Received: 10 May 2019 | Revised: 8 August 2019 | Accepted: 12 August 2019
DOI: 10.1002/er.4864

REVIEW PAPER

WILEY INTERNATIONAL JOURNAL OF ENERGY RESEARCH

Towards maximising the integration of renewable energy hybrid distributed generations for small signal stability enhancement: A review

Olusayo A. Ajeigbe[1] | **Josiah L. Munda**[1] | **Yskandar Hamam**[1,2]

[1]Department of Electrical Engineering/French South African Technology Institute, Tshwane University of Technology, Pretoria, South Africa
[2]Boulevard Blaise Pascal, Cité Descartes, Noisy-le-Grand CEDEX, France

Correspondence
Olusayo A. Ajeigbe, Department of Electrical Engineering, French South African Technology Institute, Tshwane University of Technology, Private Bag X680, Pretoria 0001, South Africa.
Email: sayoaje376@yahoo.com

Present Address
Department of Electrical Engineering, French South African Technology Institute, Faculty of Engineering and the Built Environment, Tshwane University of Technology, Staatsartillerie Rd, Pretoria, South Africa

Summary

Integrating renewable energy hybrid distributed generation (REHDG) into distribution network systems (DNSs) has become increasingly important because of various technical, economic, and environmental advantages accruing from it. However, the output power of REHDGs from photovoltaic (PV) and wind is highly variable because of its dependency on intermittent parameters such as solar irradiance, temperature, and wind speed. Such variability of generated power from large-scale REHDGs or load introduces small signal instabilities (oscillations). Meanwhile, different locations of integration and sizes of REHDGs in the DNS affect the system oscillation modes by either improving or depriving the small-signal stability (SSS) of the network. Consequently, a significant number of research has been conducted on the planning of optimal allocation of REHDGs in DNS. In this regard, this paper reviews the existing planning models, optimisation techniques, and resources' uncertainty modelling employed in REHDGs allocations in terms of their capability in obtaining optimal solutions and enhancing SSS of the system. Planning models with optimisation algorithms are evaluated for modelling renewable resource uncertainties and curtailing SSS variables. Research works on planning of optimal allocation of these generations attain minimum cost, but were unable to satisfy the SSS requirements of the system. The existing models for the planning and design of optimal timing, sizing, and placement of REHDGs will need to be improved to optimally allocate REHDGs and satisfy the SSS of the DNS after the integration.

KEYWORDS

distributed generation, distribution network, optimisation methods, renewable energy, small-signal stability

1 | INTRODUCTION

Globally, the usage and demand of energy are increasing exponentially, and the present and expected energy resources cannot satisfy the demand projections.[1,2] Exploiting distributed generations (DGs), therefore, are the effective strategies to meet increasing energy demand and solve power system economic and ecological environment issues.[3]

DGs are power generation units located in distribution networks close to the load centres in order to meet immediate power demand, reduce on-peak operating costs, defer network upgrades, reduce losses, reduce transmission and distribution (T&D) loading, reduce T&D costs, improve reliability, diversify energy resources, and enhance power quality and system stability.[4-11] Moreover, DGs, in contrast to centralised generations, are modular units that occupy small landmass or area using smaller generators, lower capital costs, and shorter construction times. The conventional DG can be grid-connected or standalone.[2] DG systems are in various sizes and power levels for different applications and needs. They range from single DG units of 1 kW to multiple DG units for plants of up to 300 MW. Based on their power rating, DG systems can be categorised into micro-scale DGs (1-5 kW), small-scale DGs (≥5 kW-5 MW), medium-scale DGs (≥5-50 MW) and large-scale DGs (≥50-300 MW).[5,12] From the perspective of active and reactive power, DGs are categorised into four types. These are type 1 DGs or P-type DGs that generate active power only, without interchanging reactive power with distribution network; type 2 DGs or Q-type DGs that generate or absorb only reactive power from distribution network; type 3 DGs or PQ^+ DGs that generate both real and reactive power into the distribution network; and type 4 DGs or PQ^- DGs that generate real power but absorb reactive power from the system.[4,5] DG may also be renewable energy based or nonrenewable energy sources or a hybrid of both.

The renewable energy based hybrid DGs provide a viable option. They are inexhaustible, complementary, eco-friendly, technologically mature, and economically profitable.[1,13] However, the output power of renewable energy hybrid distributed generations (REHDGs) such as wind and solar photovoltaic (PV) are highly variable because it depends on solar irradiation, temperature, and wind speed, which are intermittent.[3,4,14] Hence, substantial body of research has unequivocally agreed that the variability (sudden changes) of generated power, due to these renewable resources intermittencies, relative to load or vice versa results in power system oscillations.[15-22] In essence, small signal power angle instabilities occur when there is an imbalance between the total power generated from the REHDGs and other plants and the aggregate power demand at a time in the distribution network.[14,17] These issues occur more often in the power system. At high-scale penetration level, the small signal instabilities (oscillations) due to variability of REHDGs power can have significant consequences on the distribution networks. Undamped oscillations in the system for a period of time result in serious power quality and small signal stability issues.[23,24] The small signal instability with its oscillatory behaviour can greatly threaten the power system security as it is one of the main cause of power system failures (blackout).[18,21,22] These have made it difficult to integrate intermittent renewable energy hybrid DG systems into power distribution systems.[19,20] Meanwhile, different locations of integration and sizes of REHDG units in the DNS affect the system oscillation modes by either improving or depriving the small signal stability of the network.[4,15,25-32] The aforementioned issues make the formulation of REHDGs' optimal allocation problems tasking to solve using simple mathematical models. To obtain a realistic model, it is very important to represent the network as a dynamic model, use multiple periods for the planning horizon, and include all the pivotal constraints. The problem, therefore, is to optimally assign the renewable active and reactive power outputs into distribution networks and minimise the total cost under the capacity, investment, safety, and stability conditions over the planning horizon.

A significant number of research have been conducted in the last two decades on the planning of optimal allocation of REHDGs in DNS to proffer optimal solutions.[3,11,33,34] Such studies on optimal planning of REHDGs allocation have become extremely important in technical and economic terms for policymakers, regulators, distribution system operators (DSO), and energy producers as well as consumers by providing useful inputs for the derivation of regulatory measures and incentives and an efficient service delivery. Likewise, various researchers have conducted reviews on some aspects of the REHDGs allocation expansion planning (REHDGs-AEP) problem. Several solution strategies, formulation planning models, and emerging technologies employed in REHDGs-AEP have been previously presented.[4,5,7-10,13,35-37] Georgilakis and Hatziargyriou[7] presented an overview of some formulation models and optimisation techniques used in solving optimal DG placement problem taking into account DG capacity constraints. Jodehi[4] classified the previous works on distributed generation allocation problem from the perspective of used optimisation algorithm, constraints, DG technologies and types, and the kinds of uncertainties modelled. He concluded by generalising that all the associated technical, environmental, economic, and geographical constraints be included and more efficient meta-heuristic algorithm be developed. In Zubo et al,[5] a state-of-the-art review of uncertainty modelling methods applied in modelling renewable DGs, uncertain parameters, and some approaches for the planning of distributed generations allocation in distribution networks were presented. The authors briefly suggested the need to assess long-term dynamic stability of renewable DG schemes when integrating into the DNS. Abdmouleh et al[8] reviewed some optimisation methods, vis-a-vis conventional and intelligent search, applied to solve the problem of allocating REHDG units into distribution network. They also classified and analysed the drivers responsible for developing interests in REHDGs integration. However, their study did not include the planning model formulation. Theo et al[9] presented a comprehensive survey on DG system planning and optimisation techniques focusing on more issues other than those presented by Abdmoulehi et al. The authors extended their discussion to load demand analyses and renewable resources assessment models taking into consideration different forecasting models based on computational needs and prediction horizons. A review study presented by Ehsan and Yang[35] on the planning of optimal integration of renewable DGs briefly discussed few conventional and meta-heuristic methodologies that are being used for addressing optimal DGs placement planning problem. The authors' main contribution is on survey of many analytical strategies applied in optimal planning of renewable DGs. Intelligent algorithmic multi-objective optimisation methods for solving integration and generation side problems of renewable energy resources have been presented in Acharya.[37] The classification of multi-objective optimisation problem is grouped into generation side and integration side optimisation problems. Considering the contribution of the existing reviews already conducted on REHDG-AEP problem, this work distinguishes itself in the following ways:

- To the authors' knowledge, no literature has ever presented an evaluation of long-time dynamic voltage and small signal stabilities of REHDGs in distribution networks.
- This is the first time a detailed and realistic formulation model for REHDGs-AEP is being presented taking into consideration all necessary components to replicate and optimise practical distribution network system.
- Unlike previous reviews, this review presents the variables and constraints that are necessary in REHDGs' optimisation for enhancing long-time dynamic voltage and small signal stabilities of distribution networks.
- A more substantial and diverse number of optimisation algorithms used to solve REHDG-AEP problem is surveyed in this study.
- Unlike most existing reviews, this review presents the uncertainty parameters in REHDGs' allocation problem and evaluated various methods to take them into account in the existing works.

Notwithstanding a significant number of review literature on DGAEP studies, there are some aspects that have not been adequately investigated, reviewed, and presented. These subjects are comprehensively dealt with in this paper. Some of these subjects include dynamic stability evaluation of REHDGs in DNS, and realistic expansion planning formulation model that is grouped under subjects such as objective functions, decision variables, uncertainty modelling, load models of distribution networks, optimisation algorithms, optimal solutions as well as stability and reliability evaluation. Further, subjects considered in this article are the modelling of uncertainties in REHDG-AEP models to account for the renewable resources intermittency, comprehensive review of large number of optimisation methods, evaluation of the existing research works on REHDGs allocation, and inclusion of load modelling in distribution network suitable for dynamic stability assessment. This paper serves as a repertoire of knowledge on the review of REHDG-AEP problem, which identified and addressed the mentioned research gaps. It is however important to emphasise that the focus of this study is not extended to power system planning other than the optimal allocation of REHDGs in distribution expansion planning (DEP).

The paper is organised as follows: Section 2 presents the model formulation of the REHDG allocation problem as well as the enumeration of uncertain parameters that are usually modelled in power systems. The variables and constraints that are pivotal to putting in check, the effect of uncertainties and the variability of non-dispatchable renewable energy resource (RES) output power in the distribution network are also discussed. Section 3 presents a review of the published models and optimisation methods, featuring a large number of previous and recent research works, and some potential algorithms newly developed and applied to solve DGs allocation optimisation problems. The evaluation of the existing works based on objective function, constraints and decision variable used, network of implementation, uncertainty parameter(s) modelled and modelling method used, and their shortcomings are discussed in Section 4. Section 5 concludes the paper and recommends future research actions necessary for attaining optimal allocation of REHDG units at a minimised cost under the required level of dynamic and voltage stabilities.

2 | FORMULATION OF REHDG ALLOCATION PLANNING PROBLEM

The REHDG allocation problem can be formulated as either planning and design or real-time operations problem. The typical REHDG allocation expansion planning is the problem of finding optimal type, size, location, and time of REHDGs installed in a distribution network that is constrained with electrical network operating, investment, and REHDG restrictions in order to obtain maximum potential advantages of REHDGs with the least costs over a planning horizon. Electrical network operating constraints refer to line flow capacity, radiality of the network, safety factors, reliability, and stability indices. Minimum cost is attained by the optimisation of economic targets such as minimisation of investment and operating costs, minimisation of energy loss and emission,

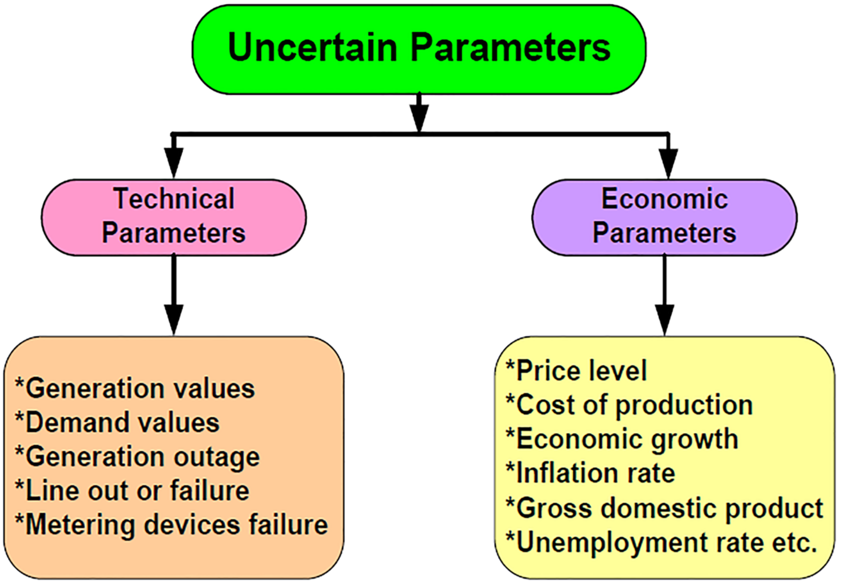

FIGURE 1 REHDG allocation expansion planning formulation model. DG, distributed generation; REHDG, renewable energy hybrid distributed generation [Colour figure can be viewed at wileyonlinelibrary.com]

reduction of power purchased from the conventional grid, and minimisation of reliability costs. REHDG allocation planning is, therefore, a non-linear, complex mixed integer, multi-objective, and highly restricted optimisation problem where finding a global optimum solution is very tasking. Optimal allocation planning of intermittent hybrid DG requires the consideration of conflicting objective functions (eg, maximisation of DG capacity and minimisation of network stability, etc), constraints (DG voltage magnitude limits, line flow constraint, etc), and complex decision variables (eg, DG type, number, size, location, power factor, etc) as well as the requirements (inaccurate mathematical model) for modelling uncertainty (intermittency) of the constituting DG units[4,5,9] and evaluating the impact of the variability of their output power on the long-term dynamic stability of the system. The components of a realistic REHDGs allocation planning (REHDGAP) model is presented in Figure 1.

2.1 | Objectives of REHDG allocation problem

The mathematical formulation of objective function(s) of a REHDG can be linear or non-linear functions. The mathematical definition and presentation of an allocation problem with exclusively linear functions gives linear objective function(s) while non-linear mathematical representation presents non-linear objective function(s). The objective functions of optimal REHDG allocation can either be single-objective or multi-objective.

2.1.1 | Single objectives of REHDG allocation problem

Single-objective allocation can be formulated from many perspectives, eg, from a perspective of distribution energy resources developer, from a perspective of distribution system operator (DSO), etc.[4,7,8] In the existing research works, the most common single-objective functions usually used in descending commonality are the following:

- Minimisation of system losses (copper, power, and energy).
- Minimisation of voltage deviations and voltage drops or enhancement of voltage profile and stability.
- Minimisation of costs (total, energy/operation, investment, maintenance, and emissions) and penalties in compensating for losses.
- Minimisation of total harmonic distortions (THD) levels (current and voltage).
- Maximisation of social welfare and profit.
- Maximisation of benefit/cost ratio.
- Maximisation of renewable DG penetration
- Maximisation of DG capacity.
- Maximisation of network system loadability limits.
- Maximisation of system reliability metrics (eg, system average interruption duration index [SAIDI]).
- Minimisation of short circuit level.
- Maximisation of distribution system revenue.
- Maximisation of uniform power flow among feeders.

A single-objective optimisation problem optimises one objective function subject to some inequality and equality constraints as can be written in mathematical form as the following:

$$\text{Min or Max} \quad F_s(x) = f_s(x). \tag{1}$$

With the constraints

$$R(x) \le 0, \tag{2}$$

$$S(x) = 0, \tag{3}$$

where $F_s(x)$ is the objective function with one objective and expressions (2) and (3) are inequality and equality constraints, respectively.

2.1.2 | Multi-objectives of REHDG allocation problem

Multi-objective function of a DG allocation problem involves combination or addition of many single objectives in Section 2.1.1 with an inevitable conflict in which a single solution is incapable of solving all the diverse objectives. These multi-objective functions are required to be minimised or maximised simultaneously into a single-objective formulation.[33,38-41] The multi-objective formulations are grouped into[5,7]

(i) Multi-objective weighted sum formulation: weighted sum of each objective is used to transform multi-objective formulation into a single objective function problem with the use pre-specified weights. Weighted sum approach is simple to formulate but difficult to apply in non-convex optimisation problems.
(ii) Multi-objective formulation with many contrasting objectives: many contrasting objectives are considered and the best compromised solution is chosen among a set of feasible solutions.
(iii) Goal multi-objective index: goal programming method is used to change a multi-objective formulation to a single objective function.

Each of these multi-objective formulations has its merits and demerits that makes it suitable for a particular allocation problem. A multi-objective optimisation problem simultaneously optimises n objective functions subject to some inequality and equality constraints as in (4) to (6).

$$\text{Min or Max} \quad F_m(x) = [f_{m1}(x) + f_{m2}(x) + \ldots + f_{mn}(x)]. \tag{4}$$

With the constraints

$$R(x) \leq 0, \tag{5}$$

$$S(x) = 0, \tag{6}$$

where $F_m(x)$ is the objective function that consists of n objectives and expressions (5) and (6) are inequality and equality constraints, respectively.

2.2 | Decision variables

The decision or design variables are the unknowns that are usually computed for in REHDG allocation problems. The decision variables can be one or a combination of these variables: DG type, size, location, unit number, power factors, and installation year/time, active power or reactive power of DG, storage device or generated power of DG, slack bus power, bus voltage magnitude, and phase angle.[4,7,35,37] The bus voltage magnitude and phase angle are the variables used for the decisions on the stability of the network. While bus voltage magnitude is responsible for voltage stability and evaluation of voltage collapse, voltage phase angle determines what happens to the small signal stability of the system.

2.3 | Constraints

Constraints are applied on the DG allocation problem to exert restrictions over the optimisation of the objective function(s) in respect of some decision variables. The most common constraints used in the optimal REHDG allocation problem formulations are grouped into seven.[4,7-10,13,35-37,42] These are

(i) Technical constraints: These are the technical constraints:
   - The set of power balance equality constraints placed on real and reactive power at each bus of the network (Kirchoff's current law).
   - The set of inequality constraints such as transformer or line overloading or capacity limits, transmission supply limits, limited buses for DG installation, etc.

(ii) System reliability constraints: They ensure continuous and constant transmission and supply of power to the end users.
   - The set of inequality constraints such as maximum SAIDI, short-circuit level limits, radiality constraints, etc.

(iii) Safety constraints: The constraints ensure safety of the network and the populace.
   - The set of inequality constraints such as right of way constraints, etc.

(iv) DG capacity constraints: These constraints border on the generation limits of the distributed generation units.
   - The set of inequality constraints such as DG penetration limit, DG capacity bounds, DGs' constant power factor, DG units' discrete size, DGs' maximum number, etc.

(v) Power quality constraints: These constraints ensured the quality of power in the distribution system.
   - The set of inequality constraints such as current and voltage total harmonic distortion (THD) limits, voltage rise limits, voltage sag limits, etc.

(vi) Investment constraints: These are the constraints imposed on investment. They can be continuous or discrete or binary constraints

- The set of inequality constraints such as budget limit, differs investment options, divestment constraints, etc.

(vii) Network stability constraints: Network stability constraints such as voltage drop or deviation or bus voltage magnitude limits, and voltage angle constraints are the parameters considered for power system stability. The two network stability constraints are briefly explained.

- The voltage magnitude limits often require very strict standards when imposed on the network to enforce voltage stability of the system. Too low or too high voltage magnitudes could cause damage to end users' power devices, apparatus and equipment, or voltage stability issue in power system. This can result to economically expensive and unwanted partial availability of electricity for the users.

$$V_i^{min} \leq V_i \leq V_i^{max}; \quad OR \quad \Delta V_i^{min} \leq \Delta V_i \leq \Delta V_i^{max}; \quad i = 1, \ldots N. \tag{7}$$

The inequality constraint (7) is enforced on all the buses of the network. Though, the upper and lower voltage limits of some buses (mostly generator buses) are equal. That is, the voltage magnitudes of such buses are numerically given.

- Above and beyond, phase angle limits must be formulated based on some stability criteria if dynamic stability of a network is expected to be maintained or enhanced. Voltage angle constraint is as important to dynamic stability (small signal) as voltage magnitude constraint is to voltage stability of the system. In fact, violating voltage angle limits can result in serious dynamic stability issues that can lead to total outage of power and other severe economic losses. In actual sense, the small signal stability of any power system is the prerequisite for such system to operate in practice.[17] However, almost all the works on DG allocation planning optimisation problems do not include phase angle constraints in their formulation models.

$$\theta_{ij}^{min} \leq |\angle V_i - \angle V_j| \leq \theta_{ij}^{max}; \ OR \ \theta_{ij}^{min} \leq \theta_{ij} \leq \theta_{ij}^{max}. \tag{8}$$

The constraint in (8) should be applied to all the network buses based on the set stability criterion.

2.4 | Modelling of uncertainties in the REHDGs planning

The planning of DG problem in a DNS involves many sources of uncertainty and variability, especially with the integration of intermittent RES. These are due to randomness and variability in time of operational situations.[6] The variabilities caused by the intermittent hybrid DGs (solar PV and wind), power outputs, demand, market, and other power system uncertainties are considered during several operational states for modelling to cushion their impacts.

