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TOPICAL REVIEW

Comprehensive Review on Static and Dynamic Distribution Network Reconfiguration Methodologies

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ABSTRACT Reconfiguration of a distribution network is one of the main approaches to control and enhance distribution network indices, such as voltage profile and power losses. Distribution network operators perform reconfiguration for long-term or short-term periods based on network equipment and intended objectives. Long-term or static reconfiguration is suitable for traditional and modern networks with conventional switches. On the other hand, modern distribution networks that are equipped with one or more remote control switches can perform reconfigurations within short-term periods, to maximize predefined objectives. This paper presents a comprehensive review of recent literature on network reconfiguration. Reconfiguration methodologies are classified into five groups: classical methods, heuristic methods, metaheuristic methods, hybrid methods, and methods based on machine learning. The paper provides a general definition and comparison of the categories and discusses their application in dynamic and static reconfiguration. The paper introduces dynamic reconfiguration as the future challenges in smart and modern distribution networks and for the first time categorizes various methodologies in dynamic reconfiguration. The paper serves as a guide to assist engineers and researchers in selecting the most suitable methodology based on their system equipment and objectives.

INDEX TERMS Distribution network, optimization, machine learning, static reconfiguration, dynamic reconfiguration, metaheuristic algorithms.

I. INTRODUCTION

As the final stage of an electrical power system, electrical power distribution networks (DNs) deliver the electricity from the transmission system to individual consumers. DNs have considerable losses due to their dispersion over vast rural and urban areas, and their comparatively higher line resistance. Therefore, the greatest portion of power system losses occurs in distribution networks. Several methods are proposed and have already been implemented to decrease power losses of DNs such as the installation of capacitor banks [1], increasing distributed generation (DG) penetration [2], and network reconfiguration [3]. Among these, the power loss reduction methods based on distribution network reconfiguration (DNR) are known to be practical solutions, that can often be implemented without much additional equipment and with minimum investment.

DNs are often operated radially to simplify the protection and to lower the feeder short-circuit levels. However, especially in urban areas, DNs are designed with more sophisticated structures such as a mesh to provide the possibility of faster restoration after a fault. Therefore, there are some normally open switches or tie switches in a DN to restore any power outage to customers through connecting them to

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the healthy sections of the feeder by transferring interrupted customers to other feeders.

In addition to the restoration, in normal operations, DN operators can close one or more of the normally open switches and open the same number of normally closed switches to achieve some defined operational objectives for DNs. Moreover, for DN planning studies, the optimal network configurations can be designed to achieve some defined planning objectives. Therefore, in normal conditions, a DNR can be generally defined as a configurational change in a DN with normally open and normally closed switches to achieve specific objectives [4].

A. LITERATURE REVIEW

In 1975, Merlin proposed a DNR for the first time as a method for power losses reduction [5]. Merlin used a branch-and-bound algorithm to solve the reconfiguration problem with DC load flow. Shirmohammadi and Hong developed branch and bound with an optimal flow pattern and an AC load flow for power loss reduction [6]. Civanlar in 1988 proposed a branch exchange heuristic method to solve the DNR problem for power losses [7]. Baran and Wu improved the branch exchange method with approximate load flows [8]. They also implemented reconfiguration for load balancing and introduced the benchmark IEEE 33 bus for DNRs. With the rapid advancements in computational power during the following years, the use of more complex techniques such as meta-heuristic methods became popular [9]. In 1992 for the first time, a genetic algorithm (GA) was implemented for DNRs for power loss reduction [10]. In 1994 a modified simulated annealing method was applied to DNRs for loss reduction [11].

In addition to several solution methods proposed for the DNR problem, the literature also varies in terms of its objectives [12]. Decreasing the power losses has been the main and the most common objective of the reconfiguration problem. Reconfiguration with transferring loads from heavy feeders to light feeders decreases the power losses of the DN. In recent years some other objectives have been considered for DNRs. Reconfiguration can change the flow of active power and reactive power in a distribution network in a targeted way to improve the voltage profile of all busses or some specific busses [13]. DNR can improve the ability of the system under planned conditions as defined with reliability [14]. Changing the flow of active and reactive power modifies the current magnitude of branches and improves reliability indices [15]. Moreover, reconfiguration can modify the harmonic current flow in branches in a way that the total harmonic distortion of busses [16] and harmonic losses [17] of the DN are improved. Furthermore, reconfiguration can decrease the voltage flicker [18] and the voltage sag [19] by changing the fault current path. Also, reconfiguration in a three-phase DN can improve voltage unbalance and related power losses by changing the phase loads [20], [21]. There are also studies on decreasing the operational costs such as

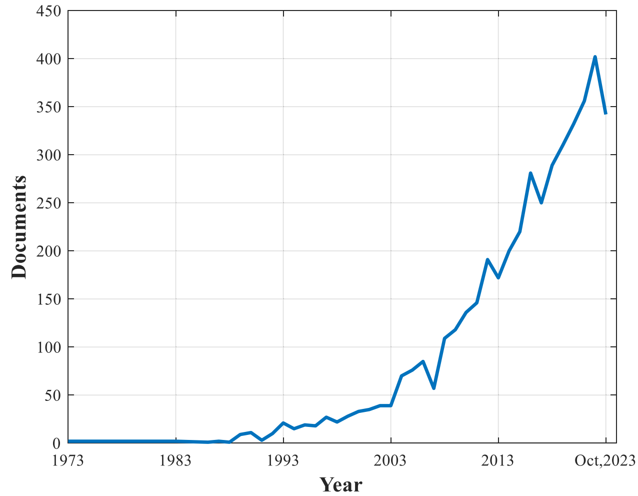

FIGURE 1. Number of publications in distribution network reconfiguration from 1973 until October 2023.

the cost of demand response participation [22], operational cost of microgrids [23], [24], cost of power losses [25], and switching cost [26] by reconfiguration. Recently, the capability of DNRs to increase DG hosting capacity has also gained attention [27], [28], [29].

B. BIBLIOMETRIC ANALYSIS

The graph illustrates the trend of published papers in the field of distribution network reconfiguration from 1973 to October 2023 in Fig. 1. Considering the inclusion of ten months of 2023, the number of papers in 2023 is lower than in 2022. The graph indicates an increasing trend in the number of published articles in this field in recent years.

C. MOTIVATION AND AIMS

In the context of Distribution Network Automation (DNA), the reconfiguration of distribution networks is a core task aimed at optimizing and controlling distribution network metrics while striving to maximize predefined objectives. Nonetheless, given the multitude of approaches that have been proposed over more than 50 years of research in this field, the selection of a suitable reconfiguration methodology remains a significant challenge.

