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ORIGINAL PAPER

A comprehensive review on power distribution network reconfiguration

Sivkumar Mishra[1] · **Debapriya Das**[2] ·
Subrata Paul[3]

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Abstract Reconfiguration of radial distribution networks is becoming a viable solution for improving the performance of distribution networks. Configurations may be varied with manual or automatic switching operations so that all of the loads are supplied and reduce power loss, increase system security, and enhance power quality. Reconfiguration also relieves the overloading of the network components. The change in the network configuration is performed by opening sectionalizing (normally closed) and closing tie (normally open) switches of the network. These switchings are performed in such a way that the radiality of the network is maintained and all of the loads are energized. Several researchers have attempted to solve the power distribution network reconfiguration problem using various techniques. This paper presents a comprehensive survey on network reconfiguration to bring out a clear idea for future research.

Keywords Distribution systems · Network reconfiguration · Power loss minimization · Load balancing

1 Introduction

Starting from the first reported method by Merlin and Back [1] in 1975, power distribution network reconfiguration (PDNR) methods have travelled a long path from

✉ Sivkumar Mishra
sivmishra@yahoo.com; sivkumar@iiit-bh.ac.in

1 International Institute of Information Technology, Bhubaneswar, Odisha, India

2 Indian Institute of Technology, Kharagpur, West Bengal, India

3 Jadavpur University, Kolkata, West Bengal, India

the early single objective, computationally slow and mostly heuristic methods to the present day modern, multi-objective stochastic PDNR methods equipped with super-fast simulators and latest visualizing tools. Looking at the vast number of published papers on this topic during the last three decades, one can always say that PDNR is undoubtedly one of the most discussed power system optimization problems for the researchers. The two fundamental challenges of PDNR methods for radial distribution networks (RDNs), as pointed out by Abadei and Kavasseri [2], are the extremely large combinatorial solution space and the requirement of a very fast loss estimation technique for repeated and continuous evaluation of each these configurations. Moreover, the gradual emergence of smart distribution systems with growing penetration of distributed generators (DGs) and modern FACTS devices, advance applications of information and communication techniques (ITC) for ensuring high-quality reliable power distribution, availability of new meta-heuristic optimization techniques and growing stochastic environment have, in fact, made the PDNR methods more challenging. Thus, initially only meant for overall active power loss reduction and feeder load balancing, the present day PDNR methods serve several other objectives (including even some conflicting objectives!!) with a clear focus on improving reliability and power quality indices in a stochastic environment.

Several review papers are available on PDNR methods in the literature. In 1994, Sarfi et al. [3] presented a survey of the state of the art in PDNR methods, which is quite old. Enacheanu et al. [4] presented a useful survey on encoding techniques for network topology meant for various meta-heuristic PDNR methods. Santos et al. [5] presented a very brief literature review of various PDNR approaches. Tsai and Hsu [6] briefly reviewed the various multi-objectives used in PDNR analysis. In 2011, Ferdavani et al. [7] presented a review of PDNR methods through heuristic approaches only. In [8], a thorough comparative analysis of population-based AI techniques for PDNR is presented. However, this population-based AI techniques include the genetic algorithm, particle swarm optimization and ant colony optimization only. Lavarato et al. [9] presented a brief literature review of the PDNR methods imposing radiality constraints. Guedes et al. [10] presented a short literature review of papers with a classification of PDNR methods as single or multi-objective. Kalambe and Agnihotri [11] presented a bibliographic review of the loss minimization methods in power distribution systems with PDNR as one among the various loss minimization options, so it could not throw lights on all related aspects of PDNR methods. Some of the patents on PDNR methods can also be seen [12–16].

In the light of above developments, this paper attempts to comprehensively review and classify the PDNR methods by tracing the evolution of the method with gradual automation of distribution system (DS) and the emergence of smart grid. This review has the following distinct features.

- It traces the development of the modern multi-objective PDNR methods from the early single objective PDNR.
- It classifies the PDNR approaches and presents a detailed chronological review.
- It reviews the PDNR results with the most commonly referred test DSs.
- It presents current trends in research and future research directions concerning PDNR.

2 PDNR methods: mono objective to multi-objectives

In 1975, Merlin and Back [1] took up the PDNR problem as finding the minimum spanning tree (MST) with least total active power loss and ever since; even today, minimization of power loss (PL) has remained the single most important objective. In fact, the main objective of PDNR, in normal conditions, is to minimize PL and in emergency, following a fault or during a planned outage, is to provide services to as many customers as possible, known as service restoration (SR). Energy loss minimization (ELM) is also considered instead of loss minimization (LM) in some papers. The early PDNR methods also considered feeder load balancing (FLB) or transformer load balancing (TLB), prevention of transformer and feeder overload (TFO), minimizing switching cost (SWC) and number of switching (NS), maximization of voltage stability index (VSI) as the other objectives but mostly achieved via LM.

2.1 Mono objective PDNR

Most of the papers reviewed consider the PDNR problem as a single objective of LM subject to current, voltage and radiality constraints (SOLMCVRC) as [4]:

$$Min \sum_{b=1}^{N_{br}} |I_b|^2 \cdot R_b \cdot K_b \rightarrow \text{Minimization of PL.} \tag{1}$$

Subject to constraints

$$K_b \cdot |I_b| < \mathrm{I}_{\mathrm{m}ax} \rightarrow \text{Current constraints} \tag{2}$$

$$V_{i\ \min} < V_i < V_{i\ \max} \rightarrow \text{Voltage constraint} \tag{3}$$

$$g_I(I, k) = 0 \rightarrow \text{Kirchoff's current law (KCL)} \tag{4}$$

$$g_V(V, k) = 0 \rightarrow \text{Kirchoff's voltage law (KVL)} \tag{5}$$

$$\psi(k) = 0 \rightarrow \text{Radial topology constraints.} \tag{6}$$

In above, N_{br} is the number of closed branches. R_b, I_b and K_b are resistance, the current and topological status of the closed branch respectively. V_i is the voltage of the ith bus and $V_{i,min}$ and $V_{i,max}$ are the concerned minimum and maximum bus voltages respectively. The constraints (such as voltage or current as explained above) can be formulated as penalty functions in the objective function e.g Zhang et al. [17] considered LM as the main component whereas bus voltage deviation (BVD) and branch current limit (BCL) as the penalty functions given below:

$$M = PL + p_1.f_V + p_2.f_C. \tag{7}$$

Here, f_V and f_C are the penalty functions for BVD and BCL respectively; p_1 and p_2 are the corresponding penalty coefficients. Gomes et al. [18] minimized the total cost of PDNR with two components such as cost for PL and branch utilization cost. Siti et al. [19] combined minimization of PL with phase and load balancing (PLB).

Bahadoorsingh et al. [20] formulated an objective function for PDNR to minimize financial losses due to voltage sags without including cost due to power loss as

$$M = Min \left| \sum_{b=1}^{N_b} f \cdot P_c \cdot P_f \cdot C \right| \tag{8}$$

where f is the frequency of voltage sags at a particular site, P_c is the probability of a particular load composition at the site, P_f is the probability of equipment/process failure, C is the cost associated with the tripping of the equipment/process and N_b is the number of buses of interest. Prasad et al. [21] proposed an objective as combination of LM and maximization of system load balancing as:

$$LB_{sys} = \frac{1}{N_{br}} \sum_{j=1}^{N_{br}} \frac{S_j}{S_{jmax}}. \tag{9}$$

In above, S_j is the maximum apparent power flowing through branch-j and S_{jmax} is the maximum capacity of the branch-j. Carcamo-Gallardo et al. [22] defined energy not supplied (ENS) and set it as the PDNR objective. Cebrian and Kagan [23] considered to minimize the cost of energy loss (EL) with power quality costs like long duration interruptions (LDI) and customer process disruptions (CPD) due to voltage sags. Shariatkhah et al. [24] proposed a PDNR to minimize a cost function due to EL, customer interruption (CI) and SWC. Rosetti et al. [25] combined the minimization of EL with optimized DG allocation. Ghasemi and Moshtagh [26] combined several objectives in terms of minimizing cost as:

$$M = \min(LC + SWC - CIV). \tag{10}$$

Here, *LC*, *SWC* and *CIV* represent the loss cost, switching cost and cost saved due to voltage profile improvement respectively. In norm-2 type, several objectives are considered as a vector and its distance between the vector containing the worst values of corresponding objectives are maximized. In PDNR case, these worst values refer to the values of the objective functions with the initial configuration. Niknam [27] and Niknam [28] used this approach to minimize PL, BVD, NS and FLB as below:

$$\begin{aligned} &Maximize\ J \\ &= \sqrt{(PL - PL_0)^2 + (BVD - BVD_0)^2 + (NS - NS_0)^2 + (FLB - FLB_0)^2} \end{aligned} \tag{11}$$

PL_0, BVD_0, NS_0 and FLB_0 are the values of the corresponding objective functions before reconfiguration. Thus, various objectives in PDNR can be classified [22] as a) minimization of *PL* or *EL* and b) minimization of restoration time c) optimization of reliability and power quality based cost functions.

2.2 Multi-objective PDNR methods

In literature several approaches are adopted when more than one objective are dealt in PDNR. The major approaches are discussed here.

2.2.1 Weighted sum multi-objective (WSMO) PDNR

Roytelman et al. [29] proposed a WSMO PDNR formulation to minimize PL, worst voltage drop (WVD), service interruption frequency (SIF), TLB and balanced service of important customers (BSIC).

$$M = w_1 \cdot P_{Loss} + w_2 \cdot TLB + w_3 \cdot WVD + w_4 \cdot SIF + w_5 \cdot BSIC \tag{12}$$

Santos et al. [5] formulated a WSMO based objective function considering PL, NS and number of out of service loads (NOSL). Macedo Braz and DeSouza [30] proposed a WSMO with objectives to minimize EL and NS. Zhang et al. [31] proposed reliability oriented WSMO PDNR with the following objectives

$$M = w_1 \cdot PL + w_2 \cdot EENS + w_3 \cdot SAIFI + w_4 \cdot SAIDI + w_5 \cdot ASAI \tag{13}$$

Where, EENS→ Expected Energy Not Supplied, SAIFI →System Average Interruption Frequency Index, SAIDI→ System Average Interruption Duration Index and ASAI → Average Service Availability Index.

However, in order to tackle the imprecision and ambiguity in reliability inputs, electrical parameters, and load data interval analysis is adopted in the paper [31]. Jazebi and Vahidi [32] considered the power quality based indices such as minimizing total harmonic distortion (THD) of the critical buses of the system and minimizing the voltage sag (VS) for a WSMO PDNR, where the individual objectives are normalized suitably. Ptfischer et al. [33] proposes analytic hierarchy analysis (AHA) for multi-criteria decision making considering objectives like minimizing EL, expected SAIFI (ESAIFI), expected ENS (EENS) subjected to constraints like over current limit, minimum and maximum bus voltage magnitudes. Benardon et al. [34] proposed a reliability-oriented WSMO as

$$M = w_1 \cdot EL + w_2 \cdot EENS + w_3 \cdot ESAIFI \tag{14}$$

Recently, Duan et al. [35] proposed a WSMO for objectives like minimizing PL, and reliability indices like SAIDI, SAIFI and EENS.

2.2.2 Fuzzy multi-objective (FMO) PDNR

When several objectives are simultaneously considered for optimization, it is preferred to go for optimization with soft limits (rather than hard limits) in terms of fuzzy membership values (MV), the approach popularly known as fuzzy multi-objective (FMO). Zhou et al. [36] proposed to minimize NS for RS and FLB by defining three fuzzy MVs. Another example as formulated by Huang [37] is

$$Max\ M = w_1 \cdot \mu_p + w_2 \cdot \sum_{i=1}^{nb} \mu_{vi} + w_3 \cdot \sum_{i=1}^{nbr} \mu_{ii} + w_4 \cdot \mu_S \tag{15}$$

Where M is the objective function to be maximized and $\mu_P, \mu_{Vi}, \mu_{Ii}, \mu_S$ are the MVs to minimize the *PL*; sum of MVs to minimize the BVDs; sum of MVs to minimize the current violation and *NS* respectively. The corresponding weighting factors are w_1, w_2, w_3 and w_4 respectively. Hsiao [38] proposed an FMO for PL, BVD, NS and ensuring the reliability of services (ERS) in terms of minimizing the capacity margin of feeders and transformers. Venkatesh et al. [39] proposed an FMO PDNR for PL and VDI. Das [40] proposed an FMO formulation of PDNR method to minimize power loss (PL), bus voltage deviation (BVD), branch current loading (BCL) with FLB. Bernardon et al. [41] proposed a FMO PDNR to minimize PL and number of interrupted customers per year (NICY) subject to voltage, current and radiality constraints. Falagi et al. [42] formulated FMO PDNR with MFs defined for EENS and cost of sectionalizing switches (CSS) with DGs. Gupta et al. [43] proposed an FMO by formulating MVs for PL, BVD, BCL and NS. To take care of the changing degree of fuzzy MFs at different operating conditions, Grey Co-Relation Analysis (GCRA) based MO optimization is used by Tsai and Hsu [6]. Hooshmand and Soltani [44] implemented jointly PDNR and phase balancing as an FMO formulation defining three MFs for objectives LM, minimization of feeder neutral current (FNC) and phase balancing index (PBI). Malekpour et al. [45] proposed FMO with 4 objectives to optimize EL, the cost of electricity generation (CEG), emissions produced (CEP) and BVD.

