Energy Syst (2018) 9:473–509
https://doi.org/10.1007/s12667-018-0276-x

ORIGINAL PAPER

Optimization techniques applied to planning of electric power distribution systems: a bibliographic survey

Mariana Resener[1] · **Sérgio Haffner**[1] · **Luís A. Pereira**[1] · **Panos M. Pardalos**[2]

Received: 12 November 2017 / Accepted: 23 January 2018 / Published online: 31 January 2018

Abstract Optimization models for the solution of planning problems related to power distribution system (PDS) have been studied and used for decades. The main objective is to optimize investments and minimize total costs, including investment and operation costs. Some of the major concerns of the short-term expansion planning carried out by utilities are high energy losses, low power factor, and inadequate voltage magnitudes. A common solution to address these concerns and improve the performance of a PDS is the installation of capacitor banks (CBs) and voltage regulators (VRs). These devices can be installed at many different points along the PDS, leading to so-called optimal CB and VR allocation problems. Another common alternative is the replacement of conductors of feeders, which leads to the problem of optimal selection of conductors. These can be viewed as classical optimization problems regarding the PDS expansion. This paper presents a comprehensive survey of the models and methods used to solve planning problems of PDS expansion, the focus being on classical optimization problems. Furthermore, models including distributed energy resources in a modern power system era are discussed, showing future research possibilities and trends.

Keywords Power distribution systems · Optimization · Planning · Capacitor allocation · Voltage regulator allocation · Optimal conductor selection

✉ Mariana Resener
mariana.resener@ufrgs.br

1 Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, Brazil

2 University of Florida, Gainesville, FL, USA

Abbreviations

ABC	Artificial Bee Colony
AC	Ant Colony
BA	Bat algorithm
BFA	Bacterial foraging algorithm
CB	Capacitor bank
CSA	Cuckoo search algorithm
DE	Differential evolution
DER	Distributed energy resource
DG	Distributed generation
DP	Dynamic programming
ESS	Energy storage systems
FPA	Flower pollination algorithm
GA	Genetic algorithm
GSA	Gravitational search algorithm
HS	Harmony search
IA	Immune-based algorithm
IHA	Improved Harmony algorithm
IMDE	Intersect mutation differential evolution
MILP	Mixed integer-linear programming
MINLP	Mixed integer-nonlinear programming
MIQP	Mixed integer quadratic programming
MS	Monkey search
NSGA	Nondominated sort genetic algorithm
OPF	Optimal power flow
PABC	Particle Artificial Bee Colony
PDS	Power distribution system
PEV	Plug-in electric vehicles
PGSA	Plant growth simulation algorithm
PS	Pattern search
PSO	Particle swarm optimization
SA	Simulated annealing
SOCP	Second-order cone programming
SSO	Shark smell optimization
TLBO	Teaching learning based optimization
TS	Tabu search
VR	Voltage regulator

1 Introduction

Planning the operation and expansion of electric power systems is essential to assure that the growing demand can be satisfied. The main objective of planning is to determine a minimum cost plan for expansion of generation, transmission, and distribution systems, in order to supply the forecasted load, considering constraints related to technical, economic, and political aspects. Strategic decisions are the result of long-term power generation expansion models [53,67,88,117]. Then, the transmission system planning determines the timing and type of new transmission facilities, which are required to provide an adequate transmission capacity considering the future additional generation power requirements [81,82,105,131]. Finally, the planning of distribution systems, closer to consumers, is also important to guarantee an economic and reliable service.

The use of mathematical optimization models for planning the expansion of power distribution systems (PDS) can help obtain an efficient and low-cost investment plan, which includes reinforcement of existing network, construction of new feeders or substations, as well as the determination of the capacity, location, and installation of new equipment. Among the main constraints to be considered are: the capacity of distribution lines, continuity indicators for distribution reliability, and the safety and reliability standards defined by regulatory agencies. The inherent characteristics of PDS, along with the aspects to be accounted for their design, requires, in general, a nonlinear optimization problem involving a significant number of decision variables (integer and continuous), which makes the problem complex [110].

The PDS planning can be divided into operation planning, short-term expansion planning (1 to 4 years), and long-term expansion planning (5 to 20 years). In order to provide a cost effective, affordable, and reliable service, it becomes essential from a strategic point of view to connect short-term investments, operation and maintenance decisions with a long-term vision [45]. Long-term expansion planing usually involves longer-term actions, such as the construction of new substations and new feeders. In contrast, short-term expansion planning usually proposes investments not requiring major changes to the network, such as the installation of capacitor banks (CBs) and voltage regulators (VRs), replacement of conductors (reconductoring), or the installation of switches.

Depending on the adopted model, the expansion planning of PDS can be carried out in a single stage or in several stages (multistage). Single-stage planning models consider that resources are applied at one specific time over the planning horizon. In multistage planning, several single-stage problems are solved and resources are distributed according to needs in each stage of the planning horizon [45,59]. Short-term planning is usually modeled through a single-stage model, which considers the immediate needs of the network.

In addition to expansion planning, PDS planning also involves the operation planning. When the operation planning is included, the objective becomes the determination of the optimal adjustment of the control variables of the network, in order to improve the performance of the system, while considering the physical and operational limits of the network [120]. Control variables include the adjustment of VRs, the number of CBs in operation, the active and reactive power injections of the distributed generators (DGs) and the voltage control at the substation bus. The operation planning can be defined as a subproblem of the expansion, since this involves the analysis of the operation of the system along the planning horizon. The diagram in Fig. 1 illustrates the information flow that occurs between these two problems. The expansion problem informs the operation problem of the investment plan to be evaluated, defining what,

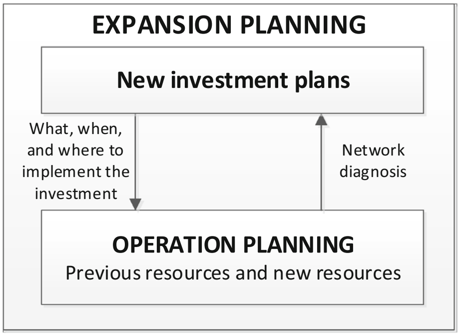

Fig. 1 Information flow between expansion and operation planning problems

when, and where to implement it. Through the solution of the operation problem, a network diagnosis is provided to the expansion problem.

Among others, the reduction of energy losses is a relevant technical aspect that has to be considered in planning studies. For distribution companies, this aspect is of special concern as it can reduce their revenues. Energy losses can be minimized through adequate investments, which from a financial point of view means making the PDS operation more efficient and more cost-effective. Yet another aspect to be included in planning studies is the operation with steady-state voltages within those ranges prescribed by regulatory agencies. In this respect, it should be observed that both distributors and consumers benefit from a suitable voltage profile, as it leads to a reduction of energy losses and to an increase in customer satisfaction with the quality of the energy being supplied. Most importantly, maintaining adequate voltage levels helps to avoid financial compensation, paid to consumers in case of inadequate service.

Distribution network planning should also consider the increasing number of DG connections, which give rise to new technical problems to be addressed by planners [32,42,76,78,111,148,149,152]. For instance, DGs can negatively impact the voltage levels of the feeders, with the extent of this impact depending on the injected power and the characteristics of the system. In case of maximum injected power and minimum load in the feeder, overvoltages can result, thus reducing the quality of the power supplied to consumers connected to the system. Furthermore, impacts on energy losses are expected, depending on the location of generators, the feeder load, and the specific control mode applied in case of synchronous generators (voltage or power factor regulation). Therefore, a big challenge for the planner consists of how to incorporate such complexities into an optimization problem to minimize energy losses [108,120].

Some of the solutions applied to achieve a reduction in energy losses and improvement in voltage profiles are:

- *Installation of CBs*: widely used to correct the power factor, reducing the reactive power flow and active power losses. CBs can be of two types: (1) fixed, which are constantly connected; and (2) automatic, which are connected according to the control type (reactive power flow, voltage or time);

- *Installation of VRs*: it is one of the most commonly used techniques for voltage control in PDS. These devices have a positive impact on the voltage profile with consequent reduction of losses [130];
- *Reconductoring or network extension*: the load growth or the end of lifetime of existing conductors may indicate the need to replace them, extend the existing branches, or even construct new networks;
- *Reconfiguration and load transfers between distribution feeders*: this is a technique widely used in the operation planning to better distribute the loads and thus reduce the losses [15,97];
- *Tap-setting of distribution transformers*: this action aims to regulate the voltage at the low voltage side of the transformer.

The minimization of losses in PDS is essentially a nonlinear, combinatorial optimization problem with the following features [155]:

- mixed continuous and integer control variables;
- nonlinear objective function and operating constraints;
- non-convex objective function and solution space;
- high-dimension optimization problem, resulting from modeling large distribution systems with a large number of buses and branches.

The installation of capacitor banks (CBs) represents an interesting initial solution to reduce losses because they cost less compared to other alternatives [8,122]. Given that CBs can be installed at different points along the network, their installation sites can be defined through the solution of the so-called problem of optimal allocation of CBs, which among others considers financial aspects. Due to its practical and technical relevance, this problem has been studied over past decades and solved using different models and methods; many of the approaches known so far have been reviewed in [8,104]. The nonlinearities arising when minimizing losses usually requires that the allocation of CBs be modeled as a mixed integer-nonlinear programming (MINLP) problem, in which the objective is to minimize the costs of energy losses and the investment [14]. Furthermore, the number of viable alternatives increase significantly with the size of the PDS, especially when different load levels and automatic CBs, along with their operation strategy, must be considered. Considering the non-convexity of optimization problems, a global optimal solution can be achieved if all of the alternatives in the search space are compared, as in the case of an exhaustive enumeration, which, however, may require a high computational processing time.

Although capacitors can contribute to improving the voltage profile at lower initial costs, these devices alone cannot provide an acceptable degree of voltage regulation in certain configurations and loading of PDS [47]. In order to keep the voltages at all buses within specified limits, it may be also necessary to install VRs. Similar to the allocation of CBs, the allocation of VRs can be modeled as a MINLP problem, where the objective function usually involves investment costs and energy losses [121]. Some methods also consider voltage deviations through multiobjective approaches [94]. Most of the methodologies found in the literature use heuristic methods to solve the problem of the allocation of VRs, using a load flow to determine the steady-state operation point.

In PDS expansion planning, the solution of the problem of selecting conductors determines for each branch the conductor that minimizes the cost of investment and energy losses, subjected to operating constraints. Several factors are included in the model of this problem, such as the lifetime of conductors, acquisition and installation costs, type of network (aerial or underground), and the estimated growth of the load. On the other hand, the problem of reconductoring deals with the replacement of conductors in existing network segments. Among the reasons to replace conductors is the violation of the current capacity, excessive active power losses, voltages below the limit stated by regulatory agencies [46], or even the improvement of the reliability through the use of insulated cables.

According to [9], the costs related to a conductor basically include two parts: the initial cost of investment (acquisition and installation) and the cost of power losses calculated over the lifetime of the conductor. In general, the required investment increases with the conductor size for a given voltage class. On the other hand, losses decrease as conductor size increases. As the costs of energy losses over the lifetime of a cable can be significant, selecting a conductor larger than required by the load can result in lower losses and, consequently, in a lower overall cost. The problem of conductor choice is usually modeled as a MINLP problem.

The solution methods applied to problems of PDS expansion planning can be, generally, divided into three categories: analytical methods, exact optimization methods, and heuristic methods. Using an exact optimization approach, it is possible to explicitly represent constraints, which together with the possible optimality guarantee makes this approach attractive [59]. In the 1980s and 1990s, heuristic methods were successfully applied to the planning of large power systems, because nonlinear constraints and nonlinear objective functions can be easily considered, even when solving complex MINLP problems. When heuristic or metaheuristic methods are used, no clear separation can be drawn between the mathematical model and the solution technique as in classical optimization. Therefore, at that time, the search for new mathematical models attracted almost no attention of researchers. However, since commercial solvers based on classical optimization techniques are now more efficient with new techniques based on modern branch-and-bound algorithms, the development of mathematical models for optimization problems in power systems has become a relevant research topic in recent years. This fact, along with the guarantee of optimality and the current processing capacity of computers, makes approaches based on mixed integer linear programming (MILP) models very attractive [47,55,119,120].

The planning actions can be considered isolated or simultaneously in the optimization models. When considered simultaneously, a better solution can be obtained, since important benefits can result from the joint operation of equipment and control variables. On the other hand, the formulation can become computationally unmanageable as the number of variables and constraints can be significantly large, especially in the case of exact optimization methods. Yet, when using heuristic methods, the solution can represent a local minimum. Obtaining an exact method capable of dealing with all control variables, without excessive simplifications, still represents a challenge.

In this paper we survey models and methods proposed to solve PDS expansion planning problems; we mainly focus on works that include the optimal allocation of

CBs, VRs, and the optimal conductor selection in the context of distribution networks. In addition, models including distributed resources, such as energy storage, DGs, and demand response, are discussed, showing future research trends. We aim to provide a starting point and a handy resource, which summarizes the most relevant publications related to models applied to the planning of PDS. Toward this end, we summarize the contributions of each article, so that researchers can easily identify relevant references to their own research field.

The main contributions of this paper are:

– a comprehensive survey of the literature including optimal allocation of CBs, VRs, and optimal conductor selection in the context of distribution networks;
– a comparative table including the contributions of each work;
– a discussion about future research trends including distributed energy resources.