There is a need to establish clear categories and conduct a thorough comparative analysis of the advantages, prerequisites, and constraints associated with various reconfiguration methods. This analysis is particularly crucial in the context of modern and intelligent distribution networks. The objective is to create a practical guide for selecting the most appropriate reconfiguration technique for a specific system.

D. CONTRIBUTION

This paper reviews a relatively large number of different studies on the DNR problem proposed for either dynamic or static reconfiguration. The techniques are classified and compared from various aspects including the objectives considered, and the solution techniques proposed to serve as a guide for engineers and researchers to select the most appropriate method based on the problem and the related objectives.

E. PAPER ORGANIZATION

In Section II, effect of distribution system automation in the context of DNR is investigated. In section III, the paper presents a definition for the DNR problem and classifies different methods based on their study time frame. Section IV presents a methodological classification and an extensive review of different DNR methods, where the details and comparisons of different classes are presented in different subsections. Finally, Section V presents the future trends and the conclusions.

II. DISTRIBUTION SYSTEM AUTOMATION IN THE CONTEXT OF DNR

Distribution System Automation (DSA) plays a crucial role in the process of distribution network reconfiguration. It involves the integration of advanced technologies, intelligent devices, and decision-making algorithms to optimize the operation and configuration of the distribution network. In the context of DNR, DSA has more focus on using remote control switches in dynamic reconfiguration.

DSA in distribution network reconfiguration consists of the following components:

- Network Monitoring and Measurement: DSA relies on real-time network monitoring and measurement techniques to collect data such as load demand, distributed generation profile, etc [30]. This data is obtained through various intelligent devices, such as smart meters, sensors, and communication systems.
- Decision-Making Algorithms: Advanced decision-making algorithms according to defined objectives such as power losses [31], THD [17], reliability [32], etc. are employed to analyse the collected data and make informed decisions regarding network reconfiguration.
- Remote Control and Switching Devices: After finding the optimum configuration DSA utilizes remote control switches to operate and manage the switching devices within the distribution network [33].
- Communication Infrastructure: A robust communication infrastructure is essential for the operation of remote control switches and the exchange of real-time data in the automation of distribution network reconfiguration [34].

DSA has some benefits in reconfiguration. DSA allows for quick fault detection and isolation, minimizing the impact of faults and enhancing system reliability. By fast reconfiguration, power can be restored to affected areas more rapidly. DSA optimizes the distribution network indices such as power losses, power quality, and voltage profile. Also, DSA enables the seamless integration of renewable energy sources, energy storage systems, and electric vehicles with the network. Furthermore, DSA allows for real-time adaptation to changing network conditions, load demands, and environmental factors.

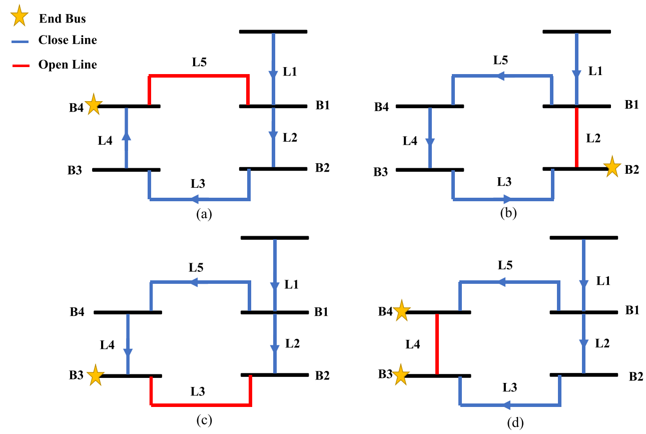

FIGURE 2. Possible configurations for a simple distribution network with different flows and end busses.

III. DISTRIBUTION NETWORK RECONFIGURATION PROBLEM

DNR, in general, is defined as topological changes in a DN by normally open and normally closed switches to achieve specific planning or operational objectives.

Fig. 1 depicts the effect of reconfiguration on a simple DN. It is designed with a loop configuration, but it is operated radially. As shown, the network has four busses, four normally closed switches or lines (L1, L2, L3, L4), and one normally open switch or line (L5). With closing L5, there are three alternative lines to open (L2, L3, L4) to maintain the radial operation. Generally, in this simple network, having one normally open line provides four possible configurations for the DN operator. The amount and direction of current flow, and consequently power system indices (e.g., voltage profile), are different for the four configurations. For example, the direction of the current in line L3 in configurations a and d is different from configuration b. Also, as shown in Fig. 2, end busses that have a minimum voltage in this simple DN are different for each topology, and each topology has a specific voltage profile.

Every configuration in DN can be presented as a graph, where the vertices represent the branches, and the nodes represent the busses. Due to the radial operation of a DN, only trees between all possible graphs are acceptable. Therefore, DNR in graph theory can be defined as finding the optimal tree within the possible graphs representing the DN. As shown in Fig. 3, the DNR problem for this simple network is the process of identification of the optimal tree among the four possible trees, as the one satisfying some predefined objectives, such as a better voltage profile or lower power losses.

As mentioned before, reconfiguration can either be implemented for long-term or short-term periods. The following section describes the short-term and the long-term reconfiguration problems and highlights their differences.

A. STATIC RECONFIGURATION

Static reconfiguration is usually considered for the planning or long-term operation of a DN for a period such as

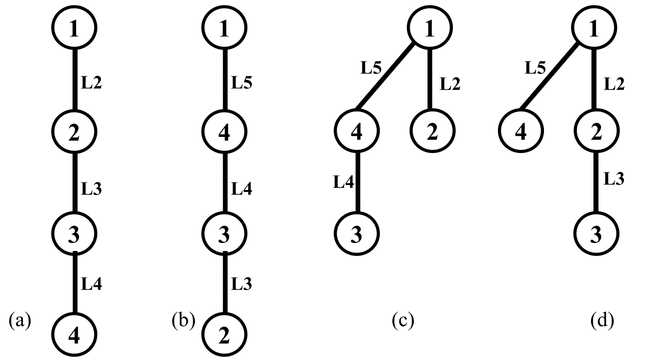

FIGURE 3. Possible trees for the simple distribution network of Fig. 1.

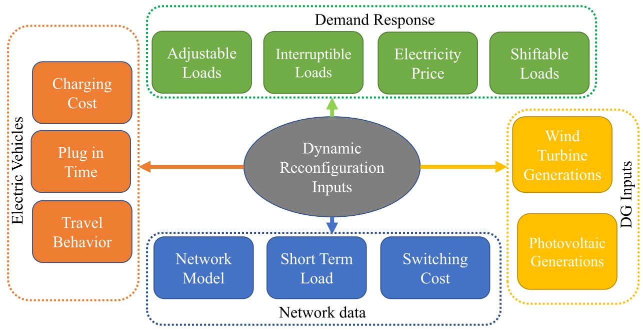

FIGURE 4. Dynamic reconfiguration inputs.

a season or a year. In a static reconfiguration, loads and production are assumed to be constant for the computations during the study time frame. Static reconfiguration can be done with both manual switches and remote-control switches. Therefore, static reconfiguration is a more practical approach for the reconfiguration of traditional DNs that are equipped with manual switches. Static reconfiguration always provides a fixed topology over a long-desired study time frame.

