled by using common probabilistic distribution functions such as Beta and Weibull pdfs.

The genetic algorithm is the most recent among the aforementioned three evolutionary methods which came after EP and ES. The capability of GA in solving optimal DGA has been investigated in Ref. [156]. A comparison has been carried out in Ref. [17] between their own proposed Improved Herefoord Ranch Algorithm (IHRA) and three other methods: Simple GA (SGA), Herefoord Ranch Algorithm (HRA), and Improved GA (IGA). All of those methods were utilized to minimize the active power losses through a single objective function. Single objective function [48,157] and Multi Objective (MO) models [42,85,89,115] are properly handled by GA, while the MO model has been subjected to ε-constraint technique in Refs. [78,79]. The service restoration under cold load pickup has been investigated in Ref. [125], using GA in a MO model for DGA. The authors in Refs. [48,104,107], have studied DG and DGA impact on reliability with GA integration. The combination of optimal power flow and GA has also been employed in DGA. It has been stated that, the combination of GA and OPF can result in best connection points for a specified number of DG units [65]. A Non-Dominated Sorting Genetic Algorithm (NSGA) along with a multi-objective programming method is integrated to find the best and maximum implementation configuration of Distributed Wind Generation (DWG) with respect to voltage and thermal constraints in Ref. [114].

The Rayleigh and Beta probability density function have been utilized in Ref. [31] to build probabilistic generation model for wind and solar based DGs. The load variation has been modeled by IEEE Reliability Test System (IEEE-RTS) and then the optimization problem has been solved by GA, with the harmonic load flow based on forward/backward sweep method for THD calculation. Five DGs, with predefined rating values and unity power factor, have been allocated on a preselected set of candidate buses, based on voltage profile and THD values at the buses of non-linear loads while the first bus voltage has been set to 1 pu with the angle of 0. The premature convergence has been checked in the middle of generation. In case of unsatisfactory, the algorithm has been considered as being converged if the iteration reaches to the maximum generation number. In another study [98], the authors have taken many criteria into account to optimally allocate and maintain multiple wind turbines in the distribution network. They have included costs of operating, downtime, and environment penalty to be minimized. Reliability, however, was another objective to be maximized. Pareto front set of solutions has been found by GA method subjected to the maximum iteration number as its stopping criteria. Then, the final solution could be chosen by the system planners depending on their needs. The Weibull distribution has been employed for wind speed distribution and the probabilistic of wind power intermittency and load uncertainty have also been modeled by the moment method.

Haesen and Driesen et al. [102], highlight the drawbacks of their own proposed analytic method by offering a novel framework based on GA and Monte Carlo (MC) simulation. They have also taken into account the weather conditions, switching, and load growth to optimize hybrid wind, solar, and CHP DGs site and size in the standard IEEE 34 bus radial network. The results are presented as trade-off optimal front among four objective values to optimize the location and size of a single DG. In Ref. [73], the authors have optimized the location and size of DG in the network using GA, although locations of DGs were predetermined to several candidate bus, to maximize the savings in cost of upgrade, energy loss, and interruption. In this study, two types of DGs including natural gas and wind have been considered and have been installed in 33 bus distribution network. To avoid using weighting factors among different objectives, money value ($) has been used to measure all of the costs and savings. Islanding mode has also been considered in the reliability study. The uncertainty of DG units has been considered using the probabilistic model, enabling the method to generate (MC) simulation models to cater for all possible operating conditions.