2 Allocation of capacitors and voltage regulators

Due to its practical and technical impact, the problem of optimal CB allocation has been studied for decades, with a great number of papers being dedicated to this topic. On the other hand, the problem of optimal VR allocation has been the subject of relatively fewer published works. This section reviews the most relevant papers on these two subjects.

2.1 Capacitor allocation

Given that computational resources were expensive or even unavailable, the first papers published on this topic presented analytical methods for the solution of optimal allocation of CBs in PDS. One of the first approaches to this problem was presented in [103], where the authors determined the location and size of fixed CBs which minimized the losses for a given load level. The results were based on a model of the system assuming a uniform load distribution and one conductor type while neglecting the voltage drops and the cost of capacitors. This work also introduced the “2/3-rule”, stating that the power of the capacitor has to correspond to 2/3 of the total reactive power of the feeder and be installed at 2/3 of the distance from the substation to the end of the network. This method is very simple and valid only when the same assumptions can be made. In some cases, as in the example presented in [85], the application of this rule can even result in financial losses if a more realistic distribution of the reactive load is assumed along with conductors of different size.

The effects of fixed capacitors on distribution networks were analyzed in [29] considering load variation. In [30], switched capacitors were considered and this work was later extended in [127]. Analytical methods are simple to apply [61], however, most of them consider the nominal power of CBs as a continuous variable, rounding being necessary to obtain a feasible solution, which can lead to significant differences in the value of the objective function. The method proposed in [29,30] was generalized in [57] to include radial systems, conductors of different size, and loads unevenly distributed.

For methods based on exact optimization, the mathematical problems are formulated so that it is possible to solve them through numerical algorithms. With the availability of advanced computational resources, these methods have gained attention. The approach followed in [14] used a MINLP model to solve the problem of optimal allocation of fixed and switched CBs, considering the variation of load through different load levels. The objective was to minimize active power losses while assuming voltage constraints. The problem was divided into two hierarchical levels: master and slave. The master problem consisted of an integer programming problem and was used to determine the number and location of CBs. The slave problem was used by the master to determine the type and size of the capacitors to be installed. Later, in [21,22] the method presented in [14] was extended, considering that the cost of CBs is represented by a non-differentiable function, since CBs are allocated in groups of defined sizes, and the nominal power and control settings are treated as discrete variables. In nonlinear programming, the objective function is usually approximated by a differentiable function, since this makes the solution easier. In contrast, the formulation proposed in [21] used simulated annealing (SA) to solve the same problem.

Using the model proposed in [21], the problem of optimal allocation of fixed CBs was solved through a genetic algorithm (GA) in [16]. According to the authors, GA does not require a differentiable objective function. GA was also applied in [140] to minimize the costs related to (i) peak power losses, (ii) energy losses, and (iii) installation of CBs. First, using a method based on sensitivity analysis, the potential buses for the installation of CBs were selected, and then the capacitors were specified through GA.

Ng et al. [104] reviewed the evolution of researches regarding the allocation of CBs in PDS published until the year 2000, classifying the solution techniques into four categories: analytical programming, exact optimization (named *numerical programming* in the paper), heuristics, and based on artificial intelligence. The paper described some of the techniques mentioned, helping researchers and engineers to find the best suited technique according to the topology and size of the PDS, the desired accuracy of the results, and the available data.

A hybrid method based on the tabu search algorithm (TS) was proposed in [48], using characteristics of GA and SA, besides sensitivity analysis. The objective function included the cost of losses for each load level and the cost of the capacitors, through a non-differentiable function. The algorithm is divided into three phases. The first phase generates the initial configurations, using a constructive heuristic algorithm, to obtain the options that serve as the basis for the next phase. The second phase uses TS to search for the optimal solution.

Chiou et al. [24] introduced a heuristic method based on differential evolution (DE) and ant colony (AC) algorithms. In this method, the search concept of the ant colony is used as a mutation operator to accelerate the search for the optimal solution. The objective function considered the minimization of costs of active power losses and acquisition of capacitors, as well as constraints to keep the bus voltages within limits. However, only fixed CBs and a single load level were considered. The method was tested using data of systems with 9 buses, 33 buses, 66 buses, and 132 buses. The results were compared with methodologies that employ hybrid evolutionary algorithms without mutation operator, verifying a better computational performance with the proposed method.

Milosevic and Begovic [96] proposed a multiobjective approach to find optimal locations of CBs in distribution networks, solved through a nondominated sorting genetic algorithm (NSGA). The authors considered as objectives the minimization of (i) the deviation of bus voltages with regard to the substation voltage; (ii) active power losses; (iii) total active power demand at the substation through the voltage control, considering loads with voltage-dependent characteristics; (iv) costs of acquisition, installation, and maintenance of CBs. The method was tested on a 69-segment feeder, in which 10% of the loads were assumed to have constant power behavior and 90% constant impedance behavior. For the cost-benefit analysis of installing capacitors, the authors considered the volatility in energy prices.

A method was proposed in [20] to solve the problem of optimal reconfiguration of distribution networks and optimal allocation of CBs through an AC search algorithm. The results showed a greater loss reduction when both reconfiguration and CB placement are simultaneously considered. Furthermore, the method performed computationally better compared with GA and SA.

In [35] a particle swarm optimization (PSO) algorithm was applied to solve the optimal CB allocation problem. The method was based on a power flow algorithm considering harmonics in conjunction with the discrete PSO algorithm, thus leading to a hybrid algorithm. The objective function consisted of the minimization of the costs of power losses and investment in CBs. The active power losses were obtained from the fundamental component of the losses and accounting for harmonic components. Different solutions were obtained when considering or not the presence of harmonics. The authors concluded that it is necessary to include the harmonics into the model of the allocation problem to avoid problems resulting from excessive harmonic distortion. In addition, this method requires a more detailed model of loads, making its application difficult in some practical cases.

El-Fergany [37] presented a method based on the DE and pattern search (PS) algorithms. The objective function considered (i) the improvement of the voltage profile, through the application of constraints on bus voltages, (ii) the reduction of power losses in lines, and (iii) the maximization of net savings with the installation of reactive power compensation. To reduce the search space, the method identifies potential buses for the installation of capacitors by calculating a loss index and/or sensitivity factors. The loss index is calculated by comparing the results of load-flow for a given feeder without CBs with corresponding results including total compensation of the reactive part of the load at each bus. The sensitivity factors of the network branches are calculated to predict the bus with the greatest impact coming from reducing losses and reactive power compensation. The main advantage of the method is that only a few parameters have to be adjusted, making it attractive in terms of computational implementation; in addition, it can be easily applied and adapted to radial systems, too.

Based on the simulation of the intelligent reproductive behavior of cuckoos, the cuckoo search algorithm (CSA) was applied to solve the optimal CB allocation problem in [38]. The most suitable buses for the installation of CBs are initially identified through the calculation of a loss index. The objective function considered the minimization of losses and the costs of acquisition, installation, and maintenance of capacitors. Penalties are applied when constraints are violated; the objective function contains such constraints to ensure that the solution remains inside the feasible solutions space. The method was tested in some distribution systems with different loading levels, with the results indicating that the CSA algorithm is robust and performs well. The author concluded that the proposed method is competitive with other heuristic methods, although presented a longer computational time.

The method proposed in [39] used the artificial bee colony (ABC) algorithm. The objective function considered investment costs in equipment, costs of losses, and a voltage stability factor. The loss sensitivity factors are calculated to determine candidate buses for capacitor installation, thus reducing the search space. Fixed and switched capacitors were considered, with load variation represented by defining different load levels. Distribution systems with 34 buses and 118 buses were used in the tests. The results of the proposed method surpassed the results of other methods in terms of solution quality and computational performance.

A heuristic method to allocate CBs was proposed in [40], where the candidate buses are initially chosen through the analysis of loss sensitivity factors and a voltage stability index. The voltage stability index identifies the most sensitive bus regarding a voltage collapse, while the loss sensitivity factor indicates buses leading to the greatest loss reduction resulting from reactive power compensation. Then, a modified PSO algorithm was used to allocate and determine the nominal power of the capacitors. The objective was to minimize active power losses and investment, as well as improve the operation with respect to the static stability limit. Fixed as well as switched CBs were considered. The authors found that the results obtained are better in comparison to other heuristic methods analyzed in terms of the quality of the solution and computational efficiency. The main advantage of the proposed algorithm is that no adjustment of control parameters is required, in contrast to GA, PSO, and other evolution algorithms.

In [107] the problem of optimal allocation of CBs was solved using a MINLP model. The authors claimed as advantages of the approach (i) the application not only to radial but also to meshed networks, (ii) the easy implementation and achievement of a solution, (iii) the solver is able to determine the optimal solution in a reasonable time. However, the model excluded switched capacitors. Radial systems with 10, 34 and 85 buses, as well as a meshed system, were used in the tests. The results obtained with the proposed method were compared with other methods, presenting better results with respect to the minimization of losses and costs.

In order to minimize energy losses, in [66], the bat algorithm (BA) and the CSA were used to solve the problem of optimal allocation of fixed and switched capacitors. Both methods were tested on two distribution systems, with 34 and 85 buses, and the results compared with similar results obtained with equivalent methods such as AG, teaching learning based optimization (TLBO), and plant growth simulation algorithm (PGSA). According to the authors, their methods can outperform similar methods in terms of solution quality.

In an attempt to reduce the search space, Shuaib et al [132] proposed the use of sensitivity analysis, where the nominal power of the capacitors was determined using the gravitational search algorithm (GSA). The authors found that with the GSA algorithm it is possible to determine the optimal solution of optimization problems through the movement of agents based on the gravitational force. The results were compared with other methods, such as PGSA, direct search (DS), and TLBO. The proposed method presented better results regarding the reduction of costs achieved in the optimal solution.

The formulation presented in [31] used a loss sensitivity factor and voltage stability index to solve the problem of optimal allocation of CBs. The nominal rating of CBs was selected through the bacterial foraging optimization algorithm (BFOA), aiming to minimize energy losses. In this work, loads were modeled as having constant power. Furthermore, the authors considered the load varying linearly from 50 to 160% of the nominal value, in steps of 1%, to evaluate the impact of load variation on capacitor allocation. The results obtained were considered of higher quality, compared with equivalent results obtained with methods based on MINLP, PGSA, PSO, and heuristic strategies.

In [23] a hybrid method based on CODEQ was proposed to solve the problem of optimal allocation of CBs. The objective was to minimize costs related to investment and energy losses. CODEQ is a meta-heuristic algorithm based on concepts of chaotic search, opposition-based learning, differential evolution, and quantum mechanics. The method requires a large population, this being its main drawback. Thus, to overcome this difficulty, the authors proposed acceleration and migration operations with CODEQ. Such operations increased the speed of convergence without reducing the diversity among individuals.

Duque et al. [34] outlined a method for optimal allocation of fixed capacitors in PDS using the monkey search (MS) algorithm. This algorithm is based on the behavior of monkeys looking for food in a forest. The objective function considered the costs of power losses and investment in capacitors. The algorithm proved robust and efficient when applied to test cases; in addition, its computational performance was considered satisfactory.

In [84] a method was presented that applies PSO approaches with operators based on Gaussian and Cauchy probability distribution functions, besides chaotic sequences. In the traditional PSO algorithm, a uniform probability distribution is used to generate random numbers. However, the authors showed that the algorithm performs better and local minima can be avoided when alternative probability distributions are used, which is the main contribution of the paper.

Muthukumar and Jayalalitha [100] conceived a method to minimize losses and improve voltage levels through the optimal allocation of DGs and CBs. Using harmony search (HS) and particle artificial bee colony (PABC) concepts, the authors defined a new hybrid algorithm. This hybrid algorithm handles the allocation and sizing of DGs and CBs, while the candidate buses are determined through a loss sensitivity factor. Yet another method to allocate both DGs and CBs has been proposed in [75], using the intersect mutation differential evolution (IMDE) algorithm. The objective function considered the costs of power losses and investment in CBs and DGs.

Loss sensitivity factors were applied in [3] to identify candidate buses for capacitor installation. With a set of candidate buses defined, the flower pollination algorithm (FPA) was then applied to allocate and choose capacitors. As its main advantage, FPA requires only one key parameter to be adjusted, which makes its implementation simple. This parameter switches the type of pollination from local to global (and converse), thus avoiding local minima. The objective function considered the costs of investing in CBs and the costs of power losses.

In [7] an improved harmony algorithm (IHA) was applied to solve the problem of optimal CB allocation. Initially, a loss index is used to identify suitable candidate buses to receive CBs. The IHA is then applied to allocate and choose the capacitors. The IHA algorithm is inspired by the improvisation ability of musicians. The objective function considered the costs of power losses and investment costs. Systems with 15, 69 and 118 buses were used in the tests and the results were compared with other methods. The solutions obtained through the proposed method showed more attractive.

Karimi and Dashti [71] presented a methodology for optimal allocation of CBs in PDS, where the objective function included the cost of (i) active and reactive power losses, (ii) capacitors, and (iii) penalties for violation of voltage limits. The optimization problem was solved using a PSO algorithm with three different objective functions considering: (i) only the cost of active power losses, (ii) active and reactive power losses and the costs of CBs, and (iii) the same objective function proposed in the paper. The authors concluded that the third objective function resulted in greater benefits to the distribution company.

Also to solve the problem of optimal allocation of CBs, Gnanasekaran et al. [54] used the shark smell optimization (SSO), an algorithm based on the hunting behavior of sharks. The objective function considered the minimization of energy losses and the costs of reactive power compensation. The proposed methodology was tested using data from systems with 34 buses and 118 buses. The results showed superior in comparison to the results obtained using the GSA, CSA, HSA and ABC algorithms.

