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Reconfiguration of Electric Power Distribution Systems: Comprehensive Review and Classification

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ABSTRACT Distribution systems play an important role, delivering the electric power of generation system to individual consumers. Distribution system reconfiguration (DSR) is a large-scale combinatorial optimization problem. For the last 45 years, the DSR problem has been widely studied; nowadays, DSR, combined with new challenges, is being highly investigated, as researchers aim to reach a better solution. This paper presents a complete review and classification of the most significant works to date, providing a literary framework for DSR specialists. A categorization of solution methods, case studies, and novelties of the most relevant works regarding DSR are provided. In order to establish a complete background, not only traditional approaches, but also those involving uncertainty, reliability, electricity market, power quality, distributed generation, capacitor placement, and switching time in DSR are highlighted. This framework can help researches to improve previous formulations and methods and can propose more efficient models to better exploit the existing infrastructure.

INDEX TERMS Distributed generation, literary framework, network reconfiguration, power distribution systems, uncertainty.

NOMENCLATURE

Abbreviations used throughout the manuscript are reproduced below for quick reference.

AACO	Adaptive ant colony optimization.
AC	Alternating current.
ACO	Ant colony optimization.
ADC	Automated distribution control.
ADP	Approximated dynamic programming.
AENS	Average energy not supplied.
AGA	Adoptive genetic algorithm.
AIS	Artificial immune system.
AMPL	A Mathematical Modeling Language.
ANN	Artificial neural network.
APSO	Adaptive particle swarm optimization.

ASIFI	Average system interruption frequency index.
BAS	Beetle antennae search.
B&B	Branch and bound.
BB	Big bang.
BB-BC	Big bang-big crunch.
BC	Big crunch.
BD	Benders decomposition.
BE	Branch exchange.
BFOA	Bacterial foraging optimization algorithm.
BPSO	Binary particle swarm optimization.
CDBAS	Chaos disturbed beetle antennae search.
CPLEX	C Programming Language Simplex method.
CSA	Cuckoo search algorithm.
DAOP	Discrete ascent optimal programming.

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DC	Direct current.	HEP	Croatian electric power company.
DDSR	Dynamic distribution system reconfiguration.	HPSO	Hybrid particle swarm optimization.
DS	Deep search.	HSA	Harmony search algorithm.
DG	Distributed generation.	LBI	Load balancing index.
DGA	Dedicated genetic algorithm.	IA	Immune algorithm.
DISCOs	Distribution companies.	IGA	Improved genetic algorithm.
DISTOP	Distribution network optimization.	IHSA	Improved harmony search algorithm.
DEWorkstation	Distribution Engineering Workstation.	IP	Integer programming.
CLONR	Clonal reconfiguration.	ITS	Improved tabu search.
DM	Decision maker.	LCF	Linear current flow.
DR	Demand response.	LOL	Loss of load.
DP	Dynamic programming.	MAIFI	Momentary average interruption frequency index.
DPSO	Discrete particle swarm optimization.	MAS	Multi-agent system.
DSR	Distribution system reconfiguration.	MBFOA	Modified bacterial foraging optimization algorithm.
DTLBO	Discrete teaching-learning based optimization.	MBPSO	Modified binary particle swarm optimization.
EA	Evolutionary algorithm.	MCS	Monte Carlo simulation.
EESs	Energy storage systems.	MICP	Mixed-integer conic programming.
EGA	Efficient genetic algorithm.	MIHDE	Mixed-integer hybrid differential evolution.
EICPSO	Enhanced integer coded particle swarm optimization.	MILP	Mixed-integer linear programming.
ENS	Energy not supplied.	MIQP	Mixed-integer quadratic programming.
EP	Evolutionary programming.	MP	Mathematical programming.
EPRI	Electric Power Research Institute.	MPC	Model predictive control.
ESA	Efficient simulated annealing.	MPSO	Modified particle swarm optimization.
EVs	Electric vehicles.	MTS	Modified tabu search.
FA	Firefly algorithm.	MSU	Multiple switch updating.
FACO	Fuzzy ant colony optimization.	NCUP	Neighbour-chain updating process.
FACTS	Flexible AC transmission system.	NDE	Node-depth encoding.
FAGA	Fuzzy adoptive genetic algorithm.	NS	Normal search.
FAPSO	Fuzzy adaptive particle swarm optimization.	NSGA	Non-dominated sorting genetic algorithm.
FCM	Fuzzy C-means.	NVQI	Node voltage quality index.
FDD	Flexible DC device.	OLTC	On-load tap changers.
FEP	Fuzzy evolutionary programming.	OSU	One switch updating.
FGA	Fuzzy genetic algorithm.	OPF	Optimal power flow.
FMPSO	Fuzzy modified particle swarm optimization.	PIEFI	Power interruption equivalent frequency index.
FNSGA	Fast non-dominated sorting genetic algorithm.	PP&L	Pennsylvania Power and Light Company.
FPGA	Fuzzy parallel genetic algorithm.	PSO	Particle swarm optimization.
FPSO	Fuzzy particle swarm optimization.	PV	Photovoltaic.
FVSI	Fast voltage stability index.	QCP	Quadratically constrained programming.
GA	Genetic algorithm.	ReGA	Restricted genetic algorithm.
GAMS	General Algebraic Modeling System.	RGA	Refined genetic algorithm.
GAMT	Genetic algorithm based on Matroid theory.	SA	Simulated annealing.
GCR	Graph chains representation.	SAIDI	System average interruption duration index.
GCRA	Grey correlation analysis.	SAIFI	System average interruption frequency index.
GWO	Gray wolf optimization.	SDSR	Static distribution system reconfiguration.
HACO	Hybrid ant colony optimization.	SOCP	Second-order cone programming.
HCA	Heuristic constructive algorithm.	SOE	Switch opening and exchange.
HC-ACO	Hyper cube ant colony optimization.	SOReco	Single objective reconfiguration.
HDE	Hybrid differential evolution.	SYSRAP	System Reconfiguration Analysis Program.
		Taipower	Taiwan Power Company.
		TEPCO	Tokyo Electric Power Company.
		TLBO	Teaching-learning based optimization.
		TPC	Taiwan Power Company.

TS	Tabu search.
VDI	Voltage deviation index.
VSI	Voltage stability index.
VSO	Vector shift operation.
XFDPF	Extended fast decoupled power flow.

I. INTRODUCTION

Distribution network is an important part of the power system infrastructure that links transmission network to end-users of electric grid. Its main task is to deliver electricity produced by generating units to individual customers of electric energy [1].

Power distribution networks in urban areas are typically constructed as a meshed structure and are usually operated in a suitable radial topology, which can be set or changed by opening normally closed sectional switches and closing normally open tie line switches, which is commonly denoted as distribution system reconfiguration (DSR). Tie lines interconnect ends of radial feeders and/or provide connections to alternative supply points, while sectionalizing switches provide interconnections for the main sections or branches of each radial feeder. Both types of switches may be controlled manually, or may be operated automatically, as remotely controlled switches [2]. Modern power distribution systems feature a number of remotely controlled switches, which are activated to provide emergency supply connections for reliability improvement or to allow for maintenance and servicing works, or to adjust optimal system configuration during normal operation. In term of both system protection and normal operation, sectionalizing switches along the feeders are automated and can be controlled using dedicated communication links [3]. The main reason for distribution utilities (or distribution companies (DISCOs) in deregulated power systems) to invest in switching devices is to prevent prolonged failures and to reduce the number of customers isolated by faults [4].

Power losses of the distribution system are more than transmission network due to higher ratio of current to voltage (higher line impedance) of distribution lines compared to transmission ones. Power losses directly affect the operational cost and the voltage profile, especially in heavily loaded power systems. For this, the DSR was initiated with the purpose of obtaining the lowest power losses during normal operating conditions. Nevertheless, today, it also includes other objectives such as power quality improvement, an increase of voltage security margin, reliability enhancement, supply capacity expansion, load balancing, increase of distributed generation (DG) penetration, service restoration, and quick fault isolation [5].

Merlin and Back [6] were the first researchers who solved the DSR problem based on the minimum energy losses. A static DSR (SDSR) approach (i.e., distribution system topology and load are considered to be fixed during specific timeframes) was formulated as a mixed-integer nonlinear optimization problem and solved by using a discrete branch-and-bound technique. Improving the SDSR approach

presented in [6], a dynamic (multi-period) concept for the DSR solution (DDSR) was introduced in [7]. Differently from SDSR, in DDSR, the load is not constant and network topology frequently changes with the real-time operational conditions using automatic (smart) switches. In this approach, features such as load fluctuations, generation variability, the uncertainty of renewable sources, market behavior, switching time, and climate changes can be taken into account, which leads to a more accurate and realistic assessment of the network. Nevertheless, the adoption of the DDSR increases the complexity and requires higher computational effort when compared to the SDSR [8], [9].

The DSR is a large-scale combinatorial optimization problem including decision variables, one or more objective functions, and a set of constraints that can often contain nonlinearities. The feasible search space in DSR is typically large, nonconvex, and hard to explore. Hence, determining good-quality solutions for the DSR problem is always a challenging task. In order to cope with this issue, distribution system researchers have dedicated their efforts to develop efficient methodologies to find the best possible solution for the DSR. In this regard, classical optimization, heuristic, and metaheuristic methods have played prominent roles in the DSR solution. Since the DSR problem was first proposed in 1975 [6], classical optimization methods have been presented as important tools in order to find good quality solutions for this problem. Later, heuristic techniques were adopted in the DSR as a solution strategy to avoid limitations presented by classical optimization methods, for example, there is no complete mathematical model, high nonlinearities or extremely high computational effort. Finally, by improving heuristic performances in the DSR, metaheuristic approaches were introduced.

Lately, as distribution system challenges continue to grow, researchers of several areas need systematic and well-elaborated classifications of previous works in order to achieve new solutions and relevant innovations in their fields [10], [11]. In 1994, [10] presented a literature review of publications for the DSR problem. Nevertheless, the work presented in [10] is old and has no longer been updated. Later, [11] presented a review related to reliability improvement and power loss minimization in distribution systems through network reconfiguration. However, this literature has only focused on the reliability issue disregarding new important challenges such as renewable and distributed generators, uncertainty, loadability, DG hosting, investment return, and smart agents. The novel contributions of this review paper, if compared to previous ones are as follows:

- To classify most important papers regarding DSR considering its complete scope.
- To present complete, up-to-date and broad literary framework that can be used as a base for any further investigations related to the DSR.

Therefore, three major categorizations are presented, showing the major advances regarding solution methods

(Section II), objective functions (Section III), and innovations (Section IV). Also, implementation methods for real distribution networks and specific applications are presented in Sections V and VI, respectively. Finally, general conclusions about the complete development of DSR research are shown.

II. LITERATURE CLASSIFICATION BASED ON SOLUTION METHODS

In this section, the advantages and disadvantages of several methods were employed toward the DSR problem, and their classifications are presented.

A. MATHEMATICAL OPTIMIZATION METHODS

Mathematical optimization methods are known to be effective to solve simple and linear optimization problems with a relatively small search space, guaranteeing convergence toward the best solution. However, in combinatorial optimization problems with large search space, these methods tend to demand higher and sometimes unaffordable computational efforts. Over time, numerous works regarding DSR have used these methods, evidencing their efficiency in this field.

In 1975, a branch and bound (B&B) algorithm was first used to solve the DSR problem in [6]. Although the proposed approach found the optimal solution, its convergence process was slow. In 1995, Sarma and Rao [12] presented a binary integer programming (binary IP) method to solve the SDR problem, in which distribution feeders were partitioned into several circuits. In this way, connection of each bus to corresponding circuits was represented by binary numbers 0 and 1. However, the proposed approach suffered computational limitations in large-size distribution systems. Later, a new approach based on Newton power flow method was introduced by [13] to solve the SDR problem. Although the approximations used in loss formulation caused the method to be very fast, it may prevent the algorithm to find high-quality solutions for large-scale networks. Later, Benders decomposition (BD) for solving SDR was presented in [14], dividing the formulation into a master problem and a subproblem (slave problem). In master problem, optimal radial topologies with minimum losses were determined considering line power flow constraints, while the feasibility of these radial solutions was investigated in the slave problem. Although the results demonstrate the effectiveness and robustness of the proposed methodology for network reconfiguration, the efficiency of BD degrades with increase in nonlinear terms of model.

In 2012 and subsequent years, more formal proposals appeared to represent radiality constraints in a precise way, as the proposals presented in [15] and [16]. From these works, increasingly complex mathematical models appeared. Thus, a mixed-integer conic programming (MICP) was employed to formulate the SDR problem in [17]. The results showed that solutions obtained by MICP are the same as those obtained by mixed-integer linear programming (MILP). Nevertheless, rewriting the nonlinear power flow equations in terms

of rotated conic quadratic constraints requires additional mathematical efforts. Later, Taylor and Hover [18] formulated the SDR using mixed-integer quadratic programming (MIQP), quadratically constrained programming (QCP), and second-order cone programming (SOCP) as a convex problem. The results indicated that the performance of MIQP, QCP, and SOCP is better than BD, but allocation of two continuous variables instead of binary variables to power flow direction of each line have decreased the efficiency of the proposed methodologies. Furthermore, MILP was presented in [19] to solve an SDR problem by approximating power losses using piecewise linear functions. Although the proposed linear model can be easily solved by commercial optimization solvers such as C Programming Language Simplex (CPLEX) solver, the approximations used may degrade the performance of this model to solve highly nonlinear combinatorial DSR problems.

