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Review

Expansion Planning of Power Distribution Systems Considering Reliability: A Comprehensive Review

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Abstract: One of the big concerns when planning the expansion of power distribution systems (PDS) is reliability. This is defined as the ability to continuously meet the load demand of consumers in terms of quantity and quality. In a scenario in which consumers increasingly demand high supply quality, including few interruptions and continuity, it becomes essential to consider reliability indices in models used to plan PDS. The inclusion of reliability in optimization models is a challenge, given the need to estimate failure rates for the network and devices. Such failure rates depend on the specific characteristics of a feeder. In this context, this paper discusses the main reliability indices, followed by a comprehensive survey of the methods and models used to solve the optimal expansion planning of PDS considering reliability criteria. Emphasis is also placed on comparing the main features and contributions of each article, aiming to provide a handy resource for researchers. The comparison includes the decision variables and reliability indices considered in each reviewed article, which can be used as a guide to applying the most suitable method according to the requisites of the system. In addition, each paper is classified according to the optimization method, objective type (single or multiobjective), and the number of stages. Finally, we discuss future research trends concerning the inclusion of reliability in PDS expansion planning.

Keywords: distribution system; expansion planning; reliability; optimization models

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1. Introduction

A power distribution system (PDS) can be defined as the connection existing between power substations and consumers, including primary feeders, power transformers, and secondary circuits [1]. A typical distribution system is constantly growing to meet the increasing load demand of consumers and reliability requirements. Hence, expansion planning studies are constantly under analysis to economically and efficiently meet the load demand growth, within a planning horizon and respecting technical criteria and constraints imposed on the system [2].

Concerning the horizon of expansion planning, three categories can be defined: short-term expansion planning (1–5 years), long-term expansion planning (5–20 years), and operation planning [3]. Short-term expansion planning excludes major changes to the network, prioritizing the installation of devices such as capacitor banks, voltage regulators, or switching elements. Network changes are proposed in long-term planning, since constructing new feeders and distribution substations demands a longer execution time, generally available in this planning horizon. The objective of operation planning is to meet the load demand within the physical and operational limits of equipment and network through optimal control strategies. Therefore, the operation planning problem can be defined as a sub-problem of the expansion planning problem, as it performs a network diagnosis for each investment alternative, allowing one to properly define the new system components to be installed [4].

The use of distributed energy resources (DER) in PDS, including distributed generation (DG), requires the inclusion of additional technical aspects into PDS planning. Firstly, the connection of DER transforms passive networks into active networks, which has technical and financial impacts, depending on the specific characteristics of DG, such as DG installation node and type of DG—firm or variable. Secondly, from a technical point of view, DG impacts the energy losses and voltage profile, as it changes the flow of energy within the network, in addition to altering system maintenance and restoration practices.

Microgrids can feed loads in areas far from the power supply grid efficiently and economically. Additionally, the planning of PDS generally considers energy supplied by distributed renewable energy sources, conventional generators, electrical energy storage systems, heat energy storage systems, and natural gas heaters, among others [5,6]. However, predicting the operation of microgrids is complex due to uncertainties related to the randomness of renewable energy and to the declining cost of investing in energy storage [5].

Furthermore, through the use of smart grid (SG) devices, it becomes possible to obtain large amounts of data, which can, in turn, be used to better plan the PDS. SG concepts are related to networks with the considerable integration of information technology, telecommunication, sensing techniques, measurement devices, and automation. The use of SG concepts makes it possible to improve the system operation and the capacity to operate with DG, thus increasing the system reliability as a whole. Therefore, although competing with traditional methods, paradigms, and traditional planning techniques, the concepts of SG can lead to lower operating and investment costs.

Utilities currently face a scenario in which consumers increasingly demand high supply quality, including few interruptions and continuity. Interruptions in energy supply can result in significant financial and social losses, both for utility and consumers. Therefore, it becomes important to consider reliability indices when planning the PDS expansion. However, even when complex network models are used, the quality of the service, as expressed by reliability indices and failure rates, remains a great challenge for planning engineers.

The models applied to solve the PDS expansion planning problem usually do not include reliability criteria. Although the execution of expansion plans can positively influence the quality of service, estimating the gains in terms of reliability indices is not trivial. Under the gains to be estimated as the result of a given expansion plan, we can include the reduction in supply interruptions. Further, the decision-making process concerning a given expansion plan can be supported by a comparison between the reliability indices and the penalties applied to utilities before and after the effective implementation of the plan, thus weighing the potential benefits from the utility side and customer side in terms of reliability.

One of the difficulties to including reliability indices into models used to plan the expansion of PDS is the need to estimate performance indices, which requires knowledge of the failure rates not only of the network but also of different devices [7]. However, generalizing these rates is challenging due to the specific characteristics and different performance targets of rural and urban feeders, overhead and underground feeders, feeders with different rated voltages, and feeders of different lengths. Furthermore, the extent of automation and protection schemes of these feeders also impose difficulties to the determination of their failure rates.

Several papers addressing reliability in PDS can be found in the literature. A search on the Scopus database results in approximately 2100 papers from 1990 to 2022, retrieved using the keywords reliability, power distribution system and planning. Figure 1 presents the number of papers over this period, where it is possible to observe that the research topic has been receiving more attention in recent years. Note that Figure 1 includes not only expansion planning but also operation and other related problems addressing reliability in PDS.

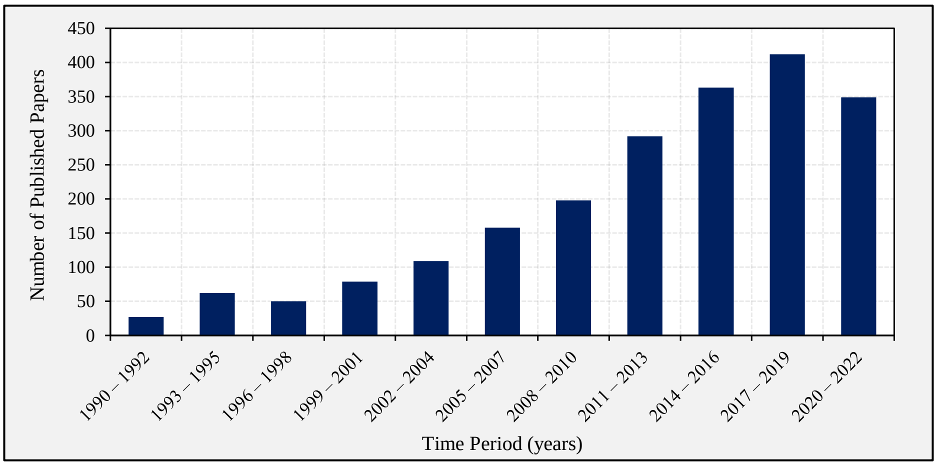

Figure 1. Number of published papers found on Scopus database.

Aiming to provide a handy resource guide to engineers and researchers, we selected and reviewed the most relevant papers on the PDS expansion planning models that include reliability. These papers have been published from 1996 to 2022 in international journals and conferences, all of them indexed in the Scopus database. However, to highlight the newest research findings, papers published in the last 3 years account for more than 32% of the total. On the other hand, the papers have been retrieved using the keywords reliability, power distribution system, expansion and planning. Further, we analyzed the papers with attention to the expansion alternatives considered in each model. At the same time, we also compared and analyzed 63 papers, which were categorized from different perspectives including (i) the optimization method used to solve the problem; (ii) the number of stages (single stage or multistage); (iii) the type of objective in which the problem is formulated (single objective or multiobjective); (iv) the reliability indices used to insert reliability criteria into the models; and (v) the larger-scale test system used. Furthermore, this review paper also provides a discussion on research prospects which can guide future research trends.

Regarding review papers, a literature search revealed that several authors reviewed the PDS planning problem and the associated solution. In [8–10], for example, the authors address the optimal planning of DG in distribution systems, yet do not address other expansion alternatives commonly considered in the planning of PDS. Other review papers analyze and compare the optimization models and methods applied to the problem of PDS expansion planning, but without attention to the reliability [4,11–13]. In addition, Ref. [14] focuses only on multiobjective approaches. Other review papers studied the inclusion of energy storage systems (ESS) into distribution networks [15–19], focusing on the technologies and impacts of ESS rather than on the expansion planning of PDS. An overview of works that propose the allocation of protection and control devices in distribution systems is presented in [20]. In [21], a review of advances in SGs is presented, where pricing policy is discussed, as well as components of SGs and data management schemes. Therefore, to our knowledge, up to now, no review paper has addressed the assessment of reliability within optimization models for PDS expansion planning as in the present paper.

Within the context outlined above, the main contributions of this paper are:

- A comprehensive survey of works that address the expansion planning problem considering reliability in PDS;
- A comparison including the main features and contributions of each work;

- A comparison of methods including decision variables, reliability indices, and the larger-scale test system used of each article; this comparison can be used as a guide to applying the most suitable method according to the requisites of the system;
- An analysis on the computational complexity of optimization models applied to solve the PDS expansion problem considering reliability;
- A discussion about future research trends in optimization models applied to the problem of PDS expansion planning considering reliability.

2. Expansion Planning and Reliability in Power Distribution Systems

In general, PDS expansion planning includes many investment options, the most common being the reconductoring of existing circuits, the construction of new circuits or substations, and the determination of the capacity, location and installation of new devices [22]. Investment in the reconductoring of existing circuits can reduce excessive energy losses, occurring when the maximum current capacity of conductors is exceeded, when the voltages are lower than the minimum [23], or even when the reliability of the energy supply must be improved [24].

Investing in new circuits may occur when it is necessary to expand the PDS to meet load demands in areas not yet supplied. Even so, depending on the alternative routes, investments in new circuits may require ideal routes for the feeders, this being an important aspect in the PDS expansion planning [25]. On the other hand, defining ideal routes can also result in lower energy losses, improved voltage levels, and higher reliability.

