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# Overview of Electric Energy Distribution Networks Expansion Planning

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**ABSTRACT** Planning of the electric distribution networks is complex and about upgrading the system to satisfy the demand and constraints with the best economic plan. The planning alternatives include the expansion of substations, installing new distributed generation (DG) facilities, upgrading distribution feeders, etc. In the modern networks, distribution planners must gain the confidence of the reversibility of the investment where renewable energy resources (RERs) inject clean and cost-effective electrical power to respond to the rising demand and satisfy environmental standards. This paper is an exhaustive review on the distribution network expansion planning (DEP) including the modelling of DEP (possible objective functions, problem constraints, different horizon time, and problem variables), optimization model (single/multi-objective), the expansion of distributed energy resources (DERs), problem uncertainties, etc. We discuss the requirements of integrated energy district master planning to avoid conflicts between the goal of independence of district planning on energy, e.g. heat and electricity, and that of dependencies on the local electric utilities regarding instant power balance and stability services. Finally, we describe the primary future R&D trends in the field of distribution network planning.

**INDEX TERMS** Distribution expansion planning, distributed energy resources, multi-objective optimization, decomposition optimization, uncertainty handling.

## I. INTRODUCTION

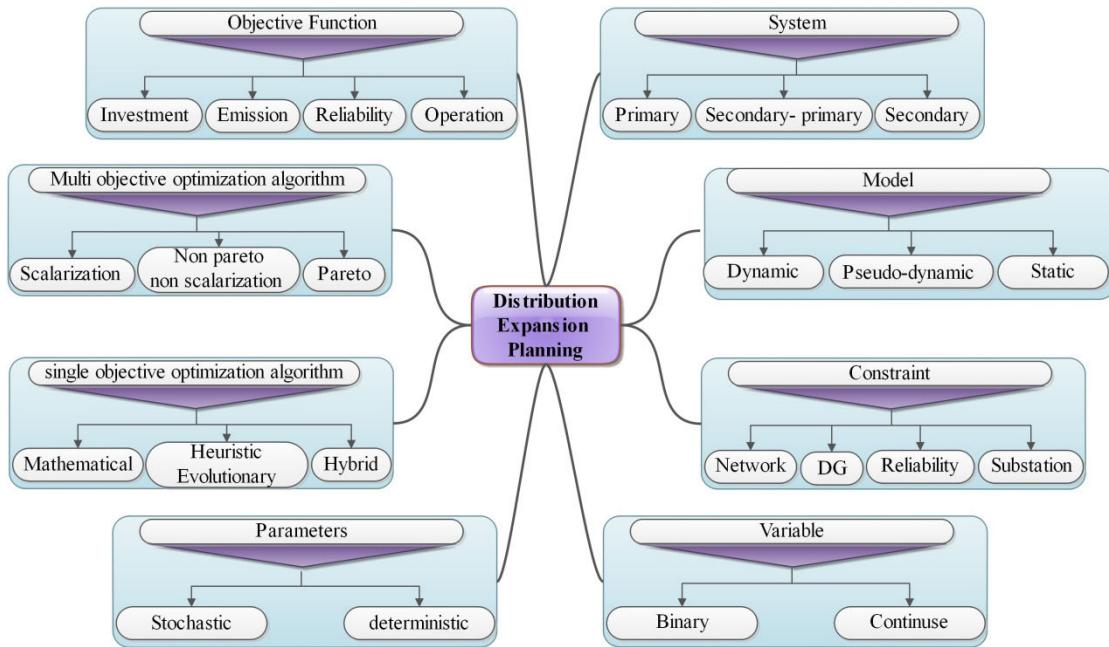
Distribution networks start from distribution substations to the service entrance of the electricity consumers, including distribution substations, primary feeders, distribution transformers, and secondary systems [1]–[3]. The existing distribution networks can only serve the requirements and standards of past decades and are not able to meet renewed duties and upcoming challenges. Distribution systems and loads will be subject to dramatic changes over the next 20 to 50 years. To name a few of the changes, we can mention customers' expected services, the reliability level of the system, the characteristic of the new loads, marginal costs, and existing numerous DG generators.

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We can classify the planning horizon for the distribution network expansion planning (DEP) problems into short-term, long-term, and horizon year planning. Short term planning typically contains 1–4 years, while the long-term and horizon year planning periods are 5–20, and more than 20 years, respectively [4].

Rapidly increasing of the electricity loads, forces power system authorities to perform expansion planning schemes periodically. The aim of a generic DEP is to site and size distribution substations, DGs, and distribution feeders to optimally meet the future demands, in a timely and cost-effective manner, while responding to all the constraints and technical requirements [5]–[8].

An optimum DEP can bring economic advantages for the planners, and also enhance the satisfaction level of electric customers, which is crucial in the restructured power market



**FIGURE 1.** Distribution expansion planning: a graphical abstract.

environment [5], [9]. Several researchers introduced Different mathematical and meta-heuristic optimization methods to find an optimal solution to DEP whose complexity can be increased due to problem dimensionality. The added complexity can also be caused by making complicated decisions on the allocation of transformers and substations, finding feeders' routing for the primary and secondary systems, the time of investment, choice of complex objective functions, and different uncertainty resources [8], [10], [11].

Feeders' reinforcement, the expansion of distribution substations, and also the installation of distribution alternatives such as new feeders, substations, transformers, and typically open switches, are conventional DEP decision options. In recent years, the researchers and stakeholders are focused on expansion planning of DGs, and purchasing their generated power [12], [13], due to the advantages including economic benefits, reliability improvement, ancillary services, emission reduction, postponing and reducing other expansion requirements in both the transmission and distribution levels, and socio-political acceptance [14]–[17].

Moreover, in reliability and service quality of DEP, allocating protective devices and automatic/manual switches, cost-effectively is a significant trend [18]. In recent years, many researchers have developed optimization algorithms to assign the sectionalizing switches optimally.

Sectionalizing switches are generally utilized in medium-voltage distribution systems with the aim of improving service reliability. Plug-in Electric Vehicles (PEVs) integration is one of the other subjects of interest due to their capabilities to incorporate in the ancillary service market, participate in demand response programs, integrate into microgrids, as well as their ability to generate reactive power [19]–[21]. With the rising penetration of PEVs, we can improve the

general system performance along with the consumption of fuel-based resources [19]. At the same time, high penetration of DGs may cause some problems in the conventional distribution networks with HV/MV substations as the sole power sources [22], [23], which we must consider in establishing a reliable and cost-effective operation of distribution networks [24].

Traditional and non-traditional DGs (in different studies the “distributed” part is also called dispersed, decentralised, district or with some modifications embedded, local, and on-site generation) must provide economically viable solutions and reliable services to consumers [25]. We usually divide the DG units into traditional combustion generators (e.g. diesel reciprocating generators and natural gas turbines), and non-traditional generators (e.g. fuel cells, storage devices and RERs such as wind turbines and photovoltaic units) [1]. In a DEP programming problem, binary variables describe installing new feeders and distribution substations, changing the type of conductors, and upgrading the capacity of resources (RERs). Limited sources of fossil fuels and its environmental hazards, make the RERs as a dominant choice in the planning decisions [26], [27] with the low investment risk and flexibility [27]–[30]. Fig. 1 shows an illustration of different aspects of a DEP problem.

## II. DISTRIBUTION EXPANSION PLANNING MODEL

### A. VARIABLES

The decision variables of a DEP problem are generally, the place, size, and investment scheduling to install new equipment or upgrade the pre-existed facilities, as well as the number, state (open/close), and location of switches. DG owners make decisions on the location, size and the

type of DGs to install based on geographical conditions, fuel resources, and feasibility of using RERs like wind turbines, photovoltaic panels, biomass, etc. [31].