In static reconfiguration, inputs are the network model, the static estimated values of active and reactive loads of busses, and DG generations in the study time frame, and the output is the optimal configuration for a long-term period.

The dimension of the search space of the static reconfiguration problem can be calculated according to *(1)* for each study time frame:

$$SS = \underbrace{2 \times \ldots \times 2}_{n_{SW}} = 2^{n_{SW}} \tag{1}$$

where n_{SW} shows the number of switches.

B. DYNAMIC RECONFIGURATION

Dynamic reconfiguration is performed for shorter-term periods such as an hour, a day, or a week taking into account load and production variations. Dynamic reconfiguration relies on remote-control switches with fast and frequent opening and closing capabilities and the required communication infrastructure. Therefore, it can only be applied to more modern DNs equipped with such infrastructures. In static reconfiguration, the loads and production are assumed to be constant in peak or average of them, while for dynamic reconfiguration their time variations can be considered [35].

For dynamic reconfiguration, the required inputs include the network model, the estimated time series of active and reactive loads of busses, and DGs in the study time frame. As shown in Fig. 4, dynamic DNR studies can consider the time-variations of DGs (e.g., PV units) and loads (e.g., EV chargers) and operation programs such as demand response. The output is an optimal configuration for each time interval during the study time frames.

1) TIME INTERVALS IN DYNAMIC RECONFIGURATION

Dynamic reconfiguration of the distribution network is an *NP* (nondeterministic polynomial time) optimization problem taking into account the time-varying nature of loads and distribution generation [36]. In order to reduce the search space and also due to the integrations that might take place between the periods, dynamic reconfiguration can be limited to smaller-size multi-period problems in multiple time intervals to prevent excessive switching [37].

Time intervals in a dynamic reconfiguration are the periods where DN dynamic inputs such as load, electricity price, and DGs power are considered to be constant and there is no new dynamic input that would change network indices, such as voltage profile and power losses. Therefore, reconfiguration can be simply implemented for each time interval. In [38], a 24-hour dynamic reconfiguration problem with time-varying electricity prices and different load levels with the effect of distributed generations is divided into multiple time intervals to make the problem more flexible.

2) SEARCH SPACE IN DYNAMIC RECONFIGURATION

Dynamic reconfiguration can be implemented for short time frames such as hours, days, and weeks. In this part, the search space of dynamic reconfiguration for one day with variable hourly loads is discussed. Similar conclusions can be made for other study time frames and time intervals.

Two approaches can be considered for the 24-hour dynamic reconfiguration problem. Those are described hereafter.

Approach One: without considering hourly switching operation cost. Neglecting the switching cost makes the optimal configuration of each hour independent of the next hour. Therefore, the 24-hour dynamic reconfiguration can be divided into 24 independent static reconfiguration problems, one for each hour. Also, in some references, the 24 hours are divided into fewer time intervals [39], [40], [41]. The search space of this section can be calculated according to (2).

$$SS = n_{TI} \times \left(\underbrace{2 \times \ldots \times 2}_{n_{SW}} \right) = n_{TI} \times 2^{n_{SW}} \tag{2}$$

where n_{TI} and n_{SW} show the number of switches and the number of time intervals in the study time frame, respectively.

Approach Two: considering hourly switching operation cost. In this case, due to the consideration of switching cost between different hours, the 24 hours should be considered together in the reconfiguration problem. In other words, in some hours, the cost of switching is more than the economic benefits of saving losses between configurations. Therefore, some changes in configurations between hours may not be economically appropriate or beneficial in comparison to the first case. Consequently, taking into account switching costs can lead to a further reduction of operational costs.

(3) shows the search space for the second case [42].

$$SS = \left(\underbrace{2 \times \ldots \times 2}_{n_{SW}}\right)^{24} = 2^{(n_{SW} \times 24)} \tag{3}$$

Some research studies propose decreasing the search space in the second case by clustering the loads into a few clusters [43], [44]. In [45], the fuzzy C-mean clustering method is utilized to reduce the load condition scenarios over the study time frame.

Load clustering can reduce the search space as shown in (4).

$$SS = \left(\underbrace{2 \times \ldots \times 2}_{n_{SW}}\right)^{n_{CL}} = 2^{(n_{SW} \times n_{CL})} \tag{4}$$

In (4), n_{CL} shows the number of clusters.

In general, in situations where switching cost is non-negligible, although the first approach has a lower computational burden, the integrated consideration of 24 hours can provide more favourable results in terms of operational costs.

Either with a static or dynamic reconfiguration, there is no unique way to solve the DNR problem. Various methods have been proposed during the last four decades. The next section categorizes and discusses these reconfiguration methodologies.

IV. RECONFIGURATION METHODOLOGIES

As mentioned before, the reconfiguration problem is about determining the optimal tree in the graph representing the distribution network topology. While the location of the network switches defines the possible trees, the status of these switches turns the reconfiguration problem into an optimization problem with discrete variables. Besides, the equations of power flow and power losses bring non-linearities to the problem. Therefore, reconfiguration can be considered a Mixed Integer Nonlinear Programming (MINLP) problem with integer and continuous variables and nonlinear equations [46].

In this paper, the methods of finding optimum configuration in DNR are categorized by reviewing recent papers. Based on the reviewed literature on the DNR methods, as shown in Fig. 5, methods for solving DNR in aspects of the type of optimization are categorized into five groups: classical methods, heuristic methods, metaheuristic methods, hybrid methods, and methods based on machine learning. Classical methods mostly solve the reconfiguration problem by transforming the objective function and problem constraints into a second-order or first-order problem. Heuristic methods are algorithms that use the operator's experiences and special features of the problem to propose the optimal configuration. These methods are specifically designed for the reconfiguration problem and cannot be applied to other optimization problems [47].

Metaheuristic methods rely on iterative optimization algorithms that have often been developed based on an abstraction of nature [48]. They are also called derivative-free methods for optimization since they explore the space of solutions without computing derivatives. Hybrid methods try to reduce shortcomings and increase the advantages by combining two or more methods. Finally, machine learning methods build an optimization model and learn the parameters of the model using the given data [49]. The next subsections review and compare the methods proposed within each of the categories shown in Fig.5.