Energy losses and violations of nodal voltage limits are among the technical criteria often considered in optimization models for planning the expansion of PDS. Utilities must supply voltages within specific limits, which implies that the voltage profile must always be close to a reference value [22]. An adequate voltage profile benefits not only consumers but also utilities, given that the operation within voltage limits avoids financial compensations to be paid to consumers in case of inadequate voltages [24]. In addition, utilities are constantly concerned with energy losses, as they may imply additional costs [24]. Recently, optimization models have also considered aspects related to the reliability of the electricity supply [22,26,27].

Reliability is defined as the ability to continuously meet the load demand of consumers in terms of both quantity and quality [28,29]. Failures in PDS are responsible for more than 80% of the interruptions of the energy supply to consumers, showing that investments in reliability at the distribution level can improve the reliability of the entire power system [29]. Moreover, reliability is usually expressed through indices, the most common at the distribution level being Energy Not Supplied (ENS), the System Average Interruption Duration Index (SAIDI), and the System Average Interruption Frequency Index (SAIFI). Thus, to simultaneously meet economic and reliability requirements, when formulating the problem of planning the expansion of distribution systems, it is necessary to consider reliability indices in optimization models.

An alternative solution to improve the reliability of PDS is the use of selectivity schemes between reclosing and protection devices placed across the feeders. In addition, the intelligent allocation and coordination of switching and protection devices improves fault detection and reduces the repair time, given that such procedures divide the network into protection zones. As a result, those consumers affected by the fault are isolated, while energy is supplied to the remaining users for the time required to restore the interruptions.

Each of the works discussed in this paper proposes decision variables that depend on the optimization model used by the author. Figure 2 illustrates the decision variables, categorized into seven groups: the addition of lines (AL), reconductoring (RE), switching or protection devices (SW), substation construction or increasing the capacity of existing substations (SS), distributed generation (DG), energy storage systems (ESS), and parking lots (PL) with charging stations (CS) for electric vehicles (EV). Further, among the alternatives found in optimization models regarding decision variables related to SW are reclosers, fuses, sectionalizing switches, tie-lines, and circuit breakers (CB).

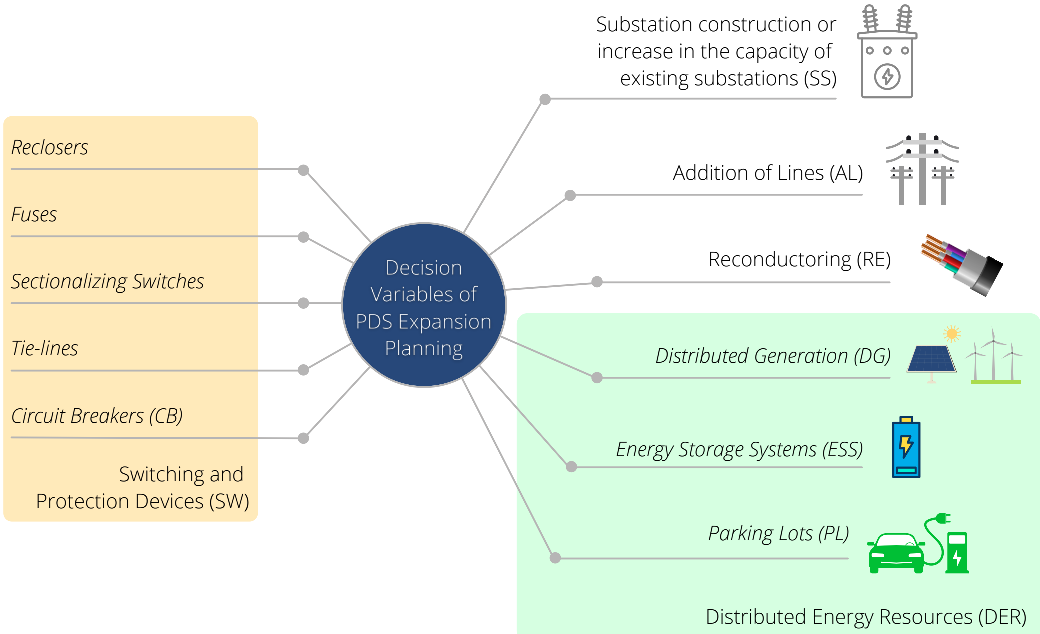

Figure 2. Decision variables of PDS expansion planning models considering reliability.

2.1. Reliability Indices

Utilities are responsible for supplying electricity to consumers while meeting reliability requirements established by regulatory agencies. Towards this end, utilities must invest in expansions of the network and also follow maintenance practices in their concession areas that help reduce their costs [30]. To quantify the PDS reliability and assess the performance of utilities, both on the regulator side and on the utility side, reliability indices are used. These indices can be related to momentary interruptions (less than 5 min) or sustained interruptions (5 min or more); further, they can also be based on the loads of PDS. IEEE Standard 1366-2012—Guide for Electric Power Distribution Reliability Indices defines the fundamental terms to be used in studies of the reliability of distribution systems as well as several reliability indices [31].

The main reliability indices used to express sustained interruption in PDS are the SAIDI, SAIFI, and Average Service Availability Index (ASAI). The following indices are customer-oriented indices: SAIFI indicates how many sustained interruptions an average customer expects to occur and SAIDI the expected number of hours of interruption of an average customer, both calculated for a given period of time; ASAI indicates the percentage of time an average customer is supplied without interruption [31]. Furthermore, the indices Customer Interruption Frequency (CIF) and Customer Interruption Duration (CID) can also be used; they express the frequency and duration of interruptions for each load node, respectively.

In contrast, the indices ENS and Average Energy Not Supplied (AENS) are load-oriented, both being equivalent to the energy not consumed due to interruptions; note that AENS is normalized by the number of consumers of the electrical set, defined as a group of utilities/consumers according to [30]. To estimate the Customer Interruption Cost (CIC) due to interruptions related to the distribution system, the Expected Interruption Cost Index (ECOST) can be used, which, in turn, is is based on the ENS index. ECOST uses the Customer Damage Function (CDF), which estimates the cost of outages normalized by the load and the duration of the outage of each customer [32]. Note that each customer class has a CDF, given that consumers can be divided into classes, such as residential, commercial, industrial, agriculture, government/institutional, large consumers, and offices [33]. Among the most relevant reliability indices related to momentary interruptions are the Momentary Average Interruption Frequency Index (MAIFI) and the Momentary Average Interruption Event Frequency Index (MAIFIe) [34].

Utilities must follow the standards established by regulatory agencies. For this purpose, they use tools that allow them to assess the network history and to support the decision making in PDS expansion planning. In this context, the historical assessment of reliability helps compare the performance of the system concerning the limit values of indices prescribed by standards. On the one hand, this type of assessment helps identify those parts of the network that most need improvements. On the other hand, predictive evaluation aims to estimate future performance, as well as the impact of expansion actions on the PDS reliability; further, predictive evaluation can also support the decision-making process on expansion investments in short- and long-term planning horizons [35].

2.2. Reliability Evaluation in Expansion Planning Studies

A review of PDS reliability is presented in [36,37], where the authors focus on studies related to SGs and propose the introduction of microgrids in models aimed to assess reliability. The review [37] describes the techniques used in each type of method (analytical, sequential Monte Carlo simulation, and others), the characteristics and influence of the main subsystems, such as DG, ESS, and EV, on reliability. Furthermore, the authors of [37] detail the estimated indices and focus on the random characteristics of DER and on the application of the methods described to real systems.

Heidari and Fotuhi-Firuzabad [38] proposed a method for inserting reliability assessments into studies of planning the expansion of PDS, where the indices SAIDI, ENS, and AENS are considered, as well as an index for the cost per interruption for a whole year. In addition, the authors applied the proposed method to a solution found in the multistage optimization model described in Heidari et al. [39] to estimate the reliability for each year in a five-year plan. Jooshaki et al. [40] proposed a linearized model to calculate SAIFI, SAIDI, and ENS that allows one to include reliability costs into mixed-integer linear programming (MILP) optimization models.

In [41], a recursive hybrid algorithm was applied to evaluate the reliability of PDS, aiming to reduce the computational cost. The authors evaluate the effects of considering the misoperation of fuses, CB, and relays and the connection of DG. The indices SAIFI, SAIDI, ASAI, ENS, and CAIDI (Customer Average Interruption Duration Index) were obtained for the test systems. The method for the assessment of reliability proposed by Escalera et al. [42] estimates the reduction in the ENS for critical consumers coming from the use of an optimal coordination schema that considers DG, ESS, and dispatchable loads during contingencies. In addition, in this study, the analytical approach followed by the authors considered the uncertainties of the generation, demand, and state-of-charge of ESS to estimate the SAIDI, SAIFI, and ENS indices.

Munoz-Delgado et al. [43] proposed a method based on linear programming for the calculation of reliability indices, in which the network topology is explicitly represented by decision variables of the optimization process. This work also presented a new mathematical formulation for ASAI, SAIDI, SAIFI, CID, CIF, and ENS. On the other hand, Tabares et al. [44] proposed evaluating the PDS reliability in an algebraic way, in which the indices SAIFI, SAIDI, ASAI, and ENS are considered. In this work, the analytical method used to assess the reliability of the network is based on the mathematical formulations for estimating reliability indices and ENS developed by Munoz-Delgado et al. [43]. However, Tabares et al. [44] claim important advantages, such as less computational effort given that only a system of linear equations is solved, instead of an optimization problem.

Wang et al. [45] developed an analytical method to evaluate reliability based on the fault incidence matrix (FIM), which can be applied to complex PDS. This method makes it possible not only to determine reliability indices but also to assess the impact of each fault on these indices under different load conditions. The proposed approach can be seen as a tool to identify critical points and for sensitivity analysis when planning the PDS expansion. In fact, FIM can be applied to distribution systems with radial structures, with one or more tie-lines, and with or without capacity restrictions. In contrast, in Zhang et al. [46], the focus of the study is the sensitivity analysis of the reliability indices of PDS considering the impact of factors that influence reliability, such as failure rate, switching and repair times, the automation of manual switches, the location of CB, sectionalizing switches, and tie-lines. The method developed in this work is derived from FIM, proposed by Wang et al. [45]. Thus, it serves as a tool o PDS expansion planning to identify the factors that contribute most to the reliability indices, while reducing computation time by avoiding repetitive evaluations of the reliability.