In a design problem, we must determine the suitable diameters of lines and conductor options (e.g. underground cables, overhead line conductors) based on the required voltage levels. Here, lines' reinforcement is aimed to increase the capacity of pre-existed substations and distribution feeders or to install new ones if required [32].

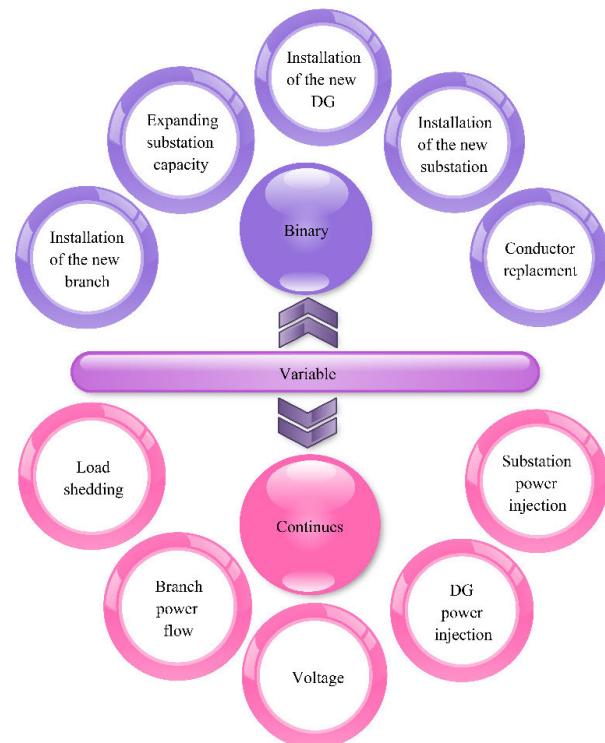
A generic DEP is inherently a complex mixed-integer non-linear programming problem with continuous and discrete (binary) variables [1]. Binary variables represent installing new feeders and distribution substations, changing the type of conductors, and upgrading the capacity of distribution substations. Continuous variables represent the amount of voltage level in each bus, power flow from the feeders, generated power with DGs, injected power from the substations, and curtailed load (see Fig. 2).

### B. MAIN OBJECTIVE TERMS

The most crucial objective function for the network expansion problem is the cost of investment and operation terms [33]. The investment cost (or fixed cost) is all the cost related to system upgrade (by installing a new instrument and enhancing the capacity of the existing facilities) [32]. The operation cost (or variable cost) is all the cost related to operational and maintenance costs of the system during the whole planning period, e.g. cost of power losses, cost of curtailed loads, and cost of DGs' power generation [15], [16], [27], [29], [30], [32], [34]–[37]. To simplify planning, we convert fixed and variable costs to the annualized Net Present Value (NPV).

Several studies proposed approaches to determine the decision variables of the DEP problem optimally and minimize various cost terms [12], [13], [15], [16], [27], [38]–[44].

As both types of costs are monetary expenditures, they can be aggregated together by considering the discount rates to compute the present value of all the cost terms [45]. With discount rates, different time cost terms can be transformed to the current values and joined together to create a single cost function. Moreover, the cost of fault frequencies, i.e. number of faults ([15], [28], [39], [45]–[48]), and the cost of not-served energy, i.e. duration of the faults [39], [47]–[50], [52]) can be aggregated as the reliability cost function to be minimized to enhance the reliability level of the network. As discussed in the literature, the consideration of energy not-supplied (ENS) as a reliability index is essential [7]–[10], [12], [13], [17], [30], [32], [34]–[36], [40], [44], [53]–[66]. By allocating the sectionalizing switches on the distribution feeders or installing new branches, the load points are fed with new routes. Hence, the load points could be de-energized if any permanent fault occurred or when maintenance services are planned to be executed [12], [13], [15], [50], [61], [67], [68]. Switching actions with sectionalizing switches can isolate some faults, and we can use tie-lines to maintain the supply to some



**FIGURE 2.** Commonly used variables in the distribution expansion planning problem.

feeders when faults occur in an upstream branch. Accordingly, in a reliability-driven DEP, the main goal is to minimize the unwanted load shedding in the case of an outage occurrence, based on the socio-economic priority of customers.

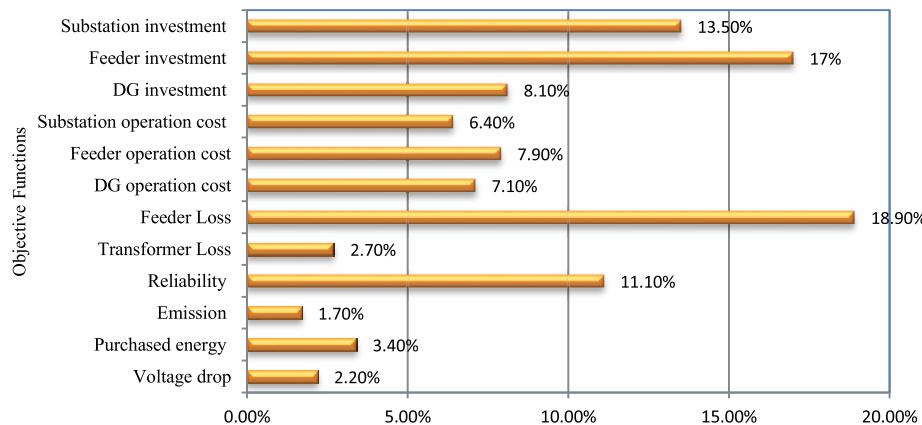
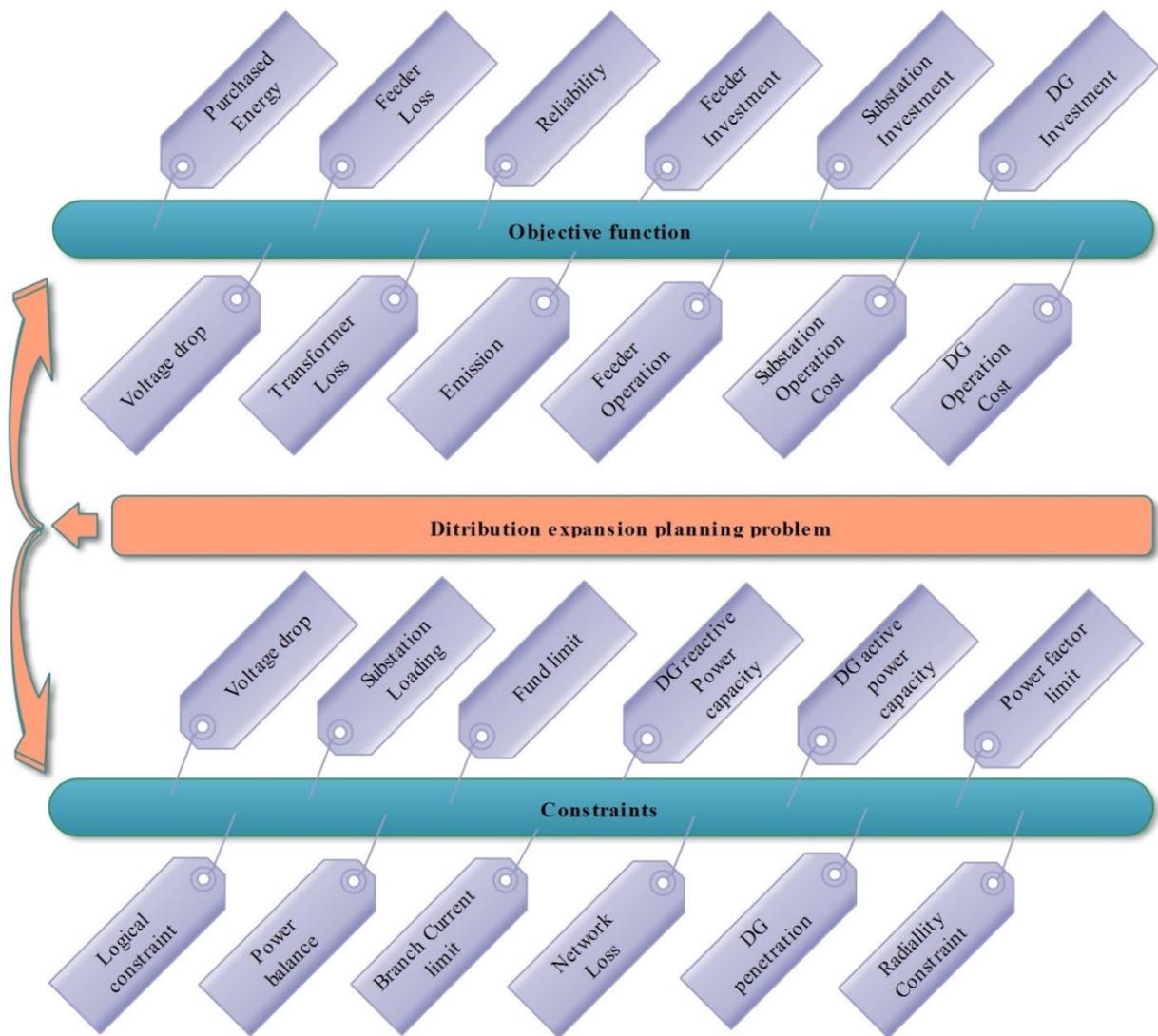
System planners focus on environmental issues these days more than before and follow several rules and protocols, e.g. Kyoto protocol, to reduce the impact of hazardous environmental factors [27]. Researchers now consider emission rate as one of the objective functions in the DEP problems [26], [27], [37], [44], [69]–[72], and reducing the pollution rate by using clean energy resources is standard practice by network planners.