A. CLASSICAL METHODS

As stated before, DNR is an MINLP problem that is very difficult to solve mathematically. In classical DNR methods, the objective functions and constraints are approximated in such a way that they are modeled as first-order or second-order functions. Therefore, the reconfiguration problem changes to a mixed integer linear programming problem (MILP) [50], [51] or a mixed integer quadratic programming problem (MIQP) [52], [53], Because it can be solved with non-commercial solvers too. In these methods, calculation time is significantly reduced but the approximations of objective functions and constraints can cause the optimum configuration obtained from the approximate network to be different from the optimum one of the actual networks. In [54] the MILP model is implemented to solve simultaneous reconfiguration and capacitor placement in the distribution network.

Some studies propose the implementation of classical techniques to solve the dynamic reconfiguration problem. In [55], a three-phase DNR with a power loss objective is formulated as a mixed integer quadratically constrained quadratic programming (MIQCQP) method, which is then solved using the CPLEX software.

B. HEURISTIC METHODS

These methods are types of algorithms that are proposed only for the reconfiguration problem and cannot be applied to other optimization problems. In these methods, the conventional rules of reconfiguration problems are used to solve and simplify the problem. A heuristic algorithm mainly determines the optimal configuration through a set of principles. They can be considered as optimization processes to

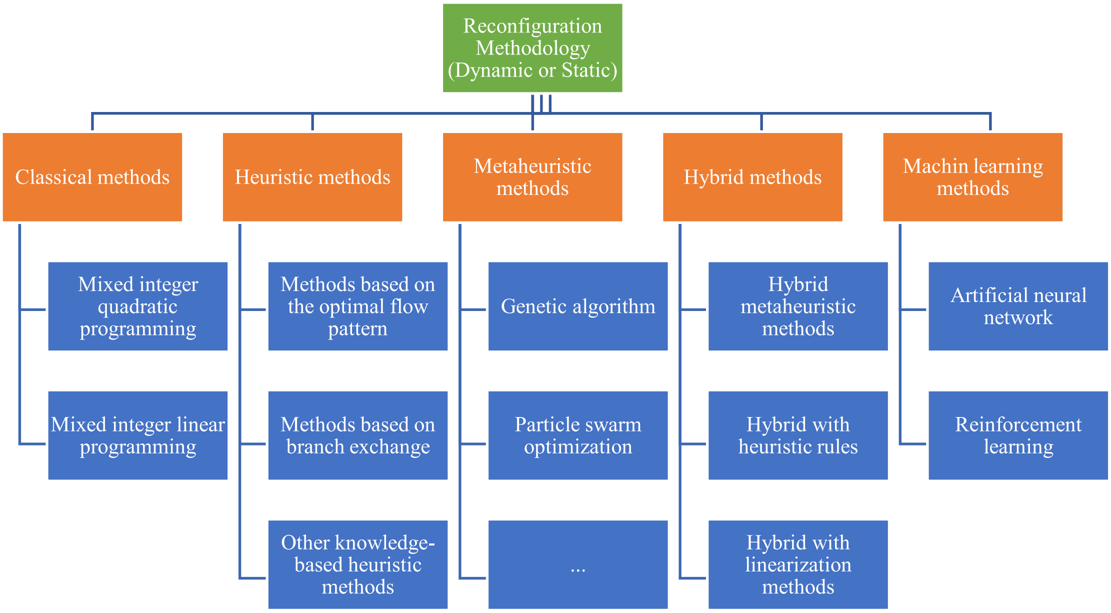

FIGURE 5. Classification of methodologies in distribution network reconfiguration.

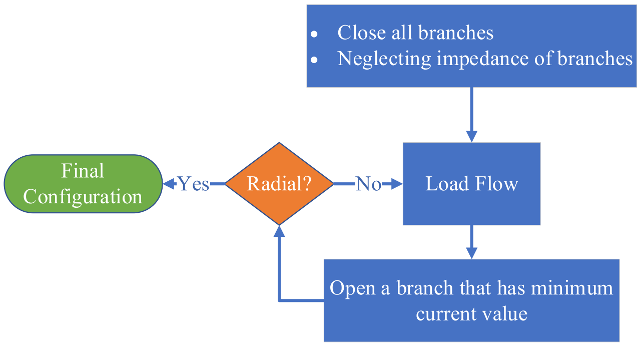

FIGURE 6. Basic flowchart of the optimal flow pattern approach.

find an approximation of the optimal solution of the DNR problem [56], [57].

1) METHODS BASED ON THE OPTIMAL FLOW PATTERN

The optimal flow pattern is a network load flow with two conditions [6]:

1- All switches are closed.
2- The reactance of lines is neglected and only their resistance is considered.

After the load flow, the optimal flow pattern opens the branch that has the minimum current value. Then, performing the load flow for this new grid topology, the next branch according to the optimal power flow pattern is opened. The process continues until a radial topology is achieved and configuration with minimum losses is attained. The flowchart of this method is shown in Fig. 6.

The main advantage of this method is that the final configuration does not depend on the initial configuration. The main shortcoming is that the final solution may not be optimal because of the mutual effects among the loops. In [58], optimal flow pattern is enhanced by considering only one loop and closing only one switch in each step. This method eliminates mutual effects among multiple loops. In [59], a global optimal flow pattern is proposed for minimizing power losses in unbalanced distribution networks.

2) METHODS BASED ON BRANCH EXCHANGE METHOD

In this class of methods, pairs of branches are considered in two cases in which one of them is opened and another one is closed. The resulting values of the objective function of the two cases are compared and the branch with the better value is selected to be opened [7], [8]. The main advantage of the branch exchange method is that a radial configuration is created during the optimization process and does not need to be checked again. The main disadvantages of this method are the dependency of the final configuration on the initial configuration and the high computational time required to reach the solution. The most common objective function of this class of methods is based on power losses [7], [8], [60]. However, recently, some studies have proposed branch exchange methods with other objectives. In [61] and [62], the branch exchange method is applied with power quality objectives such as harmonic distortion, voltage sag, and voltage unbalance.

3) OTHER KNOWLEDGE-BASED HEURISTIC METHODS

There are heuristic methods proposed based on optimal power flow. In [63], a heuristic method with a convex relaxation of the AC optimal power flow problem is introduced. In [64], first, all switches are initially closed. Then a list of candidate switches for breaking the loops is determined and one of them based on optimal power flow is chosen. Some research studies use a branch-and-bound strategy, which organizes the search space with an implicit enumeration method that uses a tree structure and bounds. In [65], a heuristic method based on a branch-and-bound strategy is proposed which constructs the search space based on the branch exchange method.

C. METAHEURISTIC METHODS

Metaheuristic methods are iterative process algorithms deployed to find optimal or near-optimal solutions using a learning strategy, exploration, and exploitation of the search spaces [57], [66], [67]. Metaheuristic algorithms, in contrast to knowledge-based methods, do not use specific features of the problem and can be utilized to solve a variety of optimization problems by adjusting their specific parameters. The computational time of these methods depends on their convergence speed which is dependent on the type of problem and the selected method parameters.