4.4.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization, which has been introduced by Kennedy and Eberchart in 1995 [158], is an optimization algorithm based on population and simulates the fish schools' or bird flocks' social behavior. In this method, the population individuals are nominated as particles which move in multidimensional search domain on time steps. During the search procedure, the particles' new position is calculated according to their current location, their own best experienced state (Individual Best), and the best position experienced by their neighbors (Global Best). PSO has been utilized in different research areas of electric systems [159,160]. The active power losses of distribution system have been minimized by optimal allocation and sizing of multi DG units using PSO algorithm including different load models [161]. The harmonic analysis has been employed along with PSO to maximize the penetration level of DGs in a 30 bus meshed network [59]. The location and size of general type DGs have been optimized aiming to improve the loadability of IEEE 33 and 69 bus test distribution systems [18]. The simulation has been done to compare the 2 objectives: active and reactive losses. It was then verified that the correlation between reactive loss and the loadability was stronger, therefore, it was selected. However, since variation in load and generation is not considered, the method is hardly applicable for renewable energy based DGs. A Multi-Objective PSO (MOPSO) has been employed in Ref. [71], they have integrated desires of distribution company as well as DG owner in their optimization target. Two objective functions are optimized simultaneously and the results appeared as Pareto-optimal solutions. Then, the best solution is chosen based on technical and economic indices, including voltage profile index, voltage stability index, total power loss index, not supplied energy index, payback period, expected rate of return, and the internal rate of return. The DG planning and viability analysis have been optimized using PSO in Ref. [94]. They have found the unavailability of DG in planning and determined the viability under competitive market or bilateral contract, considering different construction and performance costs. While an improved PSO, using penalty factor for violation of constraints has been used in Ref. [120], more advanced version of PSO named Dynamic Weighted Aggregation (DWA) multi-objective PSO with gradual changing weights has been employed for optimal DGA in Ref. [82]. The maximum number of iteration has been chosen as the stopping criteria. TRIBE PSO for the feasible solutions recognition has been accompanied with the ordinal optimization (OO) to find the optimal and near optimal solutions [68]. The PSO algorithm along with the Group Search Optimization (GSO) method have been implemented and compared for optimal DGA [37]. The paper has proposed a method for optimal power output solution of the controllable generators when one or two DGs fail or disconnect.

4.4.3. Ant Colony (AC)

The Ant Colony Optimization (ACO) which was introduced in the late 90's [162], is a social insect's behavior based method, that has the ability to solve optimization problems by simulating the insect method in identifying the shortest way to the food from the nest [163]. The Ant Colony System (ACS) as an extension to ACO has handed out better results in most engineering cases [164–167]. The ACS approach has been used as the optimal positioning method for fixed re-closer or DGA to increase the reliability in Ref. [109], the authors have also proposed to integrate the algorithm for simultaneous allocation of both DGs and re-closers.

4.4.4. Artificial Bee Colony (ABC)

The Artificial Bee Colony was proposed by Dervis Karaboga in Ref. [168], based on an idea of honey bee swarm intelligent behavior. ABC in its general form only uses three simple parameters as control parameters: colony size, iteration, and the variable limitations. These parameters need prior determination or defined by the user. This method on its early stages was only used for numerical optimization problems [168]. The method application has also been extended to the constrained, unconstrained, and combinatorial problems [169–171]. The ABC method robustness, flexibility, and simplicity have been well investigated in different studies [172,173]. ABC method is based on bees' position adjustment with respect to their own or their nest mate experience in choosing food sources, these artificial bees are called onlooker or employed bees which fly along with other bees in a multidimensional search domain. The advantage of ABC is in its only 2 controlled parameters, which are fewer and easier to be tuned correctly when compared to the well known GA or PSO. While the ABC optimization has been employed for investigation of transient performance of grid connected distributed generation [174], it has also been implemented for optimizing the distribution network configuration considering loss reduction [175]. Moreover, authors in Refs. [176] and [45] have employed ABC for DGA concentrating on system total real power losses as the objective function. Sohi and Shirdel et al. [177] extended the objective function of ABC to include the line capacity improvement in addition to the loss reduction. Moreover, the ABC has been integrated for optimal DGA and power factor improvement to minimize the network total real power consumption [24]. The authors have implemented ABC algorithm to optimize location, size, and power factor of DG. They have verified a part of their results with an exhaustive search method and the other results have been compared with analytical and GA method from other papers, which were similar and slightly better. However, the variation of load and generation is not considered in this study.

