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Influence of load alterations to optimal network configuration for loss reduction

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ABSTRACT

The paper investigates how load alterations in distribution systems influence optimal configurations for loss minimization. In the proposed methodology network reconfigurations are implemented utilizing heuristics techniques while load variations are simulated by stochastic procedures. For the examined topologies initial available load data are considered as mean values and new altered load values are produced using uniform distribution. Various scenarios examined are assumed to simulate actual load conditions in order to examine how load variability may change the optimal configuration derived from the initial mean load values. The proposed algorithm was applied in three well known distribution networks from published literature and to a real urban distribution network. The results indicate that for altered load conditions, groups of adjacent sectionalizing switches participate in all the configurations procedures. The work concludes that real management of the distribution networks for loss reduction could rely on a realistic approach which considers limited reconfigurations of the network, derived for the mean load values of the assumed time period. Divergences from optimal solutions are shown to be insignificant compared to the reduction of switching operations.

1. Introduction

Loss reduction in power systems has constituted one of the most important objectives for researchers and engineers. The constant growth of energy demand along with the polluting conventional power plants has forced engineers in searching methods to reduce losses in all three stages of a power systems' operation; generation, transmission and distribution. It is estimated that the largest proportion of losses in power networks corresponds to distribution networks; for a typical system in a developing country, distribution losses account approximately 13% of the total energy produced [1].

Over the past three decades considerable research has been conducted for loss minimization in the area of distribution systems. The basic concept for loss reduction, developed by Merlin and Back [2], aimed to take advantage of the distribution networks' structure. Although distribution systems are designed as meshed networks, they operate as radial ones due to reliability and short circuit issues. The existence of tie switches that interconnect feeders and permit load transfer among them has lead to the idea of network reconfiguration for loss reduction. Changes of the network topology are performed by opening sectionalizing (normally closed) switches and closing tie (normally open) switches. All the needed switching operations are implemented in such a way that a number of constraints, i.e. voltage and current limits, radial structure of the network, etc., are not violated.

Network reconfiguration for loss reduction has been treated by many researchers and through a great number of different approaches. Although Merlin and Back [2] were the first who introduced the concept of distribution system reconfiguration (DSR), Civanlar et al. [3] proposed a purely heuristic algorithm based on a branch exchange method. By this approach they proposed an approximate formula in order to estimate whether a particular switching operation would increase or reduce losses. Shirmohammadi and Hong [4] based their algorithm on the approach of Merlin and Back including optimal power flow as the basic criterion for the switches that should open. Baran and Wu [5] attempted to improve Civanlars' method by introducing two approximation formulas for power flow. Moreover, in [6] the methods concerning loss minimization algorithms published in IEEE transactions between years 1988 and 2002 are presented. The reconfiguration algorithms may be classified by their solution methods in three basic categories; mathematical optimization methods, heuristics, and those based on Artificial Intelligence. In [7] the authors present a mathematical model for loss minimization which consists in introducing non-conventional group of variables instead of the classical bus complex voltages. The main idea is to simplify the mathematical optimization problem by eliminating continuous and binary variables. The result is to formalize the minimization problem with a linear objective function. Heuristics have kept being proposed by researchers for loss minimization due to their simplicity. In [8] a heuristic algorithm is proposed based on the direction of the branch

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power flows while in [9] the reconfiguration problem is solved by a heuristic approach and rules base. The proposed simple rules are formed based on the system operation experiences which in turn enhances the heuristic nature of the algorithm. Some more sophisticated approaches involve artificial intelligence techniques like the genetic algorithms presented in [10,11]. More specific the algorithm presented in [10] is actually a meta-heuristic searching algorithm that combines high local search efficiency with global search ability of intelligent algorithms. The latter constitutes the basic idea presented in [12] where the proposed algorithm is based on a fuzzy approach with some heuristic rules.

In all aforementioned papers loss reduction by network reconfiguration is treated for fixed operational points, assuming constant load demand for all nodes of the examined topologies. In most of these cases, load demand is considered as the peak value. Although this practice offers a common base for the evaluation of the efficiency of all proposed algorithms, it is not suitable for simulation of real operating conditions. In practice, load patterns indicate load variations concerning the networks' consumers, which can fluctuate in high levels for different customer types. Therefore, it becomes obvious that optimal reconfiguration should adapt to account for load variability, in such way, that the frequency of the reconfigurations coincides with the assumed time periods for which minimization of losses is desired.

Broadwater et al. [13] were one of the first teams that tried to incorporate load variability in the reconfiguration problem. A simple case study was used to illustrate that when different load patterns are applied, optimal reconfiguration can actually alter subject to the aforementioned different load conditions. Moreover, in [14] the concept of short and long term operation of distribution systems is introduced. The above approach aims to simulate actual load conditions. An hourly optimal switching algorithm is utilized for the determination of the hourly optimal configuration, whereas concerning the long term operation a method is adopted for the seasonal operation of the network. Peponis et al. [15] focused their analysis in load modelling for the purposes of network reconfiguration, but they also examined load variation with respect to optimizing reconfiguration decisions. In [16] an on-line approach for loss reduction is presented based on artificial intelligence. The proposed method is based on learning classifier systems which continually propose configurations in the case of time-varying profiles of energy requirement. Huang and Chin [17] also applied actual load patterns for different customer types in their examined topology in order to identify the switches that had to change their status during specific time periods of the day. In [18] an hourly reconfiguration is evaluated compared to fixed topologies, considering maximum and average demand of the system. The paper concludes that hourly reconfiguration seems not to be so effective as compared to a simple maximum or average demand configuration. Bueno et al. [19] examined in their work a typical 24-h period for low, medium and high load values. In this case, they concluded that although the optimum loss reduction is achieved when network configurations are altered to adapt to load variations, however, an optimal fixed configuration for a specific load level and time period does not necessarily lead to a significant increase of losses.

In this paper, network reconfiguration for loss reduction has been originally obtained for a fixed operational point. Load variations, considered to simulate actual load conditions, are taken afterwards into account in order to investigate if the previous configuration is modified. The methodology adopted in this work has been applied to some of the most common used distribution topologies in the published literature, i.e. 16, 33 and 69 bus systems, as well as to a real urban distribution network of the city of Thessaloniki, Greece. In this work, stochastic active power of each examined networks' nodes is assumed to be a stochastic variable following uniform distribution.