2.4.1 | Uncertain parameters

The parameters that can be modelled in the planning and operation of renewable DGs to account for the uncertainties inherent in the distribution systems are shown in Figure 2. These uncertain parameters are grouped into two, based on either technical or economic effects they have on the system. They are as follows[5,43]:

Technical uncertain parameters

The technical uncertain parameters are uncertainty in generation values (includes those caused by intermittent nature of REHDGs) and demand values, generation outage, line outage, instrumentation, or devices failure.

Economic uncertain parameters

These parameters are uncertainty in the cost of production (includes costs of fuel, maintenance, operation, labour, etc), business taxes, market prices, inflation rates, unemployment rates, and gross domestic product to mention a few.

It is paramount to state that the review of various methodologies and approaches that have been used for modelling the aforementioned uncertain parameters is not subject of this paper. However, the paper is only interested in whether these parameters are modelled and included in the network expansion optimisation.

2.5 | Power system network model

There are two commonly used network models in the study of power system dynamics and power flow analysis: the static and dynamic models. Each of these network models has its own specific use, and the level of usage depends on the kind of problem under consideration. Studies related to small-signal stability are dynamic power studies that employ dynamic model of the power network. Thus, dynamic network model incorporating suitable load model is a subject of priority any time dynamic stability of power network is being evaluated.

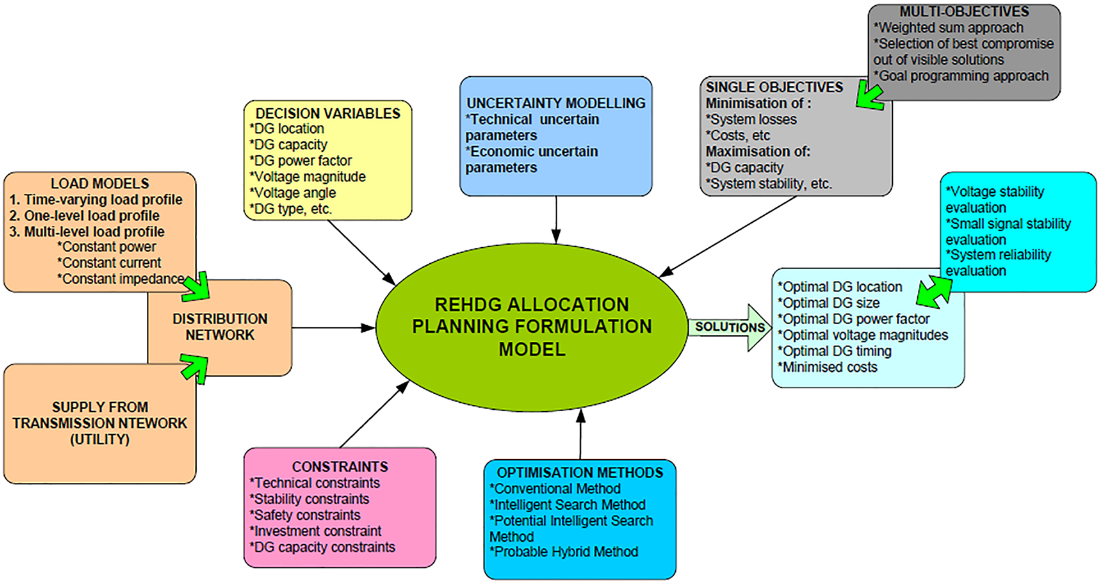

FIGURE 2 Power system uncertain parameters [Colour figure can be viewed at wileyonlinelibrary.com]

2.6 | Load profile model

The modelling of load profile of a distribution network follows either of these existing alternatives: (a) time varying, (b) single load level, (c) multi-load level, (d) fuzzy, and (e) probabilistic. However, a time-varying load model that has various numbers and types of users gives a better representation by using the load values of each hour. This model is a representation of dynamic load model that can be efficient in the evaluation of both long-term dynamic voltage and small-signal stabilities of the distribution system. Furthermore, the load connected to the distribution network can be either concentrated on the network buses or distributed along the network lines.[6,7] The concentrated static load is modelled in optimal REHDG allocation problem depending on the power relationship with voltage as either (a) constant current, (b) constant power or variable power, and (c) constant impedance.

2.6.1 | Constant power load model

A constant power model is a load representation where power has a proportionality relationship with phase angle (ie, $P \propto \theta$), but independent of voltage magnitude changes This model can be efficient in the evaluation of long-term dynamic stability of the distribution system.

2.6.2 | Constant current load model

Constant current or variable power model depends on bus voltage magnitude. This presents a static model and represents power as an exponential function of voltage magnitude (9). This load model can achieve static voltage stability of the system.

$$P = P_n V^{\alpha}. \tag{9}$$

$$Q = Q_n V^{\beta}. \tag{10}$$

where P, Q, P_n and Q_n are the actual values of real and reactive powers and nominal voltages values of real and reactive powers, respectively. α and β are the real and reactive power exponent values, and these values are common representatives of the values used in most of the literatures.

2.6.3 | Constant impedance load model

The power-voltage magnitude relationship of a constant impedance model is quadratic as shown in Table 1 based on the function of power exponents.

3 | OPTIMISATION ALGORITHMS FOR DG ALLOCATION PLANNING

This section categorises the optimisation approaches being applied to solve the DG allocation planning problems into conventional, intelligent search (IS), potential IS, and probable hybrid methods (Figure 3). These groups and subgroups are conventional - analytical, numerical, and power flow (PF) methods; intelligent search - genetic algorithm (GA), fuzzy logic (FL), simulated annealing (SA), tabu search (TS), differential evolution algorithms (DEA), particle swarm optimisation (PSO), ant colony optimisation (ACO), and harmony search (HS); potential

TABLE 1 Load models with their exponents values

Load Model	α	β
Constant impedance	2	2
Constant current	1	1
Constant power	0	0

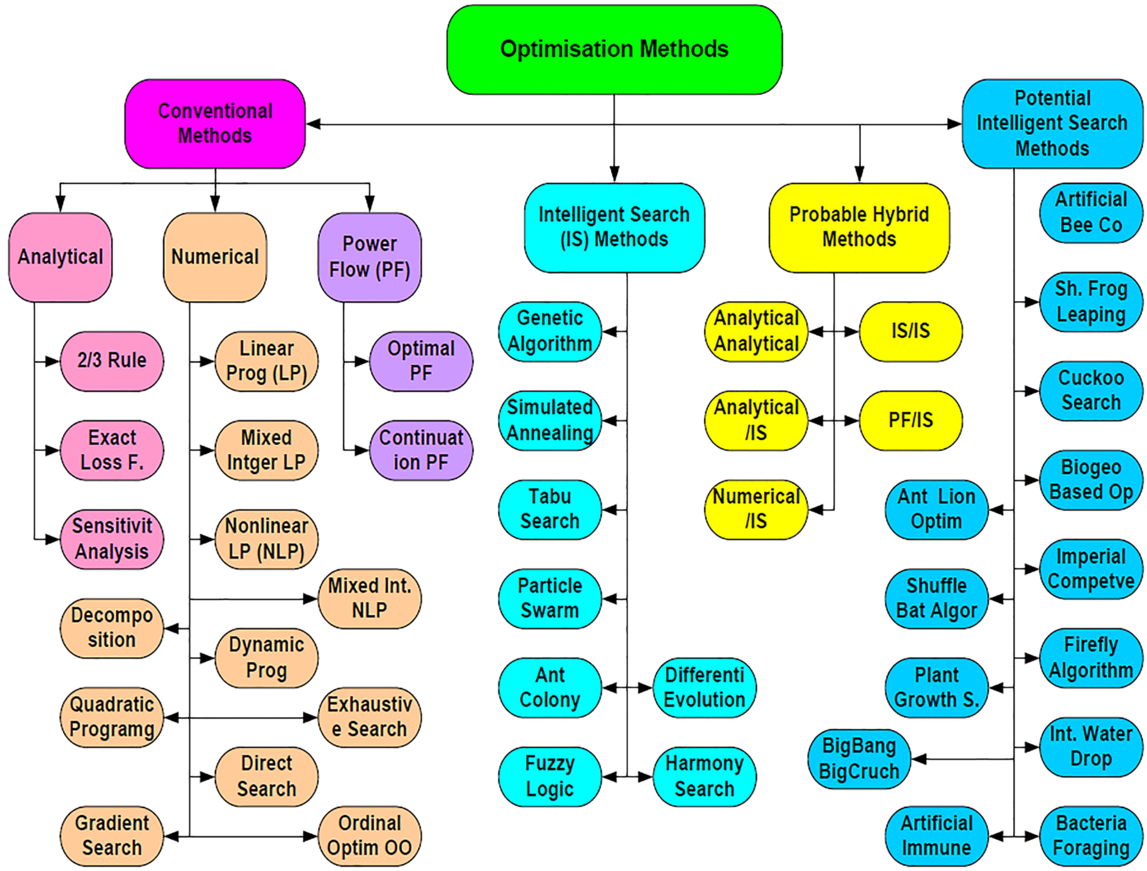

FIGURE 3 Optimisation methods for solving distributed generation allocation expansion planning problem [Colour figure can be viewed at wileyonlinelibrary.com]

IS - artificial bee colony (ABC), shuffle frog leaping algorithms (SFLA), cuckoo search (CSO), plant growth simulation (PGSA), shuffled bat (SBA), biogeography-based optimisation (BBO), imperial competitive (ICA), firefly algorithms (FA), intelligent water drop (IWD), bacteria foraging (BFO), artificial immune system (AIS), big-bang big-crunch (BBBC), and ant lion optimisation (ALO) methods; and probable hybrid heuristics - analytical/analytical, analytical/IS, numerical/IS, IS/IS, and PF/IS. The discussions of these methods are done in terms of their optimal solution attainment, power system uncertainty modelling, stability enhancement, limitations to small-signal stability enhancement, advantages, and disadvantages.

3.1 | Conventional methods

Some of the conventional methods used to solve DG allocation problems are reviewed. The interest in using analytical methods and traditional methods based on linear programming had grown greatly in recent years.

3.1.1 | Analytical methods

Analytical methods normally generate numerical equations that are applied to solve optimisation problems. These methods depend on calculations, mathematical, and theoretical analysis. The analytical methods' accuracy is highly dependent on the model developed. They can also be used with the combination of other models, by building on the simulation results gotten from the initial model. The analytical methods have the advantages of brief computation time and ease of implementation in achieving convergence of the problem. Though, the solution' accuracy during complex problem may be threatened due to some assumptions that are used in simplifying the problem. Some of the methods under analytical methods are stated below[5,7,8]:

(i) Two-third (2/3) rule: 2/3 rule is an analytical method that is based on the application of intuitive rule to approximately place DG units or capacitors in the distribution systems using power flow graphical display. The method estimated the size of the DG unit to be 2/3 of the load, and the unit is installed at 2/3 the length of the feeder line. This is to minimise the total VAR-miles of flow, losses, and voltage impacts. Willis[44] analysed the impact of voltage and feeder losses in distribution system on placement of distributed generation units using zero points 2/3 rule on a uniform radial distribution network. The DG produced 3 MW, fed 2 MW load downstream to it, and fed the remaining 1 MW towards the substation. The result showed that the optimal location for DG installation is at the end of the most loaded branch of the feeder. Its placement has little impact on protection, voltage regulation, and loading of the system when located at the substation. However, this method may be ineffective in cases where the loads are distributed nonuniformly on radial feeders. The author concluded that the algorithm is an approximate one; hence, the optimality of solution obtained can be doubted. Nehrir[45] presented analytical techniques for finding optimal placement of a fixed size, single DG in a meshed and radial DNSs to minimise power losses. The result on time-varying and invariant loads (uniformly and centrally distributed and uniformly increasing) and DG showed that 2/3 rule method significantly minimised the power losses of the system when DG is optimally located under uniformly distributed feeder load. Meanwhile, inadequate results were obtained when the other load configurations were used. 2/3 method as applied here only optimises the location while the size is fixed.

(ii) Exact loss formula: Two exact loss formula-based analytical methods are presented in Archaya et al[46] for finding optimal locations and sizes of a single DG and four types of DG units with the objective to minimise the total power losses in the distribution systems. The proposed method is an improvement of the work presented in Nehrir[45] that was limited to a single type of DG. Tawfeek et al proposes the use of exact loss formula and PSO to optimally allocate four DG types into radial DNs in order to minimise the total active power losses.[47]

(iii) Sensitivity analysis-based methods: Using these methods, the original non-linear equation is linearised around the initial operating points in order to cut down the number of viable solutions in the search space. These methods involve changing of some parameters to compare the effect on the final results. The main advantage of sensitivity analysis methods are the ability to reduce the computational time of a large-scale, real-life systems. These methods are used to appropriately locate DG units based on sensitivity indices. The methods are also very effective in assessing uncertainties especially from renewable energy intermittent nature. GÃúzel and Hocaoglu[48] present a loss sensitivity factor method that uses and equivalent current injection principle for finding optimal location and size of DG in order to minimise total power losses. A combination of loss sensitivity analysis based method and new voltage stability index (VSI) is proposed in Murty and Kumar[49] for finding optimal size and location of PQ-type DG with the objective to improve voltage profile and minimise copper losses. The optimisation results show that the proposed VSI outperformed a loss sensitivity index given in Murthy and Kumar[50] and a power stability index given in Aman et al.[51] In Lee and Park[52] loss sensitivity factor and Kalman filter methods are used for finding optimal size and location of multiple DGs. Other analytical techniques are described in Hung and Mithulananthan[53] and Hung et al[54] for finding optimal size and location, and power actor and size of different types of multiple DGs, respectively. Sensitivity analysis-based methods are disadvantaged as they only find optimal locations of DG units and even the degree of optimality of achieved solutions are unknown.[4]

3.1.2 | Numerical methods

Classical optimisation algorithms such as linear and non-linear programming have been applied to DG allocation problems in a few cases. LP and MILP suffer from lack of flexibility. They normally require preconditions like convexity, linearity, and continuity of objective functions, which are difficult to meet in practice.[8]

(i) Linear programming (LP): LP is used for solving mathematical models whose formulations exhibited linear relationships in order to minimise or maximise the objective function. LP is mostly applied to power system optimisation problems to determine optimal DG sizes, as it gives exact solutions.[5,8] Hamam et al,[55] Dicorato et al,[56] Keane and O'Malley,[57,58] Altintas et al,[41] and Alturki et al[40] use LP to achieve high penetration and maximum energy harvesting of DGs, respectively, while maintaining voltage magnitude limits. Hamam et al describes a partitioning algorithm based on LP method to solve excessive memory requirement and computation time of long-term generation plant mix problems.[55] This algorithm was an improvement on the linear programming model earlier developed by Knight for the solution of power plant mix problem. In Dicorato et al,[56] an energy flow optimisation model (EFOM) based LP is presented for exploitation of DGs with primary energy resources and optimal diffusion of energy-efficiency technologies to minimise environmental impact and operational costs. LP algorithms are used differently in Keane and O'Malley[57,58] to solve DGs' placement problems by taking advantage of bus interdependence with the constraints and maximising the amount of energy harvested from available energy resources in a geographical area. Maximisation of DG capacity and profit are the objective functions of the works respectively. Altintas et al presented a bi-objective LP optimisation algorithm to solve distribution expansion planning problem that incorporates renewable generation resources (wind and solar) with the objective to minimise total cost of investment and carbon emissions.[41] The performance of the algorithm was evaluated by evaluating solutions' spread using spacing, maximum spread values, and Central Processing Unit (CPU) time metrics. Also, sensitivity analysis on the effects of investment costs in relation to solar and wind DGs was conducted. An LP algorithm is proposed in Alturki et al[40] for determining optimal distribution grid hosting capacity with the objective of maximising the total DG capacity over the set of primal variables and minimising over the set of uncertain parameters. The results showed that LP method outperforms the traditional methods in computation time. The computational time for running the LP algorithms mentioned were very small especially when large search space is considered. However, no aspect of network stability was considered for evaluation in these research works.

(ii) Mixed integer linear rogramming (MILP): MILP is mathematical programming applied to solve a mathematical model by minimising or maximising a linear objective function subject to linear constraints of which at least one of the variables takes on integer values. MILP is difficult to implement on real-size problems and takes excessive computing time. In Santos et al,[3] MILP is used in the planning of optimal sizing and placement of smart grid technologies for maximising renewable DG integration. Muñoz-Delgado et al proposed a MILP solution to address the multi-stage expansion planning problem of a distribution system where the total cost in distributed generation (wind) and distribution network are considered.[59] In Mishra et al,[60] a two-stage chance-constrained stochastic MILP formulation for determining optimal investment decisions in DGs with operational uncertainties is modelled and further optimised with an evolutionary vertical sequencing protocol heuristic method with the objective of minimising the total cost of investment and operation. Alturki and Khodaei[61] proposed MILP to optimise DG capacity hosting of a radial distribution network through reconfiguration of existing tie and smart switches with the objective to maximise total DG capacity deployed into the network. All the works discussed here evaluated voltage stability and modelled uncertainties of renewable resources but were unable to assess the effects of the variability of renewable powers injected on the networks. Similarly, the global optimality of their solutions were not reported.

(iii) Non-linear programming (NLP): NLP is used to solve a mathematical model with non-linear objective function(s), only continuous variables and constraints. The computation in NLP is based on the derivatives of objective function(s) and constraints. To solve a non-linear problem, a search path is chosen in an iterative method by specifying the initial partial derivatives or the reduced gradient of the problem equation. This approach is called first-order method of which the reduced gradient method and other search methods are included as discussed in (x) below.[62] The second order NLP methods like Newton Raphson method[63] and successive quadratic programming [64] use the derivatives of constraints and power flow functions for solving DG allocation planning problems.

(iv) Mixed integer non-linear programming (MINLP): MINLP is utilised to solve a mathematical model with continuous and discrete variables, non-linear objective functions, and constraints. MINLP has been used severally to find optimal locations and sizes of DGs in power systems where power loss sensitivity indices are proposed to find optimal locations of DGs economically and operationally. The major drawbacks of MINLP are very substantial number of design variables and lengthy computational time.[5,8] An MINLP is employed in Porkar et al[65] and Al Abri et al[66] to optimise the allocation of different types of DGs considering electricity price, and electronically interfaced DGs for voltage stability improvement respectively. MINLP is applied in Salyani et al[67] for the mathematical formulation of optimal simultaneous expansion planning of High Voltage/Medium Voltage (HV/MV) substations, multiple DG units, and robust MV feeder routing problem while adaptive GA is used in finding the optimal sizes and locations in the network, considering the uncertainties of renewable generations, demand, electricity, and fuel prices.

(v) Decomposition method: Decomposition method is an approach where large-scale allocation problems are solved by structuring the problem in such a way that some of their constraints are removed. It usually considers the DG allocation problem in two parts. The first part being the one with the simple constraints and the other with complicating constraints. Wang et al[68] and Mena and García[69] use benders decomposition (BD) to find optimal types, sizes, and locations of DG units with PV and wind resources. The objectives of the optimisation are investment, maintenance and operation costs, emission and fuel costs, and micro-grid profits. The results prove that the proposed methods are effective, and the obtained solutions are robust under various conditions.

(vi) Dynamic programming (DP): DP is an optimisation approach that transforms a complex optimisation problem into a sequence of smaller and simpler problems. DP essential feature is the multi-stage nature of optimisation procedure. It provides a general framework with variety of optimisation techniques to analyse the problem and solve particular aspects of a more general formulation.[5] Khalesi et al[70] applies DP for determining the optimal locations of DGs in the distribution network to minimise power loss of the system and enhance voltage profile and system reliability. The work considers as case studies low, medium, and full load conditions in maximising the profit of network operator. Saif et al proposed DP algorithm to solve optimal allocation of distributed energy resources, wind, solar PV, and batteries. They conclude that properly sized and located DERs provides high reliability.[71] Popovi and Popovi[72] and Martin et al[73] are some of the other works that solve multi-period planning problems of distributed generations with the use of DP algorithms. These works assessed the voltage stability of the system during the integrations of the DG units though static voltage stability.

