

# Network Reconfiguration in Modern Power Distribution Networks



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**Abstract** This chapter introduces the Network Reconfiguration (NR) concept in Distribution Networks (DNs) as an efficient scheme to face various operational issues like reliability improvement and loss reduction. Furthermore, the potential for utilizing NR to perform voltage profile improvement under high DG or Renewable Energy Sources (RESs) penetration is presented. Finally, the coordination of the NR along with the optimal siting and sizing of DG units aiming to maximize their impact on loss reduction is also analyzed. The basic aim of this chapter is to demonstrate how specific automation upgrade in modern DNs regarding the replacement of manual switching equipment by automated controlled sectionalizers or tie-switches could allow Distribution System Operators (DSOs) to integrate real time management techniques of the DN under relatively low investment plans. Specific examples regarding both real and benchmarked DNs are included and the proposed algorithms are explained in detail.

## 1 Introduction

Modern power Distribution Networks (DNs) are experiencing significant alternations regarding both their structural and infrastructural aspects. The implementation of the Smart Grid concept, along with the high Distributed Generation (DG) and Renewable Energy Sources (RESs) penetration, have facilitated in upgrading the automation level in DNs and in establishing a more de-centralised generation model. On the one hand the installation of remote controlled elements [24], e.g. automatic

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reclosers and remote controlled circuit breakers, the enhanced metering capabilities under the Advanced Metering Infrastructure (AMI) and Phasor Measurements Units (PMUs) integration [29], as well as the upgraded Information and Communication Technology (ICT) capabilities [13] have radically changed the conventional form of the DNs by enabling the transition of their traditional passive profile to a more active one. In this latter context, all entities interact with each other in order to optimize their goals but at the same time they improve several operational aspects of the network with economic benefits for all parts. On the other hand, DG and RES penetration has reached or even exceeded saturation level in many parts of the DN, causing unexpected issues such as overvoltage and reverse power flow [1, 12]. Under these operating conditions, DNs undergo bidirectional power flow and its impact on protection schemes, e.g. one direction fault indicators and fault relays, should be faced properly to prevent the reliability level to be reduced. Additionally, the rapid penetration of Electric Vehicles (EVs) [35], the required charging lots that are scheduled to be installed, as well as the Battery Energy Storage Systems (BESSs) that are promoted as efficient storage solutions, in both distributed and centralized form, add complexity on the DN design, operation and management.

The DSOs are responsible for maintaining uninterrupted power supply via a reliable and robust DN under the minimum cost for both themselves and the consumers. Usually, the load growth demand along with mid or long term interferences to the grid are faced with respective investment plans regarding the reinforcement or the expansion of the DN [17]. Moreover, emergency situations like short circuit faults or other kind of outages have already been studied within a scenario case framework and based on simulations, emergency plans and guided actions have been developed. The problem is that the intermittent behavior of the RES generation and the time varying load demand along with the complexity added by EVs and BESS regarding the power control in the grid, render an imperative need for real time interventions. One of the most efficient ways to rearrange the power flow in the DN relies on exploiting its topology. DNs operate as radial networks, but they are designed as meshed ones. The concept here is that all main lines have at least two feeding points, but under normal operation conditions they are fed only by one. The other one plays the role of a standby alternative feeding source that is ready to supply the loads, all or some of them depending on the available capacity of the respective feeder, mainly in cases of outages. In these latter cases, appropriate switching operations could enable the line to be fed by two feeders and still preserve its radial structure. This intervention scheme is called Network Reconfiguration (NR) and it has initially been performed for reliability improvement during outages.

The implementation of NR has soon attracted a lot of interest, since it was found out that the layout alteration of the DN could change the loading level of the network's branches and yield voltage profile improvement and loss reduction. This potential is further enhanced by the fact that a great number of tie-switches in DNs enables numerous possible configurations and thus, it increases the possibility of yielding the best needed one under various loading and operational conditions of the network. Therefore, it could be found rational to believe that instead of adjusting the demand and generation power uncertainties of the current modern and rather

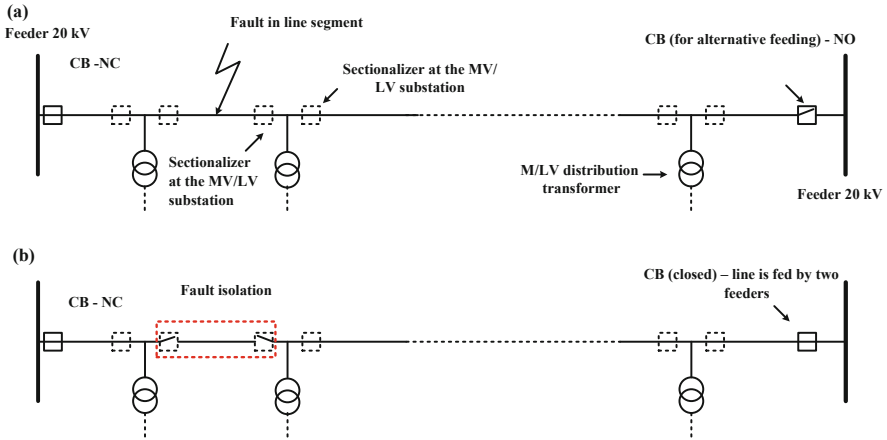
complex DN to the network's fixed topology, the opposite could more efficiently serve the Smart Grid concept towards the implementation of a more active and self-healing grid. For example, under high RES generation and reverse power flow, appropriate NR could mitigate the congestion of the DN and relief the branches overloading that cause overvoltage and loss reduction. Therefore, in this case, NR could contribute in increasing RES penetration in DNs. The same concept could also be implemented under the high load demand during the EVs charging while it could also be combined with the BESS operation to further exploit these potentials.

This chapter presents the concept of NR in DNs towards reliability improvement and loss reduction. Initially, reliability in DNs is analyzed along with its performance metrics, namely the reliability indices. Subsequently, the idea of NR in order to perform fault isolation and power restoration during an outage is described and some examples are presented. Some of the most widely utilized heuristic and metaheuristic based approaches are in turn discussed in order to highlight both the problem complexity and these aforementioned algorithms' contribution to solving the problem with less computational burden and within acceptable computational times. Next, the potential of NR to power and energy loss reduction is explained. Firstly, the respective section distinguishes power loss reduction from energy loss reduction by analyzing the problem's dependency from load variations for the latter case. Secondly, the problem formulation along with the respective NR scheme are analyzed for both cases and examples are given on benchmarked DNs. Finally, in the last section the idea of applying the NR scheme in modern DNs with high DG is examined in order to face new arising issues like reverse power flow and overvoltage and also to analyze the schemes of NR and optimal sizing and siting of DG units for loss reduction. At the end of the chapter the basic conclusions derived are discussed.

## 2 Reliability Improvement

### 2.1 Reliability in Distribution Networks

One of the earliest references in the reliability concept for DNs is presented by L.B Crann in [15], where the key role of the sectionalizing switches in DNs towards reliability improvement is explained for the first time. Moreover, reliability is directly related to the average time for which a consumer experiences an outage. Later on, other approaches pointed out that fault occurrence in DN follow a Markov chain [16] and that outages should not be considered independent to each other [18], because under such an approach the reliability level could be underestimated. Billinton [6, 7] was the first who tried to develop formulas to quantify both the frequency and the duration of the interruptions, which in turn led to the formulation of the reliability indices [34]. Reliability improvement refers to either the reduction of the interruption frequency in a DN or to the interruption time minimization after an outage. Obviously, the former has an impact on the latter but in order



**Fig. 1** Fault isolation and power restoration scheme in MV line

to efficiently manage the power restoration scheme, automation upgrade in DN switching equipment is necessary. This is due to the fact that the largest number of both sectionalizers and tie-switches is manually operated and thus the appropriate switching operations for fault isolation and power restoration could be very time consuming. Additionally, the guideline regarding the proper switching operation sequence has a vital role towards reliability improvement and several on/off real time methodologies have been presented [3, 21, 31]. In Fig. 1 a simple example referring to the fault isolation and power restoration scheme for a single radial MV feeder is presented, where CB refers to Circuit Breaker, NC to Normally Closed status, NO to Normally Open status and LV to Low Voltage.

In Fig. 1a a simple representation of the DN layout for a single line is illustrated where it is obvious that although the DN operates as a radial one it is actually designed as a meshed one since the line has the capability for simultaneous feeding by two respective MV feeders. In Fig. 1b the fault isolation and power restoration scheme are presented. The idea here is to locate the fault within the shortest possible line segment, i.e. between two adjacent MV/LV transformers, by opening the respective sectionalizers at these respective line edges. Then, the upstream part of the line will continue its feeding by the left MV feeder, while the loads of the downstream part of the line will be delivered (given that the capacity of the feeder is adequate) by the right MV feeder. In the case where the right-alternative MV feeder lacks of enough capacity to deliver all load of the downstream line part then some MV/LV transformers will inevitably be disconnected and their consumers will be out of service. In this latter case, these consumers will experience an outage and for them reliability issues will be raised.

The example shown in Fig. 1 is quite simple and the fault isolation and power restoration scheme is quite straightforward. In most MV DNs having numerous sectionalizers and many tie-switches the layout is more complex and therefore

many alternative configurations of the DN could perform the power restoration for the loads after the fault isolation. In these cases, the complexity of the problem regarding the optimal configuration that could efficiently restore power to the maximum possible number of consumers within the shortest time period is quite challenging, due to the numerous possible switching operations. Usually, such dynamic combinatorial problems with topology and operational constraints are described as Nondeterministic Polynomial time (NP) complexity class problems and they can be addressed by either real time operational schedules regarding the switching operations or by distributed advanced monitoring and operational schemes, like Multi-Agent systems [5]. Another alternative is to utilize heuristic and metaheuristic based methodologies [2, 32], in order to come up with a relatively efficient solution within acceptable computational time under a near-real time approach.

## 2.2 Reliability Assessment in DNs

The reliability level of a DN constitutes a performance indicator on the services provided to the consumers and thus within the liberalized energy market the customers are expected to have choices regarding not only the energy provider preferred but also the DSO. Thus, DSOs invest on automation upgrade and on advanced monitoring schemes in order to be able to respond to outages and to achieve power restoration as soon as possible. Alternatively, network reinforcements aim in reducing the interruption frequency across the network, causing a high reliability level that benefits both the operator and the consumers. Reliability cost is the cost for the DSO in order to reach a predefined reliability level via investments related to the two aforementioned approaches, while reliability worth is the benefit for the DSO by the obtained reliability improvement. From the economic point of view, we usually refer to cost of unreliability [20], which defines that the reliability worth should be matched with the customers' cost during an outage. Based on this clarification, the feasibility study of a DSO regarding potential investment should consider (a) the revenue after reliability improvement by the energy not supplied and (b) the benefit due to the fact that customer interruption cost would be reduced. In Fig. 2 the cost for both the DSO and the consumers in respect to reliability level is presented.