Reliability can be included into optimization models both (i) as changes to the objective function or (ii) integrated as constraints, with both alternatives requiring the evaluation of reliability during the optimization process [38]. Thus, many authors have dedicated their efforts to improving the way reliability is integrated into optimization models.

In the context discussed so far, we can now identify the major trends in the approaches used to estimate the reliability of complex PDS, which have the characteristics of real systems, such as a large number of load nodes and protection and/or sectionalizing devices. We recognize that the majority of this works focuses on the reduction in computation time required to estimate the reliability and to overcome the difficulties related to the complexity of the mathematical modeling of PDS, both aspects being fundamental for the implementation of planning tools.

Moreover, the determination of failure rates and repair times of the primary network based on real data remains a challenge due to the difficulties faced by utilities with data acquisition concerning failures, which makes the problem even more complex.

2.3. Test Systems Used in Power Distribution Studies

Test systems can be classified into actual or synthetic systems. Actual systems are modeled through real distribution networks with the protection of personal data; synthetic systems are generated through real distribution networks but modified through different techniques, as detailed in [47]. Optimal expansion planning studies of PDS usually employ test systems found in the literature, or systems modified according to the needs of the study. A representative example of test systems is the IEEE 123-node system, which is a radial distribution feeder used in several areas of studies involving PDS [48]. Further examples of test systems used in PDS studies are the IEEE 13-node, 34-node, and 37-node, described in [48], IEEE 33-node introduced in [49], and the 69-bus system used in [50]. On the other hand, a test system widely applied in reliability studies is the RBTS (Roy Billinton Test System) [51], which is composed of six medium-voltage buses with different types of consumers. In contrast, the 54-node test system described in [52] is suitable for network expansion planning due to the existence of candidate branches and substations to be constructed.

Finally, many studies concerning PDS expansion planning make no use of the test systems found in the literature. On the other hand, the case studies reported are based on actual feeders obtained from real distribution networks. These studies are usually funded through joint research projects financed by energy companies.

3. Short- and Long-Term PDS Expansion Planning Considering Reliability

The horizon of PDS expansion planning can be divided into short term (1–5 years) or long term (5–20 years) [3]. Within the context of reliability, short-term expansion planning usually encompasses the installation of protection and/or switching devices and the reconductoring of existing circuits, while long-term expansion planning may include the construction of substations and new feeders, as well as increasing the capacity of existing substations. For the purposes of analysis and comparison of planning approaches including reliability, we selected optimization models involving the integration of one or more expansion alternatives; further, the number of alternatives and type of each one depends on the particular approach chosen by the authors. In addition, in this Section we focus on models that do not consider the placement of DER as an alternative for expansion planning, although some consider pre-existing DG.

3.1. Protection and Switching Devices in the Context of PDS Expansion Planning

The installation of protection and switching devices can be considered as an expansion alternative in short-term planning, given that the installation requires less time compared to other alternatives, such as the construction of substations. Some of the devices available are (i) sectionalizing switches, (ii) normally open switches that are interconnected with adjacent feeders (tie-lines), (iii) fuses, and (iv) reclosers. In addition, as a short-term alternative, the automation of PDS can also be considered, in which manual protection and/or switching devices are replaced with automated devices. These alternatives are commonly used to improve reliability indices so that they meet the requirements of regulatory agencies concerning electricity distribution services.

Single-stage approaches to solve the problem of the optimal allocation of switches are among the first attempts found in the literature. In [53], an optimization model for the placement of switching devices was proposed and solved through simulated annealing (SA). The objective function included minimizing costs related to failures in medium-voltage distribution networks, using ECOST as a metric. The decision variables were the location and number of switching devices. Later, the ant colony optimization (ACO) algorithm was applied in [54] to solve the optimal relocation of switching devices in distribution feeders. The objective function considered the CIC, whereas investment costs and the costs of relocating switching devices were not considered. Sohn et al. [55] conceived a MILP model for the optimal allocation of switching devices, including fuses and reclosers, to minimize investment, maintenance, and interruption costs measured using the ECOST index.

Multiobjective approaches are also found in specialized research. In [56], a multiobjective approach using the ACO algorithm for the optimal placement of switching and protection devices is proposed. The alternatives included the installation and relocation of normally closed (NC) switching devices, reclosers, and fuses. Three objective functions are defined to evaluate SAIFI, SAIDI, and the costs related to interruption and the placement of devices. On the other hand, DG was included in the method presented by Falaghi et al. [57] for the optimal placement of switching devices. The method proposed is solved through an ACO algorithm and has a multiobjective characteristic similar to that described in [56]; however, the authors used a fuzzy approach. The objective function considers the ENS index and the installation costs of switches.

The automation of PDS can be considered as an expansion alternative to improve reliability indices related to the duration of interruptions. The immune algorithm (IA) was proposed in [58] for the optimal allocation of switching devices in distribution feeders. As alternatives, the method considered the installation of new devices, with manual or automatic operation, and the replacement of manual switching devices. The objective function included the costs of investment in devices and costs of reliability using CIC. Later, the trinary particle swarm optimization (TPSO) algorithm was used in [59] to solve the problem of the optimal placement of switching devices and circuit breakers, using the ECOST index as a metric to evaluate reliability. On the other hand, exact optimization methods were also used to solve the problem. In [60], an MILP model is presented to solve problem of the optimal allocation of automated switching devices. The objective function considers the ECOST index and the costs related to the acquisition, installation, operation, and maintenance of devices.

The allocation of switching devices through a multiobjective optimization model was proposed in [61], in which the authors solved the optimization problem using particle swarm optimization (PSO). The objective function is defined to minimize the number of customers not supplied (CNS) and investment costs of installing switches. In this study, the reliability indices are determined without using the failure rates. To illustrate the application of the proposed method, it was compared with the single objective approach introduced by Moradi and Fotuhi-Firuzabad [59], from which the authors concluded that better solutions can be obtained with the proposed model. Additionally, the authors compared the solutions obtained with the globally optimal solutions reported in the MILP model of Abiri-Jahromi et al. [60], thus proving the efficiency of the proposed method to find solutions close to the global optimum.

The SAIDI and SAIFI indices were also considered in works addressing the optimal allocation of switches. A model for the optimal relocation and installation of switching devices and tie-lines in medium-voltage networks was presented in [62] and solved through the memetic algorithm (MA). Additionally, the costs of ENS were included in the objective function, while the SAIDI index was integrated as a model constraint. In [63], an optimization model for the automation of sectionalizing switches and manual tie-switches using a greedy heuristic algorithm was proposed, in which the objective function considers the minimization of the number of installed switches. Later, the optimization method presented in [63] was used by Jiang et al. [64] to demonstrate the possibility of reliability improvement within the context of expansion planning of smart distribution systems. This study highlights the modernization of the network and the benefits obtained using remote-controlled switches and smart meters.

Mixed-integer linear and nonlinear optimization models were also proposed to optimally place switches, evaluating investment costs and the reliability for different installed devices and different constraints, such as those imposed on the transfer capacity of tie-lines and the tie-lines location. Heidari et al. [65] introduced a mixed-integer nonlinear programming (MINLP) model that determines the type, quantity, and location of sectionalizing switches, fuses, and CB. The objective function accounts for the minimization of total costs, which is composed of the investment and maintenance costs related to the switches, the costs of installing protection devices, and the index ECOST. Later, Zhang et al. [66] formulated a 0-1 integer linear programming model to optimally allocate sectionalizing switches and tie-lines. However, to this model, the objective function is given as the sum of the costs of interruptions based on the ENS plus the costs of acquisition and maintenance of the switches. Moreover, the authors determined the indices SAIDI, SAIFI, and ENS through the FIM, as described in [45].

Different MILP models can be found in the literature, having as their main advantage the guaranteed convergence to the global optimal solution. The allocation of fault indicator devices and sectionalizing switches were considered in Wang et al. [67], where a MILP optimization model was presented to improve reliability. In addition, the model includes tie-lines and manual- and remote-controlled switches, with the latter being capable of locating faults. Further, reliability was assessed through the indices SAIDI and ENS. Wang and Tai [68] formulated a MILP model for the expansion planning problem of PDS where the objective function seeks to minimize the investment costs to install interconnections between distribution feeders (tie-lines). Reliability is treated as a constraint to the problem and estimated through the indices CIF, CID, SAIFI, SAIDI, and ENS. The results concerning six case studies with different requirements for the SAIDI indicated the importance of building more tie-lines with stricter reliability constraints.

Some of the proposed models to optimally place switches also consider the presence of DG. In [69], a multiobjective approach was proposed to solve the problem of optimal allocation of sectionalizing switches and reclosers through genetic algorithm (GA), excluding the possibility of the islanded operation of DG. Among the objectives of the proposed model are the minimization of costs of investment in switches, the reliability indices SAIDI and SAIFI, and an index related to the unavailability of DG. The islanded operation of DG was considered by Velasquez et al. [70], who proposed the optimal installation of CB and reclosers. The optimization problem was addressed in a single-objective approach solved using the differential evolution (DE) algorithm, considering the maximization of profits related to the reduction in the amount of ENS and the costs of investment and maintenance. Additionally, a multiobjective approach is proposed and solved through the non-dominated sorting differential evolution algorithm (NSDE), considering the minimization of investment costs and SAIDI and SAIFI indices.

The automation of PDS in the presence of DG can have a significant impact, improving reliability. Pereira et al. [71] proposed a multiobjective optimization model for the allocation of protection devices and the automation of switching devices, considering that DG can operate islanded. The model considers the possibility of installing and/or relocating fuses, reclosers, sectionalizing switches, and automatic directional reclosers that react only to faults outside the DG island region. In the framework proposed by Chehardeh and Hatziadoniu [72], a two-level optimization model defines the number and location of manual NC and normally open (NO) switches to be replaced by automatic switches. The first level considers the minimization of the ECOST index through restoration, while in the second level automatic switches are allocated.