(vii) Quadratic programming (QP): QP is the optimisation of a quadratic objective function subject to some linear constraints. Bhowmik et al propose a two-stage iterative solution technique based on QP and mixed integer quadratic programming (MIQP) for the planning of radial distribution system.[74] The first stage determines the optimum substations sites while the second stage finds the optimum configuration of the network. A sequential QP (SQP) algorithm is applied in Sfikas et al[75] to determine optimal sizes of photovoltaic-, wind-, and mass-based DG units and battery devices in both standalone and grid-connected micro-grid. The objective functions of the optimisation are energy cost and annual energy losses. The method shows that mass units are more efficient DGs relative to the other two in terms of reduction in energy cost. Also, it shows that inclusion of battery devices are very beneficial in standalone micro-grid operation. Sfikas et al[75] concludes that the more the types of DG and batteries added the less the energy cost from the DG units. SQP and OPF algorithms are used to optimise the DGs allocation problem with fault level constraints in Vovos et al,[76] and without fault level constraints in AlHajri et al.[77] A mixed integer quadratically constrained QP is proposed in Lazzeroni and Repetto[78] to find optimal battery management strategies in order to minimise power losses of the DNS. D-XEMS13 optimisation procedure is used to identify best sizes of battery energy storage system (BESS) units. Some other works that used QP are Kermanshahi et al[64] and Kaur et al.[79]

(viii) Exhaustive search (ES): Exhaustive search method is also known as direct search, brute force, or generate and test method. ES method is used for discrete DG allocation problems because of its simplicity and accuracy.[80,81] ES always presents reliable results due to its propensity for high-possibility checking[81] though the solutions obtained maybe inefficient especially in large problems. It has high-computational tendency as a drawback. Pesaran et al[82] proposes a multivariable exhaustive search method for finding optimal size and location of REHDG units consisting of photovoltaic and wind. ES method is also applied in Khan and Choudhry[83] to optimise the size, number and placement of DG units using voltage profile improvement as an objective function. A two-stage exhaustive search and clustering-based approach is proposed in Rotaru et al[84] to find the optimal sizes and placement of multiple distributed generations. The optimisation objectives are minimisation of daily energy loss and improvement of voltage profile without violating the basic power system constraints.

(ix) Direct search (DS) approach: A DS approach is proposed in Raju et al[85] to obtain the optimal sizes of switched and fixed capacitors for maximising savings and minimising power losses in a radial DN. In Samui et al[86] a DS algorithm is used to inhibit inherent network difficulty and provide optimal solution for DG placement problem. Samui et al[87] applied DS method for optimal planning of DGs placement with the objective functions of maximising power reliability and minimising cost in radial distribution systems.

(x) Gradient search (GS): GS method was developed by Newton, and it is also known as gradient descent or ascent method for minimisation or maximisation problems, respectively. It is a first-order iterative optimisation algorithm where the local minimum or maximum of the objective function is determined by gradient descent or ascent. This is done by taking the current point of the steps proportional to the negative or positive of the gradient of the objective function. Rau and Wan[88] proposes gradient search method for the optimal allocation of DGs in meshed networks while Vovos and Bialek[89] proposes the same with consideration for fault level constraints.

(xi) Ordinal optimisation (OO): Li et al[90] and Lin et al[91] proposed the use of OO in the integration of electric vehicles (EVs) in order to find optimal solution for the distribution system expansion planning. In Jabr and Pal,[92] an OO approach is used to optimise the sizes and locations of multiple DG units to find balance between DG capacity maximisation and loss minimisation. Zou et al[93] proposes an OO algorithm to find optimal placement and sizes of DGs considering the uncertainties of renewable energy sources. The authors use the uncertainties' capability curve to reduce active power losses and enhance voltage profile and stability index of a radial network.

3.1.3 | Power flow (PF) methods

(i) Optimal power flow (OPF) method: The objective of OPF is to determine the optimum economic operating cost that continuously operates a power system by putting the effects of transmission and distribution systems into consideration. OPF considers the economic aspect in the optimisation of DGs allocation and sizing problems.[94-96] OPF has been used to maximise the sizes and locations of DGs in the network using obligatory constraints such as voltage and harmonics limits.[8,21] Karatepe et al[97] proposes an OPF to evaluate the DGs integration approaches by considering the variability of DGs output power in terms of network losses, line capacity, and voltage profile. Ochoa et al proposes an optimal power flow method for finding optimal DG sizes with the inclusion of active network management (ANM) in a multi-period Alternating Current (AC) distribution network.[98] Vovos et al[76] and Vovos and Bialek[89] also propose optimal power flow algorithms for finding optimal DGs sizes where the fault level constraints are converted to non-linear constraints, and fault level constraints enforced by protection equipment, switchgear, are considered in the DNS expansion planning. A three-phase unbalanced OPF algorithm is extended in Meng et al[99] for the integration of distribution energy resources (DERs) and solid state transformer (SST) in DNS with minimisation of generation cost as the objective function.

(ii) Continuation power flow (CPF): Hemdan and Kurrat[100] used CPF method to efficiently integrate DGs into distribution systems to meet up with the increasing load demand. The result showed that more benefits were obtained from the DGs and power losses were reduced and voltage profile improved. In Hedayati et al,[101] CPF was applied to determine the optimal locations of DGs in a distribution system. The method resulted in power losses reduction, voltage profile and stability enhancement, and power loading and transfer capacity increment.

3.2 | Intelligent search (IS) methods

Artificial intelligence (AI) is the application of intelligence in machines.[9] The artificial intelligence is employed in the intelligent search methods for optimal location and sizing of DGs in power systems. Heuristics are part of IS methods, which comprise algorithms that accelerate the process of finding a near or satisfactory optimal solution. Simplicity is the main advantage of heuristic methods compared with some conventional methods. Heuristic methods are robust and give satisfactory optimal solutions for large and complex optimal DG allocation problems. However, their accuracy and precision are called into question. They generally require high-computational effort.[5,8] Meta-heuristic methods are the iterative approaches that help in finding satisfactory optimal solution in a more efficient ways. The goal of meta-heuristic is to increase the capabilities of heuristic methods by combining one or many heuristics methods.[5,10] Some of the most popular methods are presented below:

3.2.1 | Genetic algorithm (GA)

GA is one of the early developed heuristic optimisation algorithms. It was introduced in 1975 by John Holland. GA is a search method that uses the principles of natural and genetics selection like mutation, selection, crossover, and inheritance.[5,8] GA allows the evolution of a population to a maximum position of fitness under a specified set of selection rules. The population of members is absorbed to form chromosomes that enables the evolution of potential members to a better position. The first population emerged randomly, and the suitability of an element is evaluated through evolution of generations. The selected element is modified to make a new population through mutation. This process is repeated until a satisfactory level or maximum number of iterations is reached by the algorithm.[4,5,7] GAs can be utilised with both continuous and discrete parameters and perform better in obtaining global optimal solution to a diverse varieties of functions. They do not use derivatives and are applicable to complex and poorly defined problems. However, GAs are faced with the problem of repeated fitness function evaluation, which is time intensive for complex large problems. GA is the most applied optimisation method used in solving DGs allocation problems in the literature.[102-109] In Silvestri et al[102] and Kashyap et al,[103] the authors proposed GA to find optimal allocation of distributed generation units in order to minimise distribution power losses. The optimal solution obtained in Kashyap et al[103] provides a maximum percentage of active power loss reduction as compared with the optimal solutions of other methods validated with it. The voltage magnitude is constrained and the voltage profile evaluated to be within the limits. However, neither the DG sources is renewable nor any power system uncertainties modelled. Also, the network of implementation is static. Therefore, the assessment of stability in both voltage and dynamic needs to be done on dynamic networks to actually obtain realistic integration of the DGs into the network. Teng et al[104,106,108] proposed a strategic method to determine the best costs/benefits ratio for the placement of DG in a DN. A method based on GA is used to determine optimal types, sizes, and locations of DG units for service reliability improvement, power cost saving, and customer interruption cost reduction. Maximisation of benefits/costs ratio of the DG is the objective function while taking voltage magnitude and DG capacity limits as the constraints. The authors concluded that the influences of uncertainties for load growth, natural gas, or fuel oil prices as well as other uncertainties of power system and environmental impacts will alter the results obtained from this work. Hence, the stability of the distribution network on integration of DGs is not evaluated. Similarly, Borges et al[105] used GA in finding optimal DG sizes and placement to maximise benefit/cost ratio of DGs. In Shaaban et al,[107] a GA-based multi-objective algorithm is presented to optimise sizes and locations of renewable (wind) and some conventional DGs in DNs with objectives to maximise the benefits of the connection by the DSO and customers in terms of annual energy losses reductions. Probabilistic and MCS methods are proposed to model the uncertainty and variability of the output power of renewable DG and load respectively. However, the effect of renewable output power variability on the stability of distribution system is not considered except the effect on the costs. There are variant configurations proposed to enhance GA method in the DG location and sizing problems such as non-dominant sorting genetic algorithms (NSGA II),[110] quantum GA (QGA),[111] adaptive genetic algorithm (AGA),[112] and genetic algorithm and multi-attribute decision making (GA-MADM).[113] In previous studies,[110-113] the proposed methods differently improved on the optimality of solutions gotten when genetic algorithms are singly used to find the optimal locations and sizes of the DGs in the distribution networks.

3.2.2 | Simulated annealing (SA)

SA was developed in 1983 by Kirkpatrick et al[114] and later defined in 1985 by Viado Cerny. It was introduced as a method that models optimisation problems as annealing processes to obtain global optimal solutions. SA algorithm is iterative and can be applied to combinatory optimisation problems that uses crystallisation processes in physical systems at discrete search spaces.[115] The centre point of this method is the cooling criterion. The algorithm utilises initial and final temperature (($t_\circ$) and (t_f) respectively), and cooling rate (β) variables. The procedure starts from a probable solution, followed by system disturbance, and the new likely solution is determined by the probabilistic acceptance criterion.[5,8,10] SA algorithms are strong in simple implementation and providing good solutions to numerous combinatory problems. They are robust. However, large computation time, no computation time upper limit, local minimum termination, and no information on amount of deviation of local minimum from global minimum are some of the drawbacks associated with SA algorithms. A lot of rigorous effort has been exerted to adapt SA to the DG planning problems. The effort includes modifications to the creation of random solutions, formation, and control of annealing schedule. SA algorithms are, thereafter, used in the literature to locate and determine the capacities and sizes of DGs by converting the original model to an equivalent model using either ϵ - constrained or weighted average method.[116-120] The results showed reduced computation time when compared with GA and TS but sacrificed the global optimality of solutions. In Nahman and Peric,[118] SA was employed to obtain optimal planning solution for radial networks so as to minimise the total cost. Injeti et al also applied SA for finding optimal locations and sizes of DGs to minimise power losses and enhance voltage profile of small, medium, and large DNSs.[119] Koziel et al[120] proposed a feasibility-preserving SA algorithm for solving DN reconfiguration problem using power loss minimisation and voltage profile improvement as the objective functions. They concluded that the proposed algorithm outperforms some recently published population based meta-heuristic algorithms in terms of solution repeatability and computational cost. However, the optimality of solution is compromised, and the algorithm is validated on static networks thereby deficient in evaluating the dynamic stability of the proposed work. An improved SA-PSO is proposed in Glover and McMillan[121] by introducing GA's mutation and crossover operators into the traditional SA-PSO algorithm. This embodied the algorithm with the capabilities for global searching and local exploration to overcome the deficiencies in location selection and capacity finding of DGs such as local optimality and slow convergence speed. The objective minimises the economic costs for finding optimal sizes and locations of dispatchable and non-dispatchable DGs in DN without considering the effects of power variability on network stability.

3.2.3 | Tabu search algorithm (TSA)

TSA is a method developed by Fred Glover and C. McMillan in [122] and formalised in [123,124] to solve optimisation problems. The method applies the principles of adaptive memory and responsive exploration that enable the search space to achieve near-optimal solutions in an economical and effective way. This algorithm has explicit memory and can be used to solve complex and large problems. It is also applicable to continuous and discrete variables. TSA is highly used in the literature for solving DG allocation problems in power system.[125-128] Golshan et al[125] and Golshan Arefifar[126] applied TSA method as a planning algorithm to obtain optimal locations, sizes, and operation of DG resources and reactive compensators and identify tap positions of voltage regulators (VRs) in a reconfigured networks. The approaches aimed at minimising the cost of power losses without violating normal constraint selections. These algorithms are implemented on a small-scale DG penetration using discretised load demand duration. The works improved the voltage profile of the system; however, renewable DGs were not included, and even at that, the dynamic stability of the systems were not investigated. Also, intensification and diversification of the search using large chunk of memories is employed in the neighbourhood of suboptimal solution as a modification to attain good solutions. Nara et al [127] implemented TSA with coordination/decomposition technique to optimise DG allocation considering total loss minimisation of the distribution system. The regression model used in this approach is a disadvantage since it must be solved by any change in the initial weight factor values to calculate the mean square error. This affects the capability of the proposed algorithm to achieve global optimal solutions. A multi-objective TSA (MOTSA) method was proposed in Maciel and Padilha-Feltrin[128] to obtain Pareto optimal set. The authors compared MOTSA and NGSA II algorithms and found that MOTSA has advantage over the NGSA II in complex analysis where time requirement is critical. Nevertheless, TS can terminate at local minima and depends on parameter settings to achieve global minima. It has, as drawback, large number of iterations and parameters to determine.[5,8] Hincapie I et al presents a bi-level mathematical model for the integrated planning of electric power distribution considering the primary and secondary networks as a single system.[129] The authors proposed TSA algorithm to solve the network expansion planning problem of sizing and placing distribution transformers, substations, and conventional DGs with the objective to minimise the total investment and operational costs of the bi-level model. The work attained global optimal solutions and voltage magnitude was constrained, but the overall dynamic stabilities of the system were merely assumed and not assessed. Furthermore, no renewable DGs and ESS were included in the planning model. Thus, the impacts of these technologies cannot be estimated in terms of their oscillation modes.

3.2.4 | Particle swarm optimisation (PSO) method

PSO method was developed in 1995 by Eberhart and Kennedy.[130] The authors were inspired by the social behaviour of bird flocking and fish schooling from which PSO method was adapted. Here, a particle is formed by single intersection of all dimensions when particles are in random movement in a multidimensional search space.[131-133] The system is modified with a set of random solutions, then the generations are updated to achieve optimisation search. At every iteration, the particles evaluate their states using their position of fitness and that of neighbouring particles to identify their historic "best" positions so as to improve the final solution.[8,132,134] PSO is robust, simple to implement, and able to run parallel computations with short computation time. It uses few parameters to adjust and converges faster. Many configurations of PSO have been presented in the literature for solving DGs' placement and sizing problems.[11,135-146] In Krueasuk and Ongsakul,[†] PSO algorithm was differently utilised for determining optimal allocation of multiple DG units either to minimise total power losses, total operational cost, improve voltage profile, and stability index or to provide maximum power quality. PSO can be used for complex DG allocation problems and has greater efficiency and probability to find global optima solutions. PSO was applied in Alinejad-Beromi et al,[142] Kansal et al,[143] and Pandi et al[144] to determine optimal types, sizes, and locations of DG units in order to minimise total costs, harmonic distortions (THDs), and losses and to enhance voltage profile of distribution systems. The results indicated that PSO outperformed GA method in terms of quality of solutions and less number of iterations. DG allocation problem with inaccurate mathematical models (considering load or resources uncertainties) can be efficiently solved using PSO.[148,149] Zeinalzadeh et al,[148] Jamian et al,[149] Jain et al,[150] and Ameli et al[151] presented PSO-based multi-objective methods for finding optimal sizes and locations of DGs to improve voltage profile and minimise power losses. Some of the new enhanced PSO methods presented in DG allocation problems are PSO by inertial weight (PSO-IW),[152] PSO by constriction factor (PSO-CF),[152] dynamic weighted aggregation PSO (DWAPSO),[153] binary PSO (BPSO),[154] improved PSO (IPSO),[154] adaptive PSO (APSO),[155] decimal-coded quantum PSO (DQPSO),[156] hybrid PSO,[157] and social learning PSO (SLPSO).[158] However, it is tasking to initialise design parameters with PSO. PSO may converge untimely and usually ends in local minima with complex problems.[5,7,159] El-Zonkoly,[136] Wong et al,[137] and Alinejad-Beromi et al[142] did not include renewable DGs while they were integrated in previous studies.[‡] Neither the uncertainties of the intermittent renewable DGs were modelled nor the effect of their output power variability on the dynamic modes of the networks considered except in Jain et al[140] that only evaluated the uncertainties of DG planning in respect to market scenarios.

† 135-137,139-141,146,147

‡ 135,139-141,143,144,146-149

3.2.5 | Ant colony optimisation (ACO) method

ACO method was developed by Dorigo et al in 1996.[160] The authors were inspired by the social behaviour of insects (ants) that finds the shortest routes to getting their food, from which ACO method was adapted.[161,162] It is a meta-heuristic algorithm whose process starts from random solutions that are absorbed into spontaneous searches of movements done by the ants. Ants left behind pheromone trails during their movements, to share information with other ants about their paths. As a result, a shorter path gives more trail density. This information is used in the optimisation search to arrive at near-optimal solutions.[5,7,8,163] Some of the advantages of this method are parallel searching ability among a population; fast determination of good solutions; guaranteed convergence; and adaptation to changes like new distances. However, change of probability distribution, dependent sequences of random decisions, uncertainty in time to converge, difficult theoretical analysis, and highly experimental research (less theoretical) are the weaknesses of ACO.[8] ACO algorithms are reported in literature to optimise the allocation and sizing of DGs.[164-170] Falaghi and Haghifam[166] and Wang and Singh[167] proposed ACO algorithms to determine optimal allocation of DGs in radial DSs while minimising power losses. In Falaghi and Haghifam,[166] the objective function is to minimise operational and investment costs of constant power sources DGs. The authors stressed that the work did not include reliability and dynamic stability assessment and the model did not include system reliability. A modified ACO algorithm for DNS reconfiguration was presented in Mirhoseini et al.[169] The objectives considered were minimisation of real power losses and power unserved index. Gomez et al,[164] Vlachogiannis et al,[165] Wang and Singh,[167] and Amohadi and Fotuhi-Firuzabad[170] presented extensions of ACO algorithm, ant colony system (ACS) algorithm, which was reported to give better performances in most engineering applications. ACS algorithms were proposed to determine the optimal allocation of DGs and re-closers in radial distribution networks with composite reliability index as the objective function. The reliability and transient stability were considered and evaluated to validate the effectiveness of the proposed methods in distribution systems. Kaur and Sharma[168] applied Ant Colony System Algorithm (ACSA) to allocate capacitors in radial DSs to reduce the total cost of losses. More so, majority of these works do not consider the integration of intermittent renewable resources DGs and cannot, consequently, evaluate their impacts on the small-signal oscillation of the networks.

3.2.6 | Fuzzy logic method

Fuzzy logic (FL) was introduced in 1979 to solve problems related to power system. It is a generalisation of classical fuzzy set theory (FST) developed in 1965 by Zadeh,[171] which involves identifying a membership function through each component's level of association as indicated by a number between 0 and 1. The membership function determines any member of a fuzzy subgroup's resemblance level.[8,172] The common membership functions are trapezoidal, Gaussian, triangular, and piecewise linear functions.[173] Momoh et al[174] showed that FL was being widely used for power system planning. In Syahputra et al[33] and Sharma et al,[175] FL controller is proposed to find the proper locations and sizes of DGs for minimising real and reactive power losses and improving voltage profile and loadability of radial DNSs. The optimality of the solutions were not reported, and the stability of the network were not evaluated. Kim et al[176] employed the use of FL-GA to optimally allocate DGs into distribution network. The authors used fuzzy set to transform the objective function and constraints into a multi-objective function in order to solve optimal DG allocation problem. The load and electricity price uncertainties were modelled by fuzzy set, and non-dominated sorting genetic algorithm (NSGA II) was used to solve the optimal DG allocation problem in Haghifam et al[177] so that operation cost and economic risks were minimised. In Lalitha et al,[147] FL is used to optimise the DG locations while PSO found the sizes of the DGs. This combined approach solved the allocation problem with objective function to minimise the system losses subject to line loading and voltage constraints. FL also found applications in the allocations and sizing of DGs problems to minimise real power losses and enhance voltage profile in Injeti and Kumar[178] and Reddy and Manoj.[179] However, the works discussed on FL were implemented on static networks. Hence, static voltage stabilities were evaluated. Also, the works did not integrate the renewable DGs and storage system technologies and thus cannot consider their impacts on the networks oscillatory modes. To obtain realistic solutions, dynamic networks are practical networks for the assessment of power systems stability (voltage, transient, and small-signal) and reliability.

3.2.7 | Differential evolution algorithm

The first article on differential evolution algorithm (DEA) was published as a technical report by R Storn and K.V. Price in 1995.[180] DEA is a type of artificial intelligence optimisation method that is natural phenomena (mutation, selection, and recombination of population members) dependent to conduct its optimisation search. DEA is a stochastic population-based optimisation algorithm developed to search for a global optimum point in a D-dimensional real parameter vectors or real valued functions. Each vector, also known as chromosome or genome, constitutes a probable solution to the multidimensional optimisation problem. It belongs to the family of evolutionary algorithms that are widely employed to solve power system planning and operation problems.[181-185] In Arya et al,[181] the authors computed the optimal DG locations based on incremental bus voltage sensitivities method and use DEA to determine optimal DG sizes. Type III DG (wind turbine DG) was integrated to small-scale DNSs, and voltage stability of the systems was accounted for. Meanwhile, the uncertainty of wind resource was unmodelled, and the effect of wind DG output power variability was not assessed in terms of small and large disturbances stability. DEA is utilised in a multi-objective optimisation for the optimal allocation of multiple DGs in distribution networks to minimise power losses and improve system reliability in Chiradeja et al.[182] The authors evaluated the reliability of DNS supply when multiple DGs (single type) were integrated. However, the optimality of the solutions obtained from this simulation results cannot be ascertained since the optimal DG locations were based on very few selected candidate buses. Kumar et al[183] proposes multi-objective opposition-based chaotic differential evolution (MOCDE) algorithm for finding optimal placement and sizes of DG units in the radial distribution networks. The logistic mapping technique is used to generate chaotic sequence for control parameters in order to prevent premature convergence. The results showed voltage profile improvement after the integration of conventional DG units. However, long-term dynamic stabilities were not considered possibly because intermittent renewable DGs were not included. Other variants of DEAs are improved DEA[184] and adaptive DEA[185] where improved and adaptive differential search algorithms are used for optimal allocation of DGs in the radial distribution system with the multi-objective to minimise losses, improve voltage profile and minimise network operating costs, and minimise total power losses, respectively. In Mahdad and Srairi,[184] the simulation results presented optimal solutions for the allocation of conventional multiple DGs into DNS. However, long-term dynamic stability of the system was not assessed though renewable resources DGs were not included.