From Fig. 2 it is evident that for the consumers the higher the reliability the lower the interruption cost, since the outage time is lower, while for the DSO the case is completely the opposite, since investments are required in order to increase the reliability level of the DN. Still, the point where these two lines intersect, i.e. point A in Fig. 2, indicates the minimum of the total cost curve for both the DSO and the consumers in terms of the best tradeoff between the individual costs. In this context, the corresponding cost indicated by point A should be considered feasible by the DSO in order to perform investment plans for reliability improvement.

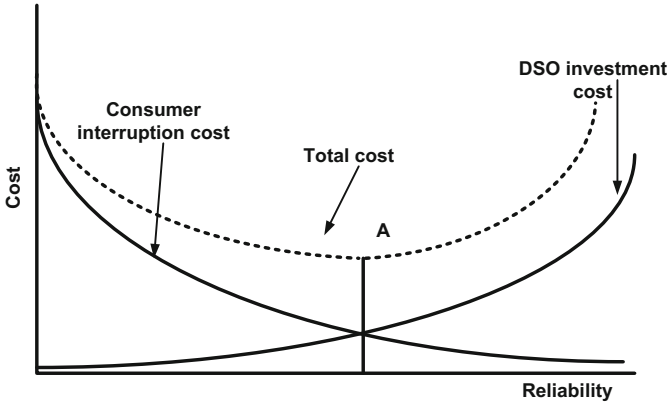


Fig. 2 Cost vs. reliability for both the DSO and the consumers

### 2.3 Reliability Indices

The most widely utilized indices for the evaluation of the reliability level for a DN are summarized as follows [34]:

- System Average Interruption Duration Index—SAIDI

$$SAIDI = \frac{\sum \text{Customer Interruption duration}}{\text{Total number of Customers served}} \tag{1}$$

For the computation of the index value, the following formulae is used:

$$SAIDI = \frac{\sum r_i N_i}{N_T} = \frac{CMI}{N_T} \tag{2}$$

where:

- $r_i$ : is the time needed for power restoration for each consumer,
- $N_i$ : is the number of consumers that experience an outage during the examined time period,
- $N_T$ : the total number of consumers served by the examined DN
- $CMI$ : outage duration for the consumer that experience the interruption
- System Average Interruption Frequency Index—SAIFI

$$SAIFI = \frac{\sum \text{Customers interrupted}}{\text{Total number of customers served}} \tag{3}$$

For the computation of the index value, the following formulae is used:

$$SAIFI = \frac{\sum N_i}{N_T} = \frac{CI}{N_T} \quad (4)$$

where:

- $CI$ : is the number of customers that experience an outage
- Customer Average Interruption Durations Index— $CAIDI$

$$CAIDI = \frac{\sum \text{Customer Interruption Duration}}{\text{Total number of customers interrupted}} = \frac{SAIDI}{SAIFI} \quad (5)$$

For the computation of the index value, the following formulae is used:

$$CAIDI = \frac{\sum r_i N_i}{N_i} \quad (6)$$

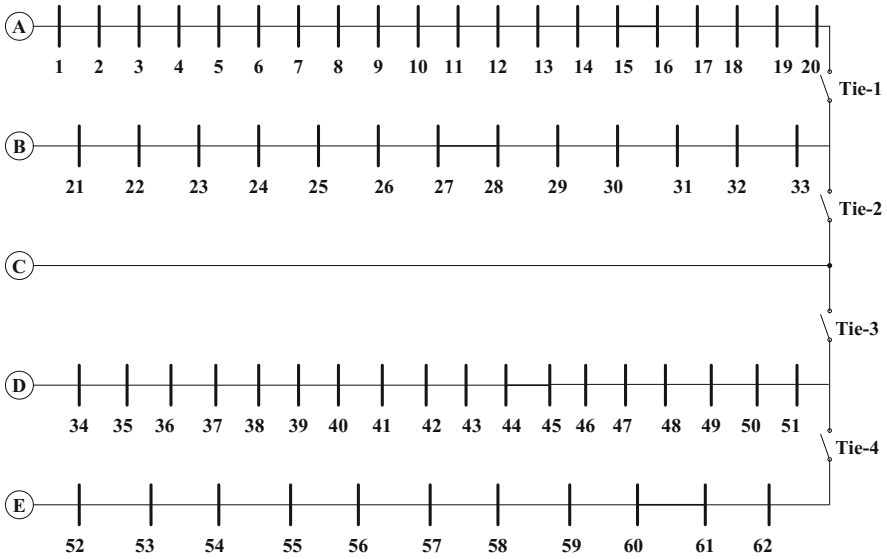
- Average Energy Not Supplied Index— $AENS$ , or Expected Energy Not Supplied— $EENS$

This index expresses the amount of energy that the consumer will fail to be provided due to the outage. Usually it is computed as the product of the average loading of the consumer during the outage to the duration of the outage and is expressed in kWh/year.

## 2.4 Selective Automation Upgrade for Reliability Improvement

In order to highlight the impact of automation upgrade in DNs towards reliability improvement, a simple example regarding the replacement of a small targeted number of manual sectionalizers with automated ones will be briefly presented. The examined real urban DN consists of five MV underground 3-phase cables and they all feed in total 62 MV/LV (20/0.4 kV) distribution transformers, as illustrated in Fig. 3. There are also four tie-switches at the ends of the lines in order to allow NR in cases of outages.

In order to keep the investment cost as lower as possible, only the case of upgrading the minimum possible number of sectionalizers will be examined and the impact on the reliability indices will be evaluated [10]. Therefore, it is considered that only the sectionalizers of the middle MV/LV transformer of each line are replaced with automated ones. Under this approach, it will be possible to immediately isolate the fault either to the first or to the second half of the faulted line, without the need for time delays caused by manual switching operations that



**Fig. 3** DN with manual sectionalizers

require human interference. After the isolation of the fault, the remaining manual switching operations have to be performed to only the half segment of the line, meaning that (a) almost half consumers will experience almost immediate power restoration (the healthy part of the line will be fed by an alternative feeder) and (b) the power restoration for the faulted line segment will be performed within a very short time period. In Fig. 4 the DN with the selected manual switches to be upgraded is presented, while in Table 1 the input data regarding the performed simulations for the reliability assessment are shown.

In Table 2 the simulation results (performed in Neplan<sup>®</sup> software package) [10] regarding the reliability improvement after the targeted automation upgrade are presented. It should be clarified that for the presented analysis only first order faults, i.e. only one fault at line segment, have been considered. It is observed that even under the examined limited automation upgrade with only two sectionalizers to be replaced by automated ones, the reliability improvement is significant for all lines. The latter is evident in both terms of SAIDI and EENS indices reduction. It should also be clarified that, as presented in Table 1, the initial CAIDI index value coincides with the considered time for power restoration in the initial state of the DN.



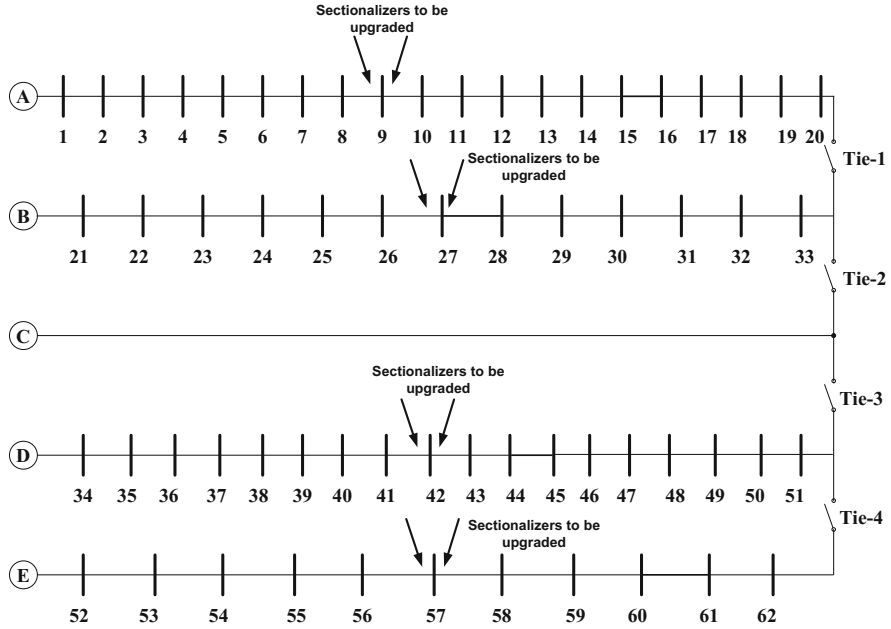


Fig. 4 Selected automation upgrade to targeted sectionalizers

Table 1 Reliability assessment input data

Number of MV/LV transformer	62
DN nominal capacity (kVA)	42.44
Total line length of DN (km)	20.743
Annual fault frequency (1/km/yr)	0.1
Average time for power restoration (h)	2

Table 2 Reliability improvement after targeted automation upgrade

Reliability Indices	Initial State				Automation upgrade state			
	Line A	Line B	Line D	Line E	Line A	Line B	Line D	Line E
SAIFI (1/yr)	0.63	0.49	0.53	0.436	0.63	0.49	0.53	0.43
SAIDI (min/yr)	74.77	58.95	64.13	51.07	45.73	28.39	34.65	38.05
CAIDI (h)	2	2	2	2	1.22	0.96	1.02	1.49
EENS (MWh)	3.41	1.288	2.60	1.12	2.10	0.66	1.335	0.85

### 3 Loss Reduction via Heuristic and Metaheuristic Algorithms for Network Reconfiguration

#### 3.1 Loss Reduction in DNs

The NR scheme that was initially utilized for reliability purposes was soon found to be an efficient technique towards loss reduction/minimization in DNs [27]. As in reliability improvement, the core concept here also relies on load transferring among feeders via tie-switches. The main idea behind this approach is that under a more efficient distribution of the network's loads to the available feeders, the loading of most lines could, as uniformly as possible, be also distributed among the feeders. Thus, since the power losses are in direct relationship with the square of the lines' current, even a small reduction of the lines' loading could yield significant loss reduction. The problem of loss reduction via NR is a mixed integer nonlinear programming problem (MINLP) with both binary and integer variables. An objective function  $OF$  could be formed as:

$$OF = \min \sum_{z=1}^{n_l} R_z I_z^2 \quad (7)$$

where:

- $n_l$ : is the total number of lines of the DN,
- $R_z$ : is the resistance of line  $z$ ,
- $I_z$ : is the rms current of line  $z$ .

The  $OF$  shown in Eq. (7) could be formed based only on the voltage values of the DN nodes, as presented in Eq. (8):

$$OF = \min \sum_{\substack{i,j=1 \\ i \neq j}}^{n_b} g_{i,j} (V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j)) \quad (8)$$

where:

- $n_b$ : is the total number of buses of the DN,
- $g_{i,j}$  is the conductance between buses  $i$  and  $j$ ,
- $V_i, V_j$  are the voltage magnitudes of buses  $i$  and  $j$ ,
- $\theta_i, \theta_j$  are the voltage angles of buses  $i$  and  $j$ .