Uncertainties were recently addressed in optimization models applied to solve the optimal allocation of switching devices. A method based on GA was presented in [73] for the optimal allocation of reclosers, switches, and fuses in distribution systems with DG. Uncertainties in the data related to loads were also considered, along with permanent and temporary failure rates, and other parameters related to the failure duration. This method considered the island operation of DG, while the objective function included the maximization of gains due to the reduction in ENS costs and interruption costs to customers; additionally, the objective function also seeks to minimize the costs required for device installation and maintenance.

3.2. Substation and Feeders within PDS Expansion Planning

The growth in consumer load demands expansion work by electric utilities, with some of the alternatives being to increase the capacities of existing substations or the construction of new substations. These alternatives fit within expansion plans considering medium- or long-term horizons, due to the longer execution time required and the need for more significant changes to be made to the network. Furthermore, the construction of new substations usually requires new feeders to supply the load, for instance, when the network is expanded to areas not yet covered by electricity supply (greenfield planning [74]). In addition, given that switching and protection devices need to be installed along the new feeders, they not only change the network topology but also have an impact on the reliability of the system. Therefore, it becomes essential to include reliability criteria in optimization models applied to solve the problem of long-term expansion planning.

Single-stage approaches are among the first proposed models that included reliability criteria in PDS expansion planning models. A greenfield planning approach was presented in [74], assuming no pre-existing branches and thus defining the routes of new feeders. Also in [74], costs related to energy losses were minimized, along with those related to reliability and investment in substations and feeders. Reliability costs were addressed through the number of interruptions, considering only a circuit breaker in the substation. A model formulated as an MINLP problem was presented in [75], in which the objective function accounted for the costs of investment in substations and feeders, costs of active power losses, and costs related to reliability. Reliability costs were addressed as a function of interruption duration. In addition, the model was solved through an evolutionary algorithm (EA) and the results showed that the routing of the feeders changes when reliability is considered in the model. The expansion planning of medium- and low-voltage networks was addressed in [76] using a discrete particle swarm optimization (DPSO) algorithm. Further, the objective function aimed to minimize the costs of acquiring new devices, in addition to costs of operation, losses, and reliability (SAIDI and SAIFI).

Given the inherent conflicting nature of objectives such as minimizing investment and maximizing reliability, researchers have proposed several multiobjective approaches to include reliability models for the expansion planning of PDS. An MINLP multiobjective model, solved through EA, was proposed in [77], whose objective functions consider expansion costs and reliability costs through the ENS index. Later, a multiobjective model based on a fuzzy possibilistic optimization model was presented in [78], in which the authors determined non-dominant solutions corresponding to the minimization of expansion costs, reliability level, and exposure to faults. Expansion costs took into account the installation of new feeders and substations, while the reliability level was assessed through the ENS during interruptions. In addition, the exposure to faults is weighted by the probability of the network, together with the associated devices, to operate overloaded.

Carrano et al. [79] proposed an MINLP model for the problem of planning the expansion of PDS, solved through a multiobjective GA. The multiobjective approach proposed considered a monetary index (including the cost of energy losses and investment costs in substations and feeders), in addition to customer interruption costs. In [80], a multiobjective approach using two algorithms was proposed: a non-dominated sorting genetic algorithm (NSGA) and strength pareto evolutionary algorithm (SPEA). The multiobjective function of the optimization model minimizes the total expansion costs (investment in substation and feeders) and maximizes the reliability of the system. In contrast, reliability is assessed using ENS during system faults. The PSO algorithm was used in [81] in both single- and multiobjective approaches. Two objective functions were considered: one that considers the investment cost and energy losses of feeders and another that considers the ENS due to system faults.

Later, the optimal placement of switching devices was included in multiobjective models [82,83], aiming to minimize the total investment and operation costs and maximize the network reliability. For instance, in [82], an optimization model was proposed that considers the optimal location of sectionalizing switches and tie-lines. Reliability is evaluated through an index defined as the ratio between the average ENS, due to the failure of all branches, considered one at a time, and the total energy. On the other hand, in [83], reliability is measured through the cost of interruption, which is calculated as a function of the costs of ENS, the repair of the fault, and the damage caused to consumers. On the other hand, this damage is usually difficult to estimate, since it requires detailed knowledge of consumer activities.

Multistage models give the advantage of making it possible to invest at different times along the planning horizon. MILP models accounting for reliability in PDS expansion were presented in [84,85]. In [84], the original nonlinear objective function was linearized using a piecewise linear function. The objective function includes the costs of maintenance, losses, and operation, whereas the expansion alternatives are represented by the reinforcement of feeders and new substations. In addition, the model allows obtaining solutions that are subsequently used to evaluate the ENS, SAIDI, SAIFI, CID, and CIF, thus providing information on the impact of each solution on the reliability. On the other hand, Munoz-Delgado et al. [85] proposed an objective function considering the minimization of costs related to (i) investment in assets; (ii) the maintenance of feeders and transformers; (iii) purchase of electricity; (iv) load shedding; (v) power losses; and (vi) reliability. The expansion plan considered the investment in the addition and reconductoring of branches, as well as in the reinforcement of substations. Additionally, the authors used the ENS to evaluate the system reliability.

Switching and restoration times required to estimate reliability indices were later addressed in a MILP formulation proposed by Jooshaki et al. [86], in which the costs of reliability refer to the costs of ENS, SAIDI, and SAIFI. The objective function considered the cost of investment, operation, and reliability. The investment costs comprise the variables associated with the addition and reconductoring of feeder sections, as well as the construction or expansion of substations. In contrast, Li et al. [27] presented a MILP model where the reliability indices CIF, CID, SAIFI, SAIDI, and ENS are included as constraints.

Recently, as in [86], Tabares et al. [87] proposed a MILP that considers switching and restoration times for the calculation of ENS employing constraints. The objective function consists of minimizing the investment and operating costs. The investment cost includes the cost for installing new circuits, substations, and transformers, as well as for reconductoring existing feeders. The operating cost is the sum of the costs of the power supplied by the substation, load shedding, ENS, and maintenance of the substations, transformers, and feeders. For the case study examined, the authors found a reduction in total costs when reliability was included in the expansion planning model for distribution systems.

4. PDS Expansion Planning Considering Reliability and DER

The integration of DER in the electrical grid can collaborate with the expansion of smart electrical grids, bringing benefits through network operation and reconfiguration strategies [69]. The use of renewable DG in distribution systems is increasing, with DG being predominantly associated with wind and solar sources, while in some countries, grid-connected ESS technologies are being implemented. Furthermore, the use of EV is already a reality in many countries. Currently, studies on the expansion of distribution systems considering reliability also allow the inclusion of DER as alternatives, among which are (i) DG, (ii) ESS, and (iii) parking lots with CS for EV.

4.1. Distributed Generation

The connection of DER, such as DG, transforms the distribution network from passive to active, thus posing additional challenges to the operation and planning of PDS. In contrast, DG also offers several relevant benefits, for instance, the reduction in energy losses and better voltage control [88]. Yet, concerning reliability, the use of DG to supply energy to isolated areas during contingencies (islanded operation) can help improve reliability indices and reduce post-fault unsupplied energy [89].

Celli et al. [88] outlined a multiobjective method for the optimal allocation of DG using GA and the $\epsilon-$constrained method. This approach allows the planner to choose the best compromise between the cost of upgrading the system, the cost of purchasing energy, the cost of energy losses, and the cost of ENS. The results show that allowing DG to operate as an island can improve the reliability of PDS. On the other hand, Khalesi et al. [90] presented a mathematical model based on dynamic programming (DP). This model aims to maximize system reliability and minimize energy losses through the optimal allocation of DG. The authors considered the possibility of the islanded operation of DG and evaluated the reliability through the ENS.

Some of the works we discuss here propose MINLP optimization models including DG integrated with other expansion alternatives, in which the islanded operation of DG is allowed [2,91]. For example, Shaaban et al. [91] proposed a model in which the objective is to determine the optimal location of DG, to reduce the cost of energy losses and system interruptions. In addition to the installation of DG, the reconductoring of feeders and replacement of substation measurement and protection devices are considered as possible investments. In [2], the objective is to minimize investment and operating costs, in addition to maximizing reliability. In this context, the decision variables of this model are related to the installation of DG, the addition and reconductoring of feeders, and the addition and reinforcement of substations. Reliability is evaluated through the ENS during system outages. Further, the proposed model is solved using a hybrid algorithm combining PSO and SFL (Shuffled Frog Leaping) algorithms.

The DG allocation problem considering reliability is usually addressed in single-objective optimization models. The method proposed by Borges and Falcão [92] uses GA to solve the problems of optimal allocation and sizing of DG, imposing constraints on the SAIDI index. Dispatchable DG was considered as always available; therefore, the method cannot handle intermittent DG, such as solar and wind generation sources. Other works, however, address the allocation of DG in addition to protection and/or switching devices [89,93]. Pregelj et al. [89] used GA and evaluated reliability through the indices SAIDI, SAIFI, and MAIFIe. Later, the allocation of reclosers and DG was considered in [93], aiming to minimize a single reliability index, which is a combination of SAIFI and SAIDI, and simultaneously to meet prescribed values for these indices. The results showed that the installation of DG and reclosers helps to obtain an expansion plan, leading to a more reliable distribution system.

Optimization models considering DG and the increase in substation capacity and the reconductoring of feeder branches were also proposed [94,95]. An optimization model solved through the modified DPSO algorithm to improve the reliability of PDS was presented in [94], in which the decision variables refer to the installation of DG, capacitors, network branches, and transformers. System reliability is evaluated through fault location, repair time, failure rate, and customer impact. In this sense, the model considers the system to be capable of isolating all consumers downstream of the fault and that the DG, if available, can operate in such a way as to restore energy to the part of the consumers located downstream the fault. Later, Bagheri et al. [95] proposed a model which considers uncertainties in load demand, the output power of renewable DG, and the cost of energy purchased from the transmission system. The model is solved through GA and allows investment in renewable and non-renewable DG, reinforcement of feeders, and substations, while the reliability is modeled using ENS. In addition, islanding and load transfer through reserve feeders is allowed to improve system reliability.