Fig. 3 and 4 show the normalized versatility of objective functions used in the different references, and constraints and objective functions of distribution planning, respectively. Table 1 show the completeness of the references in covering various constraints and objective variables.

### C. CONSTRAINTS

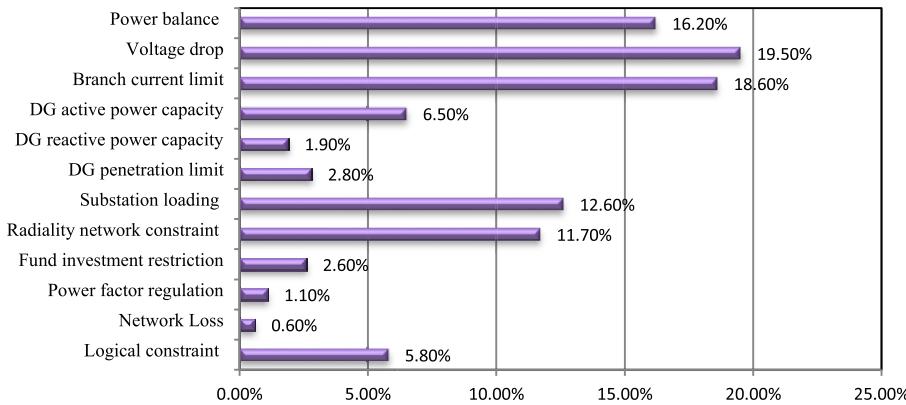
We typically define DEP as an optimization problem with several constraint variables, including:

- a) Power balance: this constraint guarantees active and reactive power generation and consumption equity in each time step.
- b) Voltage level: For stability reasons, voltage deviation must be kept within some boundaries within a voltage profile. Distribution companies (DISCOs) will generally provide the standard voltage profile for the customers [73].

**FIGURE 3.** Summary of objective functions used in the references.**FIGURE 4.** Objective functions and constraints used in the DEP problem.

**TABLE 1.** Objective functions and constraint of references in chronological order.

References	Objective Functions										Constraints										Logical constraint	
	Substation Investment	Feeder Investment	DG Investment	Substation Operation Cost	Feeder Operation Cost	DG Operation Cost	Feeder loss	Transformer loss	Reliability	Emission	Purchased Energy	Voltage drop	Power balance	Voltage drop	Branch current limit	DG active power capacity	DG reactive power capacity	DG Penetration limit	Substation loading	Radiality constraint	investment restriction	Power factor regulation
[82]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[83]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[53]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[84]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[85]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[5]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[54]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[86]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[87]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[78]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[88]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[89]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[90]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[55]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[91]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[92]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[93]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[111]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[94]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[15]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[95]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[45]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[56]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[57]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[96]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[4]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[33]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[97]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[34]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[32]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[98]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[68]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[99]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[100]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[101]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[1]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[2]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[52]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[51]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
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[27]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
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[103]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
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[70]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[42]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[43]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[71]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[116]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[66]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[79]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[117]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[118]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[119]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[120]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[121]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[122]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[123]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[124]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[125]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
[126]	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*



**FIGURE 5.** Objective functions and constraints used in the DEP problem.

c) Power flow: the power flow of the distribution feeders must be within the permissible capacity of the branches where we formulate the constraints with a set of inequality equations.

d) Controlling active and reactive output power of DG facilities: A threshold must be set for the active and reactive power generation of the DG units. Since the reactive power of DGs can affect the voltage profile and power losses, for the best allocation of DGs in the network, we must take into account their reactive capabilities in planning studies [74], [75].

e) Penetration limit of DGs: the generated power with DGs must also be within a set limit. Typically, the penetration level of DG units is  $\sim 30\text{-}40\%$  of the main substation rating [26], [75].

f) Substation capacity: the loading of substations must also be within a permissible interval [73].

g) Radiality: due to the operational issues, distribution feeders must be operated with a radial configuration. One of the necessary conditions to construct a radial network is the equality between the total number of branches and the number of buses minus one. However, other considerations must be further made to guarantee the connectivity and radiality of the network [24], [36], [52].

h) Total investment: the total amount of financial resources is limited for installing new instruments and increasing the existing facilities that will affect the expansion plan of the systems [76].

i) Power factor regulation: The amounts of power factors must satisfy the related standards [2], [44], [77].

j) Power losses: the power losses of the network are one of the most critical considerations and consist of the losses of the feeders, as well as the transformers [1], [65], [70].

k) Logical constraints: these constraints determine how the network must operate, e.g. only one type of equipment can be chosen among all options [60], [74].

Fig. 5 shows the normalized number of constraints used in the literature. There are some additional constraints such as Reliability constraint [69], [78], Capacity of energy storage

units [17] and load shedding [32], [34], [48], [79], electric vehicle charge station constraint [80] and DG emission limitation [27].

As noticed from Fig. 5, most papers have studied the voltage drop, load balance, and feeders' loading capacity constraints. At the same time, a limited number focused on other constraints like DGs' reactive capability and the penetration level of DGs. Note that the main aim of the DEP studies is to provide the customers' load. Since some of the references have used the separate load flow to give the customer's load, we do not bring such references under the category of power balance constraint. Power loss is an essential measure in distribution systems and is considered as an objective function in many papers, and that's why power loss has less share in Fig. 5 compared to the other constraints.

#### D. THE MODELING OF THE DEP

The planner models a DEP problem to optimally determine the decision variables. The modelling targets highly depend on the desired accuracy, possible assumptions to simplify the problem, the available tools and the algorithms, etc. An extract representation of a generic optimization is:

$$\begin{aligned} & \text{Minimize or Maximize } f(x) \\ & \text{Subject to } A(x) \leq b \end{aligned}$$

in which,  $x$ , and  $f(x)$ , denote the decision variables, and the objective function of the problem, respectively.