Both of the  $OF$  variants presented in Eqs. (7) and (8) are subject to the following constraints under the NR scheme:

- equality constraints referring to the power flow equations, as in Eqs. (9) and (10):

$$\sum_{i=1}^{n_b} \left\{ P_{G,i} - P_{D,i} - \sum_{\substack{j=1 \\ i \neq j}}^{n_b} |V_i| |V_j| |Y_{i,j}| \cos(\delta_{i,j} - \theta_i + \theta_j) \right\}^2 = 0 \quad (9)$$

$$\sum_{i=1}^{n_b} \left\{ Q_{G,i} - Q_{D,i} + \sum_{\substack{j=1 \\ i \neq j}}^{n_b} |V_i| |V_j| |Y_{i,j}| \sin(\delta_{i,j} - \theta_i + \theta_j) \right\}^2 = 0 \quad (10)$$

where:

- $P_{G,i}$  is the real power generation on bus  $i$ ,
- $Q_{G,i}$  is the reactive power generation on bus  $i$ ,
- $P_{D,i}$  is the real power demand on bus  $i$ ,
- $Q_{D,i}$  is the reactive power demand on bus  $i$ ,
- $Y_{i,j}$  is the magnitude of bus admittance element  $i, j$ ,
- $\delta_{i,j}$  is the angle of bus admittance element  $i, j$ .
- upper and lower voltage limits for the DN as defined by inequality constraint in Eq. (11):

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (11)$$

where:

- $V_i^{min}$ : the lower voltage limit of bus  $i$ ,
- $V_i^{max}$ : the upper voltage limit of bus  $i$ .
- Loading level of each branch lower than its ampacity level as defined in inequality constraint in Eq. (12):

$$I_z \leq I_z^{max} \quad (12)$$

where:

- $I_z$ : is the maximum thermal line limit of line  $z$ .
- DN radial structure. The switching operation of an initially open tie-switch is expected to form a loop across the DN and thus at least one sectionalizer should open within the loop in order to reestablish the radial structure of the DN. The simplest formulation of this constraint is presented in Eq. (13):

$$n_l = n_b - 1 \quad (13)$$

### 3.2 Network Reconfiguration for Loss Reduction Based on Heuristics

The optimal solution for the loss minimization problem via NR refers to the identification of the proper switching operations in terms of closing a number of initially open tie-switches and of opening a respective number of sectionalizers, while all the constraints described earlier are satisfied. The problem here is that, given the number of switches for a DN is  $m$ , then the possible switching operations to be investigated are equal to  $2^m$ . The latter means that for a real DN with numerous sectionalizers the computational burden becomes very high and the problem cannot be solved within acceptable computational time. This is due to the fact that after a switching operation, a load flow analysis should be performed in order to evaluate the value of the  $OF$  and examine whether all constraints are satisfied. In Table 3 the required time for the load flows calculations regarding three small sized DNs are presented. It should be clarified that the time for a single load flow is approximately 25 ms, as derived by a load flow analysis software on an average PC.

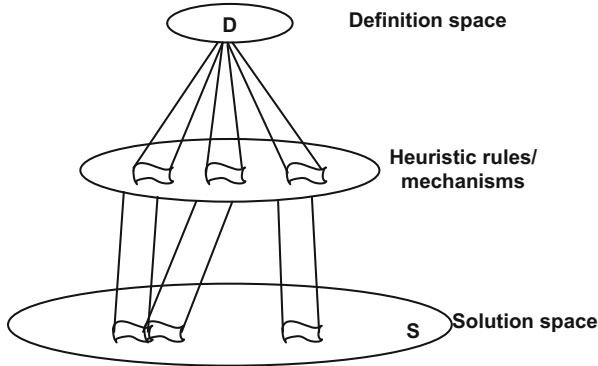
Based on the data in Table 3 it is quite evident that the exhaustive search of the solution space is very time consuming for this kind of problem. Even if the computational time for each load flow simulation may fall down to 1/1000 of the value utilized here, i.e. 25  $\mu$ s, it is clear again that the final solution could not be reached within a reasonable time period. This is where heuristics mechanisms come up to give the solution.

A heuristic mechanism is a solution search strategy that relies on prior knowledge about the problem which is used in order to facilitate the solution. Usually, this knowledge is matched with practical judgment that is ruled by common sense and is called heuristic rule. In general, the solution of problem by heuristics is faced as a form of mapping the definition space  $D$  of the problem to its solution space  $S$ . As stated earlier, the number of possible solutions for the NR problem is enormous and thus the exhaustive search of the solution space is time consuming. Heuristics mechanisms guide this search to specific parts of the solution space in order to speed up the solution procedure. In Fig. 5 a graphical representation of this scheme is illustrated.

The basic advantage of the heuristic algorithms is highlighted in Fig. 5, where it is obvious that through the heuristic rules the solution space search is limited to specific parts. The point though in this case is that since some parts are excluded,

**Table 3** Indicative simulation time for load flow simulations regarding a pair of switching operations

Number of sectionalizers for DN	Number of required load flow simulations	Total simulation time (s)
13	$2^{13}$	203
29	$2^{29}$	$1.33E + 07$
58	$2^{58}$	$7.2E + 15$



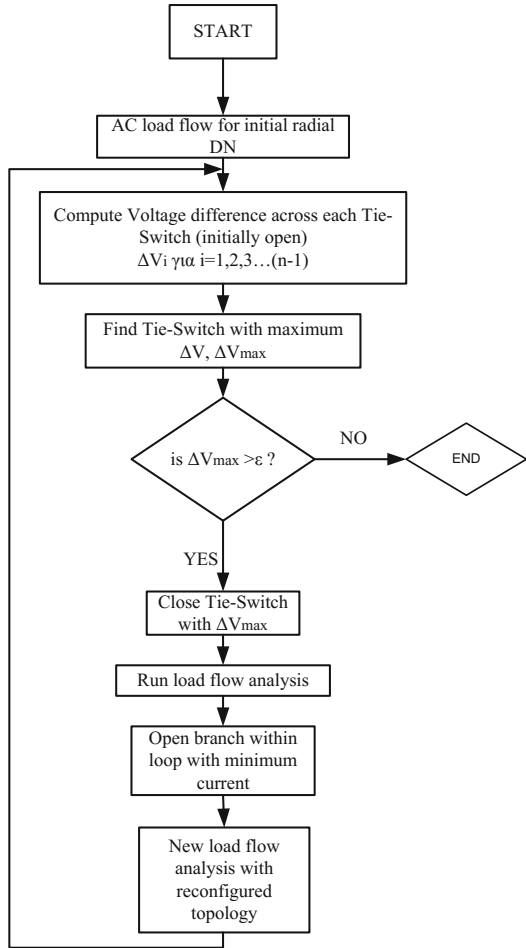
**Fig. 5** Graphical representation of heuristic mechanism

the algorithm cannot guarantee the global optimal regardless the performance of the heuristic rules. Moreover, since the heuristic rules constitute decision making rules that depend on prior knowledge about the problem, usually named as “knowledge of engineer”, they are case dependent and their efficiency is not ensured for all possible cases. Nevertheless, heuristics have been widely utilized for the NR problem, either as the sole solution algorithm or by acting as subsidiary subroutine to analytical or other optimization methodologies.

One of the first attempts to deal with the NR problems towards loss minimization was based on two simple heuristic rules [14] that aimed to guideline NR procedure in a specific manner that could perform both efficient loss reduction and minimum switching operations. The first heuristic rule prioritizes the closing of the initially open tie-switches based on the voltage difference across them, because the highest voltage difference indicates that the respective feeders at the low and high dynamic edges of the tie-switch experience low and heavy loading conditions respectively. Therefore, since the NR scheme basically aims in uniformly distributing the network’s loads to the available feeders, a good start could be the transferring of loads between feeders with low and high loading. The second heuristic rule indicates the sectionalizer to open across the formed loop after the tie-switch is closed, in order to regain the radial structure of the DN. Based on this rule the branch to open is the one carrying the minimum current within the loop, since the respective sectionalizer opening would cause the lowest transient interruption with the minimum impact on the DN. The implementation of the NR scheme based on these heuristic rules is summarized in the flowchart presented in Fig. 6.

It should be noted that the threshold  $\epsilon$  in Fig. 6 plays the role of the convergence criterion for the algorithm implementation: a low value for this threshold indicates that the respective feeders at the edges of the tie-switch are almost equally loaded and thus, no load transfer between them could lead to further loss reduction. Alternatively, the value of  $\epsilon$  could be set to zero and in this case all tie-switches of the DN will be examined, regarding their potential to contribute to further loss reduction performing further NR.

**Fig. 6** Flowchart for NR with heuristic rules



The presented algorithm in Fig. 6 is applied on the benchmarked 33 bus system [23]. The layout of the DN is illustrated in Fig. 7 and the switching operations that implement the NR scheme are presented in Table 4. The reconfigured DN is presented in Fig. 8, in which the red circles indicate the open sectionalizers at the respective branches. The application of the proposed NR scheme yields 33.65% loss reduction (from 211 kW to 139.98 kW), which is the same found in other methodologies in literature [23]. It should be stated though that under the presented heuristic approach, only 11 load flow analyses are required instead of  $2^{33}$  that would be needed if the solution space had to be exhaustively searched for the optimal solution.

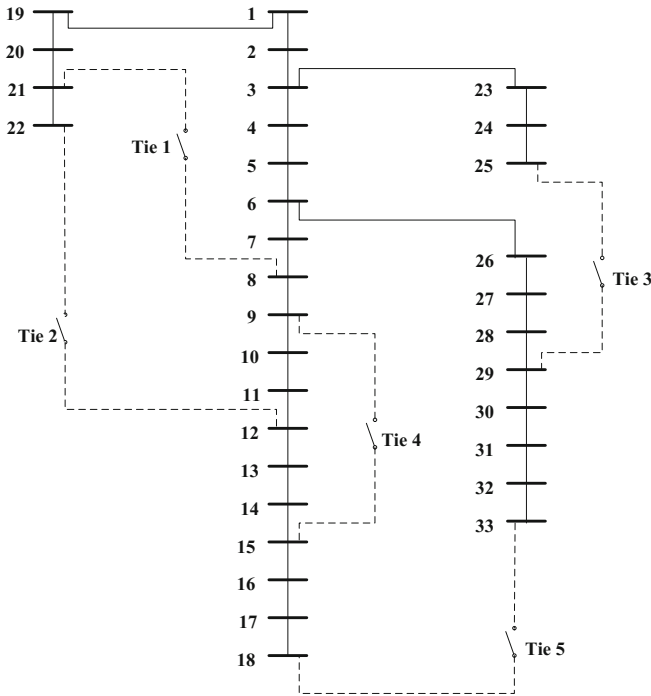


Fig. 7 33 bus system

### 3.3 Network Reconfiguration for Loss Reduction Based on Metaheuristics

The proposed technique presented in the previous section is a knowledge-based heuristic methodology that performs NR in compliance with specific rules that are formed based on system experience [33] and is considered to be the more straightforward of the relating techniques with the basic drawback to be the weakness to guarantee the optimal solution for large and complex DNs. The latter is faced by the so called meta-heuristic algorithms which are utilized for complex optimization problems since due to their structure and formulation they solve the problem iteratively without derivative information about the problem itself [33]. The basic advantage of the metaheuristic algorithms is that the possibility for local minima entrapment is less than the heuristic based algorithms and under proper parametrization they perform well providing efficient solutions. Figure 9 summarizes the NR classification methods with emphasis on metaheuristic ones [33].