4.4.5. Cuckoo Search (CS)

The Cuckoo Search Optimization (CSO) is being inspired by the parasitic egg laying of the cuckoo species in the other host birds nest, and has been proposed in 2009 [178]. The CSO can be described using the following main rules [179], first of all, every time all cuckoo lay only one egg in a nest which is randomly selected. Secondly, the next generation will be created using the optimal solutions (best nests with high quality eggs). Finally, among the fixed number of host nests, the foreign egg can be discovered by the host bird with a probability between zero and one. After discovery, the host bird may either throw the foreign egg away or just abandon the nest and construct a new nest. Before the new solution generation, a Lévy procedure is carried out, which can be more efficient if the random walk step sizes are being adjusted according to the search space size [179]. In case of random step size, the length is derived from Lévy distribution. For better performance and avoiding being trapped in local extremums, a portion of new generation should be generated randomly and far enough from the latest best solution [178]. The CSO has been employed for a combination of biomass and solar-thermal DGA considering loss reduction and voltage profile improvement in Ref. [180]. It is also implemented in Ref. [181] for voltage profile improvement, which has been expressed by two regulation and variation indexes, and power loss reduction for DGA.

4.4.6. Firefly Method (FFM)

The Firefly Method was inspired by the ideal model of the fireflies flashing behavior. In general, the flashing is being done to attract other fireflies. This method consists of three main rules as follows [182]. Firstly, fireflies in the population are of the same gender, therefore, each of them can be attractive for others. Next, the brightness of a firefly dedicates its attractiveness, thus, the brighter one pulls the less bright one towards it. Thirdly, the brightness and consequently the attractiveness fall with distance increase. In the case of equal brightness for two fireflies, their motion path will be selected randomly. Finally, the fireflies' brightness are devised or derived from the nature of objective function search space, like fitness function in GA.

The two major challenging issues in FFM are attractiveness and light intensity variation formulation. For the sake of simplicity, the attractiveness of a firefly is assumed to be determined by its brightness which in turn is derived by objective function formulation. Those issues in FFM employment have been addressed as follows [183]: i- Attraction: Generally the attractiveness can be defined as any single variable descending function over the distance of two fireflies with its maximum value at zero distance. ii- Distance: The distance is normally formulated as the Cartesian distance from the root of the sum of the square of all component distances. iii- Motion: The new position of each firefly is calculated according to the current position, the attractiveness of superior firefly, and a random value between −0.5 and 0.5.

The FFM has been employed for DGA aiming to minimize the active and reactive power losses, voltage profile improvement for various models of loads, line current, level of short circuit, and total absorbed apparent power of the network in Ref. [184]. Sulaiman and Mustafa et al. [185], applied FFM to minimize the real power losses by optimal location and size determination of DGs in distribution network.

Physical phenomena, social behavior, and nature inspired search algorithms have some disadvantages. All of those methods are highly affected by their parameters which are selected as their operator constants. They may also be trapped in local optimal points in case of wrong initial value or parameter selection. Moreover, they could have unstable movements in finding the extremum point; hence, the convergence of all these algorithms is questionable.

4.5. Hybrid Intelligent Algorithms

Generally, Hybrid Intelligent Algorithms (HIAs) refer to algorithms which are a combination of different artificial intelligent methods working in parallel or cascaded mode. There are various studies which focused on different combination of existing meta-heuristic methods for distributed generation allocation, including: Genetic-Tabu search (GATS) [186], Genetic-Particle Swarm Optimization (GAPSO) [187], Genetic-Optimal Power Flow (GAOPF) [65,188], Particle Swarm Optimization-Optimal Power Flow (PSOOPF) [189], and Particle Swarm Optimization- Gravitational Search Algorithm (PSOGSA) [90].

4.5.1. Genetic Algorithm-Tabu Search (GATS)

The Genetic-Tabu Search method was employed for optimal DGA in the distribution networks in Ref. [186]. The objective function was power losses when the harmonic power losses were included. It was illustrated that the accuracy and convergence of GATS method were better than GA in comparison. The application procedure is as follows: Firstly, a set of feasible solutions is generated randomly as the initial population. Then, the load flow calculation for each member is carried out for fitness value recognition. In the third step, a pool population is established by copying the best solution of the current generation and adding new chromosomes, with the approximate size of 3–15% of the original generation. Then, the TS algorithm comes in to randomly select these chromosomes as the neighbors of the current generation. Fourthly, chromosomes are selected from the pool population to create the new generation by crossover and mutation procedures. Finally, the algorithm returns to the second step till the convergence criterion is satisfied.