Furthermore,  $A(x) \leq b$  describes a set of inequality constraints. The decision variables must be continuous or discrete (integer). Here,  $f$  and  $A$  can accept both continuous or mixed-integer functions of the vector of decision variables with explicit/implicit or linear/ nonlinear presentation. The type of variables and functions will then determine the name of the optimization problem (for example, a problem with mixed continuous and integer variables is called mixed-integer programming [81]).

### E. THE PROGRAMMING STRATEGIES

We categorize the programming approach for the DEP problem as the dynamic, static, and pseudo-dynamic programming.

A dynamic approach is about expansion planning decisions for multiple years in a single time snapshot.

In a static approach, a horizon time with a constant load is considered as the demand of the horizon year. In this type of programming, we do not determine the time of expansion activities by solving the problem, but we can get some useful information about the expansion requirements. The other disadvantage is that it will not give practical results for all the considered horizon time, as the results for each stage depends on the system configuration in the previous step. The other approach is to make separate decisions in each stage individually. This type of problem is named as a pseudo-dynamic problem that will optimize the problem for each stage, and put the results as the input data of the next stages. This way of programming is also called as semi-dynamic, semi-static, quasi-static or quasi-dynamic planning [35], [81].

### F. EMERGING ACTIVE DISTRIBUTION NETWORKS

Recent developments in operational controlling and monitoring schemes such as advanced control techniques, complicated information and communication technologies, along with emerging multi-carrier energy systems (MCE) and demand response programs, passive dummy distribution networks have been changed to active and dynamic systems in the form of Active Distribution Networks (ADNs). Accordingly, ADN planning (ADNP) in contrast with conventional DEP comes with new objectives and concepts [127].

Due to the low penetration rate of DERs in conventional distribution networks, coordinated planning and operation was not an obligation, and the uncertainty risk analysis was not a necessity. However, conventional DEPs conduct a fit-and-forget method based on deterministic frameworks. An ADNP shall coordinate 1) planning and operation, 2) run probabilistic planning (in replace of deterministic one), 3) integrate uncertainty risk control methods, and 4) consider multi-time resolution modelling to respond to the high penetration rate of DERs in ADNs [122]. Big data resource management may be required to deal with real-time measurement and information received by several sensors in the distribution network, weather data and consumption behaviour of customers. Generally, ADNP considers allocating new optimization framework.

## III. DISTRIBUTION EXPANSION PLANNING PROGRAMMING

### A. MATHEMATICAL VS. HEURISTIC

As illustrated in Fig. 6, we categorize the optimization methods in existing DEP literature into three groups: mathematical programming methods, heuristic evolutionary algorithms (EAs) and hybrid algorithms.

### B. MATHEMATICAL PROGRAMMING

If the decision variables are a mixture of continuous and integer variables, the optimization problem is called a mixed-integer programming (MIP) problem. Linear programming (LP) methods are dimensionally scalable, computationally tractable and robust methods [11], where the optimality of the final solution can be mostly guaranteed.

If the optimization problem has non-linear functions (as the problem constraints or the objective functions), the problem is known as non-linear programming (NLP). Such techniques are also utilized in 3DEP problems [4], [33], [74], [87].

The MIP problems with non-linear objective functions or constraints, the problem is called mixed-integer non-linear programming (MINLP) [30].

Some references have employed an Ordinal Optimization (OO) method for solving the optimization problem with minimum computational burden [2].

Dynamic Programming (DP) is another mathematical method introduced in 1950 and copiously used to solve the multi-stage power system problems. DP does not need to linearize the objective function. However, this technique has a high computation complexity for solving the large-scale optimization problem [128].

Generally, DEP is a large-scale, complicated optimization problem in which the complexity will dramatically be increased with the size of the problem [8] and take long processing time. As a remedy, researchers proposed the decomposition methods to find the optimum solution within a finite number of iterations. To reduce the calculation time, J. F. Benders proposed Bender's decomposition in 1962 [129]. The disadvantage of this technique though is the complexity of implementation [128].

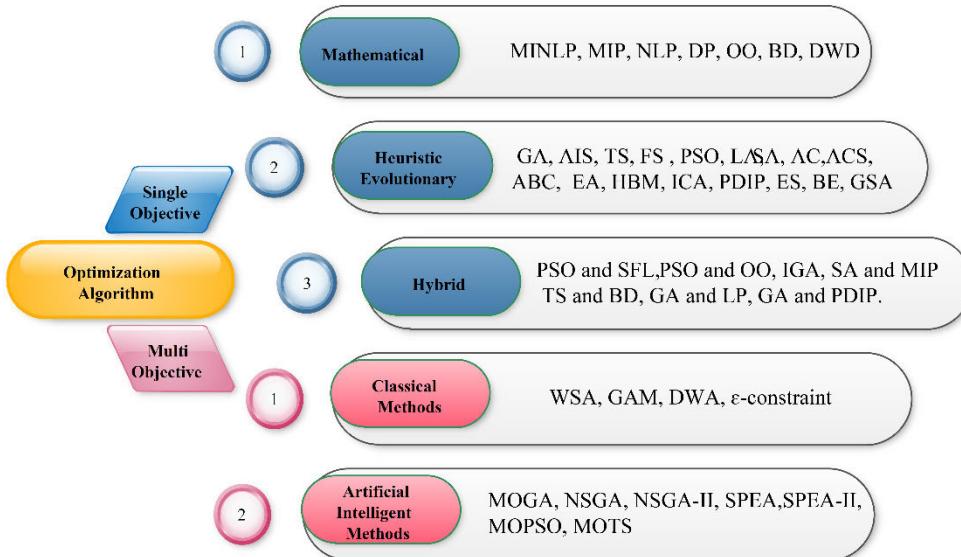
Dantzig-Wolfe decomposition (DWD) is developed by George Dantzig and Philip Wolfe to solve the LP problems with specific features known as complicated constraint problem [130]. DWD generates a problem consisting of [131]:

- ✓ A master problem (MP) to make decisions on binary variables, e.g. capacity expansions and on a base operational scheduling.
- ✓ A series of Sub-problems (SP) based on mixed-integer single period column generation

Besides, reference [132] introduced the primal-dual interior-point (PDIP) method. Also, a modified PDIP technique was proposed in [80] to decide on the size of electric vehicle charging.

### C. HEURISTIC AND EVOLUTIONARY OPTIMIZATION

Several researchers proposed heuristic EAs to optimise the complex optimisation problems directly. Besides the ease of implementation, we hardly can guarantee the global optimality of the solution. Meanwhile, the solution point is close enough to an optimum solution. Several researchers employed heuristic algorithms despite their inherent randomness [120]. The numerous heuristic evolutionary algorithms have been introduced including Genetic



**FIGURE 6.** Different kinds of optimization techniques in the DEP problem.

Algorithm (GA), fuzzy system, Artificial Immune Systems (AIS), Tabu Search (TS), Imperialistic Competition Algorithm (ICA), Particle Swarm Optimization (PSO), Learning Automata (LA), Simulated Annealing (SA), Ant Colony (AC), Harmony Search Algorithm (HSA) [125], Artificial Bee Colony (ABC), expert systems (ES), Gravitational Search Algorithm (GSA), Human Behaviour-Based Optimization (HBBO) [126], branch-exchange (BE) algorithm, etc. [133]–[142], [88], [143]–[147].

GA is an evolutionary-based method, developed by Holland in the middle of 80s and inspired by the natural selection and regeneration law concepts [133]. Compared to classical optimization approaches, heuristic algorithms (such as GA) can optimize complex and large-scale problems. Furthermore, the implementation of different types of objective functions and constraints is easily possible (no matter of being continuous, discrete, linear or non-linear). Even though GA needs high computational process and cannot ensure finding a globally optimum solution, it is applicable in the planning problem. In fact, the aim of the planning problem is to search a good solution with an acceptable optimality gap and computational tractability rather than searching a global optimum point [12], [148]. A major shortcoming of GA is that obtaining a global solution cannot be rigorously proven mathematically [13], [26], [99].