Some characteristics of metaheuristic methods can be summarized as follow.

- Metaheuristics can be applied to many types of the optimization problem.
- Metaheuristics usually allow an easy parallel implementation.
- Other methods such as heuristics can be combined with metaheuristic algorithms.
- Exploration and exploitation are the main functions of metaheuristics.
- Metaheuristics do not compute explicitly derivative of objective functions, which is why they are often also called derivative-free optimization techniques.

In Appendix, a classification of metaheuristic methods, as well as their advantages and disadvantages, are presented.

Metaheuristic methods are one of the most popular methods for solving the static reconfiguration problem [68]. Table 1 shows some applications of metaheuristic methods in solving the static DNR. In [69], the application of some popular metaheuristic methods such as Discrete Particle Swarm Optimization (DPSO), Shuffled Frog Leaping Algorithm (SFLA), and Imperialist Competitive Algorithm (ICA), to reduce power losses, are compared by considering the speed and accuracy of the methods. In [70] the GA, PSO, and Bat Algorithm (BA) are performed to improve reliability indices. In [9], the results of static DNR for a wide variety of metaheuristic methods in different case studies with the objective of power losses are compared. Recently some research works focused on introducing new metaheuristic methods for DNRs [71].

In some recent research studies, metaheuristic methods are also applied for solving the dynamic reconfiguration problem. In [42], the stochastic model predictive control concept is applied to consider dynamic and adaptable futures in the optimization problem. In this research work, a GA algorithm is implemented to solve reconfiguration for each hour by considering the value of forward-looking hours. In [25], a one-hour time interval is considered with Particle Swarm Optimization (PSO), and 24 independent reconfigurations are implemented for each hour. In [72], an improved genetic algorithm is implemented for 24-hour dynamic reconfiguration considering the dynamic behaviour of plug-in hybrid electric vehicles (PHEV) and wind generation. Operational costs including switching costs, cost of power losses, and cost of energy not supplied (ENS) are considered in this study.

D. HYBRID METHODS

Hybrid methods are a combination of two or more algorithms to achieve more advantages from their integration while minimizing their shortcomings.

1) HYBRID METAHEURISTIC METHODS

Hybrid metaheuristics are a combination of metaheuristic methods that try to overcome some of the disadvantages of metaheuristic algorithms such as: trapping into local optima due to unsuccessful exploitations, slow convergence, and incomplete exploration of the search space. The hybrid metaheuristic algorithms obtain a near-optimal solution and are shown to have a better trade-off between the exploration and exploitation quality of an algorithm [73]. In [74], hybrid SFLA and PSO are performed to solve static reconfiguration with objectives of reducing power losses, improving voltage stability, and reducing switching numbers.

Hybrid metaheuristics methods are also widely applied to solve the dynamic DNR problem. In [75], reconfiguration was performed for 24 hours. To solve this complex optimization problem, a hybrid algorithm, which is a combination of the improved particle swarm and the artificial bee colony is proposed. This study considers the power losses and it uses the hourly pattern of electric vehicles and distribution generations. In [76], a hybrid evolutionary algorithm based on a combination of the PSO and modified SFLA is proposed. In [38], a hybrid evolutionary algorithm based on a combination of PSO and Grey Wolf optimization algorithms is proposed. In this work, eight time intervals with eight different load profiles are considered for dynamic reconfiguration. In [77], the exchange market algorithm (EMA) and wild goats algorithm (WGA) are combined to solve the dynamic reconfiguration problem with an objective function of power losses. In this study, the load profile changes hourly, and the optimum configuration of each hour is independent of the others.

2) HYBRID METHODS BASED ON HEURISTIC RULES

This class of methods combines heuristic methods with other popular methods. In [78], a heuristic approach based on the Successive Branch-exchange Algorithm and a stochastic approach based on the Kruskal Algorithm is combined with the GA for static reconfiguration. The proposed hybrid method has fast convergence for large distribution networks and can find a nearly optimal value for the power losses. In [79], first, a heuristic method based on optimal power flow is conducted for the reduction of the search space. Then, a PSO is implemented to find the optimal configuration with minimum power losses.

TABLE 1. Review of different methodologies and their objectives for static DNRs.

Reference	Types of method	Optimization methodology	Objective functions	Main achievements	Case study
Teshome [51]	Classical methods	MILP	Power losses	New MILP formulation to reduce the deviation between the linear model and exact losses	136 bus DN
Gallego [50]		MILP	Power losses Voltage deviation	Reconfiguration simultaneous DG placement	16-Bus Test System IEEE 33 bus IEEE 69 bus 83 bus DN 119 bus DN 136 bus DN 202 bus DN
Jabr [53]		MIQP	Power losses	Compromise MILP and MIQP efficiency	83 bus DN 135 bus DN
Yinpeng. Qu [59]	Methods based on heuristic rules	Optimal flow pattern	Power losses in unbalanced DN	Proposing optimal flow pattern for unbalanced networks	Modified IEEE 16 bus IEEE 37 bus 1096 bus DN
Yadaiah.Ch [61]		Branch exchange	Power losses voltage sag THD Minimization of System unbalance	Proposing branch exchange for power quality indices	IEEE 33 bus 25 bus unbalanced DN
Gomes [64]		Other heuristic methods based on Optimal power flow	Power losses	Proposing a new heuristic method based on optimum power flow	IEEE 33 bus Brazilian utility DN
Duan [92]	Metaheuristic methods	GA	Power losses Reliability	Proposing enhanced GA	IEEE 33 bus IEEE 69 bus 136 bus DN
Sayadi [93]		PSO	Power losses THD	Considering nonlinear loads	IEEE 33 bus Real 77 bus
Hizarci [94]		PSO	Power losses	Proposing enhanced PSO	IEEE 33 bus IEEE 69 bus 84 bus Taiwan power company
Asrari [95]		SFLA	Power losses voltage sag THD	Considering Pareto frontier for multi-objective	136 bus DN
Dias Santos [96]		Harmony Search (HS)	Power losses	Proposing enhanced HS	14-bus DN IEEE 33 bus 84-bus DN 119-bus DN
dos Santos [97]		Harmony Search (HS)	Power losses	Proposing radial method Proposing enhanced HS	IEEE 33 bus 84-bus DN 118-bus DN
Nasiraghdam [98]		Artificial Bee Colony (ABC)	Power losses voltage stability index Cost of energy Minimization total emission	Considering hybrid energy system (PV/wind turbine/fuel cell) sizing	IEEE 33 bus
Quaderi [99]	Hybrid metaheuristic methods	Teaching Learning-Based Optimization (TLBO) & HS	Power losses Voltage profile	Proposing a new hybrid method that compared with other metaheuristic methods	IEEE 33 bus IEEE 69 bus
El-salam[100]		Grey Wolf Optimizer (GWO) & PSO	Power losses	Optimally sizing and placing distributed generators DNR simultaneous sizing and siting DGs	IEEE 33-bus IEEE 69-bus Actual 78-bus
Tolabi[101]		Improved Analytical (IA) & Bees Algorithm (BA)	Power losses Voltage profile feeder load balancing	Reconfiguration simultaneous DG placement	IEEE 33 bus
Azizivahed[74]		SFLA&PSO	Power losses Voltage Stability Index number of switching	Considering voltage stability index related to the short circuit capacity	IEEE 33 bus IEEE 95-bus
Kumar [102]		Cuckoo Search (CS)& GWO	Power losses	Proposing a new hybrid method reaches the better optimal solution	IEEE 33 bus IEEE 69 bus