2.2.3 Pareto optimal multi-objective (POMO) PDNR methods

As the DSs are continuously marching towards becoming smart grids, the reliability and power quality based objectives are becoming prominent, which are often conflicting in nature. The optimization problem gets complicated with such conflicting objectives. In such situations, when better values for all the individual objectives do not exist, non-dominant solutions having best possible trade-off among objectives are preferred, the set of such solutions is known as pareto front and are often preferred to single solutions because they can be very useful when considering problems of practical nature [46]. WSMO approach is known as convex pareto front approach, the ε-constrained MO is another approach where one of the objectives is made as the main target for minimization which sets a limit or ε for all other objectives. The ε can be decreased in a step wise manner so that various non-dominated solutions are obtained. Chiang and Jumeau [47,48] proposed a two-stage ε-constrained PDNR with LM and FLB as the two objectives. Population-based meta heuristic optimization methods have the inherent advantages of obtaining a direct pareto front iteratively. Some examples of evolutionary methods capable of POMO are non-dominated sorting genetic algorithm (NSGA), pareto archived evolution strategy (PAES), micro-genetic algorithm (μGA), strong pareto genetic algorithm (SPGA), multi-objective particle swarm optimization (MOPSO), multi-objective tabu search optimization (MOTO) etc. [49,50].

Mendoza et al. [51] considered two objectives, to minimize a cost function defined and ENS for pareto optimization. Mendoza et al. [49] considered four objectives: PL, SAIFI, system average interruption unavailability index (SAIUI), system average duration interruption index (SADII) and ENS for pareto optimization. Chandramohan et al. [46] formulated a POMO to minimize operating costs (OC) by minimizing real and reactive power loss along with maximizing operating reliability by minimizing total interruption cost (TIC) with usual voltage constraints as

$$M = Min\left(K_1 \cdot \overset{_{Operating}\text{Cost}}{\overleftrightarrow{PLoss + K_2 \cdot QLoss}} + \sum_{b=1}^{Nb} \overset{\overset{TIC}{\longleftrightarrow}}{ICb}\right) \tag{16}$$

Here, P_{Loss} and Q_{Loss} are the real and reactive power losses of the distribution system and K_1 and K_2 are respective cost coefficients. IC_b is the interruption cost of the bus-b. Niknam et al. [52] applied fuzzy clustering approach to select the best-compromised solution from a non-dominated set of solutions. Here, the objectives considered are LM, minimization of BVD, the cost of energy both by grid and renewable energy sources (CEG) and total emissions produced (CEP). Barbosa et al. [53] formulated a POMO PDNR for minimizing PL, VDI, current loading index (CLI) and NS. Guedes [10] proposed a pareto dominance based multi-objective heuristic PDNR to minimize total PL and maximum current (MC). Gupta et al. [54] formulated a POMO to minimize PL, BVD, average interruption frequency (AIF), average interruption unavailability (AIU) and ENS. Narimani et al. [55] proposed a POMO based PDNR with objectives like LM, minimizing operating cost (OC) of DGs and ENS.

3 PDNR approaches

PDNR methods are broadly classified into three categories: (1) heuristics (2) meta-heuristic and (3) mathematical optimization based approaches. Of course, a fourth category is there which includes the hybrid methods based on the first three approaches. Heuristic-based approaches are the most popular ones, mainly due to the reason that these methods always give fast reconfiguration results and are based on distribution network operational experience, hence are simple to formulate. However, these methods not necessarily always give the global optimum values whereas meta-heuristic (the Greek prefix "meta" means "high level" [56]) PDNR methods take sufficiently longer time and are often complicated to formulate. These reconfiguration methods are based on genetic algorithm, simulated annealing, ant colony search, differential algorithm, harmony search, tabu search, gravitational search, particle swarm optimization, etc. Mathematical Optimization methods, otherwise, known as deterministic methods and the examples of this approach are linear programming, quadratic programming, nonlinear programming etc.

PDNR methods mathematically belong to the class of complex combinatorial non-differentiable optimization problem, where maintenance of radiality of the network, nonlinear nature of power flow constraints and necessity of exhaustive search for all possible configurations add to the complexity of the problem. It is for that reason; most of the initial PDNR approaches are heuristic search based on simple network operating principles with much-reduced solution space. Chiang and Jumeau [47,48] termed these techniques otherwise as “the class of greedy search techniques which accepts only search movements that produce immediate improvement. As a result, these solution algorithms usually achieve local optimum solutions rather than global optimal solutions”. Sensitivity guided heuristics and several other inference mechanism based techniques are also included in this category.

The PDNR approaches can also be classified into two categories (a) branch exchange (BE) method (b) sequential switch opening method (SSO). In a branch exchange method, closure of any tie line switch must accompany with opening of any sectionalizing switch from the loop formed whereas in the second category, one or any number combination of the network tie line switches are closed first to form a meshed system and then sectionalizing switches are opened successively to regain radial configuration. Tables 1, 2 and 3 enlist a chronological order of various PDNR methods published in various journals of repute over last three decades for heuristic, mathematical optimization and meta heuristic-based approaches respectively. These tables also include brief information of the corresponding PDNR objectives and the type of load flow used. Figure 1 depicts the evolution of PDNR methods with the gradual emergence of smart grid.

4 Test systems and results

Looking at the huge number of papers available in the literature on PDNR methods, it is felt that there is a need for a review of the most commonly used test systems and reported reconfiguration results. Over the years, researchers have used several test DSs to explain their own approaches and compared it with other PDNR methods. Here, some of the most commonly referred test DSs are considered and the reconfiguration results of these systems as reported by the respective authors are presented. However, the reconfiguration results refer to LM objective only. The reported results (except for 16 bus system) include active power loss and minimum bus voltage magnitude before reconfiguration and active power loss, minimum bus voltage magnitude, open branches after reconfiguration. The reported results also include reported the number of LFs required and the execution time in second for the reconfiguration process.

4.1 16 bus test system (TS-1)

Civanlar et al. [60] introduced this three feeder test system (Fig. 2). The bus and branch numbering is kept the same as in the original case. The total active and reactive loads are 28.7 MW and 17.3 MVAr respectively. Capacitors are connected at 7 buses (5, 6, 9, 11, 12, 14 and 16) amounting a total of 11.4 MVAr. The base power and voltage are 100 MVA and 23 kV respectively. The line and load data of the system are available in [60]. This test system is mostly used by researchers to explain the corresponding proposed PDNR methods and for quick validation of results. There is unanimity for the power loss (511.4 kW) in the original network (Fig. 2) with open branches 15,

Table 1 Heuristic search based PDNR methods

S. no.	Description	Type and objective(s)	Load flow	Salient features
1	Merlin and Back [1]	LM	Meshed and radial load flow (MRLF)	Pioneer method-blend of optimization and heuristics-known as branch and bound method (BB): all tie lines are closed first and one line is opened at a time
2	Castro et al. [57]	SR and FLB	Not reported	Search based heuristic algorithm (HA)
3	Ross et al. [58]	LM and FLB	Not reported	A heuristic algorithm (HA) based on branch exchange(BE)
4	Aoki et al. [59]	LM with FLB	Not reported	An approximate method based on heuristic rules
5	Civanlar et al. [60]	LM	Approx. loss estimation formula (LEF)	A BE based heuristic method
6	Baran and Wu [61]	LM via FLB	Radial LF(RLF)	BE based HA using approximate radial LF methods
7	Liu et al. [62]	LM	LEF is used	2 HAs: one for uniformly distributed load and the other for concentrated load
8	Shirmohammadi and Hong [63]	LM	MRLF	SSO method using compensation based load flow (CLF). All tie lines are closed first and opened successively to regain radiality following an optimum power flow (OPF) pattern
9	Castro and Watanabe [64]	LM	RLF	BE HA using a approx. LEF
10	Huddleston et al. [65]	LM	RLF	BE HA using a quadratic loss function and multiple switch pair operations per iteration
11	Taylor and Lubkeman [66]	LM and prevention of TFO	RLF	Heuristics rule based best first tree searching method
12	Wagner et al. [67]	LM	Gauss Siedel (GS) LF	Compares linear programming (LP) with the two HAs (OPF and BB) for uniformly distributed loads
13	Chen and Cho [68]	Minimize EL	3 phase RLF	BE based PDNR HA with hourly optimal switching in a day
14	Goswamia and Basu [69]	LM	MRLF	SSO method: one tie line is closed first and a branch is opened from the loop so formed with minimum current
15	Broadwater et al. [70]	SOLMCVRC	RLF	BE HA PDNR for time varying load
16	Chen and Cho [71]	ELM, switching cost minimization	3phase RLF	Binary integer programming with BB technique

Table 1 continued

S. no.	Description	Type and objective(s)	Load flow	Salient features
17	Jung et al. [72]	TLB and FLB	LEM is used	Expert system based on heuristic rules
18	Augugliaro et al. [73]	LM	MRLF	2 stage HA: starts with a meshed network with all switch closed and opened sequentially, a BE method is followed
19	Borozan et al. [74]	LM	CLF	SSO method using OPF
20	Peponis et al. [75]	SOLMCVRC	MRLF	Two HAs: BE and SSO method
21	Peponisa and Papadopoulos [76]	LM and FLB	MRLF	Comparison between BE and SSO method with load model
22	Fan et al. [77]	LM	RLF	BE HA for single loop optimization
23	Roytelman et al. [29]	WSMO: optimizes PL, TLB, WVD, SIF and SBIC as per (11)	MRLF	2 stage HA: starts with all switches closed followed by BE to obtain the optimal configuration
24	Sarfi et al. [78]	LM	RLF	HA based on network partitioning approach
25	Wang et al. [79]	LM and FLB	3-Ph FBS ULF	BE based PDNR method for unbalanced distribution systems
26	Borazan et al. [80]	Cost(energy) minimization	CLF	SS0 method using OPF
27	Taleski and Rajicic [81]	ELM	PS RLF	HA based on BE method
28	Zhou et al. [36]	FMO to minimize NS for RS and FLB	Not reported	2 PDNR methods: blend of heuristics and optimization
29	Zhou et al. [82]	Minimizing operating cost (OC)	MLF	Heuristic SSO method
30	Kashem et al. [83]	LM	RLF	Modified BE method based on distance centre technique
31	Lin and Chin [84]	LM	Meshed LF	SS0 method based on switching indices of loop branches
32	Kashem et al. [85]	LM with FLB	RLF	Modified BE method based on distance centre technique
33	McDermott et al. [86]	SOLMCVRC	RLF	HA with a backtracking scheme to avoid local minima
34	Kashem et al. [87]	SOLMCVRC	RLF	Modified BE method based loss estimation formula
35	Kashem et al. [88]	SOLMCVRC	RLF	Heuristic geometric BE approach
36	Huanga and Chin [89]	LM and FLB	RLF	HA–BE with fuzzy approach

Table 1 continued

S. no.	Description	Type and objective(s)	Load flow	Salient features
37	Kashem et al. [90]	FLB	RLF	BE based HA on index measurement
38	Ghosh and Das [91]	LM	MRLF	HA: modified BE method
39	Gohokar et al. [92]	LM	MRLF	HA: SSO method based on network topology
40	Ke [93]	FLB	Not reported	HA: using G-Nets inference mechanism
41	Gomes et al. [94]	LM	MRLF	HA: SSO method
42	Sivanagaraju et al. [95]	LM and maximization of VSI	RLF	HA: BE approach to maximize VSI
43	Chuang et al. [96]	FLB	Not reported	Rule knowledge Petri Net (RKPN) based PDNR
44	Das [40]	FMO: PL, BVD, BCL and FLB	RLF	HA: BE method
45	Das [97]	FMO: PL, BVD, BCL and FLB	RLF	HA: BE method
46	Gomes et al. [18]	Minimization of cost of PDNR	MRLF	HA: SSO method using OPF
47	Savier and Das [98]	FMO: PL, BVD, BCL and FLB	Radial	PDNR HA: BE method for loss allocation
48	Siti et al. [19]	LM and PLB	URLF	2 methods: one HA and other based on ANN for UDS
49	Martin and Gil [99]	LM	MRLF	HA: BE method based on direction of power flows
50	Raju and Bijwe [100]	LM	MRLF	HA: SSO-2 stage approach based on loss sensitivity
51	Raju and Bijwe [101]	LM	URLF	HA: SSO-2 stage approach based on loss sensitivity
52	Arun and Aranvindhababu [102]	Maximize VSI	RLF	HA: BE method to improve Voltage Stability Index(VSI)
53	Bernardon et al. [41]	FMO of PL and NICY	FBS LF	HA: BE method to optimize the reliability of the system
54	Carcamo-Gallardo et al. [22]	Minimize ENS	Not reported	2 HAs: greedy search algorithm (GSA) and fast GSA
55	Singh et al. [103]	LM and RS	MRLF	SSO method: opening the branch with minimum power flow
56	Zhu et al. [104]	SOLMCVRC	PS based RLF	HA: rule based BE method
57	Subrahmanyam et al. [105]	SOLMCVRC	URLF	HA: BE method for balanced and unbalanced DS