The concept of the fuzzy logic was proposed by Lotfi A Zadeh [134] to deal with uncertainty problems and soft computing. In fuzzy logic, fuzzy variables employ the membership functions to model the uncertainties by assigning a degree of membership (or truth which is between 0 and 1) [149], [150]. Researchers use fuzzy logic extensively to solve the optimisation problem in power systems. By inspiring from theoretical immunology, AIS introduced by Farmer,

Packard and Perelson [135]. In comparison with other evolutionary methods, AIS can determine a single optimal solution, as well as delivering all the local optimum points that are stored through the optimisation process [96].

A heuristic method, TS, also proposed by Glover and Hansen [136] to solve the combinatorial problem within a reasonably short time. The main advantage of this method is the need for less iteration to achieve the desired results [1], [101].

By inspiring from the imperialistic competition, Atashpaz-Gargari and Lucas introduced ICA [137]. In this algorithm, finding a global solution starts with empires competing where each empire rules by an imperialist and several colonies. The competition continues in a way that empires gradually lose their colonies, and a solution is found when a single empire survives. The corresponding colonies to this final empire gain the same cost as the imperialist of this empire [151]. The authors in [112] discussed an example of using ICA in DEP problem.

PSO is a popular population-based heuristic algorithm inspired by bird flocking and a fish schooling that at first proposed by Kennedy and Eberhart [138]. The advantage of PSO is the ease of implementation, simple conceptual structure, and less computational bookkeeping [49].

LA is adaptive decision-making machines, introduced by Narendra and Thathachar [139]. LA performs its current action according to the previous experiences from a virtual environment. By learning the way to select the best action among several actions (by repeated interactions with the environment), the performance of the LA will be improved [73].

SA is among reliable optimizer algorithms that firstly surveyed by Kirkpatrick, Gelatt, and Vecchi [140]. Conceptually, the SA is based on the annealing of the solids. The objective function is considered as the energy function, and the

optimization procedure is based on cooling strategy of a high-temperature material to freeze point and finding the global optima.

Marco Dorigo proposed AC algorithm, which is inspired by the behaviour of ants to find the nearest path from the nest to the food sources using a chemical substance called pheromone [141]. The authors in [152] extend the AC to present the ant colony system algorithm (ACS). Compared to AC, ACS shows a more reliable solution in engineering problems [91].

ABC is a population-based method that was introduced by Karaboga [142]. It is based on food (called nectar) finding a strategy of real bees and sharing the information of food sources with other members of the hive [40].

The authors in [37] proposed Honey-bee mating (HBM) method inspired by the process of marriage in real honey-bee.

The ES methods are also used in DEP problems and are based on human experience and knowledge [88], [143]–[145].

The GSA is a heuristic method proposed in 2009. It shows better results compared to GA and PSO, and it's a simple but powerful algorithm for optimization [147]. The authors in [146] developed a BE method to solve the single-period DEP, and it has been used in the past few years to cope with the complexity and time and optimal planning of MV networks [85], [77]. Besides all the heuristic methods and evolutionary algorithm mentioned above, researchers proposed novel Evolutionary Algorithms (EA) [42], [54], [94], [115], [153], [154].

#### D. HYBRID ALGORITHM

Hybrid algorithms are also proposed to solve the DEP problem by combining different techniques (PSO and OO, PSO and SFL, etc.) that could achieve better solutions with less computational burden [9], [37]. In [16], a Multi-Objective (MO) hybrid technique is proposed by using Immune GA (IGA) with the combination of a fuzzy algorithm. Fuzzy algorithm is implemented to select the best solution among several Pareto solutions. The authors in [116] present a hybrid SA and MINLP method to solve the DEP problem by considering the presence of DG units. A hybrid TS and Benders decomposition method is proposed in [114] with the advantage of combining mathematical programming and meta-heuristics techniques, and less computation time. A hybrid Decimal Codification Genetic Algorithm (DCGA) and LP method are proposed in [41] to optimize the planning of the sub-transition system. The authors in [77] also proposed a hybrid multi-objective GA and primal and dual interior point algorithm to solve a wind turbine allocation problem. Fig. 7 shows a complete list of single and multi-objective optimization methods and their citations.

#### E. MULTI-OBJECTIVE OPTIMIZATION

In many applications, there are different or conflicting objective functions to be satisfied by the optimization process. As mentioned, a DEP problem is a multi-objective (MO)

optimization problem with different goals, including minimizing investment cost, power losses, and pollution emission as well as maximizing reliability level. The MO problems will result in a set of solutions instead of one solution where each solution has some advantages compared to others [155]. Hence, the decision-maker must pick a solution as the best solution. The classical methods are the approaches to convert all the objective functions into one function to be optimized as a Single-Objective (SO) problem. In this type of methods, different objective functions may be aggregated to construct one objective function, or one of the functions is the primary objective function, and the remaining objectives are the problem's constraints. In this way, we can optimize a single objective function while all the constraints are fulfilled.

Fig. 8 shows the frequency of single and multi-objective DEP programming in different references. As noticed, SO optimization methods appeared more than MO methods, in DEP problems. Furthermore, heuristic algorithms and hybrid methods are the most and the least implemented approaches, respectively.

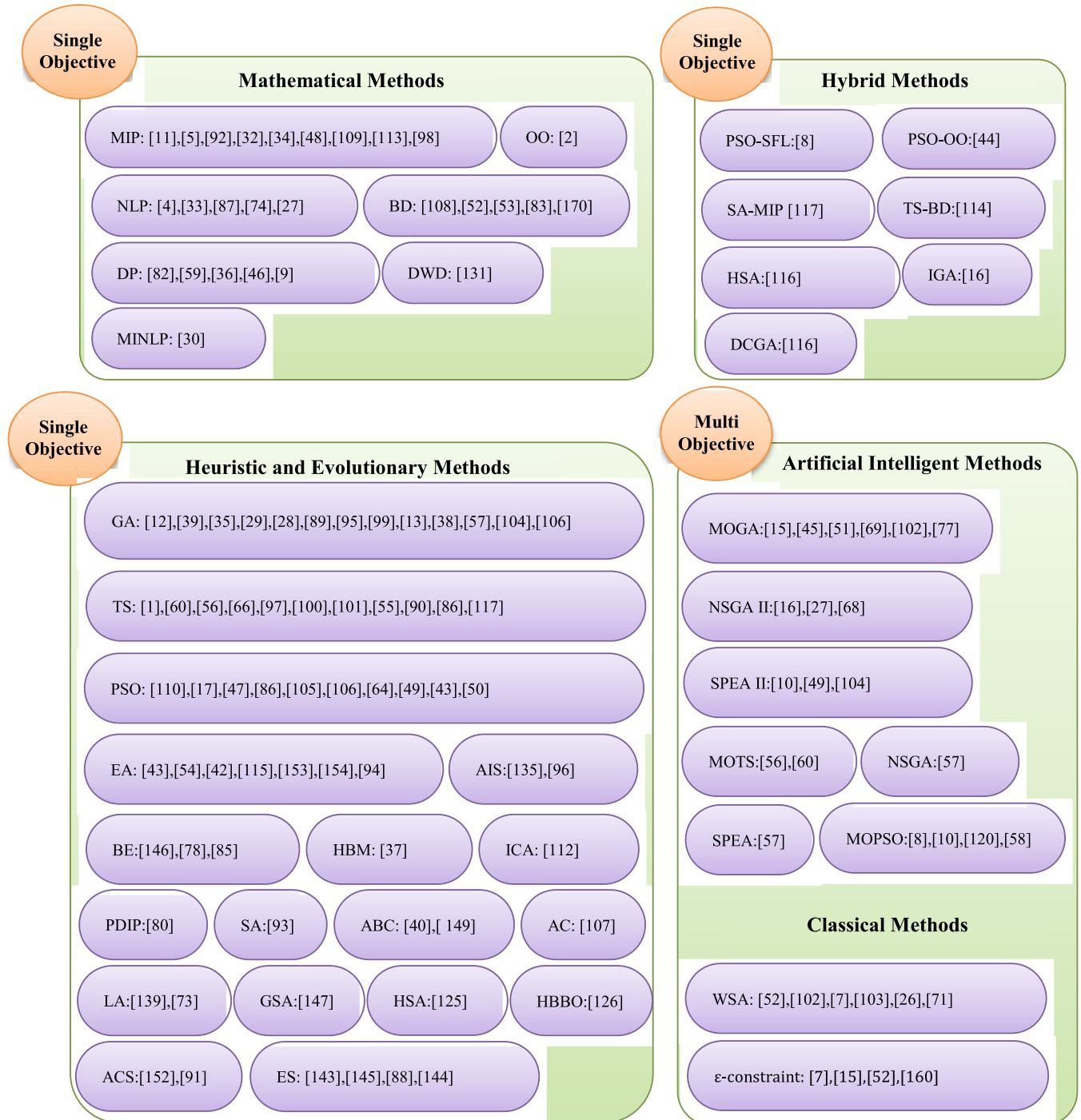
The weighted aggregation technique is one of the approaches to convert the MO problems into the SO problems using a function operator to the objective vector [7], [12], [26], [71], [102], [103]. A linear summation of the objective functions is a simple method among others. However, the main concern is the values of the weighting coefficients. Dynamic Weighted Aggregation (DWA) [156], is an augmented weighted MO method in which the weights are altered incrementally. In addition, the goal programming (or goal attainment) is a technique with the aim of minimizing the deviations from the specified goals [157]–[159].