MILP models for the multistage expansion planning problem of PDS were later proposed in [26,96]. Munoz-Delgado et al. [26] combined stochastic programming and MILP to account for uncertainties related to demand and DG sources. The expansion alternatives consisted of installing and increasing the capacity of feeders and substations, in addition to installing DG. The proposed model allows obtaining a set of solutions so that, subsequently, ENS, SAIFI, SAIDI, CIF, and CID, as well ENS cost, can be evaluated. On the other hand, Jooshaki et al. [96] included reliability costs (ENS, SAIFI, and SAIDI) in the objective function. Additionally, the installation of substations, feeders, and DG were considered; further, the model also considers the possibility of increasing the capacity of existing substations and feeders.

4.2. Energy Storage Systems

ESS can be used to reduce the peak demand of electricity by controlling the charging and discharging cycles. The improvement of the voltage profile, the reduction in energy losses, and the increase in power quality are additional benefits that can be achieved through the use of ESS [97]. In addition, ESS can be used to improve reliability indices through islanded operation, supporting the restoration of energy supply during contingency situations [98]. Moreover, the integration of ESS helps mitigate the uncertainties related to the generation of electricity from renewable energy sources [99,100]. Therefore, the simultaneous allocation of DG and ESS becomes an advantageous expansion option for smart grids.

One of the first optimization models applied to the expansion of distribution systems considering reliability and including ESS as an alternative was presented by Sedghi et al. [98]. In addition to ESS, the authors considered investment in DG, substation, feeders, and reserve feeders. Reliability was evaluated through the cost of the ENS during system interruptions, with the cost of ENS being calculated differently for each customer class connected to the nodes (residential, commercial, or industrial) and weighted by the duration of the interruptions. As one of the possible operation strategies, it was assumed that nodes are restored through interconnections, DG, and ESS. The single-objective function defined served to minimize the costs of investment, operation, and reliability. In addition, a modified PSO algorithm was used to solve the proposed model.

The allocation of photovoltaic DG and ESS was recently addressed by El-Ela et al. [101], in which the equilibrium optimization (EO) algorithm was used to solve the optimization problem. The objective function considers the minimization of costs of (i) ENS; (ii) maintenance and installation of DG and ESS; (iii) power losses; and (iv) CO_2 emissions. Hamidan and Borousan [102], on the other hand, proposed a model to size and place DG and ESS, solved through an Evolutionary Algorithm. The objective function accounts for the minimization of investment costs and operation costs related to DG and ESS and costs associated with the ENS index. Moreover, recently, Pinto et al. [103] proposed an optimization model that approaches not only the allocation of DG and ESS, but also the reconnection of branches and the allocation of switches and capacitors. This model considers uncertainties and determines the ENS by means of a Monte Carlo simulation.

Single-objective models for the optimal allocation and sizing of ESS to improve the reliability of PDS are presented in [99,100,104]. In [99,100], the objective function is defined as the total costs of installation and maintenance of ESS and the ECOST, while [104] also considers power losses. The GA [99], PSO [100], and teacher learning-based optimization (TLBO) algorithms were used to solve the models. In addition, Saboori et al. [100] also carried out a sensitivity analysis regarding the number of ESS, investment costs, and the capacity of installed ESS.

Alobaidi et al. [105] presented a multistage approach for the allocation of ESS in PDS with photovoltaic generation and data centers. The main optimization problem was formulated as a MILP problem and the objective function aims to minimize the costs of investment and battery operation, having as decision variables the capacity, location, and the date of installation of ESS. In this work, the guarantee of energy supply to the data centers and the level of reliability, which is measured by the ENS index, are considered.

Multiobjective approaches were also used to solve the problem of the optimal allocation and sizing of ESS and switching devices, aiming to improve the reliability of PDS. In [106], temporary interruptions are considered in the optimization model by minimizing the MAIFI in one of the objective functions of the problem. Further, the objective functions also consider the costs of installing devices and the index SAIDI, which is related to sustained interruptions. Later, Delgado-Antillón and Domínguez-Navarro [97] developed a multiobjective optimization model to minimize ENS, power losses, and the costs of investments, which are represented by the capacity of the storage units. Further, the island operation of DG is made possible by forming microgrids with ESS to support DG. The Pareto front was obtained through the results of the multiobjective optimization, allowing the PDS expansion planner to choose the best solutions.

4.3. Parking Lots with Charging Stations for Electric Vehicles

EV connected to the distribution grid can function as ESS through the vehicle-to-grid (V2G) capabilities, with the batteries of EV charging and discharging while connected to the power grid [107]. Therefore, EV can be considered as distributed generation sources, with the possibility of operating under energy management, storing energy during off-peak hours, and supplying energy during peak hours [108]. Furthermore, other benefits of this are the improvement of the voltage profile, the reduction in energy losses, and the improvement of reliability through islanded operation during failures [109]. In the context thus far outlined, optimization models have been proposed to improve the reliability of PDS through parking lots with CS for EV.

Moradijoz et al. [109] proposed one of the first optimization models that considers reliability criteria for the allocation and sizing of PL containing CS for EV. The objective of this is to maximize financial gains from energy supply through EV, while reducing the costs of ENS and power losses. In addition, the model considers the minimization of investment costs in EV parking and energy purchase costs for EV charging. The PL are modeled as ESS so that the utility can control the charging and discharging of the batteries. Using a multiobjective approach and an heuristic method, Xiang et al. [110] handled the expansion planning of PDS including the location and sizing of CS. The objective functions consider the minimization of (i) investment and operation costs; (ii) the CS utilization index; and (iii) ENS index.

A multistage optimization model for the expansion planning of PDS is presented in [108], in which the expansion alternatives were the installation or reinforcement of feeders and substations, fault location devices, and installation of CS for EV. Reliability was addressed through the ENS index in a multiobjective approach. On the other hand, a single-objective optimization model was developed in [111] for the allocation of automatic switching devices and PL with CS for EV connected to the grid to improve reliability. The objective function included the minimization of the SAIDI, the total costs of interruptions and investment costs. In addition, the authors solved the problem through the PSO algorithm and found that when the model considered the load uncertainties, together with the uncertainties of the energy supply to the network by CS, both the index SAIDI and the reliability costs increased.

Recently, Khan et al. [112] developed a multiobjective optimization model for sizing and placing PL connected to the grid, solved through the PSO algorithm. One of the objective functions aims to minimize the ENS index and the other aims to minimize losses. Reductions in the SAIFI, SAIDI, and ENS indices are found when EV are considered as the sources of energy during contingency situations. Further, when the model is based on centralized PL, a more significant reduction in the indices could be achieved, in comparison with the case in which CS and EV are distributed across the electric grid.

5. Comparative Analysis

In this section, we present a comparative analysis of the technical and scientific literature discussed in this paper. The works have been categorized based on (i) the optimization method used to solve each model, (ii) the type of objective function adopted, (iii) the number of planning stages, (iv) the type of decision variables, (v) the reliability indices considered in each optimization model, and (vi) the larger-scale test system used. Table 1 summarizes the comparison discussed in what follows.

According to Table 1, we classified the optimization methods used to solve the models reviewed in this paper into two categories: (i) exact methods and (ii) approximate methods. Approximate methods can be applied to nonlinear and linear optimization models and lead to acceptable practical solutions yet with no guarantee of optimality. On the other hand, exact methods can be applied to linear optimization models and result in solutions with optimality guarantee.

The classification of the optimization methods appearing in Table 1 are illustrated in Figure 3, from which it can be seen that the approximate models are predominant compared to the exact models. This predominance can be explained by the non-linear nature of the relationship between the quantities involved to consider the reliability within the optimization problem; further, the estimation of reliability indices requires the evaluation of the changes in the network associated with each optimal solution, which makes approximate methods more appropriate.

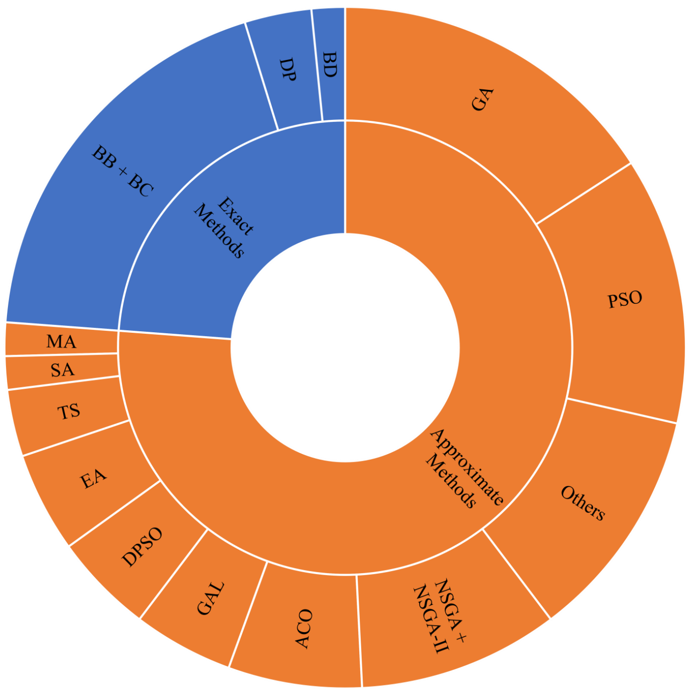

Figure 3. Classification of optimization models according to the optimization methods.

Table 1. Summary of the bibliographic survey.