This paper is organized as follows. In Section 2, the problem formulation is illustrated along with aspects concerning the time-varying loads. In Section 3, the algorithm developed for loss reduction taking into account the load variability is presented. In Section 4, case studies along with their specific parameters are shown. In Section 5 the results of the simulations are presented and finally in Section 6 the conclusions derived are discussed.

2. Problem formulation

2.1. Fixed operational point

Active power electrical losses in power systems are proportional to the square of branch current. The problem of loss minimization in distribution networks can be written for a fixed operational point in a simple form as follows [18,20–22]:

$$\min imize \quad \sum_{k=1}^{m} R_k \cdot \left|I_k\right|^2 \tag{1}$$

subject to:

$$A \cdot I = C \tag{2}$$

$$I_k \leq I_{k\max} with (k = 1, \ldots, m) \tag{3}$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{4}$$

$$m = n - n_s \tag{5}$$

where n is the total number of nodes, m is the total number of branches, n_s is the number of sources, I is the m-vector complex branch current with, C is the n-vector complex nodal current, V_i is the node voltage at node i, A is the $n \times m$ node-to-branch incidence matrix, I_k is the rms current of branch k and $I_{k,\max}$ is the maximum thermal rms current of branch k.

Eq. (2) corresponds to the balance of the load currents in each node. Eq. (3) indicates the thermal limits of the conductors that must not be violated. Eq. (4) defines the down and upper thresholds of voltage in each node. Finally Eq. (5) indicates the radiality restriction in primary distribution systems. This particular condition is not being fulfilled during the algorithm's implementation by a specific term. At the initial stage of the analysis, before the algorithm is applied, radiality is ensured since the analysis in this paper considers only radial distribution networks. During the algorithm implementation the condition is never violated due to the utilized heuristic rules. These rules define that whenever a loop is formed in a network, i.e. closing of a tie-switch, radiality is therefore achieved by the opening of a respective sectionalizing switch. It is also clarified that the link between voltages and currents is expressed by the power flow equations which are utilized for power flow analysis by the proposed algorithm.

2.2. Actual load conditions

In the case where actual load conditions, i.e. load changes defined by actual load curves, are included in the minimization function, Eq. (1) may be written as follows:

$$\sum_{\Delta T=1}^{z} \sum_{k=1}^{m} R_k \cdot \left|I_k\right|^2 \tag{6}$$

where ΔT is the time interval for which loss minimization is calculated, z is the number of time intervals that constitute the examined time period within energy minimization is aimed.

It becomes obvious from (6) that if ΔT is chosen as 1 h and z is considered equal to 24, the loss minimization problem reduces

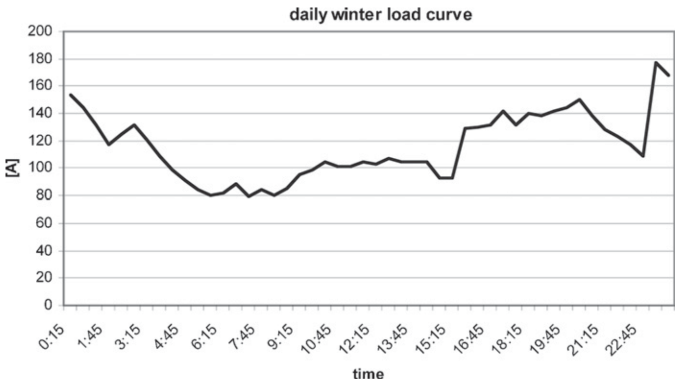

Fig. 1. Winter daily load curve of an urban MV feeder.

in acquiring 24 optimal configurations for 24 different fixed operational points of the network. This means that even for a single day the problem becomes extremely complex and time-consuming, especially when the variations in a daily load curve justify respective reconfigurations for loss minimization.

Therefore, when the network configurations are desired to adapt to load variations, the number of time intervals ΔT used is of great importance. Moreover, the alterations of loads at the nodes of a topology may influence the optimum configuration. On the other hand, if these alterations are not assumed to be extreme, then a smaller than 24 number z of time periods may be selected, for which it may be assumed that the load magnitude is constant. The loss reduction achieved for this assumed load magnitude may justify a fixed configuration concerning each selected time period, avoiding by this approach frequent switching operations. This process is justified by the observation of actual load curves, which indicates that hourly changes in load magnitude are smooth for adjacent feeders with similar customer composition. For example in Fig. 1, the mean loading value for the entire feeder between hours 10:15 and 15:15 is 102 A, whereas the upper and down loading limit within this time zone are 105 A and 93 A, respectively.

In Fig. 1 a daily winter load curve for an urban feeder is presented. The capacity of this medium voltage (MV 20 kV) feeder is 12,460 kVA and it serves 20 distribution transformers (DT) 20/0.4 kV. Moreover, every DT serves residential and small commercial customers. The observation of the feeder's load curve in comparison to the individual load curve of every DT indicates that the load pattern of the feeder during a day coincides with each of the DTs' load curve. The explanation for this lies in the similar consuming behaviour concerning similar customer types of adjacent DTs.

As aforementioned, it is expected that with hourly reconfigurations the optimal hourly solutions would not substantially differ among them. This could indicate that for times zones with relatively smooth load changes, fixed topologies, derived as optimum configurations for the mean loading value, consist a more realistic approach for real time management of the network.

3. Proposed algorithm

3.1. Proposed algorithm for network reconfiguration

The algorithm proposed in this paper for network reconfigurations is based on a heuristic approach which in turn adopts two basic rules commonly used in most of the published heuristics algorithms, such as [5–23]. In the last years many papers with new heuristic algorithms applied to the problem were published. In [24] an effective two-stage method for DSR for loss minimization is presented, using real power loss sensitivity with respect to the impedances of the candidate branches. Gomes et al. in [25] also present a new approach for DSR based on OPF in which the branch statuses (open/close) are presented by continuous functions. Although heuristic algorithms do not always provide optimal solutions, they constitute an efficient approach for what is called on-line reconfiguration, especially for large topologies with numerous tie switches. Heuristic techniques for network reconfiguration, and more specifically those utilizing stepwise switching operations for simulating real conditions, seek for a local optimum. Although this optimum may theoretically diverge from global optimum, heuristics algorithms in most of the practical cases reach this global optimum. Since the final solution constitutes a combination of the local optimums, the larger and more complex the topology the greater the possible divergence from the global optimum. For small and medium sized networks, i.e. 16, 33 and 69 bus systems, heuristic algorithms are, however, capable of providing efficient solutions.