Even in recent DSR researches, mathematical optimization continues to be widely chosen as a solution method, e.g., [5] and [20]–[25]. In [20], the epsilon-constraint method was proposed to optimize the network losses and reliability in a multi-objective SDR framework. In this method, all possible solutions were listed by ϵ -constraint approach and then unfeasible solutions were identified and discarded from the list using power flow calculations. Moreover, in [21], a MILP model was presented to solve a SDR problem using a two-stage decomposition algorithm. Although the proposed decomposition method could solve this large-scale optimization problem, the piecewise linear approximations used in [21] reduce the accuracy of solutions for reconfiguration of large distribution systems. In [5] and [22], BD and B&B algorithms were proposed to solve the DSR problem as dynamic, respectively. Nevertheless, estimated alternating current (AC) power flow equations have reduced precision of the BD method of [5]. Furthermore, efficiency of the method proposed in [22] has not been compared with other online reconfiguration techniques. In [23], an extended fast decoupled power flow (XFDPF) approach was employed to solve a SDR problem, showing its lower computing time compared to conventional power flow methods. Nevertheless, the efficiency of the proposed method is reduced in networks with high ratio of ohmic resistance to reactance (R/X) of distribution lines. Furthermore, in [24] and [25], General Algebraic Modeling System (GAMS) was employed to solve multi-objective SDR problem in presence of demand response (DR) [24] and DISCOs costs [25].

More recently, in [26], an approximated dynamic programming (ADP) approach was applied to minimize DG curtailment and load shedding in DDSR. Finally, in [1] and [27], the SDR problem was solved using A Mathematical Modeling Language (AMPL). The results showed that the methods of [1] and [27] find optimal configurations in shorter computational time when compared to other mathematical techniques, but AMPL cannot be applied to very large distribution systems. Table 1 highlights advantages and disadvantages of mathematical methods reviewed in this section.

TABLE 1. Mathematical optimization methods: Advantages and disadvantages.

Methods	Advantages	Disadvantages
[1],[27]	High accuracy and low computing time	Not applicable to very large distribution networks
[5]	Efficient for online applications because of its high convergence speed	Lower accuracy than other mathematical methods because of using estimated AC power flow equations
[6]	Good accuracy	Low convergence speed
[12]	Simple representation because of binary numbers	Computational limitations due to network partition
[13]	Fast because of linear approximations	Imprecise because of approximated losses
[14]	Good performance in linear DSR problems	Lower efficiency in non-linear problems compared to linear ones
[15]	High efficiency in networks with large numbers of buses without load and generation	High processing time
[16]	Low computational time because of using minimum spanning trees theory	Not applicable to networks with non-planar loops (planar loops have been described in [1])
[17]	Good accuracy because of exact formulation	High mathematical efforts due to write non-linear equations in terms of rotated conic quadratic terms
[18]	Better performance than BD	High processing time due to use of continues variables for representing lines power flow direction
[19]	Low computational time because of linearization	Lower accuracy than exact mathematical models
[20]	Reduction of extensive multi-objective options to a few effective solutions	High computational time
[21]	High robustness against uncertainties	Very complex
[22]	High accuracy in linear DDSR problems	Hard implementation in dynamic studies
[23]	Better performance than conventional power flow based-methods	Low efficiency in networks with high ratio of R to X
[24],[25]	High accuracy of GAMS in conventional DSR studies	Lower efficiency than commonly used multi-objective approaches
[26]	Applying DP to a large-scale DDSR problem	Low accuracy because of using approximated DP

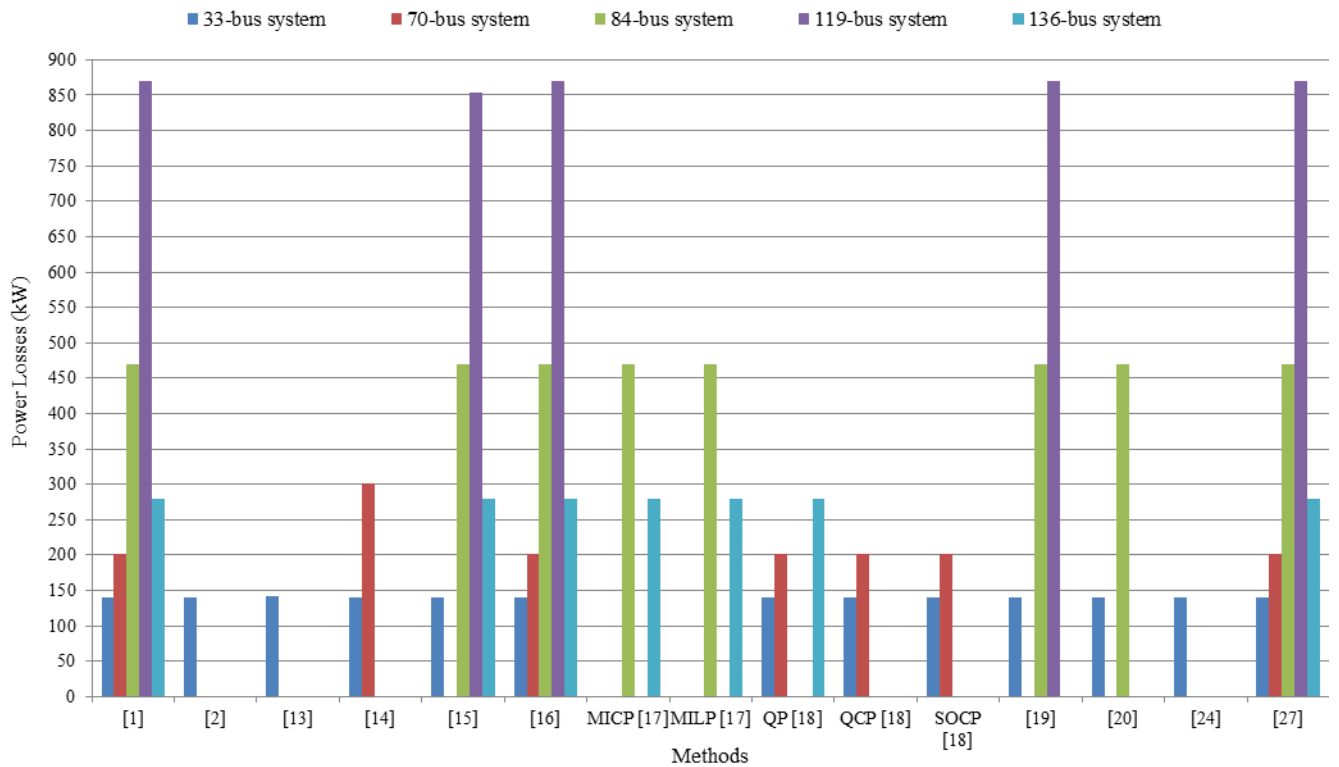


FIGURE 1. Power losses obtained by mathematical methods after reconfiguration.

In order to provide a quantified evaluation of advantages and disadvantages of mathematical techniques, power losses and computing time of some mathematical methods used

for reconfiguration of 33-bus [28], 70-bus [29], 84-bus [30], 119-bus [31], and 136-bus [32] distribution systems are shown in Fig. 1 and Table 2.

TABLE 2. Mathematical optimization methods: Computation time.

Methods	Running Time (s)				
	33-bus system	70-bus system	84-bus system	119-bus system	136-bus system
[1]	0.16	4.9	4.95	4.95	9.5
[13]	0.01	-	-	-	-
[14]	0.11	0.14	-	-	-
[15]	19	-	3030	4007	4473
[16]	3	4.2	7.8	30.1	132.5
MICP [17]	-	-	245.4	-	1800
MILP [17]	-	-	207.7	-	1800
QP [18]	0.21	0.5	-	-	2.35
QCP [18]	1.43	10.1	-	-	-
SOCP [18]	12.8	1131.48	-	-	-
[19]	1	-	1.1	4.4	-
[20]	192	-	512	-	-
[24]	72.79	-	-	-	-

B. HEURISTIC OPTIMIZATION METHODS

As shown, solving DSR through mathematical optimization typically presents processing limitations. These methods tend to be time-consuming, due to the nonconvexity of the search spaces, and this issue increases when integer decision variables are considered. Therefore, heuristic methods can be used as a solution to computational limitations. These methods analyze possible options and logically select good quality solutions, using simple step-by-step search processes. Although heuristic methods can find feasible solutions with low computational effort, they can guarantee neither good quality nor optimality of these solutions.

In 1989, a heuristic algorithm known as Distribution Network Optimization (DISTOP) was presented by [33] to solve the SDSR problem in practical networks. This heuristic-based approach using Lagrange multipliers and AC power flow equations improved the solution time when compared to heavy mathematical optimization methods used at the time. In the same year, the branch exchange (BE) method was proposed by [28] to solve an SDSR problem. In BE, new radial topologies are created by closing an open switch and opening one of closed switches of each planar loop till the best configuration is found. However, point to point searching process of BE made it a time-consuming method for reconfiguration of large distribution systems.

One year later, in [34], the SDSR problem was formulated by the loss change estimation method. In this approach, only configurations with negative loss change were selected by the algorithm. Although considering only voltage drops of tie-line extremes in loss change evaluation made the proposed algorithm as a simple method for network reconfiguration, it is time-consuming for reconfiguration of large distribution systems.

In 1994, a heuristic algorithm was developed to solve the SDSR problem in [35]. Performance indices as ratio of power losses to rated current of each branch were defined for possible switching proposals. In this process, a radial topology

with the lowest performance index was selected for network reconfiguration. However, linearized power flow equations used in this approach degrade the efficiency of the proposed method to find accurate solutions.

In order to overcome the size restrictions, a heuristic technique based on network partitioning theory was presented in [36] to solve an SDSR problem. In this approach, the distribution network was divided into groups of buses and the power losses between these groups were minimized. Unlike the other reconfiguration algorithms, in the best scenario of the proposed method, only two power flow solutions were required. However, the proposed technique was tested on a small-size distribution network. In 1999, discrete ascent optimal programming (DAOP) algorithm was introduced by [37] to solve the SDSR problem using the Distribution Engineering Workstation (DEWorkstation) software package. In DAOP, configurations with the smallest increase in total losses are selected during the addition of discrete load steps. Although this method solved the desired problem accurately, its computational time is considerable.

One year later, a systematic feeder reconfiguration technique was presented by [38] to solve the SDSR problem. In this strategy, appropriate switching sequences of planar loops with positive loss reduction are ranked using power flow calculations. Then, the best solutions are selected for BE and this process continuing till no loop with positive loss reduction appears. Although additional power flow calculations were eliminated in the proposed technique, it is still time-consuming method for network reconfiguration. Therefore, in [39], geometrical circles were allocated to planar loops of network given in [38], in which loops are selected for BE according to radius of their allocated circles. If the power losses are reduced due to a branch exchange, the size of the circle diminishes and hence a smaller circle gives better configuration. The geometrical method can reduce the processing time of DSR problem, but definition of appropriate circles is difficult in large distribution systems.

TABLE 3. Heuristic optimization methods: Advantages and disadvantages.

Methods	Advantages	Disadvantages
[28]	Simple implementation	Time-consuming due to BE
[33]	Good precision because of exact AC load-flow equations	Low convergence speed
[34]	Simple implementation due to consider only voltage drops of tie-line extremes	Low accuracy because of loss change estimation
[35]	Low computational time	Low efficiency due to linearized load-flow equations
[36]	Good performance in small networks	Hard implementation in large systems
[37]	High accuracy	Considerable computing time because of step-by- step addition of discrete loads in DAOP approach
[38]	Simple implementation due to eliminate additional power flow calculations	Time-consuming because of BE
[39]	Low convergence speed	Not applicable to large distribution systems
[40]	Acceptable precision	High processing time because of BE
[41]	Lower processing time than [40] because of use of sensitivity analysis	Lower accuracy than [40] due to ignore some possible solutions by sensitivity analysis
[42]	High accuracy of applied two-stage heuristic algorithm	High computing time due to BE
[43]	Low computational time because of employing sensitivity analysis	Lower accuracy compared to heuristic methods which do not use sensitivity analysis
[44]	Simple implementation and high accuracy	Time-consuming due to consider neighbouring switches of each tie line
[45]	Good performance for simultaneous DSR and capacitor allocation	Has not been designed well for DSR
[46]	Higher accuracy of NCUP than BE	Difficult implementation of NCUP compared to BE
[47]	Fast	Low accuracy because of using linear approximations
[48]	Simple heuristic algorithm without any power flow calculations	Low precision because of lack of power flow
[49]	Use of VSO instead of time-consuming power flow calculations	High computational time due to BE
[50]	Better performance than BE	Time-consuming because of use of branch exchange

Later, in 2005, a new BE-based heuristic method was proposed to solve the SDSR problem [40]. Ignoring the computation time, the precision of the algorithm was acceptable. In order to reduce the number of power flows and subsequent computational time of heuristic method presented in [40], [41] calculated the sensitivity of the switches by optimal power flow (OPF).