TABLE 1. ***(Continued.)*** **Review of different methodologies and their objectives for static DNRs.**

			Voltage deviation		
Ramakrishna[103]		Gravitational Search Algorithm (GSA)&Tabu search	Power losses Voltage deviation	Optimal sizing and location of DG simultaneous reconfiguration	IEEE 33 bus
Azad-Farsani[104]		Chaotic Particle Swarm Optimization (CPSO) &Teaching-Learning-Based Optimization (TLBO)	Power losses	Proposing a new hybrid method that compared with other metaheuristic methods	IEEE 33 bus 70-Bus DN
Abd-El-Hakeem[105]		Modified Tabu Search (MTS) & Harper Sphere Search (HSSA)	Power losses	Reconfiguration simultaneous capacitor allocation in an unbalanced network	IEEE 33 bus IEEE 119 bus IEEE 123 bus unbalanced DN
Silva[79]	Other hybrid methods	The heuristic method based on optimal power flow & PSO	Power losses	Proposing a hybrid heuristic method using reduction of search space	IEEE 16 bus IEEE 33 bus IEEE 69 bus
Jakus [78]		The heuristic method based on branch exchange &GA	Power losses Minimization of network loading index	Proposing a new hybrid algorithm	IEEE 33 bus 1760 bus DN 4400 bus DN

Hybrid methods based on heuristic rules can be suitable for multi-period dynamic reconfiguration. In [44], an improved fireworks algorithm taking into consideration heuristic rules for the reduction of power losses is presented, which can simultaneously improve the solving speed of the DNR and avoid falling into a local optimum configuration or producing many infeasible solutions. The essence of the heuristic rule in this method is to find the most promising branch for reducing the power loss of each loop, thereby filtering out numerous poor solutions. In this study, loads in 24 hours are clustered. Load clustering can transform a 24-hour time-varying reconfiguration into a few load reconfiguration clusters, which can greatly reduce the number of computations.

3) HYBRID METHODS BASED ON LINEARIZATION

Some methods combine linearization techniques with other methods to become more advantageous. In these methods, in part of the approach, several linearizing techniques are proposed to convert the complex DNR problem into an MILP or MIQP model [55].

In [43], nonlinear dynamic reconfiguration is transferred into a mixed integer second-order cone programming (MISOCP). A combination of a modified binary PSO and CPLEX solver is used to solve the problem. BPSO takes the switch states as random swarms and embedded CPLEX solves the problem. In this study, the calculation dimension of dynamic reconfiguration is also decreased with fuzzy c-means (FCM) clustering. FCM performs the clustering based on a fuzzy membership matrix.

Table 1 shows a summary table of different methodologies proposed for the static reconfiguration problem.

E. MACHINE LEARNING METHODS

Machine learning methods are a category of artificial intelligence that enable computers to think and learn on their own. The trained computers can perform actions with low calculations. Owing to their low online computational burden, machine learning techniques are mainly applied to dynamic reconfiguration problems. The research studies can be generally classified into methods based on ANN and the methods using the Reinforcement Learning (RL) concept.

1) METHODS BASED ON ANN

An artificial neural network (ANN) is a machine learning approach imitating the structure and functions of human brain neurons [80]. ANN is an adaptive system that learns from data by using interconnected nodes or neurons in a layered structure. Each neuron in each layer is connected to the neurons of the next layer through links, each with a certain weight. The output of each neuron is computed by applying some non-linear function on the sum of its inputs. The weights have to be determined by a training algorithm and they represent the information being used to solve a problem. ANNs can be trained to recognize patterns, classify data, and forecast future events. In reconfiguration, a well-trained ANN can provide a set of optimal topologies for each load pattern. The most desirable feature of ANN in the DNR problem is its capability to provide real-time optimal configurations without executing an extensive iterative procedure [81]. ANN-based DNR methods take into consideration active and reactive demand of loads as the inputs and optimal configuration as the output [82]. In [83] a tree layer ANN is proposed to reduce power losses in a DNR. In this study, loads are classified by fuzzy c-means clustering to reduce the size of the ANN and the computational burden.

2) REINFORCEMENT LEARNING

Recently, some papers, especially in the field of dynamic reconfiguration of distribution networks, have focused particularly on the use of reinforcement learning, for online network reconfiguration. These methods are shown to be able to perform reconfiguration in very short intervals, leading to a considerable reduction in power losses.

Reinforcement learning has many benefits: it can adapt to changing environments, make complex decisions, learn autonomously, and continuously optimize strategies based on feedback. These advantages, combined with its proven potential for loss reduction, indicate its significance for future studies. Therefore, in the following, the reinforcement learning method for DNR will be explained in more detail.

RL refers to a class of machine learning techniques in which an agent learns a policy that solves an optimal sequential decision-making problem. The resolution is made by assuming that a software agent interacts with the problem, called in RL the environment, and gets a reward from it every time it applies an action to this latter one. The final purpose of an RL agent is to find the optimum solution through simple numerical calculations with different input data. RL methods are defined with two modules: learning and execution [84]. First, often using simulations and recorded past data, the RL agent is trained within a learning module. The process of learning is time-consuming due to using a large amount of data. Secondly, in the execution phase, the trained agent can find the best action for a new set of input data fast and with minimum computations. The main advantage of RL in comparison to metaheuristic methods is the reduction of the online computational burden which makes RL suitable for online reconfiguration [85]. Therefore, RL techniques are naturally well-suited for solving the dynamics reconfiguration problem since they can find optimal configurations with low calculation in short periods.

The main components of the DNR problem with RL are as follows:

Agent: distribution system operators can be considered the agents of a DNR. The purpose is to train agents which can make automatic decisions in different situations.

Environment: the power distribution network is the environment of DNR problem.

Action: at each step, an agent can take an action from a set of defined actions. Opening or closing switches can be defined as a set of actions for DNR problems in RL.

State: the observation of the distribution network constitutes the state. Various input data including load demand, power of DGs, frequency of switch operation, and current topology configuration are all a part of the state. Interaction between environment and action can update the state.