3.2.8 | Harmony search algorithm

Harmony search algorithm (HSA) is a method that was adapted from the musicians' technique to improve the musical instruments' harmony. HSA is based on the musical production procedure that is in search of a better harmony.[8] HSA is being used to find optimal allocation of DGs in the power systems. Typical HSA needs no initialising and uses both continuous and discrete variables for optimisation. HSM does not diverge and may not terminate at local optima. However, HSA has weak ability to search for local and high-dimensional multi-modal problems. It also has high number of iterations of which some are unproductive iterations that cannot improve the solution.[6,7,186] HSAs have been variously used to find optimal allocation of DGs in the power systems. Piarehzadeh et al[187] and Rao et al[188] proposed hybrid of HSA and loss sensitivity factor approach for finding optimal locations of DG units. Piarehzadeh et al[187] concluded that HSA method performed better than PSO in improving voltage stability during optimal DG allocation in distribution system. In Camacho-Gómez et al,[186] HSA approaches are applied to jointly optimise the network topology and find optimal location of distributed renewable energy resources (micro-wind turbine and PV). The approaches are single objective and multi-objective of minimising energy losses in order to achieve Pareto front solutions. The author evaluated the performances of the two versions of HS algorithms and concluded that they produced good solutions. However, no stability evaluation (voltage and small disturbance) was done to assess the impact of the power from renewable energy resources on the network.

3.3 | Potential intelligent search methods

These are some other optimisation algorithms that are recently developed and implemented to efficiently solve the DGs allocation problems.[5,8,9]

3.3.1 | Artificial bee colony algorithm

Dervis Karaboga developed artificial bee colony algorithm (ABCA) in 2005 as a new optimisation approach. The algorithm is adapted from the swarm of honey bee's natural behaviour for finding nectar.[189] ABCAs are used in Mohandas et al[38] and Dixit et al[39] for solving optimal DGs placement and sizing problem to minimise power losses and improve the voltage stability of the distribution system. In Abu-Mouti and El-Hawary,[190] optimal allocation of DGs is achieved using ABCA by tuning control inputs, colony size, and iteration number. El-Zonkoly and Kefayat et al[191,192] applied ABCAs for solving distribution network planning problem and obtained optimal values of reinforcements and suitable commitments schedule for new DG units' installation. In Padma Lalitha et al,[193] ABC algorithms are proposed and compared with PSO method. The results proved that ABC presented superior solutions and faster convergence than PSO. However, these works did not present indices to assess long-term dynamic stability of the system.

3.3.2 | Frog leaping algorithm

Frog leaping algorithm (FLA) is adapted from mimetic behaviour of a class of frogs during their search for food in an area.[194] This algorithm has advantage of combining the benefits of GA and PSO. SFLA are applied for finding optimal locations and sizes of DGs with minimisation of system loss and enhancement of voltage profile as the objective function.[195,196] Taghikhani successfully applied SFLA to find optimal DG location and size in order to minimise line losses and improve system voltage profile.[197]

3.3.3 | Cuckoo search algorithm

Cuckoo search algorithm (CSA) is an algorithm introduced in 2009 by Yang and Deb for solving optimisation problems.[198] CSA is adapted from some species of cuckoo's brooding parasitic behaviour that compel host species in breeding by putting their eggs in the host species nest. CSAs are proposed in Moravej and Akhlaghi[199] and Aranizadeh et al[200] to minimise power losses and improve voltage profile in the optimal allocation of biomass and solar-thermal based DG units. Also, Nguyen et al[201] proposed the use of CSA for finding optimal placement and sizes of distributed generation units to minimise network losses and improve voltage stability index.

3.3.4 | Plant growth simulation algorithm

Plant growth simulation algorithm (PGSA) is inspired by the growing process of phototropism. PGSA depends on a search for the orientation of a plant in response to light. The algorithm searches for the possibilities of growing new branch on all the nodes to form a complete model during the use of each objective function. PGSA has advantage in the capability to function with no external parameters.[202] PGSA is applied in Kumar and Goud[203] to solve the optimal allocation problem with minimisation of power losses and enhancement of voltage profile as the objective of the optimisation.

3.3.5 | Shuffled bat algorithm

Shuffled bat algorithm (SBA) was developed by Yang in 2010 to solve optimisation problems. The algorithm mimics the echolocation behaviour of micro-bats.[204] The performance of SBA in the optimisation of distributed generations' placement and sizing with load enhancement in a radial distribution systems is investigated in Yammani et al.[205] In Candelo-Becerra and Hernández-Riaño,[206] the optimal sizes, numbers, and locations of DGs in radial DNS are achieved with the use of bat algorithm. A hybrid of SBA and loss sensitivity factor (LSF) is proposed for finding optimal sizes and locations of capacitor banks respectively.

3.3.6 | Biogeography-based optimisation

Biogeography-based optimisation (BBO) uses the mathematical models of biogeography in its search operation. BBO describes several natural behaviours like evolution, migration, extinction, etc of animal, fish, insects, or birds' species.[207] The algorithms are applied in Valipour et al[208] and Duong et al[209] to solve the problem of optimal allocation of DG units and capacitor banks in DNS to minimise power losses and enhance power quality by minimising the THD.

3.3.7 | Imperial competitive algorithm

Imperial competitive algorithm (ICA) was adapted from imperialists' competition and was introduced by Atashpaz and Lucas in 2007.[210] The algorithm depends on the ideologies social and political science to solve optimisation problems. Its process starts by selecting a random set of N individuals countries. The best countries selected are called imperialists, and the remaining are considered as colonies of the imperialists. Then, the colonies are divided/shared among the imperialists, based on their power, to build their first empires. ICA is applied in Mahari and Babaei[211] for finding optimal DG sizes and locations with objective to minimise the power losses in a distribution network. In Soroudi and Ehsan,[212] ICA is proposed to find DG size and location while sensitive loads are considered in an islanding mode of a DNS. The optimal DGs and capacitor banks sizing and location in DNSs as well as network reconfigurations are achieved by the application of ICA with objective to minimise power losses, maximise voltage stability index, and improve voltage profile in Moradi et al[213] and in Koong et al.[214] Poornazaryan et al[215] proposed ICA to solve optimal DGs allocation problem at any level of load demand with power losses minimisation and voltage stability improvement as the objective of the optimisation.

3.3.8 | Firefly algorithm

Firefly algorithm (FA) was developed by Yang in 2009 mainly as an efficient solution for non-linear multidimensional optimisation problems.[216] This algorithm is inspired from the natural courtship signal transfer exhibited by the fireflies wherein a firefly with maximum brightness attracts other fireflies the most regardless of their sex.[217] FAs are proposed to solve optimal DGs allocation problem by minimising active and reactive power losses and improving line loading.[218,219] Nadhir et al[220,221] differently used FA for finding optimal sizes and locations of multiple DGs on a balanced radial network aimed at minimising power loss. Othman et al[222] modified the traditional FA to efficiently solve constrained optimisation problems. The main strengths of the modified FA over the traditional one are ease of implementation, higher stability mechanism, and simpler concepts.

3.3.9 | Intelligent water drop algorithm

Shah-Hosseini originally developed intelligent water drop algorithm (IWDA) in 2007 to find the global optimal solution.[223] The algorithm was adapted from river procedure for finding optimal flow route from the origin to destination. IWDA algorithm is utilised in Moradi and Abedini[224] for finding the optimal sizes and locations of DG units in micro-grids with the minimisation of network losses and improvement of voltage stability and regulation as the objective function. Prabha et al[225] and El-Ela et al[226] propose IWD algorithm to solve optimal sizing and placement of DGs' problem in radial DNSs with the objective to minimise power losses and improve voltage profile.

3.3.10 | Bacteria foraging optimisation

Bacteria foraging optimisation (BFO) algorithm was developed by Passino in 2002 to replicate a single and set behavioural pattern of *Escherichia coli* bacteria (found in the intestines or gut of animals) to find simple hamiltonian paths in a given n-vertex graph.[227] The algorithm is proposed in Singh et al[228] to solve optimal radial distribution feeder routing problems. In Kowsalya et al[229] and Kaveh et al,[230] BFO algorithms are applied to determine optimal locations and sizes of multiple DG units with the objective to minimise operation costs and power losses and improve voltage stability of DNSs. Devabalaji et al[231] utilised BFO for finding optimal sizes of reactive compensators in distribution networks to minimise power losses while considering VSI and LSF. A modified BFO (MBFO) algorithm is proposed by Devi and Geethanjali to solve the problem of optimal placement and sizing of DGs in distribution networks with total power losses minimisation and voltage profile improvement as the objective function.[232]

3.3.11 | Artificial immune system

Artificial immune system (AIS) algorithms are applied in Aghaebrahimi et al[233] and Hatata et al[234] for finding optimal DGs placement and sizes by minimising the power losses of the network and taking cognisance of line current and bus voltage limits. Souza et al[235] applied AIS to solve DG allocation problem while the uncertainty of load demands is included in distribution network planning.

3.3.12 | Big bang crunch algorithm

Big bang crunch algorithm (BBCA) was invented by Erol and Eksin in 2006 to solve optimisation problems. This algorithm is inspired based on the evolutionary theories of the universe called Big Bang and Big Crunch Theory.[236] BBCAs are proposed in Esmaeili et al[237] and Reyes and Baeza[238] to solve the problem of optimal DGs allocation and distribution network reconfiguration aimed at minimising total real power losses, cost, and emission, and maximising voltage stability index.

3.3.13 | Ant lion optimisation

ALO algorithm was introduced by Mirjalili in[239] to mimic the hunting mechanism of ant lions in nature. Hadidian-Moghaddam et al[240] proposes ALO to solve multi-objective DG allocation units. This algorithm was validated against PSO and GA, and the results show that ALO performed better in extracting the solutions. Dinakara et al[34] applied ALO algorithm to find the optimal size of the DG while the optimal locations in the DNS was obtained by index vector method in order to minimise the network real power losses.

3.4 | Probable hybrid optimisation methods

There have been continuous efforts to adopt new optimisation methods and combine existing methods in order to improve on their quality of solutions and ease of computation and simplicity of implementation. The merged method is referred to as a hybrid method where two or more heuristic and or conventional methods are combined to function as a new method.[8] Several configurations of advanced hybrid algorithms have been proposed to address the problem of allocating and sizing DGs.[4,5] Figure 4[8] presents a combinatorial matrix of some of the hybridised methods for DGs allocation optimisation that are published in the literatures in the last two decades (years 2000 to 2019).

4 | OVERVIEW OF THE EXISTING RESEARCH WORKS ON REHDG ALLOCATION

This section presents the summary of the reviewed works and the evaluation of the previous research works on optimal allocation of REHDGs in terms of optimality of solution and assessment of optimal solutions with respect to dynamic stability and reliability of the distribution system.

4.1 | Summary and contributions of the existing works on REHDG allocation

Tables 2 and 2 show the summaries of the conventional and intelligent search algorithms applied to solve the optimisation problems of finding optimal DG sizes, time of installation, and locations in the distribution systems. They also indicate whether the power system uncertain parameters (some root causes of small signal instabilities) are modelled and the methods used for the modelling. The tables compare the type of network on which the algorithms are implemented, as well as the kind of network stability being considered as evident in the constraints imposed.

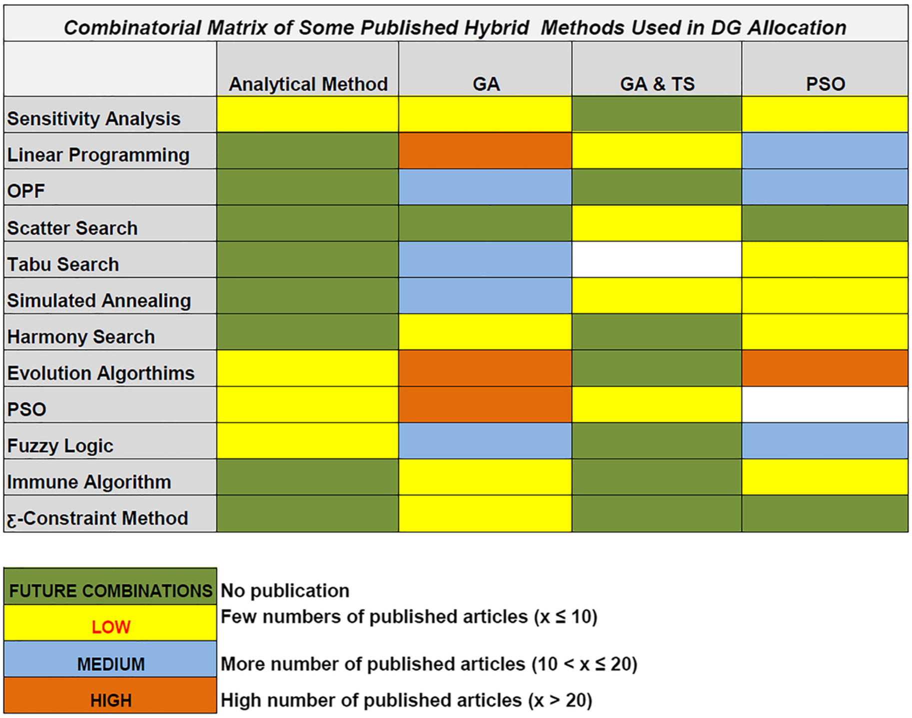

FIGURE 4 Combinatorial matrix of some published hybrid optimisation methods used in DG allocation. DG, distributed generation; GA, genetic algorithm; OPF, optimal power flow; PSO, particle swarm optimisation; TS, tabu search[8] [Colour figure can be viewed at wileyonlinelibrary.com]

5 | CONCLUSION AND RECOMMENDATIONS

This paper has presented a realistic REHDG allocation expansion planning model formulation that is capable of enhancing small signal and voltage stabilities during the integration of renewable DGs taking into the formulation, the renewable intermittent modelling, load models, decision variables, objective functions, and evaluation of system stability and reliability. The network stability constraints that can be included in optimising the allocation of distributed generations for curtailing small-signal stability issues were described.

The paper also reviewed an extensive number of research works developed on efficient and robust optimisation algorithms for solving DGs allocation (time, size, and location) planning problem. The conventional, intelligent search, potential intelligent search, and probable hybrid approaches used for optimal DG placement solutions are specifically reviewed in terms of their optimality of solution, network of implementation, modelling of renewable resources uncertainty, impact of renewable output power variability, and the kinds of stability that are constrained and enhanced. It has been revealed from the review that GA and particle swarm (PSO) are some of the very viable intelligent search optimisation algorithms applied to solve DG expansion planning optimisation problems. Also, conventional methods such as LP, MILP, and various variants of QP (especially when losses are optimised) are still very much used in recent studies due to their ability to detail the physics and mechanics of mathematical model formulation. Considering small-signal stability curtailment, which is the strong point of this work, an optimum planning formulation model has not been fully achieved on optimal sizing, timing, and placement of intermittent renewable DGs in distribution systems. Though, the optimal sizing and placement may have achieved the least cost in most cases, requirements for small-signal stability have not been met as such requirements are only assumed in the current research works. Further research is necessary to improve on the existing distributed generations expansion planning models or incorporate new algorithms to optimally allocate renewable DGs and constrain the small-signal stability variable to a required level. Consequent upon the review of previous research works on the optimisation of REHDG allocation problems, the following shortcomings and recommendations for future research are presented:

1. Allocation of distribution generations in DNSs has been examined in the past and present times by many scientific organisations, research institutes, and a large number of individual researchers. However, a small portion of existing research works uses RES such as PV, wind, and biomass (sugar-cane waste) as hybrid DG units. It has been proven that using renewable energy hybrid DGs effectively improved the technical, economic, and environmental features of distribution systems.
2. In the existing works, storage technologies are scarcely used with distribution generation units. The inclusion of storage technologies in distribution generations' allocation can smoothen output

TABLE 2 Summary of conventional methods for optimal allocation of DGs

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
A. Analytical Methods										
Two-third (2/3) rule	44	Min. power loss		Location, size	Voltage	Static	"2/3 rule" is proposed to determine the optimal DG location and size on a radial network with uniform distributed load		No uncertainty	modelled
	45	Min. power loss		Location		Static	Two analytical approaches are proposed for optimal location and size of a single DG unit in a radial and mesh networks		No uncertainty	modelled
Exact loss formula	46	Min. power loss		Location and size		Static	Exact loss formula is proposed to determine the optimal location and size of single DG with an objective function to minimise system power loss		No uncertainty	modelled
	47	Minimise total real power loss	Power balance constrain, voltage, power flow, branch current limits	Size, location	Voltage	Static	An analytical method, exact loss formula, and PSO are applied and compared for optimal allocation of DG units in a RDNs to minimise total real power losses		No uncertainty	modelled
Sensitivity analysis	48	Min. power loss		Location, size		Static	A loss sensitivity factor that is based on equivalent current injection is utilised to solve the optimal DG placement problem in radial network		No uncertainty	modelled
	49	Minimise copper losses and improve voltage profile	Voltage, DG capacity, and power flow limits	Location and size	Voltage	Static	Based on the comparison done by the authors, the proposed voltage stability index to find optimal locations and sizes of DGs outperformed a novel power loss sensitivity index[50] and a power stability index presented in[51]		No uncertainty	modelled
	52	Minimise power loss	Power flow, voltage, DG capacity limits	Size and location	Voltage	Static	Combination of Analytical method and Kalman filter is proposed to solve the DG placement and sizing problem		No uncertainty	modelled
	53	Power loss capacity limits	Power flow, bus voltage, DG	Size, location, and power factor	Voltage	Static	An improved analytical method is proposed to solve the problem of multiple DG units placement and sizing in large-scale primary distribution networks to minimise power loss			
	54	Minimise total real power loss	Power flow, bus voltage, DG capacity limits	Location and power factor	Voltage	Static	An analytical method is presented for solving the types I, II, III and IV multiple DG units placement problem in distribution networks to minimise total power loss		No uncertainty	modelled

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
B. Numerical methods										
Linear programming (LP)	56	Minimise actualised cost of energy conversion	DG capacity, penetration level, availability factor limits	DG capacity, DG type, type of energy efficient technology			An energy flow optimisation model (EFOM) based LP is proposed for exploitation of primary energy resources DGs and optimal diffusion of energy-efficiency technologies to minimise environmental impact and operational costs			
	57	Maximise DG capacity	Power flow, voltage, DG capacity limits	Location, size	Voltage	Static	Used LP to solve DG placement problem by taken advantage of bus interdependence with the constraints		No uncertainty	modelled
	58	Maximise profit	Power flow, voltage, DG capacity limits	Location, size	Voltage	Static	LP is used to maximise the amount of energy harvested from available energy resources in an area		No uncertainty	modelled
	55	Minimise cost	Power balance, power flow, reliability constraints	Plant capacity		Static	Partitioning algorithm based LP is proposed to drastically reduce the storage size and computational time of long-term planning problem of generation plant power mix		No uncertainty	modelled
	41	Minimise cost of investment and emission	Power balance, power flow, capacity limits voltage magnitude and DG	DG sizes and locations	Voltage	Static	A bi-objective optimisation algorithm based LP model is proposed to allocate optimal sizes of renewable DGs (solar PV and wind) in the DNS	Solar irradiation, wind speed	Continuou probability density/sce probabilistic method	
	40	Maximise DG total capacity	Power flow, voltage magnitude, and angle, DG capacity limits power balance constrain	DG capacity, active and reactive power exchange, active and reactive loads	Voltage	Dynamic	An LP algorithm is proposed for determining optimal distribution grid hosting capacity with the objective function of max- imising the total DG capacity over the set of primal variables and minimising over the set of uncertain parameters. The results showed that LP method outperforms the traditional methods in computation time		No uncertainty	modelled