Also, in 2008, a two-stage heuristic algorithm for solving SDSR was proposed in [42], where switches with minimum increase in losses are opened in the first stage, and the best proposals are selected by BE in the second one. In spite of high accuracy and simplicity of the proposed technique, repetitive load flows and checking all possible proposals makes it a time-consuming method for network reconfiguration. In order to resolve this issue, [43] ranked the candidate branches based on loss sensitivity to the branch impedances in heuristic algorithm proposed by [42].

One year later, in [44], SDSR aiming voltage stability enhancement was optimized by a simple heuristic algorithm. The proposed method determined the best switching sequences by opening a tie switch or one of its neighbouring sectional switches in an iterative process.

In 2010, a heuristic constructive algorithm (HCA) was employed to solve a simultaneous DSR and capacitor allocation problem [45]. In the proposed methodology, a new sensitivity index using Lagrange multipliers was defined to determine the status of switches regarding their loss reduction amount. The proposed algorithm has been well designed for optimal placement of capacitors during network reconfiguration; therefore it cannot be an efficient method for conventional DSR.

In order to increase the precision of the method presented in [42], [46] used neighbour-chain updating process (NCUP) instead of BE in the second stage of the proposed heuristic algorithm. In NCUP, each switching operation of the previous stage was updated by opening a closed switch or its neighbour one.

Recently, in [47], a new heuristic method based on the Lagrange relaxation technique was proposed to solve the DDSR problem. However, linear approximations used in formulation decreases the quality of solutions in large distribution systems. Later, in [48], a simple heuristic method without any power flow calculations was proposed to solve the SDSR problem in the presence of DG. The results showed that the proposed method could reduce power losses and improve fast voltage stability index (FVSI) efficiently. However, there is no comparison between the computing time of the proposed approach with other reconfiguration methods. Also, in [49], a vector shift operation (VSO) method was developed to minimize distribution losses through network reconfiguration in presence of DG. In the proposed algorithm, instead of time-consuming power flow calculations, loss changes due to BE are determined using the power and resistance vectors. Finally, in [50], a switch opening and exchange (SOE) method was presented to reduce power losses in DDSR and the results were verified by mathematical programming (MP). In SOE, all switches of meshed network are sequentially opened till no planar loop appears. Then, status of branches is modified to obtain better radial configurations. Table 3 lists advantages and disadvantages of above-mentioned heuristic reconfiguration methods. To provide a comparative parametric and graphical analysis, power losses and available data of

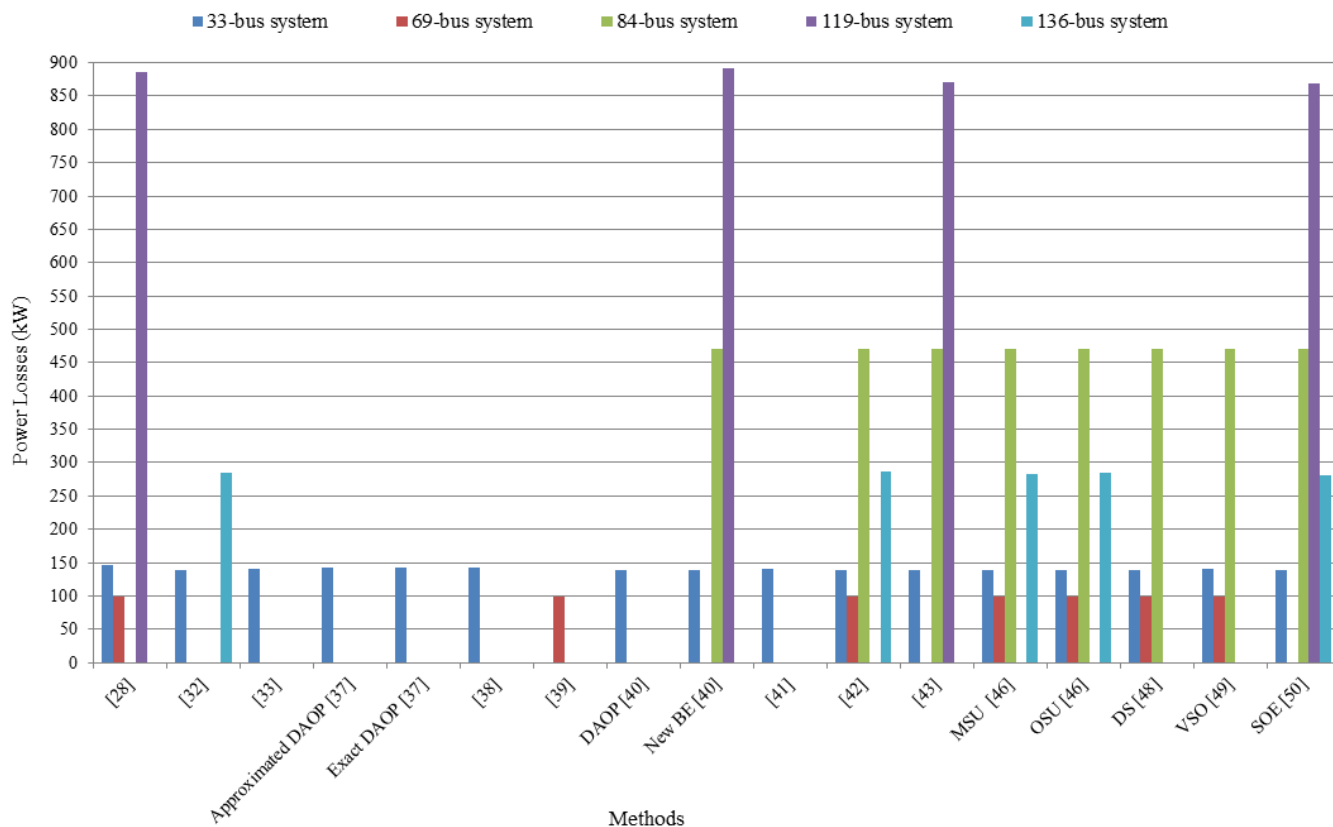


FIGURE 2. Power losses obtained by heuristic methods after reconfiguration.

TABLE 4. Heuristic optimization methods: Computation time and some parameters.

Methods	33-Bus System			69-Bus System			84-Bus System			119-Bus System			136-Bus System		
	Running time (s)	Number of power flows	Number of iterations	Run. time (s)	No. of power flows	No. of iter.	Run. time (s)	No. of power flows	No. of iter.	Run. time (s)	No. of power flows	No. of iter.	Run. time (s)	No. of power flows	No. of iter.
[28]	-	31	6	-	26	5	-	-	-	-	-	-	-	-	-
[32]	-	563	563	-	-	-	-	-	-	-	-	-	24.45	4051	4051
[33]	0.14	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Approximated DAOP [37]	20.45	12	6	-	-	-	-	-	-	-	-	-	-	-	-
Exact DAOP [37]	226.7	2	6	-	-	-	-	-	-	-	-	-	-	-	-
[38]	-	6	6	-	-	-	-	-	-	-	-	-	-	-	-
[39]	-	-	-	-	5	5	-	-	-	-	-	-	-	-	-
DAOP [40]	1.99	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Proposed [40]	1.66	135	-	-	-	-	-	670	-	-	1221	-	-	-	-
[41]	0.96	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[42]	-	11	-	-	17	-	-	17	-	3.92	41	-	8.96	64	-
[43]	-	11	-	-	-	-	-	24	-	-	26	-	-	-	-
MSU [46]	-	11	-	-	17	-	-	33	-	5.28	62	-	23.98	148	-
OSU [46]	-	11	-	-	17	-	-	22	-	-	44	-	-	76	-
DS [48]	3	0	5	11	0	5	21	0	5	-	-	-	<530	0	5
VSO [49]	0.326	-	-	0.801	-	-	1.513	18	3	-	-	-	-	-	-
SOE [50]	1	-	1	-	-	-	6.2	-	2	12.3	-	2	16.9	-	-

some heuristic methods used for reconfiguration of 69-bus network [51] and other distribution systems are shown in Fig. 2 and Table 4.

C. METAHEURISTIC OPTIMIZATION METHODS

Metaheuristic methods are randomized search algorithms based on specific rules (e.g. human evolution process,

annealing process of steal, learning and teaching mechanism, and so on) that define and use certain search criteria (e.g. operators of selection, mutation, crossover, etc.) during the optimization process. Whereas, heuristic methods are step-by-step search algorithms based on trial and error. Heuristic methods are too greedy and need to be designed for a specific application (problem-dependent methods), while metaheuristics are general search algorithms (problem-independent methods) that just need some fine-tuning of their inherent parameters for adapting to the under studied problem. Although metaheuristics represent a higher computational burden, they can lead to better solutions when compared to heuristic approaches. On the other hand, metaheuristic algorithms tend to find high-quality solutions with a lower computational time in comparison with mathematical optimization methods, even though they cannot guarantee the global optimum. In the last 30 years, many metaheuristic approaches have been presented to solve the DSR problems that the most important of them are chronologically reviewed in further text.

In 1990, simulated annealing (SA) was presented in [52] to solve the problem of [28]. SA is a point-to-point search method with a strong theoretical base that has been adopted from the physical process of solids annealing. However, the repeated runs of power flow calculations during the annealing process make this approach very time-consuming.

In 1992, a popular metaheuristic method, genetic algorithm (GA), was used to solve the SDR problem in [53]. Genetic algorithms (GAs) are efficient methods to solve complex non-linear optimization problems, mainly because of their simple implementation, flexibility, good performance, and high adaptation with other metaheuristic algorithms. However, the standard GA is a time-consuming method for reconfiguration of large distribution systems. One year later, artificial neural network (ANN) was employed in [54] to solve the SDR problem, where load level of each node is estimated according to load data and then the best reconfiguration plan is selected. However, quality of the solutions is degraded if set of training data (e.g. load characteristics of distribution system) is not defined properly. In 2001, the problem of [52] was solved by SA using a simplified set of load-flow equations in [55]. Although this modification could decrease the computing time of SA method, the quality of the DSR solutions was reduced.

In order to improve the performance of the SA, an efficient SA (ESA) was proposed to solve the SDR problem in [56]. This method presents better solutions than SA because the algorithm can escape local minima, but its implementation on the large-scale distribution networks is difficult. In order to apply the GA for reconfiguration of larger distribution systems, the refined GA (RGA) was proposed in [57]. In this method, unlike the standard GA [53], the size of chromosomes was reduced to be equal to the number of tie line switches and an adaptive mutation process with a variable rate was used to prevent algorithm premature convergence. Later, the artificial immune system (AIS) was proposed

in [58] to solve a multi-objective SDR problem considering network losses and loading unbalances. The AIS is a random search method based on an initial population of antibodies containing several antigens, representing positions of open tie line switches. The algorithm guides the antibodies toward the best objective functions using selection, crossover and mutation operators. The best switching scenarios can be obtained through interactions between multi-objective decision maker (DM) and immune algorithm (IA). Although the AIS decreases computing time of the proposed multi-objective problem when compared to mathematical optimization methods such as IP, its performance has not been evaluated for DSR in large distribution networks. Thus, [30] proposed a mixed-integer hybrid differential evolution (MIHDE) algorithm to minimize ohmic losses in SDR. The MIHDE method is a combination of hybrid differential evolution (HDE) and IP methods that requires relatively lower computational burden than SA.

In 2003, a combination of fuzzy theory and evolutionary programming (EP) was used to solve a multi-objective SDR problem, aiming loss reduction and voltage deviation index (VDI) improvement in [59]. The simulation results confirmed that the fuzzy EP (FEP) is an appropriate method for solving multi-objective DSR problems, but its performance is highly affected by fuzzy membership functions. In fuzzy theory, different objectives are embedded in a single function as weighted-sum values using membership functions. However, accurate defining of fuzzy membership functions is not easy in complex optimization problems. Later, in 2005, [60] proposed an evolutionary algorithm (EA) to minimize active power losses in the SDR problem. The EA method is a random search algorithm using principles of natural selection and recombination, which has simpler implementation than SA and tabu search (TS). However, its performance is drastically reduced by inadequate tree representation of distribution network graph, resulting in appearance of non-radial solutions (branches that cannot create a tree) during algorithm search. At the same year, [61] employed a fuzzy GA (FGA) based method to solve the problem of [59]. In the proposed FGA, fuzzy theory was used to control the mutation operator of standard GA in order to improve its convergence characteristic.