The method proposed by El-Ela et al. [36] used the loss sensitivity analysis to determine the potential candidate buses, and the AC optimization algorithm to allocate and choose the capacitors. The objective function considered the minimization of energy losses and investment costs in capacitors. The method considered fixed as well as switched capacitors and used results from a load flow based on an iterative sweeping method. The method was tested using data from systems with 34 and 85 buses, as well as data from a real Egyptian system. The results obtained using the proposed formulation were compared to methods that use the algorithms PGSA, PSO, GA, and DS. The authors verified better results with the proposed method.

A hybrid method based on TS and GA algorithms was proposed in [112] for the simultaneous allocation of CBs and DGs, considering the stochastic nature of DGs with renewable energy sources. Different types of DGs were modeled: (i) with control over the dispatch of active and reactive power; and (ii) with stochastic behavior, in which the active power is dispatched and the control over the reactive power is performed through the control of the power factor. A probabilistic approach was used to determine the dispatch of renewable energy sources with stochastic behavior. Initially, CBs and DGs are installed and the type of generators are defined through TS. Subsequently, the Chu-Beasley GA is used to solve an optimal power flow (OPF) thus determining the dispatch of DGs, as well the types and operation scheme for automatic capacitors. The results indicated that the point of operation of the system is affected by the operation mode of DGs and that, in addition, large voltage variations can result.

In [119] a MILP-based approach was proposed to optimize the volt/var control and minimize energy losses in PDS with DGs. The objective function aimed at the minimization of (i) energy losses, (ii) voltage violations, and (iii) acquisition, installation and maintenance costs of capacitors. Fixed and switched CBs were considered, along with the possibility of optimizing the operation point for DGs. In this model, loads and sources were represented by injections of current at the nodes, and CBs were represented as constant impedances through a disjunctive formulation. Voltage violations were handled by the inclusion of auxiliary variables together with linear constraints. The authors compared the results to those obtained through exhaustive enumeration based on the solution of a nonlinear load flow; this comparison revealed a very good agreement.

Ramadan et al. [116] solved the optimal CB placement in PDS with wind turbine generators using PSO technique. The objective function included the annual net saving and the cost of power losses resulting from the reduction of peak power losses, besides the total cost of CBs. According to the method proposed, when a given capacitor was not able to regulate the voltage magnitudes within specified limits, the authors applied a penalization.

A hybrid heuristic search algorithm was conceived by Muthukumar and Jayalalitha [101] to solve the optimal allocation and sizing of DGs and CBs, where the network could be reconfigured. The hybrid formulation combined HS and PABC algorithms, taking advantage of the best features of both algorithms. Moreover, loss sensitivity analysis is used to identify the most sensitive nodes regarding the installation of CBs, thus reducing the search space. Different voltage-dependent load models were tested to evaluate their influence on the optimal CB allocation. The author found that different load models lead to very different solutions.

2.2 Voltage regulator allocation

This section is dedicated to reviewing the most significant publications addressing the problem of allocation of voltage regulators. This type of problem can be stated and solved alone or in connection with the problem of allocation of capacitor banks, increasing the search space and the complexity of the problem.

Safigianni and Salis [121] defined a recursive procedure to determine not only the optimal placement of VRs but also the best tap position for the regulators in large radial distribution networks. After determining the initial number and location of the regulators, the objective function is evaluated to reduce, if possible, the number of VRs initially proposed and thus achieve a more economical solution. Furthermore, the objective function accounts for the costs of investment and energy losses. The algorithm was tested using data from a real distribution system with 229 buses, showing itself to be fast and efficient in defining the VR installation site and the tap setting.

The VR optimal allocation problem was defined as a multiobjective optimization problem by Mendoza et al. [94], where the authors considered the minimization of both active power losses and voltage violations. The problem was solved using a micro-genetic algorithm, searching for optimal Pareto solutions. Later, Mendoza and Pea [95] extended the method presented in [94] to evaluate the effects of the hourly load variation on the optimal placement of VRs. The objective function considered the losses and the voltage drops through weighting coefficients, in order to determine the relative importance of each objective. The problem was solved using GA and the objective function calculated using a load flow based on the Newton–Raphson method for each hour of the daily load curve of the feeder. The method was tested on a real system operating at 23-kV voltage and extending over 70 km. The results indicated that the optimal location of a VR depends on the load. To assist in decision making, the authors proposed an index defined as the sum of the values of the objective function for each hour of the day. This index is used to compare the results obtained for each hour. The authors found that the allocation of VRs based on an average load demand is a good criterion for selection, useful in situations where fast simulations are required.

In [77] a method was proposed to place VRs in PDS with DGs. The assumptions made were: the load at each bus of the system is known and represented as constant power; the power and location of each DG are known; the DG is modeled through a power injection with unity power factor. The objective function considered only voltage level violations. The problem of the allocation of VRs was solved using GA and tested on a 32-bus system with photovoltaic generation. The results showed how variations in the power injected by DGs influences the voltage profile of the system; the results also highlighted the importance of proper adjustments of voltage-regulation devices when DGs are connected to a feeder.

Pareto optimal solutions for the optimal VR allocation in PDS with DG were obtained by Niknam et al. [106] using a multiobjective approach based on a fuzzy adaptive PSO algorithm. The objective function included the energy price of the DGs, the power losses, and the voltage deviations with respect to a reference value. The proposed formulation was tested in a system with 70 buses, presenting better results when comparing with those obtained through AG and PSO algorithms.

A multicriteria model for the allocation of VRs in distribution networks was presented in [87]. The model took into account technical, regulatory, economic, and social criteria to evaluate the benefits coming from the installation and operation of VRs. The criteria are related to the number of transformers in a given region, the number of complaints about voltage level, the number of consumers served in the region, and the total energy consumption. For instance, the energy consumption criterion assumed that the benefit obtained from the installation of a VR increases with the energy consumption. To solve the multicriteria ordering problem, the authors used the Additive-veto Model; this model aggregates into a global value all evaluations of the alternatives for each criterion. This methodology was tested in a system that considered several substations, determining the prioritization of investments.

2.3 Capacitor and voltage regulator allocation

This section reviews the most relevant publications on the allocation of voltage regulators and capacitor banks simultaneously, which can lead to better results compared to the case where either capacitors or voltage regulators are considered as a separate problem.

Grainger and Civanlar [56] conceived a formulation for the voltage and reactive power control (volt/var) in radial PDS, with the problem of optimal CB placement decoupled from that of VR allocation. However, both problems aim to minimize peak power losses and energy losses, while keeping bus voltages within specified limits with varying loads. The algorithm solving the proposed model was described in [26], whereas the numerical results of the tests were given in [27], which also assessed the effect of reactive power compensation and voltage regulation in the reduction of the peak power losses and energy losses.

Concerning radial PDS, Abdelaziz et al. [2] proposed two methods to improve voltage profile and minimize energy losses. The first method dealt with the problem of capacitor allocation, where a specialized fuzzy-logic system was used to select candidate buses, in order to minimize losses and maximize net savings. The second method solves the problem of VR allocation, where a heuristic method was applied to determine the location and tap position of VRs to minimize losses and maintain voltage magnitudes within specified limits. The two problems were solved separately, and the allocation of VRs considered that the reactive power balance of the system is optimally achieved using alone CBs. The results showed that, compared to the allocation of CBs only, the installation of VRs can help reduce energy losses and improve the voltage profile.

In [156] a hybrid optimization method based on AG and discrete PSO was used to optimize the operation of both VRs and capacitors, and define the optimal voltage at the substation bus. Furthermore, the method considered the optimal allocation of CBs and VRs. The objective function considered the costs of power losses in the lines and the peak power losses, in addition to the investment and maintenance costs of equipment. However, the study neglected the presence of DGs. The results illustrated that the most economical planning solution is obtained when simultaneously considering CBs, VRs, and voltage control at the substation bus.

A method for simultaneous allocation of CBs and VRs was proposed in [141], using AG and OPF. The allocation method is based on GA, and then OPF is used to optimize the tap setting of VRs, to maintain the bus voltages within the limits specified by the GA. The objective function considered the annual costs of energy losses, violations of voltage levels, violation of the maximum allowable voltage drop, and equipment costs. On the other hand, the costs are evaluated for different load levels, including light, medium, and heavy loads. According to the results, the best solution in terms of total cost is obtained when CBs and VRs are allocated simultaneously. Compared to the allocation of only VRs, this solution led to a smaller investment along with lower of energy losses.

A MILP model was presented in [47] to solve the optimal allocation of VRs and CBs in PDS with DG. The steady-state operation point is obtained through a linear model, where loads are represented as constant active and reactive power. The objective function considered the annual costs of investment and the annual costs of losses. The optimal allocation of CBs and VRs was also modeled as a multiobjective optimization problem, with one objective being associated with the total annual cost (investment and operation), and the other associated with the maximum deviation of the voltage magnitudes. Additionally, the authors proposed a heuristic method to obtain the Pareto front.

Ahmadi and Marti [5] presented a formulation for optimization of PDS, considering automatic CBs and VRs as control variables, as well as the possibility of network reconfiguration. A linearized power flow [92] was used to determine the steady state operation point, while the optimization problem was formulated as a mixed integer quadratic programming (MIQP) model. The authors concluded that the optimal control of VRs and the installation of CBs at optimal locations significantly improves the system performance regarding losses and voltage profile.

3 Models for power distribution planning

Several works can be found in the literature on the problem of planning the expansion of PDS. In [18,50,68,74,134,145] reviews of the models and methods applied to the solution of this optimization problem were presented. In [51] a review was also presented, focusing on works that consider modern PDS, i.e. those containing distributed energy resources. The authors presented an overview of articles published after the year 2005 together with a classification of the models according to the voltage level of each system (low voltage and medium voltage), number of planning stages (single stage or multistage), decision variables, and objective function.

One of the relevant problems related to the planning of PDS is the optimal selection of conductors. Thus, several approaches have been proposed to solve this problem based on different models, the most commonly used being the MINLP model. One of the first models was presented in [115], which considers the costs of energy losses, the costs of voltage regulation, and the cost of feeders as a function of the conductor size; the thermal capacity of conductors, however, was disregarded. To solve the problem, the authors used dynamic programming. Also in the year of 1982, Sun et al [139] presented a methodology for long-term planning to determine substation sites and feeder routing using a branch-and-bound algorithm. In the same line, El-kady [41] proposed a method for optimal planning of subtation and primary feeder using MILP.

In [123] a heuristic method to define a reconductoring plan in a long-term planning horizon was proposed, considering an annual load growth. The objective function considered the annual cost of energy losses plus the cost of investment and maintenance of conductors. Tested on a real system, the method led to interesting practical results, indicating that the economy coming from loss reduction could be greater than the investment. However, the reconductoring alone was unable to improve the voltage drops appearing in the fourth year of the planning horizon; solving problem would require additional means, such as the installation of VRs and CBs.

A heuristic method was proposed in [150] to solve the optimization problem of determining the conductor size for a given system topology. This formulation considers only a single load level (peak) over a planning horizon of one year. Further, this method used a selection process taking into account economic criteria, followed by technical criteria using a sensitivity index to ensure that bus voltages are within prescribed limits. Applied to large systems, the proposed method presented a good computational performance.

A MILP-based approach for the dynamic planning problem of PDS with DGs was proposed in [59,60], where loads were modeled as constant current injections. The expansion alternatives evaluated by this method included the installation of new feeders and substations, the use of DGs, in addition to the installation, replacement or removal of network branches. The objective function considered investment and operation costs. The investment cost, given by the cost of expanding the system, is determined at the beginning of each stage of the planning horizon. On the other hand, the operation cost corresponds to the annual costs of operation and maintenance of the networks, the energy not supplied, and the energy supplied by DGs.

In [72] a method for solving the problem of conductor selection was proposed. Initially, economic criteria are considered, determining the type of conductor that should be used in each branch of the network. In a second step, a systematic enumeration process based on logical rules is used to determine the best alternative. The objective function considered the costs of conductors and the present value of the cost of losses (power and energy), considering the effect of load growth and the diversity of load peaks along the feeder. The results showed that neglecting the load diversity, some conductors can be oversized.

Franco et al. [46] established a MILP model to solve the problem of optimal conductor selection in radial distribution networks. The steady-state operation point was calculated through linear expressions, considering that the loads are modeled as 100% constant power, in the same way as in [47]. The objective function took into account investment costs (installation or replacement of conductors) and operating costs (losses).

In [44] a method was presented to solve the reconductoring and optimal CB allocation problems using GA. The objective function considered the investment costs of capacitors and conductors, besides the costs of energy losses over the planning horizon. The model contained the following constraints: limits for voltage harmonic distortion, capacity of conductors, and bus voltages magnitudes. The model was applied to an existing system and taking into account different scenarios: allocation of CBs only, reconductoring only, allocation of CBs and reconductoring simultaneously. The results showed that the harmonic content was confined within acceptable limits in all scenarios; therefore, it could not be taken as a criterion for comparison. Furthermore, the method proved effective concerning the minimization of losses.

In the model presented in [79], the PDS planning was solved considering the presence of wind power generation and the possibility of voltage and reactive power control through DGs. The model is formulated as a MIQP problem, where the investment alternative is represented by the replacement of conductors, with the conductor selection occurring under two different conditions: maximum load and minimum generation, and minimum load and maximum generation. The model was validated using data from a system with 18 buses and two wind farms, each one with 4 MVA.