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
Mixed integer linear programming (MILP)	[3]	Minimise NPV of total cost of Investment, maintenance, energy, unserved power and emission	Power flow, voltage limits, radiality and energy storage constraints	DG unit number, location, time	Voltage	Dynamic	A multi-stage model that minimises the NPV of total cost using MILP to find optimal sizes, time and locations of renewable DGs and the smart-grid technologies	Wind speed and solar PV irradiation	Scenario-based probabilistic	
	[59]	Minimise NPV of total cost	Power flow, voltage, DG capacity limits, radiality	Number of DG and transformer, length and type of feeder	Voltage	Static	Proposed a distribution expansion planning formulated as a MINLP problem but linearised to minimise the NPV of total cost using MILP that guarantees finite convergence to the optimum solution		No uncertainty	modelled
	[60]	Minimise total costs of investment and operation	power flow, voltage, DG capacity limits, power balance constrain	Size, location	Voltage	Dynamic	A two-stage chance-constrained stochastic MILP formulation for determining optimal investment decisions in DGs with operational uncertainties is modelled and further optimised with an evolutionary vertical sequencing protocol heuristic method in order to minimise the total cost		No uncertainty	modelled
	[61]	Maximise DG total capacity	Power flow, voltage magnitude and angle, DG capacity limits, power balance constrain	DG capacity and sizes, tie locations and smart switches location and sizes	Voltage	static	An MILP algorithm is proposed to optimise DG capacity hosting of radial distribution network through reconfiguration of existing tie and smart switches with objective to maximise total DG capacity deployed into the network.		No uncertainty	modelled
Non-linear programming (NLP)	[62]	Minimise cost	Power flow, voltage limits	Active and reactive power	Voltage	Static	A two stage constrained non-linear optimisation algorithm is employed to solve the large-scale optimal power flow problem by exploiting the structural properties of the constrained non-linear optimisation problem formulation.		No uncertainty	modelled
	[63]	Maximise reactive power margin	Voltage and generation reactive limits, load constraint	Reactive load	Voltage	Static	Proposes a method to compute the reactive power margin at a given set of load buses of a power system		No uncertainty	modelled

(*Continues*)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
Mixed integer non-Linear	[65]	Minimise cost and maximise total system benefit	Power balance constraint, power flow, voltage, Synchronous condenser capacity and DG capacity limits	Location, size	Voltage	Static	A two-stage methodology for finding optimal allocation of multiple DG units considering electricity market price uncertainty is presented		No uncertainty	modelled
Mixed integer non-Linear	[65]	Minimise cost and maximise total system benefit	Power balance constraint, power flow, voltage, Synchronous condenser capacity and DG capacity limits	Location, size	Voltage	Static	A two-stage methodology for finding optimal allocation of multiple DG units considering electricity market price uncertainty is presented		No uncertainty	modelled
	[66]	Maximise voltage index	Power balance constraint, power flow, voltage, and DG capacity limits	DG Type, size and location	Voltage	Static	MINLP algorithm is proposed to improve the voltage stability of distributed generation problem whole the intermittent nature of both solar PV and wind resources and load demand are considered.	Solar irradiance, wind speed and load demand	Scenario-based probabilistic approach	
	[67]	Minimise investment, energy not supplied and energy purchasing costs	Power balance constraint, power flow, voltage, and DG capacity, feeder current, substation capacity limits and radiality constraints	Sizes, locations of DGs and substations	Voltage	Dynamic	MINLP is applied for the mathematical formulation of optimal simultaneous expansion planning of HV/MV substations, multiple DG units and robust MV feeder routing problem while Adaptive GA is presented for finding optimal sizes and locations of DGs in DNS, taking into consideration the uncertainties of renewable generations, demand, electricity and fuel prices.	Wind turbine generation solar power generation, electricity price, fuel price, future demand	Scenario-based probabilistic and geometric Brown motion (GBM)	
Decomposition Method	[68]	Minimise cost and maximise profit	Power balance, power flow, voltage limits	Type, size, location	Voltage	Static	Bender decomposition method is proposed for optimal placement and sizing of DG under difftainty under different simulation settings.	Load demands, wind and PV DGs' uncertainty	Polyhedral uncertainty sets robust optimisation	

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
Dynamic Programming (DP)	70	Minimise loss, improve reliability and voltage profile	Power balance, power flow, voltage limits	Location, size	Voltage	Static	DP is utilised to solve optimal allocation problem of multiple distributed generations considering low, medium and full load conditions under the objective of loss reduction and reliability improvement		No uncertainty modelled	
	71	Minimise total annual cost, dumped energy,	Power balance, power flow, voltage limits, battery discharged only if grid connection is lost, MG not grid connected	Location, size of DG and battery	Voltage	Dynamic	DP is used to determine optimal locations and sizes of renewable DGs and battery units and concluded that if DER's are properly sized and located provide high reliability	PV, wind DGs' uncertainty	Time series modelling	
	72	Minimise total cost	Power balance, power flow, voltage limits, reliability and budgetary constraints	Size, location	Voltage	Static	DP is proposed to solve a multi-period distribution expansion planning problem formulated in terms of graph theory by finding optimal locations and sizes		No uncertainty	modelled
Quadratic programming (QP)	74	Minimise cost of expansion and energy losses	Power flow, voltage limits and power balance constraint	Substation capacity, feeder resistance or capacity	Voltage	Static	Both QP (QMIP) and heuristic methods are proposed for finding optimum substation locations and optimum network configurations in the planning of a radial DNS		No uncertainty modelled	
	75	Minimise total annual energy losses and energy cost	Voltage, apparent power, DG capacity, battery power discharge limits	Size of DGs and storage devices	Voltage	Static	SQP is proposed for simultaneous capacity optimisation of DGs and battery storages in standalone and grid-connected micro-grids considering certain characteristics of the grid, units and local weather data. It can be shown from the results that the inclusion of biomass DGs is very beneficial in power cost savings and battery devices are very important for standalone MG		No uncertainty	modelled
	76	Maximise profit	power flow, voltage limits, fault level constraints	DG and capacitor capacity	Voltage	Static	Quadratic cost function is optimised with OPF to find optimal generation capacity while constraining network fault level through the enforcement of protection equipment (switchgear) constraints		No uncertainty	modelled

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
	77	Minimise network active power losses	Power flow, voltage limits	Location, size and number	Voltage	Static	Optimal DG units allocation is obtained using stability sensitivity analysis and sequential QP		No uncertainty	modelled
	79	Minimise real power losses	DG power factor, voltage, DG and substation capacity and number of DG	Size, location	Voltage	Static	Combined loss sensitivity is used for candidate bus selection, and SQP and branch and bound (BAB) hybrid algorithms are proposed for optimal location and sizing of single and multiple DG units in DNS		No uncertainty modelled	
	64	Minimise DG and annual reactive power equipment costs and annual transmission loss	Power flow, voltage limits, power balance constraint	Active and reactive power capacity	Voltage	Static	A new formulation for optimal reactive power equipment operation and planning problem is proposed for providing maximum active power supply margin (transmission margin)		No uncertainty modelled	
	78	Minimise power losses	Quadratic constraints on battery reactive power, radiality, voltage drop, power flow limits, power balance constraint	Battery sizes and types		Static	A mixed integer quadratically constrained QP is proposed to find optimal battery management strategies in order to minimise power losses in the DNS. D-XEMS13 optimisation procedure is used to identify best sizes of battery energy storage system (BESS) units		No uncertainty	modelled
Exhaustive Search (ES)	82	Minimise power losses	Power flow, voltage limits, power balance	Number, size, location of DGs	Voltage	Static	An ES based multi-variable algorithm is presented for finding optimal sizes and locations of renewable DG units (wind and solar PV). The proposed algorithm works better for small DGs allocation.		No uncertainty modelled	
	83	Minimise voltage profile	Voltage, power flow limits, power balance equality	Location, size, number of DG	Voltage	Static	ES is applied to optimise the number, size and locations of DG units to improve voltage profile		No uncertainty	modelled
	84	Minimise power losses and voltage profile	Power flow, voltage, thermal limits, power balance equality	Size, location of DG	Voltage	Static	Develops a two-stage approach where a clustering-based method based on normalised loss sensitivity factor is used for location selection and ES algorithm finds upgraded DG sizes.		No uncertainty	modelled
Direct Search (DS)	85	Minimise power losses and maximise net savings	Power flow, voltage, thermal limits, power balance equality	Size, location	Voltage	Static	DS algorithm is applied to determine the optimal sizes and locations of switched and fixed capacitors in a radial DNS		No uncertainty	modelled

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
	[87]	Minimise total annual costs of expansion, energy losses and interruption	Power flow, voltage, thermal limits, power balance equality, radiality constraints	Number, location of DGs	Voltage	Static	DS is proposed for solving DG placement problem by tracking and estimating the total cost of optimal radial paths		No uncertainty	modelled
	[86]	Minimise total annual cost	Power flow, voltage drop, thermal limits, power balance equality, radiality constraints	Number, location	Voltage	Static	DS method proposed is more computational efficient in finding optimal feeder routing and ensured radiality constraints system reliability at a minimised total annual cost of a radial DNS expansion		No uncertainty	modelled
Gradient search (GS)	[88]	Minimise power loss	Power flow, voltage limits, power balance equality	Size	Voltage	Static	A generalised reduced GS method is applied to find the optimal size of DGs in selected buses		No uncertainty	modelled
	[89]	Maximise profit	Power flow, voltage limits, power balance equality	Size		Static	GS method is used to convert constraints enforced by fault levels to simple non-linear inequality constraints described by the OPF variables		No uncertainty	modelled
Ordinance optimisation (OO)	[91]	Minimise cost	Voltage drop, power flow, charging station capacity limits	Location,capacity of charging station	Voltage	Static	OO is applied for optimal capacity planning of electric vehicle (EV) charging stations in a radial DNS		No uncertainty	modelled
	[92]	Minimise losses and maximise DG capacity	Power flow, voltage limits, power balance equality	DG location, capacity	Voltage	Static	OO algorithm is used to specify the locations and sizes of multiple DGs to achieve balance between loss minimisation and capacity maximisation in a distribution system		No uncertainty	modelled

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
C. Power flow methods										
	[93]	Minimise total cost	Power flow, voltage limits, power balance equality	DG location, capacity	Voltage	Static	OO is proposed to solve an optimal DG allocation problem focusing on the renewable DG systems uncer tainty and reactive capabilities		No uncertainty	modelled
Optimal power flow (OPF)	[21]	Minimise generation cost DG capacity limits, power balance equality, small-signal stability constraints	Power flow, voltage and	Active and reactive power capacity	Small-signal stability	Dynamic	Small-signal stability constrained OPF problem is solved with SQP and gradient sampling algorithm to guarantee small-signal stability of DNS		No uncertainty	modelled
	[97]	Minimise power losses	Power flow, voltage and DG capacity limits, power balance equality	Size, location	Voltage	Static	An OPF algorithm considering the uncertainties modelling of renewable DGs output power is presented for the investigation and comparison of single and multiple DGs concepts	Renewable DG output power	Scenario-based approach	
	[95]	Maximise DG capacity	Power flow, voltage step change, voltage level and DG capacity limits, power balance equality, loss of generation constraint	Size, location	Voltage	Static	OPF method that includes many other relevant technical and physical constraints is proposed to assess the DNS in order to integrate renewable DG. Additional voltage step limit proved to be more effective in restricting DG capacity than a voltage level limit		No uncertainty	modelled
	[94]	Maximise DG capacity	Power flow, voltage, thermal and DG capacity limits, power balance equality	Size, location	Voltage	Static	OPF is applied to solve optimal DG problem by identifying available headroom and maximising the capacity of DG in the system		No uncertainty	modelled

(Continues)

TABLE 2 Continued

Conventional Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Method	Modelling
	[99]	Minimise total generation costs	Power flow, voltage and DG capacity limits, power balance equality	Size, location	Voltage	Dynamic	A three-phase unbalanced OPF algorithm is extended for the integration of distribution energy resources (DERs) and solid state transformer (SST) in DNS with minimisation of generation cost as the objective function		No uncertainty	modelled
	[96]	Minimise energy losses	Power flow, voltage and DG capacity limits, power balance equality	Size	Voltage stability	Dynamic	Multi-period AC OPF is proposed to determine the optimal integration/placement of renewable DGs in order to minimise system energy losses	Renewable DG output power, load demand	Scenario-based probabilistic approach	
	[98]	Maximise DG capacity	Power flow, voltage and DG capacity limits, power balance equality	DG capacity	Voltage stability	Dynamic	A multi-period OPF algorithm is presented for finding optimal DGs capacities in an ANM controlled distribution network		No uncertainty	modelled
	[76]	Maximise profit	Power flow, voltage and DG capacity limits, power balance equality	size	Voltage	Static	OPF algorithm is deployed to find optimal DG capacity considering fault-level restrictions that are enforced through protection equipment, switch-gear, constraints.		No uncertainty	modelled
	[89]	Maximise profit	Power flow, voltage and DG capacity limits, power balance equality	size	Voltage	Static	OPF method is proposed for transforming FLCs into simple non-linear constraints in DNS expansion planning problem.		No uncertainty	modelled
Continuatic Power Flow (CPF)	[100]	Maximise voltage limit loadability	Power flow, voltage and DG capacity limits, power balance equality	Location, DG capacity	Voltage	Static	CPF methodology is proposed for efficient integration of DG power into DNS with the objective to maximise the voltage limit loadability of the distribution network		No uncertainty	modelled
	[101]	Minimise power losses and improve voltage profile	Power flow, voltage and DG capacity limits, power balance equality	Location, size	Voltage	Static	Optimal placement of DG units is based on the analysis of continuation power flow and determination of most sensitive buses to voltage collapse.		No uncertainty	modelled

TABLE 3 Summary of intelligent search methods for optimal allocation of DGs

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
Genetic algorithm (GA)	[105]	Minimise network losses and maximise benefit/cost ratio	Power flow, voltage, DG capacity limits, power balance equality	Size, location	Voltage	Static	GA is introduced to solve optimal DG allocation problem in order to minimise network losses and guarantee acceptable system reliability and voltage profile		No uncertainty modelled
	[107]	Minimise costs of expansion, energy losses and interruption	Power flow, voltage, DG capacity and penetration limits, power balance equality	Location	Voltage	Static	GA is presented for finding optimal Carlos Simulation (MCS) is utilised to model the uncertainty and variability of the renewable DGs output power and load variability locations of renewable DGs while Monte	Power output of natural gas, load demand	MCS
	[108]	Maximise profit	Power flow, voltage magnitude, DG capacity limits, power balance equality	Location, size	Voltage	Static	GA is applied to obtain optimal DGs sizes while loss sensitivity method is used to find optimal DGs locations		No uncertainty modelled
	[103]	Maximise total active power losses	Power flow, voltage magnitude, DG capacity and thermal limits, power balance equality	DG locations and sizes	Voltage	Static	GA is proposed to determine the optimal locations and sizes of DG units. The result presents a maximum percentage of active power loss reduction compared with other methods validated with it		No uncertainty modelled
	[102]	Maximise DG benefit	Power flow, voltage, DG capacity limits, power balance equality	Size, location	Voltage	Static	GA is proposed to determine optimal size and locations in the planning of DNS		No uncertainty modelled
	[106]	Maximise benefit/cost ratio	Voltage drop and feeder load transfer capability, power flow, voltage and DG capacity limits, Maximum average system interruption index (ASIDI), power balance equality	DG type, number, size and location	Voltage	Static	GA is proposed for finding optimal type, number, size and location of multiple DGs in the DNS by using a valued-based method to find the best trade off between the costs and benefits of DG allocation		No uncertainty modelled
	[104]	Maximise benefit/cost ratio	Voltage drop, feeder load transfer capability, power flow, voltage level and DG capacity limits, power balance equality	Types, size, location	Voltage	Static	A GA-based strategic DG allocation method is proposed for searching the best costs/benefits ratio in determining optimal DGs types, sizes and locations in a DNS		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
	[110]	Minimise total imposed cost, total network losses and load interruption cost	Power flow, voltage, DG capacity limits, power balance equality	Size and location of DGs	Voltage	Static	NSGA II is proposed for optimal allocation of micro-gas-turbine DG with and power distribution system uncertainties is modelled with point estimate method (PEM)	Load, generation power	PEM
	[111]	Minimise total operation cost	Power flow, voltage, DG capacity limits, power balance equality	DG capacity	Voltage	Static	GA is used to solve DG units economic dispatch problem to determine the plant power mix when wind DG is incorporated into the network		No uncertainty modelled
	[109]	Maximise DG capacity	Power flow, voltage level, DG capacity, penetration fault current and losses limits, power balance equality	Size, location	Voltage	Static	GA determines the optimal sizes of DG units while voltage sensitivity index (VSI) and loss sensitivity index (LSI) find the coordinated and optimal location f DG units and reclosers in a security constrained DNS		No uncertainty modelled
	[112]	Maximise DG capacity	Power flow, voltage, DG capacity limits, power balance equality	Size, location	Voltage	Static	An improved adaptive GA (AGA) is proposed for expansion planning of DNS by finding optimal sizes and locations of DGs focusing wind, solar PV and biogas		No uncertainty modelled
	[113]	Minimise values of fitness function consisting of total losses, bus voltage, etc	Power flow, voltage, DG capacity and loss limits, power balance equality	DG capacity, location	Voltage	Static	GA with Multi-Attribute Decision Making (MADM) algorithm is proposed based on economic and environmental considerations for solving DGs optimal placement and sizing problem of a distribution system		No uncertainty modelled
Simulated annealing (SA)	[116]	Minimise total system losses	Power flow, voltage, DG capacity limits, power balance equality	Number of DG, location	Voltage	Static	SA is utilized to determine the optimal solutions for the problem of optimal placement and sizing of DG units in DNS		No uncertainty modelled
	[119]	Minimise network power losses	Power flow, voltage, DG capacity limits, power balance equality, radiality	Size, location	Voltage	Static	SA is proposed to find optimal sizes of DG units at feasible locations determined by the power loss sensitivity factor in the unspecified power factor distribution network		No uncertainty modelled
	[118]	Minimise total annual cost of network expansion, interruption and energy losses	Power flow, voltage level, voltage drop and DG capacity limits, power balance equality	Size	Voltage	Static	A steepest descent and SA algorithm are presented as initial and improved solutions respectively, to solve the optimal planning problem of radial distribution network		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
	117	Minimise power loss, emission and severity index	Power flow, voltage, DG generation limits, power balance equality	Size, location		Static	SA is applied to solve a multi-objective optimal DG placement problem		No uncertainty modelled
	120	Minimise power losses and Maximise voltage profile	Power flow, voltage magnitude, DG capacity limits, power balance equality	Network reconfiguration, DG sizes and locations	Voltage	Static	A feasibility-preserving SA algorithm is proposed to solve DN reconfiguration and DG allocation problem. The authors concluded that the results obtained outperformed some published population based meta-heuristic algorithms in terms of solution repeatability and computational cost		No uncertainty modelled
	121	Minimise economic costs	Power flow, voltage magnitude, DG capacity and conductor current limits, power balance equality	DG sizes, locations	Voltage	static	An improved SA-PSO (ISA-PSO) algorithm is proposed by introducing GA's mutation and crossover operators into traditional SA-PSO algorithm. This algorithm is applied to optimally integrate diverse types of DGs (PV, wind and micro-turbines) into DNS by finding their optimal locations and sizes		No uncertainty modelled
Tabu search algorithms (TSA)	126	Minimise costs of losses, line loading and total reactive power capacity	Power flow, voltage, DG capacity limits, power balance equality, tap changers positions	Size	Voltage	Static	TSA is proposed to compute the optimal sizes of DGs and reactive power sources (RPSs) in selected buses of DNS		No uncertainty modelled
	125	Minimise cost of power losses and reactive power capacity	Power flow, voltage, DG capacity limits, power balance equality, tap changers positions	DG capacity	Voltage	Static	TS method is presented to solve comprehensive DG and network configuration planning problem by simultaneously finding optimal sizes of DGs and reactive power sources in selected buses of DNS considering the status of sectionalising switches		No uncertainty modelled
	128	Finding Pareto optimal solution set		Size, location, computation time	Voltage	Static	A TSA-based multi-objective and NSGA II algorithms are evaluated and compared in finding pareto optimal set of solution, taking into consideration total active power loss index, three-phase short circuit level index and voltage regulation index as the objective function and basis of comparison		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
	127	Minimise distribution power losses	Power flow, voltage, DG capacity limits, power balance equality, number of DG	Location, DG discrete capacity	Voltage	Static	TSA is proposed to solve optimal DGs placement problem in a distribution system with uniform distributed load and unity power factor in order to minimise the distribution loss		No uncertainty modelled
	129	Minimise total costs of investment and operation	Power flow, voltage magnitude, DG capacity limits, power balance equality, utilisation constraints	Size and location	Voltage	Static	TSA is proposed to solve DEP problem for sizing and placing distribution transformers, substations, and conventional DGs		No uncertainty modelled
Particle swamp	141	Minimise total cost and power losses	Power flow, voltage, DG capacity limits, power balance equality	Size, location number of DG	Voltage	Static	A modified PSO is proposed for solving multi-stage distribution expansion planning problem including DGs using non-linear formulations for minimising total costs.		No uncertainty modelled
	136	Minimise total power losses and voltage profile index	Power flow, voltage, DG capacity limits, power	Size, location	Voltage	Static	A multi-objective index-based is proposed to optimally determine the sizes and locations of multiple DG units in DNS with different load models		No uncertainty modelled
	139	Minimise total reactive power losses	power flow, voltage, DG balance equality	Size, location	Voltage	Static, dynamic	PSO algorithm is presented for finding optimal sizes and locations of DG units in radial DNS in order to enhance line loadability of distribution system by minimising reactive power losses		No uncertainty modelled
	145	Minimise cost of demand response and network loss	Voltage magnitude, tap change number, tap operation limits, thermal and line current limits	Switch control	Voltage	Dynamic	A modified PSO (MPSO) is utilised to find optimal switching combination of household appliances and on-load tap changers (OLTCs) positions for the voltage management of the LV distribution network rooftop photovoltaic PV hosting capacity		No uncertainty modelled
	140	Minimise system losses	Power flow, voltage, DG capacity limits, power balance equality	Location		Static	A MCS based probabilistic load flow is used to model the unavailability of DGs under competitive electricity market scenario while the planning of optimal DG locations is done by PSO method	unavailable DG power	MCS