Table 1 continued

S. no.	Description	Type and objective(s)	Load flow	Salient features
58	Abadei and Kavasseri [2]	SOLMCVRC	FBS radial LF	BE method: random walks based loss estimation technique
59	Abul'Wafa [106]	LM	RLF	HA: BE based method
60	Savier and Das [107]	FMO: PL, BVD, BCL and FLB	RLF	PDNR HA: BE method for loss allocation
61	Bouhouras and Labidris [108]	SOLMCVRC	MRLF	BE method with load variations by stochastic procedures
62	Gonzalez et al. [109]	Minimizes non deliverable power	RLF	Knowledge HA for planning studies
63	Mena and Garcia [110]	LM	NR MRLF	BE based on branch active and reactive power flows
64	Zhang et al. [31]	WSMO: PL, EENS, SAIFI, SAIDI, ASAI	Interval LF	BE: based on neighborhood search with interval technique
65	Zin et al. [111]	SOLMCVRC	MRLF	SSO based PDNR: using a circular updating
66	Bayat [112]	LM	FBS RLF	BE: based on uniform voltage distribution algorithm (UVDA)
67	Guedes et al. [10]	POMO to minimize PL and MC	RLF	BE: Pareto dominance is used to prune the search space
68	Pfitscher et al. [33]	Minimize EL, ESAIFI and EENS	FBS radial LF	BE method for real time PDNR using AHA
69	Rosetti et al. [25]	Minimize EL with DG allocation	NR LF	Combined heuristic constructive algorithm
70	Ahmadi and Marti [113]	LM	Mesh LF	SSO based HA solves PDNR problem considering MST
71	Benardon et al. [34]	WSMO as per (14)	FBS radial LF	BE method for real time PDNR with DGs
72	Ding and Laparo [114,115]	SOLMCVRC	URLF	BE based HA
73	Ghasemi and Moshtagh [26]	Minimize cost as per (8)	URLF	Improved BE based HA
74	Oliveira et al. [116]	SOLMCVRC	NR-MRLF	BE based HA works sensitivity calculation

21 and 26 whereas the final power loss is 466.13 kW after reconfiguration with open branches 17, 19 and 26 (Fig. 3). The overall loss reduction is 8.85 %. The minimum voltage magnitude buses before and after reconfiguration are $V_{12} = 0.9693$ pu and $V_{13} = 0.9716$ pu respectively. Table 4 presents the number of load flows required by some PDNR methods (as reported in the concerned paper) for obtaining the minimum

Table 2 Mathematical optimization based PDNR methods

S. no.	Description	Objective	Load flow	Salient features
1	Aoki et al. [117]	SOLMCVRC with substation capacity as constraint	MRLF	PDNR based on recursive quadratic programming with uniformly distributed load
2	Glaomocanin [118]	SOLMCVRC	Radial LF	PDNR formulated as a transshipment problem with quadratic costs
3	Augugliaro et al. [119]	LM	MRLF	SSO based PDNR adopting non linear programming
4	Wagner et al.[67]	LM	GS-LF	Compares linear programming (LP) with the two HAs (OPF and BB) for uniformly distributed loads
5	Abur [120]	SOLMCVRC	Radial load flow	Linear programming-simplex method
6	Morton and Mareels [121]	LM	LF is avoided	Brute force solution through an exhaustive search
7	Ramos et al. [122]	SOLMVRC	Radial LF	Mixed integer linear programming method (MILP)
8	Schmidt et al. [123]	LM	Radial LF	Mixed integer nonlinear programming method (MINP)
9	Khodr et al. [124]	LM and FLB	Radial LF	MINP method with Bendors decomposition and OPF
10	Oliveira et al. [125]	LM with capacitor allocation	MRLF	SSO-MINP with primal dual interior point method
11	Ramos et al. [126]	SOLMCVRC	Radial LF	MI quadratically constrained programming (MIQCP)
12	El Ramli et al. [127]	LM	Radial LF	PDNR using Ordinal Optimization
13	Borghetti [128]	SOLMCVRC	Radial LF	MILP
14	Ibbora et al. [129]	Loss minimization	Radial LF	MILP
15	Jabr et al. [130]	LM with constraints with DGs	Radial LF	Mixed integer convex programming and MILP
16	Taylor and Hover[131]	LM, FLB	Not reported	MI quadratically constrained SOCP PDNR
17	Franco et al. [132]	LM in presence of DGs	FBS Radial LF	MILP method in presence of DGs
18	Dall'Anese and Giannakkis [133]	WSMO: FLB, minimize PL, DG cost	3-phase LF	Novel convex PDNR formulation
19	Deese [134]	LM	NR LF	Dynamic programming based method using OPF

Table 3 Meta heuristics based PDNR methods

S. no.	Description	Objective	Load flow	Salient features
Genetic algorithm (GA) based PDNR methods				
1	Nara et al. [135]	SOLMCVRC	LEF is used	Earliest GA based PDNR method
2	Lin et al. [136]	SOLMCVRC	NR-MRLF	Refined GA PDNR method with OPF and heuristic rule based Tabu search process
3	Huang [37]	FMO as given in (15)	RLF	FMO enhanced GA PDNR algorithm
4	Zhu [137]	SOLMCVRC	FBS RLF	Shortened genetic strings consists of set of tie lines only
5	Shin et al. [138]	Minimize Loss cost and Interruption cost	Not reported	Genetic Tabu search (TS) PDNR algorithm with RS
6	Hong and Ho [139]	FMO to minimize PL and VD	RLF	refined GA with Prufer number encoding for mesh check
7	Prasad et al. [140]	Minimization of PL and VDI	RLF	Fuzzy mutated GA PDNR
8	Ramos et al. [122]	SOLMVRC	RLF	Both MILP and GA based PDNR with path based approach
9	Mendoza et al. [51]	POMO: minimize construction cost and ENS	MRLF	Application of non sorting GA, NSGA and strong pareto GA, SPGA for PDNR
10	Mendoza et al. [141]	SOLMCVRC	RLF	GA using “accentuated crossover” and “directed mutation”
11	Bahadoorsingh et al. [20]	Minimization of voltage sag cost as (8)	RLF	Double point cross over and adaptive mutation
12	Carreno et al. [142]	SOLMCVRC	RLFl	A new codification based on Chu-Beasly algorithm
13	Enacheanu et al. [4]	SOLMCVRC	N R- RLF	GA based on Matroid theory
14	Prasad et al. [21]	Minimize PL and maximize LB_{sys} as (9)	FBS RLF	GA based BE PDNR algorithm
15	Mendoza et al. [49]	POMO: PL, SAIFI, SAIUI, SADII, ENS	PS RLF	Micro GA(μGA)
16	Queiroz and Lyra [143]	Energy loss minimization	Radial energy flow	Network random keys (NRK) representation for MST followed, BE based local search Hybrid GA
17	Cebrian and Kagan [23]	Minimize cost for EL, LDI and CPD	RLF	MI GA, Prim and Kruskal algorithm to generate MST
18	Chandramohan et al. [46]	POMO: OC and TIC as per (16)	RLF	NSGA method

Table 3 continued

S. no.	Description	Objective	Load flow	Salient features
19	Gupta et al. [43]	FMO to minimize PL, BVD, BCL, NS	RLF	GA adapting graph theory
20	Santos et al. [5]	WSMO to minimize PL, NS and NOSL	FBS radial LF	Node depth encoding EA and use of sub population table
21	Macedo Braz and D'Souza [30]	WSMO to minimize PL and NS	MRLF	GA with subtractive and additive sequential encoding
22	Swarnkar et al. [144]	SOLMCVRC	RLF	GA with heuristics spark and novel codification
23	Barbosa et al. [53]	POMO: PL, CLI, VDI and NS	FBS RLF	NSGA-II based PDNR
24	Tomoiaga et al. [145]	SOLMCVRC	FBS RLF	GA based on connected graphs
25	Torres et al. [146]	SOLMCVRC	Not reported	GA with edge window decoder encoding technique
26	Wang and Gao [147]	SOLMCVRC	Mesh LF	Non Revisiting GA based PDNR
27	Barbosa et al. [148]	Minimize PL, CLI, VDI and NS	FBS RLF	Interval MO NSGA-PDNR
28	Gupta et al. [54]	POMO: PL, BVD, AIF, AIU and ENS	RLF	GA with modified crossover and mutation
29	Maza et al. [50]	POMO to minimize EL, ENS and LBI	RLF	NSGA-II based PDNR method
30	Duan et al. [35]	WSMO: PL, SAIDI, SAIFI and EENS	RLF	Enhanced GA which always generates radial configurations
Simulated annealing (SA) based methods				
31	Chiang and Jumeau [47]	ε-constrained MO: LM and FLB	RLF	2 stage PDNR using a modified SA algorithm
32	Chiang and Jumeau [48]			
33	Chang and Kuo [149]	LM	RLF	Simplified line flow equations to speed up SA process
34	Jiang and Baldick [150]	SOLMCVRC	FBS radial LF	SA for network reconfiguration with capacitor control
35	Su and Lee [151]	LM and voltage profile improvement	RLF	PDNR mixed with optimal capacitor placement
36	Jeon et al. [152]	LM	RLF	SA: polynomial time cooling schedule based

Table 3 continued

S. no.	Description	Objective	Load flow	Salient features
37	Jeon and Kim [153]	LM	RLF	Hybrid PDNR: TS is mixed with SA to improve local search
38	Chen et al. [154]	SOLMCVRC	RLF	Simulated annealing immune algorithm
Evolutionary programming (EP) based PDNR				
39	Song et al. [155]	SOLMCVRC	RLF	Fuzzy controlled evolutionary programming based PDNR
40	Venkatesh and Ranjan [156]	FMO: minimize PL and VDI	RLF	Fuzzy adaption of EP based BE method
41	Hsiao [38]	FMO: minimize PL, NS, BVD and ERS	RLF	EP PDNR for fuzzy MO with reliability considerations
42	Venkatesh et al. [39]	FMO: PL and VDI	RLF	Fuzzy adaption of the EP based BE method
43	Delbem et al. [157]	LM, distribution planning and ER	RLF	EA close to EP with graph chain representation
44	Tsai and Hsu [6]	GCRA-MO: FLB, LM, BVD and NS	RLF	GCRA based MO PDNR
Differential evolution (DE) based PDNR				
45	Su and Lee [158]	SOLMCVRC	RLF	PDNR using improved MI hybrid DE
46	Chiou et al. [159]	SOLMCVRC	RLF	Variable scaling hybrid DE based PDNR
47	Jazebi and Vahidi [32]	WSMO: LM, THD and VS minimization	RLF	DE based PDNR with power quality improvement
ANN based PDNR				
48	Kim and Hung [160]	LM	LF not reqd.	PDNR based on ANN mapping ability for a minimum PL
49	Kashem et al. [161]	LM	LF not reqd.	PDNR based on ANN mapping ability for a minimum PL
50	Salazar et al. [162]	LM	LF is not reqd.	Improved ANN based PDNR using clustering technique
51	Siti et al. [19]	LM and PB	URLF	2 methods: one HA and other based on ANN for UDS
Tabu search (TS) based PDNR				
52	Augugliaro et al. [163]	LM	MRLF	3 methods based on TS, GA and SA are presented
53	Li et al. [164]	SOLMCVRC	RLF	Tabu list is used to prevent getting trapped in local maxima
54	Mishima et al. [165]	LM in presence of DGs and constraints	RLF	TS based PDNR with DGs