Reward: The reward is similar to the objective function in metaheuristic optimization problems. In most DNR problems, the cost of operation including the cost of power losses, the cost of switching action, and other operating costs, are considered within the rewards.

The agent in state S_t, with action A_t, reaches reward $R_{t+1} = r(S_t, A_t)$, and the environment changes to S_{t+1}, at each discrete time step t. The process ends when *t=terminal state*. The goal of the RL is to train an agent to find the optimal policy which means the best action in a specific state S_t. The action value function can help to find the optimal

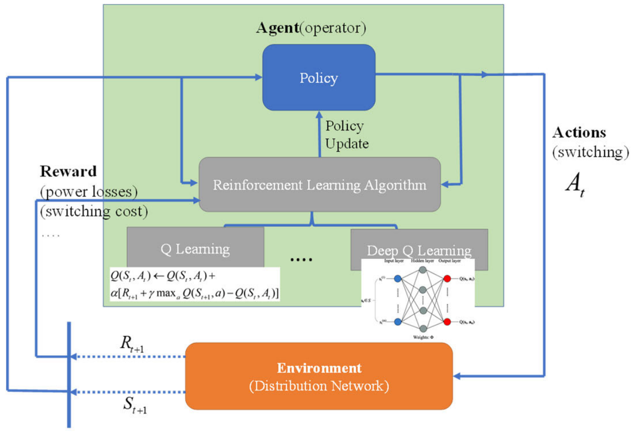

FIGURE 7. Reinforcement learning framework in dynamic distribution network reconfiguration.

policy. Fig. 7 shows the reinforcement learning framework in dynamic distribution network reconfiguration.

RL methods applied to the DNR problem can be either on-policy or off-policy. On-policy methods learn to improve and evaluate the policy that is used to take actions. It is costly and risky to apply an insufficiently trained control policy on real networks [86]. In contrast, off-policy methods improve a policy independently of the actions taken by the agent. In the reconfiguration problem, the agent should be trained with historical data. In some cases, historical data is insufficient for training. Therefore, considering the time series of active and reactive loads and generating configuration, several synthetic operational experiences are created [87].

For the DNR problem, off-policy methods are more suitable because they can use historical data or synthetic data and have a much higher sample efficiency [85], [88].

One of the most widely used RL algorithms is Q-learning, which was first introduced by Watkins and Dayan [89]. In Q-learning, the action-value function $Q(S_t, A_t)$ updates iteratively to reach the optimal action-value function [90] and optimal control policy. In large distribution networks with a large dimension of state and action space, learning the exact Q-function is impossible. In these cases, the action-value function $Q(S_t, A_t)$ can be approximated with a neural network.

In [91], a Noisy Net deep Q-learning network (DQN) is implemented to solve dynamic DNR problems based on RL.

In this study, a compromise has been made between different types of DQN such as Nature-DQN, Double-DQN, and NoisyNet-DQN. The main disadvantage of methods based on RL is related to their difficulty and time-consuming learning phase, especially for large DNs that have a large number of normally open switches and a wide search space.

Table 2 shows a summary of different methodologies proposed for the dynamic reconfiguration problem. Considering switching costs and integrations between the hours lead to the optimal configuration of different hours depending on each other. Therefore 24 hours in the dynamic reconfiguration of one day should be considered together in the optimization

TABLE 2. Review of different methodologies and their objectives for dynamic DNRs.

Reference	Types of method	Considering integration between hours and switching cost	Optimization methodology	Objective functions	Main achievements	Case study
Zhai [55]	Classical methods	✓	MIQCQP	Power losses switching costs	Considering unbalance network	Modified IEEE 34 bus
Santos [106]		×	Stochastic MILP	Energy not supplied Cost of emission Cos of switching	Considering uncertainty Considering DG and Energy Storage Systems	IEEE 199 bus Real Portuguese network
Guo[107]		✓	MIQP	Power losses switching cost	Considering electric vehicles	IEEE 33 bus
Liu[36]	Methods based on heuristic rules	✓	Branch exchange with considering matrix shift operation	Power losses Switching cost	Use hash table and matrix shifting and interval merger to reduce the calculation burden	IEEE 33 bus 84 bus Taiwan power company IEEE 117 bus
Mosbah[35]		×	Minimum spanning tree-based Kruskal's algorithm	Power losses	Proposing a new heuristic method	116 bus DN IEEE 33 bus IEEE 84 bus
Rahmani-Andebili[42]	Metaheuristic methods	✓	GA	Cost of losses Switching cost	Considering 10 forward-looking hours	167 bus DN
Asrari[45]		✓	Fuzzy-based parallel GA	Yearly power losses Switching cost Voltage deviation	Parallel computing Load clustering	119-bus DN
Esmaeili[25]		×	PSO	Power loss Switching cost cost of purchasing power from DG cost of purchasing/selling active power from/to day-ahead wholesale market	Considering demand response	IEEE 33 bus
Xu[39]		×	Quantum PSO	Power losses	Considering DG	IEEE 33 bus
Jangdoost[72]		✓	Improved GA with radial checking	Operational costs including switching cost, cost of power losses, and cost of energy not supplied (ENS)	considering plug-in hybrid electric vehicles (PHEV) and distributed wind generation (RDG)	IEEE33 bus
Lotfi[108]	Hybrid metaheuristic methods	×	Improved PSO & modified SFLA	Operation cost Reliability Voltage stability index	DNR along with capacitor allocation	95 bus DN
Noruzi Azghandi[75]		×	Improved PSO & ABC	Energy loss Operational cost Energy not supplied.	Considering DG, electrical vehicles, and demand response application	95 bus DN
Azizivahed [38]		✓	PSO & GWO	operation cost, power loss, energy not supplied considering switching cost	DNR with flexible electricity price	95bus DN
Jafari[77]		×	Exchange market Algorithm (EMA) & WGA	Active power loss Reliability indexes	Parallel processing method for reducing the running time	IEEE 15 bus IEEE 33 bus IEEE 69 bus IEEE 85-bus
Gao[43]	Other hybrid methods	✓	BPSO & Linearization	Operation costs Load balancing	Clustering periods	148 bus DN 297 bus DN
Ji[44]		✓	Improved fireworks algorithm	Power losses	Clustering loads into a few classes	IEEE 33 bus IEEE 119 bus

TABLE 2. ***(Continued.)*** **Review of different methodologies and their objectives for dynamic DNRs.**

			considering heuristic rules			84 bus Taiwan power company
Nafisi [109]		✓	GA & Branch exchange	Cost of losses Switching cost	Considering microgrid	Real 77 bus
Vlachogiannis [110]		×	RL (Q learning)	Power losses	Proposing a simple Q learning and comparison with other algorithms	IEEE 33 bus
Malekshah [111]		✓	RL (Deep Q learning)	Power loss Voltage deviation Reliability index	Considering reliability	IEEE 33 bus IEEE118 bus
Wang[91]	Machine Learning Methods	✓	RL (NoisyNet deep Q-learning)	Power loss Voltage profile	Comparison of different reinforcement learning technique	IEEE 33 bus IEEE 69 bus
Zhao[112]		×	RL (Monte Carlo tree search)	Power losses	Considering uncertainty of DG	IEEE 14 bus
Gao[86]		✓	RL(Batch-constrained RL)	Cost of power losses and switching cost	Proposing a new RL algorithm	IEEE 16 bus IEEE 33 bus IEEE 70 bus IEEE 119 bus

to avoid frequent switching operations that lead to additional costs.