4.5.2. Genetic Algorithm-Simulated Annealing (GASA)

The Genetic-Simulated Annealing has been employed for optimal locating and sizing of energy storage within LV networks [60] with the objective of minimizing the cost per power and DG unit capacity. They have investigated the proper configuration and topologies of the storages to solve the voltage rise problem caused by the increase in

PV penetration. The objective function has been subjected to the over voltage limitation on buses by a penalty factor. The Roulette Wheel (RW) has been chosen as the mating and crossover operators while the SA has been implemented for the mutation operator. They have concluded that a configuration of single phase storage installed within the customer side of the meter can solve the voltage problem in a more efficient way than a three phase system on the street.

4.5.3. Genetic Algorithm-Particle Swarm Optimization (GAPSO)

A novel Genetic-Particle Swarm Optimization method has been presented in Ref. [187] for optimal DGA by minimizing the power losses and improving the voltage regulation and stability. The method has been implemented on a radial distribution network within the security and system operation constraints. The problem is divided into two parts, optimal positioning which has been solved by GA and optimal sizing which has been handled by PSO. The GA has been selected for location identification due to its binary nature and PSO dealt with DG size recognition. The whole procedure can be explained as: The initial population chromosomes, containing the possible positions of GDs are created randomly. The sizes of DGs are initialized for PSO using reasonable random values. All chromosomes in combination with DG sizes are evaluated. The local and global best members are recorded and used for velocity and position update. The new chromosomes are generated using GA rules (selection, crossover, and mutation) with respect to objective function value for the installation sites. The old PSO population is replaced by the updated values. The procedure stops if the convergence criterion is satisfied, otherwise, continues by returning back to the third step.

4.5.4. Genetic Algorithm-Optimal Power Flow (GAOPF)

Harrison and Piccolo et al. [65] have illustrated the robustness of Genetic-Optimal Power Flow for determining the installation sites of specified number of DGs. By using this method, the common issue of capacity identification could be solved because of OPF integration. This method enables network operators to select the most suitable sites and sizes in DGA among a huge number of available options. They first initialized random population for GA as installation sites for DGs and then the OPF identified the optimal size of DGs for the current positions. Then, the fitness function was evaluated for all GA chromosomes to find the most suitable combination for a predefined number of DGs. In Ref. [188], GA has been utilized for optimal positioning again and the OPF has been implemented for minimizing the operation, maintenance, and network upgrade costs along with cost for load growth causing losses. They have also considered the year dependency in their calculations which create the dynamic aspect of their proposed algorithm. The load curve for the duration of one year in combination with the customer load changes, have been modeled as the impact of load variation in the network.

4.5.5. Particle Swarm Optimization-Optimal Power Flow (PSOOPF)

The Particle Swarm Optimization-Optimal Power Flow by a combination of discritized PSO and OPF has been applied in Ref. [189] for optimal DGA within a distribution network for site and size recognition of a specified number of DGs. In this algorithm, the objective function has been defined as simultaneous minimization of losses and maximization of DG capacity. The discrete particles have been initialized as DG installation locations and then the OPF procedure identified the optimal size for DG units considering the imposed constraints for distribution network. The results have illustrated the reliability of the proposed method for optimal DGA in comparison to the pure genetic algorithm. Saif and Pandi et al. [58] have passed a set of system configuration to PSO on outer layer. The Dynamic Optimal Power Flow (DOPF) has been executed to evaluate the fitness function for each iteration. They have examined their approach on a simplified network from the UK generic rural distribution network with 16 bus and voltage level of 33 kV.

4.5.6. Particle Swarm Optimization-Gravitational Search Algorithm (PSOGSA)

Various objectives including power loss, voltage profile, line loading, and environmental impact of generation have been addressed in Ref. [90]. The optimization has been solved by a hybrid method combining Particle Swarm Optimization and Gravitational Search Algorithm, utilizes the advantages of both algorithms such as social thinking Global Optimality from PSO, and local search from GSA. Population has been initialized at first with the given population number. Then, the fitness function has been evaluated for each individual, and if constraints have been violated, a penalty factor of maximum value would be added to the function. The formulas of gravitational force or velocity have been utilized in parameter calculation and particle position update. The search procedure stopped when the maximum generation reaches 150 or the tolerance of 10^{-6} was met.