Reference	Published	Optimization Method	Obj. Type [a]	Stages [b]	Decision Variables [c]							Reliability Indices [d]								Test System
			SO/MO	S/M	AL *	RE	SW	SS	DG	ESS	PL	ENS	SAIFI	SAIDI	CIF	CID	RIC	Others	
[53]	1996	Approximate	SO	S			✓					✓		✓			✓		RBTS bus-4/6
[75]	2000	Approximate	SO	S	✓			✓									✓		real 22-node
[77]	2001	Approximate	SO/MO	S/M	✓			✓				✓					✓		real 182-node
[74]	2002	Approximate	SO	S	✓			✓									✓		real 396-node
[54]	2003	Approximate	SO	S			✓										✓		178 buses
[78,113]	2004, 2006	Approximate	MO	S	✓			✓				✓							real 182-node
[88]	2005	Approximate	MO	S					✓			✓	✓	✓			✓		142-node
[79]	2006	Approximate	MO	S	✓			✓				✓					✓		100-node
[55]	2006	Exact	SO	S			✓										✓		RBTS bus-5
[92]	2006	Approximate	SO	S					✓				✓	✓			✓		real 43-node
[58]	2006	Approximate	SO	S			✓						✓	✓			✓		real 92-node
[89]	2006	Approximate	SO	S			✓		✓				✓	✓				✓	69-bus
[80]	2006	Approximate	MO	S	✓			✓				✓							43-node
[59]	2008	Approximate	SO	S			✓										✓		IEEE 123-node
[93]	2008	Approximate	SO	S			✓		✓				✓	✓					394-bus
[57]	2009	Approximate	MO	S			✓					✓							real 53-bus
[56]	2009	Approximate	MO	S			✓						✓	✓			✓		real 51-bus
[90]	2011	Approximate	SO	S					✓			✓					✓		9-node
[81]	2011	Approximate	SO/MO	S	✓	✓		✓				✓							real 182-node
[84]	2011	Exact	SO	M	✓	✓		✓				✓	✓	✓	✓	✓	✓	✓	27-node
[76]	2011	Approximate	SO	S	✓			✓					✓	✓			✓		72-node
[60]	2012	Exact	SO	S			✓										✓		RBTS bus-4
[82]	2012	Approximate	MO	S	✓	✓	✓	✓										✓	100-node
[91]	2013	Approximate	SO	S		✓	✓		✓								✓		real 38-node
[94]	2013	Approximate	SO	M		✓		✓	✓			✓					✓		205-bus
[2]	2013	Approximate	MO	M	✓	✓		✓	✓			✓							18-node
[83]	2013	Exact	SO	S	✓	✓		✓				✓					✓		100-node
[109]	2013	Approximate	MO	S							✓	✓					✓		9-bus
[98]	2013	Approximate	SO	M	✓		✓	✓	✓	✓		✓					✓		67-node
[99]	2014	Approximate	SO	S						✓		✓					✓		33-bus
[108]	2015	Approximate	MO	M	✓	✓		✓			✓	✓							24-node
[62]	2015	Approximate	SO	S			✓					✓		✓			✓		real 472-node
[61]	2015	Approximate	MO	S			✓										✓	✓	IEEE 123-node
[95]	2015	Approximate	SO	S	✓	✓	✓	✓	✓			✓					✓		real 104-node
[100]	2015	Approximate	SO	S						✓		✓					✓	✓	real 30-bus

Table 1. *Cont.*

Reference	Published	Optimization Method	Obj. Type [a]	Stages [b]	Decision Variables [c]							Reliability Indices [d]							Test System
			SO/MO	S/M	AL *	RE	SW	SS	DG	ESS	PL	ENS	SAIFI	SAIDI	CIF	CID	RIC	Others	
[69]	2016	Approximate	MO	S			✓						✓	✓				✓	real 94-bus
[63,64]	2016, 2016	Approximate	SO	S			✓						✓	✓					1069-node
[26]	2016	Exact	SO	M	✓	✓		✓	✓			✓	✓	✓	✓	✓	✓		138-node
[110]	2016	Approximate	MO	S	✓			✓			✓	✓							54-node
[70]	2016	Approximate	SO/MO	S			✓					✓	✓	✓					real 70-node
[106]	2017	Approximate	MO	S			✓			✓				✓				✓	real 94-node
[97]	2018	Approximate	MO	S						✓		✓							IEEE 123-node
[85]	2018	Exact	SO	M	✓	✓		✓				✓					✓		54-node
[65]	2018	Exact	SO	S			✓										✓		RBTS bus-4
[71]	2018	Approximate	MO	S			✓					✓					✓		real 135-bus
[72]	2019	Approximate	SO	S			✓					✓					✓		1069-node
[96]	2019	Exact	SO	M	✓	✓		✓	✓			✓	✓	✓			✓		54-node
[66]	2019	Approximate	SO	S			✓					✓	✓	✓			✓		real 94-bus
[67]	2020	Exact	SO	S			✓							✓			✓	✓	real 144-node
[104]	2020	Approximate	SO	S						✓		✓					✓		69-bus
[111]	2020	Approximate	SO	S			✓				✓			✓			✓		RBTS bus-4
[68]	2020	Exact	SO	S			✓					✓	✓	✓	✓	✓			54-node
[73]	2020	Approximate	SO	S			✓					✓					✓		69-bus
[86]	2021	Exact	SO	M	✓	✓		✓				✓	✓	✓			✓		138-node
[27]	2021	Exact	SO	M	✓	✓	✓	✓				✓	✓	✓	✓	✓	✓		54-node
[101]	2021	Approximate	SO	S					✓	✓		✓					✓		69-bus
[105]	2021	Exact	SO	M						✓		✓							IEEE 34-bus
[112]	2021	Approximate	MO	S							✓	✓	✓	✓					IEEE 37-node
[102]	2022	Approximate	SO	S					✓	✓		✓					✓		69-bus
[103]	2022	Approximate	SO	S		✓	✓		✓	✓		✓							IEEE 123-bus
[87]	2022	Exact	SO	M	✓	✓		✓				✓					✓		54-node

[a] Single Objective (SO); Multiobjective (MO); [b] Single stage (S); Multistage (M); [c] Addition of Lines (AL); Reconductoring (RE); Switching or protection devices (SW); Substation construction, or increase in the capacity of existing substations (SS); Distributed Generation (DG); Energy Storage Systems (ESS); Parking Lots (PL); [d] Energy Not Supplied (ENS); System Average Interruption Frequency Index (SAIFI); System Average Interruption Duration Index (SAIDI); Customer Interruption Frequency (CIF); Customer Interruption Duration (CID); Reliability indices associated with interruption cost (RIC); * The decision variable AL can include the installation of switches.

However, in more recent works, authors have dedicated efforts to propose linear models to be solved by exact optimization methods [27,85,86]. Nevertheless, many challenges still remain related to the determination of reliability indices using analytical formulations. These indices depend on the topology of the network, which is in part unknown at the beginning of the optimization process, thus requiring disjunctive formulations. Further, one of the major difficulties of models based on exact optimization methods is the low computational efficiency in complex problems and the linearization applied to model the network.

Figure 3 also gives details about the optimization methods classified as approximate and exact in Table 1. The optimization models solved by genetic algorithm (GA), particle swarm optimization (PSO), non-dominated sorting genetic algorithm II (NSGA-II), ant colony optimization (ACO), greedy algorithm (GAL), discrete particle swarm optimization (DPSO), evolutionary algorithm (EA), tabu search (TS), simulated annealing (SA), memetic algorithm (MA), non-dominated sorting genetic algorithm (NSGA) and others form the set of approximate methods. On the other hand, the optimization models solved through branch and bound (BB) and/or branch and cut (BC), dynamic programming (DP), and benders decomposition (BD) form the set of exact methods.

Additionally, Figure 3 highlights the predominance of the optimization models solved by GA, PSO, NSGA-II, and ACO within the set of the approximate methods. In general, GA, PSO, NSGA-II, and ACO optimization methods are frequently used because they are classical approximate methods. Furthermore, among the exact methods, the optimization models solved by BB and/or BC are predominant. This predominance comes from the fact that most optimization models solved by exact methods use commercial solvers, in which BB and/or BC methods are implemented.

In general, the objective function of optimization models adopts either a single-objective or a multiobjective approach. When the single-objective approach is chosen, the objective function is composed of one or more objectives, which are combined using weights. In contrast, the objective function in the multiobjective approach consists of more than one optimization objective, usually conflicting and to be solved simultaneously. Therefore, multiobjective optimization models result in optimal solutions that form the Pareto front. Table 1 shows that, concerning the estimation of reliability, single-objective as well as multiobjective approaches can be adopted. To make this point clearer, it can be observed in Table 1 that 67% of the reviewed papers use a single-objective approach, whereas 33% use a multiobjective approach. This confirms that conflicting objectives can, in principle, be used, such as reducing asset investment costs while improving reliability indices, but in practice, most optimization models use a single-objective function.

In general, the single-objective functions of the optimization models consist of the costs of investment, operation, and reliability. The investment cost relates to the installation of new assets or an increase in the capacity of existing assets, whereas the operating cost refers to the operation and maintenance of system assets. In contrast, reliability cost is the cost to consumers related to interruptions at the distribution network level. Moreover, in multiobjective optimization models, the Pareto front is usually formed by the sum of the investment and operating costs of assets, as well as by the index chosen to assess the reliability of the distribution system. In this context, some optimization models try to determine the best compromise between (i) ENS and total expansion costs [2,77,80] and (ii) SAIDI, SAIFI and total expansion costs [70,106], among other possibilities [61,82,97].

Regarding the planning stages, two approaches are possible: single-stage and multistage methods. In the single-stage approach, the investments occur at the beginning, whereas in the multistage approach they occur along the planning horizon. In general, investments in multistage optimization models occur annually, given that the load is assumed to grow yearly, too. Table 1 shows that 79% of the models are single stage, while only 21% are multistage models. The predominance of single-stage models can be explained by the fact that this type of model is simpler and requires fewer variables, thus demanding lower computational effort to be solved.

Figure 4 is based on Table 1 and illustrates the percentages of single-stage/multistage and single-objective/multiobjetive optimization models. The selected optimization models present the following approaches: SO & S, SO & M, MO & S, or MO & M. Optimization models that address SO & S are more common and represent 51% of the works selected in the comparative analysis, while MO & M characterize only 5% of the models.