A multistage model for solving the PDS expansion planning problem was presented in [89]. In this work, the objective function to be minimized was defined by the net present value of the sum of investment, losses, operation, and maintenance costs. The model also included the possibility of addition, reinforcement or replacement of feeders and substations. A piecewise linear function was used to linearize the objective function that was originally nonlinear, and the optimization problem was solved using mathematical programming. The results consisted of a set of solutions, a reliability index and the corresponding costs being calculated for each solution. In order to validate the model, several simulations were performed using data from a system composed of three substations.

The back propagation algorithm was used in [64] in a multistage approach. The allocation of DGs, the construction of substations and feeders, the increase of existing substation capacity, and reconductoring constituted the expansion alternatives of the model. Initially, the expansion alternatives are selected, then the time schedule for the investments are defined according to the planning horizon. A MILP model was used to solve the first step, whereas losses are estimated using a loss factor determined at the beginning of the optimization process. The objective function is defined by the net present value of the total investment and operating costs. Systems with 32 buses and 69 buses were used in the tests to demonstrate the validity of the model.

In [113] the TS algorithm was applied to solve the problem of planning PDS in several stages for a 54-bus distribution system. The model was formulated as a multiobjective MINLP problem, in which the objective functions considered investment, operation, and reliability costs. Reliability was assessed through the cost of the energy not supplied due to permanent failures in the network. The authors defined the following alternatives for the expansion: a capacity increase of existing substations, construction of new substations, conductor replacement, construction of new feeders, reconfiguration, and installation of switches.

A multistage model to solve expansion planning problems related to distribution networks was presented in [6]. Allocation of DGs along with upgrading of existing networks were integrated into the model. Further, the authors designed a heuristic method to minimize the possible load shedding, in this way optimizing the system reliability. Investment and operating costs were defined as the objective function. The authors also proposed an evolutionary algorithm, called binary chaotic shark smell optimization, to solve the optimization problem.

In [4] a heuristic method for optimal conductor selection in PDS was proposed. According to this method, in a first step the conductor is selected, and in a second step the voltage violations are evaluated and the conductor modified, if necessary. The objective function is composed of the investment in conductors and the costs of energy losses, with a load flow used to evaluate the alternatives. The results demonstrated that the approach is able to provide good solutions in a reasonable computational time.

Gonçcalves et al. [55] presented a single stage MILP model to solve the problem of planning the short-term expansion of radial distribution systems. The model defines the construction of new circuits, the reconductoring of existing circuits, and the allocation of CBs and VRs to minimize investment and operating costs. The steady state operation point was calculated using a linearized model, considering the loads as constant active and reactive power. Additionally, the system was assumed radial and balanced; hence, it was represented by a single-phase equivalent circuit. A test system with 54 buses and a real system with 201 buses were used to demonstrate the accuracy of the mathematical model. By comparing the result obtained with the proposed method with those obtained through a non-linear load flow, the authors concluded that the steady-state operation point was accurately calculated. Also, by selecting an appropriate expansion alternative, the proposed model reduced the investment and operating costs considerably.

A multistage MILP model for PDS expansion planning was proposed in [142]. The expansion alternatives evaluated by this method include the increase of the capacity of existing substations, construction of new substations, allocation of CBs and VRs, construction or reinforcement of feeders and modification of feeder topology. The model assumed that the system is balanced and thus represented by a single-phase equivalent circuit; loads were represented as constant power, following the linearization procedure detailed in [47]. The objective function considered the minimization of investment and operation costs of PDS in a defined planning horizon. According to the results, allowing multiple expansion alternatives as solution to the planning problem results in solutions with lower total costs, avoiding unnecessary large investment to meet new loading conditions.

A multistage MILP model for PDS expansion planning was proposed In [99] a model for planning the expansion of PDS considering uncertainties and reliability was defined. The alternatives considered are the construction and reconfiguration of networks, the installation of transformers and DGs. The proposed algorithm finds the solution in two sequential steps. During the first step, different topologies are obtained for the network using a stochastic programming approach. Then, a MINLP model is obtained and transformed into an equivalent MILP. The objective of this step is to minimize the present value of the investment and operating costs while considering uncertainties related to loads and renewable sources. In the second step, reliability indexes are calculated for each solution obtained in the first step, allowing the planner to analyze the impact of reliability on the system expansion alternatives and make a decision.

Samal et al. [124] applied the DE algorithm to a model aimed to determine the optimal conductors and optimal phase balancing of unbalanced distribution systems. The objective function was defined by the minimization of total unbalance of the apparent power, total power losses, average voltage drop, voltage unbalance factor, and total current of the neutral conductor. In order to obtain the steady-state operation point, the authors applied a three-phase load flow based on an iterative sweeping method. The results indicated that better solutions are obtained when phase balancing and conductor selection are simultaneously considered.

4 Discussion and comments

From what we presented so far, we observed that the greatest part of the papers on PDS planning deals with the optimal allocation of CBs, whereas few papers deal with the allocation of VRs. The problem of reconductoring is usually treated in conjunction with other planning alternatives, such as the construction of new feeder branches and new substations, which proved very effective because it results in a more comprehensive solution for the planning horizon. Moreover, most of the proposed methods use heuristic and metaheuristic algorithms, because it is easier to consider constraints and nonlinear objective functions. Few models use classical optimization techniques.

Regarding the load behavior, most of the works detailing the load model represent the load through constant active and reactive power. This load model, commonly used for the analysis of transmission systems, may, however, yield inaccurate results when applied to the analysis of PDS, where greater uncertainty regarding load behavior is expected. This uncertainty is even more evident when three-phase models are used. Furthermore, a hypothesis commonly adopted by the major part of the authors consists of assuming the capacitor as a constant source of reactive power. Knowingly, this model is not very accurate since a capacitor behaves, in fact, more as a constant impedance element [73]. Additionally, voltage levels are usually imposed through strict constraints on the lower and upper limits for bus voltages, instead of including them into the objective function. Such constraints, especially significant financial constraints, can render the problem unfeasible.

5 Active power distribution systems planning and research trends

In recent years, the increasing use of demand response, distributed generation, and energy storage systems, known as Distributed Energy Resources (DERs), has transformed PDS from passive to active networks. This transition brought new technical issues to be addressed [83,90,118,126,144,151,154], leading to a new dimension and further complexity to PDS planning problems. Traditional PDS planning models and practices consider a given load forecast and no control over the DG generation output when determining new distribution network assets [80]. Recently, optimization models for the planning of distribution network expansion and generation considering the connection of DGs with renewable sources, demand response, and energy storage have been proposed [65,99,153].

In [11,12] a model was proposed to jointly plan the expansion of PDS and DGs with renewable sources, considering demand response and energy storage. The problem was formulated as a stochastic-programming-based model, with an associated deterministic equivalent formulated as MILP. The objective function considered the maximization of the net social benefit. The expansion alternatives consisted of DG and storage units allocation, together with reinforcement or replacement of distribution assets. Based on the results, the authors came to the conclusion that DERs can positively impact the definition of the best investments.

In [153] a mixed integer second-order cone programming (SOCP) model was proposed to be applied to the active distribution network expansion planning (ADNP). SOCP problems are non-linear and convex, with a feasible solution domain defined by a second-order cone. The ADNP includes not only investment plans but also management schemes for PDS. The authors considered four active management schemes: (i) DG curtailment, (ii) demand management, (iii) on-load tap-changer adjustment, and (iv) reactive power compensation. The planning alternatives included new wiring, new substation, substation expansion, and DG installation. The results suggested that such management schemes can help minimize investments.

Shen et al. [129] defined a multistage model for planning active PDS, considering centralized and distributed energy storage systems (ESS). Long-term investment were evaluated along with short-term operation strategies of active PDS. The alternatives of expansion included the replacement or addition of network branches and the installation of ESS to enhance short-term daily operation strategies. Loads were modeled as constant current injections. Furthermore, this model requires accurate daily load curves, which can be difficult to obtain in practice and increase the problem dimension, resulting in convergence difficulties. The reactive power compensation and voltage control were not considered.

In [65] a multistage model was proposed for long-term distribution planning, considering expansion in DGs, substations, capacitors, and feeders. Moreover, the authors considered plug-in electric vehicles (PEV) with controlled (smart) and uncontrolled charging demand, as well as demand response. A back-propagation algorithm was used in conjunction with a cost-benefit analysis to determine investment plans. The results showed that uncontrolled PEV charging loads can lead to investment plans with higher costs.

A multiobjective formulation for the optimal allocation of DERs, including CBs, was proposed in [69]. An improved PSO procedure was applied, including a guided search algorithm based on node sensitivity to reduce the search space without loss of diversity. After placing DERs, the model evaluates possible reconfigurations of the feeders.

A method for planning and operating modern PDS with active elements was presented in [70]. This method co-optimizes planning and operating stages by sharing information between them. Offline OPF are executed based on load consumption and renewable energy sources forecasts, determining the optimal behavior of controlled DERs. The objective function considered the minimization of losses and the cost of using active measurements. The authors also accounted for costs of active power curtailment and reactive power control. The results showed that it is possible to postpone investments if adequate flexibility is allowed/provided during the operation stage through the control of DERs.

In [80] a multistage planning method for active distribution networks was proposed. In this method, the reinforcement of the existing substations and distribution lines were considered as alternatives for expansion, along with CB and VR placement, and active management of DG. The PDS problem was modeled as a MINLP problem, with an objective function considering the net present value of investment costs during the planning period. Loads and CBs were modeled as constant power. In a first stage, GA is applied to solve the formulated PDS planning problem for a condition corresponding to the maximum stress of the network. In this stage, the necessary investments are defined so that they guarantee the safe operation at a minimum cost up to the last stage. Then, in a second stage, a heuristic approach is applied to define the installation period of the network investments. The results showed that by incorporating DG active management into the solution of PDS planning, investments can be postponed.

From the context we described thus far, we see a change in the paradigms that guided the planning of PDS to date [28,33]. This change is due to factors such as policy changes motivated by environmental concerns, advances in renewable generation technology, automation and supervision of distribution systems, and customer participation in demand management. All these factors lead to a new type of network, the so-called “smart grids”, and to a visible change in the way PDS have been planned and operated over the last decades. The increasing use of demand response, DG, and ESS, known as distributed energy resources, has a significant impact on distribution networks and is part of the solution to the challenges concerning energy and environment. Optimizing the use of these resources in conjunction with investments is a key part of the future development of PDS.

Furthermore, transforming researches published to date into computational tools that can be used in the planning sectors of distribution companies still represents a challenge. It is generally required that a computational tool be capable of interacting with the legacy systems of the utility, allowing access to technical and commercial information that will serve as input data for the optimization model. In addition, a good computational performance is demanded, regardless of feeder size and number of consumers. Such requirements can limit the practical application of some models, since they may not be able to solve optimization problems of large distribution systems in a reasonable time.

In this way, the following topics can be seen as promising prospects in the development of models and solution techniques for the problem of planning the expansion of distribution networks:

- representing renewable sources and uncertainties related to them;
- representing consumer behavior more accurately, considering demand response, ESS, and distributed generation;
- incorporating real technical and commercial data into the models;
- quantifying and incorporating reliability costs into other costs;
- incorporating maintenance information to assess reliability in the definition of investment plans, optimizing the operation under normal and emergency conditions;
- considering budgetary constraints and an appropriate treatment of them, allowing for solutions with minimal violations;
- consideration of the return of investment to the utility, according to the regulatory model;
- obtaining reliable forecast data to apply to long-term models.

6 Comparative analysis

In this section, we present the main characteristics of the solution methods applied to problems of PDS expansion planning, see Table 1. Furthermore, in Table 2 a comparative analysis of several works related to PDS planning is presented, the focus being on classical optimization problems (CB allocation, VR allocation, and conductor selection). The works have been categorized based (i) on the models and methods used to solve each specific problem, (ii) on available resources to perform the expansion of PDS, (iii) on types of costs considered in the objective functions, (iv) on the objective function type, (v) on the number of stages, (vi) and on the environment of the model.