Later, in [62], TS algorithm was used to solve the SDR problem in networks with DG. The TS is a random search algorithm that utilizes movements and memory operations. The movement operator is used for “jumping” from one solution to another, while memory operator guides the search to avoid cycling between solutions. The obtained simulation results in [62] confirm better performance of TS algorithm compared to SA from both computational time and solution accuracy points of view. Nevertheless, the global search ability of TS depends on tabu list length: small size tabu lists cause the algorithm to be captured in some of local minima easily, while large size lists increase the processing time of TS method. Moreover, in [63], researchers solved the SDR problem using ant colony optimization (ACO). The ACO is a

powerful intelligent method that has been inspired by natural behavior of the ant colonies in finding the food source that has better performance than SA.

In 2006, a restricted GA (ReGA) was presented in [64] to solve the SDSR problem. This kind of GA has a set of modified genetic operators and an efficient form of generation of the initial population with the aim of finding only radial configurations for large-size distribution systems. However, this approach can check only the isolation of exterior buses and does not search for the isolation of interior ones. Therefore, this strategy does not guarantee connectivity of network and may produce radial topologies with isolated buses, which are effectively infeasible solutions. In order to resolve the issue regarding selection of proper elements for training data set in [54], a clustering technique was used in ANN method of [65]. The low processing time of the proposed method makes it suitable for online (dynamic) applications. However, clustering the loads based on their values without considering their locations can decrease the quality of DSR solutions. One year later, improved TS (ITS) was proposed to resolve premature convergence of TS algorithm in [31]. In ITS method, mutation operator of GA was used to weaken the dependence of global search ability on tabu list length. At the same year, [66] presented a hybrid algorithm based on AIS and ACO (AIS-ACO) to solve a multi-objective DSR problem, showing its better performance than HDE method.

In 2008, [67] presented an efficient GA (EGA) to minimize network losses in SDSR capable of generating only radial topologies. The proposed GA was adopted from [68] with some modifications in the recombination operator. In order to maintain radiality of proposed topologies after genetic operations, in [69], a GA based on Matroid theory (GAMT) was proposed to solve the SDSR problem. However, some non-radial solutions still appear during algorithm evolutionary process in GAMT. Then, in [70], a binary particle swarm optimization (BPSO) algorithm was employed to minimize customer interruption costs via DSR. Also, a discrete particle swarm optimization (DPSO) algorithm was used in [71] to minimize power losses and load balancing index (LBI) in SDSR. However, BPSO and DPSO methods in their standard forms are very time-consuming for large distribution networks. Therefore, a modified binary particle swarm optimization (MBPSO) was presented in [72], where some parameters of BPSO method, such as inertia weight, number of iterations and population size, were modified. The modified settings allow the particle swarm optimization (PSO) to explore a larger area at the start of the simulation and to continue its searching in a smaller area nearer to global optimum. This feature makes the algorithm faster than DPSO, BPSO, SA, and TS, but it increases the probability of capturing in the local minima.

Later, hyper cube ACO (HC-ACO) was proposed in [73] to minimize active power losses via DSR. In this method, two heuristic rules were used to improve ACO performance. The aim of local heuristic rule is to prepare the candidate configurations for successive random selection, whereas the

aim of global rule is to maintain some already found successful configurations. Harder implementation and shorter computational time are two important features of HC-ACO algorithm when compared to ACO.

In 2010, the problem of [72] was solved by a modified TS (MTS) algorithm in [74]. In MTS method, the size of tabu list is set to vary with the system size and a random multiplicative move is used in the searching process to diversify the search toward unexplored regions, to escape local optimums and to prevent cycling around the sub-optimum solutions. The simulation results show that accuracy of MTS is higher than that of TS and SA methods. At the same year, a dedicated GA (DGA) was used to solve an SDSR problem considering capacitor placement [75]. In the proposed GA, the initial population was constructed by a heuristic algorithm based on sensitivity analysis to avoid the creation of non-radial configurations. Although the sensitivity analysis significantly reduces the search space of DGA algorithm, it may decrease the accuracy of solutions, because all possible switching sequences are not evaluated.

In order to improve the solution method presented in [59], [76] proposed grey correlation analysis (GCRA) instead of fuzzy theory. The GCRA by providing a quantitative measurement of candidate solutions in EP method led to more accurate solutions than FEP and FGA methods. In [77], the graph chains representation (GCR) used in [60] was replaced by the node-depth encoding (NDE) to reduce computational time of EA method. In order to enhance the performance of FGA presented in [61], a fuzzy adoptive GA (FAGA) was proposed in [78]. The adoptive GA (AGA) is a modified version of GA presented in [64] that, in addition to fundamental loops, uses common branches of each bus and prohibited group of switches to avoid the generation of any non-radial solutions. The proposed FAGA technique is more efficient than SA and FGA, but performance of fuzzy rules-based methods, such as FGA and FAGA, strongly depends on the selected fuzzy membership functions. Therefore, a non-dominated sorting GA (NSGA) was used in [79] to solve a multi-objective DSR problem. The NSGA is a combination of GA and pareto techniques that enables to evaluate different objectives without integrating them into one objective function. Although the proposed method gives various options to the decision makers, the accuracy of the obtained solutions has not been verified.

In 2011, [80] proposed fuzzy ACO (FACO) to solve the problem of [52], showing that its performance is better than SA. At the same year, harmony search algorithm (HSA) was employed in [81] to solve the SDSR problem, with results demonstrating that the HSA converged to optimal solution (minimum losses) more quickly than TS. However, determination of the penalty coefficients of fitness function in HSA is more difficult than other metaheuristic algorithms. In order to decrease computational time of PSO method and increase accuracy of modified PSO (MPSO) method, the enhanced integer coded PSO (EICPSO) was developed for loss minimization in DSR problem in [82]. In the EICPSO method, the

modified inertia weight of MPSO was employed and binary numbers (0 for open and 1 for closed switches) were used instead of integer values (bus numbers) for the representation of each particle. The presented results show that EICPSO method is much faster than PSO and MPSO, but its accuracy is lower than in the standard PSO methods. Then, an adaptive ACO (AACO) was presented in [83] to solve the SDSR problem. In this method, graph theory was adapted to create always feasible radial topologies during the whole evolutionary process. It was shown that reconfiguration of the distribution system by AACO method is better than ACO, GAMT, EGA, and ITS approaches. Nevertheless, the performance of AACO algorithm has not been tested on large distribution systems. One year later, in [84], the bacterial foraging optimization algorithm (BFOA) was proposed to minimize power losses in SDSR. The BFOA is a global optimization algorithm that uses chemotaxis, reproduction, elimination and dispersal operators to guide the particles/bacterium toward the best solution using appropriate fitness function. The simulation results indicate that the BFOA can reduce losses more than ACO, but the computing time of this method has not been compared to other DSR algorithms.

In 2013, a multi-objective DSR problem was solved by fuzzy adaptive PSO (FAPSO) method in [85]. The adaptive PSO (APSO) method was based on modifications of some features (e.g. inertia weight and swarm movement) in PSO. At the same year, a hybrid ACO (HACO) was applied to minimize the power losses in SDSR [86], where crossover operator of GA was used to improve the ACO method. It was shown that efficiency of the proposed method is better than HDE. However, there is no comparison between performance of proposed method and other ACO-based approaches. In order to enhance the performance of GA for solving the DSR problem, new improvements for genetic operators were considered in [87]. In the proposed GA, after producing the initial population using BE method, the integer variables are decoded based on branch list, instead on nodes-branches incidence matrix. Also, selection operator was defined as an exponential function using ecological niche method, instead of tournament mechanism. It was shown that the proposed single objective reconfiguration (SOREco) GA is simple enough to obtain a fast convergence and complex enough to obtain a good quality solution in comparison with other GAs. However, non-radial topologies may be created after applying genetic operators and that will degrade efficiency of the proposed algorithm (SOREco) for reconfiguration of large distribution networks.

One year later, in [88], the SDSR problem was solved by clonal reconfiguration (CLONR) algorithm. The CLONR is a metaheuristic method based on AIS and clonal selection with better performance than MIHDE method. Later in [89], a big bang-big crunch (BB-BC) algorithm was employed to solve a SDSR problem. The BB-BC is a combination of big bang (BB) and big crunch (BC) methods

that converges to optimal solution using center of mass and the best position of each solution operators. The simulation results indicated that the BB-BC minimizes losses better than HSA and ACO.

In 2015, a multi-objective SDSR problem was optimized using fast NSGA (FNSGA) algorithm [90]. In this method, the convergence speed of NSGA was improved by employing the codification method of AGA and a guided mutation operator. The results evaluation revealed that the proposed method could find the optimal solution faster than NSGA. In order to improve performance of BFOA for solving DSR problems, a modified BFOA (MBFOA) method was developed in [91]. One year later, a discrete teaching-learning based optimization (DTLBO) algorithm was employed by [92] to solve the SDSR problem in the presence of DG. Teaching-learning based optimization (TLBO) is a new metaheuristic technique based on teaching and learning process with better performance than PSO method. At the same year, fuzzy parallel GA (FPGA) was proposed to minimize losses, voltage deviation, and number of switching operations in a smart grid with variable loads [3].

In order to help researchers to develop efficient metaheuristic methods for solving large-scale DSR problems, the search space and a detailed analysis of the main operators of metaheuristic algorithms were addressed in [93]. Later, in [94], a combination of TLBO and ϵ -constraint method was presented to solve simultaneous DSR and DG allocation problem, indicating better performance of proposed method compared to PSO. In order to reduce the computational time of the multi-objective DDSR problems, a chaos disturbed beetle antennae search (CDBAS) algorithm was presented in [95] to minimize power losses, loading unbalances and nodal voltage deviations. The beetle antennae search (BAS) algorithm was inspired by the foraging principle of beetles. Grey target decision-making technology was used to adopt CDBAS for multi-objective frameworks. The results confirmed better performance of the proposed methodology compared to other reconfiguration methods for multi-objective DSR applications. More recently, a fuzzy modified PSO (FMPSO) based on Kruskal algorithm was employed to solve a multi-objective SDSR problem in [96]. The Kruskal algorithm can generate a radial topology directly without checking the loops and islands. Also, an improved cuckoo search algorithm (CSA) was presented to solve a multi-objective SDSR problem in presence of DG and DR in [97]. The CSA was inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds (of other species). In this method not-so-good solutions are replaced by new and potentially better solutions (cuckoos) in the nests. Table 5 describes advantages and disadvantages of reviewed metaheuristic methods briefly. Also, power losses, running time and some parameters of metaheuristic algorithms are presented in Table 6 and Figs 3 and 4. Finally, a complete classification of the methods used in the DSR relevant literature is supplied

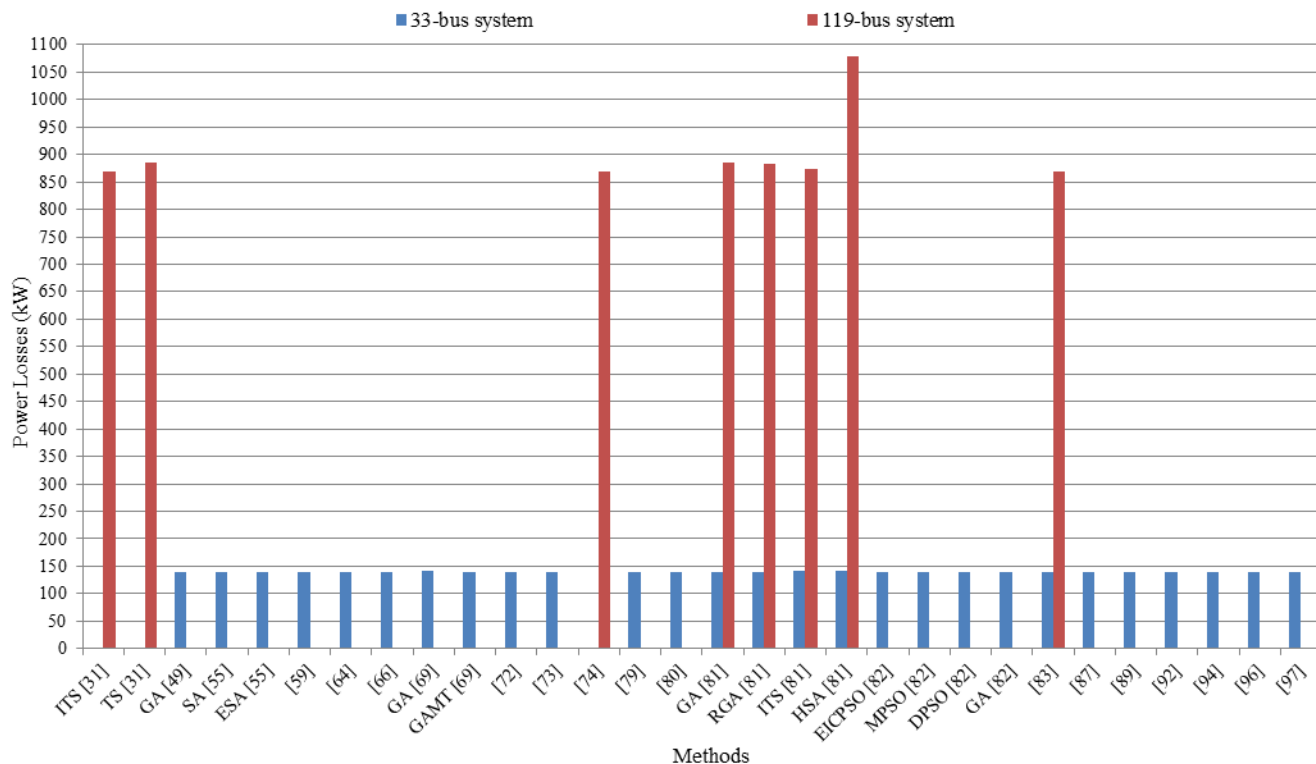


FIGURE 3. Power losses obtained by metaheuristic methods after reconfiguration of 33-bus and 119-bus test systems.