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
	[138]	Minimise power losses and improve voltage profile	Power flow, voltage, DG capacity limits, power	Size, location	Voltage	Static	PSO method is applied for finding optimal sizes andlocations for the placement of DGs in the radial DNS	No uncertainty modelled	
	[135]	Minimise total real power losses	Power flow, voltage, DG capacity limits, power balance equality	Location	Voltage	Static	PSO is proposed for determining optimal locationsof multiple DG units in the DNS		No uncertainty modelled
	[11]	Minimise power losses	Power flow, voltage, DG capacity limits, power balance equality	location	Voltage	Static	A quantum behaved PSO is employed for optimal placement of DG units in the distribution network		No uncertainty modelled
	[137]	Minimise total power losses	Power flow, voltage, DG capacity limits, power balance equality	Location, size	Voltage	Static	A combined PSO and Newton Raphson load flow method is proposed for determining optimal sizes and locations of DG units in a radial DS		No uncertainty modelled
	[142]	Minimise power losses, THD and cost of expansion	Power flow, voltage, DG capacity limits, power balance equality	Size, location	Voltage	Static	PSO is applied for solving optimal DG location and sizing problem using load flow and harmonic reduction in decision-making		No uncertainty modelled
	[143]	Minimise power distribution loss	Power flow, voltage, DG capacity limits, power balance equality,right of way	Size, location	Voltage	Static	PSO technique is proposed for finding optimal locations and sizes of different types of DGs and minimising the power distribution loss		No uncertainty modelled
	[144]	Maximise DG penetration level with respect to total system capacity	Power flow, voltage, DG capacity, THD and over-current relay time limits, power balance equality, protective coordination constraint	Type, size location	Voltage	Static	PSO approach is proposed to simultaneously find the optimal type, size and location of inverter-based and synchronous-based DG units in the DNS to achieve maximum DG penetration level considering standard THD limits and protection coordination constraints		No uncertainty modelled
	[153]	Minimise total power losses and voltage stability improvement	Power flow, voltage, DG capacity limits, power balance equality	Number of DG and location	Voltage	Static	A dynamic weighted aggregation PSO (DWAPSO) algorithm is proposed for finding optimal sizes and locations of wind turbine-based and PV-based DG units in a radial distribution network		No uncertainty modelled
	[155]	Minimise total energy losses and cost of power	Power flow, voltage, DG capacity limits, power balance equality, radiality, fuel cell constraints	DG capacity, location			An interactive fuzzy algorithm based on adaptive PSO (APSO) is employed to solve stochastic distribution network reconfiguration problem by determining optimal locations and sizes of wind-based DG and fuel cell DG units	Uncertainty in wind DG power output and load demand	PEM

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
	156	Minimise real power loss	Power flow, voltage, DG capacity and branch capacity limits, power balance equality, radiality	DG capacity, location	Voltage	Static	A decimal coded quantum PSO (DCQPSO) is proposed for solving distribution feeder reconfiguration problem considering different models of renewable DGs	renewable DG power output	MCS
	158	Minimise system losses	Power flow, voltage, DG capacity limits, power balance equality	Size, location	Voltage	Static	Social learning PSO (SLPSO) and maximum power stability index are applied respectively to find optimal sizes, and locations of DG units in the distribution networks		No uncertainty modelled
Ant colony optimisation	166	Minimise DG operation and investment costs	Power flow, voltage, DG capacity limits, power balance equality	Size, location	Voltage	Static	ACO is proposed to find optimal sizes and locationsof DG sources in DNS		No uncertainty modelled
	164	Minimise costs of investment and operation	Power flow, voltage, DG capacity limits, power balance equality, radiality	Location	Voltage	Static	ACO is presented for solving expansion planning problem of electric energy distribution system constraints		No uncertainty modelled
	168	Minimise total cost of power losses, energy losses and capacitor	Power flow, voltage, DG capacity limits, power balance equality	Size, time, number and location of capacitors	Voltage	Static	ACO algorithm is proposed for determining optimal types time, sizes and locations of installation of multi-period shunt capacitors in a radial distribution system		No uncertainty modelled
	169	Minimise real power losses and unserved power index	Power flow, voltage, DGcapacity limits, power balance equality, radiality and isolation constraints	DG capacity		Static	A modified ACO algorithm is proposed to solve a multi-objective distribution network reconfiguration problem with the minimisation of real power loss and energy unserved as the objective function		No uncertainty modelled
	165	Minimise real power losses	Power flow, voltage, DG capacity limits, power balance equality	Aactive and reactive power control	Voltage	Static	ACO method is proposed for findingoptimal solution of network-constrained load flow optimisation problem		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
	167	Minimise composite reliability index and customer interruption costs	Power flow, voltage, DGcapacity limits, power balance equality	Location	Voltage	Static	ACO is applied for deriving optimal locations of reclosers and DGs in the distribution networks		No uncertainty modelled
Fuzzy logic (FL) method	176	Minimise cost of power losses	Power flow, voltage and DG capacity limits, power balance equality	Location	Voltage	Static	Fuzzy-GA is proposed to solve the fuzzy non-linear goal programming problem by converting the original single objective problem into multi-objective problem using fuzzy sets		No uncertainty modelled
	177	Minimise total cost, technical and economic risks	Power flow, voltage and DGcapacity limits, power balance equality	Location	Voltage	Dynamic	Fuzzy number is proposed to model electricity price and load demand uncertainties while DG placement is achieved with non-dominant sorting genetic algorithm (NSGA-II)	Load demand, electricity price	Fuzzy numbers
	178	Minimise real power losses	Power flow, voltage and DGcapacity limits, power balance equality	Location, size	Voltage	Static	FL and an analytical method are used for finding optimal DG placement and size in a radial DNS		No uncertainty modelled
	175	Minimise active and reactive power losses	Power flow, voltage and DG capacity limits, power balance equality	DG locations, sizes	Voltage	Static	Fuzzy logic controller is utilised for finding optimal capacities and locations of DG units in DNS		No uncertainty modelled
	33	Minimise power losses, improve voltage profile and network loadability	Power flow, voltage magnitude, feeder current and DG capacity limits, power balance equality	DG locations, sizes	Voltage	Static	A novel method based on FL is proposed to solve complex multi-objective optimisation of DNS. Fuzzy set is used to transform multi-objective function into single-objective.		No uncertainty modelled
	179	Minimise power losses	Power flow, voltage and DG capacity limits, power balance equality	DG capacity, location		Static	BA is proposed to optimise the locations and sizes of capacitors in radial distribution network.		No uncertainty modelled
	147	Minimise power losses	current flow, voltage, line loading limits, power balance equality	location size	Voltage	Static	Fuzzy and PSO are proposed for optimal DG placement and sizing in a radial DNS respectively		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
Differential evolution algorithms (DEA)	[181]	Minimise transmission power losses	Power flow, voltage and DG capacity limits, power balance equality, line flow constraint	DG capacity, location		static	DEA is used to evaluate the optimum DG capacity while incremental voltage sensitivity method selected the location buses considering wind-turbine DG		No uncertainty modelled
	[182]	Minimise power losses and improve system reliability	Power flow, voltage and DG capacity limits, power balance equality	Location	Voltage	Static	DEA is proposed to determine the SAIFI, SAIDI and the expected interruption cost (ECOST) are taken as reliability indices while the DEA is proposed to determine optimal allocation of DG in the distribution system		No uncertainty modelled
	[184]	Minimise losses and operating cost, and improve voltage profile	power flow, voltage and DG capacity limits, power balance equality, apparent power limit	Sizes, locations	Voltage	Static	An improved DSA is proposed for finding pareto optimal solution of DGs sizes and locations in radial DSs		No uncertainty modelled
	[183]	Minimise power loss, yearly economic loss and voltage deviation	power flow, voltage and DG capacity limits, power balance equality	Location, size	Voltage	Static	A multi-objective based chaotic differential evolution (MOCDE) algorithm is presented to avoid premature convergence in finding optimal sizes and locations of DGs in radial DNSs		No uncertainty modelled
	[185]	Minimise total power losses	Power flow, voltage and DG capacity, DG penetration, branch flow, SVC limits, power balance equality	Location, size	Voltage	Static	An adaptive (flexible variant) DS algorithm is proposed to solve optimal location and size of multi-DGs in the distribution systems		No uncertainty modelled
Harmony search (HS)	[187]	Maximise voltage stability index	Power flow, voltage and DG capacity limits, power balance equality	DG capacity, locations	Voltage	Static	HS is proposed to find optimal sizes and locations of DG units in the distribution system and was adjudged to perform better than PSO in voltage stability improvement		No uncertainty modelled
	[188]	Minimise real power loss and improve voltage profile	Power flow, voltage and DG capacity and line current limits, power balance equality	Location	Voltage	Static	HS algorithm is used simultaneously for the reconfiguration of the distribution network and determination of optimal locations of the DG units in the network in order to minimise real power loss		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
Differential evolution algorithms (DEA)	[181]	Minimise transmission power losses	Power flow, voltage and DG capacity limits, power balance equality, line flow constraint	DG capacity, location		static	DEA is used to evaluate the optimum DG capacity while incremental voltage sensitivity method selected the location buses considering wind-turbine DG		No uncertainty modelled
	[182]	Minimise power losses and improve system reliability	Power flow, voltage and DG capacity limits, power balance equality	Location	Voltage	Static	DEA is proposed to determine the SAIFI, SAIDI and the expected interruption cost (ECOST) are taken as reliability indices while the DEA is proposed to determine optimal allocation of DG in the distribution system		No uncertainty modelled
	[184]	Minimise losses and operating cost, and improve voltage profile	power flow, voltage and DG capacity limits, power balance equality, apparent power limit	Sizes, locations	Voltage	Static	An improved DSA is proposed for finding pareto optimal solution of DGs sizes and locations in radial DSs		No uncertainty modelled
	[183]	Minimise power loss, yearly economic loss and voltage deviation	power flow, voltage and DG capacity limits, power balance equality	Location, size	Voltage	Static	A multi-objective based chaotic differential evolution (MOCDE) algorithm is presented to avoid premature convergence in finding optimal sizes and locations of DGs in radial DNSs		No uncertainty modelled
	[185]	Minimise total power losses	Power flow, voltage and DG capacity, DG penetration, branch flow, SVC limits, power balance equality	Location, size	Voltage	Static	An adaptive (flexible variant) DS algorithm is proposed to solve optimal location and size of multi-DGs in the distribution systems		No uncertainty modelled
Harmony search (HS)	[187]	Maximise voltage stability index	Power flow, voltage and DG capacity limits, power balance equality	DG capacity, locations	Voltage	Static	HS is proposed to find optimal sizes and locations of DG units in the distribution system and was adjudged to perform better than PSO in voltage stability improvement		No uncertainty modelled
	[188]	Minimise real power loss and improve voltage profile	Power flow, voltage and DG capacity and line current limits, power balance equality	Location	Voltage	Static	HS algorithm is used simultaneously for the reconfiguration of the distribution network and determination of optimal locations of the DG units in the network in order to minimise real power loss		No uncertainty modelled

(Continues)

TABLE 3 Continued

Intelligent Search Methods	References	Objective Functions	Constraints	Decision Variables	System Stability Considered	Network	Contribution of the Paper	Uncertain Parameter	Uncertainty Modelling Method
ϵ - Constraint method	[241]	Maximise DG owner's profit and minimise DisCos' costs	Power flow, voltage and DG capacity and line current, security limits, power balance equality, radiality constrain	Size, location	Voltage	Static	An ϵ - constraint method is applied to obtain solutions for optimal distribution system reconfiguration (DSR) and DG allocation problem while fuzzy is proposed for selecting the best compromised solution when DSO costs is minimised and DG owner's profit is maximised	Wind turbine power output, load demand	Scenario-based probabilistic
	[186]	Minimise energy losses	Power flow, voltage magnitude, DG capacity and line current limits, power balance equality	DG sizes, locations, network line expansion	Voltage	Static	HS is applied to both single- and multi-objective optimisation problem of finding optimal locations and sizes of distributed renewable energy resources (PV, micro-wind turbine)		No uncertainty modelled

power and reduce the intermittent effects of REHDG in the distribution network. Addition of storage devices with REHDG allocation problem will provide ancillary services to optimal REHDG solutions by cushioning the renewable resources intermittent effects.

3. The renewable energy resource, biomass, has been rarely used in REHDG allocation. Biomass is promising to replace storage devices since biomass power plants are fast-response generation units. More so that an efficient and economical electrical storage system is still in search. The use of biomass inclusive hybrid DG units in the REHDG allocation is recommended. It is very necessary to assess its effect on REHDG objectives and allocation optimisation solutions and compare the effect to other DG allocation solutions that include electrical storage systems.
4. Mostly, REHDG (solar PV and wind) are P-type DGs that generate only active power. Capacitors being sources of reactive power (Q-type DGs) can be included in the REHDG allocation and distribution network to compensate the reactive power deficit in the system. Reactive power compensators will also help in enhancing network voltage stability.
5. Nearly all the existing research works neglected to include all the related technical, DG capacity, investment, power quality, safety, system reliability, and network stability constraints in their REHDG allocation problem formulations. In most of the research works, constraints for right of way issues on some buses are neglected while small-signal stability is merely assumed but never constrained. All these necessary and related constraints need to be included in obtaining a realistic solution from a REHDG allocation problem.
6. The wind and photovoltaic DGs output power depend on wind speed and solar irradiance and temperature, which are variable and intermittent. Most of the existing works do not consider and model the intermittencies of these renewable DG units. The impact of the highly variable output power on the distribution system in terms of dynamic stability is not evaluated. Adequate modelling and consideration of these intermittencies and variability result to more realistic solutions to REHDG allocation problems.
7. Development of efficient methodologies and strategies capable of finding optimal types of DG units that are the best for each bus of distribution network is lacking in the majority of the previous research works. They only strived to find optimal locations and sizes of DG units without finding the optimal type of DGs that are suitable for each bus.
8. The exiting researches on planning and design of optimal placement and size of REHDGs are optimised on static networks but not on dynamic ones. A dynamic network is the practical (real-life) power system where dynamical instabilities (small-signal instabilities) occur more often than the steady-state ones. Research must focus on dynamic networks (ie, extended period load profile mostly on hourly basis over a dynamic planning horizon) in order to fully capture the inherent characteristics of distribution system especially the dynamic stability of the system.
9. Based on the reviewed works, optimal planning of REHDGs guaranteed voltage stability since their solutions satisfy power flow constraints in static networks. The solutions might have defined the smallest distance (stability margin) to prevent voltage collapse; a sudden fluctuation of power from renewable generations may be large enough to produce a system collapse in a dynamic system. This review work recommends the development of methodologies or strategies to impose small-signal stability constraint(s) in future research studies. Also of particular importance is the enhancement of small signal stability of the system by optimally allocating REHDG units in the distribution system.
10. Generally, literatures on optimal allocation of DGs acknowledge high improvements, but an optimal allocation of REHDG had not been fully achieved especially on small signal stability requirements of the distribution systems. Developing more comprehensive planning formulation model and efficient metal-heuristic optimisation algorithm with strong capability to discover global optimum is imperative to obtaining optimal REHDG allocation solution that will enhance small-signal stability of distribution systems. This is because nearly all the existing works strive to optimise steady state features of distribution systems.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the research supports received from Tshwane University of Technology (TUT) and ESKOM Power Plant Engineering Institute (EPPEI) Specialisation Centre in Renewable Energy, and Power System Studies, Stellenbosch University, South Africa.

ORCID

Olusayo A. Ajeigbe https://orcid.org/0000-0001-6828-3228

REFERENCES

1. Ajeigbe OA, Chowdhury SP, Olwal TO, Abu-Mahfouz AM. Harmonic control strategies of utility-scale photovoltaic inverters. *Int J Renew Energy Res*. 2018;8(3):1354-1368.
2. Hosenuzzaman M, Rahim N, Selvaraj J, Hasanuzzaman M, Malek A, Nahar A. Global prospects, progress, policies, and environmental impact of solar photovoltaic power generation. *Renew Sustain Energy Rev*. 2015;41:284-297.
3. Santos SF, Fitiwi DZ, Shafie-Khah M, Bizuayehu A, Catalao J, Gabbar H. Optimal sizing and placement of smart grid enabling technologies for maximising renewable integration. 2017:47-81.
4. Jordehi AR. Allocation of distributed generation units in electric power systems: a review. *Renew Sustain Energy Rev*. 2016;58:893-905.
5. Zubo RHA, Mokryani G, Rajamani HS, Aghaei J, Niknam T, Pillai P. Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: a review. *Renew Sustain Energy Rev*. 2017;72:1177-1198.
6. Georgilakis P, Hatziargyriou N. A review of power distribution planning in the modern power systems era: models, methods and future research. *Electr Power Syst Res*. 2015; 121:89-100.
7. Georgilakis P, Hatziargyriou N. Optimal distributed generation placement in power distribution networks: models, methods, and future research. *IEEE Trans Power Syst*. 2013;28(3):3420-3428.
8. Abdmouleh Z, Gastli A, Ben-Brahim L, Haouari M, Al-Emadi NA. Review of optimization techniques applied for the integration of distributed generation from renewable energy sources. *Renew Energy*. 2017;113:266-280.
9. Theo WL, Lim JS, Ho WS, Hashim H, Lee CT. Review of distributed generation (DG) system planning and optimisation techniques: comparison of numerical and mathematical modelling methods. *Renew Sustain Energy Rev*. 2017;67:531-573.
10. HA MP, Huy PD, Ramachandaramurthy VK. A review of the optimal allocation of distributed generation: objectives, constraints, methods, and algorithms. *Renew Sustain Energy Rev*. 2017;75:293-312.
11. Nazari-Heris M, Madadi S, Pesaran HM, Mohammadi-Ivatloo B. Optimal distributed generation allocation using quantum inspired particle swarm optimization. 2018:419-432.
12. Ackermann T, Andersson G, Söder L. Distributed generation: a definition. *Electr power syst res*. 2001;57(3):195-204.
13. Pourbehzadi M, Niknam T, Aghaei J, Mokryani G, Shafie-khah M, Catalao JP. Optimal operation of hybrid AC/DC microgrids under uncertainty of renewable energy resources: a comprehensive review. *Int J Electr Power Energy Syst*. 2019; 109:139-159.
14. Ayodele T, Jimoh A, Munda J, Agee J. Challenges of grid integration of wind power on power system grid integrity: a review. *World*. 2012;3.
15. Slootweg J, Kling W. The impact of large scale wind power generation on power system oscillations. *Electr Power Syst Res*. 2003;67(1):9-20.
16. Liu H, Jin L, Le D, Chowdhury A. Impact of high penetration of solar photovoltaic generation on power system small signal stability. In: 2010 International Conference on Power System Technology IEEE; 2010:1-7.
17. Gibbard MJ, Pourbeik P, Vowles DJ. Small-signal stability, control and dynamic performance of power systems. In: Small-signal stability, control and dynamic performance of power systems. University of Adelaide Press; 2015.
18. Pan Y, Liu F, SHen C, CHen L, Mei S. Robust small-signal stability region of power systems considering uncertain wind generation. In: 2015 IEEE Power and Energy Society General Meeting; 2015:1-5.
19. Shukla DM. Impact of wind turbine generators on stability of power systems. *Int J Eng Sci*. 2017;7(5): 11596-11599.
20. Canizares C, Ferdinandes T, Geraldi E, et al. Benchmark models for the analysis and control of small-signal oscillatory dynamics in power systems. *IEEE Trans Power Syst*. 2017;32(5):715-722.
21. Li P, Qi J, Wang J, Wei H, Bai X, Qiu F. An SQP method combined with gradient sampling for small-signal stability constrained OPF. *IEEE Trans Power Syst*. 2017;32: 2372-2381.
22. Pan Y, Liu F, CHen L, Wang J, Qiu F, SHen C, Mei S. Towards the robust small-signal stability region of power systems under perturbations such as uncertain and volatile wind generation. *IEEE Trans Power Syst*. 2018;33(2):1790-1799.
23. Kundur P, Balu NJ, Lauby MG. *Power System Stability and Control*, Vol. 7. New York: McGraw-hill; 1994.
24. Ramasamy AK, Teng AM, Ahmed SK, et al. Effects of variations in generator inputs for small signal stability studies of a three machine nine bus network. *Int J Electr Comput Eng*. 2011;5(2):167-170.
25. Bu SQ, Du W, Wang HF. Investigation on probabilistic small-signal stability of power systems as affected by offshore wind generation. *IEEE Trans Power Syst*. 2015;30(5): 2479-2486.
26. Qin X, Liu W, Yang J, Yang Y. Small-signal stability constrained optimal power flow based on real-time data. In: 2015 5th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT). IEEE; 2015:1294-1298.
27. Amin M, Molinas M. Small-signal stability assessment of power electronics based power systems: a discussion of impedance-and eigenvalue-based methods. *IEEE Trans Ind Appl*. 2017;53(5):5014-5030.
28. Mosetlhe TC, Yusuff AA, Hamam Y. Assessment of small signal stability of power systems with wind energy conversion unit. In: 2017 IEEE Africon. IEEE; 2017:1089-1094.
29. Condren J, Gedra TW. Expected-security-cost optimal power flow with small-signal stability constraints. *IEEE Trans Power Syst*. 2006;21(4):1736-1743.
30. Dheer D, Doolla S, Bandyopadhyay S, Guerrero JM. Effect of placement of droop based generators in distribution network on small signal stability margin and network loss. *Int J Electr Power Energy Syst*. 2017;88:108-118.
31. Xie D, Lu Y, Sun J, Gu C. Small signal stability analysis for different types of PMSGs connected to the grid. *Renew energy*. 2017;106:149-164.
32. Rahman AU, Syed I, Ullah M. Small signal stability of a balanced three-phase ac microgrid using harmonic linearization: parametric-based analysis. *Electron*. 2018;8(1).
33. Syahputra R, Wiyagi RO, Suripto S, Jamal A, Putra KT, Mujaahid F. A novel fuzzy approach for multi-objective