7 Conclusions

Models and techniques to solve problems of PDS expansion planning have been studied for decades. In this paper, a comprehensive survey about the state-of-the-art regarding models and methods applied to the solution of these problems has been presented, focusing on the optimal CB allocation, optimal VR allocation, and reconductoring problems. These are classical optimization problems and part of short-term expansion planning carried out by utilities, since they represent common solutions applied to minimize energy losses and control of the voltage along the feeders. The solution

Table 1 Characteristics of the solution methods

Characteristics	Method/model		
	Analytical	Exact optimization	Heuristic
Representation of the problem	Large simplifications are needed to represent PDS	Mathematical complexities for modeling can arise	Nonlinear constraints and objective functions can be easily handled
Guaranteed convergence to global optimum	No	Yes	No
Development effort	Short development times are expected, since the models are simple	A considerable development time can be expected to represent the problem through expressions mathematically tractable, since simplifications are needed	Development time is much shorter than when using more traditional approaches
Computational effort	Small	Large computational times can be expected depending on the size of the problem	Relatively small computational effort in finding good feasible solutions
Constraints	Explicitly represented	Explicitily represented, help to reduce the search space	Some can be represented explicitily, others need to be handled through penalties

Table 2 Summary of the bibliographic survey

Reference	Method/model	Decisions[a]				Obj. function[b]			Obj. type[c]	Stages[d]	Envir.[e]
		CB	VR	C	O	Inv	Op	O	SO/MO	S/M	D/S
Neagle and Samson [103]	Analytical	x					x		SO	S	D
Cook [29], Cook [30]	Analytical	x					x		SO	S	D
Schmill [127]	Analytical	x					x		SO	S	D
Grainger and Lee [57], Lee and Grainger [85], Grainger and Lee [58]	Analytical	x					x		SO	S	D
Baran and Wu [14]	MINLP	x				x	x		SO	S	D
Chiang et al. [21], Chiang et al. [22]	SA	x				x	x		SO	S	D
Boone and Chiang [16]	GA	x				x	x		SO	S	D
Sundhararajan and Pahwa [140]	GA	x				x	x		SO	S	D
Abdel-Salam et al. [1]	Heuristic	x				x	x		SO	S	D
Huang et al. [63]	TS	x				x	x		SO	S	D
Chis et al. [25]	Heuristic	x				x	x		SO	S	D
Levitin et al. [86]	GA	x				x	x		SO	S	D
Huang [62]	IA	x				x	x		SO	S	D
Gallego et al. [48]	Hybrid TS	x				x	x		SO	S	D
Milosevic and Begovic [96]	NSGA	x				x	x	x	MO	S	D
Chiou et al. [24]	Hybrid DE AC	x				x	x		SO	S	D
de Souza et al. [136]	Micro GA and Fuzzy	x				x	x		SO	S	D
Pires et al. [114]	TS	x				x	x		MO	S	D
Chang [20]	AC	x			x		x	x	SO	S	D
da Silva et al. [133]	Heuristic	x				x	x		SO	S	D
Eajal and El-Hawary [35]	Hybrid PSO	x				x	x		SO	S	D
Segura et al. [128]	Heuristic	x				x	x		SO	S	D

Table 2 continued

Reference	Method/model	Decisions[a]				Obj. function[b]			Obj. type[c]	Stages[d]	Envir.[e]
		CB	VR	C	O	Inv	Op	O	SO/MO	S/M	D/S
Farahani et al. [43]	GA	x			x	x	x		SO	S	D
El-Fergany [37]	Hybrid DE PS	x				x	x		SO	S	D
Naik et al. [102]	Heuristic	x			x		x	x	SO	S	D
El-Fergany and Abdelaziz [38]	CSA	x				x	x		SO	S	D
El-Fergany and Abdelaziz [39]	ABC	x				x	x	x	SO	S	D
El-Fergany and Abdelaziz [40]	Accelerated PSO	x				x	x	x	SO	S	D
Sultana and Roy [138]	TLBO	x				x	x		SO	S	D
Nojavan et al. [107]	MINLP	x				x	x		SO	S	D
Injeti et al. [66]	BA and CSA	x				x	x		SO	S	D
Shuaib et al. [132]	GSA	x				x	x		SO	S	D
Devabalaji et al. [31]	BFOA	x					x		SO	S	D
Chiou and Chang [23]	Hybrid CODEQ	x				x	x		SO	S	D
Duque et al. [34]	Modified MS	x				x	x		SO	S	D
Lee et al. [84]	PSO	x				x	x		SO	S	D
Muthukumar and Jayalalitha [100]	Hybrid HS	x			x		x		SO	S	D
Khodabakhshian and Andishgar [75]	IMDE	x			x		x		SO	S	D
Abdelaziz et al. [3]	FPA	x				x	x		SO	S	D
Ali et al. [7]	Improved HS	x				x	x		SO	S	D
Karimi and Dashti [71]	PSO	x				x	x	x	SO	S	D
Gnanasekaran et al. [54]	SSO	x				x	x		SO	S	D
El-Ela et al. [36]	AC	x				x	x		SO	S	D
Pereira et al. [112]	Hybrid TS GA	x			x	x	x		SO	S	S/D

Table 2 continued

Reference	Method/model	Decisions[a]				Obj. function[b]			Obj. type[c]	Stages[d]	Envir.[e]
		CB	VR	C	O	Inv	Op	O	SO/MO	S/M	D/S
Resener et al. [119]	MILP	x			x	x	x		SO	S	D
Ramadan et al. [116]	PSO	x				x	x		SO	S	D
Muthukumar and Jayalalitha [101]	Hybrid HSA	x			x	x	x		MO	S	D
Melgar Dominguez et al. [93]	MILP	x			x	x	x	x	SO	S	D
Santos et al. [126], Santos et al. [125]	MILP	x			x	x	x	x	SO	M	S/D
Safigianni and Salis [121]	Recursive		x			x	x		SO	S	D
Mendoza et al. [94]	Micro GA		x				x	x	MO	S	D
Mendoza and Pea [95]	GA		x				x	x	SO	S	D
Kobayashi and Aoki [77]	GA		x					x	SO	S	D
Niknam et al. [106]	Fuzzy adaptive PSO		x		x		x	x	MO	S	D
de Lima et al. [87]	Additive-veto model		x			x	x	x	SO	S	D
Grainger and Civanlar [56], Civanlar and Grainger [26], Civanlar and Grainger [27]	Heuristic	x	x				x		SO	S	D
Abdelaziz et al. [2]	Fuzzy	x	x			x	x	x	SO	S	D
de Souza and de Almeida [135]	Fuzzy	x	x			x	x		MO	S	D
Ziari et al. [156]	Hybrid AG PSO	x	x			x	x		SO	S	D
Szuvovivski et al. [141]	GA and OPF	x	x			x	x	x	SO	S	D
Franco et al. [47]	MILP	x	x			x	x		MO	S	D
Ahmadi and Marti[5]	MIQP	x	x		x	x	x	x	SO	S	D
de Araujo et al. [10]	OPF and GA	x	x			x	x		SO	S	D
Ponnavaikko and Rao [115]	MINLP			x		x	x		SO	S	D
Sun et al. [139]	MILP			x	x	x	x		SO	S	D
El-kady [41]	MILP			x	x	x	x		SO	S	D

Table 2 continued

Reference	Method/model	Decisions[a]				Obj. function[b]			Obj. type[c]	Stages[d]	Envir.[e]
		CB	VR	C	O	Inv	Op	O	SO/MO	S/M	D/S
Tang [143]	MINLP			x	x	x	x	x	SO	M	D
Salis and Safigianni [123]	Heuristic			x		x	x		SO	M	D
Wang et al. [150]	Heuristic			x		x	x		SO	S	D
Boulaxis and Papadopoulos [17]	DP			x		x	x	x	SO	M	D
Paiva et al. [109]	MILP			x	x	x	x	x	SO	S	D
Vaziri et al. [146], Vaziri et al. [147]	MILP			x	x	x	x		SO	M	D
Carrano et al. [19]	GA			x	x	x	x	x	MO	S	D
Haffner et al. [59], Haffner et al. [60]	MILP				x	x	x		SO	M	D
Kaur and Sharma [72]	Heuristic			x		x	x		SO	S	D
Ganguly et al. [49]	PSO			x	x	x	x	x	MO	S	D
Ziari et al. [157]	PSO	x		x	x	x	x	x	SO	M	D
Franco et al. [46]	MILP			x		x	x		MO	S	D
Farahani et al. [44]	GA	x		x		x	x		SO	S	D
Koutsoukis et al. [79]	MIQP			x	x	x	x		SO	M	D
Lotero and Contreras [89]	MILP			x	x	x	x		SO	M	D
Humayd and Bhattacharya [64]	Heuristic			x	x	x	x		SO	M	D
Pereira Júnior *et al.* [113]	TS			x	x	x	x	x	MO	M	D
Ahmadigorji and Amjady [6]	Binary Chaotic SSO			x	x	x	x	x	SO	M	D
AbulWafa [4]	Heuristic			x		x	x		SO	S	D
Gonçcalves et al. [55]	MILP	x	x	x		x	x		SO	S	D
Munoz-Delgado et al. [98]	MILP			x	x	x	x	x	SO	M	D
de Souza et al. [137]	MILP/Heuristic			x	x	x	x	x	SO	M	D

Table 2 continued

Reference	Method/model	Decisions[a]				Obj. function[b]			Obj. type[c]	Stages[d]	Envir.[e]
		CB	VR	C	O	Inv	Op	O	SO/MO	S/M	D/S
Tabares et al. [142]	MILP			x	x	x	x		SO	M	D
Muñoz-Delgado, Contreras e Arroyo [99]	Heuristic				x	x	x	x	SO	M	S/D
Samal et al. [124]	DE				x	x	x	x	MO	S	D
Asensio et al. [11], Asensio et al. [12]	Dynamic stochastic programming				x	x		x	SO	M	S/D
Xing et al. [153]	SOCP				x	x	x	x	SO	S	S/D
Shen et al. [129]	MILP				x	x	x	x	SO	M	D
Humayd and Bhattacharya [65]	Back-propagation	x		x	x	x	x	x	SO	M	D
Kanwar et al. [69]	Improved PSO	x		x	x	x	x	x	SO	S	D
Karagiannopoulos et al. [70]	OPF			x	x	x	x	x	SO	S	D
Koutsoukis et al. [80]	MINLP	x	x	x	x	x	x	x	SO	M	D
Asensio et al. [13]	MILP				x	x		x	SO	M	S/D
Mansor and Levi [91]	MINLP				x	x	x	x	SO	M	D
Ghadiri et al. [52]	Heuristic			x	x	x	x	x	SO	S	D

[a] CB Placement (CB); VR Placement (VR); Reconductoring and condutor selection (C); Others (O): substation construction, increase the capacity of existing substations, DG placement, optimization of operation point of DGs, reconfiguration, ESS, PEV, demand response
[b] Investment costs (Inv); Operation costs (Op); Other costs (O): voltage, stability, reliability, DERs costs
[c] Single objective (SO); Multiobjective (MO)
[d] Single stage (S); Multistage (M)
[e] Deterministic (D); Stochastic (S); Stochastic and Deterministic (S/D)

methods applied to problems of PDS expansion planning can be, generally, divided into three categories: analytical, exact optimization methods, and heuristic methods. The major part of the models, especially those applied to the optimal CB allocation, are based on meta-heuristic methods, hybrid algorithms being proposed and successfully applied recently. Furthermore, these methods have been successfully applied to solve larger problems of PDS expansion planning largely because nonlinear constraints and objective functions can be easily handled.

Finally, with the integration of distributed energy resources and the active PDS, we believe that future research work will concentrate on these new, modern concepts. Further, an ever-increasing amount of data will be available, since the automation and data necessary to operate the grid also steadily increases. These data can improve models and help engineers in the decision-making process while developing expansion planning studies. A further consequence is that the existing techniques can be extended in a more realistic and precise manner.

Acknowledgements Work of P.M. Pardalos is partially supported by the Paul and Heidi Brown Preeminent Professorship at ISE, University of Florida.

References

1. Abdel-Salam, T.S., Chikhani, A.Y., Hackam, R.: A new technique for loss reduction using compensating capacitors applied to distribution systems with varying load condition. IEEE Trans. Power Deliv. **9**(2), 819–827 (1994). https://doi.org/10.1109/61.296262
2. Abdelaziz, A., Mekhamer, S., Nada, M.: A fuzzy expert system for loss reduction and voltage control in radial distribution systems. Electr. Power Syst. Res. **80**(8), 893–897 (2010). https://doi.org/10.1016/j.epsr.2009.12.020. http://www.sciencedirect.com/science/article/pii/S0378779610000106
3. Abdelaziz, A., Ali, E., Elazim, S.A.: Flower pollination algorithm and loss sensitivity factors for optimal sizing and placement of capacitors in radial distribution systems. Int. J. Electr. Power Energy Syst. **78**, 207–214 (2016). https://doi.org/10.1016/j.ijepes.2015.11.059. http://www.sciencedirect.com/science/article/pii/S0142061515004901
4. AbulWafa, A.R.: Multi-conductor feeder design for radial distribution networks. Electr. Power Syst. Res. **140**, 184–192 (2016). https://doi.org/10.1016/j.epsr.2016.06.023. http://www.sciencedirect.com/science/article/pii/S0378779616302310
5. Ahmadi, H., Marti, J.: Distribution system optimization based on a linear power-flow formulation. IEEE Trans. Power Deliv. **30**(1), 25–33 (2015)
6. Ahmadigorji, M., Amjady, N.: A multiyear DG-incorporated framework for expansion planning of distribution networks using binary chaotic shark smell optimization algorithm. Energy **102**, 199–215 (2016). https://doi.org/10.1016/j.energy.2016.02.088. http://www.sciencedirect.com/science/article/pii/S0360544216301505
7. Ali, E., Elazim, S.A., Abdelaziz, A.: Improved harmony algorithm and power loss index for optimal locations and sizing of capacitors in radial distribution systems. Int. J. Electr. Power Energy Syst. **80**, 252–263 (2016). https://doi.org/10.1016/j.ijepes.2015.11.085. http://www.sciencedirect.com/science/article/pii/S0142061515005165
8. Aman, M., Jasmon, G., Bakar, A., Mokhlis, H., Karimi, M.: Optimum shunt capacitor placement in distribution system—a review and comparative study. Renew. Sustain. Energy Rev. **30**, 429–439 (2014). https://doi.org/10.1016/j.rser.2013.10.002. http://www.sciencedirect.com/science/article/pii/S1364032113007016
9. Anders, G., Vainberg, M., Horrocks, D., Foty, S., Motlis, J., Jarnicki, J.: Parameters affecting economic selection of cable sizes. IEEE Trans. Power Deliv. **8**(4), 1661–1667 (1993). https://doi.org/10.1109/61.248270
10. de Araujo, L.R., Penido, D.R.R., Carneiro, S., Pereira, J.L.R.: Optimal unbalanced capacitor placement in distribution systems for voltage control and energy losses minimization. Electr. Power Syst.