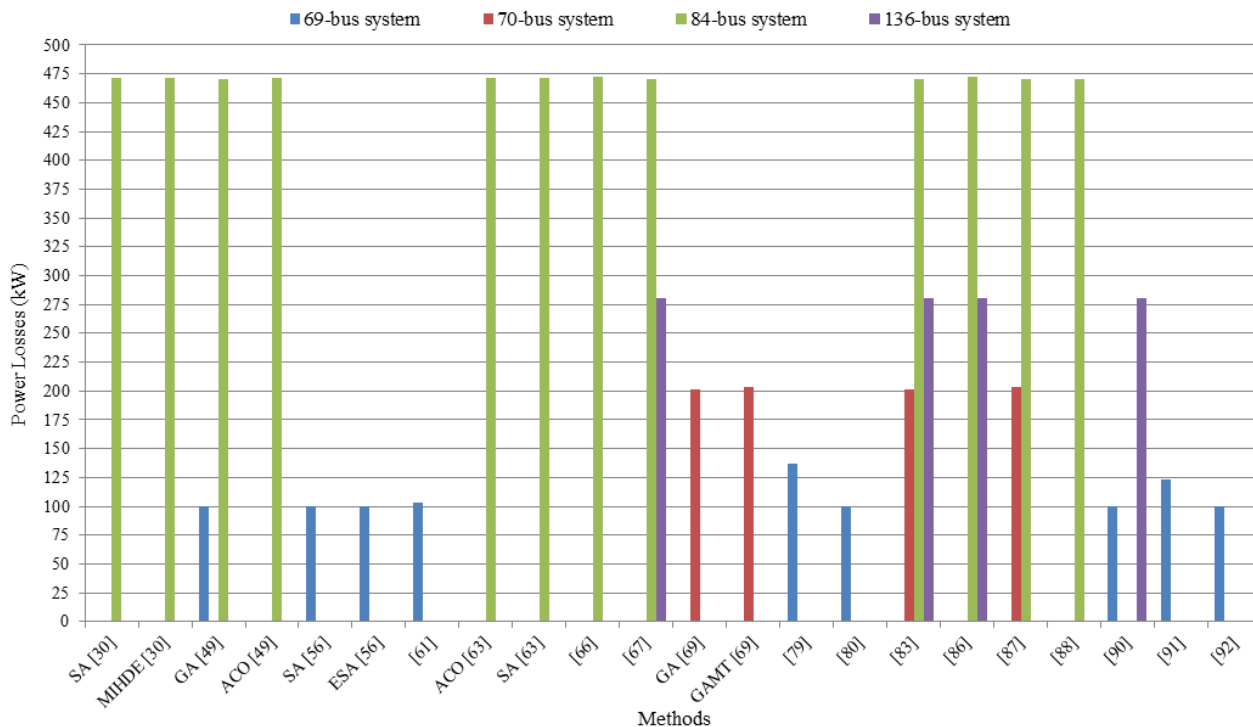


FIGURE 4. Power losses obtained by metaheuristic methods after reconfiguration of 69-bus, 70-bus, 84-bus, and 136-bus test systems.

in Table 7. Figure 5 illustrates portion of mathematical, heuristic and metaheuristic approaches from reconfiguration methods.

According to Fig. 5, a great share (58.3%) of works related to DSR have employed metaheuristic optimization techniques as their solution method.

TABLE 5. Metaheuristic optimization methods: Advantages and disadvantages.

Methods	Advantages	Disadvantages
[30]	Lower computational burden than SA	Performance of MIHDE has not been evaluated for large networks
[31]	Lower dependence of global search on tabu list length when compared to TS	Still tabu list length dependency exists in ITS method
[52]	Using SA with strong theoretical base when compared to other metaheuristic algorithms	Time-consuming repeated runs of power flow calculations during the annealing process
[53]	Simple implementation, high flexibility, and adaptation	High processing time because of using GA in standard form
[54]	Efficient method for DSR in networks with variable loads	Optimality of solutions decreases with choosing improper training data sets
[55]	Lower processing time than SA of [52] due to use simplified power flow equations	Lower accuracy than solutions obtained in [52] because of simplifications used in power flow equations
[56]	Better solutions than SA	Harder implementation than SA in large distribution networks
[57]	Better performance when compared to standard GA	Creation of non-radial solutions is possible in RGA approach
[58]	AIS is an efficient method for solving multi-objective DSR problems	Efficiency of proposed method in large systems has not been proved
[59]	FEP is an appropriate method for solving multi-objective DSR problems	Highly affected by fuzzy membership functions
[60]	Simpler implementation than SA and TS methods	Performance of EA is drastically reduced by inadequate tree representation
[61]	Efficient for solving multi-objective DSR problems because of use of controlled genetic mutation	Highly affected by fuzzy membership functions
[62]	Better performance than SA	Dependence of global search ability on tabu list length
[63]	Powerful intelligent method with better performance than SA	Non-radial solutions may be created during the evolutionary process of ACO algorithm
[64]	Only radial configurations are created during optimization process, because of restricted search space of GA	ReGA cannot guarantee network connectivity, because radial configurations with isolated buses may be created
[65]	Better performance than ANN of [54] for reconfiguration of networks with variable loads	Lower accuracy compared to other ANN based-methods because of clustering loads without considering their locations
[66]	Better performance than AIS and HDE in multi-objective DSR problems	Its efficiency for large networks has not been evaluated
[67],[69]	Higher efficiency than GA and RGA	Still non-radial solutions are created after applying genetic operators
[71]	Simple implementation	Very time-consuming for large distribution networks
[72]	MBPSO solves the DSR faster than DPSO, SA, and TS	Higher probability of capturing in the local minima compared to DPSO
[73]	Shorter computational time than ACO	Harder implementation than ACO
[74]	Higher accuracy of MTS when compared to TS and SA	Its implementation is more difficult than TS because of variable tabu list size
[75]	Lower computational time than standard GA	Lower accuracy compared to other GA methods due to sensitivity analysis
[76]	Higher accuracy than FEP and FGA because of ignorance of fuzzy membership functions	GCRA is more complicated than fuzzy theory
[77]	Lower computational time than EA due to replace GCR by NDE	Performance of proposed EA has not been tested on large distribution systems
[78]	FAGA by employing AGA instead of GA has better accuracy than FGA in multi-objective DSR problems	Highly affected by fuzzy membership functions
[79]	NSGA does not use fuzzy membership functions	Lack of comparison with fuzzy-based methods to show improved efficiency of the proposed method
[80]	FACO solves DSR problem in shorter computing time than SA	Its performance has not been compared with other fuzzy-based methods
[81]	Lower computational time than TS	Determination of penalty coefficients in HSA is more difficult than other metaheuristic methods
[82]	EICPSO is much faster than PSO and MPSO	Its accuracy is lower than standard PSO methods
[83]	Higher accuracy than ACO and ITS methods because of use of graph theory for creating radial topologies	The performance of AACO has not been tested on large distribution systems
[84]	Higher accuracy than ACO because of using efficient operators	There is no comparison between computing times of BFOA and other DSR methods
[85]	Better performance than fuzzy PSO (FPSO) due to use of APSO rather than PSO	Highly affected by fuzzy membership functions
[86]	Higher efficiency than HDE because of use of both GA and ACO operators	Performance of AACO has not been compared with other ACO algorithms
[87]	Simple and fast when compared to other GA algorithms	Non-radial configurations may be created after genetic operations
[88]	Higher efficiency than MIHDE due to use of clonal selection	Its performance has not been compared with other AIS-based methods
[89]	Higher accuracy than HSA and ACO	BB-BC operators have not been compared with genetic and PSO ones
[90]	Faster than NSGA because of using AGA instead of GA	No comparison with fuzzy-based methods
[91]	Better efficiency than BFOA	MBFOA has not been tested on large systems
[92]	Better performance than DPSO	Higher computational time than some genetic algorithms
[94]	More accurate than PSO	Higher computational time than TS and HSA
[95]	Lower computing time than other multi-objective methods	Its accuracy is not compared with other multi-objective DSR approaches
[96]	Lower processing time than other PSO algorithms in multi-objective DSR applications	Some non-radial solutions may be generated during optimization process
[97]	Good performance for solving complicated DSR problems	Its application to large networks is not simple

TABLE 6. Metaheuristic optimization methods: Computation time and some parameters.

Methods	Systems	Run. Time (s)	No. of Iter.	Population Size	Methods	Systems	Run. Time (s)	No. of Iter.	Pop. Size
MIHDE [30]	84-bus	36.15	1000	5	ITS [81]	33-bus	8.1	-	-
SA [30]	84-bus	195.21	1000	-		119-bus	9.038	-	-
ITS [31]	119-bus	9.038	600	9	HSA [81]	33-bus	7.2	-	-
TS [31]	119-bus	-	600	9		119-bus	69.3	-	-
SA [56]	33-bus	0.3	-	-	[74]	119-bus	18000	-	-
	69-bus	2.5	-	-	EICPSO [82]	33-bus	6.343	1000	10
ESA [56]	33-bus	0.34	-	-	MPSO [82]	33-bus	5.693	1000	10
	69-bus	2.57	-	-	DPSO [82]	33-bus	6.075	1000	10
[59]	33-bus	55.04	103	5	GA [82]	33-bus	6.012	1000	10
[61]	69-bus	-	200	30	[83]	33-bus	0.3	100	10
ACO [63]	84-bus	241.5	500	10		70-bus	19.72	100	25
SA [63]	84-bus	257.4	500	5		84-bus	95.88	100	40
[64]	33-bus	6.3	35	15		119-bus	430.75	100	70
[66]	84-bus	15	100	100		136-bus	894.2	100	85
[67]	33-bus	-	-	10	[84]	33-bus	-	-	20
	84-bus	0.2	-	10	[86]	84-bus	883	50	20
136-bus	0.4	11	10	136-bus		5120	100	20	
GA [69]	33-bus	160	50	40	[87]	33-bus	5.704	7	10
	70-bus	1900	100	70		70-bus	4.639	6	-
GAMT [69]	33-bus	7.2	15	30	84-bus	7.809	9	10	
	70-bus	160	40	50	[88]	84-bus	160	100	-
GA [71]	69-bus	23.1452	50	10	[89]	33-bus	-	100	50
DPSO [71]	69-bus	5.1521	50	10	[90]	69-bus	20.2	10	-
[72]	33-bus	-	40	5		136-bus	32.6	20	50
[73]	33-bus	-	1000	10	[91]	33-bus	2.3512	25	-
[79]	33-bus	18	50	30		69-bus	2.6931	25	-
	69-bus	37	250	30	[92]	33-bus	-	20	20
GA [81]	33-bus	19.1	200	85		69-bus	-	20	20
	119-bus	24.45	200	85	[94]	33-bus	-	150	90
RGA [81]	33-bus	13.8	200	85	[96]	33-bus	7.24	40	30
	119-bus	17.53	200	85	[97]	33-bus	-	100	50

■ Mathematical methods ■ Heuristic methods ■ Metaheuristic methods

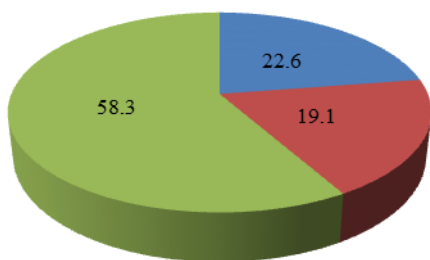


FIGURE 5. Percentage of mathematical, heuristic, and metaheuristic techniques from reconfiguration methods (%).

III. LITERATURE CLASSIFICATION BASED ON OBJECTIVE FUNCTIONS

Lately, the inclusion of DSR-related areas, such as load balancing, voltage stability, capacitor placement, renewable energy sources, electricity market, and associated fields (e.g., uncertainty and reliability) have gained strong relevance. Therefore, this section presents a classification for DSR works based on the proposed studies from different power system aspects. A short description of the relevant works embracing the most important DSR related areas is presented as follows.