The first heuristic rule is based on Civanlars' approximate formula [3] concerning the estimated amount of loss change resulting from load transfer between two feeders. It is actually an intuitive approach in order to determine whether an open tie switch should be chosen for reconfiguration. This rule indicates that a significant voltage drop across an open tie switch is expected to cause significant loss reduction. The second rule is utilized in order to regain radial configuration after a tie-switch is closed. The corresponding sectionalizing switch that must open in the performed loop is the one with minimum current.

3.2. Load variation

As stated previously, using 1-h intervals in (6) would lead to an extremely large number of loss minimization problems. On the other hand, using the usual three feeder load conditions, namely light-, medium- and heavy-load conditions, would be too simple and misleading. In the not unusual case where loads in every node would equally vary, the three conditions may not lead to reconfiguration. Actual load variation in every node of the network, i.e. the actual load composition, is of greater importance. This would lead to a far better decision concerning the reconfiguration question and it would obviously contain the above three load conditions as a special case.

The probabilistic modelling of loads, especially residential ones, is well justified by the fact that electricity demand is largely a stochastic process exhibiting diversity [26–31]. Load daily variations may therefore follow a distribution of data having an equal probability. Hence, in this work the load variation has been assumed to follow a uniform distribution.

The load P_i will be uniformly distributed between the values:

$$P_i^{lower} = \overline{P_i}\left(1 - \frac{s_u}{100}\right) \tag{7}$$

$$P_i^{upper} = \overline{P_i}\left(1 + \frac{s_u}{100}\right) \tag{8}$$

where $\overline{P_i}$ is the mean load value, P_i^{lower} is the lower limit of the uniform distribution interval, P_i^{upper} is the upper limit of the uniform distribution interval, s_u is a percentage parameter of the mean value, defining the length of the uniform distribution.

Mean load values for every examined network, well defined for the 16, 33 and 69 bus systems [3,32,33], were considered as initial load values. In the real topology case, mean load values were calculated using historical total current measurements at the feeding end of each line, provided by the Greek Public Power Corporation (PPC) during 1 year. The active power at each node was computed assuming the nominal medium voltage (MV) value (i.e. 20 kV) and a typical power factor equal to 0.9.

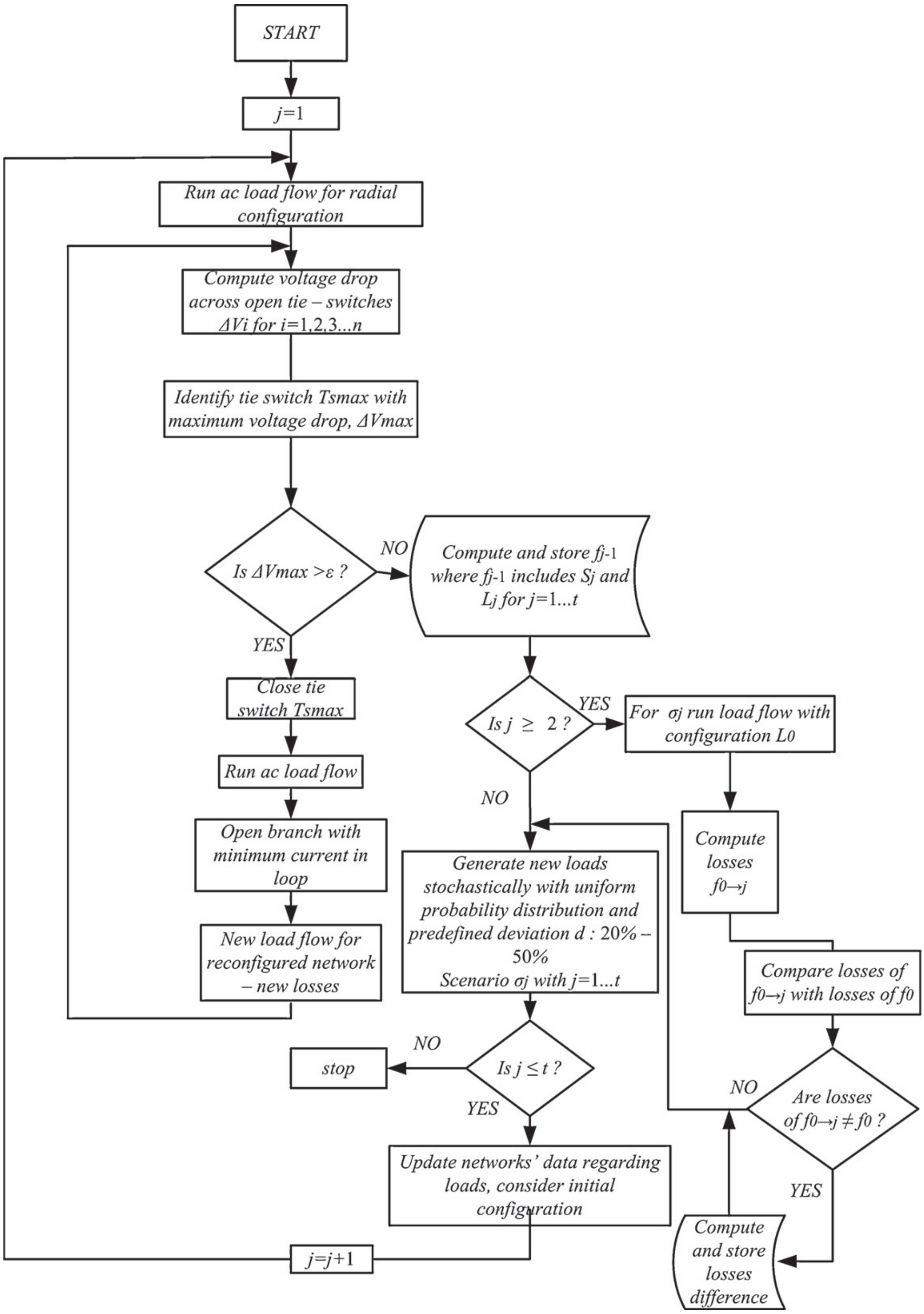

Fig. 2. Flowchart of the proposed algorithm.