Res. **154**, 110–121 (2018). https://doi.org/10.1016/j.epsr.2017.08.012. http://www.sciencedirect.com/science/article/pii/S0378779617303309
11. Asensio, M., de Quevedo, P.M., Munoz-Delgado, G., Contreras, J.: Joint distribution network and renewable energy expansion planning considering demand response and energy storage Part I: stochastic programming model. IEEE Trans. Smart Grid **PP**(99), 1–1 (2016). https://doi.org/10.1109/TSG.2016.2560339
12. Asensio, M., de Quevedo, P.M., Munoz-Delgado, G., Contreras, J.: Joint distribution network and renewable energy expansion planning considering demand response and energy storage Part II: Numerical results and considered metrics. IEEE Trans. Smart Grid **PP**(99), 1–1 (2016). https://doi.org/10.1109/TSG.2016.2560341
13. Asensio, M., Munoz-Delgado, G., Contreras, J.: Bi-level approach to distribution network and renewable energy expansion planning considering demand response. IEEE Trans. Power Syst. **32**(6), 4298–4309 (2017). https://doi.org/10.1109/TPWRS.2017.2672798
14. Baran, M., Wu, F.: Optimal capacitor placement on radial distribution systems. IEEE Trans. Power Deliv. **4**(1), 725–734 (1989a). https://doi.org/10.1109/61.19265
15. Baran, M.E., Wu, F.F.: Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Trans. Power Deliv. **4**(2), 1401–1407 (1989b). https://doi.org/10.1109/61.25627
16. Boone, G., Chiang, H.D.: Optimal capacitor placement in distribution systems by genetic algorithm. Int. J. Electri. Power Energy Syst. **15**(3), 155–161 (1993). https://doi.org/10.1016/0142-0615(93)90030-Q. http://www.sciencedirect.com/science/article/pii/014206159390030Q
17. Boulaxis, N.G., Papadopoulos, M.P.: Optimal feeder routing in distribution system planning using dynamic programming technique and gis facilities. IEEE Trans. Power Deliv. **17**(1), 242–247 (2002). https://doi.org/10.1109/61.974213
18. C619 CWG (2013) Planning and optimization methods for active distribution systems. CIGRE
19. Carrano, E.G., Soares, L.A.E., Takahashi, R.H.C., Saldanha, R.R., Neto, O.M.: Electric distribution network multiobjective design using a problem-specific genetic algorithm. IEEE Trans. Power Deliv. **21**(2), 995–1005 (2006). https://doi.org/10.1109/TPWRD.2005.858779
20. Chang, C.F.: Reconfiguration and capacitor placement for loss reduction of distribution systems by ant colony search algorithm. IEEE Trans. Power Syst. **23**(4), 1747–1755 (2008). https://doi.org/10.1109/TPWRS.2008.2002169
21. Chiang, H.D., Wang, J.C., Cockings, O., Shin, H.D.: Optimal capacitor placements in distribution systems. I. a new formulation and the overall problem. IEEE Trans. Power Deliv. **5**(2), 634–642 (1990a). https://doi.org/10.1109/61.53065
22. Chiang, H.D., Wang, J.C., Cockings, O., Shin, H.D.: Optimal capacitor placements in distribution systems. II. solution algorithms and numerical results. IEEE Trans. Power Deliv. **5**(2), 643–649 (1990b). https://doi.org/10.1109/61.53066
23. Chiou, J.P., Chang, C.F.: Development of a novel algorithm for optimal capacitor placement in distribution systems. Int. J. Electr. Power Energy Syst. **73**, 684–690 (2015). https://doi.org/10.1016/j.ijepes.2015.06.003. http://www.sciencedirect.com/science/article/pii/S0142061515002598
24. Chiou, J.P., Chang, C.F., Su, C.T.: Ant direction hybrid differential evolution for solving large capacitor placement problems. IEEE Trans. Power Syst. **19**(4), 1794–1800 (2004). https://doi.org/10.1109/TPWRS.2004.835651
25. Chis, M., Salama, M.M.A., Jayaram, S.: Capacitor placement in distribution systems using heuristic search strategies. IEE Proc. Gen. Transm. Distrib. **144**(3), 225–230 (1997). https://doi.org/10.1049/ip-gtd:19970945
26. Civanlar, S., Grainger, J.: Volt/var control on distribution systems with lateral branches using shunt capacitors and voltage regulators Part II: the solution method. IEEE Trans. Power Apparatus Syst. **PAS–104**(11), 3284–3290 (1985). https://doi.org/10.1109/TPAS.1985.318843
27. Civanlar, S., Grainger, J.: Volt/var control on distribution systems with lateral branches using switched capacitors and voltage regulators Part III: the numerical results. IEEE Power Eng. Rev. **PER–5**(11), 54–54 (1985). https://doi.org/10.1109/MPER.1985.5528389
28. Conti, S., Rizzo, S.A.: An open source tool for reliability evaluation of distribution systems with renewable generators. Energy Syst. (2017). https://doi.org/10.1007/s12667-017-0264-6
29. Cook, R.: Analysis of capacitor application as affected by load cycle. IEEE Trans. Power Apparatus Syst. **78**(3), 950–956 (1959). https://doi.org/10.1109/AIEEPAS.1959.4500475

30. Cook, R.: Optimizing the application of shunt capacitors for reactive-volt-ampere control and loss reduction. IEEE Trans. Power Apparatus Syst. **80**(3), 430–441 (1961). https://doi.org/10.1109/AIEEPAS.1961.4501064
31. 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. **71**, 383–390 (2015). https://doi.org/10.1016/j.ijepes.2015.03.008. http://www.sciencedirect.com/science/article/pii/S014206151500143X
32. Dixit, M., Kundu, P., Jariwala, H.R.: Integration of distributed generation for assessment of distribution system reliability considering power loss, voltage stability and voltage deviation. Energy Systems (2017). https://doi.org/10.1007/s12667-017-0248-6
33. Donadel, C.B., Fardin, J.F., Encarnação, L.F.: Electrical distribution network operation with a presence of distributed generation units in a pre smart grid environment using a clustering-based methodology. Energy Sys. **6**(4), 455–477 (2015). https://doi.org/10.1007/s12667-015-0150-z
34. Duque, F.G., de Oliveira, L.W., de Oliveira, E.J., Marcato Jr., A.L., ICS, : Allocation of capacitor banks in distribution systems through a modified monkey search optimization technique. Int. J. Electr. Power Energy Syst. **73**, 420–432 (2015). https://doi.org/10.1016/j.ijepes.2015.05.034. http://www.sciencedirect.com/science/article/pii/S0142061515002392
35. Eajal, A., El-Hawary, M.: Optimal capacitor placement and sizing in unbalanced distribution systems with harmonics consideration using particle swarm optimization. IEEE Trans. Power Deliv. **25**(3), 1734–1741 (2010). https://doi.org/10.1109/TPWRD.2009.2035425
36. El-Ela, A.A.A., El-Sehiemy, R.A., Kinawy, A.M., Mouwafi, M.T.: Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. IET Gen. Transm. Distrib. **10**(5), 1209–1221 (2016). https://doi.org/10.1049/iet-gtd.2015.0799
37. El-Fergany, A.: Optimal capacitor allocations using evolutionary algorithms. IET Gen. Transm. Distrib. **7**(6), 593–601 (2013). https://doi.org/10.1049/iet-gtd.2012.0661
38. El-Fergany, A., Abdelaziz, A.: Capacitor allocations in radial distribution networks using cuckoo search algorithm. IET Gen. Transm. Distrib. **8**(2), 223–232 (2014a). https://doi.org/10.1049/iet-gtd.2013.0290
39. El-Fergany, A., Abdelaziz, A.: Multi-objective capacitor allocations in distribution networks using artificial bee colony algorithm. J. Electr. Eng. Technol. **9**(2), 441–451 (2014b). https://doi.org/10.5370/JEET.2014.9.2.441
40. El-Fergany, A., Abdelaziz, A.: Efficient heuristic-based approach for multi-objective capacitor allocation in radial distribution networks. IET Gen. Transm. Distrib. **8**(1), 70–80 (2014c). https://doi.org/10.1049/iet-gtd.2013.0213
41. El-kady, M.A.: Computer-aided planning of distribution substation and primary feeders. IEEE Trans. Power Apparatus Syst. **PAS–103**(6), 1183–1189 (1984). https://doi.org/10.1109/TPAS.1984.318447
42. El-Khattam, W., Hegazy, Y.G., Salama, M.M.A.: An integrated distributed generation optimization model for distribution system planning. IEEE Trans. Power Syst. **20**(2), 1158–1165 (2005). https://doi.org/10.1109/TPWRS.2005.846114
43. Farahani, V., Vahidi, B., Abyaneh, H.A.: Reconfiguration and capacitor placement simultaneously for energy loss reduction based on an improved reconfiguration method. IEEE Trans. Power Syst. **27**(2), 587–595 (2012). https://doi.org/10.1109/TPWRS.2011.2167688
44. Farahani, V., Sadeghi, S., Abyaneh, H., Agah, S., Mazlumi, K.: Energy loss reduction by conductor replacement and capacitor placement in distribution systems. IEEE Trans. Power Syst. **28**(3), 2077–2085 (2013). https://doi.org/10.1109/TPWRS.2013.2251012
45. Fletcher, R.H., Strunz, K.: Optimal distribution system horizon planning Part I: formulation. IEEE Trans. Power Syst. **22**(2), 791–799 (2007). https://doi.org/10.1109/TPWRS.2007.895173
46. Franco, J.F., Rider, M.J., Lavorato, M., Romero, R.: Optimal conductor size selection and reconductoring in radial distribution systems using a mixed-integer LP approach. IEEE Trans. Power Syst. **28**(1), 10–20 (2013a). https://doi.org/10.1109/TPWRS.2012.2201263
47. Franco, J.F., Rider, M.J., Lavorato, M., Romero, R.: A mixed-integer LP model for the optimal allocation of voltage regulators and capacitors in radial distribution systems. Int. J. Electr. Power Energy Syst. **48**, 123–130 (2013b). https://doi.org/10.1016/j.ijepes.2012.11.027. http://www.sciencedirect.com/science/article/pii/S0142061512006801
48. Gallego, R., Monticelli, A., Romero, R.: Optimal capacitor placement in radial distribution networks. IEEE Trans. Power Syst. **16**(4), 630–637 (2001). https://doi.org/10.1109/59.962407

49. Ganguly, S., Sahoo, N.C., Das, D.: A novel multi-objective pso for electrical distribution system planning incorporating distributed generation. Energy Syst. **1**(3), 291–337 (2010). https://doi.org/10.1007/s12667-010-0014-5
50. Ganguly, S., Sahoo, N.C., Das, D.: Recent advances on power distribution system planning: a state-of-the-art survey. Energy Syst. **4**(2), 165–193 (2013). https://doi.org/10.1007/s12667-012-0073-x
51. Georgilakis, P.S., Hatziargyriou, N.D.: A review of power distribution planning in the modern power systems era: models, methods and future research. Electr. Power Syst. Res. **121**, 89–100 (2015). https://doi.org/10.1016/j.epsr.2014.12.010. http://www.sciencedirect.com/science/article/pii/S0378779614004490
52. Ghadiri, A., Haghifam, M.R., Larimi, S.M.M.: Comprehensive approach for hybrid ac/dc distribution network planning using genetic algorithm. IET Gen. Transm. Distrib. **11**(16), 3892–3902 (2017). https://doi.org/10.1049/iet-gtd.2016.1293
53. Ghalehkhondabi, I., Ardjmand, E., Weckman, G.R., Young, W.A.: An overview of energy demand forecasting methods published in 2005–2015. Energy Syst. **8**(2), 411–447 (2017). https://doi.org/10.1007/s12667-016-0203-y
54. Gnanasekaran, N., Chandramohan, S., Kumar, P.S., Imran, A.M.: Optimal placement of capacitors in radial distribution system using shark smell optimization algorithm. Ain Shams Eng. J. **7**(2), 907–916 (2016). https://doi.org/10.1016/j.asej.2016.01.006. http://www.sciencedirect.com/science/article/pii/S2090447916000149
55. Gonçalves, R., Franco, J., Rider, M.: Short-term expansion planning of radial electrical distribution systems using mixed-integer linear programming. IET Gen. Transm. Distrib. **9**(3), 256–266 (2015). https://doi.org/10.1049/iet-gtd.2014.0231
56. Grainger, J., Civanlar, S.: Volt/var control on distribution systems with lateral branches using shunt capacitors and voltage regulators Part I: The overall problem. IEEE Trans. Power Apparatus Syst. **PAS–104**(11), 3278–3283 (1985). https://doi.org/10.1109/TPAS.1985.318842
57. Grainger, J., Lee, S.H.: Optimum size and location of shunt capacitors for reduction of losses on distribution feeders. IEEE Trans. Power Apparatus Syst. **PAS–100**(3), 1105–1118 (1981). https://doi.org/10.1109/TPAS.1981.316577
58. Grainger, J., Lee, S.H.: Capacity release by shunt capacitor placement on distribution feeders: A new voltage-dependent model. IEEE Trans. Power Apparatus Syst. **PAS–101**(5), 1236–1244 (1982). https://doi.org/10.1109/TPAS.1982.317385
59. Haffner, S., Pereira, L.F.A., Pereira, L.A., Barreto, L.S.: Multistage model for distribution expansion planning with distributed generation Part I: problem formulation. IEEE Trans. Power Deliv. **23**(2), 915–923 (2008a). https://doi.org/10.1109/TPWRD.2008.917916
60. Haffner, S., Pereira, L.F.A., Pereira, L.A., Barreto, L.S.: Multistage model for distribution expansion planning with distributed generation Part II: numerical results. IEEE Trans. Power Deliv. **23**(2), 924–929 (2008b). https://doi.org/10.1109/TPWRD.2008.917911
61. Haque, M.H.: Capacitor placement in radial distribution systems for loss reduction. IEE Proc. Gen. Transm. Distrib. **146**(5), 501–505 (1999). https://doi.org/10.1049/ip-gtd:19990495
62. Huang, S.J.: An immune-based optimization method to capacitor placement in a radial distribution system. IEEE Trans. Power Deliv. **15**(2), 744–749 (2000). https://doi.org/10.1109/61.853014
63. Huang, Y.C., Yang, H.T., Huang, C.L.: Solving the capacitor placement problem in a radial distribution system using tabu search approach. IEEE Trans. Power Syst. **11**(4), 1868–1873 (1996). https://doi.org/10.1109/59.544656
64. Humayd, A.S.B., Bhattacharya, K.: Comprehensive multi-year distribution system planning using back-propagation approach. IET Gen. Transm. Distrib. **7**(12), 1415–1425 (2013). https://doi.org/10.1049/iet-gtd.2012.0706
65. Humayd, A.S.B., Bhattacharya, K.: Distribution system planning to accommodate distributed energy resources and pevs. Electr. Power Syst. Res. **145**, 1–11 (2017). https://doi.org/10.1016/j.epsr.2016.12.016. http://www.sciencedirect.com/science/article/pii/S0378779616305296
66. Injeti, S.K., Thunuguntla, V.K., Shareef, M.: Optimal allocation of capacitor banks in radial distribution systems for minimization of real power loss and maximization of network savings using bio-inspired optimization algorithms. Int. J. Electr. Power Energy Syst. **69**, 441–455 (2015). https://doi.org/10.1016/j.ijepes.2015.01.040. http://www.sciencedirect.com/science/article/pii/S0142061515000708