The  $\varepsilon$ -constraint is another approach that optimizes one of the objectives, while other objectives are considered as problem restrictions bound by some allowable range  $\varepsilon$  [7], [15], [52], [160]. Such methods generate a Pareto front by running the optimization problem iteratively and renewing weights. Generally, the optimization results are local nadir points. Note that the overall efficiency of the solution highly depends on efficiency of the SO solver on the efficiency [161]. Despite their ease of implementation, their efficiency depends on the characteristics of the Pareto curve.

#### F. ARTIFICIAL INTELLIGENT TECHNIQUES

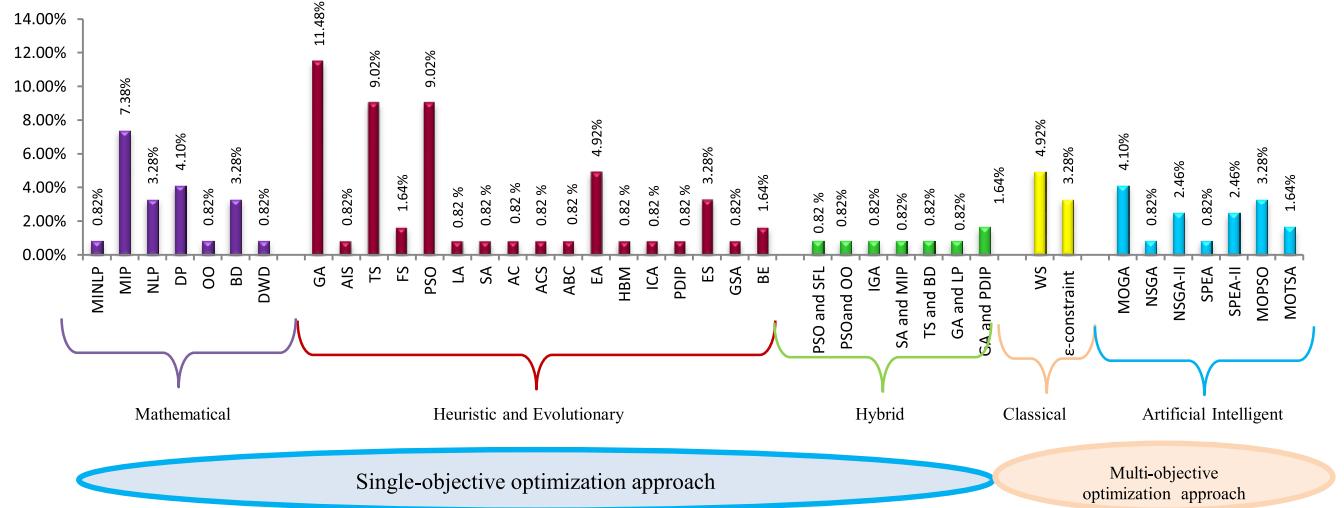
Some intelligent algorithms can directly find the Pareto solutions by simultaneously optimizing the individual objective functions. One of the advantages of the population-based methods is to evaluate multiple potential solutions in a single iteration. Moreover, such methods provide more flexibility for the decision-maker, especially if there is no information about the priorities of the decision-maker. However, one of the key challenges is the search of the optimum Pareto-front and maintain the diversity of the populations (to prevent premature convergence) [162].

Evolutionary computing is primarily proposed for the simulation of biological evolution procedures. A population is a set of individual solutions that are generated to solve the

**FIGURE 7.** Single and multi-objective optimization methods and their.

optimization problem. In each iteration, the fittest individuals are selected, and then by using some operations, the next generation (new solutions) is generated. EAs have been successfully applied to cases with complicated objectives such as discrete, non-differentiable objectives or objectives for which, no standard analytical solution exists [163].

The authors in [9], [42], [54], [153] use Pareto-ranking to determine the probability of proliferation of an individual and to find the set of non-dominated or nadir individuals in the population. They use a niching mechanism to avoid the convergence of the optimization procedure to a single region of the Pareto front. In an iterative process, the next



**FIGURE 8.** Percentage of references for single and multi-objective optimization.

generation of the population is generated based on mutation and crossover rules.

Multi-Objective GA (MOGA) is a simple and efficient method implemented by Fonseca and Fleming (1993) [15], [45], [51], [69], [102]. Non-dominated Sorting Genetic Algorithm (NSGA), is another method that utilizes a layered classification technique [57]. The NSGA introduced by Srinivas and Deb (1994) and its improved version, NSGA-II, used in [16], [27], [68]. Zitzler and Thiele's suggested Strength Pareto Evolutionary Algorithm (SPEA) approach with the combination of elitism and the concept of non-domination. SPEA stores non-dominated point during the iterations using an external archive. The authors in [57] investigate the performance of NSGA and SPEA in the planning problem of distribution systems. SPEA-II, however, incorporates density information to assign a fine-grained fitness function [49].

In the Multi-objective PSO (MOPSO) method, the optimum solutions obtained by the particles in different iterations create a set of non-dominated solutions. Since the DEP is a MO problem; numerous strategies have been introduced to specify the Pareto solutions (such as SPEA-II based MOPSO, hybrid PSO, and SFL method) [8], [10], [120], [164].

In [40], the ABC algorithm is used to solve the DEP and unit commitment problems.

TS algorithm improves the searching strategy using a memory mechanism which benefits historical records. The Multi-Objective Tabu Search (MOTS) method is presented in [56], [60] to optimize the multi-objective DEP.