Table 3 continued

S. no.	Description	Objective	Load flow	Salient features
55	Zhang et al. [17]	LM with penalty functions as (7)	RLF	Improved TS method with mutation operation
56	Abdelaziz et al. [166]	SOLMCVRC	RLF	TS method with dynamic tabu list with variable size
Ant colony optimization (ACO) based PDNR				
57	Su et al. [167]	LM with penalty functions (8)	Radial LF	ACO based PDNR compared with SA and GA based PDNR
58	Ahuja et al. [168]	POMO: LM, TLB and BVD	Not reported	Hybrid ACO and AIS POMO PDNR
59	Carpaneto and Chicco [169]	LM with penalty functions similar to (8)	FBS RLF	Hyper Cube ACO based PDNR
60	Chang [170]	LM with penalty functions as in (8)	RLF	ACO based PDNR with capacitor placement
61	Falaghi et al. [42]	FMO: For EENS and CSS	Not reported	ACO based PDNR with DGs and reliability considerations
62	Niknam [28]	MO (norm2): PL, BVD, NS and FLB as (11)	Not reported	Hybrid PSO and ACO MO PDNR
63	Wu et al. [171]	LM with FLB and TLB	Not reported	ACO based PDNR with DGs
64	Saffar et al. [172]	FMO: to minimize PL and maximize LBI	RLF	PDNR using ACO
65	Swarnkar et al. [173]	SOLMCVRC	RLF	ACO based PDNR using graph theory and heuristics spark
66	Abdelaziz et al. [174]	SOLMCVRC	FBS RLF	ACO and HS based PDNR
67	Ahuja et al. [175]	SOLMCVRC	Not reported	ACO based PDNR with pheromone directed crossover
Artificial immune system (AIS) algorithm based PDNR				
68	Ahuja et al. [168]	POMO: LM, TLB and BVD	Not reported	Hybrid ACO and AIS POMO PDNR
69	Oliveira et al. [176]	Minimization of cost of EL at various load levels	RLF	PDNR based on clonal selection AIS algorithm
Bacterial foraging (BF) based PDNR				
70	Satish ana Jayabharthi [177]	SOLMCVRC	NR LF	BF based PDNR
71	Hooshmand and Soltani [44]	FMO: PL, FNC, PBI	3-Ph LF	BF combined with Nelder Mead algorithm

Table 3 continued

S. no.	Description	Objective	Load flow	Salient features
Honey bee mating optimization (HBMO)				
72	Niknam [27]	MO (norm2): PL, BVD, NS and FLB as (11)	RLF	Hybrid PSO and HBMO PDNR algorithm
73	Niknam [178]	FMO: PL, BVD and NS for pareto optimality	RLF	Multiobjective HBMO algorithm
74	Niknam and Sadeghi [179]	FMO: PL, BVD, NS for pareto optimality	RLF	Multiobjective HBMO algorithm
75	Niknam et al. [52]	Fuzzy clustering POMO: minimize PL, BVD CEG, CEP, with constraints	RLF	Modified HBMO PDNR algorithm for DS with wind generators, Photo voltaic cells and fuel cells
76	Olamaei et al. [180]	MO: PL, BVD and NS	RLF	Modified HBMO PDNR algorithm
Particle swarm optimization (PSO) algorithm				
77	Sivanagaraju et al. [181]	LM and FLB	RLF	Discrete PSO (DPSO) algorithm
78	Abdelaziz et al. [182]	SOLMCVRC	RLF	Modified PSO with an inertia weight based on BE
79	Niknam [27]	MO(norm2): PL, BVD, NS and FLB as (11)	RLF	Hybrid PSO and HBMO PDNR Algorithm
80	Assadian et al. [183]	SOLMCVRC	Mesh LF	Guaranteed convergence PSO PDNR with graph theory
81	Niknam and Farsani [184]	SOLMCVRC	RLF	Hybrid PSO and modified shuffled frog leaping PDNR
82	Gupta et al. [185]	SOLMCVRC	Mesh LF	Adaptive PSO BE method using graph theory and heuristics
83	Niknam et al. [186]	SOLMCVRC	RLF	Hybrid fuzzy adaptive PSO and DE PDNR algorithm
84	Wu and Tsai [187]	SOLMCVRC	RLF	Enhanced integer coded EIC-PSO with a local optimal list
85	Amanulla et al. [188]	Minimize PL and maximize reliability	RLF	Binary PSO PDNR with probabilistic reliability evaluation
86	Li and Xuefeng [189]	LM and FLB with CVRC	RLF	PDNR based on Niche binary(NB)-PSO algorithm
87	Niknam et al. [190]	LM with various constraints	MRLF	Hybrid Fuzzy Adaptive PSO and NM Algorithm
88	Malekpour et al. [45]	FMO: minimize EL, CEG, CEP, BVD with constraints	Probabilistic LF using PEM	Stochastic – Point estimate method(PEM) PDNR based on adaptive PSO for DS with wind generators and fuel cells

Table 3 continued

S. no.	Description	Objective	Load flow	Salient features
89	Sedighizadeh et al. [191]	FMO: LM, VD, FLB	Radial LF	Hybrid Big Bang–Big Crunch PSO algorithm
Harmony search algorithm (HSA)				
90	Rao et al. [192]	SOLMCVRC	Radial LF	HSA based PDNR method
91	Shariatkhah et al. [24]	Minimize cost for EL, CI and switching	Not reported	2 stage PDNR: 1st stage: HSA and graph theory 2nd stage dynamic programming
92	Abdelaziz et al. [174]	SOLMCVRC	FBS RLF	ACO and HS based PDNR
93	Rao et al. [193]	SOLMCVRC	RLF	HSA PDNR method with sensitivity based DG placement
Plant growth simulation (PGS)				
94	Wang and Cheng [194]	SOLMCVRC	RLF	PGS PDNR algorithm
Gravitational search algorithm (GSA)				
95	Narimani et al. [55]	POMO: minimize PL, ENS and OC of DGs	RLF	Enhanced gravitational search algorithm (EGSA)
96	Shuaib et al. [195]	LM and VDI subjected to VD constraint	PS RLF	Gravitational search algorithm (GSA) based PDNR
Fire works optimization (FWO)				
97	Imran and Kowsalya [196]	Minimise PL and BVD	Topological LF(TLF)	FWO based PDNR method
98	Imran et al. [197]	minimization of PL and BVD	TLF	FWO based PDNR integrated with DG placement
Teaching learning based optimization (TLBO)				
99	Azad-Farsani et al. [198]	Loss minimization	RLF	hybrid Chaotic PSO-TLBO based PDNR
100	Kavousi-Fard et al. [199]	POMO: minimize EL, CEG, EP, BVD	RLF	Probalistic TLBO PDNR
Quantum firefly algorithm (QFA)				
101	Shareef et al. [200]	Minimize SAIFI, ASIFI, MAIFI, SARFI and PL	RLF	QFA based PDNR
Imperialist competitive algorithm (ICA)				
102	Mirhoseini et al. [201]	LM and VPI with constraints	Mesh LF	SSO PDNR: adaptive ICA algorithm
Shuffled frog leaping algorithm (SLFA)				
103	Niknam and Farsani [184]	SOLMCVRC	RLF	Hybrid self adaptive PSO and modified SFLA PDNR
104	Niknam et al. [202]			

Table 3 continued

S. no.	Description	Objective	Load flow	Salient features
105	Kavousi-Fard and Zadeh [203]	POMO: PL, SAIFI, SAIDI, AENS	RLF	Improved SFLA PDNR for reliability enhancement
Discrete artificial bee colony (DABC)				
106	Aman et al. [204]	Minimize VDI and maximize loadabilty margin	RLF	Graph theory based DABC **P**DNR
Binary group search optimization (BGSO)				
107	Teimourzadeh and Zare [205]	SOLMCVRC	FBS RLF	BGSO based PDNR
Bat algorithm (BA)				
108	Kavousi-Fard and Niknam [206]	Fuzzy clustering POMO: minimize SAIFI, AENS, PL, CEG	Probabilistic LF using PEM	Self adaptive modified BA based PDNR with reliability objectives

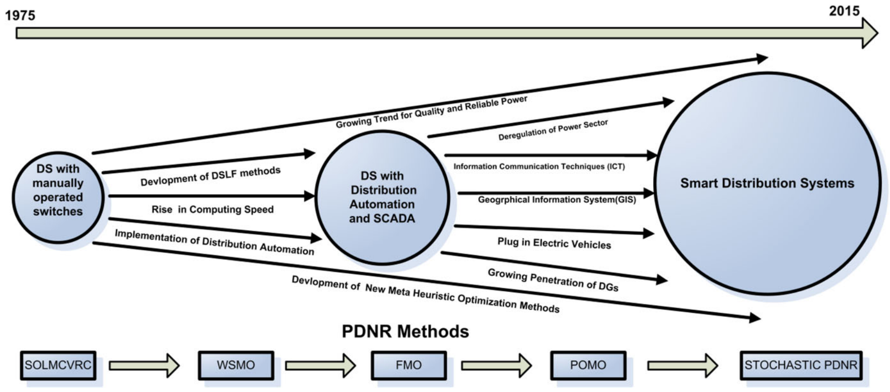

Fig. 1 Evolution of PDNR methods

loss network from the original network (TS-1), which clearly shows that heuristic based PDNR methods are much faster than the meta-heuristic methods.

4.2 33 Bus test system (TS-2)

This test system is extremely popular among the researchers for validation of reconfiguration methods and results. However, in literature two topologically same 33 bus systems are referred which lead to ambiguity. In fact, there is very little difference between the two as far as the line data are concerned. The load data and tie-line data are exactly the same. In this paper, the original 33 bus system (popularly known as Baran and Wu system) is named as TS-2A and the latter revised version is named as TS-2B. Baran and Wu [61] introduced the test system TS-2A (Fig. 4). The figure

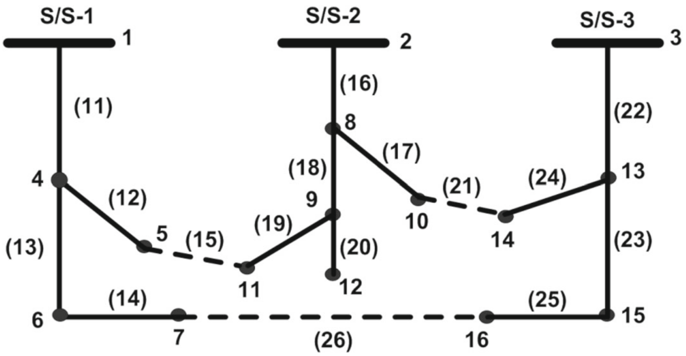

Fig. 2 TS-1 before reconfiguration

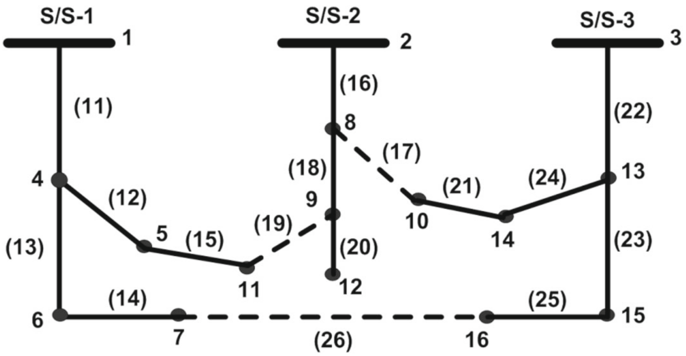

Fig. 3 TS-1 after reconfiguration

(as reported in [61]) has been redrawn and the bus numbering is slightly changed as followed by most of the researchers. The branches are indexed as 1 less than the corresponding receiving end bus and tie lines are numbered as shown in the Fig. 4. The total active and reactive loads are 3715 kW and 2300 kVAr respectively. The base power and voltage are 10 MVA and 12.66 kV respectively. The line and load data of the system are available in [61]. The total active power loss of the original network is 202.65 kW (by authors' method) with open branches 33, 34, 35, 36 and 37.

On the other hand, in literature, some researchers [35,204] refer to a 33 bus test system as Baran and Wu test system but with slightly changed line data. For this system (named here as TS-2B), the line reactance of the line-1 (connecting bus 1 and 2 of Fig. 4) is 0.0477 Ω instead of 0.0470 Ω. Similarly, the line resistance and reactance of line 7 (connecting bus 7 and 8 of Fig. 4) are 1.7114 Ω and 1.2351 Ω instead of 0.7111 Ω and 0.2351 Ω respectively. All other data including that of load and tie-line data are same as TS-2A. As a result, the total active power loss of TS-2B comes out to be 210.97 kW (by authors' method) with open branches 33, 34, 35, 36 and 37. The various reconfiguration results for the TS-2A and TS-2B are presented in Table 5, which clearly shown how the two systems' results have been mixed up leading to confusion. The reconfiguration results of TS-2B are shown as bold results in

Table 4 LF required by the PDNR methods for TS-1

PDNR methods	Civanlaret al. [60]	Castro and Watanabe [64]	Raju and Bijwe [101]	Gomes et al. [94]	Gomes et al. [18]	Oliveira et al. [116]	Carreno et al. [142]	Chiou et al. [159]	Wang and Gao [147]
No. of LF reqd.	3[a]	2	7	36[b]	18 + 3 (OPF)[b]	6	17	250	25

[a] As reported in Castro and Watanabe [64]
[b] As reported in Raju and Bijwe [101]

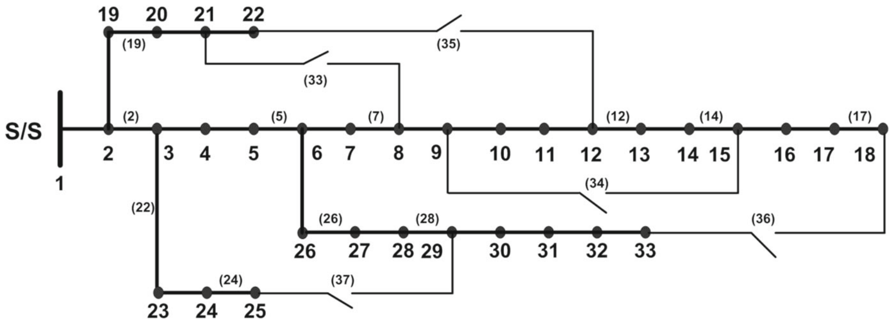

Fig. 4 33 bus test system-TS-2 (A&B)

Table 5. The global minimum loss for TS-2A and TS-2B are reported to be 139.55 kW, however, many researchers report lesser values marked also as bold results in Table 5.