optimization of distribution network configuration in complex system. *Int J Appl Eng Res*. 2018;13(2):1120-1127.
34. Reddy PDP, Reddy VV, Manohar TG. Ant lion optimization algorithm for optimal sizing of renewable energy resources for loss reduction in distribution systems. *J Electr Syst Inf Technol*. 2018;5(3):663-680.
35. Ehsan A, Yang Q. Optimal integration and planning of renewable distributed generation in the power distribution networks: a review of analytical techniques. *Appl Energy*. 2018;210:44-59.
36. Twaha S, Ramli MA. A review of optimization approaches for hybrid distributed energy generation systems: off-grid and grid-connected systems. *Sustain Cities Soc*. 2018;41:320-331.
37. Acharya PS. Intelligent algorithmic multi-objective optimization for renewable energy system generation and integration problems: a review. *Int J Renew Energy Res (IJRER)*. 2019;9(1):271-280.
38. Mohandas N, Balamurugan R, Lakshminarasimman L. Optimal location and sizing of real power DG units to improve the voltage stability in the distribution system using ABC algorithm united with chaos. *Int J Electr Power Energy Syst*. 2015;66:41-52.
39. Dixit M, Kundu P, Jariwala HR. Integration of distributed generation for assessment of distribution system reliability considering power loss, voltage stability and voltage deviation. *Energy Syst*. 2019;10(2):489-515.
40. Alturki M, Khodaei A, Paaso A, Bahramirad S. Optimization-based distribution grid hosting capacity calculations. *Appl Energy*. 2018;219:350-360.
41. Altıntaş O, Okten B, Karsu Ö, Kocaman AS. Bi-objective optimization of a grid-connected decentralized energy system. *Int J Energy Res*. 2018;42(2):447-465.
42. Babatunde OM, Munda JL, Hamam Y. A comprehensive state-of-the-art survey on power generation expansion planning with intermittent renewable energy source and energy storage. *Int J Energy Res*. 2019:1-30.
43. Aien M, Hajebrahimi A, Fotuhi-Firuzabad M. A comprehensive review on uncertainty modeling techniques in power system studies. *Renew Sustain Energy Rev*. 2016;57:1077-1089.
44. Willis HL. Analytical methods and rules of thumb for modeling DG-distribution interaction. In: 2000 Power Engineering Society Summer Meeting (cat. no.00ch37134), Vol. 3; 2000:1643-1644 vol. 3.
45. Wang C, Nehrir MH. Analytical approaches for optimal placement of distributed generation sources in power systems. *IEEE Trans Power Syst*. 2004;19(4):2068-2076.
46. Acharya N, Mahat P, Mithulananthan N. An analytical approach for DG allocation in primary distribution network. *Int J Electrical Power Energy Syst*. 2006;28(10):669-678.
47. Tawfeek TS, Ahmed A, Hasan S. Analytical and particle swarm optimization algorithms for optimal allocation of four different distributed generation types in radial distribution networks. *Energy Procedia*. 2018;153:86-94.
48. GÃűzel T, Hocaoglu MH. An analytical method for the sizing and siting of distributed generators in radial systems. *Electric Power Syst Res*. 2009;79(6):912-918.
49. Murty V, Kumar A. Optimal placement of DG in radial distribution systems based on new voltage stability index under load growth. *Int J Electr Power Energy Syst*. 2015;69:246-256.
50. Murthy V, Kumar A. Comparison of optimal DG allocation methods in radial distribution systems based on sensitivity approaches. *Int J Electr Power Energy Syst*. 2013;53(1).
51. Aman M, Jasmon G, Mokhlis H, Bakar A. Optimal placement and sizing of a DG based on a new power stability index and line losses. *Int J Electr Power & Energy Syst*. 2012;43(1):1296-1304.
52. Lee S-H, Park J-W. Selection of optimal location and size of multiple distributed generations by using Kalman filter algorithm. *IEEE Trans Power Syst*. 2009;24(3):1393-1400.
53. Hung DQ, Mithulananthan N. Multiple distributed generator placement in primary distribution networks for loss reduction. *IEEE Trans Ind Electron*. 2013;60(4):1700-1708.
54. Hung DQ, Mithulananthan N, Bansal RC. Analytical expressions for DG allocation in primary distribution networks. *IEEE Trans Energy Convers*. 2010;25(3):814-820.
55. Hamam YM, Renders M, Trecat J. Partitioning algorithm for the solution of long-term power-plant mix problems. In: Procedings of the Institution of Electrical Engineers, 9, vol. 126. IET Digital Library; 1979:837-839.
56. Dicorato M, Forte G, Trovato M. Environmental-constrained energy planning using energy-efficiency and distributed-generation facilities. *Renew Energy*. 2008;33(6):1297-1313.
57. Keane A, O'Malley M. Optimal allocation of embedded generation on distribution networks. *IEEE Trans Power Syst*. 2005;20(3):1640-1646.
58. Keane A, O'Malley M. Optimal utilization of distribution networks for energy harvesting. *IEEE Trans Power Syst*. 2007;22(1):467-475.
59. Munoz-Delgado G, Contreras J, Arroyo JM. Joint expansion planning of distributed generation and distribution networks. *IEEE trans Power Syst*. 2015;30:2579-2590.
60. Mishra S, Bordin C, Tomasgard A, Palu I. A multi-agent system approach for optimal microgrid expansion planning under uncertainty. *Int J Electr Power Energy Syst*. 2019;109: 696-709.
61. Alturki M, Khodaei A. Increasing distribution grid hosting capacity through optimal network reconfiguration. In: 2018 North American Power Symposium (NAPS) IEEE; 2018: 1-6.
62. Wu FF, Gross G, Luini JF, Look PM. A two-stage approach to solving large-scale optimal power flows. In: IEEE Conference Proceedings Power Industry Computer Applications Conference, 1979. pica-79. IEEE; 1979:126-136.
63. Van Cutsem T. A method to compute reactive power margins with respect to voltage collapse. *IEEE Trans Power Syst*. 1991;6(1):145-156.
64. Kermanshahi B, Takahashi K, Zhou Y. Optimal operation and allocation of reactive power resource considering static voltage stability. In: Powercon'98. 1998 International Conference on Power System Technology. Proceedings (cat. no. 98ex151), Vol. 2. IEEE; 1998:1473-1477.
65. Porkar S, Poure P, Abbaspour-Tehrani-fard A, Saadate S. Optimal allocation of distributed generation using a two-stage multi-objective mixed-integer-nonlinear programming. *Eur Trans Electr Power*. 2011;21(1):1072-1087.
66. Al Abri R, El-Saadany EF, Atwa YM. Optimal placement and sizing method to improve the voltage stability margin in a distribution system using distributed generation. *IEEE trans power syst*. 2013;28(1):326-334.
67. Salyani P, Salehi J, Gazijahani FS. Chance constrained simultaneous optimization of substations, feeders, renewable and non-renewable distributed generations in distribution network. *Electr Power Syst Res*. 2018;158:56-69.

68. Wang Z, Chen B, Wang J, Kim J, Begovic MM. Robust optimization based optimal DG placement in microgrids. *IEEE Trans Smart Grid*. 2014;5(5):2173-2182.
69. Mena A, García JAM. An efficient approach for the siting and sizing problem of distributed generation. *Int J Electr Power Energy Syst*. 2015;69:167-172.
70. Khalesi N, Rezaei N, Haghifam M-R. DG allocation with application of dynamic programming for loss reduction and reliability improvement. *Int J Electr Power Energy Syst*. 2011;33(2):288-295.
71. Saif A, Pandi VR, Zeineldin H, Kennedy S. Optimal allocation of distributed energy resources through simulation-based optimization. *Electric Power Syst Res*. 2013;104:1-8.
72. Popovi Z, Popovi D. Graph theory based formulation of multi-period distribution expansion problems. *Electric Power Syst Res*. 2010;80(10):1256-1266.
73. Martin B, De Jaeger E, Glineur F, Latiers A. A dynamic programming approach to multi-period planning of isolated microgrids. *Advances in energy system optimization*: Springer; 2017:123-137.
74. Bhowmik S, Bhattacherjee PK, Goswami SK. Distribution system planning through combined heuristic and quadratic programing approach. *Electr Mach Power Syst*. 2000;28(1):87-103.
75. Sfikas E, Katsigiannis Y, Georgilakis P. Simultaneous capacity optimization of distributed generation and storage in medium voltage microgrids. *Int J Electr Power Energy Syst*. 2015;67:101-113.
76. Vovos PN, Harrison GP, Wallace AR, Bialek JW. Optimal power flow as a tool for fault level-constrained network capacity analysis. *IEEE Trans Power Syst*. 2005;20(2):734-741.
77. AlHajri M, AlRashidi M, El-Hawary M. Improved sequential quadratic programming approach for optimal distribution generation deployments via stability and sensitivity analyses. *Electr Power Components Syst*. 2010;38(14):1595-1614.
78. Lazzeroni P, Repetto M. Optimal planning of battery systems for power losses reduction in distribution grids. *Electr Power Syst Res*. 2019;167:94-112.
79. Kaur S, Kumbhar G, Sharma J. A MINLP technique for optimal placement of multiple DG units in distribution systems. *Int J Electr Power Energy Syst*. 2014;63:609-617.
80. Goldberg D. Genetic algorithms in search, optimization and machine learning. In: Genetic Algorithms in Search, Optimization and Machine Learning. Reading, Mass, Addison-Wesley Pub Co; 1989.
81. Haddow BP, Tufte G. Goldberg DE genetic algorithms in search, optimization and machine learning. In: 2000 Congress on Evolutionary Computation CEC00. Addison-Wesley Longman Publishing Co; 2010.
82. Pesaran M, Zin AAM, Khairuddin A, Shariati O. Optimal sizing and siting of distributed generators by a weighted exhaustive search. *Electr Power Components Syst*. 2014;42(11): 1131-1142.
83. Khan H, Choudhry MA. Implementation of distributed generation (IDG) algorithm for performance enhancement of distribution feeder under extreme load growth. *Int J Electr Power Energy Syst*. 2010;32(9):985-997.
84. Rotaru F, Chicco G, Grigoras G, Cartina G. Two-stage distributed generation optimal sizing with clustering-based node selection. *Int J Electr Power Energy Syst*. 2012;40(1):120-129.
85. Raju MR, Murthy KR, Ravindra K. Direct search algorithm for capacitive compensation in radial distribution systems. *Int J Electr Power Energy Syst*. 2012;42(1):24-30.
86. Samui A, Singh S, Ghose T, Samantaray SR. A direct approach to optimal feeder routing for radial distribution system. *IEEE Trans Power Deliv*. 2012;27(1):253-260.
87. Samui A, Samantaray S, Panda G. Distribution system planning considering reliable feeder routing. *IET Gener Transm Distrib*. 2012June;6:503-514(11).
88. Rau NS, Wan Y-h. Optimum location of resources in distributed planning. *IEEE Trans Power syst*. 1994;9(4):2014-2020.
89. Vovos PN, Bialek JW. Direct incorporation of fault level constraints in optimal power flow as a tool for network capacity analysis. *IEEE Trans Power Syst*. 2005;20(4):2125-2134.
90. Li Q, Li M, Zhan J. Mean-variance model for power system economic dispatch with wind power integrated. *Energy*. 2014;72:510-520.
91. Lin X, Sun J, Ai S, Xiong X, Wan Y, Yang D. Distribution network planning integrating charging stations of electric vehicle with V2G. *Int J Electr Power Energy Syst*. 2014;63:507-512.
92. Jabr R, Pal B. Ordinal optimisation approach for locating and sizing of distributed generation. *IET Gener Transm Distrib*. August;3:713-723(10).
93. Zou K, Agalgaonkar AP, Muttaqi KM, Perera S. Distribution system planning with incorporating DG reactive capability and system uncertainties. *IEEE Trans Sustain Energy*. 2012;3(1):112-123.
94. Harrison G, Wallace A. Optimal power flow evaluation of distribution network capacity for the connection of distributed generation. *IEE Proc-Gener Transm Distrib*. 2005;152(1):115-122.
95. Dent C, Ochoa L, Harrison G. Network distributed generation capacity analysis using OPF with voltage step constraints. *IEEE Trans on Power Syst*. 2010;25(1):296-304.
96. Ochoa LF, Harrison GP. Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation. *IEEE Trans Power Syst*. 2011;26(1):198-205.
97. Karatepe E, UgranlÄś F, Hiyama T. Comparison of single- and multiple-distributed generation concepts in terms of power loss, voltage profile, and line flows under uncertain scenarios. *Renewable and Sustainable Energy Reviews*. 2015;48: 317-327.
98. Ochoa LF, Dent CJ, Harrison GP. Distribution network capacity assessment: variable DG and active networks. *IEEE Trans Power Syst*. 2010;25(1):87-95.
99. Meng F, Chowdhury B, Hossan MS. Optimal integration of DER and SST in active distribution networks. *Int J Electr Power Energy Syst*. 2019;104:626-634.
100. Hemdan NGA, Kurrat M. Efficient integration of distributed generation for meeting the increased load demand. *Int J Electr Power Energy Syst*. 2011;33(9):1572-1583.
101. Hedayati H, Nabaviniaki SA, Akbarimajd A. A method for placement of DG units in distribution networks. *IEEE Trans Power Deliv*. 2008;23(3):1620-1628.
102. Silvestri A, Berizzi A, Buonanno S. Distributed generation planning using genetic algorithms. In: International Conference on Electric Power Engineering, Powertech Budapest 99. abstract records.(cat. no. 99ex376). IEEE. IEEE; 1999:257.
103. Kashyap M, Mittal A, Kansal S. Optimal placement of distributed generation using genetic algorithm approach. In:

Proceeding of the Second International Conference on Microelectronics, Computing & Communication Systems (MCCS 2017). Springer; 2019:587-597.

104. Teng J-H, Luor T-S, Liu Y-H. Strategic distributed generator placements for service reliability improvements. *IEEE Power Engineering Society Summer Meeting,* Vol. 2: IEEE; 2002:719-724.
105. Borges C, FalcÃŏ D. Optimal distributed generation allocation for reliability, losses, and voltage improvement. *Int J Electr Power Energy Syst*. 2006;28(6):413-420.
106. Teng J-H, Liu Y-H, Chen C-Y, Chen C-F. Value-based distributed generator placements for service quality improvements. *Int J Electr Power Energy Syst*. 2007;29(3):268-274.
107. Shaaban MF, Atwa YM, El-Saadany EF. Dg allocation for benefit maximization in distribution networks. *IEEE Trans Power Syst*. 2013;28(2):639-649.
108. Shukla TN, Singh SP, Srinivasarao V, Naik KB. Optimal sizing of distributed generation placed on radial distribution systems. *Electr Power Components Syst*. 2010;38(3):260-274.
109. Popović D, Greatbanks J, Begović M, Pregelj A. Placement of distributed generators and reclosers for distribution network security and reliability. *Int J Electr Power Energy Syst*. 2005;27(5-6):398-408.
110. Dehghanian P, Hosseini SH, Moeini-Aghtaie M, Arabali A. Optimal siting of DG units in power systems from a probabilistic multi-objective optimization perspective. *Int J Electr Power Energy Syst*. 2013;51:14-26.
111. Liao G-C. Solve environmental economic dispatch of smart microgrid containing distributed generation system-using chaotic quantum genetic algorithm. *Int J Electr Power Energy Syst*. 2012;43(1):779-787.
112. Ma Y, Yang P, Guo H, Wu J. Power source planning of wind-PV-biogas renewable energy distributed generation system [j]. *Power Syst Technol*. 2012;9(624):001.
113. Kamalinia S, Afsharnia S, Khodayar ME, Rahimikian A, Sharbafi MA. A combination of MADM and genetic algorithm for optimal DG allocation in power systems. In: 2007 42nd International Universities Power Engineering Conference; 2007:1031-1035.
114. Kirkpatrick S, Vecchi M. Optimization by simulated annealing. *Sci*. 1983;4598:671-680.
115. Santoso S, Saraf N, Venayagamoorthy GK. Intelligent techniques for planning distributed generation systems. In: 2007 IEEE Power Engineering Society General Meeting; 2007:1-4.
116. Aly AI, Hegazy YG, Alsharkawy MA. A simulated annealing algorithm for multi-objective distributed generation planning. In: IEEE PES General Meeting. IEEE; 2010:1-7.
117. Sutthibun T, Bhasaputra P. Multi-objective optimal distributed generation placement using simulated annealing. In: ECTI-CON2010: The 2010 ECTI International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology; 2010:810-813.
118. Nahman JM, Peric DM. Optimal planning of radial distribution networks by simulated annealing technique. *IEEE Trans Power Syst*. 2008;23(2):790-795.
119. Injeti SK, Kumar NP. A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems. *Int J Electr Power Energy Syst*. 2013;45(1):142-151.
120. Koziel S, Rojas AL, Moskwa S. Power loss reduction through distribution network reconfiguration using feasibility-preserving simulated annealing. In: 2018 19th International Scientific Conference on Electric Power Engineering (EPE). IEEE; 2018:1-5.
121. Su H. Siting and sizing of distributed generators based on improved simulated annealing particle swarm optimization. *Environ Sci Pollut Res*. 2019;26(18):17927-17938.
122. Glover F, McMillan C. The general employee scheduling problem. An integration of MS and AI. *Comput Oper Res*. 1986;13(5):563-573. Applications of Integer Programming.
123. Glover F. Tabu search—part I. *ORSA J Comput*. 1989;1(3): 190-206.
124. Glover F. Tabu search—part II. *ORSA J Comput*. 1990;2(1): 4-32.
125. Hamedani Golshan M, Arefifar S. Distributed generation, reactive sources and network-configuration planning for power and energy-loss reduction,; 2006:127-136(9).
126. Golshan MEH, Ali Arefifar S. Optimal allocation of distributed generation and reactive sources considering tap positions of voltage regulators as control variables. *Eur Trans Electr Power*. 2007;17(3):219-239.
127. Nara K, Hayashi Y, Ikeda K, Ashizawa T. Application of tabu search to optimal placement of distributed generators. In: 2001 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (cat. no.01ch37194), Vol. 2; 2001:918-923 vol.2.
128. Maciel R, Padilha-Feltrin A. Distributed generation impact evaluation using a multi-objective tabu search. In: 2009 15th International Conference on Intelligent System Applications to Power Systems IEEE; 2009:1-5.
129. Mantovani JR, et al. A decomposition approach for integrated planning of primary and secondary distribution networks considering distributed generation. *Int J Electr Power Energy Syst*. 2019;106:146-157.
130. Eberhart R, Kennedy J. A new optimizer using particle swarm theory. In: Mhs'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science; 1995: 39-43.
131. Zhu Z. *Computer Vision Research Progress*. 1st ed. Commack, NY, USA: Nova Science Publishers, Inc.; 2008.
132. del Valle Y, Venayagamoorthy GK, Mohagheghi S, Hernandez J, Harley RG. Particle swarm optimization: basic concepts, variants and applications in power systems. *IEEE Trans Evol Comput*. 2008;12(2):171-195.
133. Bhatti AR, Salam Z, Sultana B, Rasheed N, Awan AB, Sultana U, Younas M. Optimized sizing of photovoltaic grid-connected electric vehicle charging system using particle swarm optimization. *Int J Energy Res*. 2019;43(1):500-522.
134. AlRashidi MR, El-Hawary ME. A survey of particle swarm optimization applications in electric power systems. *IEEE Trans Evol Comput*. 2009;13(4):913-918.
135. Krueasuk W, Ongsakul W. Optimal placement of distributed generation using particle swarm optimization. In: Power Engineering Conference in Australasian Universities. Citeseer; 2006; Australia:47-81.
136. El-Zonkoly A. Optimal placement of multi-distributed generation units including different load models using particle swarm optimization. *Swarm Evol Comput*. 2011;1(1):50-59.
137. Wong LY, Rahim SRA, Sulaiman MH, Aliman O. Distributed generation installation using particle swarm optimization. In: 2010 4th International Power Engineering and Optimization Conference (PEOCO); 2010:159-163.