V. GENERAL COMPARISON OF THE METHODS

The static reconfiguration problem is often solved to find an optimal configuration for a long study period considering constant values for loads and generations. Hence, for static reconfiguration, the accuracy of the algorithm has a higher priority compared to its computational time. Therefore, the methods with higher accuracy are more suitable for static reconfiguration, even if they have a high computational time. Among the methods, classical methods, due to some approximation in linearization, and heuristic methods, due to trapping in local optima have not been favoured widely by the researchers. The researches on static DNRs are more focused on metaheuristic and hybrid metaheuristic methods due to their ease of implementation for various objectives and also their satisfactory accuracy.

In contrast to static DNR, dynamic reconfiguration should be performed online and within a short time period. Assessing switching costs and integration between hours in dynamic reconfiguration makes the search space much wider than in a static reconfiguration problem. Therefore, the methods that have a good speed and less computational burden are more appropriate for dynamic reconfiguration. Among the methods, classical methods, some hybrid methods, and machine learning methods have presented superior computational speeds.

Classical methods have a low calculation burden but, linearization of various objectives and constraints together with the consideration of integrations between hours is performed with many approximations in this class of methods. Although hybrid methods usually have more calculations, to perform dynamic DNR with this class of methods, researchers reduce search space by clustering loads and using longer time intervals. Some of the most popular methods for dynamic reconfiguration are the methods based on machine learning approaches. Although these methods have a considerable offline learning time, a trained agent can obtain the optimal configuration in a short time and with few online calculations. Therefore, these methods are more suitable for online dynamic reconfiguration. The main challenge for this approach is the difficulty of training for a large network with a large number of variables.

VI. STATE OF THE ART

Given the considerably higher benefits of dynamic reconfiguration, it appears that future research in this field will predominantly concentrate on dynamic reconfiguration. The development of efficient algorithms capable of handling large-scale networks, the implementation of machine learning methods, and the exploration of hybrid approaches represent potential areas for future investigation. Future challenges in DNR may involve integrating dynamic reconfiguration with other controllable devices and resources in the distribution network, including soft open points, electric vehicles, energy storage systems, and distributed generation resources. Moreover, future research can be conducted for intelligent coordination strategies to optimize the utilization of these resources alongside dynamic reconfiguration.

VII. CONCLUSION

A DNR is one of the most popular approaches that operators perform to control and improve power system indices, such as voltage profile. DNR methods can be categorized into dynamic and static approaches. A static reconfiguration presents a fixed topology for planning or long-term operation. On the other hand, dynamic reconfiguration presents optimal configurations for short-term operation, such as an hour, taking into consideration the dynamics of loads, generation, prices, etc. This paper presents a methodological framework for categorization the techniques proposed in the literature

TABLE 3. Main advantages and disadvantages of metaheuristic methods.

Algorithm	Main advantages	Main shortcomings
Genetic Algorithm (GA) *Holland (1975)*	• Applicable for discrete and continuous parameters • More chance to find the global optima for a wide variety of problems	Highly time consuming for large and complex problems
Particle Swarm Optimization (PSO) *Eberhart & Kennedy (1995)*	• Simplicity of implementation • Fast convergence • Few parameters to adjust	Converging to the local optimum
Simulated Annealing (SA) *Kirkpatrick (1983)*	• Simplicity of implementation • Rapid	The final optimum depends on the initial configuration Highly time consuming
Tabu Search (TS) *Glover and McMillan (1986)*	• Low computational burden	Difficult to implement Many parameters to adjust
Ant Colony Optimization (ACO) *Dorigo (1992)*	• Simplicity of implementation	Uncertain convergence time
Harmony search (HS) *Geem (2001)*	• Fewer adjustable parameters	Unnecessary iterations without improvement
Artificial Bee Colony (ABC) *Karaboga & Basturk (2007)*	• Fast convergence	Trapping in local optimum

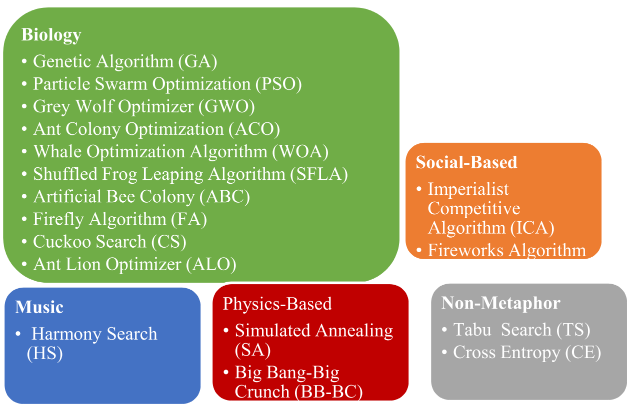

FIGURE 8. Classification of metaheuristic methods according to their source of inspiration.

on static and dynamic reconfiguration. A large number of the papers have been reviewed and the methods are grouped into five groups: classical methods, heuristic methods, metaheuristic methods, hybrid methods, and machine learning methods. The paper provides a detailed review and comparison of methods within each group from different aspects.

Classical methods mostly solve the problem by transforming it into a second-order or first-order problem. Heuristic methods use special features of the problem to find optimal solutions. Metaheuristic methods such as GA and PSO rely on iterative optimization algorithms based on an abstraction of nature to find the optimal configuration. Hybrid methods are a combination of different methods to increase their advantages and overcome their limitations. The methods based on machine learning have an online training phase which enables them to make quick online decisions. This class of methods is more suitable for dynamic reconfiguration. A general comparison of the methods shows that metaheuristic methods have turned into the most popular class of methods for static reconfiguration due to their good accuracy and ease of implementation with various objectives. On the other hand, machine learning methods are more effective for dynamic reconfigurations due to their capabilities for performing fast online calculations.

APPENDIX

Metaheuristic methods can be categorized according to their source of inspiration. Fig. 8 shows that most of the metaheuristic methods originate from the biological behaviour of humans and animals.

Table 3 compares the main advantages and shortcomings of the most popular metaheuristic methods in the context of the DNR problems.

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