4.3 69 bus test system-TS-3

Like TS-2, in literature researchers have also considered two topologically same 69 bus networks, referred as TS-3A and TS-3B in this paper.

4.3.1 TS-3A

Baran and Wu [207] introduced this 12.66 kV test system (Fig. 5). The initial network has open branches 69 (11–43), 70 (13–21), 71 (15–46), 72 (50–59) and 73 (27–65). The total active and reactive loads are 3802.19 kW and 2964.6 kVAr respectively. The base power and voltage are 10 MVA and 12.66 kV respectively. The reconfiguration results for this test system are presented in Table 6. Although, the global minimum value is reported to be 99.6 kW, many researchers reported lesser values shown as bold results in Table 6. Here, again, heuristic methods are proven to be much faster.

4.3.2 TS-3B

Chiang and Jimeau [47,48] introduced this test system (Fig. 6). The bus and branch numbering are maintained same as in the first paper. The initial network has open branches 69 (10–70), 70 (12–20), 71 (14–90), 72 (38–48) and 73 (26–54). The total active and reactive loads are 1107.91 kW and 897.93 kVAr respectively. For this test system, two sets of different reconfiguration results are reported. As pointed out by Ramos et al. [126], this is due to the value of base voltage considered. Chiang and Jimeau, considered the base voltage as $11/\sqrt{3}$ kV resulting initial power loss as 69.76 kW, whereas, in papers where the base voltage is considered as 11 kV, the initial loss is 20.88 kW. The reported global minimum values are shown as bold results in Table 7.

Table 5 TS-2A and TS-2B reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
202.68[b]	Not reported	139.55[b]	Not reported (nr)	nr	nr	Shirmohammadi and Hong [63][b]
211.0[a]	nr	147.99[a]	11, 28, 31, 33, 34[a]	nr	nr	Baran and Wu [61][a]
205.81	$V_{18} = 0.9125$	140.8154	7, 9, 14, 32, 37	$V_{32} = 0.9376$	0.87s[d]	Goswami and Basu [69]
203.2	0.9130	139.7	7, 9, 14, 32, 37	0.9378	48 s	Chang and Kuo [149]
191.427	nr	134.950	nr	nr	8	Fan et al. [77]
202.67[d]	0.913[d]	139.53[d]	7, 9, 14, 32, 37[d]	0.9378[d]	1.99s[d]	McDermott et al. [86]
204.14	0.91	143.21	6, 9, 14, 32, 37	0.9378	6	Kashem et al. [87]
203	nr	139.76	7, 9, 14, 32, 37	nr	61[e]	Lin et al. [136]
202.674	$V_{18} = 0.9131$	139.532	7, 9, 14, 32, 33	nr	nr	Zhu [137]
211.22	**0.9038**	**139.83**	**7, 9, 14, 32, 37**	**0.9378**	**55.04s**	**Venkatesh and Ranjan** [156]
176.6	0.92	127.4	7, 9, 14, 32, 37	0.939	0.017 s	Jeon and Kim [153]
196.5	nr	136.355	7, 9, 14, 32, 37	nr	0.043 s	Li et al. [164]
211.22	**0.9038**	**128.26**	**6, 9, 14, 32, 37**	**0.9378**	**62.07s**	**Venkatesh et al.** [39]
202.68[b]	nr	139.55[b]	Nr	nr	135[b]	Gomes et al. [94]
nr	nr	139.54	7, 9, 14, 32, 37	$V_{32} = 0.9378$	0.8 s	Ramos et al. [122]
202.68	nr	139.55	7, 9, 14, 32, 37	nr	37/0.41 s	Martin and Gil. [99]
202.68	nr	139.55	7, 9, 14, 32, 37	nr	11	Raju and Bijwe [101]
202.7	nr	139.5	7, 9, 15, 32, 37	nr	<0.5 s	Wang and Cheng [194]
202.677	$V_{18} = 0.9131$	139.55	7, 9, 14, 32, 37	$V_{32} = 0.9378$	nr	Khodr et al. [124]

Table 5 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
202.67	0.913	139.53	7, 9, 14, 32, 37	0.938	6 s	Niknam [27]
202.05	$V_{18} = 0.9136$	139.21	7, 9, 14, 32, 37	$V_{33} = 0.9379$	nr	Singh et al. [103]
202.674	nr	141.541	7, 10, 14, 33, 37	nr	nr	Zhu et al. [104]
207.92	nr	129.7	7, 9, 14, 32, 37	nr	nr	Chandramohan et al. [46]
210.993	**nr**	**109.5909**	**11, 28, 31, 34, 37**	**nr**	**8/0.361s**	**Abul'Wafa** [106]
202.68	0.9131	139.55	7, 9, 14, 33, 37	0.9378	nr	Ramos et al. [126]
204.14	nr	126.01	7, 11, 14, 28, 36	nr	nr	El Ramli et al. [127]
202.68	0.9131	139.55	7, 9, 14, 32, 37	0.9378	2.34 s	Gupta et al. [185]
202.7	0.9131	139.5	7, 9, 14, 32, 37			Macedo-Braz and Desouza [30]
202.67	0.913	139.53	7, 9, 14, 32, 37	0.9378	~8	Niknam and Sadseghi [179]
202.771	$V_{18} = \mathbf{0.9131}$	**138.067**	**7, 10, 14, 36, 37**	$V_{33} = \mathbf{0.9342}$	**7.2s**	**Rao et al.** [192]
202.743	**nr**	**136.806**	**7, 10, 14, 32, 37**	**nr**	**nr**	**Safar et al.** [172]
202.68	0.9131	139.516	7, 9, 14, 32, 37	0.9378	32/0.3 s	Swarnakar et al. [173]
210.98	**nr**	**139.55**	**7, 9, 14, 32, 37**	**nr**	**nr**	**Amanulla et al.** [188]
nr	nr	139.552	7, 9, 14, 32, 37	$V_{32} = 0.9378$	nr	Borghetti [128]
202.67	nr	139.98	7, 9, 14, 28, 32	nr	nr	Bouhouras and Labridis. [108]
nr	nr	139.55	7, 9, 14, 32, 37	0.9378	1 s	Ibbora et al. [129]
nr	nr	139.55	7, 9, 14, 28, 32	nr	19 s	Lavarto et al. [9]
202.71	nr	135.78	7, 9, 13, 14, 32	nr	nr	Satish and Jaybharthi [177]

Table 5 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Remarks	
Before reconfiguration		After reconfiguration					
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)			
202.7	0.91309	139.5	nr	0.94128	12.8 s	Taylor and Hover [131]	
211.0	nr	139.55	7, 9, 14, 32, 37		6	Zin et al. [111]	
203	$V_{17} = 0.9129$	139.5	7, 9, 14, 32, 37	$V_{31} = 0.9378$	–	Abdelaziz [174]	
nr	nr	nr	7, 9, 14, 32, 37	nr	2.13 s	Barbosa et al. [53]	
202.68	nr	139.55	7, 9, 14, 32, 37	nr	0.12 s	Bayat [112]	
202.67	**0.9131**	**138.06**	**7, 9, 14, 32, 37**	**0.9342**	**nr**	**Rao et al.** [193]	**Normally loaded**
575.27	0.8529	380.43	7, 9, 14, 32, 37	0.8967	nr		Heavily loaded (1.6)
47.06	0.9583	33.27	7, 9, 14, 32, 37	0.9698	nr		Lightly loaded (0.5)
202.677	0.913	139.55	7, 9, 14, 32, 37	0.9378	3.05 s	Sedighizadeh et al. [191]	
202.68	nr	139.55	7, 9, 14, 32, 37	nr	5.704 s	Tomoiaga et al. [145]	
202.68[c]	nr	139.55[c]	7, 9, 14, 32, 37[c]	nr	27m4.98s[c]	Brute force Algorithm[c]	
202.7	nr	139.5	7, 9, 14, 32, 37	nr	360	Torres et al. [146]	
	nr	139.55	7, 9, 14, 32, 37	$V_{31} = 0.9378$	482	Wang and Gao [147]	
202.7	nr	139.9	7, 9, 14, 28, 32		0.037 s	Ahmadi and Marti [113]	
210.99	**0.9038**	**129.52**	**6, 10, 14, 28, 32**	**0.9445**	**nr**	**Aman et al.** [204]	
202.68	Nr	140.28	7, 10, 14, 32, 37	nr	2.7 s	Dall'Anese and Giannakis [133]	
202.67	0.9131	139.98	7, 9, 14, 28, 32	0.9413	6.4 s	Imran and Kowsalya [196]	
202.67	$V_{18} = 0.9131$	139.98	7, 9, 14, 28, 32	$V_{32} = 0.9413$	nr	Imran et al. [197]	Normally loaded
575.31	$V_{18} = 0.8529$	381.24	7, 9, 14, 28, 32	$V_{32} = 0.9027$	nr		Heavily loaded (1.6)

Table 5 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
47.06	$V_{18} = 0.9583$	33.39	7, 9, 14, 28, 32	$V_{32} = 0.9714$	Nr	Lightly loaded (0.5)
202.68	**0.9131**	**136.57**	**7, 9, 14, 32, 37**	**0.9375**	**~0.31s**	**Ghasemi and Moshtagh** [26]
202.68	nr	139.5	7, 9, 14, 32, 37	nr	6.73 s	Narimani [55]
202.5	nr	139.51	7, 9, 14, 32, 37	nr	nr	Mirhoseini et al. [201]
202.68	**V = 0.9131**	**136.57**	**7, 9, 14, 32, 37**	**V = 0.9378**	**10/0.41s**	**Oliveiraet et al.** [116]
202.68	nr	139.5	7, 9, 14, 32, 37	nr	16.9 s	Oliveira et al. [176]
202.418	$\mathbf{V_{18} = 0.9237}$	**134.61**	**7, 9, 14, 28, 32**	$\mathbf{V_{32} = 0.9604}$	**nr**	**Shuaib et al.** [195]
202.6	0.9131	139.5	7, 9, 14, 32, 37	0.9378	3.38 s	Teimourzadeh [205]
210.99	–	**139.55**	**7, 9, 14, 32, 37**	–	**0.6s**	**Duan et al.** [35]

[a] Reported in Zin et al. [111]
[b] Reported in Raju and Bijwe [101]
[c] Reported in Tomoiaga et al. [145]
[d] Reported in Niknam and Sadseghi [178]
[e] Carreno et al. [142]

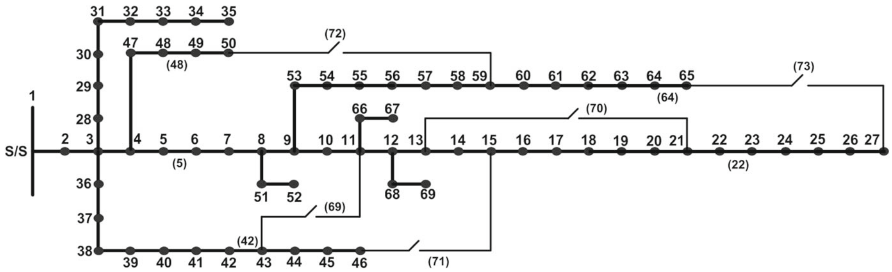

Fig. 5 69 bus test system-TS-3A

4.4 70 Bus test system-TS-4

Two topologically same 70 bus test distribution systems are commonly considered by researchers, known as TS-4A [40] and TS-4B [97] in this paper.