Initially, [102] estimated power loss changes in SDRS using direct current (DC) power flow, showing that the proposed formulation enables fast reconfiguration for online applications. Two years later, the problem of [20] was formulated as a two-stage multi-objective optimization problem using SA in [52] and [103]. In simple words, the objective functions of losses and maximum load balancing were minimized in the first and second stages of the proposed approach, respectively.

In order to achieve a more realistic assessment of power loss reduction through network reconfiguration, [33] formulated the SDRS problem using AC power flow equations. Also, [28] investigated network losses and load balancing separately in SDRS using exact and estimated forward-backward power flows, concluding that the type of load flow affects the convergence speed and precision of the proposed reconfiguration algorithm. Later, [54] considered load type in the formulation of the SDRS. Also, [118] maximized system reliability via static reconfiguration of distribution network, concluding that SAIFI (system average interruption frequency index) minimization leads to minimal SAIDI (system average interruption duration index). Then, [35] proposed a linear model for SDRS, defining the active losses of each branch over its rating current, by linearized power flow equations. Also, [12] introduced a new model for network

TABLE 7. Classification of DSR literature based on solution method.

Methods	References
Mathematical Optimization	AMPL [1],[27]; SOCP [2],[4],[18]; BD [5],[14]; B&B [6],[15],[22]; compensation technique [9]; Binary IP [12]; Newton method [13]; graph theory [16]; MICP [17]; MIQP [18],[98]; QCP [18]; MILP [19],[99]; ϵ -constraint method [20]; decomposition method [21]; fast decoupled Newton–Raphson method [23]; GAMS [24],[25]; ADP [26]; BD and MIQP [100].
Heuristic Optimization	BE [28],[101]; fuzzy-based heuristic method [29]; DISTOP [33]; Loss change estimation [34],[102]; MILP-based heuristic algorithm [35]; heuristic based on partitioning theory [36]; DAOP [37]; systematic feeder reconfiguration technique [38]; geometrical approach [39]; new BE-based heuristic method [40]; BE with OPF [41]; two-stage heuristic algorithm with BE [42]; two-stage heuristic algorithm with sensitivity analysis [43]; neighboring updating-based heuristic method [44]; HCA [45]; two-stage heuristic algorithm with NCUP [46]; Lagrange relaxation technique [47]; simple heuristic method without load flow [48]; VSO [49]; SOE [50].
Metaheuristic Optimization	FPGA [3]; HPSO [8]; MIHDE [30]; HDE [30]; ITS [31]; FGA [51],[61]; SA [52],[55],[103]; GA [53],[104],[105]; ANN [54]; ESA [55]; RGA [57]; AIS [58]; FEP [59]; EA with GCR [60]; TS [62]; ACO [63],[106]–[108]; ReGA [64]; ANN with clustering technique [65]; AIS-ACO [66]; EGA [67]; GAMT [69]; BPSO [70]; DPSO [71],[109]; MBPSO [72]; HC-ACO [73]; MTS [74]; DGA [75]; EP with GCRA [76]; EA with NDE [77]; FAGA [78]; NSGA [79]; FACO [80]; HSA [81], [110]; EICPSO [82]; AACO [83]; BFOA [84]; FAPSO [85]; HACO [86]; SOReco [87]; CLONR [88]; BB-BC [89]; FNSGA [90]; BFOA [91]; TLBO [92]; TLBO and ϵ -constraint method [94]; CDBAS [95]; FMPSO [96]; CSA [97]; AIS and Prime’s algorithm [111]; GA and FCM [112]; EA [113]; IHSA [114]; IHSA and BE [114]; GWO [114]; modified GWO [115]; IGA [116]; FA [117].

reconfiguration, allocating distribution feeders to different circuits, by representing network losses in terms of circuits’ currents.

In addition, [101] minimized energy losses via network reconfiguration and optimal installation of shunt capacitors using different load models. The results showed that method of load formulation affects the solutions of DSR and capacitor placement problem significantly. Furthermore, [55] showed that network power loss is more reduced by simultaneous capacitor setting and DSR compared to conventional distribution network reconfiguration. Also, [59] optimized power losses and improved voltage profile in a multi-objective DSR framework, reducing voltage deviation of load buses. Later, [119] presented a new multi-objective framework for SDR by replacing loss minimization with loadability maximization in [59].

In [51], a new index was defined to measure the voltage stability of each bus. The voltage stability of each node was presented in terms of voltage magnitude of neighboring buses and the power flow between them and related node. Moreover, [50] considered daily load and photovoltaic (PV) output variations in DDSR. Also, [29] formulated a multi-objective SDR problem, considering active losses, load balancing, voltage deviation, and branch current violation; meanwhile, [106] solved simultaneous SDR and capacitor placement problem.

In [14], minimum active and reactive power of substation, nodal voltage angle limit, and transformer tap restriction were added to constraints of SDR problem. In addition, [45] considered a daily load curve in simultaneous SDR and capacitor placement problem, introducing a new sensitivity index for switches. Later, [76] included maximum voltage drop in objective functions of [28], while [78] considered the number of switching operations in the problem of [29], aiming at reducing the operating cost and switching transients.

In [107], distributed generators considered in formulation of SDR, concluding that lower system loss and better load balancing can be obtained in the presence of DG. Furthermore, [80] proposed a multi-objective formulation for network reconfiguration in a deregulated electricity market, considering the operation cost of DISCOs, customer interruption cost, and voltage deviation.

Also, in [18], new radiality constraints were proposed for SDR, allocating two continues variables to the power flow direction of each line. In addition, in [120], the voltage dependency of loads was considered in SDR formulation, highlighting the importance of load type in network reconfiguration.

Later, [110] modelled composite SDR and DG placement problem, concluding that simultaneous DG allocating and network reconfiguration reduces the losses more effectively. In addition, [121] developed a linear model of [19] to include a voltage dependency of loads and distributed generators. Also, [85] considered uncertainty in demand, distributed wind power generation, and fuel cells in SDR, aiming minimization of power loss, bus voltage deviation, generation cost, and total emissions. Moreover, [104] included switching and losses costs in a probabilistic SDR problem considering uncertainty in the generation of wind, solar, and biomass DG units.

Also, [122] concluded that reconfiguration is more effective than network reinforcement for increasing DG hosting capacity in static and dynamic reconfigurations. Furthermore, [16] modelled radiality constraint of traditional SDR as a spanning tree minimization problem using graph theory, considering the voltage dependency of loads. At the same year, a new model based on the linear power flow equations was presented for formulation of the SDR problem in [98].

Afterwards, the SDR was formulated as a multi-objective optimization problem, minimizing reliability criterion of PIEFI (power interruption equivalent frequency index) in [111]. Also, [99] presented simple linear current flow (LCF) equations to formulate the conventional SDR problem, showing higher efficiency of the proposed formulation compare to models presented in [17] and [18]. In addition, [112] considered load (both active and reactive demands) and distributed generation variability in SDR, showing that more accurate losses can be obtained in this way.

In order to improve models presented in [17] and [18], [123] developed a binary convex formulation for SDR. Also, [21] proposed a robust model for network reconfiguration

with the aim of loss minimization under load and renewable generation uncertainties. For a more realistic assessment of the SDSR problem, [124] included losses and voltage deviation in the objective function considering the coordination of protective devices. Moreover, [108] formulated SDSR in presence of DG considering capacitor switching and cost of buying power from the substation, indicating that the proposed model reduces the total grid cost efficiently. In addition, [5] proposed a disjunctive integer linear formulation for DDSR in order to increase DG integration in distribution systems.

In order to show the importance of voltage security in deregulated energy markets, [105] maximized separately voltage security index and node voltage quality index (NVQI) via network reconfiguration. Moreover, [109] solved the DDSR problem in order to increase the annual investment return considering the hourly load profile. Also, [125] proposed a robust stochastic model for DDSR including DG, minimizing daily operational cost (total hourly power loss and switching costs) of systems managed by local distribution companies using model predictive control (MPC) technique. Then, [114] optimized reactive power losses in SDSR for enhancement of distribution system loadability limit.

Afterwards, [22] determined the optimal switching time in conventional DDSR problem. Later, in order to increase network security, [116] included $N-1$ contingency criterion in SDSR problem with the objective of power loss minimization. Also, for service restoration during continues small load changes, [126] presented a multi-agent system (MAS)-based model for DDSR considering load priority and distributed generators. Also, [8] formulated a DDSR problem in order to increase the daily DG hosting capacity under distributed generation uncertainties. In [96], random and fuzzy uncertainties of the wind and PV power generation and load demand were considered in SDSR for power loss reduction and voltage stability enhancement.

Furthermore, in [97], the effect of DR on the single and multi-objective SDSR problem was studied in a stochastic environment considering wind and PV units, electric vehicles (EVs), and cost of DR participation. The results reveal that the DR strategy along with the DSR can provide new opportunities to improve system situations in modern power systems. In [100], a new voltage stability constraint was introduced for SDSR problem, aiming network losses reduction considering switched capacitor banks and DG units. The results show that the model can concisely describes the influence of DG output fluctuations on bus voltages.

Moreover, in [113], the DSR problem and distribution expansion planning problem were solved simultaneously. The simulation results indicate that solving reconfiguration and expansion planning problem at the same time leads to decrease the network losses efficiently. Also, in [115], the DSR problem considering voltage and reactive power control devices (on-load tap changers (OLTC), shunt capacitor

banks, and voltage regulators) in presence of PV based DG units was studied, aiming minimization of energy losses and consumption. Furthermore, in [89], power losses, DG costs, and greenhouse gas emissions were optimized in SDSR using BB-BC algorithm.

In [127], network reliability was formulated in a multi-objective DSR problem based on minimal cut sets between substation node and load buses, indicating that the proposed strategy can formulate system reliability better than Monte Carlo simulation (MCS). Also, in [117], power quality (number of voltage sags) and reliability criteria of SAIFI, ASIFI (average system interruption frequency index), and MAIFI (momentary average interruption frequency index) were optimized in SDSR problem using firefly algorithm (FA). Moreover, in [128], a Weibull-Markov stochastic-based model was presented instead of time-consuming MCS method for reliability assessment in a multi-objective simultaneous network reconfiguration and capacitor placement. In addition, [129] proposed a robust model for simultaneous DSR and DG allocation problem using a combination of GA, BE, and sensitivity analysis.

In [130], a comprehensive MILP model was presented for SDSR problem in presence of DG, by embedding exact network losses in power flow equations instead of considering losses as estimated power injections at each node. Furthermore, in [131], it was shown that simultaneous network reconfiguration and expansion planning in presence of DR reduces the expansion costs more efficiently compared to when only network expansion planning is performed. Later, [132] formulated SDSR in presence of power flow controllers, showing that flexible DC device (FDD) improves DSR solutions by adjusting line power flows in coordination with switching sequences. Finally, DDSR in presence of renewable energy resources and energy storage systems (EESs) was solved in [133].

Table 8 lists the most relevant areas that can affect the decisions of operators in a distribution network. Moreover, it presents a complete classification of the papers from relevant aspects point of view. Hence, Table 8 represents an important tool for DSR modelling.

According to Table 8, it can be seen that loss reduction via DSR has been always important for researchers and it comprises a great share of objective functions in DSR studies. After loss minimization, power quality improvement via DSR and reconfiguration of distribution systems in presence of DG have been major concerns of network operators. Also, Table 8 indicates that recent research tends to study DSR problem in presence of energy storage systems, electric vehicles, demand response, and communication systems. It seems that reconfiguration of smart distribution systems in presence of renewable energy sources, electric vehicles, energy storage systems and flexible loads (DR) will be the most important research theme in future. This issue also imposes many uncertainties to DSR problem and challenges current DSR models and methods.

TABLE 8. Classification of DSR literature based on relevant aspects.