3.3. Flowchart of complete process

The procedures analyzed above regarding network reconfiguration and the simulation of load alterations, were combined in order to produce a unified algorithm for network reconfigurations considering load variations. In Fig. 2 the flowchart of this algorithm is illustrated. It is clarified than in the flowchart counter *j* corresponds to the examined scenarios (σ_j) regarding load alterations. At first it is assumed that the final reduced losses for a static problem with a specific load composition after the reconfigurations are a function of the status of all switches (S_j) in the network and of the load composition (L_j) for the examined scenario *j*. Therefore, losses are presented as $f_j\left(S_j, L_j\right)$. For *j* = 1 (1st scenario-based case with initial mean load values) final losses could be written as: $f_0\left(S_0, L_0\right) = g_0$.

Table 1
Bus systems.

Bus systems	Sect. switches	Tie switches	Nominal voltage (kV)	Load (MW)	Load (MVar)	Computed initial losses (kW)
16	13	3	11	28.7	17.3	511.44
33	32	5	12.66	3.715	2.3	202.67
69	69	5	12.66	38.022	26.946	229.83

Variable ε is an arbitrary voltage threshold chosen to increase the algorithm speed by reducing the sensitivity concerning the investigated network reconfigurations. In our analysis ε was considered equal to zero and thus, all tie switches were examined at the reconfigurations procedures. It is obvious that due to the heuristic nature of the algorithm, value selection for ε would possibly affect the divergence from optimal solution.

In flowchart shown in Fig. 2 the basic and initially examined scenario is the one concerning the initial mean load values. That means that the algorithm solves the reconfiguration problem for a fixed operational point. The first solution g_0 includes the final configuration with reduced losses, including the status of all sectionalizing and tie switches (S_0) of the network along with the initial load composition (L_0). This solution is considered in this work as the base case. For the second scenario, $j=2$, loads change stochastically under uniform probability distribution within the limits defined by deviation d. It must be noted that this deviation d corresponds to the parameter s_u defined in (7) and (8). Deviation d equals to parameter s_u as they both define the range ($\pm d$% or $\pm s_u$%) within which the load magnitudes change around their initial mean values. New loads along with the initial radial configuration constitute scenario 2, a new reconfiguration problem for a different fixed operational point.

The proposed algorithm solves the problem again and leads to solution g_1 which includes the final reconfigured topology along with the new losses, including this time the new status of all switches (S_1) with the new altered load composition (L_1). This procedure, namely the generation of various different load compositions for the network, is used to simulate actual load curves, and continues until j becomes equal to t. It becomes obvious that deviation d, or parameter s_u, determines the time zone of a load curve that is desired to be simulated. The latter has the following explanation: it is expected that long periods in a daily load curve would present intense load variations since they involve time zones with different consuming behaviours by the customers. Therefore, a high value for s_u or d could be assumed to simulate these aforementioned time periods, whereas a relative low value could refer to short time zones for which load fluctuations are not expected to be extreme.

While the above procedure continues, an intermediate step has been added aiming to examine whether the reconfigured topology derived for the initial mean load values could produce satisfactory results for all other cases. According to the flowchart, for $j \geq 2$, i.e. for every scenario with loads different from the initial mean values ($L_j \neq L_0$), a load flow is implemented under the following assumptions:

i. The network loads are considered to be the loads stochastically generated for scenario σ_j (L_j).
ii. The configuration of the network is considered to be the one resulting by solution g_0 (S_0).

This particular part of the proposed algorithm is formulated by the following.

For $j \geq 2$ we define $f_{0\to j}\left(S_0, L_j\right)$ as the final losses for a network with the load status as derived in the first scenario (S_0) and the load composition (L_j) as resulted by Eqs. (7) and (8). Consequently, based on the latter, for a random scenario z ($j=z$) we could accordingly write $f_{0\to z}(S_0, L_z) = g_{0\to z}$ of optimality validation of the reconfigured topology (S_0) derived from the basic case (1st scenario) is implemented based on the following:

if $|g_{0\to z} - g_z| > m$ then, switching status S_z is considered optimal or near optimal for scenario z with load composition L_z, otherwise, if $|g_{0\to z} - g_z| \leq m$ then, switching status S_0 is considered optimal or near optimal for scenario z with load composition L_z. In this case the reconfigured topology that resulted for the initial problem with the mean load values could still be considered as the optimal solution for the new state with altered load composition since the additional loss reduction that solution g_z could yield is considered negligible. Maximum loss increase m defines the tolerance in divergence by optimal solution in loss reduction, resulted by considering the reconfigured topology of the base case as the optimal topology regardless the load composition of the network.

Simulations presented more analytically in Section 5, showed that especially for small values of the deviation d, the optimum configuration proposed by the specific heuristic algorithm utilized in this work was almost identical to the one concerning the initial mean load values. When d was larger, most of the new optimal configurations included sectionalizing switches adjacent to the ones of solution g_0. The algorithm completes this additional investigation by comparing reduced losses resulting by this intermediate load flow to the corresponding ones for the optimal configuration concerning each examined scenario.

4. Parameters of test cases

4.1. Examined networks

The algorithm described in the previous section was applied on the 16, 33 and 69 bus systems. In Table 1 basic data for the networks are presented.

A typical urban power distribution network segment was selected as the real test case in the study. The selected segment lies in the eastern part of Thessaloniki, Greece. It consists of five MV power lines which start at the same HV (high voltage)/MV power substation, and run mostly underground, with only a small section consisting of overhead lines. These lines are used to feed a number of MV/LV power transformers as presented in Fig. 3.

PPC provided all the essential information regarding the rated power of all MV/LV step down transformers, length, type (overhead or underground) and electrical parameters of all line segments interconnecting the transformers, as well as load curves for all feeders.