#### G. DEALING WITH UNCERTAINTIES

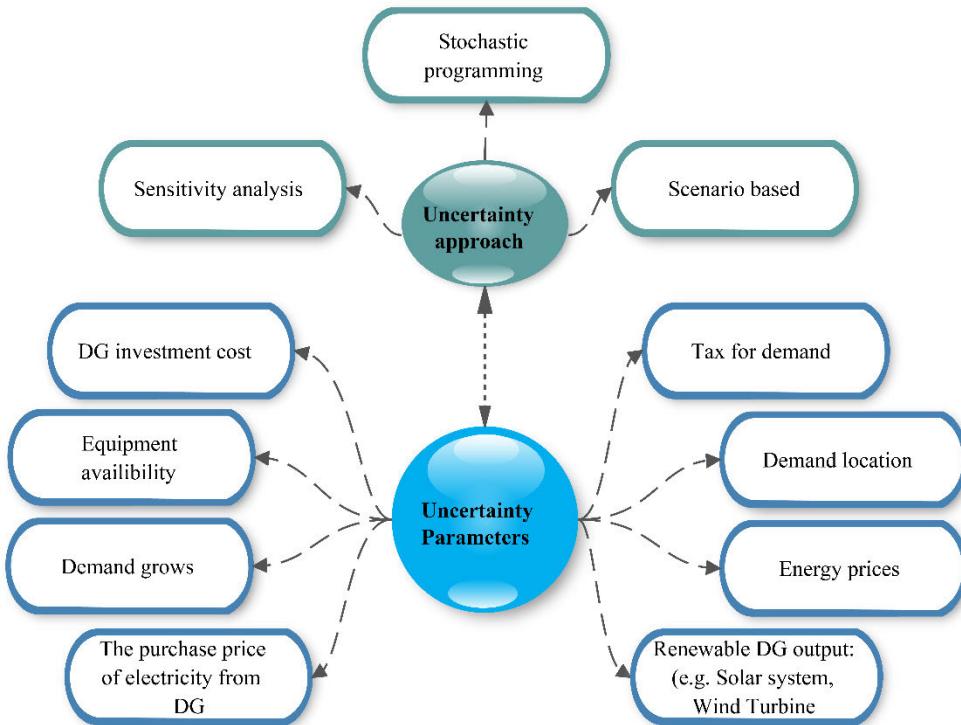
Due to the different kinds of uncertain parameters (like economic or technical; controllable or uncontrollable; non-stochastic or stochastic; and measurable or unmeasurable), the way of modelling the uncertainties is a difficult

task [81]. The main uncertainties in the DEP problem are: load level [7], [12], [13], [30], [44], [55], [96], [112], [154], the location of load points [89], [154], tax for demand [96], energy price [27], [112], price of purchasing electricity from DG [4], investment cost [154], and power supplied by DG [7], [12], [13], [26], [30], [61], [112]. The unavoidable impacts of uncertainty resources in real-world problems force planners to consider the effects of such resources in the decision making using probabilistic tools [120]. Fig. 9 lists the uncertainty parameters and Fig. 10 illustrates the frequency percentile graph of papers considering different types of uncertainty parameters. In the following, we briefly discuss several methods in the literature to deal with uncertain parameters.

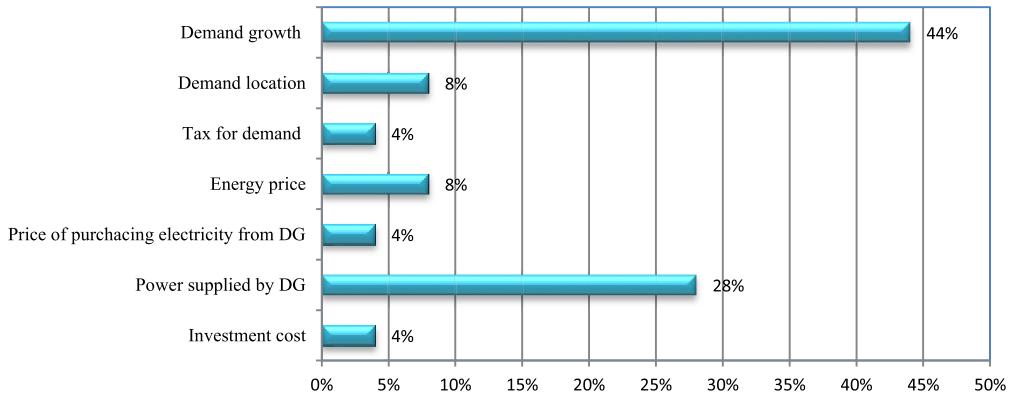
#### H. PROBABILISTIC VS. DETERMINISTIC

As mentioned, the problems with all known or specific input data are considered as a deterministic problem. In real problems, however, uncertain resources substantially impact the quality of the results. Among many methods to handle uncertainties, probabilistic methods enumerate the uncertainty parameter affecting the results by generating scenarios out of probability distribution function (pdf), which is extracted from historical data. In power system studies, we can model the uncertain parameters in wind-turbine power outputs and solar radiations by generating PDFs of these uncertain parameters.

Two main well-known methods to generate PDFs are numerical and analytical techniques. Numerical techniques estimate PDFs using Monte Carlo Simulation (MCS), and analytical ones apply arithmetic calculations on PDFs of uncertain parameters. MCS is mainly based on sample generation to mimic the long run of an uncertain parameter. In this regard, different MCS techniques use different sample generation methods such as Latin hypercube sampling



**FIGURE 9.** Uncertainty parameters and approaches for dealing with them.



**FIGURE 10.** Frequency percentile graph of papers considering different uncertainty parameters.

and Markov chain [165]. However, the main shortcoming of MCS is computational intractability in models with several uncertainty parameters due to generating numerous samples. Thanks to sample reduction methods and chance-constrained optimizations, the computational efficiency of MCS is enhanced [25].

On the other hand, analytical techniques utilize several methods to generate efficient samples such as linearization-based and PDF approximation techniques. Popular linearization techniques are convolution, cumulants, expansion of Taylor series, and first-order second-moment methods [166]. Well-known PDF approximation methods are also point-estimate and unscented transformation methods.

### I. STOCHASTIC PROGRAMMING

Stochastic Programming (SP) allocates a specific probability to a set of scenarios representing the uncertain parameter. Although scenario generation drastically considers the inherent nature of uncertain parameters, computational efficiency is reduced by the increasing number of scenarios. Researchers proposed scenario-reduction techniques to enhance tractability; to name a few, backward and forward scenario reduction, clustering methods, interval programming, Taguchi's orthogonal testing array, and in the context of DEP we can mention the works in [123], [124], [118], [167]–[173]. In [123], a framework is proposed to solve a stochastic DEP problem, and in [167], a coordinated stochastic DEP and

renewable expansion planning are presented considering demand response and storage systems. The authors consider power transfer capacity as an uncertainty resource in a stochastic DEP problem in [170]. In [118], multi-stage stochastic optimization is proposed to consider both generation and network expansion planning in a DEP problem.

### J. ROBUST OPTIMIZATION

Unlike scenario-based optimizations, where PDF information of uncertain parameter is a prerequisite, the robust optimization deals with uncertain parameters using bounded intervals. The two end sides of bounded intervals known as respective ranges are extracted based on a specific confidence interval (CI) range (e.g. 90%, 95%). Robust optimization is a PDF free scenario. However, the optimality of the worst-case solution is retained at the cost of the conservativeness of the results [174].

In [175], authors propose a robust DEP model which is adaptively adjustable to uncertainty realizations and can make optimal decisions on sizing and siting of conventional DGs and wind-based DGs with feeder installation schedules. In [121], DEP and PEV charging allocation are considered jointly in a robust optimization framework against the uncertainty of electricity demand modelled with polyhedral uncertainty set. Authors in [176] proposed resilience enhancement in a DEP problem using robust optimization and minimizing the damage to the distribution system in the face of natural disasters.