Different types of GDs considering their generations have been studied in this paper such as: active power generators, active and reactive generators, active generators and reactive absorbers, and a mixture of all the three types. The load flow analysis was done on 69 buses system using forward/backward sweep load flow algorithm and the loads have been modeled in 2 scenarios: invariant and variant. Then, the location and size of multiple DGs have been optimized while only the types have been specified as above. However, the generation variation of DGs has not been taken into account.

4.5.7. Particle Swarm Optimization-Shuffled Frog Leaping (PSOSFL)

Hybrid of Particle Swarm Optimization and Shuffled Frog-Leaping algorithms has been employed in Ref. [84], which take the advantages of both methods. Since SFL divides frogs into several memplexes and search in different parts of solution space, it can rectify the drawback of PSO, which is said to be a premature convergence, where the particles tend to fly to the best solution which might lead to local optimum. Fixed load and generation are considered in this study and the network analysis has been carried out by DIgSILENT. A multi-objective comprising minimization of power losses, voltage profile, and transient stability improvement has been considered. In case of constraints violation, a big value penalty term has been added to the objective function.

While each individual in the population contains the info of location and size of all DGs, the convergence criterion is pre-specified to the max number of iteration. After this has been satisfied, the last contents are considered as Pareto solutions. One best compromised solution is chosen by a decision-maker, based on a normalized membership function. The transient stability is determined by simulating different contingencies of various fault location (3 phase short circuit), and Critical Clearing Time (CCT) is measured when first DG becomes unstable (loss of synchronism). The authors have highlighted the advantages of DIgSILENT in dynamic modeling over MATLAB.

4.5.8. Fuzzy based hybrid algorithms

There are a few hybrid algorithms implemented for DGA using a combination of Fuzzy Set along with one of the other artificial intelligent algorithms. For instance Genetic-Fuzzy (GAFZ) has been presented in Refs. [100,128,150] and Tabu-Fuzzy (TSFZ) has been reported in Ref. [153].

The Genetic-Fuzzy algorithm has been proposed as a solution for DGA in the distribution systems in Ref. [150]. They have composed the objective function based on the cost of distribution system for power losses, while the size or the number of DG units and the bus voltage deviations have been considered as the constraints. In common employment of fuzzy algorithm, the composed objective function and

Table 1
Summary of base optimization algorithms in literatures and the covered criteria.

Optimization algorithm			**Constraints**					**Optimization objectives**								**Control Variables**		**Number of DGs**		**Research**
Classic Approaches	Basic Search	Artificial Intelligent	Bus Voltage	Branch Flow	Penetration	THD	Economics	Reduce Losses	Voltage Profile	DG Efficiency	Stability	Reliability	Power Factor	Economics	Perform. Index	DG Site	DG Size	Single	Multi	
AM			√	√	√			√	√		√			√	√	√	√	√	√	[20–22,27,29,32,38,39,41,43,54,91,101,105,119]
ES			√	√	√	√		√	√				√	√	√	√	√	√	√	[28,61,80,92,117,127,140]
AM, MCS				√			√							√		√	√	√		[25,72]
LP			√					√	√							√	√	√	√	[11,17,52]
MILP			√	√										√		√			√	[70]
MINLP			√	√	√			√			√			√	√	√	√		√	[40,63,67,93,111]
DP			√		√			√				√		√		√	√		√	[99,116]
LC								√	√						√	√	√		√	[33,77]
	OPF		√	√				√	√	√			√	√				√	√	[50,51,55–57,62,66,75]
	CPF		√					√			√					√			√	[19]
		SA	√					√							√	√	√		√	[86]
		IC	√	√			√	√	√					√		√	√	√	√	[145–147]
		TS	√					√						√		√	√		√	[35,97]
		HS	√					√	√							√	√		√	[76]
		HA	√	√			√	√						√		√	√		√	[95]
		MBO	√											√		√	√	√		[69]
		EP	√	√	√			√							√		√		√	[26]
		DE	√					√	√	√				√	√	√	√		√	[36]
		GA	√	√	√	√		√	√	√		√		√	√	√	√	√	√	[31,34,42,44,48,73,78,79,85,88,89,98,104,107,115,122,125,156,157]
		PSO	√	√		√	√	√			√	√		√	√	√	√	√	√	[68,71,82,94,120,161]
		ABC	√	√				√	√							√	√	√	√	[24,45,174,176,177]
		AC													√	√	√		√	[109]
		CS	√					√	√							√	√		√	[180,181]
		FF	√					√	√						√	√	√		√	[184,185]
		FZ						√	√							√	√		√	[151]

Table 2
Summary of combined optimization algorithms in literatures and the covered criteria.