4.2. Selected parameters for implemented simulations

For the 16, 33 and 69 bus systems the initial load values were considered to be the mean values. Moreover, for the real topology every month was examined separately. It was observed that the daily load curves within each month followed approximately the same pattern during common days for all feeders. Daily time zones were selected for each month in such a way that the mean loading value within each zone would not diverge significantly from its

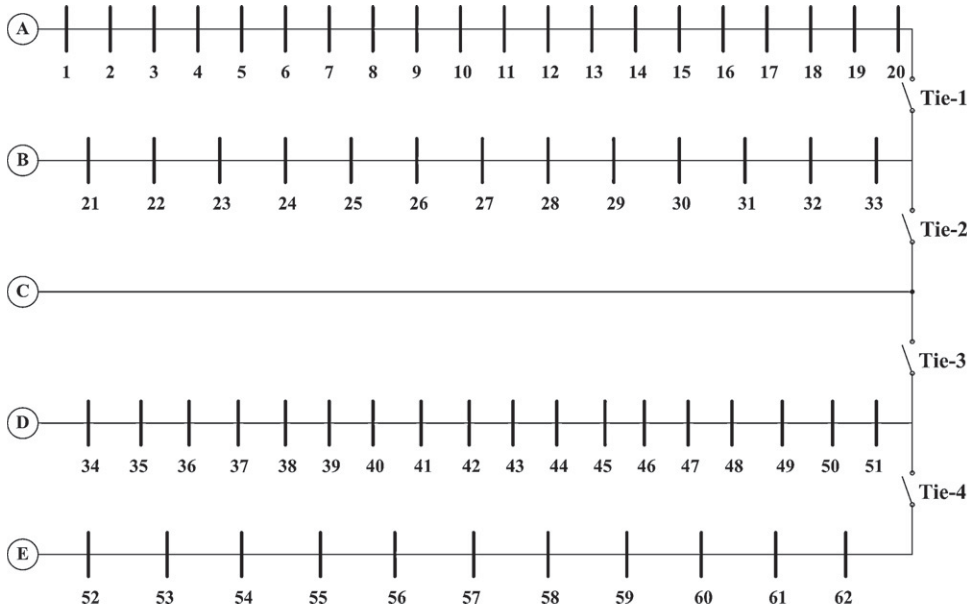

Fig. 3. Real network segment.

upper and lower limits. In this work the indicative results regarding month March 2007 are illustrated in the next section.

Furthermore, two basic simulation sets were implemented regarding the value of deviation d. In the first set, $d = 20\%$ was used, assuming normal load alterations among feeders. In the second, the value $d = 50\%$ was chosen in order to simulate scenarios with extreme load alterations. Such extreme variations could correspond to different customer composition of adjacent feeders and thus, different consuming behaviours. For every examined network, 10,000 simulations, i.e. 10,000 different load conditions were implemented for each of the two deviation values.

5. Results

5.1. 16 bus system

In Fig. 4 the layout of the IEEE 16 bus system is presented. It was expected that due to the small network size, load alterations would not affect significantly the switching operations for optimal configuration. The proposed algorithm was applied for the two deviation values and for 10,000 different loading scenarios.

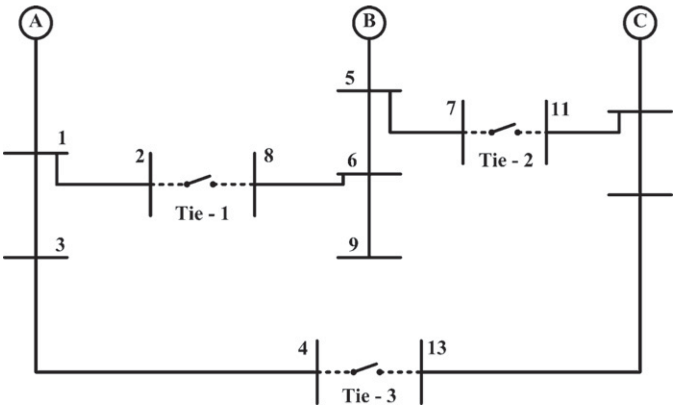

Fig. 4. 16 bus system.

Table 2
Base case for 16 bus system.

Tie switch—closed	Branch that opens	Loss reduction
Tie-1	8–6	
Tie-2	5–7	8.86%
Tie-3	Tie-3	

The results concerning the solution g_0 show that the close-open switching operations correspond to pairs Tie-1/branch 8–6 and Tie-2/branch 5–7, shown in Table 2. Operating switch Tie-3 would not contribute in further loss reduction. Table 3 presents the % participation of the proposed switches for the final topology in the 10,000 loading scenarios, for both deviation values.

As mentioned above, 16 bus system is a small network and load alterations are expected to slightly affect the optimal configuration. For all 10,000 loading scenarios with $d = 20\%$, the final reconfigured topology is identical to the one resulted for the initial mean load values. Moreover, for the simulation set with $d = 20\%$, Tie-3 remains open irrespectively of the load composition of the network. Concerning the simulation set with $d = 50\%$, the only difference is that for a small percentage of loading scenarios, namely 858 among 10,000, Tie-3 participates in the network reconfiguration. In these cases branch 4–13 opens. The participating percentages for Tie-1 and Tie-2 could be considered negligible. The basic conclusion arising by Table 2 is that for a small network, a fixed configuration could be considered as the optimum one for actual loading conditions.

Table 3
Load variation and corresponding switching pairs.

	Deviation $d = 20\%$ branch that opens at % of cases	Deviation $d = 50\%$ branch that opens at % of cases
Tie-1	6–8 at 100%	6–8 at 99.43% Tie-1 at 0.57%
Tie-2	5–7 at 100%	5–7 at 99.99% Tie-2 at 0.01%
Tie-3	4–13 at 100%	4–13 at 91.42% 3–4 at 8.58%

Table 4
Base case for 33 bus system.

Tie switch—closed	Open branch	Loss reduction
Tie-1	7–8	
Tie-2	9–10	
Tie-3	28–29	30.93%
Tie-4	14–15	
Tie-5	32–33	

Table 5
Load variation and corresponding switching pairs.