138. Kansal S, Sai B, Tyagi B, Kumar V. Optimal placement of distributed generation in distribution networks. *Int J Eng Sci Technol*. 2011;3(3):47-55.
139. Hien NC, Mithulananthan N, Bansal RC. Location and sizing of distributed generation units for loadabilty enhancement in primary feeder. *IEEE Syst J*. 2013;7(4):797-806.
140. Jain N, Singh SN., Srivastava SC. A generalized approach for dg planning and viability analysis under market scenario. *IEEE Trans Ind Electron*. 2013;60(11):5075-5085.
141. Aghaei J, Muttaqi KM, Azizivahed A, Gitizadeh M. Distribution expansion planning considering reliability and security of energy using modified PSO (particle swarm optimization) algorithm. *Energy*. 2014;65:398-411.
142. Alinejad-Beromi Y, Sedighizadeh M, Sadighi M. A particle swarm optimization for sitting and sizing of distributed generation in distribution network to improve voltage profile and reduce THD and losses. In: 2008 43rd International Universities Power Engineering Conference; 2008:1-5.
143. Kansal S, Kumar V, Tyagi B. Optimal placement of different type of dg sources in distribution networks. *Int J Electr Power Energy Syst*. 2013;53:752-760.
144. Pandi VR, Zeineldin HH, Xiao W. Determining optimal location and size of distributed generation resources considering harmonic and protection coordination limits. *IEEE Trans Power Syst*. 2013;28(2):1245-1254.
145. Rahman MM, Arefi A, Shafiullah G, Hettiwatte S. A new approach to voltage management in unbalanced low voltage networks using demand response and OLTC considering consumer preference. *Int J Electr Power Energy Syst*. 2018;99:11-27.
146. Zeb MZ, Imran K, Janjua AK, Nadeem M, Amin A. Optimal allocation and sizing of solar panels generation via particle swarm optimization algorithm. In: 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (ICOMET). IEEE; 2019:1-5.
147. Lalitha MP, Reddy VV, Usha V, Reddy NS. Application of fuzzy and PSO for DG placement for minimum loss in radial distribution system. *ARPN J Eng Appl Sci*. 2010;5(4):32-37.
148. Zeinalzadeh A, Mohammadi Y, Moradi MH. Optimal multi objective placement and sizing of multiple DGs and shunt capacitor banks simultaneously considering load uncertainty via MOPSO approach. *Int J Electr Power Energy Syst*. 2015;67:336-349.
149. Jamian J, Mustafa M, Mokhlis H. Optimal multiple distributed generation output through rank evolutionary particle swarm optimization. *Neurocomputing*. 2015;152:190-198.
150. Jain N, Singh SN, Srivastava SC. Planning and impact evaluation of distributed generators in Indian context using multi-objective particle swarm optimization. In: 2011 IEEE Power and Energy Society General Meeting; 2011:1-8.
151. Ameli A, Bahrami S, Khazaeli F, Haghifam M. A multiobjective particle swarm optimization for sizing and placement of DGs from DG owner's and distribution company's viewpoints. *IEEE Trans Power Deliv*. 2014;29(4):1831-1840.
152. Ganguly S, Sahoo NC, Das D. Multi-objective planning of electrical distribution systems using particle swarm optimization. In: Epecs'09 International Conference on Electric Power and Energy Conversion Systems. IEEE; 2009:1-6.
153. Kayal P, Chanda C. Placement of wind and solar based DGs in distribution system for power loss minimization and voltage stability improvement. *Int J Electr Power Energy Syst*. 2013;53:795-809.
154. Yustra MA, Soeprijanto A. Optimal distributed generation (DG) allocation for losses reduction using improved particle swarm optimization (IPSO) method. *J Basic Appl Sci Res*. 2013;2(7):7016-7023.
155. Malekpour AR, Niknam T, Pahwa A, Kavousi Fard A. Multi-objective stochastic distribution feeder reconfiguration in systems with wind power generators and fuel cells using the point estimate method. *IEEE Trans Power Syst*. 2013;28(2):1483-1492.
156. Guan W, Tan Y, Zhang H, Song J. Distribution system feeder reconfiguration considering different model of DG sources. *Int J Electr Power Energy Syst*. 2015;68:210-221.
157. Senthil kumar J, Charles Raja S, Srinivasan D, Venkatesh P. Hybrid renewable energy-based distribution system for seasonal load variations. *Int J Energy Res*. 2018;42(3):1066-1087.
158. Arasi SM, Sasiraja R. Optimal location of DG units with exact size for the improvement of voltage stability using SLPSO; 2015.
159. Cheng S, Chen M-Y, Fleming PJ. Improved multi-objective particle swarm optimization with preference strategy for optimal DG integration into the distribution system. *Neurocomputing*. 2015;148:23-29.
160. Dorigo M, Di Caro G. Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 Congress on Evolutionary Computation-cec99 (cat. no. 99th8406), Vol. 2; 1999:1470-1477 Vol. 2.
161. Dorigo M, Birattari M. Ant colony optimization. *Encyclopedia of machine learning*. Boston, MA: Springer US; 2010: 36-39.
162. Lai LL, Ma JT. Application of evolutionary programming to reactive power planning-comparison with nonlinear programming approach. *IEEE Trans Power Syst*. 1997;12(1): 198-206.
163. Chu S-C, Roddick JF, Pan J-S. Ant colony system with communication strategies. *Inf Sci*. 2004;167(1):63-76.
164. Gomez JF, Khodr HM, De Oliveira PM, et al. Ant colony system algorithm for the planning of primary distribution circuits. *IEEE Transactions on Power Systems*. 2004;19(2):996-1004.
165. Vlachogiannis JG, Hatziargyriou ND, Lee KY. Ant colony system-based algorithm for constrained load flow problem. *IEEE Trans Power Syst*. 2005;20(3):1241-1249.
166. Falaghi H, Haghifam M. ACO based algorithm for distributed generation sources allocation and sizing in distribution systems. In: 2007 IEEE Lausanne Power Tech; 2007: 555-560.
167. Wang L, Singh C. Reliability-constrained optimum placement of reclosers and distributed generators in distribution networks using an ant colony system algorithm. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*. 2008;38(6):757-764.
168. Kaur D, Sharma J. Multiperiod shunt capacitor allocation in radial distribution systems. *Int J Electr Power Energy Syst*. 2013;52:247-253.
169. Mirhoseini SH, Hosseini SM, Ghanbari M, Gandomkar M. Multi-objective reconfiguration of distribution network using a heuristic modified ant colony optimization algorithm. *Model Simul Electr Electron Eng*. 2015;1(1):23-33.
170. Amohadi M, Fotuhi-Firuzabad M. Optimal placement of automatic switching equipment in radial distribution networks

based on protective coordination. *J Electr Eng Technol*. 2019; 14(3):1127-1137.
171. Zadeh LA. Fuzzy sets. *Inf control*. 1965;8(3):338-353.
172. Eslami M, Shareef H, Mohamed A. Application of artificial intelligent techniques in PSS design: a survey of the state-of-the-art methods. *PrzeglĂĔd Elektrotechniczny Electrical Review*. 2011;87(4):188-197.
173. Tsoukalas LH, Uhrig RE. *Fuzzy and neural approaches in engineering*: John Wiley and Sons, Inc; 1996.
174. Momoh J, Ma X, Tomsovic K. Overview and literature survey of fuzzy set theory in power systems. *IEEE Trans Power Syst*. 1995;10(3):1676-1690.
175. Sharma SK, Palwalia D, Shrivastava V. Distributed generation integration optimization using fuzzy logic controller. *AIMS Energy*. 2019;7(3):337-348.
176. Kim K-H, Lee Y-J, Rhee S-B, Lee S-K, You S-K. Dispersed generator placement using fuzzy-GA in distribution systems. In: IEEE Power Engineering Society Summer Meeting, Vol. 3. IEEE; 2002:1148-1153.
177. Haghifam M-R, Falaghi H, Malik O. Risk-based distributed generation placement. *IET Gener Transm Distrib*. 2008; 2(2):252-260.
178. Injeti SK, Kumar NP. Optimal planning of distributed generation for improved voltage stability and loss reduction. International journal of computer applications. *J Basic Appl Sci Res*. 2011;15(1):40-46.
179. Reddy V, Manoj A. Optimal capacitor placement for loss reduction in distribution systems using bat algorithm. *IOSR J Eng*. 2012;2(10):23-7.
180. Storn R. Differrential evolution-a simple and efficient adaptive scheme for global optimization over continuous spaces, technical report. *Int Comput Sci Inst*. 1995;11.
181. Arya L, Koshti A, Choube S. Distributed generation planning using differential evolution accounting voltage stability consideration. *Int J Electr Power Energy Syst*. 2012;42(1):196-207.
182. Chiradeja P, Yoomak S, Ngaopitakkul A. Optimal allocation of multi-DG on distribution system reliability and power losses using differential evolution algorithm. *Energy Procedia*. 2017;141:512-516.
183. Kumar S, Mandal K. K., Chakraborty N. Optimal dg placement by multi-objective opposition based chaotic differential evolution for techno-economic analysis. *Appl Soft Comput*. 2019;78:70-83.
184. Injeti SK. A Pareto optimal approach for allocation of distributed generators in radial distribution systems using improved differential search algorithm. *J Electr Syst Inf Technol*. 2018;5(3):908-927.
185. Mahdad B, Srairi K. Adaptive differential search algorithm for optimal location of distributed generation in the presence of SVC for power loss reduction in distribution system. *Eng Sci Technol Int J*. 2016;19(3):1266-1282.
186. Camacho-Gómez C, Jiménez-Fernández S, Mallol-Poyato R, Del Ser J, Salcedo-Sanz S. Optimal design of microgrid*ĂŹ*s network topology and location of the distributed renewable energy resources using the harmony search algorithm. *Soft Comput*. 2018:1-16.
187. Piarehzadeh H, Khanjanzadeh A, Pejmanfer R. Comparison of harmony search algorithm and particle swarm optimization for distributed generation allocation to improve steady state voltage stability of distribution networks. *Res J Appl Sci Eng Technol*. 2012;4(15):2310-2315.
188. Rao RS, Ravindra K, Satish K, Narasimham S. Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. *IEEE trans power syst*. 2013;28(1):317-325.
189. Karaboga D. An idea based on honey bee swarm for numerical optimization, Technical report-tr06, Erciyes university, engineering faculty, computerâę; 2005.
190. Abu-Mouti FS, El-Hawary M. Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm. *IEEE trans power deliv*. 2011;26(4):2090-2101.
191. El-Zonkoly AM. Multistage expansion planning for distribution networks including unit commitment. *IET Gener Transm Distrib*. 2013;7(7):766-778.
192. Kefayat M, Ara AL, Niaki SAN. A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources. *Energy Conver Manag*. 2015;92:149-161.
193. Padma Lalitha M, Veera Reddy V, Sivarami Reddy N. Application of fuzzy and ABC algorithm for DG placement for minimum loss in radial distribution system. *Iran J Electr Electron Eng*. 2010;6(4).
194. Eusuff M, Lansey K, Pasha F. Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization. *Eng Optim*. 2006;38(2):129-154.
195. Yammani C, Siripurapu N, Maheswarapu S, Matam SK. Optimal placement and sizing of the der in distribution systems using shuffled frog leap algorithm. In: 2011 IEEE Recent Advances in Intelligent Computational Systems IEEE; 2011:062-067.
196. Onlam A, Yodphet D, Chatthaworn R, Surawanitkun C, Siritaratiwat A, Khunkitti P. Power loss minimization and voltage stability improvement in electrical distribution system via network reconfiguration and distributed generation placement using novel adaptive shuffled frogs leaping algorithm. *Energ*. 2019;12(3):553.
197. Taghikhani M. DG allocation and sizing in distribution network using modified shuffled frog leaping algorithm. *Int J Autom Power Eng*. 2012;1(1):10-18.
198. Yang X-S, Deb S. Cuckoo search via lévy flights. In: 2009 World Congress on Nature & Biologically Inspired Computing (NABIC). IEEE; 2009:210-214.
199. Moravej Z, Akhlaghi A. A novel approach based on cuckoo search for DG allocation in distribution network. *Int J Electr Power & Energy Syst*. 2013;44(1):672-679.
200. Aranizadeh A, Niazazari I, Mirmozaffari M. A novel optimal distributed generation planning in distribution network using cuckoo optimization algorithm. *Eur J Electr Eng Comput Sci*. 2019;3(3).
201. Nguyen TT, Truong AV, Phung TA. A novel method based on adaptive cuckoo search for optimal network reconfiguration and distributed generation allocation in distribution network. *Int J Electr Power & Energy Syst*. 2016;78:801-815.
202. Jaeger M, De Reffye P. Basic concepts of computer simulation of plant growth. *J Biosci*. 1992;17(3):275-291.
203. Kumar SA, Goud KJ. Power loss reduction in radial distribution system by using plant growth simulation algorithm. *Power*. 2012;3(1).
204. Yang X-S. A new metaheuristic bat-inspired algorithm. *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*: Springer; 2010:65-74.

205. Yammani C, Maheswarapu S, Matam SK. Optimal placement and sizing of distributed generations using shuffled bat algorithm with future load enhancement. *Int Trans Electr Energy Syst*. 2016;26(2):274-292.
206. Candelo-Becerra JE, Hernández-Riaño HE. Distributed generation placement in radial distribution networks using a bat-inspired algorithm. *Dyna*. 2015;82(192):60-67.
207. Simon D. Biogeography-based optimization. *IEEE trans Evol Comput*. 2008;12(6):702-713.
208. Valipour K, Dehghan E, Shariatkhah M. Optimal placement of capacitor banks and distributed generation for losses reduction and voltage THD improvement in distribution networks based on BBO algorithm. *Int Res J Appl Basic Sci*. 2013;4(7):1663-1670.
209. Duong MQ, Pham TD, Nguyen TT, Doan AT, Tran HV. Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems. *Energ*. 2019;12(1):174.
210. Atashpaz-Gargari E, Lucas C. Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In: 2007 IEEE Congress on Evolutionary Computation. IEEE; 2007:4661-4667.
211. Mahari A, Babaei E. Optimal DG placement and sizing in distribution systems using imperialistic competition algorithm. In: 2012 IEEE 5th India International Conference on Power Electronics (IICPE) IEEE; 2012:1-6.
212. Soroudi A, Ehsan M. Imperialist competition algorithm for distributed generation connections. *IET Gener Transm Distrib*. 2012;6(1):21-29.
213. Moradi MH, Zeinalzadeh A, Mohammadi Y, Abedini M. An efficient hybrid method for solving the optimal sitting and sizing problem of DG and shunt capacitor banks simultaneously based on imperialist competitive algorithm and genetic algorithm. *Int J Electr Power Energy Syst*. 2014;54:101-111.
214. Koong GI, Mokhlis H, Jamian J, Illias H, Dahalan W, Aman M. Simultaneous network reconfiguration with distributed generation sizing and tap changer adjustment for power loss reduction using imperialist competitive algorithm. *Arab J Sci Eng*. 2018;43(6):2779-2792.
215. Poornazaryan B, Karimyan P, Gharehpetian G, Abedi M. Optimal allocation and sizing of DG units considering voltage stability, losses and load variations. *Int J Electr Power Energy Syst*. 2016;79:42-52.
216. Yang X-S. Firefly algorithms for multimodal optimization. In: International Symposium on Stochastic Algorithms. Springer; 2009:169-178.
217. Yang X-S. Firefly algorithm, stochastic test functions and design optimisation. arXiv preprint arXiv:1003.1409; 2010.
218. Sulaiman MH, Mustafa MW, Azmi A, Aliman O, Abdul Rahim SR. Optimal allocation and sizing of distributed generation in distribution system via firefly algorithm. In: 2012 IEEE International Power Engineering and Optimization conference Melaka, Malaysia; 2012:84-89.
219. Gerez C, Silva LI, Belati EA, Sguarezi Filho AJ, Costa EC. Distribution network reconfiguration using selective firefly algorithm and a load flow analysis criterion for reducing the search space. *IEEE Access*. 2019.
220. Nadhir K, Chabane D, Tarek B. Distributed generation location and size determination to reduce power losses of a distribution feeder by firefly algorithm. *Int J Adv Sci Technol*. 2013;56:61-72.
221. Nadhir K, Chabane D, Tarek B. Firefly algorithm based energy loss minimization approach for optimal sizing & placement of distributed generation. In: 2013 5th International Conference on Modeling, Simulation and Applied Optimization (ICMSAO) IEEE; 2013:1-5.
222. Othman M, El-Khattam W, Hegazy Y, Abdelaziz AY. Optimal placement and sizing of voltage controlled distributed generators in unbalanced distribution networks using supervised firefly algorithm. *Int J Electr Power Energy Syst*. 2016;82:105-113.
223. Hosseini HS. Problem solving by intelligent water drops. In: 2007 IEEE Congress on Evolutionary Computation IEEE; 2007:3226-3231.
224. Moradi M, Abedini M. A novel method for optimal DG units capacity and location in microgrids. *Int J Electr Power Energy Syst*. 2016;75:236-244.
225. Prabha DR, Jayabarathi T, Umamageswari R, Saranya S. Optimal location and sizing of distributed generation unit using intelligent water drop algorithm. *Sustain Energy Technol Assessments*. 2015;11:106-113.
226. El-Ela AAA, El-Sehiemy RA, Abbas AS. Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm. *IEEE Syst J*. 2018;12(4):3629-3636.
227. Passino KM. Biomimicry of bacterial foraging for distributed optimization and control. *IEEE Control Syst Mag*. 2002;22(3):52-67.
228. Singh S, Ghose T, Goswami S. Optimal feeder routing based on the bacterial foraging technique. *IEEE Trans Power Deliv*. 2012;27(1):70-78.
229. Kowsalya M, et al. Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization. *Swarm Evol Comput*. 2014;15:58-65.
230. Kaveh MR, Hooshmand R-A, Madani SM. Simultaneous optimization of re-phasing, reconfiguration and DG placement in distribution networks using BF-SD algorithm. *Appl Soft Comput*. 2018;62:1044-1055.
231. Devabalaji K, Ravi K, Kothari D. Optimal location and sizing of capacitor placement in radial distribution system using bacterial foraging optimization algorithm. *Int J Electr Power Energy Syst*. 2015;71:383-390.
232. Devi S, Geethanjali M. Application of modified bacterial foraging optimization algorithm for optimal placement and sizing of distributed generation. *Expert Syst Appl*. 2014;41(6):2772-2781.
233. Aghaebrahimi M, Amiri M, Zahiri S. An immune-based optimization method for distributed generation placement in order to optimize voltage profile. In: 2009 International Conference on Sustainable Power Generation and Supply IEEE; 2009:1-7.
234. Hatata A, Osman G, Aladl M. An optimization method for sizing a solar/wind/battery hybrid power system based on the artificial immune system. *Sustain Energy Technol Assessments*. 2018;27:83-93.
235. Souza BB, Carrano EG, Neto OM, Takahashi RH. Immune system memetic algorithm for power distribution network design with load evolution uncertainty. *Electr Power Syst Res*. 2011;81(2):527-537.
236. Erol OK, Eksin I. A new optimization method: big bang–big crunch. *Adv Eng Softw*. 2006;37(2):106-111.
237. Esmaeili M, Sedighizadeh M, Esmaili M. Multi-objective optimal reconfiguration and DG (distributed generation) power allocation in distribution networks using big bang–big

crunch algorithm considering load uncertainty. *Energy*. 2016;103:86-99.

238. Reyes LM, Baeza JM. Simultaneous optimization of topology, distributed generation and energy storage systems in distribution networks using the MOHBB-BC algorithm. In: 2018 IEEE International Conference on Automation/XXIII Congress of the Chilean Association of Automatic Control (ICA-ACCA) IEEE; 2018:1-6.
239. Mirjalili S. The ant lion optimizer. *Adv Eng Softw*. 2015;83:80-98.
240. Hadidian-Moghaddam MJ, Arabi-Nowdeh S, Bigdeli M, Azizian D. A multi-objective optimal sizing and siting of distributed generation using ant lion optimization technique. *Ain Shams Eng J*. 2018;9(4):2101-2109.
241. Kianmehr E, Nikkhah S, Rabiee A. Multi-objective stochastic model for joint optimal allocation of DG units and network reconfiguration from DG ownerĂŹs and discoâĂŹs perspectives. *Renew Energy*. 2019;132:471-485.

How to cite this article: Ajeigbe OA, Munda JL, Hamam Y. Towards maximising the integration of renewable energy hybrid distributed generations for small signal stability enhancement: A review. *Int J Energy Res*. 2020;44:2379–2425. https://doi.org/10.1002/er.4864