4.4.1 TS-4A

An 11 kV, 70 bus radial distribution system with 2 sub stations and 4 main feeders [40] is shown in Fig. 7. The base values for voltage and power are 11 kV and 100 MVA respectively. The substation buses are numbered as 1 and 70 respectively. The details of the test system with 11 tie lines are presented in [40]. The various reconfiguration results are presented in Table 8, where a minimum value of the loss is reported as 201.395 kW (marked bold in Table 8).

4.4.2 TS-4B

TS-4B is topologically the same as TS-4A network with same line data. However, it has 8 tie lines as shown in Fig. 8 and the load data are also different. The details of the test system with 8 tie lines are available in [97]. The various reconfiguration results are presented in Table 9, where a minimum value of the loss is reported as 301.6 kW.

4.5 84-bus test system-TS-5

Su and Lee [158] introduced this 11.4 kV test system (Fig. 9), which has 11 feeders, 13 tie-lines, and 83 branches. All most all methods confirm the global minimum loss of 469.88 kW except in [26] and [178] which report a minimum loss of 463.29 kW shown as bold results in Table 10.

4.6 119 bus test system-TS-6

This system [17] is an 11 kV distribution system with 118 normally closed branches and 15 tie switches as shown in Fig. 10. The total active and reactive power loads are

Table 6 TS-3A reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks	
Before reconfiguration		After reconfiguration					
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)			
225[a]	nr	99.62[a]	14, 56, 62, 70, 71[a]	nr	nr	Baran and Wu [61][a]	
224.93	0.909	119.91	nr	0.9410	101.81 s	Jiang and Baldik [150]	
225.05	0.9092	99.61	nr	0.9428	19.4 s	Kashem et al. [83]	
224.96	nr	104.93	10, 13, 56, 61, 70	nr	3.28 s	Ghosh and Das [91]	
224.97	**nr**	**96.06**	**12, 20, 56, 63, 69**	**nr**	**nr**	**Prasad et al.** [21]	
224.7	$V_{65} = 0.9093$	99.6	15, 58, 62, 70, 71	$V_{61} = 0.9428$	8 s	Gupta et al. [43]	
225	nr	99.62	Diff. fig. given	nr	~4 s	Niknam et al. [186]	
224.95	$V_{65} = 0.9092$	99.59	14, 56, 63, 69, 70	$V_{63} = 0.9483$	1.8 s	Savier and Das [107]	
224.69	0.9093	99.59	14, 56, 61, 69, 70	0.9428	3.3 s	Swarnakar et al. [173]	
225	nr	99.62	15, 56, 62, 70, 71	nr	10	Zin et al. [111]	
nr	**nr**	**94.026**	**13, 21, 56, 62, 70**	**nr**	**9.4s**	**Barbosa et al.** [53]	
224.95	**nr**	**98.581**	**15, 56, 62, 70, 71**	**nr**	**0.42s**	**Bayat** [112]	
225	0.9092	99.35	13, 18, 56, 61, 69	0.9428	nr	Rao et al. [193]	Normally loaded
652.53	0.8445	271.42	13, 18, 55, 61, 69	0.9048	nr		Heavily loaded (1.6)
51.61	0.9567	23.72	14, 57, 61, 69, 70	0.9722	nr		Lightly loaded (0.5)
nr	nr	nr	Nr	nr	4.639 s	Tomoiaga et al. [145]	
nr	nr	99.62	14, 55(−58), 61, 69, 72	$V_{50} = 0.9428$	539	Wang and Gao [147]	
224.95	**nr**	**98.59**	**14, 55, 61, 69, 70**	**Nr**	**nr**	**Aman** [204]	
225	**0.91**	**98.59**	**14, 58, 61, 69, 70**	**0.95**	**0.5s**	**Ding and Laparo** [115]	

Table 6 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks	
Before reconfiguration		After reconfiguration					
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)			
224.93	**0.909**	**98.59**	**14, 58, 61, 69, 70**	**0.9495**	~0.315 s	**Ghasemi and Moshtagh** [26]	
224.96	$\mathbf{V_{65} = 0.9092}$	**98.59**	**14, 56, 61, 69, 70**	$\mathbf{V_{61} = 0.9495}$	**nr**	**Imran et al.** [197]	**Normally loaded**
652.42	$V_{65} = 0.8445$	267.08	14, 56, 61, 69, 70	$V_{61} = 0.9165$	nr		Heavily loaded (1.6)
51.60	$V_{65} = 0.9567$	23.61	14, 56, 61, 69, 70	$V_{61} = 0.9754$	nr		Lightly loaded (0.5)
224.646	**Nr**	**98.5707**	**14, 57, 61, 69, 70**	**nr**	**nr**	**Mirhoseini et al.** [201]	
224.894	$\mathbf{V_{65} = 0.9092}$	**98.5718**	**14, 58, 61, 69, 70**	$\mathbf{V_{61} = 0.9495}$	**nr**	**Shuaib et al.** [195]	
224.99	**0.9092**	**98.78**	**12, 55, 61, 69, 70**	**0.9495**	**8.82s**	**Teimourzadeh** [205]	
225	nr	99.62	15, 59, 62, 70, 71	nr	8.31 s	Duan et al. [35]	

[a] Reported in Zin et al. [111]

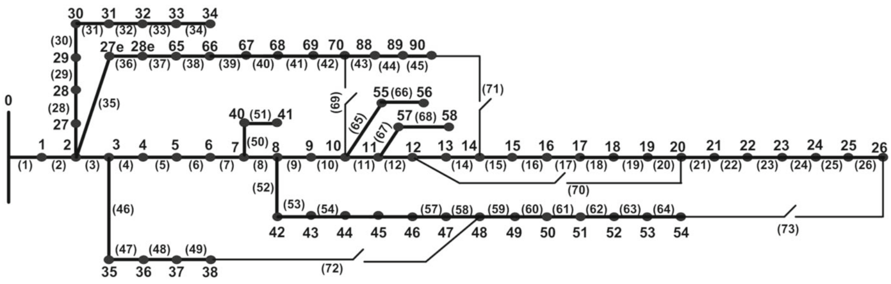

Fig. 6 69 bus test system-TS-3B

22,709.7 kW and 17,041.1 kVAr. The reconfiguration results as reported in various papers are presented in Table 11.

4.7 136 bus test system-TS-7

This is a 13.8 kV real distribution system with 136 buses and 156 branches located in Brazil [142]. The total active and reactive power load for the system is 18,313.8 kW and 7932.5 kVAr respectively [111]. The reconfiguration results for this test system as reported by various researchers are presented in Table 12. Most of the authors report a minimum reconfiguration network with total active power loss of 280.1 kW with the exception of Swarnakar et al. [144, 173] reporting the lowest power loss of 279.75 kW marked as blue cell in Table 12. The fastest method is found to be that of Zin et al. [111], a heuristic method, which takes only 51 load flows.

4.8 205 bus test system

The 205 bus test system is developed by [122] by triplicating the 69 bus TS-3B. The configuration and tie-line data are as presented in [122]. The reconfiguration results as reported in several papers are presented in Table 13.

4.9 Unbalanced test distribution systems (UTDS)

In literature, not many reconfiguration results with unbalanced radial systems have been reported. Here, some of the results are presented in Table 14.

5 Stochastic PDNR

With more uncertainties coming in smart distribution operations, PDNR with the stochastic environment has become the important current trend in research and perhaps has emerged as the most important future direction in PDNR research. With the growing trend of increased penetration of wind turbines (WTs), solar photo voltaic cells, fuel cells, plug-in hybrid electric vehicles(PHEVs) along with shift of focus to adopt

Table 7 TS-3B reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks	
Before reconfiguration		After reconfiguration					
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)			
69.76	0.9126	**30.085**	14, 56, 61, 69, 70	0.9439	nr	Chiang and Jemeau [48]	Normally loaded
104.229	0.8930	44.817	12, 14, 56, 61, 69	0.9319	nr		Heavily loaded
16.052	0.9583	8.11	9, 14, 19, 53, 61	0.9720	nr		Lightly loaded
20.88	0.9725	**9.43**	15, 56, 62, 70, 71	0.9824	165 s	Chang and Kuo [149]	Normally loaded
30.36	nr	13.66	15, 56, 62, 70, 71	nr	nr		Heavily loaded
5.09	nr	2.32	15, 56, 62, 70, 71	nr	nr		Lightly loaded
20.88	nr	**9.43**	15, 56, 62, 70, 71	nr	0.189 s	Li et al. [164]	
nr	nr	30.12[b]	nr	nr	212[b]	Gomes et al. [94]	
nr	nr	30.09	14, 58, 61, 69, 70	$V_{50} = 0.9452$	2.4 s	Ramos et al. [122]	
20.88	nr	**9.43**	14, 58, 61, 69, 70	nr	58/0.69 s	Martin and Gil [99]	
69.77	nr	30.09	13, 55, 61, 69, 70	nr	10	Raju and Bijwe [100]	
20.89	V_{54}=0.9724	**9.4**	14, 55, 61, 69, 70	$V_{50} = 0.982$	nr	Abdelaziz et al. [182]	
20.88	$V_{54} = 0.9724$	**9.4**	nr	$V_{50} = 0.98$	nr	Abdelaziz et al. [166]	Normally loaded
30.36	$V_{54} = 0.9669$	13.66	nr	$V_{50} = 0.978$	nr		Heavily loaded
5.09	$V_{54} = 0.9865$	2.32	nr	$V_{50} = 0.9913$	nr		Lightly loaded
69.77	0.9126	**30.085**	14, 56, 61, 69, 70	0.9439	nr	Ramos et al. [126]	Normally loaded
104.3	0.8930	44.77	12, 55, 63, 69, 70	0.9319	nr		Heavily loaded
16.034	0.9583	7.674	14, 56, 63, 69, 70	0.9727	nr		Lightly loaded
22.8465	nr	9.2229	12, 57, 61, 69, 70	nr	nr	Safar et al. [172]	Normally loaded

Table 7 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks	
Before reconfiguration		After reconfiguration					
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)			
33.2663	nr	13.3579	12, 57, 61, 69, 70	nr	nr		Heavily loaded
5.5590	nr	2.2731	12, 57, 61, 69, 70	nr	nr		Lightly loaded
nr	nr	30.093	15, 59, 62, 70, 71	$V_{61} = 0.9452$	nr	Borghetti [128]	Normally loaded
nr	nr	44.21	15, 59, 62, 70, 71	$V_{61} = 0.9335$	nr		Heavily loaded
nr	nr	7.177	15, 59, 62, 70, 71	$V_{61} = 0.9734$	nr		Lightly loaded
nr	nr	30.09	14, 58, 61, 69, 70	0.9452	0.7 s	Ibbora [129]	
69.78	$V_{66} = 0.9126$	30.09	15, 56, 62, 70, 71	$V_{62} = 0.9452$	nr	Franco et al. [132]	
20.87	nr	9.43	15, 58, 62, 69, 70	nr	3.35 s	Tomoiaga et al. [145]	
[a]20.87	nr	[a]9.43	[a]15, 58, 62, 69, 70	nr	[a]6h2m 15.715 s	Brute force algorithm[a]	

[a] Reported in Tomoiaga et al. [145]
[b] Reported in Raju and Bijwe [101]

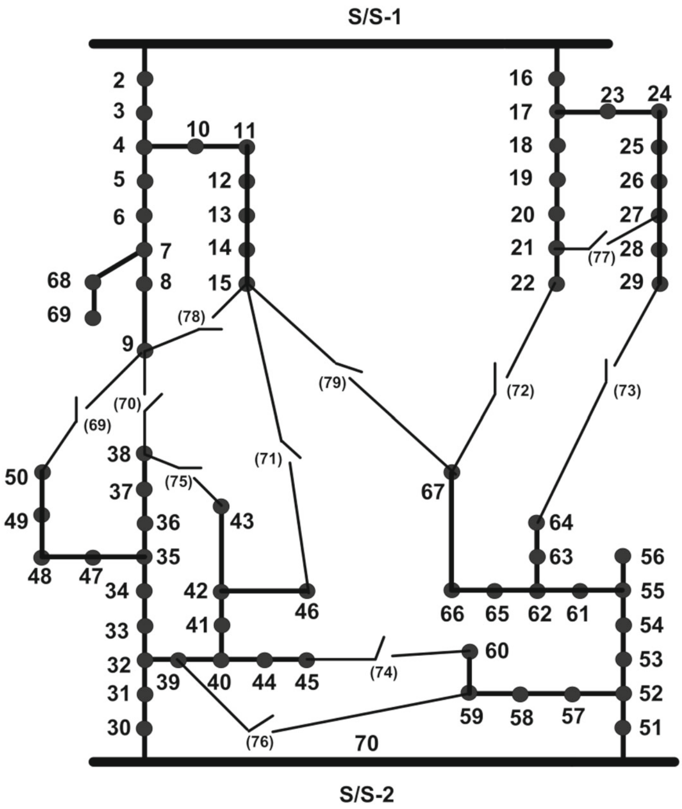

Fig. 7 70 bus test system-TS-4A

probabilistic reliability models have brought in uncertainties into the system. These uncertainty effects are handled through the following methods: (1) Monte Carlo simulation (MCS), which is the most popular method but requires very high computational effort. (2) Analytical methods, which is computationally more efficient but require some mathematical assumptions to solve the problem. (3) Approximate methods: which overcome the shortcomings of the previous two, hence are more useful. Most well-known approximate methods are: First order second-moment method and point estimation method.