Objective Functions	References
Losses	[1]–[3],[6],[7],[9],[12]–[24],[27]–[31],[34]–[43],[45]–[50],[52]–[65],[67]–[69],[71]–[93],[95]–[116],[120],[121],[123],[125],[127]–[130]
Load balancing	[28],[29],[52],[58],[66],[71],[80],[90],[95],[103],[107],[123]
Load type	[54],[101],[115]
Load variations	[3],[45],[95],[112],[115]
Load voltage	[16],[120],[121]
Load priority	[126]
Load uncertainty	[6],[24],[25],[50],[85],[96],[97],[131]
Capacitor setting	[55],[100],[108]
Capacitor placement	[44],[75],[106],[115],[128]
DG power	[9],[21],[26],[49],[50],[85],[92],[95]–[97],[100],[104],[107],[108],[112],[121],[125],[126],[130]–[133]
DG sizing	[2],[48]
DG allocation	[2],[25],[89],[94],[110],[129]
DG hosting	[5],[8],[120],[122]
Generation cost	[26],[85],[89],[97],[133]
Generation uncertainty	[8],[21],[25],[51],[85],[95]–[97],[104],[131]
Generation variability	[112],[115],[125]
Switching frequency	[3],[8],[47],[78],[90]
Switching cost	[104],[125],[133]
Switching time	[25]
System restoration	[77],[115],[123],[126]
System security	[116]
System reliability	[4],[5],[20],[24],[26],[70],[79],[108],[111],[117],[118],[127],[128],[133]
System loadability	[29],[78],[94],[119]
System radiality	[1],[27],[15],[16],[18],[105],[121]
System protection	[109],[124]
Power quality	[1],[3],[8],[29],[44],[48],[51],[59],[61],[66],[76],[78],[79],[85],[90],[92],[95]–[97],[100],[105],[109],[113],[117],[119],[132],[133]
Electricity market	[70],[79]
Emission	[85],[89],[97]
Substation cost	[108]
Investment return	[109]
DR	[24],[97],[131]
Expansion planning	[113],[131]
FACTS	[115],[132]
Smart grid	[3],[112],[126]
EVs	[131]
EESs	[133]
DISCOs	[25]

IV. LITERATURE CLASSIFICATION BASED ON INNOVATIONS

As mentioned, for the last 45 years, the DSR problem has been widely studied. Therefore, one last classification is proposed in this section, aiming to cite and honour those works that have brought the most significant innovations in the different fields related to DSR. This classification represents a great tool for new researchers because it collects the research basis regarding DSR most important features. Hence, Table 9 sorts DSR research from the novelty point of view.

It can be seen that these innovations are related to methods and/or studied issues—a comprehensive combination of the classifications previously presented.

TABLE 9. Classification of DSR literature based on innovations.

Innovations		References
Solution Methods	Mathematical	[1],[6],[9],[12]–[15],[17]–[21],[23],[26],[27]
	Heuristic	[28],[33],[35]–[50],[125],[129]
	Metaheuristic	[3],[8],[29]–[31],[52]–[67],[69]–[76],[78]–[97],[102],[103],[111],[114],[117]
Models	A SOCP model for DG allocation and sizing in DSR	[2]
	A SOCP model for DSR considering reliability indices	[4]
	Linear formulation of DG hosting considering DG curtailment	[5]
	Dynamic reconfiguration	[17]
	Radiality constraints for networks containing several buses without load and generation	[15]
	Minimal spanning tree based on dual graph theory	[16]
	Switching time	[22]
	DR in multi-objective DSR	[24]
	DISCOs cost and DG owner’s profit in DSR	[25]
	Loss change estimation using AC power flow	[33]
	New voltage stability index	[51]
	Efficient linearized power flow equations	[98]
	LCF equations	[99]
	New voltage stability index in presence of DG	[100]
	Effect of load modelling method on DSR	[101]
	Integration of switching cost, power losses, and uncertainties of wind, solar and biomass DG units	[104]
	Voltage security and radiality improvements in deregulated electricity markets via DSR	[105]
	Simultaneous DSR and capacitor placement	[106]
	Distributed generation	[107]
	Simultaneous online distribution lines and capacitor switching in active smart grids	[108]
	Annual investment return	[109]
	Simultaneous DSR and DG allocation	[110]
	Effect of load and distributed generation variability on DSR in smart grids	[112]
	Distribution system expansion planning using network reconfiguration	[113]
	Voltage and reactive power control devices in presence of DG	[115]
	N–1 security criterion	[116]
	Reliability enhancement	[118]
	Loadability maximization	[119]
	Load type impact on DSR	[120]
	A MILP model for DSR in presence of DG	[121]
	Effect of network reconfiguration on DG hosting improvement	[122]
	Binary convex model for DSR	[123]
	Protective devices	[124]
	Smart agents and load priority	[126]
Reliability formulation in DSR using minimal cut sets theory	[127]	
Weibull-Markov stochastic-based model for simultaneous DSR and capacitor placement	[128]	
Comprehensive MILP model for DSR in presence of DG	[130]	
Statistic DR in simultaneous network reconfiguration and expansion planning	[131]	
Use of flexible DC power flow controller in DSR	[132]	
Energy storage systems in DSR	[133]	

V. IMPLEMENTATION METHODS

Table 10 shows some implementation methods used by different companies and organizations in the world such as

Iraqi power utilities [134], Croatian electric power company (HEP) [135], Brazilian utility companies [23], [136], Athens Utilities Board (AUB) [7], Tokyo Electric Power Company (TEPCO) [22], Pennsylvania Power and Light Company (PP&L) [138], Taiwan Power Company (Taipower or TPC), Korea Electric Power Corporation (KEPCO) [57], Pacific Gas and Electric Company of San Francisco in United States [33], and Electric Power Research Institute (EPRI) [37].

TABLE 10. Some implementation methods in real networks.

Companies/ Institutes	Methods	Objective Functions	Horizon times	Studied Networks
Iraqi power utilities	Harmonic power flow [134]	Losses	One year	City of Baghdad
HEP	MPC	Losses	24 hours	City of Koprivnica
Brazilian utility companies	XDFPF, TS, BE and AC power flow [40], and BE with OPF and sensitivity analysis [41]	Losses	One year	City of Tres Lagoas and a practical 1531-bus system
AUB	System Reconfiguration Analysis Program (SYSRAP) [7]	Losses	One year	City of Athens
TEPCO	B&B	Losses	One day	City of Tokyo
PP&L	Automated distribution control (ADC) [137]	Losses & capacitor siting	One hour and a week	City of Allenton
Taipower (TPC)	MILP-based heuristic algorithm [35] and MIHDE	Losses	One year	A 6-feeder urban network
KEPCO	SA and ESA	Losses	One year	KEPCO
Pacific Gas & Electric Company	DISTOP	Losses	One year	A practical 3086-bus system
EPRI	DEWorkstation software package [32]	Losses & power quality	One year	33-bus test system

VI. OUTCOMES

In order to help the DSR researchers to know which reconfiguration method is suitable for which application, outcomes of DSR approaches for specific applications are presented in this section.

A. LOSS REDUCTION

Tables 11 to 16 present approaches used for power loss minimization in DSR. In these tables, methods were ranked first according to power loss reduction (accuracy), then reported computational time (convergence speed), and afterward regarding the number of algorithm iterations and number of power flow calculations (computational burden).

TABLE 11. SDR for power loss minimization: 33-bus system.

Methods	Open Switches	Initial Losses (kW)	Losses After DSR (kW)	Run. Time (s)
[14]	7,9,14,32,37	202.54	139.55	0.11
QP [18]	7,9,14,32,37	202.7	139.55	0.21
ESA [56]	7,9,14,32,37	202.7	139.55	0.34
SA [56]	7,9,14,32,37	202.7	139.55	0.3
[19]	7,9,14,32,37	202.68	139.55	1
QCP [18]	7,9,14,32,37	202.7	139.55	1.43
New BE [40]	7,9,14,32,37	202.68	139.55	1.66
DAOP [40]	7,9,14,32,37	202.68	139.55	1.99
[64]	7,9,14,32,37	202.68	139.55	6.3
[96]	7,9,14,32,37	202.68	139.55	7.24
SOC [18]	7,9,14,32,37	202.7	139.55	12.8
[24]	7,9,14,28,32	202.68	139.55	72.79
[72]	7,9,14,32,37	202.6	139.55	-
[89]	7,9,14,32,37	202.67	139.55	-
[73]	7,9,14,32,37	176.4	139.55	-
[67]	7,9,14,32,37	202.68	139.55	-
[59]	7,9,14,32,37	211.22	139.83	55.04
[16]	7,9,14,28,32	202.7	139.98	3
MPSO [82]	7,9,14,28,32	203.33	139.98	5.693
GA [82]	7,9,14,28,32	203.33	139.98	6.012
PSO [82]	7,9,14,28,32	203.33	139.98	6.075
EICPSO [82]	7,9,14,28,32	203.33	139.98	6.343
[15]	7,9,14,28,32	202.68	139.98	19
[20]	7,9,14,28,32	202.68	139.98	192
[94]	7,9,14,28,32	210.99	139.98	-
[2]	7,9,14,28,32	202.68	139.98	-
[13]	7,9,14,28,31	194.53	142.03	0.01
[33]	7,10,14,32,37	202.68	140.26	0.14
[41]	7,10,14,32,37	202.68	140.26	0.96
[79]	7,10,14,32,37	202.74	140.26	-
Approximated DAOP [37]	7,9,14,31,37	196.91	142.6	20.451
Exact DAOP [37]	7,9,14,31,37	196.91	142.6	226.7
GA [69]	7,10,14,36,37	202.68	142.68	160
[38]	6,9,14,32,37	204.14	142.83	20.45
[28]	11,28,31,33,34	202.68	146.84	-
[57]	7,9,14,32,33	202.674	Infeasible	-
[84]	7,9,13,14,32	202.71	Infeasible	-

TABLE 12. SDR for power loss minimization: 70-bus system.

Methods	Open Switches	Initial Losses (kW)	Losses After DSR (kW)	Run. Time (s)
[1]	13,30,45,51,66,70, 75-79	227.5	201.4	4.9
GAMT [69]	14,30,38,46,51,66, 70,71,76,77,79	227.53	203.17	160
[87]	13,28,45,51,67,70, 73,75,76,78,79	227.346	203.67	4.639
[29]	14,28,39,46,51,67, 70,71,73,76,79	227.53	205.32	3

B. VOLTAGE IMPROVEMENT

Tables 17 to 20 show reconfiguration methods used to improve voltage profile of distribution systems. Methods

TABLE 13. SDRS for power loss minimization: 69-bus system.

Methods	Open Switches	Initial Losses (kW)	Losses After DSR (kW)	Run. Time (s)
[92]	14,57,61,69,70	224.9	99.62	-
[61]	12,20,56,61,63	224.97	103	-
[91]	18,43,56,61,69	225	123.51	2.693

TABLE 14. SDRS for power loss minimization: 84-bus system.

Methods	Open Switches	Initial Losses (kW)	Losses After DSR (kW)	Run. Time (s)
VSO [49]	7,13,34,39,42,55,62,72,83,86,89,90,92	531.77	469.88	1.513
GA [49]	7,13,34,39,42,55,62,72,83,86,89,90,92	531.77	469.88	33.575
MILP [17]	7,13,34,39,42,55,62,72,83,86,89,90,92	531.99	469.88	207.7
MICP [17]	7,13,34,39,42,55,62,72,83,86,89,90,92	531.99	469.88	245.4
DS [48]	7,13,34,39,42,63,72,83,84,86,89,90,92	531.81	470.01	21
[50]	7,13,34,39,42,55,63,72,83,86,89,90,92	531.99	470.06	6.2
MIHDE [30]	7,13,34,39,41,55,62,72,83,86,89,90,92	531.99	471.1	36.15
SA [30]	7,13,34,39,41,55,62,72,83,86,89,90,92	531.99	471.1	195.21
ACO [63]	7,13,34,39,41,55,62,72,83,86,89,90,92	531.99	471.1	241.51
SA [63]	7,13,34,39,41,55,62,72,83,86,89,90,92	531.99	471.1	257.43
ACO [49]	7,13,34,39,41,55,62,72,83,86,89,90,92	531.77	471.1	-
[86]	7,13,34,39,42,55,62,72,86,89,90,91,92	531.99	472.32	883

TABLE 15. SDRS for power loss minimization: 119-bus system.

Methods	Open Switches	Initial Losses (kW)	Losses After DSR (kW)	Run. Time (s)
ITS [31]	24,27,35,40,43,52,59,72,75,96,98,110,123,130,131	1294.3	869.7	9.038
[83]	24,27,35,40,43,52,59,72,75,96,98,110,123,130,131	1298.1	869.7	430.74
[74]	24,27,35,40,43,52,59,72,75,96,98,110,123,130,131	1294.3	869.7	18000
ITS [81]	24,27,35,40,43,52,59,72,75,96,98,110,120,130,131	1301.9	874.7	9.038
RGA [81]	23,27,33,40,43,49,52,62,73,74,77,83,110,126,131	1301.9	883.13	17.53
TS [31]	23,27,33,40,43,49,52,62,72,74,77,83,110,126,131	1294.3	884.163	-
GA [81]	24,31,35,40,43,49,51,62,73,74,77,83,110,120,126	1301.9	885.56	24.45
HSA [81]	23,27,33,43,53,62,72,75,123,125,126,129-132	1301.9	1078.4	8.61

were ranked in tables first according to highest minimum voltage and voltage stability index (VSI) and then computational time reduction.

TABLE 16. SDRS for power loss minimization: 136-bus system.

Methods	Open Switches	Initial Losses (kW)	Losses After DSR (kW)	Run. Time (s)
[27]	7,35,51,90,96,106,118,126,135,137,138,141,142,144,148,150,151,155	320.37	280.19	9
[90]	7,51,53,90,96,106,118,126,135,137-139,141,144-148,150,151,155		280.69	-
MSU [46]	7,55,38,51,90,97,106,118,126,137,138,141,144-148,150,151,152,155	320.36	282.77	23.98
OSU [46]	7,9,38,51,90,96,98,106,120,126,128,138,142,144-148,150,151,152,	320.36	285.1	-
[32]	51,106,136-139,141-152,154-156	320.17	285.5	-
[42]	7,9,38,51,55,90,92,95,104,106,120,126,128,135,138,141,144-146,148,150	320.36	286	8.96

TABLE 17. SDRS for minimum voltage maximization: 33-bus system.