67. Jin, S., Ryan, S.M., Watson, J.P., Woodruff, D.L.: Modeling and solving a large-scale generation expansion planning problem under uncertainty. Energy Syst. **2**(3), 209–242 (2011). https://doi.org/10.1007/s12667-011-0042-9
68. Jordehi, A.R.: Optimisation of electric distribution systems: a review. Renew. Sustain. Energy Rev. **51**, 1088–1100 (2015). https://doi.org/10.1016/j.rser.2015.07.004. http://www.sciencedirect.com/science/article/pii/S1364032115006516
69. Kanwar N, Gupta N, Niazi K, Swarnkar A, Bansal R (2017) Simultaneous allocation of distributed energy resource using improved particle swarm optimization. Applied Energy 185:1684–1693. https://doi.org/10.1016/j.apenergy.2016.01.093. http://www.sciencedirect.com/science/article/pii/S0306261916300800
70. Karagiannopoulos, S., Aristidou, P., Hug, G.: Hybrid approach for planning and operating active distribution grids. IET Gen. Transm. Distrib. **11**(3), 685–695 (2017). https://doi.org/10.1049/iet-gtd.2016.0642
71. Karimi, H., Dashti, R.: Comprehensive framework for capacitor placement in distribution networks from the perspective of distribution system management in a restructured environment. Int. J. Electr. Power Energy Syst. **82**, 11–18 (2016). https://doi.org/10.1016/j.ijepes.2016.02.025. http://www.sciencedirect.com/science/article/pii/S0142061516302873
72. Kaur, D., Sharma, J.: Optimal conductor sizing in radial distribution systems planning. Int. J. Electri. Power Energy Syst. **30**(4), 261–271 (2008). https://doi.org/10.1016/j.ijepes.2007.07.005. http://www.sciencedirect.com/science/article/pii/S0142061507001007
73. Kersting, W.: Distribution System Modeling and Analysis. CRC Press, Boca Raton (2001)
74. Khator, S.K., Leung, L.C.: Power distribution planning: a review of models and issues. IEEE Trans. Power Syst. **12**(3), 1151–1159 (1997). https://doi.org/10.1109/59.630455
75. Khodabakhshian, A., Andishgar, M.H.: Simultaneous placement and sizing of DGs and shunt capacitors in distribution systems by using IMDE algorithm. Int. J. Electr. Power Energy Syst. **82**, 599–607 (2016). https://doi.org/10.1016/j.ijepes.2016.04.002. http://www.sciencedirect.com/science/article/pii/S0142061516306342
76. Khodayifar, S., Raayatpanah, M.A., Pardalos, P.M.: An accelerating benders' decomposition approach to the integrated supply chain network design with distributed generation. Energy Syst. (2017). https://doi.org/10.1007/s12667-017-0256-6
77. Kobayashi, T., Aoki, H.: Svr optimal placement problem in distribution network with distributed generators. In: Proceedings of the IEEE Power and Energy Society General Meeting, San Diego, California, USA, pp. 1–7, (2012). https://doi.org/10.1109/PESGM.2012.6345261
78. Kou, W., Jung, S.H., Park, S.Y.: Optimal location strategy for distributed generation to maximize system voltage stability based on line sensitivity factors. Energy Syst. (2017). https://doi.org/10.1007/s12667-017-0260-x
79. Koutsoukis, N.C., Georgilakis, P.S., Hatziargyriou, N.D.: Multi-stage power distribution planning to accommodate high wind generation capacity. In: Proceedings of the IEEE PowerTech, Eindhoven, The Netherlands, pp. 1–6 (2015). https://doi.org/10.1109/PTC.2015.7232754
80. Koutsoukis, N.C., Georgilakis, P.S., Hatziargyriou, N.D.: Multistage coordinated planning of active distribution networks. IEEE Tran. Power Syst. **PP**(99), 1–1 (2017). https://doi.org/10.1109/TPWRS.2017.2699696
81. Krishnan, V., Ho, J., Hobbs, B.F., Liu, A.L., McCalley, J.D., Shahidehpour, M., Zheng, Q.P.: Co-optimization of electricity transmission and generation resources for planning and policy analysis: review of concepts and modeling approaches. Energy Syst. **7**(2), 297–332 (2016). https://doi.org/10.1007/s12667-015-0158-4
82. Latorre, G., Cruz, R.D., Areiza, J.M., Villegas, A.: Classification of publications and models on transmission expansion planning. IEEE Trans. Power Syst. **18**(2), 938–946 (2003). https://doi.org/10.1109/TPWRS.2003.811168
83. Lazaroiu, G.C., Dumbrava, V., Costoiu, M., Sima, C.A., Leva, S.: Optimizing discos planning for networks with distributed energy resources. In: 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I CPS Europe), pp. 1–6 (2017). https://doi.org/10.1109/EEEIC.2017.7977694
84. Lee, C.S., Ayala, H.V.H., dos Santos, Coelho L.: Capacitor placement of distribution systems using particle swarm optimization approaches. Int. J. Electr. Power Energy Syst. **64**, 839–851 (2015). https://doi.org/10.1016/j.ijepes.2014.07.069. http://www.sciencedirect.com/science/article/pii/S0142061514005134

85. Lee, S.H., Grainger, J.: Optimum placement of fixed and switched capacitors on primary distribution feeders. IEEE Trans. Power Apparatus Syst. **PAS–100**(1), 345–352 (1981). https://doi.org/10.1109/TPAS.1981.316862
86. Levitin, G., Kalyuzhny, A., Shenkman, A., Chertkov, M.: Optimal capacitor allocation in distribution systems using a genetic algorithm and a fast energy loss computation technique. IEEE Trans. Power Deliv. **15**(2), 623–628 (2000). https://doi.org/10.1109/61.852995
87. de Lima, M.A.X., Clemente, T.R.N., de Almeida, A.T.: Prioritization for allocation of voltage regulators in electricity distribution systems by using a multicriteria approach based on additive-veto model. Int. J. Electr. Power Energy Syst. **77**, 1–8 (2016). https://doi.org/10.1016/j.ijepes.2015.11.006. http://www.sciencedirect.com/science/article/pii/S0142061515004251
88. Lohmann, T., Rebennack, S.: Tailored benders decomposition for a long-term power expansion model with short-term demand response. Manag. Science. **63**(6), 2027–2048 (2017). https://doi.org/10.1287/mnsc.2015.2420
89. Lotero, R.C., Contreras, J.: Distribution system planning with reliability. IEEE Trans. Power Deliv. **26**(4), 2552–2562 (2011). https://doi.org/10.1109/TPWRD.2011.2167990
90. Madaeni, S.H., Sioshansi, R.: The impacts of stochastic programming and demand response on wind integration. Energy Syst. **4**(2), 109–124 (2013). https://doi.org/10.1007/s12667-012-0068-7
91. Mansor, N.N., Levi, V.: Integrated planning of distribution networks considering utility planning concepts. IEEE Trans. Power Syst. **32**(6), 4656–4672 (2017). https://doi.org/10.1109/TPWRS.2017.2687099
92. Marti, J., Ahmadi, H., Bashualdo, L.: Linear power-flow formulation based on a voltage-dependent load model. IEEE Trans. Power Deliv. **28**(3), 1682–1690 (2013)
93. Melgar Dominguez, O.D., Pourakbari Kasmaei, M., Lavorato, M., Mantovani, J.R.S.: Optimal siting and sizing of renewable energy sources, storage devices, and reactive support devices to obtain a sustainable electrical distribution systems. Energy Syst. (2017). https://doi.org/10.1007/s12667-017-0254-8
94. Mendoza, J., Morales, D., Lopez, R., Lopez, E., Vannier, J.C., Coello, C.: Multiobjective location of automatic voltage regulators in a radial distribution network using a micro genetic algorithm. IEEE Trans. Power Syst. **22**(1), 404–412 (2007). https://doi.org/10.1109/TPWRS.2006.887963
95. Mendoza, J.E., Pea, H.E.: Automatic voltage regulators siting in distribution systems considering hourly demand. Electr. Power Syst. Res. **81**(5), 1124–1131 (2011). https://doi.org/10.1016/j.epsr.2010.12.012. http://www.sciencedirect.com/science/article/pii/S0378779610003354
96. Milosevic, B., Begovic, M.: Capacitor placement for conservative voltage reduction on distribution feeders. IEEE Trans. Power Deliv. **19**(3), 1360–1367 (2004). https://doi.org/10.1109/TPWRD.2004.824400
97. Mishra, S., Das, D., Paul, S.: A comprehensive review on power distribution network reconfiguration. Energy Syst. **8**(2), 227–284 (2017). https://doi.org/10.1007/s12667-016-0195-7
98. Munoz-Delgado, G., Contreras, J., Arroyo, J.M.: Joint expansion planning of distributed generation and distribution networks. IEEE Trans. Power Syst. **30**(5), 2579–2590 (2015). https://doi.org/10.1109/TPWRS.2014.2364960
99. Munoz-Delgado, G., Contreras, J., Arroyo, J.M.: Multistage generation and network expansion planning in distribution systems considering uncertainty and reliability. IEEE Trans. Power Syst. **31**(5), 3715–3728 (2016). https://doi.org/10.1109/TPWRS.2015.2503604
100. Muthukumar, K., Jayalalitha, S.: Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique. Int. J. Electr. Power Energy Syst. **78**, 299–319 (2016). https://doi.org/10.1016/j.ijepes.2015.11.019. http://www.sciencedirect.com/science/article/pii/S0142061515004391
101. Muthukumar, K., Jayalalitha, S.: Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks. Applied Soft Computing **52**, 1262–1284 (2017). https://doi.org/10.1016/j.asoc.2016.07.031. http://www.sciencedirect.com/science/article/pii/S156849461630357X
102. Naik, S.G., Khatod, D., Sharma, M.: Optimal allocation of combined dg and capacitor for real power loss minimization in distribution networks. Int. J. Electr. Power Energy Syst. **53**, 967–973 (2013). https://doi.org/10.1016/j.ijepes.2013.06.008
103. Neagle, N.M., Samson, D.R.: Loss reduction from capacitors installed on primary feeders [includes discussion]. IEEE Trans. Power Apparatus Syst. **75**(3), (1956). https://doi.org/10.1109/AIEEPAS.1956.4499390