In this section the binary Particle Swarm Optimization (PSO) is presented with the  $OF$  shown in Eq. (8). PSO is a population based algorithm initially proposed in [22]. In PSO a swarm of particles is designated to explore the solution space.

**Table 4** Switching operations for NR based on heuristics—33 bus system

$\Delta V$ across tie-switches (kV)	Closing tie-switch with maximum $\Delta V$	Formed loop after closing tie-switch	Branch within formed loop to open
<i>1st step</i>			
(Tie 1) 0.64427	No	*	*
<b>(Tie 2) 0.81897</b>	Yes	2-19-20-21-22-12-11-10-9-8-7-6-5-4-3-2	<b>9–10</b>
(Tie 3) 0.55514	No	*	*
(Tie 4) 0.22737	No	*	*
(Tie 5) 0.44180	No	*	*
<i>2nd step</i>			
(Tie 1) 0.27206	No	*	*
<b>(Tie 3) 0.4374</b>	Yes	3-23-24-25-29-28-27-26-6-5-4-3	<b>28–29</b>
(Tie 4) 0.5773	No	*	*
(Tie 5) 0.26459	No	*	*
<i>3rd step</i>			
(Tie 1) 0.08963	No	*	*
<b>(Tie 4) 0.24029</b>	Yes	2-19-20-21-22-12-13-14-15-9-8-7-6-5-4-3-2	<b>14–15</b>
(Tie 5) 0.16382	No	*	*
<i>4th step</i>			
(Tie 1) 0.23699	No	*	*
<b>(Tie 5) 0.24649</b>	Yes	3-23-24-25-29-30-31-32-33-18-17-16-15-9-8-7-6-5-4-3	<b>32–33</b>
<i>5th step</i>			
<b>(Tie 1) 0.23699</b>	Yes	2-19-20-21-8-7-6-5-4-3-2	<b>7–8</b>

The asterisk shows that no particular loop has been formed, since no tie-switch has closed  
 Bold values indicate the best solution reached at every step of the solving method

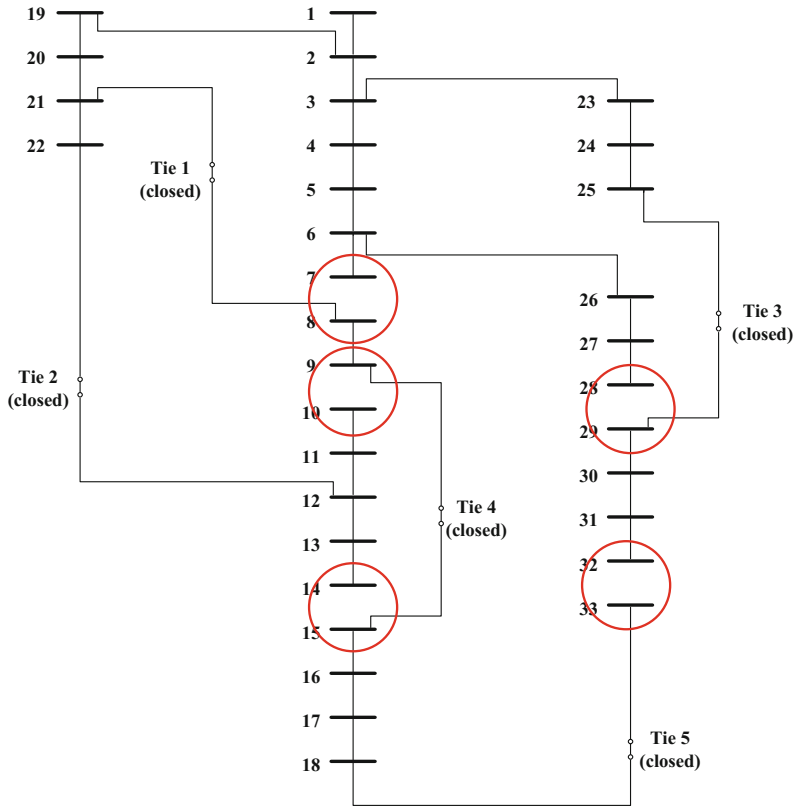
The particles’ position changes depending on their personal experience (personal best—pbest), that of either the whole swarm (global best—gbest) in the case of Global PSO (GPSO), or that of their neighbors’ (local best—lbest), in the case of Local PSO (LPSO), and finally that of their previously obtained velocity, as shown in Fig. 10.

In Eqs. (14) and (15) the expressions describing the velocity and the position alteration of each particle are presented [22].

$$v_i(t + 1) = \chi \left[ v_i(t) + c_1 R_1 \left( P_i(t) - X_i(t) \right) + c_2 R_2 \left( P_g(t) + X_i(t) \right) \right] \quad (14)$$

$$X_i(t + 1) = X_i(t) + v_i(t + 1) \quad (15)$$





**Fig. 8** Reconfigured topology for the 33 bus system via heuristic rules

where:

- $i = 1, 2, \dots, N$  and  $N$ : is the number of particles,
- $X_i(t)$ : the current position of particle  $i$ ,
- $X_i(t + 1)$ : its future position,
- $v_i(t)$ : its current velocity,
- $v_i(t + 1)$ : its future velocity,
- $P_i(t)$ : its personal best, pbest,
- $P_g(t)$ : gbest or lbest,
- $c_i$ : weighting factors, also called the cognitive and social parameters, respectively,
- $R_i, i \in [1, 2]$ : random variables uniformly distributed within  $[0, 1]$ ,
- $\chi$ : the constriction coefficient or factor, formulated as:

$$\chi = \frac{2}{|2 - (c_1 + c_2) - \sqrt{(c_1 + c_2)^2 - 4(c_1 + c_2)}|} \tag{16}$$

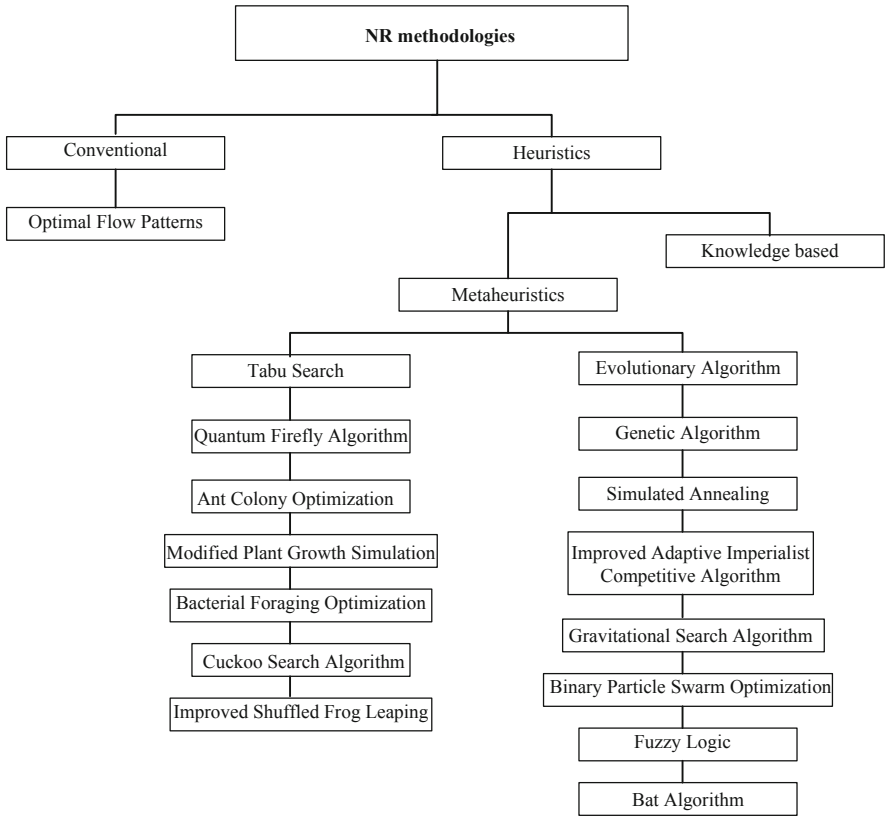


Fig. 9 NR classification methodologies

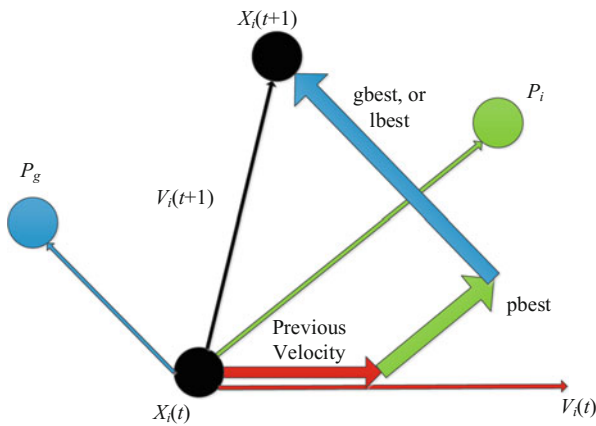


Fig. 10 Factors determining particle's motion within solution space

The GPSO and LPSO constitute two PSO variants with advantages and drawbacks since they either promote exploration or exploitation of the solution space. In order to harness their aforementioned merits while neutralizing their flaws the Unified PSO (UPSO) variant has been proposed [28]. For UPSO in Eqs. (17) and (18), the global and local velocities of the particles are calculated using the GPSO, Eq. (17), and the LPSO versions, Eq. (18), respectively, while in Eqs. (19a) and (19b) the unified velocity is given. The particle position equation remains as in Eq. (15).

$$GV_i(t+1) = \chi \left[ v_i(t) + c_1 R_1 (P_i(t) - X_i(t)) + c_2 R_2 (P_g(t) - X_i(t)) \right] \quad (17)$$

$$LV_i(t+1) = \chi \left[ v_i(t) + c_1 R_1 (P_i(t) - X_i(t)) + c_2 R_2 (P_l(t) - X_i(t)) \right] \quad (18)$$

for  $u \leq 0.5$ :

$$v_i(t+1) = u R_3 GV_i(t+1) + (1-u) LV_i(t+1) \quad (19a)$$

for  $u > 0.5$ :

$$v_i(t+1) = u GV_i(t+1) + (1-u) R_3 LV_i(t+1) \quad (19b)$$

where:

- $u \in [0, 1]$ : is a parameter, called unification factor, and controls the influence of the global and local velocity update. Evidently, lower values of  $u$  correspond to distributions biased towards the LPSO, i.e. exploration, and higher values of  $u$  towards GPSO, i.e. exploitation.
- $R_3$ : is a random variable uniformly distributed within  $[0, 1]$ , is applied either to the global, or the local velocity, depending on the value of  $u$ , infusing partial stochasticity and enhancing in this way even further the exploration capabilities of the technique.