Optimization algorithm				Constraints					Optimization Objectives								Control Variables		Number of DGs		Research
Classic approaches	Basic search	Artificial intelligent	Hybrid artificial intelligent	Bus voltage	Branch flow	Penetration	THD	Economics	Reduce losses	Voltage profile	DG efficiency	Stability	Reliability	Power factor	Economics	perform. index	DG site	DG size	Single	Multi	
NLP	CPF			√	√	√			√			√				√	√	√		√	[81]
MINLP	OPF			√	√	√			√								√	√		√	[30]
AM		FZ		√	√				√	√							√	√	√	√	[46,118]
AM		GA		√		√			√						√		√	√		√	[104]
MCS		GA		√				√	√						√		√	√	√		[102]
	OPF	GA		√	√				√		√				√		√	√		√	[65,188]
	OPF	PSO		√	√								√				√	√		√	[58]
	CPF	PSO		√					√			√					√	√	√	√	[18]
			GA+SA		√				√	√					√		√	√		√	[60]
			GA+TS						√									√	√		[186]
			GA+PSO	√					√	√								√	√		[187]
			PSO+OPF	√					√		√						√	√		√	[189]
			PSO+HS	√					√	√						√	√	√		√	[59]
			PSO+GSA	√	√				√	√						√	√	√		√	[90]
			PSO+SFL	√	√				√	√		√				√	√	√		√	[84]
			FZ+TS	√							√				√		√	√		√	[153]
			FZ+GA	√	√	√			√	√	√	√			√	√	√	√	√	√	[100,128,150]
			FZ+PSO	√	√				√								√	√		√	[23,103]