Ammanulla et al. [188] used probabilistic reliability evaluation models for PDNR problem applying the minimal cutsets of components between the source and the load. A probabilistic power flow based on 2m PEM is employed to include uncertainty in the wind power generation output and demand concurrently[45,199], wind speed variations, failure rate, repair rate forecast errors [206], and cost of power loss and customer interruption cost [211,212]. In [213,214] the 2m PEM is used to capture uncertainty associated with the load demand prediction error as well as the variation of price rise of natural gas for proton exchange membrane fuel cell power plants (PEM-FCPPs), tariff for buying electricity from PEM-FCPP and grid, tariff for selling electrical energy, operation and maintenance cost, hydrogen selling price and fuel

Table 8 TS-4A reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
227.53	V_{67} (0.9052)	205.32	14, 28, 39, 46, 51, 67, 70, 71, 73, 76, 79	V_{29} (0.9268)	nr	Das [40]
227.523	nr	nr	14, 30, 38, 46, 51, 66, 70, 71, 76, 77, 79,	nr	160 s	Enacheanu et al. [4]
227.53	nr	203.861	13, 28, 45, 51, 67, 70, 73, 75, 76, 78, 79	nr	83/0.98 s	Martin and Gil [99]
227.53	0.9052	205.32	14, 28, 39, 46, 51, 67, 70, 73, 74, 78, 79	0.9268	8 s	Niknam [27]
227.5	0.9045	203.1	13, 30, 45, 51, 66, 70, 75–79	nr	Nr	MacedoBraz and Desouza [30]
227.53	nr	202.18	30, 46, 51, 66, 70.71, 75–79	nr	Nr	Niknam and Farsani [184]
227.53	nr	202.18	30, 46, 51, 66, 70.71, 75–79	nr	Nr	Niknam et al. [186]
227.53	0.9052	**201.395**	13, 30, 45, 51, 66, 70, 75–79	0.9312	382/19.72 s	Swarnakar et al. [173]
	nr	201.412	13, 30, 45, 51, 66, 70, 75–79	nr	36	Mena and Garcia [110]
227.346	nr	203.675	13, 28, 45, 51, 67, 70, 73, 75–79	nr	4.639 s	Tomoiaga et al. [145]
227.346[a]	nr	203.675[a]	13, 28, 45, 51, 67, 70, 73, 75–79[a]	nr	2d7h5m 13.354s[a]	Brute force algorithm[a]
227.5	nr	203.6	14, 30, 39, 45, 51, 66, 71, 75–78	nr	0.106 s	Ahmadi and Marti [113]
227.53	nr	202.149	30, 39, 45, 51, 66, 70, 71, 76–79	nr	Nr	Narimani et al. [55]

[a] Reported in Tomoiaga et al. [145]

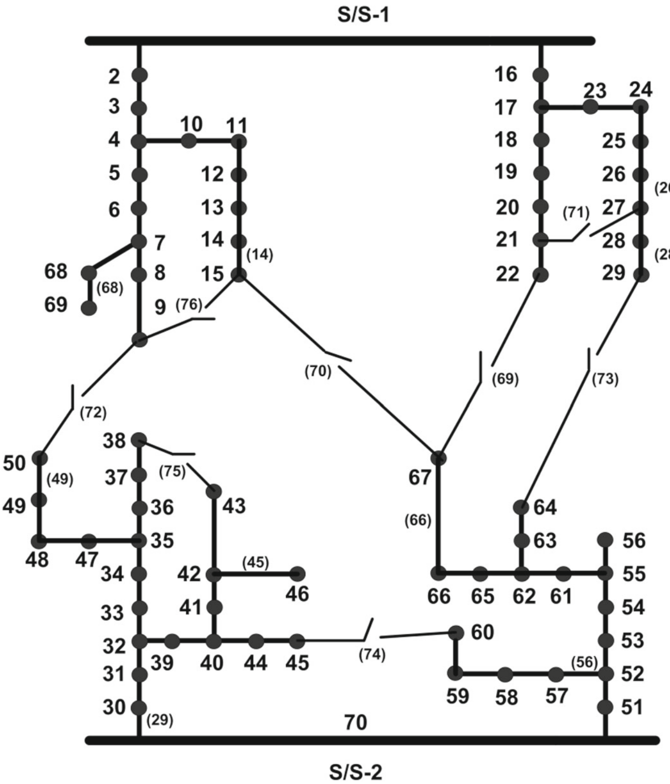

Fig. 8 70 bus test system-TS-4B

cost for supplying residential loads. Niknam et al. [215] considered uncertainty due to wind power generation output and demand and adopted a scenario based two-stage methodology. Rostami et al. [216] and Kavousi-Fard et al. [217] used MCS solving probabilistic optimal power flow to model stochastic charging behavior of plug-in hybrid electric vehicles (PHEVs) under different charging strategies. In [218,219], the 2m+1 PEM is used to capture the uncertainty of load and failure rate and repair rate forecast errors. Recently, Kavousi-Fard et al. [220] developed PDNR for smart grids with high penetration of PHEVs and wind power generation using a new stochastic framework based on unscented transformation (UT), which is an approximate method.

6 Present trends and future directions in research

The review also identifies following research directions concerning PDNR methods.

6.1 Application of new meta-heuristic approaches to the problem

This review reveals many new meta-heuristic methods, which are being proposed aiming to improve the PDNR approach such as GSA [55,195], FWO [196,197], TLBO [198,199], QFA [200], ICA [201], DABC [204], BGSA [205], BA [206] which also

Table 9 TS-4B reconfiguration results

Reconfiguration results					No. of LF reqd./ exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
337.45	V_{67} 0.88389	302.05	28, 46, 51, 67, 70, 73, 75, 76	V_{29} 0.91214	2 s	Das [97]
341.427	V_{67} 0.88389	301.645	nr	V_{29} 0.91551	nr	Khodr et al. [124]
341.4	V_{67} 0.8839	301.6	nr	nr	0.5 s	Taylor and Hover [131]
341.4	V_{67} 0.8839	301.6	nr	nr	2.8 s	Dall'Anese et al. [133]

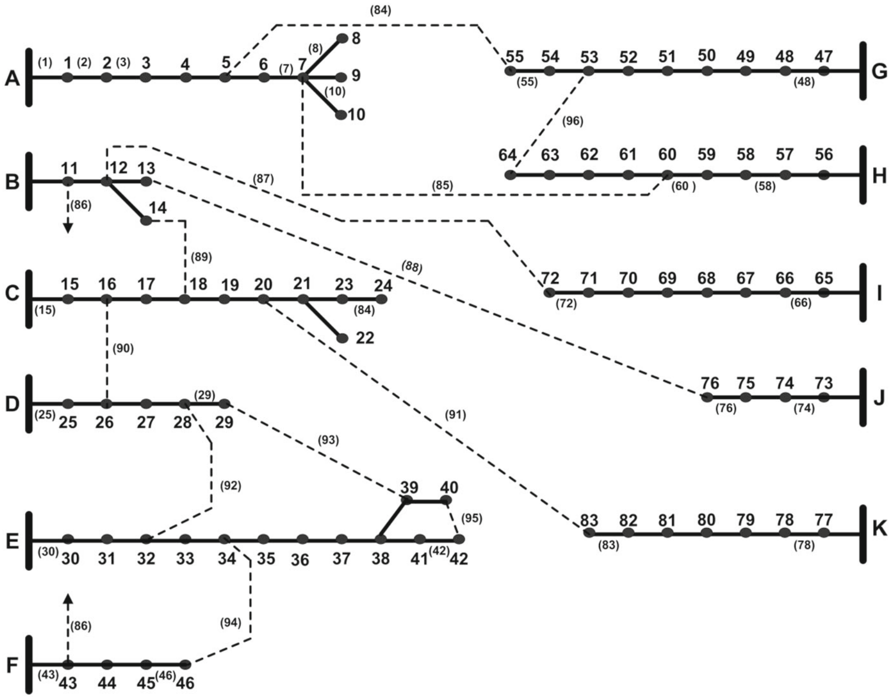

Fig. 9 84 bus test system-TS-5

confirms the scope of applying other new meta-heuristic optimization algorithms. Parameters of these heuristic approaches are selected by trial and error. These parameters can be tuned adaptively and automatically to improve the computational efficiency of the PDNR algorithms.

6.2 Inclusion of power quality and reliability indices in the objective

The review also reveals that for PDNR as far as the objectives are concerned, the focus has clearly shifted from traditional objectives like; minimization of PL, BVD, BCL, NS to maximization of reliability and power quality based indices. Most of the recently propose methods [20,26,31–35,41,49,50,54,55,188,200,203,206] include these objectives. The review also reveals that researchers prefer meta-heuristic approaches while dealing with reliability and power quality indices. All these research work on PDNR has been carried out for a particular load level, or at light, medium and high load levels or based on a load profile data of a day. However, load growth, addition or expansion of lines need to be included in the PDNR algorithms. Many utilities use voltage regulators in the distribution networks. Therefore, it will be interesting to investigate the network reconfiguration considering voltage regulators.

Table 10 TS-5 reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
531.99	V_9 (0.9285)	469.88	7, 13, 34, 39, 41, 55, 62, 72, 8386, 89, 90, 92	V_{71} (0.9531)	36.5 s	Su and Lee [158]
531.99	V_9 (0.9285)	469.88	7, 13, 34, 39, 41, 55, 62, 72, 83, 86, 89, 90, 92	V_{71} (0.9531)	2500[d]	Chiou et al. [159]
[b]531.99	nr	[b]470.88	nr	nr	[b]670	Gomes et al. [94]
nr	nr	469.87	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	291/0.2 s513/0.3 s	Carreno et al. [142]
531.99	nr	469.88	nr	nr	nr	Chang [170]
711.73	nr	624.81	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	133/1.73 s	Martin and Gil [99]
531.99	nr	469.877	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	40	Raju and Bijwe [100]
531.99	nr	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	113.25 s	Wang and Cheng [194]
531.99	nr	471.0706	7, 13, 34, 39, 41, 55, 62, 72, 83, 86, 89, 90, 92	nr	nr	Wu et al. [171]
531.99	0.9285	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	0.9532	92.19 s	Gupta et al. [185]
531.99	0.948	**463.2896**	7, 14, 34, 39, 42, 55, 62, 72, 83, 86, 88, 90, 92	0.9532	13 s	Niknam [178]
531.99	0.9285	468.68	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	0.9532	36.43 s	Swarnakar et al. [144]

Table 10 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
531.99	0.9285	469.311	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	0.9532	457/ 95.88 s	Swarnakar et al. [173]
nr	nr	469.878	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	$V_{71} = 0.9532$	nr	Borghetti [128]
nr	nr	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	0.9532	1.1 s	Ibbora et al. [129]
531.99	nr	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	207.7 s	Jabr et al. [130]
nr	nr	469.88	7, 13, 34, 39, 62, 72	nr	3030 s	Lavarto et al. [9]
nr	nr	470.89	7, 34, 39, 42, 55, 63, 72, 82, 86, 88, 89, 90, 92	nr	48	Zin et al. [111]
nr	nr	471.73[c]	7, 33, 39, 42, 63, 72, 82, 84, 86, 88, 89, 90, 92[c]	nr	nr	Shirmohammadi and Hong [63][c]
531.99	nr	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	0.77 s	Bayat [112]
531.99	0.9285	471.62	7, 33, 38, 55, 62, 72, 83, 86, 88, 89, 90, 92, 95	0.95318	13.25 s	Sedighizadeh et al. [191]
531.995	nr	469.878	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	7.809 s	Tomoiaga et al. [145]
531.995[c]	nr	469.878[a]	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	3d2h8m 21.587s[a]	Brute force Algorithm[a]
531.99	nr	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	nr	1233	Torres et al. [146]

Table 10 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
nr	nr	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	V_{71} 0.9532	nr	Wang and Gao [147]
532	nr	470.08	7, 34, 39, 42, 63, 72, 83, 84, 86, 89, 90, 92	nr	0.174 s	Ahmadi and Marti [113]
531.99	0.948	**463.29**	7, 14, 34, 39, 42, 55, 62, 72, 83, 86, 88, 90, 92,	0.9532	1.21 s	Ghasemi and Moshtagh [26]
nr	V_9 (0.9324)	nr	7, 34, 39, 42, 55, 63, 72, 82, 86, 88, 89, 90, 92	V_{71} 0.9557	26/2.34 s	Oliveira et al. [116]
531.99	V_9 (0.93)	469.88	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	V_{71} (0.95)	nr	Oliveira et al. [176]