As for assigning value to the unification factor, there are a lot of schemes. One of them, called swarm partitioning, is a particle-level scheme, where the swarm is divided in partitions consisting of a predefined number of particles. All particles in the same partition share the same  $u$ , while each partition has a different value, i.e. a value from the set  $W = \{0, 0.1, \dots, 0.9, 1\}$ . In order to avoid any search bias of the swarm, due to the entanglement of neighborhoods and partitions, particles of the same partitions are spread in different ring neighborhoods, by assigning particles to partitions in a non-sequential order, such that the  $i$ -th particle is assigned to the  $(1+(i-1)\text{mod}k)$ -th partition. For example, the first  $k$  particles are assigned to partitions 1 to  $k$ , respectively, one particle per partition. Then, it starts over by assigning  $x_{(k+1)}$  to partition 1,  $x_{(k+2)}$  to partition 2, and so on.

The particle formulation for the UPSO is a vector with its dimension to be equal to the sum of the sectionalizers and the tie-switches as presented in Eq. (20). For each dimension a binary variable is considered with values 0 or 1 to denote the

**Table 5** NR under UPSO for 33 and 69 bus systems

	NR under UPSO algorithm				
	Initial losses (kW)	Sectionalizers open	Tie-switches closed	Loss reduction reduction (%)	Final losses (kW)
33 bus system	211.0	7, 9, 14, 28, 32	All	33.65	140.0
69 bus system	229.8	14, 58, 62	Tie 3, Tie4, Tie5	54.70	104.1

status of the respective switch, either open or closed.

$$X = [S_1, S_2, \dots, S_{n_b}, T_1, T_2, \dots, T_w] \quad (20)$$

where:

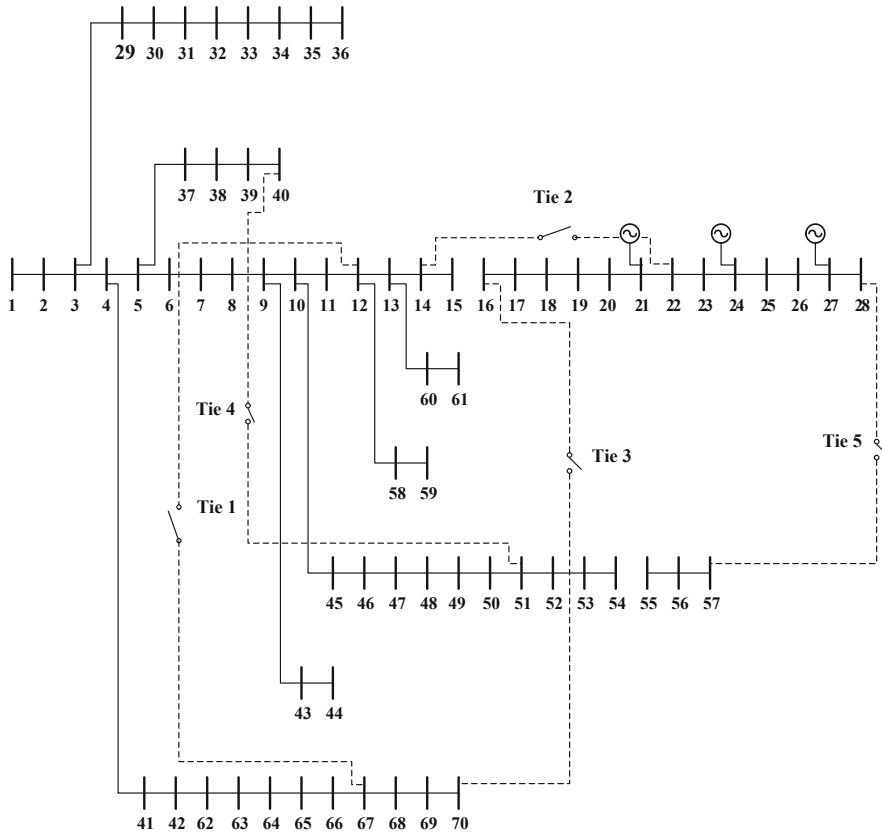
- $S_i$ : refers to sectionalizer,
- $n_b$ : the number of buses of the DN,
- $T_j$ : refers to tie-switch,
- $w$ : is the number of tie-switches of the DN.

The results after the UPSO application for NR for both 33 bus system and 69 bus system [4] are presented in Table 5 and the initial layout of the 69 bus system in Fig. 11 [19].

## 4 Power and Energy Loss Minimization under Network Reconfiguration

### 4.1 Load Variation Consideration

The application of the NR scheme for loss reduction refers to seeking for the optimal network reconfiguration given specific operating conditions for the DN in terms of active and reactive load demand. The latter is the case of the so called snapshot of the DN's operation and it constitutes a reference case with fixed load composition of the network, that allows the concept of load transferring among feeders to be implemented. The problem though is that the final solution depends directly on the load composition, since the solution algorithm will determine the required switching operations to perform the NR based on load level differences among feeders and on the layout of the network. Given an altered load composition for the DN, it is rational to accept that the final reconfigured topology after NR could also alter. An issue is raised here regarding the definition of the optimal solution under load variations: if for any different operating snapshot of the DN with altered load composition a possibility for a different optimal solution exists, then under real load variations the topology should be continuously being reconfigured. Fortunately, this is not the case due to the reason that, under smooth load variations, the optimal reconfigured



**Fig. 11** Layout of the 69 bus system

topology proves to be quite fixed. Also, under more intense load variations, a fixed reconfigured topology can be efficient enough regarding the loss reduction, even if it is not the optimal one for every single snapshot with different load composition. Given these clarifications, the problem under load variations is known as energy loss reduction via NR and a simple formation of the  $OF$  is presented in Eq. (21).

$$OF = \min \sum_{\Delta t=1}^T \sum_{z=1}^{n_l} R_z I_z^2 \tag{21}$$

where:

- $\Delta t$ : is the time interval for which a fixed load composition is considered
- $T$ : is the time period for which energy loss minimization is examined

The number of  $\Delta t$  intervals in Eq. (21) has a great impact on the problem's computational burden. For example, if  $T$  is equal to 1 day, then it is possible to break down the problem to 24 sequential sub-problems when  $\Delta t = 1$  h or even to 3600 sequential sub-problems when  $\Delta t = 1$  min. Given the problem's complexity for a single snapshot, it becomes obvious that special attention about the assumed number of the  $\Delta t$  intervals should be given.

If the load alterations between sequential time intervals, corresponding to at least two consecutive snapshots, are considered to be performed equally and uniformly for all loads of the DN, then the final solution concerning the reconfigured topology is not affected. The latter means that for a different load composition with all loads uniformly increased or reduced, the same switching operations are required to perform the optimal NR scheme. In order to investigate the impact of load variations to the optimal NR problem, the 33 bus system is again examined under a series of different loading conditions regarding its load composition. The load alterations are performed randomly because the probabilistic modelling of loads, especially the residential ones, is well justified by the fact that electricity demand is largely a stochastic process exhibiting diversity [25, 26]. Therefore, the load variations for the examined DN are assumed to follow a uniform distribution [8] and the corresponding lower and upper limits are computed as in Eqs. (22) and (23):

$$P_i^{lower} = \overline{P}_i \left( 1 - \frac{l_u}{100} \right) \quad (22)$$

$$P_i^{upper} = \overline{P}_i \left( 1 + \frac{l_u}{100} \right) \quad (23)$$

where:

- $P_i^{lower}$ : is the lower limit of the uniform distribution interval of bus  $i$
- $P_i^{upper}$ : is the upper limit of the uniform distribution interval of bus  $i$
- $\overline{P}_i$ : is the mean load value of node  $n$  (initial snapshot of the DN)
- $l_u$ : is the number defining the length of the uniformly distribution interval

The flowchart of the methodology that performs optimal NR under load variations is illustrated in Fig. 12. It should be clarified that the NR scheme is based on the heuristic rules that have been presented previously in this chapter. The proposed algorithm considers for each new scenario different load composition for the DN and applies the heuristic rules to perform optimal NR for loss minimization. Furthermore, the algorithm examines the performance of the optimal reconfigured topology resulted for the initial load composition of the DN (mean load values), regardless the actual load composition. The latter means that the algorithm computes the loss reduction that the initial reconfigured topology yields for every different snapshot formed by the uniform distribution. The goal here is to investigate whether it is actually necessary to apply the NR scheme under load variations. For example, if the initial optimal NR with the mean load values performs well concerning the loss reduction regardless the load variations, then this solution could be considered

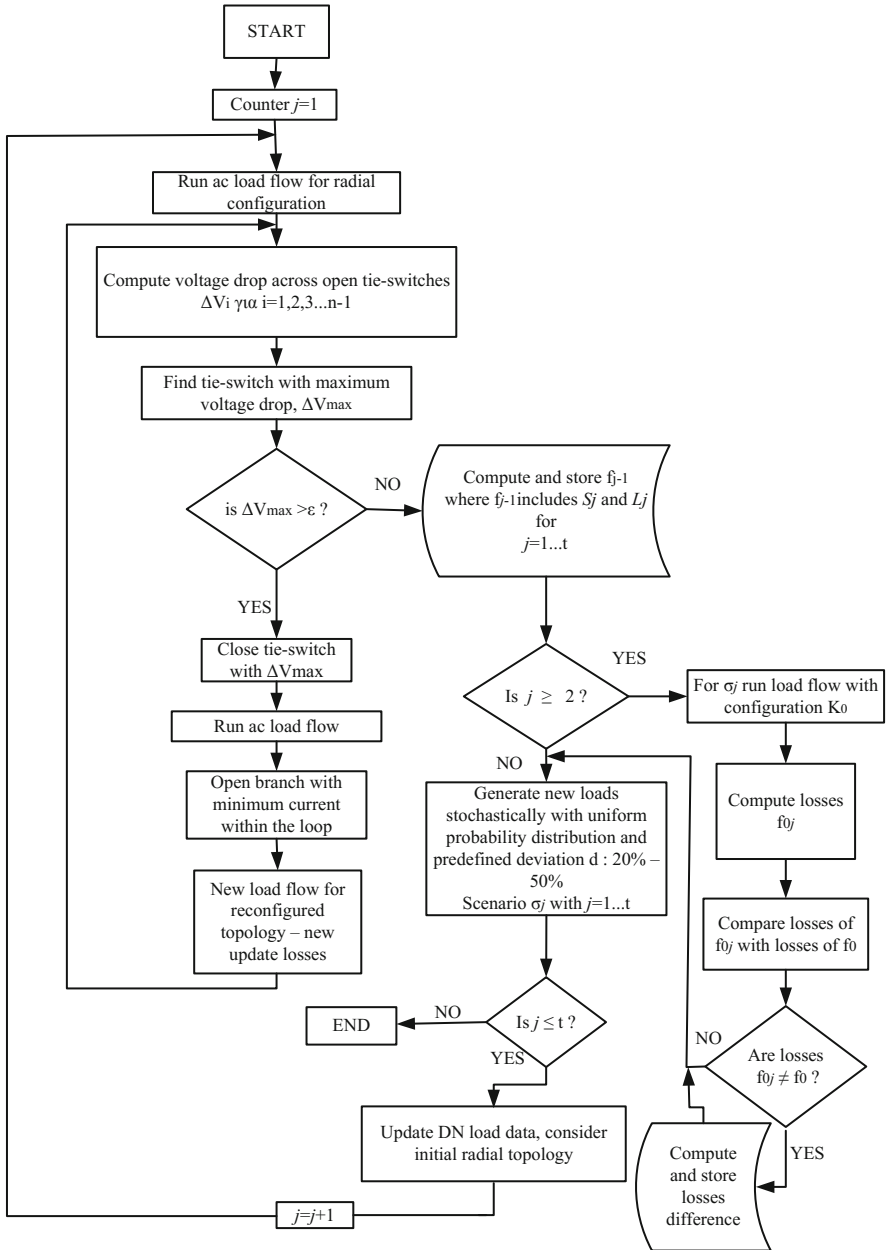


Fig. 12 NR algorithm with load variations consideration

**Table 6** Sectionalizers operation for NR under smooth load variations for 33 bus system

Close tie-switch	Open branch	$l_u = \pm 20\%$ participation	
		frequency of branch (%) to 10,000 scenarios	Open branch
Tie 1	7–8	100	7–8
	8–9	100	8–9
Tie 2	9–10	81.44	9–10
	10–11	17.49	10–11
Tie 3	28–29	100	28–29
Tie 4	14–15	100	14–15
	32–33	99.98	17–18
Tie 5	17–18	0.02	31–32
			32–33