Methods	Open Switches	Minimum Voltage (p.u.)		Run. Time (s)
		Before DSR	After DSR	
[97]	7,9,14,28,32	0.9131	0.9457	-
QP [18]	7,9,14,28,32	0.9131	0.9413	2.09
QCP [18]	7,9,14,28,32	0.9131	0.9413	7.34
SOCP [18]	7,9,14,28,32	0.9131	0.9413	18.67

TABLE 18. SDRS for minimum voltage maximization: 69-bus system.

Methods	Open Switches	Minimum Voltage (p.u.)		Run. Time (s)
		Before DSR	After DSR	
[90]	10,14,57,61,70	0.909	0.943	-
[44]	14,58,61,69,70	0.875	0.931	-
[51]	12,20,58,64,69	0.875	0.916	-

TABLE 19. SDRS for voltage stability enhancement: 69-bus system.

Methods	Open Switches	VSI		Run. Time (s)
		Before DSR	After DSR	
[44]	14,58,61,69,70	0.587	0.754	-
[51]	12,20,58,64,69	0.587	0.705	3.19

TABLE 20. SDRS for voltage deviation minimization: 33-bus system.

Methods	Open Switches	VDI		Run. Time (s)
		Before DSR	After DSR	
[92]	9,14,28,32,33	0.0298	0.0163	-

TABLE 21. SDRS for feeder load balancing: 33-bus system.

Methods	Open Switches	LBI		Run. Time (s)
		Before DSR	After DSR	
QCP [18]	9,14,28,31,33	0.08211	0.04146	2.31
SOCP [18]	9,14,28,31,33	0.08211	0.04146	18.06
[80]	6,9,14,31,37	0.11968	0.07537	-

C. LOAD BLANCING

One of important objectives of DSR is minimization of loading unbalances in distribution feeders to use lines transmission capacity more efficiently. Tables 21 and 22 rank

TABLE 22. SDSR for feeder load balancing: 69-bus system.

Methods	Open Switches	LBI		Run. Time (s)
		Before DSR	After DSR	
DPSO [71]	10,13,20,25,58	0.9438	0.5692	5.152
GA [71]	10,14,15,25,56	0.9438	0.5895	23.14

TABLE 23. SDSR for loss reduction and voltage improvement: 136-bus system.

Methods	Open Switches	Losses (kW)		Min. Voltage (p.u.)		Run. Time (s)
		Before DSR	After DSR	Before DSR	After DSR	
		DS [48]	7,38,51, 54,84,90, 96,106,119, 126,135,137, 138,141,144, 145,147,148, 150,151,155	320.35	281	
NS [48]	9,38,51, 54,84,90, 96,106,120, 126,135,136, 138,141,144, 145,147,148, 150,151,155	320.35	282.6	0.9307	0.9582	87.6

TABLE 24. SDSR for loss reduction and voltage improvement: 69-bus system.

Methods	Open Switches	Losses (kW)		VDI		Run. Time (s)
		Before DSR	After DSR	Before DSR	After DSR	
[61]	12,20,58, 61,69	224.97	102.3	0.0266	0.0127	-

TABLE 25. SDSR for loss reduction and feeder load balancing.

Methods	Open Switches	Power losses (kW)		LBI	
		Before DSR	After DSR	Before DSR	After DSR
		[80]	33-bus system 6,9,14, 32,37	202.74	142.83
	69-bus system 12,57,61, 69,70	228.46	99.81	0.01546	0.00907

TABLE 26. SDSR for loss reduction, voltage improvement, and feeder load balancing: 69-bus system.

Methods	Open Switches	Losses After DSR (kW)	Min. Voltage After DSR (p.u.)	LBI		Run. Time (s)
				Before DSR	After DSR	
				[90]	19,55,61, 69,71	

reconfiguration methods for load balancing according to their accuracy and then computation time.

D. MULTI-OBJECTIVE DSR APPLICATIONS

In order to give a general overview to readers about multi-objective applications of DSR, outcomes of some reconfiguration methods based on their application are listed in Tables 23 to 28.

TABLE 27. SDSR for loss reduction and reliability improvement: 33-bus system.

Methods	Best solutions for loss minimization			Best solutions for reliability improvement		
	Without DR		With DR	Without DR		With DR
	[20]	[24]	[24]	[20]	[24]	[24]
Open Switches	7,9,14, 17,28	-	-	10,13,16, 28,33	-	-
Power Losses (kW)	146.29	182	130	161.58	275	176
SAIFI (f/yr.)	1.004	NN	NN	0.9841	NN	NN
AENS (kWh)	0.3998	NN	NN	0.3935	NN	NN
ENS (kW)	-	0.89	0.132	-	0	0.088

TABLE 28. SDSR for loss reduction, and voltage and reliability improvement.

Methods	[79]	
	33-bus system	69-bus system
Open Switches	7,9,14,32,37	14,23,51,60,72
Power Losses (kW)	139.55	136.87
VDI Before DSR	0.02	0.12
VDI After DSR	0.002	0.002
Annual Interruption Cost Before DSR (\$)	72.27	15.7
Annual Interruption Cost After DSR (\$)	54.0822	12.45
Running Time (s)	142	37

TABLE 29. SDSR for loss reduction, voltage deviation minimization, and transformer load balancing: 84-bus system.

Methods	Objectives	Open Switches	Losses (kW)	Voltage Dev. (p.u.)	Loading Unbalances (p.u.)
[66]	Minimum power losses	7,13,34, 39,42,55, 62,72,86, 89,90,91, 92	472.32	0.0468	1.587
	Minimum voltage deviation	7,13,32, 33,39,42, 54,64,72, 86,89,90, 91	491.08	0.0451	2.85
	Minimum transformer load balancing	7,13,14, 34,39,42, 55,62,70, 86,90,91, 92	509.73	0.0552	1.171

E. DSR APPLICATIONS IN ACTIVE DISTRIBUTION SYSTEMS

In this section, results of DSR in presence of DG units (active distribution systems) are presented in Tables 30 to 35.

TABLE 30. SDSR for loss reduction in presence of DG: 69-bus system.

Methods	Open Switches	Losses (kW)		Running Time (s)
		Before DSR	After DSR	
DS [48]	14,57,61, 69,70	70.3	35.42	154
[92]	12,57,63, 69,70	152.3	67	-
[110]	13,17,58, 61,69	86.76	51.3	-

TABLE 31. SDSR for loss reduction in presence of DG: 84-bus system.

Methods	Open Switches	Losses (kW)		Running Time (s)
		Before DSR	After DSR	
DS [48]	14,34,39,42,54, 64,81,85,86,87, 90,93,94	359.2	326.36	430
VSO [49]	7,13,33,39,42, 55,63,72,83, 86,89,90,92	424.9895	380.58	-
GA [49]	7,13,33,39,42, 55,63,72,83, 86,89,90,92	424.9895	380.58	-
ACO [49]	7,13,34,39,41, 55,62,72, 83, 86,89,90,92	424.9895	382.98	-

TABLE 32. SDSR for energy loss reduction in presence of DG: 70-bus system.

Methods	Open Switches	Energy Losses (MWh)		Running Time (s)
		Before DSR	After DSR	
[21]	7,14,22,39,46,65, 68,71,75,76,78	5.12	3.92	1283

TABLE 33. Multi-objective SDSR for loss reduction and voltage stability enhancement in presence of DG: 69-bus system.

Methods	Open Switches	Losses (kW)		FVSI		Run. Time (s)
		Before DSR	After DSR	Before DSR	After DSR	
DS [48]	14,57,61, 69,70	70.3	35.49	0.73	0.4559	142

TABLE 34. Multi-objective DDSR for loss reduction, voltage improvement, and minimization of switching operations: 119-bus system.

Methods	Annual Energy Losses (MWh)	No. of Switching Operations Per Year	Min. Voltage (p.u.)	Run. Time (s)
FPGA [3]	1126.31	1494	0.9709	73448
PGA [3]	1141.48	1694	0.9693	72360
GA [3]	1155.14	1760	0.9682	252723
PSO [3]	1207.03	1879	0.9593	267871

F. COMBINATION OF MULTI-OBJECTIVE DSR APPLICATIONS WITH OTHER METHODS

In order to approach more optimal solutions, DSR can be solved with DG allocation and capacitor placement problems simultaneously. In this case, lower power losses, better

TABLE 35. Stochastic multi-objective SDSR for loss reduction and minimization of voltage deviation, electricity generation costs, and air emissions in presence of DG: 84-bus system.

Methods	Losses (kW)	Generation Costs (\$)	Voltage Deviation (p.u.)	Emissions (lp)	Run. Time (s)
FAPSO [85]	406.877	1223.59	0.527425	55038.87	8150.22
FPSO [85]	410.418	1240.23	0.529968	55400.12	10672.9
FGA [85]	419.934	1251.76	0.530128	55838.45	11603.8

TABLE 36. Simultaneous SDSR and capacitor placement for loss reduction.

Methods	[45]	
	33-bus system	84-bus system
Open Switches	7,9,14, 32,37	7,34,39,42,55,63,72, 82,86,88,89,90,92
Energy Losses (MWh)	436.1	2239.9
Losses Cost (US\$)	218069.5	144346.5
Capacitors Cost (US\$)	16200.0	7200
Total Cost (\$)	234269.5	151546.5
Running Time (s)	-	85.8

TABLE 37. Simultaneous stochastic DDSR and DG allocation for switching cost minimization and reliability improvement: 33-bus system with a 50% increase in peak load.

Methods	[26]			
	Period 2		Period 8	
Open Switches	6,8,14, 21,26	6,8,14, 21,26	6,14,20, 26,28,	6,14,20, 26,28,
DG Output of Bus 11	60	240	60	240
DG Output of Bus 28	60	240	60	240
Switching Cost (US\$)	4550	4550	4550	4550
LOL Cost (US\$)	0	1350	0	0
DG Curtailment Cost	0	0	0	0
Excepted Costs	5870	6180	6230	6310
Total Cost	10420	12080	10780	10860

TABLE 38. Simultaneous stochastic multi-objective SDSR and DG allocation for maximization of DG owner's profit and minimization of DISCO's cost: 33-bus system with a 20% increase in peak load.

Methods	[25]	
	Deterministic	Stochastic
Open Switches	10,13,14, 20,26	6,10,14, 28,32
DG Locations (Buses)	7,23,29	7,23,29
DG Owner's Profit (US\$/h)	100.68	107.77
DISCO's Cost (US\$/h)	217.22	217.79
Running Time (s)	-	8527

voltage stability, more efficient load balancing, and higher reliability can be achieved compared to when capacitor placement and/or DG allocation are carried out before or after reconfiguration. Optimally siting and sizing shunt capacitors (reactive power compensators) and/or DG units (flexible generation sources) at the same time with DSR enhance effectiveness of reconfiguration strategies, capacitor placement plans, and DG allocation programs. However, solving such complex large-scale and highly non-linear problem is hard,

time consuming and needs extensive computational efforts. Tables 36 to 38 show outcomes of combination of multi-objective DSR applications with capacitor placement and DG allocation strategies.

VII. CONCLUSION

A complete review and classification of the most significant works regarding distribution system reconfiguration (DSR) has been presented, including not only traditional approaches, but also those involving renewable energy resources, reliability, generation and demand uncertainties, electricity markets, capacitor placement, capital saving, and associated fields (e.g., switching frequency and cost). The DSR in its complete scope was categorized into three major classifications, i.e., solution methods, objective functions, and innovations. This work represents a valuable tool for anyone associated with this research field, as it provides a broad literary framework that can be used as a base for any further investigations related to DSR and its upcoming challenges. Therefore, distribution system operators can use this framework in order to improve upon previous formulations and methods, and they can propose more efficient models to better exploit existing infrastructure.

The presented classifications evidence that most researchers have focused on the solution of the DSR problem from a static point of view, although a number of works were found to have used a dynamic approach. Moreover, due to the large-scale combinatorial feature of the DSR problem, metaheuristics have been the most commonly used solution method in this matter.

Nowadays, most of distribution systems contain distributed generation (DG) and renewable energy sources in presence of flexible and variable loads (demand response) with high uncertainty in generation that need more realistic analysis and complex models. This issue increases importance of stochastic DDSR problems with different objectives from DG owners, distribution companies, and energy consumers point of views. Therefore, the important challenge for DSR researchers is to find more efficient and accurate mathematical models and techniques to solve such complex large-scale optimization problem in an acceptable computational time.

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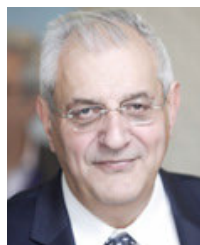


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