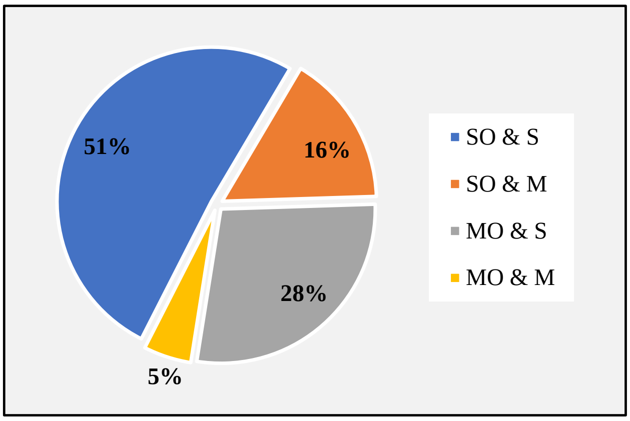

Figure 4. Percentage of optimization models according to the type of objective function and stages.

5.1. Decision Variables

In the works thus far described, different types of decision variables are defined; further, the choice of decision variable depends on the optimization model chosen, as shown in the sixth column of Table 1. Moreover, the decision variables can be categorized into seven groups, according to the specific change they indicate in the solution: addition of lines (AL), reconductoring (RE), switching or protection devices (SW), substation construction, or increase in the capacity of existing substations (SS), distributed generation (DG), energy storage systems (ESS) and parking lots (PL). In addition, SW-related decision variables can include the following devices as alternatives: (i) reclosers, (ii) fuses, (iii) sectionalizing switches, (iv) tie-lines, and (v) circuit breakers (CB). The optimization models selected for comparison use decision variables related to one or more groups, as can be seen in Figure 5. The most common approaches consider decision variables related to: (i) SW, (ii) AL and SS, and (iii) AL, RE and SS. These decision variables are considered in approximately 56% of the papers, as shown in Figure 5. Note also that several types of variables can be included in the optimization model to describe a given device, such as (i) number, (ii) location, (iii) capacity, (iv) type, or even (v) the installation date.

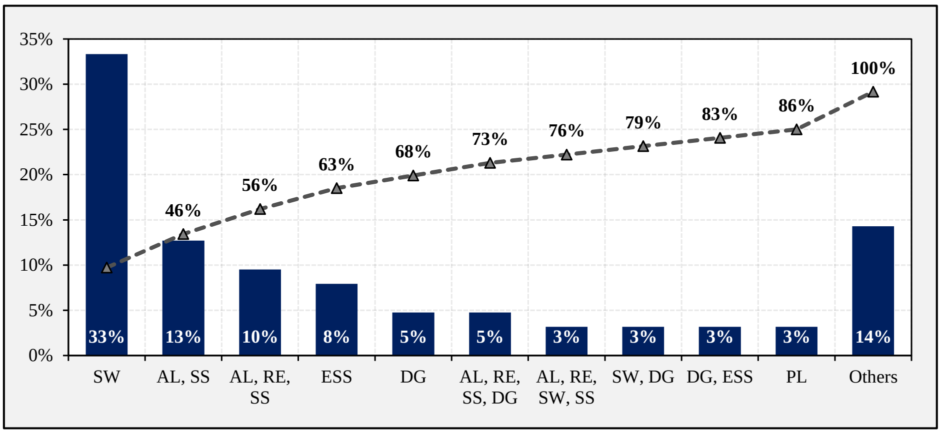

Figure 5. Possible approaches regarding decision variables.

In many works, the decision variable AL is considered in the optimization models, such as in [27,85,86], among others. In addition to handling the decision variable AL, some optimization models include the decision variable RE; see, for example, [27,85,86]. Note also that including reconductoring as a decision variable makes the optimization model more attractive from the point of view of reliability, as installing conductors with a lower failure rate increases the reliability of the distribution network. For instance, replacing existing conductors for insulated conductors and replacing overhead lines with underground lines are options with usually lower failure rates. It should be noted that the load growth may also require reconductoring. Finally, some authors also propose models that use the RE decision variable, without incorporating the AL variable [91,94].

In general, most optimization models that include the decision variables AL or RE also include a decision variable concerning substation construction, or increasing the capacity of existing substations (SS), as is the case in [27,85,86] and many others. This joint use of decision variables comes from the fact that each solution of the expansion planning assumes a load increase which, in turn, may require a corresponding increase in the capacity of substations. Note that reconductoring, as well as building sections of feeders, can improve the conditions for switching between feeders during failure contingencies. In this case, it is necessary to analyze additional loads when defining the capacity of substations, allowing the load transfer between different feeders.

The decision variable SW has different approaches in the optimization models we analyzed so far. Further, this variable in general refers to:

- Allocation of NC switches [53,61,111];
- Allocation of switches or tie-lines [27,68,95];
- Allocation of NC switches and tie-switches or tie-lines [62,66,72];
- Replacement of protection devices [91];
- Allocation of NC switches and fault indicator devices [67];
- Allocation of NC switches, fuses and reclosers [55,56,73];
- Allocation of single-phase or three-phase fuses and reclosers [89];
- Allocation of NC switches and CB [59];
- Allocation of reclosers and CB [70];
- Allocation of reclosers [93];
- Allocation of sectionalizing switches, fuses and CB [65].

Our literature review indicates that the use of DG in PDS, as long as island operation of DG is possible after the occurrence of failures, can help improve the system reliability. For this reason, some optimization models consider decision variables related to the placement and sizing of DG integrated with protection and/or switching devices such as (i) fuses and reclosers [89], (ii) reclosers [93], and (iii) replacement of protection devices [91]. The installation of protection and/or sectionalizing switches enables DG to operate in situations of contingencies, in which the faulty part of the network is isolated and DG supplies energy. However, to reconfigure the network to operate in island mode, it must define the number and location of the switching devices to be installed at strategic points across the network .

Some works that address expansion planning with the allocation of protection devices and/or sectionalizing switches (decision variables related to SW) consider the presence of existing DG with the possibility of islanded operation. The allocation of (i) circuit breakers and reclosers [70]; (ii) fuses, reclosers and sectionalizing switches [71,73]; and (iii) NC and NO automatic switches [72] are considered. However, in [69], the allocation of sectionalizing switches and reclosers with existing DG is studied, but without considering the possibility of islanded operation with DG. This work also discusses the lack of regulation in certain countries and the practical difficulties to reconfigure the network to enable the island operation of DG. Yet other approaches consider the expansion planning with the installation of DG integrated with (i) installation of capacitors, network branches, and transformers [94]; (ii) installation of and increase in the capacity of feeders and substations [2,26,96]; and (iii) installation of and increase in the capacity of feeders and substations, and installation of reserve feeders [95].

Some other works discuss the allocation of ESS and DG of the types: (i) renewable with photovoltaic sources [101]; (ii) dispatchable [102]; (iii) dispatchable DG with substations, feeders and reserve feeders [98]; and (iv) renewable with photovoltaic and wind sources, reconnection of branches and the allocation of switches and capacitors [103]. In the multi-stage planning approach proposed by [98], in addition to the decision variable related to the location and capacity of DG and ESS, the stages of installation of expansion alternatives are considered. ESS help during the islanded operation of DG with renewable sources, given their intermittent nature [97]. Other works, however, propose the allocation of ESS only in distribution systems with existing DG of the types: (i) dispatchable and intermittent with existing wind energy [99]; (ii) intermittent with solar and wind sources [97]; and (iii) dispatchable and intermittent with a solar source [105]. The integration of ESS in the electricity grid favors a higher penetration of renewable DG [99]. Additionally, some authors also address systems without the presence of DG, the allocation of only ESS [100,104] and the allocation of ESS with sectionalizing switches [106].

Parking lots with CS for electric vehicles connected to the distribution network can also contribute to improving reliability when V2G is considered. The consideration of the impact of V2G becomes an alternative to the PDS expansion and operation planning, although complexities are introduced in the modeling of DER, given the uncertainties related to EV load and location [109]. Some works propose the allocation of just PL [109,112]. On the other hand, the allocation of PL can also be integrated with (i) the installation or reinforcement of feeders and substations and allocation of fault location devices [108], (ii) AL and substation construction or increasing the capacity of existing substations [110], and (iii) the installation of automatic switching devices [111].

5.2. Reliability Indices

The reliability indices commonly used by power distribution utilities and used in optimization models are ENS, SAIFI, SAIDI, CIF, and CID. In the works we analyzed here, the assessment of the reliability included other indices too, which appear as others in Table 1 and represent the following indices: MAIFIe [89], ASAI [84], CNS [61], AENS [67,100], MAIFI [106], CLLI (Contingency-Load-Loss Index) [82] and DGUI (Distributed Generation Unavailability Index) [69]. Several works also included reliability indices related to interruption costs (RIC). The ECOST and CIC indices, as well as ENS costs, are some of the indices associated with reliability costs, which are usually incorporated in the objective function of optimization models along with the costs of installation, operation, and maintenance of devices.

Figure 6 presents a summary of the reliability indices used in the works mentioned in Table 1; the percentage of each index refers to the total number of works appearing in Table 1.

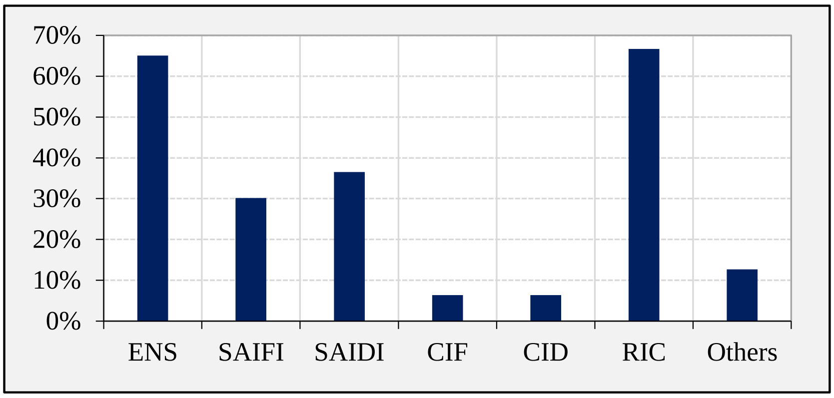

Figure 6. Percentage distribution of the reliability indices of the works mentioned in Table 1.