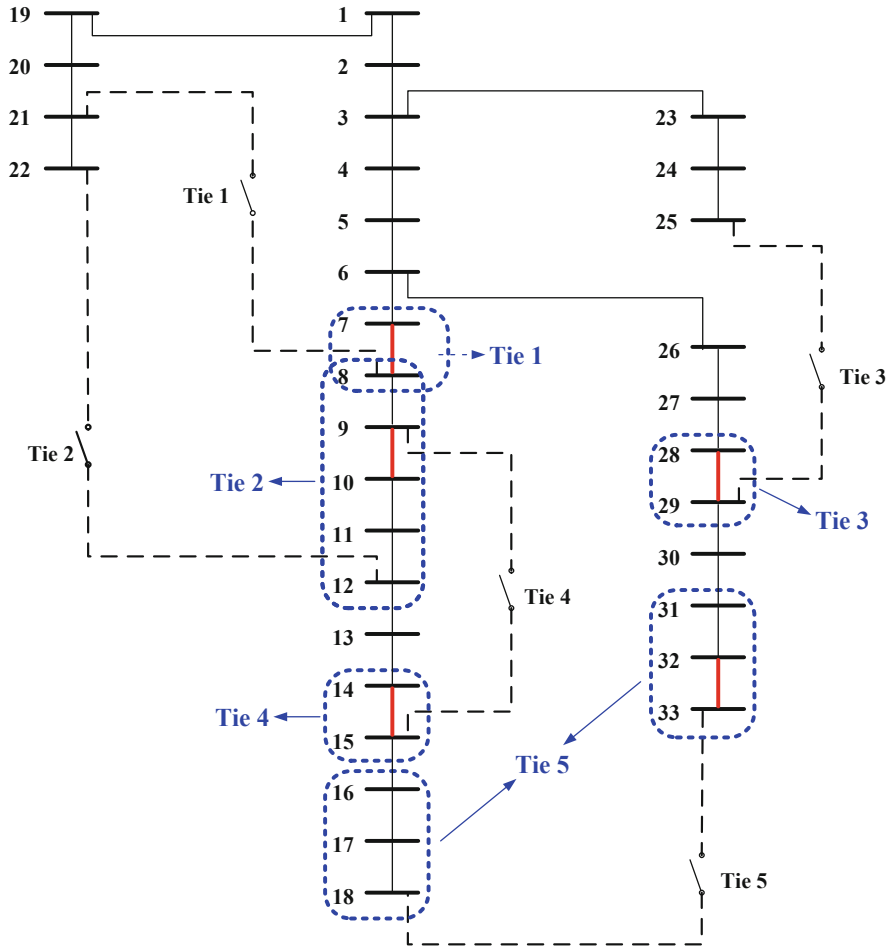
**Table 7** Sectionalizers operation for NR under intense load variations for 33 bus system

Close tie-switch	Open branch	$l_u = \pm 40\%$ participation	
		frequency of branch (%) to 10,000 scenarios	Open branch
Tie 1	7–8	100	7–8
	8–9	14.44	8–9
Tie 2	9–10	55.59	9–10
	10–11	29.85	10–11
	11–12	0.12	11–12
Tie 3	28–29	100	28–29
Tie 4	14–15	100	14–15
	16–17	0.01	16–17
Tie 5	17–18	2.13	17–18
	31–32	1.40	31–32
	32–33	96.46	32–33

fixed and assumed to be the near optimal under load variations. In Tables 6 and 7 the results regarding 4 values for  $l_u$ , i.e. 20, 30, 40, 50, are presented. The latter means that all loads have been considered to randomly alter within  $\pm 20\%$ ,  $\pm 30\%$ ,  $\pm 40\%$ ,  $\pm 50\%$  from their mean initial values respectively. For each  $l_u$  value 10,000 scenarios with different load composition for the 33 bus system have been produced and for each one of them the NR scheme under the heuristic based approach has been applied.

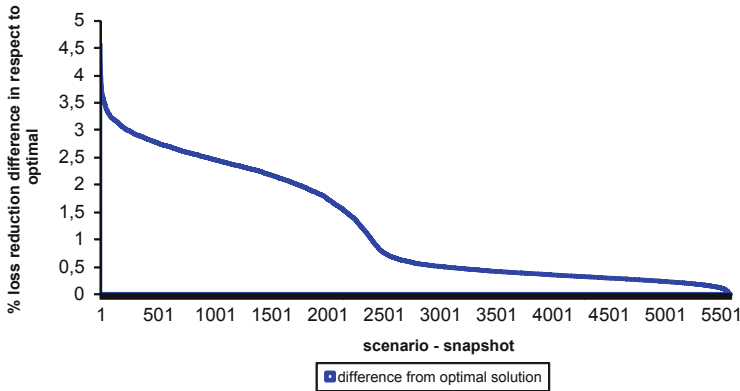
The results in Table 6 indicate that for smooth load variations, i.e. within  $\pm 30\%$  from the mean load value, and regardless the load composition the sectionalizers that have to be operated for the initial NR with the mean load values seem to also participate in the vast majority of the solutions for all other snapshots. Even under more intense load variations, as the results in Table 7 show, these sectionalizers still keep high participation frequency to the reconfigured topology. Nevertheless, the





**Fig. 13** Schematic representation of corresponding sectionalizers to open for each tie-switch regardless load composition for 33 bus system

analysis shows that from the 32 available sectionalizers of the 33 bus system, only 11 of them (33%) should be expected to participate in the NR scheme, regardless the load composition of the DN. Moreover, this number could be considered further reduced since for some of them the probability to be operated is quite low. In Fig. 13 the layout of the 33 bus system with all participated sectionalizers for all possible NRs is illustrated in order to highlight that, for each tie-switch, the expected sectionalizers to open after the tie-switch operation are sectionalizers within specific neighborhoods of the DN. Based on these results, it is up to the DSO to proceed with selective automation upgrade to targeted sectionalizers in order to exploit the benefits for real time NR towards energy loss reduction under relatively low investment cost.



**Fig. 14** Loss reduction difference yielded by fixed NR in regard to optimal one for each snapshot

Finally, in Fig. 14 the performance evaluation of the fixed NR derived by the initial load composition with mean load values, regardless the load variations, is presented. More specifically, for each snapshot the aforementioned NR is applied and the difference in loss reduction in respect to the optimal NR for this snapshot is computed. All these differences are placed in descending order and as clearly presented the worst case refers to a difference of approximately 4.5% by the optimal NR for this snapshot. Thus, it is rational to consider that for time periods within which the load variations of the network's loads are not intense, a fixed reconfigured topology could be assumed as an efficient solution for energy loss reduction due to low investment cost for the DSO, regarding the automation upgrade of the DN in terms of replacing manual sectionalizers with automated ones.

The results corresponding to the 69 bus system are presented in Tables 8 and 9 and are schematically summarized in Fig. 15, in which the blue dotted frames indicate the sectionalizers to be operated after the respective tie-switch is closed.

## 5 Network Reconfiguration Under DG Penetration in DNs

### 5.1 Overloading Mitigation in DNs due to High DG Penetration

In general, it is expected that DG penetration in power systems has shifted power generation to a more decentralized model, which could benefit the grid in terms of improving the voltage profile and alleviating the lines' loading. The increased and without proper guideline installation of DG units has driven parts of the DNs in saturation conditions, in which overvoltage and reverse power flow issues cause

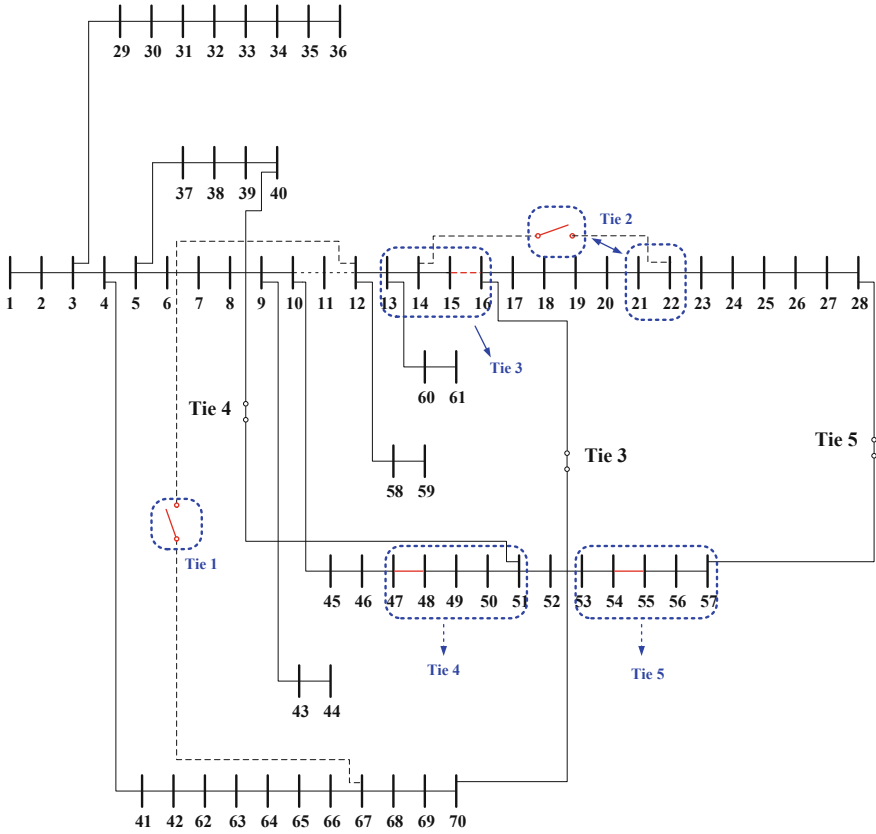
**Table 8** Sectionalizers operation for NR under smooth load variations for 69 bus system