The information gap decision theory (IGDT) is a more specific feature of robust optimization which evaluates the deviations between the realizations and the approximations of the uncertain parameters. A risk-averse decision maker maximizes robustness function to decide robustly against unfavourable disparities of the uncertain parameter. Oppositely, a Risk-seeker decision-maker minimizes Opportunity function to benefit from the favourable divergence of the uncertain parameter from the expected value [177].

The method is applied to solve DEP in many papers. For instance, in [178], DEP is solved while considering uncertainties from renewable generations and load. The authors in [179] investigate voltage stability, and voltage congestion constrained problems in distribution systems with a high penetration rate of renewables using IGDT platform.

## IV. URBAN DISTRICT PLANNING

In recent years, zero energy buildings (ZEB) has been playing a significant role in performing energy management systems of distribution network, facilitating renewables integration, and enhancing energy efficiency. However, European standard EN15603:2008 recommends replacing conventional yearly weighted primary energy balance in ZEBs with finer time resolutions such as monthly or shorter time intervals for energy balance. This can be realised by accurately designing energy-efficient generation in combination with renewables, virtual and real energy storage systems, and seamless integration with heating demand to prevent localised emissions

and better air quality. In this regard, the zero-energy district (ZED) concept is proposed to spatiotemporally smooth demand and generation for augmented efficiencies in energy consumption of electricity, heating, and transportation [180]. In the last decade, district planning is increasingly adopted once we have witnessed the benefits of ZEDs. Beyond the conventional sustainability principles, district planning now includes versatile measures such as high penetration rate of DERs, ultra-low energy buildings, multi-career energy systems, district integrated heating systems and transportation. District planning starts with a district master plan including standards and guidelines for site design key urban architectural elements, allocating signage and landscaping. In common practices, however, district planning designs do not engage electric utilities and regulators in the planning process. As a result, the goal of district planning toward independency in energy procurement may conflict with that of dependencies on the local electric utilities regarding instant power balance and stability services. As a remedy, local utilities and regulators engage in developing ZED's unique operating code for the technical and regulatory solutions. In this regard, recent academic researches that consider the joint DEP and ZED planning structures are briefly discussed in the upcoming section [181].

### A. PLANNING VS. OPERATION

In the context of district planning, the primary objectives are allocating new distribution feeders optimally, upgrading existing network and siting and sizing of energy storage systems and DERs. Meanwhile, operation scheduling determines optimal generation dispatch for energizing the expected demand. The added value of integrating these two optimization problems is that the expansion planning results construct the basis of the operational problem, and day-to-year-time span operation problem will decide on installing a new component or reinforcing the existing grid. Moreover, there is an increasing tendency to encounter operational constraints for dealing with intra-hour/hourly intermittency and variability of non-dispatchable resources during expansion planning. Disregarding variability impacts may cause increased wear and tear costs owing to frequent voltage deviations on load-tap changers. From ZED point of view with almost a unique climate regime, minute time resolution scheduling may have an essential influence on operational situations. Considering the ZED requirements, the objectives are minimizing annual net electricity import, carbon emissions, system losses and voltage fluctuations. Besides, due to unbalanced low-voltage lines which in single or two phases, we require considering AC power flow in an operational model to capture reactive power changes.

### B. MULTI-MICROGRID WITH MULTI-ENERGY SYSTEMS

Microgrids, with their different scales (e.g. from a large grid size to a small aggregator), can play an essential role in constructing a self-sufficient district. However, multi-microgrids can enhance the flexibility of districts by adding the

complexity of an intermediate control layer. This flexibility can alleviate stresses on overflowed branches or overvoltage situations [182]. Moreover, multi-energy systems can add values in the context of sustainability-oriented ZED, such as reaching carbon neutrality, reduced water consumption, and energy security during high impact events [183]. Seamless integration of electricity, water, heating, cooling, and gas local networks is required to obtain a holistic approach. As stated in – an integrated power flow instead of optimal power flow should be considered. In such an operational problem, an efficiency conversion matrix is applied to replace the power balance equation and optimally schedule resources. In the literature, co-optimization of both multi-microgrids and multi-energy systems are suggested to grab the advantages of both models.

### C. DISTRICT PLANNING AND DEP

As mentioned, in a district master plan, electric utility among other serving utilities (e.g. heating-cooling, and gas) should be engaged in, to both proactively confront operational challenges and move toward high efficient energy systems. In this field, some papers consider both power system infrastructure planning and building energy management facilities such as demand response programs called a grid-to-building integrated plan. From ZED's standpoint, once the infrastructure allocation is done, finer time resolution operational scheduling problem must be carried out to analyze near real-time operation situation (e.g. enabling demand response, charging status of electric vehicle parking lots, heat ventilation and air conditioning (HVAC) optimal setpoints) [184]. In this level, power system operation information can be feed iteratively back to the building operations level. Note that in practice, building-to-grid (B2G) feedback requires installing building sensors, control devices and several communication layers to pre-processing the collected data, post-processing sensitivity and economic analyses.

### V. CONCLUSION AND SUMMARY

This paper reviews the various aspects related to DEP problem. It considers explicitly system development, the horizon of development, problem constraints, the required variable types in the planning of distributed systems, optimization algorithms, single and MO nature of the problem, as well as the uncertain variables and methods to deal with them. We discussed in detail the conflicts between district planning goals to move toward zero energy district and conventional DEP limitations.

The presented survey of the DEP problem in this paper opens new avenues for further studies in this field. DEP problems can be classified into subjects (but not limited to) objective functions, constraints, variables, and optimization methods. We presented a comprehensive literature survey (around 130 references from 1990 until 2019) and reviewed several methods and their enhancements to solve a DEP problem. We studied several optimization methods used in solving a DEP problem with different objective functions

and constraints. These important general conclusions can be made, cf. Fig. 6:

(1) Compared with AI techniques, analytical/mathematical methods yield more accurate results. However, due to the presence of integer variable and inherent nonlinearities, the conventional methods may become less efficient and demand for more computational time. In practice, AI techniques can resolve these issues.

(2) GA has been extensively used to obtain the local optimum solution (near-global solution). However, useful methods like AC have been not applied as much as GA-based algorithm in the literature of DEP. Note that Fuzzy set theory has been proved helpful to model uncertainties in DEP problems and must be investigated further in coming years.

(3) Hybrid techniques are suitable to reduce computational time in the process of searching optimum solutions a comparatively short duration.

(4) Optimization problems are mainly a tradeoff between the precision of solutions and reliability and the duration of the solving procedure.

(5) The integration of DGs with the DEP problem can provide better expansion plans that are more economical and reliable. Furthermore, due to pollution, renewable energy resources will replace fossil-based supplies.

The complexity of the distribution systems is the main DEP problem. Several constraints must be fulfilled, including power balance, voltage profiles, branches capacity, DG limits, radiality constraint, network loss, as well as pollution emissions. Therefore, the researchers divided the DEP problems into sub-parts and proposed various solutions to tackle specific problems. In any case, we must have adequate details of the DEP models to achieve a realistic solution. As the trend suggests, the future optimization problems must take into account electricity supply, the integration of RERs, and heat networks to provide more optimal solutions.

Future directions in this field can be including:

- ✓ A whole-system approach for multi-vector expansion planning of the distributed energy systems;
- ✓ Using a system-of-systems framework for coordinated expansion planning of the distribution networks with other energy distribution networks like gas distribution, district heating and cooling, traffic and water distribution.
- ✓ Application of new convexification techniques to solve the complex non-convex expansion planning of the distribution grids of the future.
- ✓ DEP with focusing on mitigating variability impacts regarding the increasing penetration rate of RES aside from uncertainty impacts while considering versatile time scales (i.e. hourly and sub-hourly time scales for operational purposes).
- ✓ Application of local energy/ reserve markets in DEP problem considering community microgrids for energy/ reserve procurement through new local settlement mechanisms.

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