According to Figure 6, most of the works that we analyzed use reliability indices that refer to the whole distribution system, given that 66.6%, 65.1%, and 36.5% of the works mentioned in Table 1 use, respectively, RIC, ENS, and SAIDI. In contrast, only about 6.35% of the works mentioned in Table 1 uses indices that evaluate the nodes with load, given that effectively only 6.35% of the works uses the indices CIF and CID. Furthermore, Figure 6 shows that a small percentage of the works mentioned in Table 1 uses indices named as others.

5.3. Computational Complexity

Our literature search reveals that, up to now, authors usually did not address the computational complexity analysis of optimization algorithms used to solve PDS expansion planning problems. In general, optimization methods aimed to select investment plans used some type of combinatorial approach [56], in which the most appropriate options is selected to minimize a given objective function respecting some constraints. The number of options depends on the specific problem and the number of alternatives allowed as solutions for each choice. Additionally, the number of alternatives related to each choice can range from a decision to install or not a device, often represented by a binary variable, to the selection of the best device among several possible, represented by an integer variable or by binary, mutually exclusive variables [114]. Note that the number of options is not directly related to the size of the electrical system under analysis, but the type of decision variables represented in the optimization model. In contrast, the number of choices to be made is generally associated with the size of the electrical system, since the number of devices to be defined depends directly on the size of the network (larger systems require more devices to be selected than smaller systems). Thus, the solution space of these optimization models depends (i) on the number of choices (generally associated with the dimension of the system) and (ii) on the number of alternatives associated with each choice; both define the number and type of decision variables in the model.

In addition, some optimization models consider several stages to represent the evolution of the system along the planning horizon. In these cases, besides the location and type of investment, it becomes necessary to define the time at which each investment is made [84]. Hence, the number of variables is multiplied by the number of stages, thus increasing the dimension of multistage models. Although using a larger number of stages increases the number of variables (and so the dimension of the problem), the number of constraints also increases proportionally, which makes the problem more restricted, since all constraints must be respected in all stages.

Furthermore, the number of variables can increase due to (i) the need to represent changes in the network to operate under contingency, especially when the model includes active components such as DG and the possibility of reconfiguration of PDS [96] and (ii) consideration of the stochastic nature of the problem concerning load behavior and DG [95]. To assess the network considering reliability criteria, it is necessary to determine reconfiguration plans to minimize the impact of possible contingencies. Such contingencies can be defined by an enumeration process [85] or through Monte Carlo Simulations [42]. On the other hand, the stochastic nature of the problem can be considered through typical loads and generation scenarios, along with their probabilities of occurrence [95], which can also be obtained by Monte Carlo Simulations. Nevertheless, whichever approach is selected to address the aspects commented, a significant increase in the computational effort is expected.

A superficial analysis of optimization models may indicate that the difficulties to solve them are mainly due to the dimension of the search space (number and type of decision variables). In fact, to understand such difficulties two additional aspects must be considered: (i) the method used to solve the model (exact or approximate) and (ii) the number of choices effectively needed to solve the problem. When exact methods are used, the constraints of the optimization model are always considered so that the search is restricted to the feasible region of the problem [85]. In addition, investment constraints are often included thus limiting the possible extensions to the system and significantly reducing the size of the feasible region of the problem. On the other hand, when approximate methods are used, the form chosen to represent the solutions and constraints directly impacts the efficiency of the algorithm. For instance, handling constraints through penalties tends to be very inefficient; therefore, embedding at least part of the constraints into the representation of solutions makes the problem easier to solve.

To illustrate the difficulties related to the models solved in the papers thus far reviewed, the last column of Table 1 contains the largest system used by each cited paper. Although the information in this column is directly associated with the size of the distribution network successfully solved, attention should be given to the fact that not only the models but also the solution methods applied by each author can be significantly different.

6. Future Research Trends

The recent technical and scientific literature discussed throughout this paper made it clear that the PDS expansion planning problem still has several aspects and characteristics that deserve attention in future research work. For instance, it seems clear that only a few optimization models address the problem of allocation of tie-lines, protection devices, and/or switching devices simultaneously with the problem of routing the feeders of distribution systems. In the works reviewed here, the models presented in [27,95,98] can simultaneously handle the aforementioned problems to determine the best expansion plan.

Although the optimization models proposed in [27,95,98] can jointly handle the problem of allocation of tie-lines and protection and/or switching devices and the problem of routing feeders of the distribution system, only the model introduced in [27] evaluates the reliability of the distribution system through SAIFI, SAIDI, CIF, and CID indices. Therefore, the introduction of usual reliability indices into optimization models can be seen as an interesting option to extend optimization models used for planning the expansion of PDS.

The application of indices related to temporary interruptions seems to be of little interest to researchers up to now, given that we found only a few works using this type of indices [89,106]. Pregelj et al. [89] proposed the optimal allocation of fuses, reclosers, and DG using the MAIFIe index, in addition to the indices related to sustained interruptions SAIFI and SAIDI. On the other hand, Ref. [106] proposed the optimal allocation of switches and ESS considering the MAIFI index. Further, both MAIFI and MAIFIe have been the focus of recent works, due to the increasing number of loads sensitive to temporary failures, such as those found at homes, businesses, and industries, and also due to the relevance of avoiding temporary interruptions to keep consumers satisfied [89,106]. Therefore, it becomes essential to include indices associated with temporary interruptions in optimization models for planning the PDS expansion as a means to mitigate the impacts of failures on the quality of electricity supplied to consumers.

Recently, optimization models solved by exact methods have been proposed to obtain the best expansion plan considering the reliability of distribution systems [27,86,87]. In this context, even today, the inclusion into the optimization models of (i) temporary failures, (ii) tie-lines, (iii) the connection of ESS, and (iv) DG represent challenges for researchers, especially regarding the computational effort to solve the optimization models. Furthermore, to our knowledge, no optimization model solved by exact methods can handle the conflicting characteristics of investment costs and the reliability of distribution systems through a multiobjective approach.

7. Conclusions

This paper presents a bibliographic survey of the state of the art regarding models and methods applied to the solution of the PDS expansion planning problem considering reliability. Firstly, we presented a survey of the main methods to estimate the reliability indices of distribution systems. Then, a survey of the main optimization models that address the problem was presented. Finally, we compared the most usual optimization models and discussed some trends and aspects that we believe can guide future research work.

As discussed throughout this paper, several strategies can be used to increase the reliability of distribution systems, such as proper feeder routing, reconductoring, switch allocation, fuse allocation, recloser allocation, and DG connection. Each of the mentioned strategies can result in favorable changes in the operating conditions that in turn can increase the reliability of distribution systems. However, as more reliability-enhancing strategies are envisioned, the complexity of the optimization model inevitably increases. On the other hand, more computational resources are required to solve complex optimization problems.

The importance of considering reliability in expansion planning models becomes evident when the results shown in the reviewed papers are analyzed. These results indicate that system reliability can be significantly improved when DER are included in the models. Furthermore, including switching devices capable of locating faults can substantially improve reliability indices. On the other hand, the lack of data regarding the failure rates of the network and associated devices is still a big challenge.

The comparison presented in this paper indicates that exact methods to solve optimization problems power systems have only recently been receiving more attention. However, the use of approximate methods to solve such problems still predominates. Further, the advances in computational resources and availability of commercial solvers based on classical optimization techniques, now more efficient and with solving techniques based on modern branch-and-bound algorithms, made the development of mathematical models for optimization problems a relevant research subject.

Finally, several models can be simplified considering only some of the strategies leading to reliability improvements. In fact, the mathematical modeling concerning the operating conditions, including all reliability-enhancing strategies, remains a challenge to researchers interested in finding the best expansion plan at a minimum cost and simultaneously considering reliability.

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Abbreviations

The following abbreviations are used in this paper:

ACO	Ant Colony Optimization
AENS	Average Energy Not Supplied
AL	Addition of Lines
ASAI	Average Service Availability Index
BB	Branch and Bound
BC	Branch and Cut
CAIDI	Customer Average Interruption Duration Index
CB	Circuit Breakers
CDF	Customer Damage Function
CIC	Customer Interruption Cost
CID	Customer Interruption Duration
CIF	Customer Interruption Frequency
CNS	Customers Not Supplied

CS	Charging Stations
DER	Distributed Energy Resources
DP	Dynamic Programming
DPSO	Discrete Particle Swarm Optimization
DG	Distributed Generation
EA	Evolutionary Algorithm
EV	Electric Vehicles
ECOST	Expected Interruption Cost Index
ENS	Energy Not Supplied
ESS	Energy Storage Systems
FIM	Fault Incidence Matrix
GA	Genetic Algorithm
GAL	Greedy Algorithm
IEEE	Institute of Electrical and Electronics Engineers
M	Multistage
MA	Memetic Algorithm
MAIFI	Momentary Average Interruption Frequency Index
MAIFIe	Momentary Average Interruption Event Frequency Index
MILP	Mixed-integer Linear Programming
MINLP	Mixed-integer Nonlinear Programming
MO	Multiobjective
NC	Normally Closed
NO	Normally Open
NSGA	Non-dominated Sorting Genetic Algorithm
PDS	Power Distribution Systems
PL	Parking Lots
PSO	Particle Swarm Optimization
RE	Reconductoring
RBTS	Roy Billinton Test System
RIC	Reliability indices associated with interruption cost
S	Single stage
SA	Simulated Annealing
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SS	Substation
SG	Smart Grid
SO	Single Objective
SW	Switching and protection devices
TS	Tabu Search
V2G	Vehicle to Grid

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