Close tie-switch	Open branch	$I_u = \pm 20\%$ participation frequency of branch (%) to 10,000 scenarios	Open branch	$I_u = \pm 30\%$ participation frequency of branch (%) to 10,000 scenarios
Tie 1	12–67	100	12–67	100
Tie 2	14–22	100	14–22	100
Tie 3	15–16	100	14–15	0.01
			15–16	99.99
	47–48	57.23	47–48	45.32
Tie 4	48–49	12.20	48–49	13.78
	49–50	14.42	49–50	17.16
	50–51	16.15	50–51	23.74
	53–54	28.26	53–54	34.63
	54–55	37.52	54–55	29.48
Tie 5	55–56	33.92	55–56	35.39
			56–57	0.05

**Table 9** Sectionalizers operation for NR under intense load variations for 69 bus system

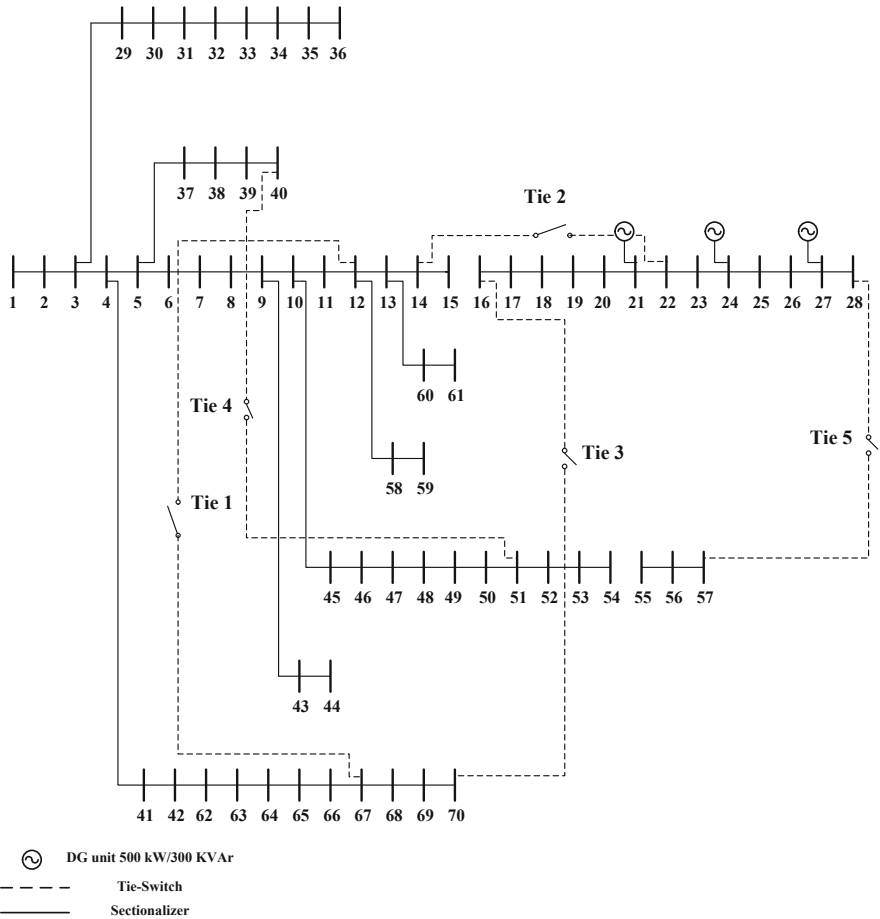
Close tie-switch	Open branch	$I_u = \pm 40\%$ participation frequency of branch (%) to 10,000 scenarios	Open branch	$I_u = \pm 50\%$ participation frequency of branch (%) to 10,000 scenarios
Tie 1	12–67	100	12–67	100
Tie 2	14–22	99.96	14–22	99.26
	21–22	0.04	21–22	0.74
	13–14	0.22	13–14	1.09
Tie 3	14–15	0.35	14–15	1.31
	15–16	99.43	15–16	97.60
	47–48	38.12	47–48	34.02
Tie 4	48–49	13.80	48–49	15.08
	49–50	19.33	49–50	19.15
	50–51	28.75	50–51	31.75
	53–54	38.73	53–54	42.47
Tie 5	54–55	24.42	54–55	20.71
	55–56	33.74	55–56	31.28
	56–57	3.11	56–57	5.54

power quality problems and increased power losses. The latter is usually the case in DN with increased RES penetration either during midday and night, when the Photovoltaic (PV) and the Wind Generation (WG) power units, respectively, are active. Since these effects are present for specific lines-parts of the DN, it is possible to face them by NR due to the fact that power flow allocation within the DN could more efficiently exploit the power surplus by the DG or RES units. In Fig. 16 the 69 bus system is presented, in which the carrying capacity for branches 1-9 is 400



**Fig. 15** Schematic representation of corresponding sectionalizers to open for each tie-switch regardless load composition for the 69 bus system

A, for branches 46–49 and 52–64 is 300 A and for all the remaining the ampacity is 200 A [30]. It is considered that three DG units, with 500 kW and 300 kVAr active and reactive power generation respectively, are installed as shown in Fig. 16 and thus a low DG penetration scenario is examined [11]. In Fig. 17 the carrying current for each branch normalized to its ampacity level for the cases before and after the DG installation is illustrated. It is observed that the DG power generation causes for some branches reduction of their current flow, while for some other the opposite happens. The results in Fig. 17 show no constraint violations for the branches’ loading, but this is due to the low penetration level of the DG. Still, the trend is evident since for high DG penetration it is high possible to experience heavy loading conditions subject to reverse power flow. Therefore, NR could prove to be an efficient scheme to mitigate both possible overvoltage and reverse power flow conditions.



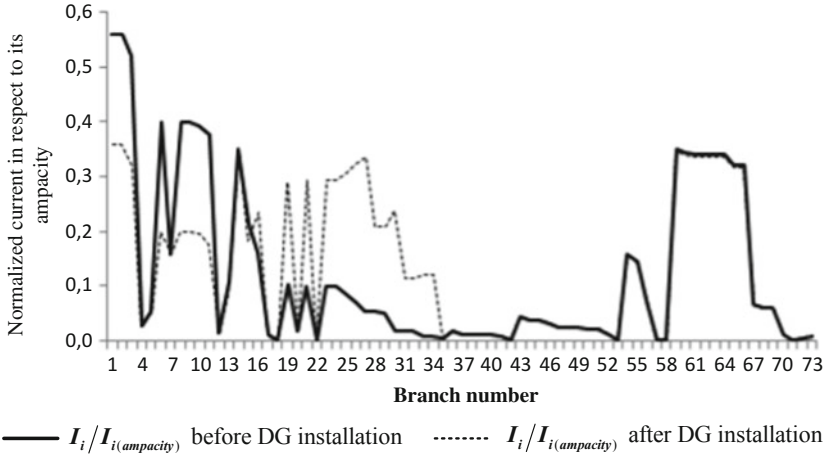
**Fig. 16** The 69 bus system with low DG penetration

The problem is addressed through a linear  $OF$  that is formed based on the indices shown in Eqs. (24) and (25) [11]:

$$CCIF = \frac{\sum_{z=1}^{[(n_b-1+t)]} \frac{I_{b_z}^k}{I_{a_z}}}{[(n_b - 1 + t)]} \tag{24}$$

where:

- $CCIF$ : is the current index,
- $n_b$ : is the number of buses of the DN,
- $t$ : is the number of tie-switches of the DN



**Fig. 17** The 69 bus system branch currents before and after DG installation

- $k$ : is the operation state of the DN, i.e. the load and generation composition for the snapshot solved,
- $z$ : is the line  $z$ , with  $i = 1, 2, \dots, [(n - 1) + t]$ ,
- $I_{bz}^k$ : is the current (rms value) of line  $z$ ,
- $I_{az}$ : is the ampacity level of line  $z$ .

$$VCIF = \frac{\sum_{i=1}^{n_b} \frac{V_i^k}{V_r}}{n_b} \tag{25}$$

where:

- $VCIF$ : is the voltage index,
- $V_i^k$ : is the voltage of bus  $i$  for state  $k$ ,
- $V_r$ : is the nominal voltage of the DN.

The proposed algorithm performs the NR scheme based on the simple heuristic rules that explained earlier in this chapter in order to optimize either the  $CCIF$  or the  $VCIF$  index under a weighted factor approach. The flowchart of the proposed algorithm is shown in Fig. 18. Initially the algorithm checks whether the DG penetration has increased either the  $CCIF$  or the  $VCIF$  index and then based on the index optimization prioritization, NR is applied. The results for 100 scenarios concerning random allocation of 15 DG units with random power generation between 100–850 kW (with a fixed power factor equal to 0.9) are presented in