[a] Reported in Tomoiaga et al. [145]
[b] Reported in Raju and Bijwe [101]
[c] Reported in Zin et al. [111]
[d] Reported in Carreno et al. [142]

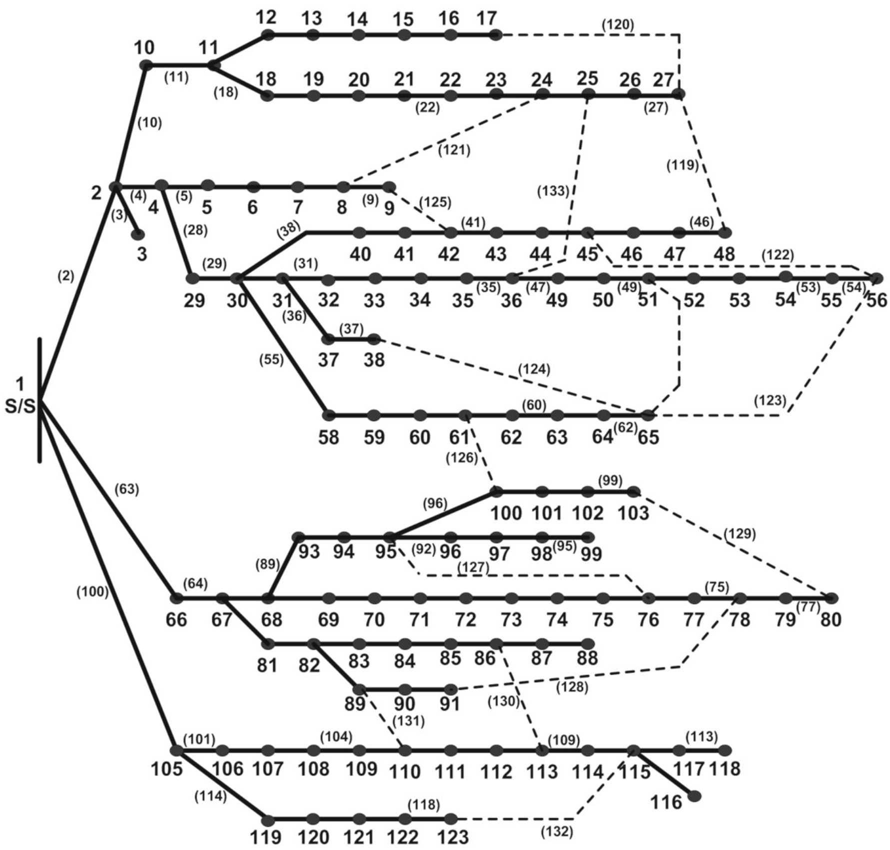

Fig. 10 119 bus test system-TS-6

6.3 Pareto optimality in multi-objectives

Clearly, the trend in MO-PDNR is for finding a set of non-dominated solutions or pareto fronts instead of going for a single optimized solution as this is best suited for practical operating conditions. Based on the requirement referring to a particular operating condition, a suitable solution can be selected out of the set of non-dominated pareto optimized solutions, e.g the fuzzy clustering approach used in [52,55,203,206].

6.4 PDNR involving DGs and FACTS devices

With the growing penetration of DGs, many researchers have already proposed PDNR methods involving DGs [25,34,45,55,114,115,128,132,171,193,195,197,199,202,206].

Jazebi et al. [208] have proposed optimal placement of D-STATCOMs with PDNR in DS. Hence, further research is required to investigate PDNR with simultaneous placement of DGs, capacitors, FACTS devices and protection devices [209]. Issues

Table 11 TS-6 reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
1298.09[a]	nr	[a]881.96	nr	nr	[a]1221	Gomes et al. [94]
1294.3	V_{116} (0.9321)	865.865	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	V_{116} (0.9323)	9.038 s	Zhang et al. [17]
nr	nr	874.858[b]	23, 34, 39, 42, 48, 50, 58, 71, 74, 95, 97, 109, 119, 129, 130[b]	nr	177[b]	Martin and Gil [99]
1298.09	nr	870.35	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 99, 110, 123, 130, 131	nr	26	Raju and Bijwe [101]
1294.3	V_{116} (0.866)	865.86	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	V_{116} (0.9321)		Abdelaziz et al. [166]
nr	nr	869.726	23, 26, 34, 39, 42, 51, 58, 71, 74, 95, 97, 109, 122, 129, 130	nr	53	Mena and Garcia [110]
1298.09	V_{116} (0.8783)	854.205	23, 27, 33, 43, 53, 62, 72, 75, 125, 126, 129, 130, 131, 132, 133	V_{116} (0.9323)	8.61 s	Rao et al. [192]
1298.1	0.8688	865.865	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	0.9323	1942/ 430.74 s	Swarnakar et al. [173]
nr	nr	869.69	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 99, 110, 123, 130, 131	0.9323	4.4 s	Ibbora et al. [129]
nr	nr	853.58	nr	nr	4007 s	Lavarto et al. [9]
1294.68	nr	865.322	23, 27, 33, 40, 43, 49, 52, 62, 72, 74, 77, 83, 110, 126, 131	nr	15min	Abdelaziz [174]

Table 11 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
1282.5	nr	853.58	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	nr	1.45 s	Bayat [112]
nr	nr	854.03	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	V_{111} 0.9323	nr	Wang and Gao [147]
1298.1	nr	883.5	23, 26, 34, 39, 42, 52, 58, 70, 73, 75, 95, 109, 122, 129, 130	nr	0.284 s	Ahmadi and Marti [113]
1298.1	$V_{77} = 0.869$	nr	nr	0.932	7.82 s	Ding, Laparo [115]
1301.9	0.8783	865.86	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	0.9323	2.47 s	Ghasemi and Moshtagh [26]
1298.09	V_{78} 0.8688	854.06	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	0.9323	7.72 s	Imran and Kowsalya [196]
1296.6	V_{77} 0.87	853.58	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	V_{111} (0.93)	704.1 s	Oliveira et al. [176]
1294.3	0.9711	793.04	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 107, 122, 130, 131	0.9825	18.34 s	Teimourzadeh and Zare [205]

[a] Reported in Raju and Bijwe [101]
[b] As reported in Mena and Garcia [110]

Table 12 TS-7 reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
320.36[a]	nr	293.29[a]	9, 35, 50, 51, 54, 90, 92, 96, 104, 106, 126, 135–36, 138, 143, 144–46, 148, 150, 155[a]	nr	nr	Shirmohammadi and Hong [63][a]
320.3	nr	280.1	7, 35, 51, 90, 96, 106, 118, 126, 135, 137–38, 141–42, 144–48, 150–51, 155	nr	0.4 s	Carreno et al. [142]
320.4	0.9307	280.22	7, 51, 83, 84, 90, 96, 106, 118, 126, 128, 137, 138, 139, 141, 144–45, 147–48, 150–51, 156	0.9580	3600 s	Cebrian and Kagan [23]
320.3	V_{117} 0.9307	280.13	51, 53, 90, 96, 106, 118, 136–139, 141, 144–148, 150, 151, 154–156	nr	nr	Gupta et al. [43]
320.17		281.72	38, 51, 53, 90, 96, 106, 119, 126, 136–38, 144–48, 150–52, 155, 156	nr	nr	El Ramli et al. [127]
320.4	0.9307	279.75	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142, 144–148, 150–51, 155	0.9602	403.83 s	Swarnakar et al. [144]
320.3	0.9307	279.75	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142, 144–148, 150, 151, 155	0.9602	3540/894.2 s	Swarnakar et al. [173]
nr	nr	280.166	7, 35, 51, 90, 96, 106, 118, 126, 135, 137–38, 141–42, 144, 145, 146–48, 150–51, 155	V_{105} 0.9589	nr	Borghetti [128]

Table 12 continued

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
320.36	nr	280.19	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142, 144–48, 150, 151, 155	nr	1800 s	Jabr et al. [130]
nr	nr	280.19	nr	nr	4473 s	Lavarto et al. [9]
nr	nr	280.13	nr	nr	2.35 s	Taylor and Hover [131]
320.36	nr	280.19	7, 35, 51, 90, 95, 106, 118, 126, 135, 137, 138, 141, 142, 144–48, 150, 151, 155	nr	51	Zin et al. [111]
320.36	nr	280.19	7, 35, 51, 90, 96, 106, 118, 126, 135, 137–38, 141–42, 144, 145–48, 150, 151, 155	nr	2.01 s	Bayat [112]
320.36	V_{116} 0.9306	280.19	7, 35, 51, 90, 96, 106, 118, 126, 135, 137–38, 141–42, 144–48, 150–51, 155	V_{105} 0.9589	nr	Franco et al. [132]
nr	nr	280.19	34, 94, 116, 128, 137–39, 141, 143–54	V_{105} 0.9589	nr	Wang and Gao [147]
320.4	nr	286.4	9, 35, 51, 54, 90, 96, 106, 126, 135–36, 138, 141, 143–48, 150–51, 155	nr	0.577 s	Ahmadi and Marti [113]
320.36	nr	280.19	7, 35, 51, 90, 96, 106, 118, 126, 135, 137–38, 141–42, 144–48, 150–51, 155	nr	33.98 s	Duan et al. [35]

[a] As reported in Zin et al. [111]

Table 13 TS-8 reconfiguration results

Reconfiguration results					No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration				
Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
Nr	nr	[a]87.07	13, 58, 61, 69, 70, 83, 85, 91, 97, 131, 134, 147, 148, 161, 168, 169, 206, 209, 217, 222[a]	0.9451 50C	134 s	Ramos et al. [122]
Nr	nr	87.718[a]	14, 58, 61, 69, 70, 85, 131, 134, 137, 142, 147, 148, 162, 206, 209, 217, 218, 222, 224[a]		213[a]	Martin and Gil [99]
Nr	nr	85.12		0.9452	153.9 s	Iborra et al. [120]
Nr	nr	85.986	12, 58, 61, 69, 70, 85, 98, 131, 133, 142, 143, 147, 148, 161, 168, 169, 206, 209, 217, 222	nr	71	Mena and Garcia [110]

[a] As reported in Mena and Garcia [110]

Table 14 Reconfiguration results of UTDSs

Reconfiguration results						No. of LF reqd./exec. time (s)	Method/remarks
Before reconfiguration		After reconfiguration					
Initial open branches	Initial PLoss (kW)	V_{min} (pu)	Final PLoss (kW)	Final open branches	V_{min} (pu)		
45 tie lines	506.84	nr	471.48	nr	nr	nr	Wang et al. [79]: 292-bus UTDS
25, 26, 27	450.38	nr	400.47	15, 17, 22	nr	10	Raju and Bijwe [101]: 25-bus UTDS
25, 26, 27	150.12	0.92841	136.13	15, 17, 22	0.93890	3/1.02 s	Subrahmanyam et al. [105]: 25-bus UTDS
		0.92839			0.94018		
		0.93890			0.94599		
19, 20	13.78	0.95196	8.42	10, 11	0.97043	6/1.56 s	Subrahmanyam et al. [105]: 19-bus UTDS
		0.95015			0.96954		
		0.94823			0.96724		
33, 34, 35, 36, 37	207.82	0.9225	143.87	7, 9, 14, 28, 32	0.9533	35/4.59 s	Swarnakar et al. [173]: 33-bus UDS
		0.9099			0.9300		
		0.9003			0.9323		
nr	42.37	nr	41.45	nr	nr	2.8 s	Dall'Anese [133]: IEEE 37-bus UTDS
25, 26, 27	150.12	0.93	44.53	6, 17, 26	0.954	0.28 s	Ding and Laparo [115]: 25-bus UTDS

such as maximizing the available delivery capability of UDSs with high penetration of DGs using PDNR [210] can be another interesting direction of research. It will be interesting to solve PDNR problem with the simultaneous placement of renewable DGs and energy storage devices considering future load growth.

7 Conclusions

In this paper, more than two hundred papers on PDNR methods have been reviewed. This review has clearly identified the various techniques adopted by researchers to solve PDNR problem. From this review it has been observed that heuristics methods mostly converge very fast to yield optimal configuration, however, the global optimal value cannot be guaranteed and in some cases these methods are not independent of initial configurations. Although, many meta heuristic methods have been proposed but out of all meta-heuristic PDNR methods, GA based PDNR methods are most popular and effective. Meta-heuristics methods although mostly give guaranteed global optimal results, but take long computational time to converge and hence, in some cases are blended with heuristics to increase the speed of convergence to make it suitable for real-time applications. Moreover, population-based meta-heuristic methods are preferred for POMO PDNRs and stochastic PDNRs.

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