	Deviation d = 20% branch that opens at % of cases	Deviation d = 50% branch that opens at % of cases
Tie-1	7–8 at 100% of cases	7–8 at 100% of cases
Tie-2	8–9 at 1.2% of cases	8–9 at 19.85% of cases
	9–10 at 80.79% of cases	9–10 at 46.71% of cases
	10–11 at 18.01% of cases	10–11 at 32.35% of cases
		11–12 at 1.09% of cases
Tie-3	28–29 at 100% of cases	28–29 at 100% of cases
Tie-4	14–15 at 100% of cases	14–15 at 100% of cases
Tie-5	31–32 at 0.01% of cases	16–17 at 0.03% of cases
	32–33 at 99.99% of cases	17–18 at 5.71% of cases
		31–32 at 2.1% of cases
		32–33 at 92.16% of cases

5.2. 33 bus system

Regarding the 33 bus system, Table 4 illustrates the base case solution for the initial load values. Although this solution is not the optimum one, the resulting loss reduction is very close to loss minimization for this network. Table 5 includes all the examined scenarios concerning load variability along with the corresponding sectionalizing and tie switches. As it may be easily observed, for both deviation values the switches resulting for the base case present the higher participating values in network reconfigurations. Even for d = 50%, for three of the five tie switches (Tie 1, 3 and 4) of base case, the corresponding branches open in all scenarios in the final topology.

In Fig. 5 the set of all participating switches in the network reconfiguration is illustrated for d = 20%. For every tie switch the corresponding neighbouring sectionalizing switches are presented in dotted frames. For tie switches 2 and 5, up to three sectionalizing switches adjacent to the one resulted for the base case, are expected to participate in network reconfiguration. Despite the latter, according to Table 5 for d = 20% the percentage of participation for these aforementioned switches is low, and only for d = 50% it may reach higher values. It is very important to note that for every tie switch the corresponding sectionalizing switch always presents the higher level of participation regardless of load alterations.

5.3. 69 bus system

In 69 bus systems shown in Fig. 6, Tie-2 only for 74 cases out of 10,000 for altered load composition of the network with d = 50% participates in reconfigurations. In these scenarios an adjacent branch, i.e. 21–22, opens instead of the tie switch. In Tables 6 and 7 the base case and the examined scenarios for the 69 bus system are shown, respectively, when load variability is applied.

In Fig. 6 the set of all participating switches in network reconfiguration, for d = 20%, is illustrated as in the previous case of the 33 bus system.

Table 6
Base case for 69 bus system.

Tie switch—closed	Open branch	Loss reduction
Tie-1	Tie-1	
Tie-2	Tie-2	
Tie-3	15–16	54.3%
Tie-4	47–48	
Tie-5	54–55	

Table 7
Load variation and corresponding switching pairs.

	Deviation d = 20% branch that opens at % of cases	Deviation d = 50% branch that opens at % of cases
Tie-1	12–67 (Tie-1) at 100%	12–67 (Tie-1) at 100%
Tie-2	14–22 at 100%	14–22 (Tie-2) at 99.26%
		21–22 at 0.74%
Tie-3	15–16 at 100%	13–14 at 1.09%
		14–15 at 1.31%
		15–16 at 97.6%
Tie-4	47–48 at 56.54%	47–48 at 34.02%
	48–49 at 11.94%	48–49 at 15.08%
	49–50 at 15.68%	49–50 at 19.15%
	50–51 at 15.84%	50–51 at 31.75%
Tie-5	53–54 at 28.64%	53–54 at 42.47%
	54–55 at 38.14%	54–55 at 20.71%
	55–56 at 33.22%	55–56 at 31.28%
		56–57 at 5.54%

Table 8
Base case for real network.

Tie switch—closed	Open branch	Loss reduction
Tie-1	15–16	
Tie-2	27–28	33.6%
Tie-3	44–45	
Tie-4	60–61	

5.4. Real distribution network

As aforementioned in Section 4, real data regarding the network and the load values were provided by PPC for the examined real network. In particular, for each feeder, it was considered that its load is divided among the step down transformers it feeds in proportion to their rated power. This is a policy followed by PPC itself due to the lack of measurements at the MV/LV transformers. The analysis was implemented for month March 2007 and the results are presented to Tables 8 and 9. It is assumed that the base case for this topology also considers a fixed operation point for the network. Initial load values were the mean values for a specific time zone

Table 9
Load variation and corresponding switching pairs.

	Deviation d = 20% branch that opens at % of cases	Deviation d = 50% branch that opens at % of cases
Tie-1	14–15 at 0.69%	13–14 at 0.26%
	15–16 at 93.85%	14–15 at 14.73%
	16–17 at 5.46%	15–16 at 57.91%
		16–17 at 27.01%
		17–18 at 0.09%
Tie-2	27–28 at 100%	26–27 at 7.77%
		27–28 at 86.66%
		28–29 at 5.56%
		29–30 at 0.01%
Tie-3	44–45 at 95.8%	42–43 at 0.01%
	45–46 at 4.2%	43–44 at 6.36%
		44–45 at 69.16%
		45–46 at 24.34%
		46–47 at 0.13%
Tie-4	59–60 at 0.07%	59–60 at 11.02%
	60–61 at 98.29%	60–61 at 73.22%
	61–62 at 1.64%	61–62 at 15.76%