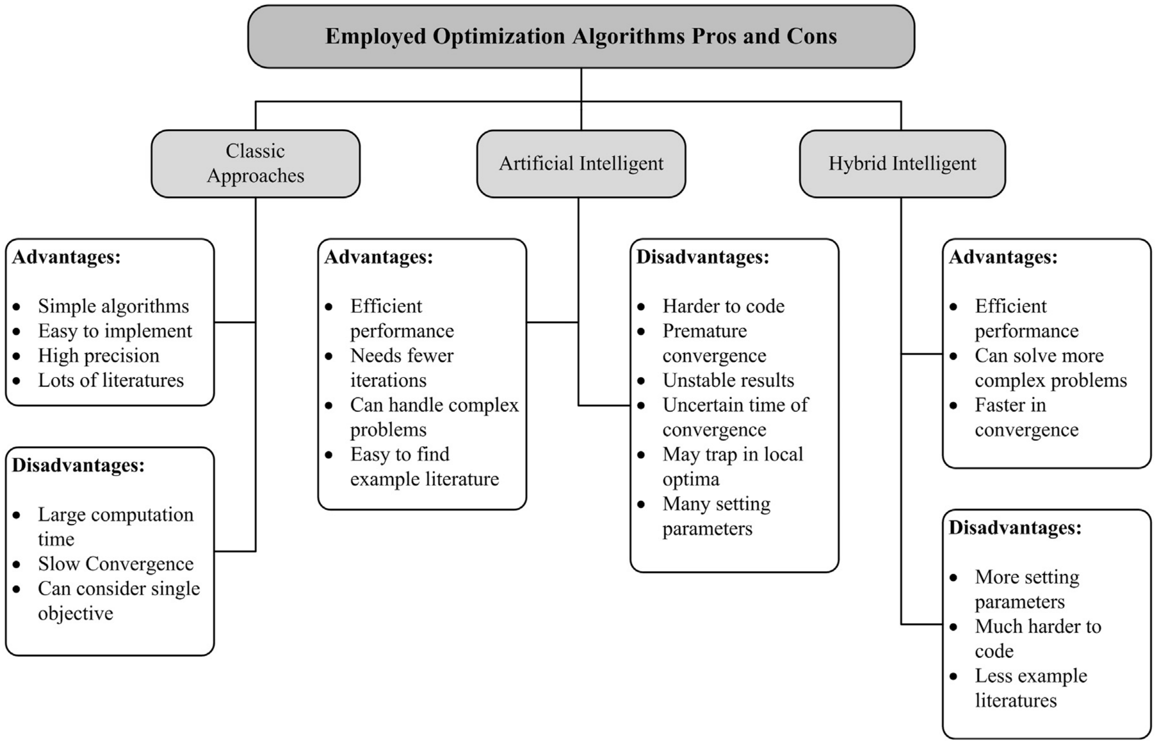

Fig. 4. Advantages and disadvantages of employed optimization algorithms.

constraints need to be transformed to an equivalent multi-objective model. In the proposed hybrid method, the imprecise information for the fuzzy algorithm and multi objectives have been evaluated directly using GA, escaping any additional nonlinear to linear transformation. Another multi-objective model considering technical and economic risks together with planning, operation, and monetary cost index has been proposed in Ref. [128]. The load and electricity prices and risks have been modeled by fuzzy algorithm, while a NSGA has been integrated for solving the MO model. The results demonstrated the robustness of the proposed algorithm for risk management and distributed generation planning (DGP) in distribution networks. The GAFZ combination has also been applied in Ref. [100], the authors have selected economic profit maximizing and loading margin of the system as objectives and used fuzzy set to combine these objectives to form a single objective. Finally, the single objective has been optimized by a genetic algorithm.

Lalitha and Reddy et al. [23] have optimally placed and sized DGs through a two-step algorithm. In the first step, they optimized the DG installation point using a fuzzy approach, then, in the second step, they used PSO to find the optimal size of DG which can imply the most reduction on the system power losses. Tabu search has been combined with a fuzzy set algorithm in Ref. [153] for optimal DGP. The authors have employed fuzzy method to model multi fuzzy objectives such as reliability, economic cost, and network robustness. Fuzzy set has been implemented to form a non-dominated multi-objective model from the aforementioned objectives for simultaneous optimization. The resulted model has been optimized by TS based algorithm. The model determines the optimal expansion size and sites of feeders and substations for the future, which were larger than what have been recognized in other literatures. The optimal reserve feeder including the site and size can also be determined using this model. The recognized reserve feeder can improve the network reliability for a dedicated robustness level at a minimum cost. Another two-step optimization has been employed in Ref. [69]. The authors have integrated a multi-objective Bee Optimization (MBO) to optimize the location and size of a grid connected solar farm. Then, they implement Fuzzy C-Means (FCM), a data clustering technique, to reduce the number of Pareto sets. A binary PSO has been implemented to find the Pareto optimal solutions for micro turbine, wind turbine, and gas turbine with pre-specified sizes. Then, the fuzzy satisfying method selects the optimal solution for the location, size, and investments timing of multiple DGs, depending on the planners' desires [103].

5. Comparison of optimization algorithms

All reviewed literatures are summarized in Table 1 and Table 2 with regard to their employed optimization algorithms. Moreover, the number of DGs, considered constraints, selected objectives for optimization, and the control variables are also presented in the same tables. Fig. 4 focuses on base and pure optimization algorithms which have been integrated in the researches. On the other hand, Table 2 covers the combined methods, including the combination of simple algorithms or more advanced hybrid intelligent algorithms.

The advantages and disadvantages of the employed methods are also concluded in Fig. 4. The pros and cons of the employed algorithms are summarized under three main categories: the classic algorithms, basic intelligent algorithms, and hybrid intelligent algorithms.

6. Conclusion

It can be stated that DG installation in power networks changes the network characteristics. There are a lot of methods employed in DGA due to their objectives operation constraints. Moreover, the studies on DGA can also be classified with respect to their employed optimization algorithms. A fitness function comprises of a combination of multi objectives and weight factors, is examined in the literatures. To form a single value objective function, weight factors are the most proper technique. However, the analytic methods combined with simple or exhaustive search can always result in an accurate solution, but they are not applicable for large networks. Due to the explained disadvantages of nature inspired optimization algorithms, a hybrid optimization algorithm seems to be more suitable for DGA, especially when renewable resources are also included.

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