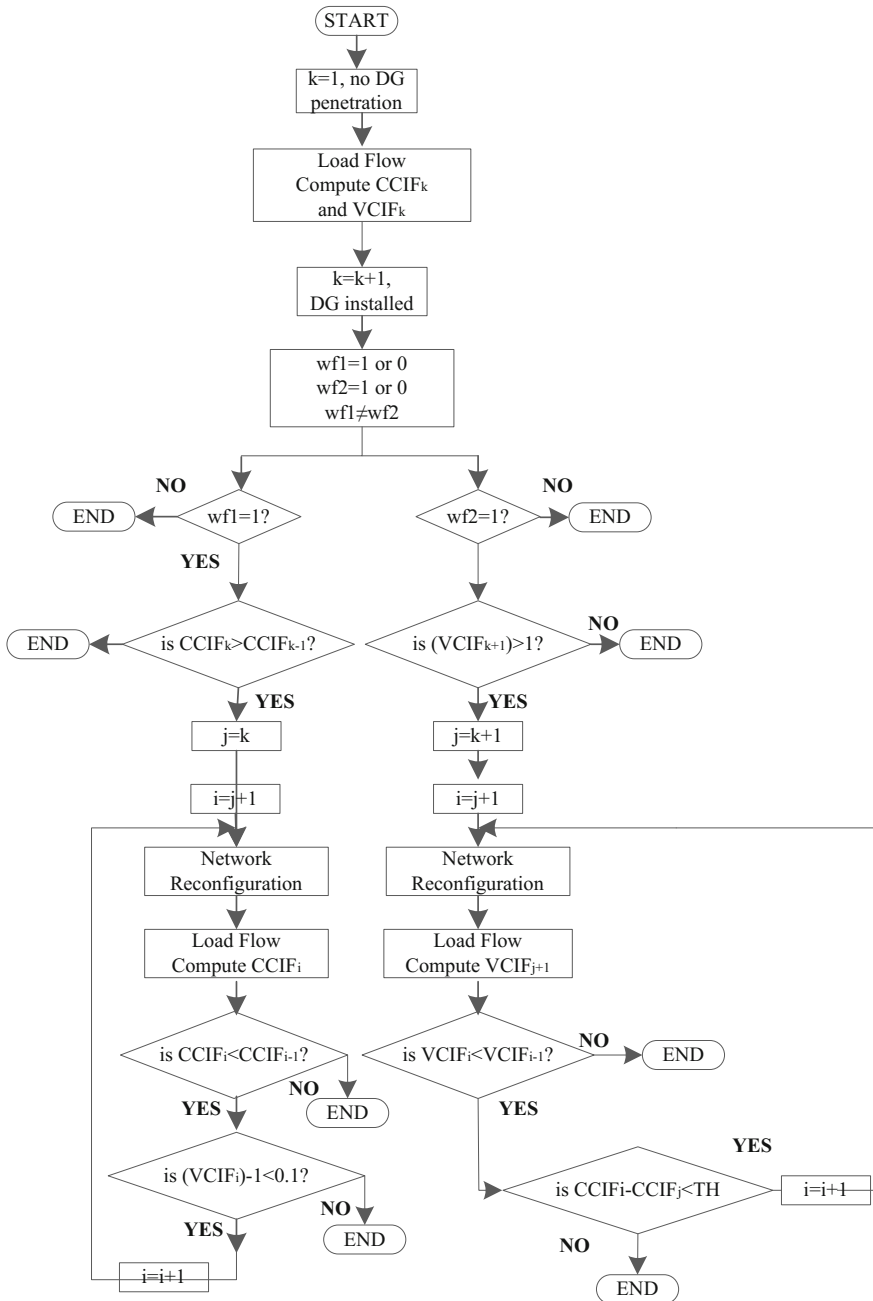
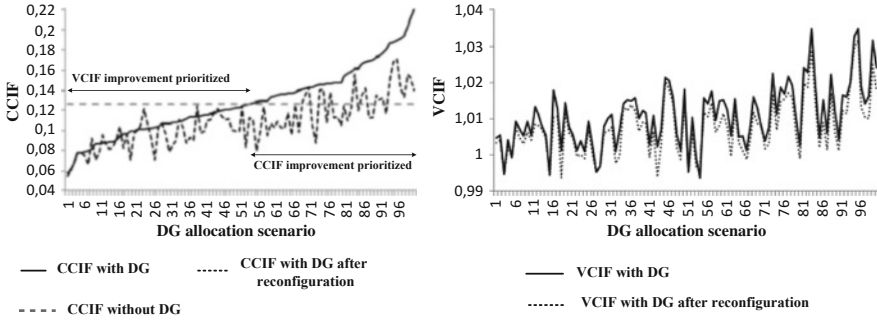
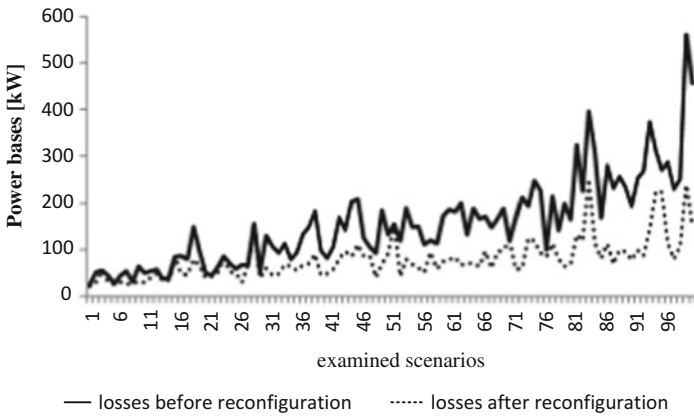


Fig. 18 Flowchart for NR towards CCIF and VCIF optimization due to DG penetration



**Fig. 19** CCIF and VCIF values for 100 scenarios with DG penetration after NR



**Fig. 20** Loss reduction under DG penetration via NR

Fig. 19 [11]. At the left graph of Fig. 19 the NR is performed aiming to optimize the *VCIF* index but as observed this scheme leads also to *CCIF* improvement in most examined scenarios. When *CCIF* is prioritized, the algorithm applies the NR scheme and in all cases the index is reduced yielding by this way more balanced branch loading across the DN. For the right part of Fig. 19 the results presented show that the voltage profile of the DN has been improved under the NR scheme for all cases with DG penetration. Finally, the impact of improving the voltage profile and of mitigating the branch loading is also reflected on the network’s power loss, as presented in Fig. 20, where in all cases the reconfigured topology caused loss reduction. The latter is important since the *OF* is not formed directly to express the power loss for the DN but to reduce the branch current across the DN, that is a linear simplified and approximating approach of the loss reduction *OF*.



### 5.2 Optimal Siting and Sizing of DG and NR Towards Loss Reduction in DNs

In the previous section the NR scheme is applied in DNs given the penetration of DG in terms of siting and sizing of the DG units. In this section, the application order of NR and the so called Optimal Distributed Generation Placement (ODGP) problem for loss reduction is examined. The basic concept is to investigate whether it is more efficient, in terms of higher loss reduction, to apply the NR scheme and then the ODGP or vice versa. Both schemes are implemented by the UPSO algorithm that has been explained in section 3.3 but for the ODGP problem the particle’s formulation is different [12] and is presented in Fig. 21. Each particle is a nine dimension vector for the 33 bus system, since the first 3 dimensions refer to the 3 candidate nodes of the DN for DG installation, the other 3 dimensions concern the active power generation of each DG unit and the remaining 3 dimensions refer to the reactive power of each DG unit. Using this approach, it becomes evident that only three nodes of the DN are considered as candidates for DG installation and moreover, the algorithm will determine the power generation for each installed unit.

In Table 10 the UPSO parameters are presented and they are the same either for the ODGP or the NR scheme implementation. Using the OF shown in Eq. (8), the NR scheme is initially applied first and then the ODGP scheme is applied in order to further reduce power losses by defining the optimal siting and sizing of three DG units. The concept here is to firstly exploit the current structure of the DN by NR for potential loss reduction and then proceed in optimal DG penetration. The alternative application order of these schemes refers to firstly perform optimal DG penetration and then examine whether the NR could further reduce power losses. The results of these two approaches are presented in Table 11 [9].

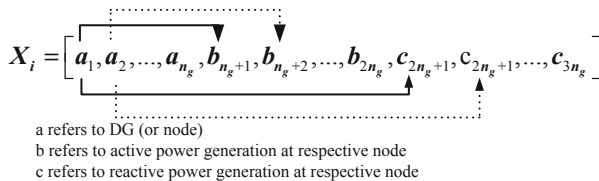


Fig. 21 Particle formulation in ODGP for UPSO algorithm

Table 10 UPSO parameters

Parameter	Value
Cognitive and social coefficient $c_i$	2.05
Number of particles $N$	50
Neighborhood radius $r$	2
Maximum iteration number $T_{max}$	500
Convergence tolerance	$10^{-7}$

**Table 11** NR and ODGP for loss reduction

NR scheme applied 1st and ODGP scheme applied 2nd					
	Initial losses (kW)	Sectionalizers open	Tie-switches closed	–	Loss reduction (%) and final losses (kW)
NR applied	211	7, 9, 14,	All	–	33.65%
		28, 32		–	140
ODGP scheme applied 1st and NR scheme applied 2nd					
	Initial Losses (kW)	Nodes to host DG units	Active power of each DG unit (kW)	Reactive power of each DG unit (kVAr)	Loss reduction (%) and final losses (kW)
ODGP applied	140	6	681.7	317.8	87.36%
		8	933.2	435.5	17.7
		30	1234.3	1108.3	
ODGP scheme applied 1st and NR scheme applied 2nd					
	Initial Losses (kW)	Nodes to host DG units	Active power of each DG unit (kW)	Reactive power of each DG unit (kVAr)	Loss reduction (%) and final losses (kW)
ODGP applied	211	3	1633.3	800.2	91.37%
		14	741.4	346.9	19.2
		30	987.4	990.4	
NR scheme applied 1st and ODGP scheme applied 2nd					
	Initial Losses (kW)	Sectionalizers open	Tie-switches closed	–	Loss reduction (%) and final losses (kW)
NR applied	19.2	7, 8,	Tie 1, Tie 2,	–	15.38%
		9, 28	Tie 3, Tie 4	–	15.4

The basic observation from the results shown in Table 11 is that, although both approaches regarding the application order for the NR and ODGP schemes yield almost the same final loss reduction, the application order of the schemes has an individual impact on them. More specifically, if the NR scheme is applied firstly, the aggregated DG penetration is approximately 2.85 GW, while if it is applied secondly then the total DG capacity is close to 3.36 GW. The obtained difference of approximately 500 kW could have a great impact on the total investment cost regarding the DG penetration, thus it seems that the ODGP should be applied on the most efficient network topology, i.e. the one after NR, in order to minimize the installation cost.

## 6 Conclusions

In this chapter, the NR scheme in DNs is examined related mainly to reliability improvement and loss reduction issues. NR is based on changing the layout of the DN by appropriate switching operations. These operations concern the closing of normally open tie-switches and the opening of normally closed sectionalizers within

the performed loops. The idea behind these switching operations relies on allocating the network's load within its feeders in order to somehow balance overall network's loading level. It is expected that under a more balanced load profile both loss reduction and voltage improvement could be achieved. Moreover, the NR technique also enables fault isolation and power restoration after an outage in DNs which in turn contributes in reliability improvement.

The first part of the chapter describes the importance of establishing a high automation level in DNs in order to be able to remotely perform the required switching operations during an outage aiming to isolate the fault within the shortest possible line segment of the network and restore power to the maximum number of consumers within the shortest possible time framework. A brief presentation of the reliability assessment in DNs is presented based on the respective reliability indices and a simple approach concerning targeted automation upgrade is analyzed. This approach refers to limited investment interventions subject to guided switching replacement in order to yield efficient reliability improvement subject to low cost. An example of a real urban DN is illustrated where it is shown that the claimed scheme is possible.

The second part of the chapter analyzes the loss reduction problem under NR via heuristic and metaheuristic based algorithms. The distinction between these two aforementioned algorithms is highlighted and their application on benchmarked DNs is presented. For heuristic approaches two well established and widely utilized heuristic rules are described while for the metaheuristic approaches a binary PSO variant, namely the Unified PSO, is presented along with the respective results. Subsequently, the problem of energy loss reduction is presented by explaining how load alterations are expected to influence the NR implementation. An analysis regarding numerous load compositions is shown in order to explain how the problem of energy loss minimization under NR is actually faced. The results presented indicate that even under intense load variations the expected switching operations in order to perform optimal NR could be considered somehow previously known based on prior knowledge for their participation frequency to the NR scheme.

Finally, the chapter also examines the potential for utilizing the NR concept with DG penetration. On the one hand, the NR is applied under high RES or DG penetration in order to mitigate branch overloading, reduce the current flow and improve voltage profile via the optimization of proposed indices. On the other hand, NR along with ODGP are treated as effective schemes for loss minimization in DNs and their application order is investigated. It has been proven to be more efficient to apply NR firstly, and then the optimal siting and sizing of DG units scheme, since in this way the aggregated DG or RES capacity is lower, while the loss reduction percentage is not affected.

The chapter succeeds to highlight the contribution of the NR scheme on several operational issues especially within the current smart grid concept, where immediate decisions have to be made and respective responses of the DN layout to several challenges related with load and generation uncertainties have to be faced.

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