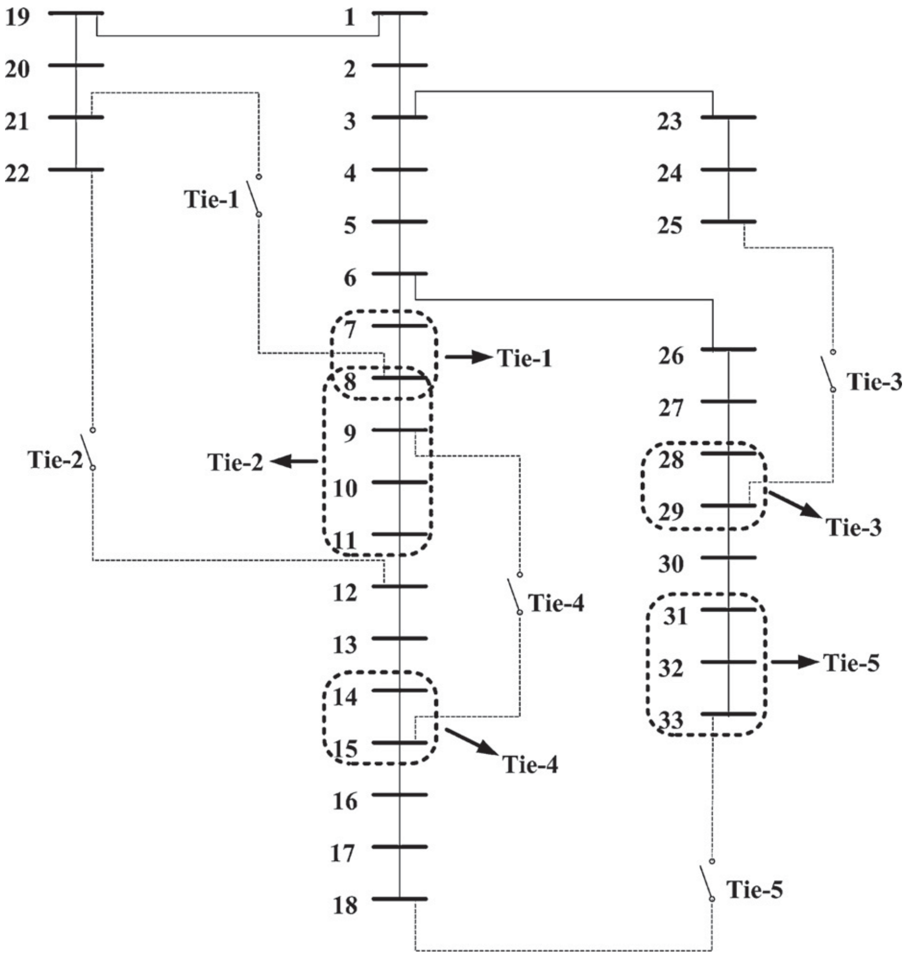

Fig. 5. Tie switches with corresponding adjacent sectionalizing switches including load alterations with $d = 20\%$.

of a daily load curve. Although the basic notion of this approach has been adopted in all IEEE bus systems, it is assumed to be more appropriate in this real data topology. Initial losses of the network were computed equal to 48.18 kW and initial network load was taken equal to 12.31 MW and 4.86 MVar. Final losses after network reconfiguration were found equal to 32 kW which corresponds to 33.6% loss reduction, as presented in Table 8. Divergence of optimal solution was approximately 1%. Simulations including load alterations showed that for a deviation of 20% as compared to the mean initial load value, sectionalizing switches derived by the base case participated in most scenarios. Again, even for $d = 50\%$, the switches of base case participated at least to the 50% examined scenarios.

In Fig. 7 the set of all participating switches in network reconfiguration for $d = 50\%$, is illustrated. It has become obvious so far that for $d = 50\%$ a larger group of adjacent sectionalizing switches correspond to every tie switch. Yet, as illustrated in Table 9, switches at both ends of the dotted framed sets participate in network reconfiguration only for a small number of scenarios.

5.5. Loss reduction results among examined scenarios

As mentioned above, an intermediate simulation step has been added between different load composition scenarios. The aim of this step is to evaluate the efficiency in loss reduction that is achieved by the fixed configuration for mean load values, when applied for different operational points of the networks, i.e. altered loads. Table 10 presents the maximum loss increase m defined in Section 3.2, in the case where optimal configuration derived for initial mean load values was considered fixed for all loading scenarios. As observed in this table, for $d = 20\%$ a fixed configuration that does not adapt to load alterations would cause a maximum divergence in optimal loss reduction on the order of 3.9% for all test cases.

Moreover, the basic conclusion derived by the observation of Figs. 5–7 is that optimal configuration for loss reduction provided for a fixed operational point may be slightly altered due to load variations. The alterations will be less significant for smaller deviations from the initial mean load values. In most cases the different switches that participate in the network reconfigurations are adjacent to the ones considering the initial fixed operational point. In addition, in most of the simulated scenarios with load variations, the final solution for optimal network configuration includes the same sectionalizing and tie switches.

Table 10
Maximum loss increase *m* for fixed configuration in all loading conditions with deviation *d*.

Network	*d* [%]	*m* [%]
16	20	0
	50	2.6
33	20	3.9
	50	5.3
69	20	1
	50	7
Real	20	0.6
	50	2.8

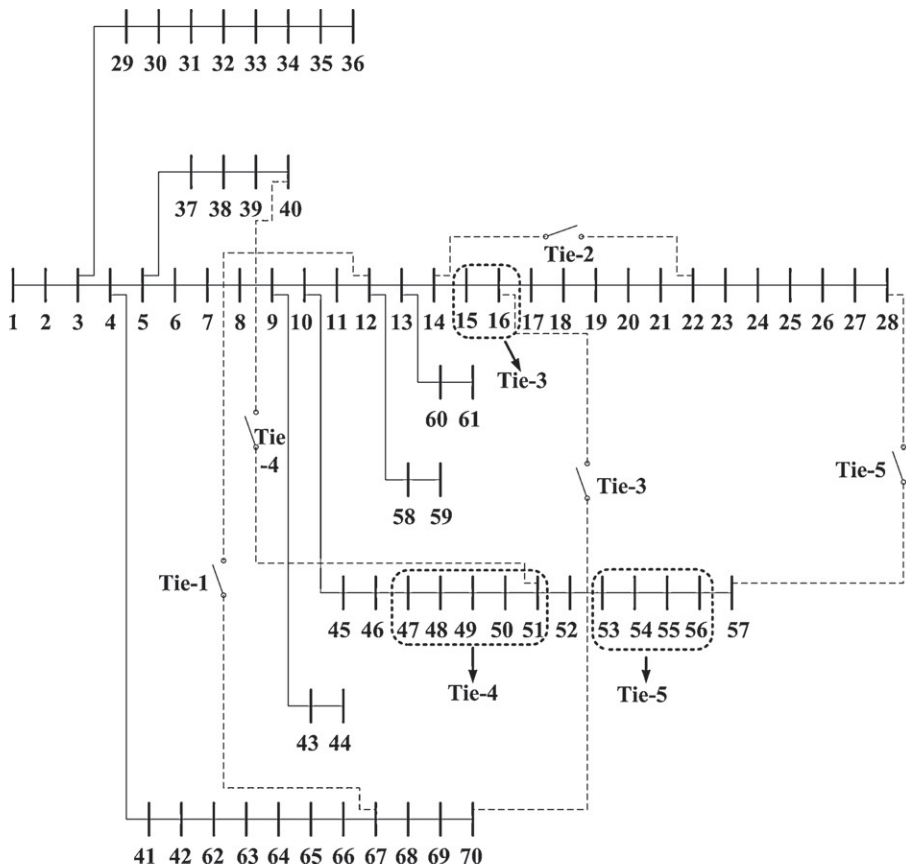

Fig. 6. Tie switches with corresponding adjacent sectionalizing switches including load alterations with $d = 20\%$.