104. Ng, H.N., Salama, M., Chikhani, A.: Classification of capacitor allocation techniques. IEEE Trans. Power Deliv. **15**(1), 387–392 (2000). https://doi.org/10.1109/61.847278
105. Niharika, Verma S., Mukherjee, V.: Transmission expansion planning: a review. In: 2016 International Conference on Energy Efficient Technologies for Sustainability (ICEETS), pp. 350–355 (2016). https://doi.org/10.1109/ICEETS.2016.7583779
106. Niknam, T., Narimani, M.R., Azizipanah-Abarghooee, R.: A multi-objective fuzzy adaptive pso algorithm for location of automatic voltage regulators in radial distribution networks. Int. J. Control Autom. Syst. **10**(4), 772–777 (2012). https://doi.org/10.1007/s12555-012-0413-6
107. Nojavan, S., Jalali, M., Zare, K.: Optimal allocation of capacitors in radial/mesh distribution systems using mixed integer nonlinear programming approach. Electr. Power Syst. Research **107**, 119–124 (2014). https://doi.org/10.1016/j.epsr.2013.09.019. http://www.sciencedirect.com/science/article/pii/S0378779613002708
108. Ochoa, L., Harrison, G.: Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation. IEEE Trans. Power Syst. **26**(1), 198–205 (2011). https://doi.org/10.1109/TPWRS.2010.2049036
109. Paiva, P.C., Khodr, H.M., Dominguez-Navarro, J.A., Yusta, J.M., Urdaneta, A.J.: Integral planning of primary-secondary distribution systems using mixed integer linear programming. IEEE Trans. Power Syst. **20**(2), 1134–1143 (2005). https://doi.org/10.1109/TPWRS.2005.846108
110. Pardalos, P., Resende, M.: Handbook of Applied Optimization. Oxford University Press, Oxford (2002)
111. Pavani, P., Singh, S.N.: Economic Aspects of Distributed Generation, pp. 731–748. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-51343-0
112. Pereira, B.R., da Costa, G.R.M., Contreras, J., Mantovani, J.R.S.: Optimal distributed generation and reactive power allocation in electrical distribution systems. IEEE Trans. Sustain. Energy **7**(3), 975–984 (2016). https://doi.org/10.1109/TSTE.2015.2512819
113. Pereira Júnior, B.R., Cossi, A.M., Contreras, J., Mantovani, J.R.S.: Multiobjective multistage distribution system planning using tabu search. IET Gen. Transm. Distrib. **8**(1), 35–45 (2014). https://doi.org/10.1049/iet-gtd.2013.0115
114. Pires, D.F., Martins, A.G., Antunes, C.H.: A multiobjective model for var planning in radial distribution networks based on tabu search. IEEE Trans. Power Syst. **20**(2), 1089–1094 (2005). https://doi.org/10.1109/TPWRS.2005.846068
115. Ponnavaikko, M., Rao, K.S.P.: An approach to optimal distribution system planning through conductor gradation. IEEE Power Eng. Rev. **PER–2**(6), 56–57 (1982). https://doi.org/10.1109/MPER.1982.5521021
116. Ramadan, H., Bendary, A., Nagy, S.: Particle swarm optimization algorithm for capacitor allocation problem in distribution systems with wind turbine generators. Int. J. Electr. Power Energy Syst. **84**, 143–152 (2017). https://doi.org/10.1016/j.ijepes.2016.04.041, http://www.sciencedirect.com/science/article/pii/S0142061516307268
117. Rebennack, S.: Generation expansion planning under uncertainty with emissions quotas. Electr. Power Syst. Res. **114**, 78–85 (2014). https://doi.org/10.1016/j.epsr.2014.04.010. http://www.sciencedirect.com/science/article/pii/S0378779614001503
118. Resch, M., Bhler, J., Klausen, M., Sumper, A.: Impact of operation strategies of large scale battery systems on distribution grid planning in Germany. Renew. Sustain. Energy Rev. **74**, 1042–1063 (2017). https://doi.org/10.1016/j.rser.2017.02.075. http://www.sciencedirect.com/science/article/pii/S1364032117302976
119. Resener, M., Haffner, S., Pereira, L.A., Pardalos, P.M.: Mixed-integer LP model for volt/var control and energy losses minimization in distribution systems. Electr. Power Syst. Res. **140**, 895–905 (2016). https://doi.org/10.1016/j.epsr.2016.04.015. http://www.sciencedirect.com/science/article/pii/S0378779616301328
120. Resener, M., Haffner, S., Pardalos, P.M., Pereira, L.A.: A Convex Model for the Optimization of Distribution Systems with Distributed Generation, pp. 231–245. Springer International Publishing, Cham (2017)
121. Safigianni, A., Salis, G.: Optimum voltage regulator placement in a radial power distribution network. IEEE Trans. Power Syst. **15**(2), 879–886 (2000). https://doi.org/10.1109/59.867188
122. Safigianni, A., Salis, G.: Optimum VAR control of radial primary power distribution networks by shunt capacitor installation. Int. J. Electr. Power Energy Syst. **23**(5), 389–401 (2001).

https://doi.org/10.1016/S0142-0615(00)00071-5. http://www.sciencedirect.com/science/article/pii/S0142061500000715
123. Salis, G., Safigianni, A.: Long-term optimization of radial primary distribution networks by conductor replacements. Int. J. Electr. Power Energy Syst. **21**(5), 349–355 (1999). https://doi.org/10.1016/S0142-0615(99)00003-4. http://www.sciencedirect.com/science/article/pii/S0142061599000034
124. Samal, P., Ganguly, S., Mohanty, S.: Planning of unbalanced radial distribution systems using differential evolution algorithm. Energy Syst. **8**(2), 389–410 (2017). https://doi.org/10.1007/s12667-016-0202-z
125. Santos, S.F., Fitiwi, D.Z., Shafie-khah, M., Bizuayehu, A.W., Cabrita, C.M.P., Catalo, J.P.S.: New multi-stage and stochastic mathematical model for maximizing res hosting capacity—part ii: numerical results. IEEE Trans. Sustain. Energy **8**(1), 320–330 (2017a). https://doi.org/10.1109/TSTE.2016.2584122
126. Santos, S.F., Fitiwi, D.Z., Shafie-Khah, M., Bizuayehu, A.W., Cabrita, C.M.P., Catalo, J.P.S.: New multistage and stochastic mathematical model for maximizing res hosting capacity—part i: problem formulation. IEEE Trans. Sustain. Energy **8**(1), 304–319 (2017b). https://doi.org/10.1109/TSTE.2016.2598400
127. Schmill, J.V.: Optimum size and location of shunt capacitors on distribution feeders. IEEE Trans. Power Apparatus Syst. **84**(9), 825–832 (1965). https://doi.org/10.1109/TPAS.1965.4766262
128. Segura, S., Romero, R., Rider, M.J.: Efficient heuristic algorithm used for optimal capacitor placement in distribution systems. Int. J. Electr. Power Energy Syst. **32**(1), 71–78 (2010). https://doi.org/10.1016/j.ijepes.2009.06.024
129. Shen, X., Shahidehpour, M., Han, Y., Zhu, S., Zheng, J.: Expansion planning of active distribution networks with centralized and distributed energy storage systems. IEEE Trans. Sustain. Energy **8**(1), 126–134 (2017). https://doi.org/10.1109/TSTE.2016.2586027
130. Short, T.: Electric Power Distribution Handbook. Electric Power Engineering. Taylor & Francis, UK (2003)
131. Shortle, J., Rebennack, S., Glover, F.W.: Transmission-capacity expansion for minimizing blackout probabilities. IEEE Trans. Power Syst. **29**(1), 43–52 (2014). https://doi.org/10.1109/TPWRS.2013.2279508
132. Shuaib, Y.M., Kalavathi, M.S., Rajan, C.C.A.: Optimal capacitor placement in radial distribution system using gravitational search algorithm. Int. J. Electr. Power Energy Syst. **64**, 384–397 (2015). https://doi.org/10.1016/j.ijepes.2014.07.041. http://www.sciencedirect.com/science/article/pii/S0142061514004736
133. da Silva, I.C., Carneiro, S., de Oliveira, E.J., de Souza, Costa J., Pereira, J.L.R., Garcia, P.A.N.: A heuristic constructive algorithm for capacitor placement on distribution systems. IEEE Trans. Power Syst. **23**(4), 1619–1626 (2008). https://doi.org/10.1109/TPWRS.2008.2004742
134. Singh, B., Sharma, J.: A review on distributed generation planning. Renew. Sustain. Energy Rev. **76**, 529–544 (2017). https://doi.org/10.1016/j.rser.2017.03.034. http://www.sciencedirect.com/science/article/pii/S1364032117303568
135. de Souza, B.A., de Almeida, A.M.F.: Multiobjective optimization and fuzzy logic applied to planning of the volt/var problem in distributions systems. IEEE Trans. Power Syst. **25**(3), 1274–1281 (2010). https://doi.org/10.1109/TPWRS.2010.2042734
136. de Souza, B.A., Alves, H.N., Ferreira, H.A.: Microgenetic algorithms and fuzzy logic applied to the optimal placement of capacitor banks in distribution networks. IEEE Trans. Power Syst. **19**(2), 942–947 (2004). https://doi.org/10.1109/TPWRS.2004.825901
137. de Souza, J., Rider, M.J., Mantovani, J.R.S.: Planning of distribution systems using mixed-integer linear programming models considering network reliability. J. Control Autom. Electr. Syst. **26**(2), 170–179 (2015). https://doi.org/10.1007/s40313-014-0165-z
138. Sultana, S., Roy, P.K.: Optimal capacitor placement in radial distribution systems using teaching learning based optimization. Int. J. Electr. Power Energy Systems **54**, 387–398 (2014). https://doi.org/10.1016/j.ijepes.2013.07.011. http://www.sciencedirect.com/science/article/pii/S0142061513003086
139. Sun, D.I., Farris, D.R., Cote, P.J., Shoults, R.R., Chen, M.S.: Optimal distribution substation and primary feeder planning via the fixed charge network formulation. IEEE Trans. Power Apparatus Syst. **PAS–101**(3), 602–609 (1982). https://doi.org/10.1109/TPAS.1982.317273
140. Sundhararajan, S., Pahwa, A.: Optimal selection of capacitors for radial distribution systems using a genetic algorithm. IEEE Trans. Power Syst. **9**(3), 1499–1507 (1994). https://doi.org/10.1109/59.336111

141. Szuvovivski, I., Fernandes, T., Aoki, A.: Simultaneous allocation of capacitors and voltage regulators at distribution networks using genetic algorithms and optimal power flow. Int. J. Electr. Power Energy Syst. **40**(1), 62–69 (2012). https://doi.org/10.1016/j.ijepes.2012.02.006. http://www.sciencedirect.com/science/article/pii/S0142061512000336
142. Tabares, A., Franco, J.F., Lavorato, M., Rider, M.J.: Multistage long-term expansion planning of electrical distribution systems considering multiple alternatives. IEEE Trans. Power Syst. **31**(3), 1900–1914 (2016). https://doi.org/10.1109/TPWRS.2015.2448942
143. Tang, Y.: Power distribution system planning with reliability modeling and optimization. IEEE Trans. Power Syst. **11**(1), 181–189 (1996). https://doi.org/10.1109/59.486711
144. Tang, Y., Low, S.H.: Optimal placement of energy storage in distribution networks. IEEE Trans. Smart Grid **8**(6), 3094–3103 (2017). https://doi.org/10.1109/TSG.2017.2711921
145. Temraz, H.K., Quintana, V.H.: Distribution system expansion planning models: an overview. Electr. Power Syst. Res. **26**(1), 61–70 (1993). https://doi.org/10.1016/0378-7796(93)90069-Q
146. Vaziri, M., Tomsovic, K., Bose, A.: A directed graph formulation of the multistage distribution expansion problem. IEEE Trans. Power Deliv. **19**(3), 1335–1341 (2004a). https://doi.org/10.1109/TPWRD.2004.829146
147. Vaziri, M., Tomsovic, K., Bose, A.: Numerical analyses of a directed graph formulation of the multistage distribution expansion problem. IEEE Trans. Power Deliv. **19**(3), 1348–1354 (2004b). https://doi.org/10.1109/TPWRD.2004.829948
148. Veeramsetty, V., Venkaiah, C., Kumar, D.M.V.: Hybrid genetic dragonfly algorithm based optimal power flow for computing lmp at dg buses for reliability improvement. Energy Syst. (2017). https://doi.org/10.1007/s12667-017-0268-2
149. Vita, V., Ekonomou, L., Christodoulou, C.A.: The impact of distributed generation to the lightning protection of modern distribution lines. Energy Syst. **7**(2), 357–364 (2016). https://doi.org/10.1007/s12667-015-0175-3
150. Wang, Z., Liu, H., Yu, D., Wang, X., Song, H.: A practical approach to the conductor size selection in planning radial distribution systems. IEEE Trans. Power Deliv. **15**(1), 350–354 (2000). https://doi.org/10.1109/61.847272
151. Xi, X., Sioshansi, R., Marano, V.: A stochastic dynamic programming model for co-optimization of distributed energy storage. Energy Syst. **5**(3), 475–505 (2014). https://doi.org/10.1007/s12667-013-0100-6
152. Xing, H., Sun, X.: Distributed generation locating and sizing in active distribution network considering network reconfiguration. IEEE Access **5**, 14,768–14,774 (2017). https://doi.org/10.1109/ACCESS.2017.2732353
153. Xing, H., Cheng, H., Zhang, Y., Zeng, P.: Active distribution network expansion planning integrating dispersed energy storage systems. IET Gen. Transm. Distrib. **10**(3), 638–644 (2016). https://doi.org/10.1049/iet-gtd.2015.0411
154. Xu, Y., Dong, Z.Y., Zhang, R., Hill, D.J.: Multi-timescale coordinated voltage/var control of high renewable-penetrated distribution systems. IEEE Trans. Power Syst. **32**(6), 4398–4408 (2017). https://doi.org/10.1109/TPWRS.2017.2669343
155. Yang, F., Li, Z.: Improve distribution system energy efficiency with coordinated reactive power control. IEEE Trans. Power Syst. **31**(4), 2518–2525 (2016). https://doi.org/10.1109/TPWRS.2015.2477378
156. Ziari, I., Ledwich, G., Ghosh, A.: Optimal voltage support mechanism in distribution networks. IET Gen. Transm. Distrib. **5**(1), 127–135 (2011). https://doi.org/10.1049/iet-gtd.2010.0277
157. Ziari, I., Ledwich, G., Ghosh, A., Platt, G.: Optimal distribution network reinforcement considering load growth, line loss, and reliability. IEEE Trans. Power Syst. **28**(2), 587–597 (2013). https://doi.org/10.1109/TPWRS.2012.2211626