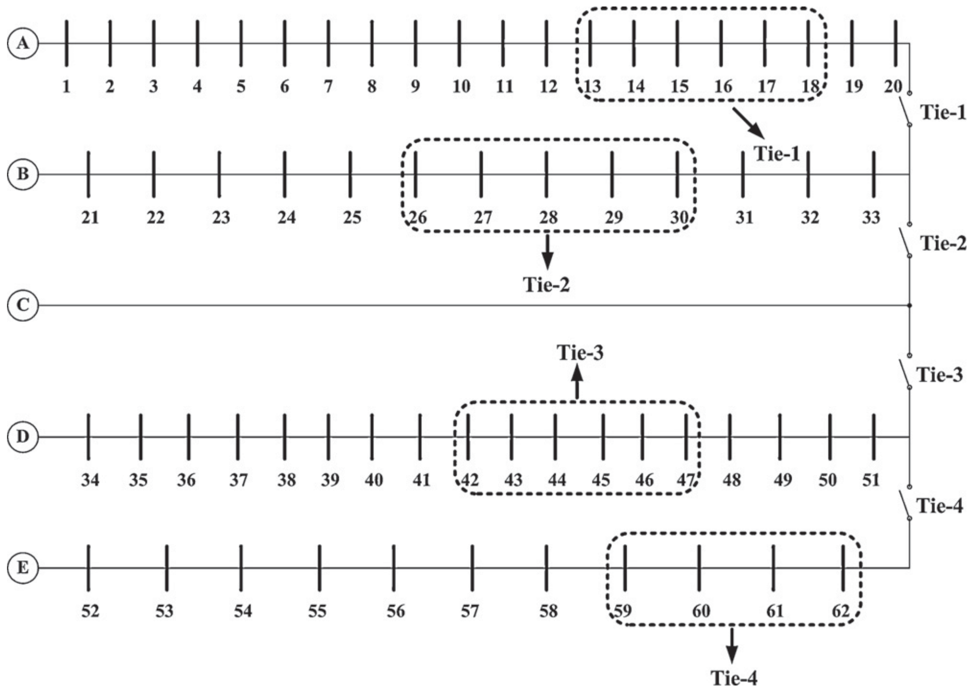

Fig. 7. Tie switches along with corresponding adjacent sectionalizing switches including load alterations with $d = 50\%$, for the real distribution system.

6. Conclusions and discussion

The first contribution of this paper is an expansion of network reconfiguration for loss reduction in a way to incorporate load alterations and thus simulate real operating conditions. The conclusions derived by such approach may constitute the guideline for centralized real management of the network for loss reduction. Secondly, the proposed algorithm may be used as a forecasting technique for network reconfigurations considering that load conditions tend to follow normally expected annual load growth. This algorithm combines heuristic techniques for network reconfigurations and at the same time considers load variations. Simulations were implemented in some of the most common used distribution networks from the published literature and to a real segment of an urban distribution network. The results illustrated that the optimal configuration for a fixed operational point of the network is slightly affected by normal load alterations.

The management of distribution networks concerning online reconfigurations has not been yet investigated in depth. The problem is a complex one and many parameters should be taken into account. Two among the most important ones are the frequency of switching operations and the justification for network reconfiguration due to load variations. Furthermore, it has become clear so far that automation in distribution networks comprises a prerequisite in order to implement the above analyzed management of the network. However, the extent of the achieved automation in any distribution network constitutes a compromise between the respective investment cost and the resulting benefits. For example, a recent study by the authors shows that the replacement of all MV load switches in a power distribution network segment is only marginally feasible [34]. The analysis in this paper showed that the replacement of the manual MV load switches by corresponding remote controlled ones could be selective and yet could yield efficient management of the network for loss reduction. Such an investment approach indicates a reduced investment cost in the direction of upgrading the automation level in distribution networks, while at the same time it permits near optimal management of the network concerning loss reduction. The proposed algorithm could therefore be used for feasibility studies, when automation level upgrade in distribution networks is under investigation. This feasibility study, based on the results from the proposed algorithm, will be presented in a following paper.

Furthermore, results in Table 10 verify that limited switching operations during a day constitute a realistic approach for online reconfigurations in order to reduce losses taking into account load alterations. This will lead in a small only increase in losses, as compared to the non-realistic case of hourly optimal reconfigurations. This is because, as shown in Table 10, a fixed reconfigured topology derived for mean load values could be considered as the optimal, or at least near optimal, regardless the load composition of the network. For example the 2nd row in Table 10 shows that for a time period during which load magnitudes of a network vary within $\pm 50\%$ of their mean values, the worse possible case is that for a specific load composition (usually extreme alterations in load composition with limited duration) the reconfigured topology derived for the initial problem with mean load values would cause a divergence in optimal loss reduction on the order of 5.3%.

The closure of this paper includes a brief comparison of the proposed algorithm with some existing ones that take into account load variations to the optimal reconfiguration problem. In [13] a relatively similar, to this paper, investigation is attempted. The main disadvantge of this method is that during the analysis various simplifications are considered regarding the complexity of the distribution networks examined and the electrical characteristics of the branches. More specific, the branch length is considered too small and the resistance of each branch is asuumed equal to $1\,\Omega$/mile. In [15] the basic problem is that load alterations are formed based on a typical load pattern and the simulations concern only a summer day while in [16] the loading scenarios are limited, and no tolerance in load variations for investigating a more efficient solution is defined. Finally in [17] the implemented analysis refers to a short-term management of the network, i.e. extreme load variations are not included, and in [19] only a simple network is examined under the consideration of only three basic loading conditions, namely *low*, *medium* and *high* loading levels. All the above problems are considered to be dealt by the proposed algorithm in his paper.

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