Electric Power Systems Research 116 (2014) 355–366

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Optimal reconfiguration of radial MV networks with load profiles in the presence of renewable energy based decentralized generation

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A R T I C L E I N F O

Article history:
Received 2 July 2013
Received in revised form 18 June 2014
Accepted 6 July 2014
Available online 26 July 2014

Keywords:
Decentralized generation
Network reconfiguration
Load profiles
Energy loss
Tabu Search
Branch Exchange

A B S T R A C T

The main concern of integration the renewable energy into the supply grid, in Germany, is to reach about 35% of the total generation by 2030. In this case, a large amount of the produced power will be provided as Decentralized Generation (DG). Therefore, the future distribution networks with the high penetration of DG power have to be planned and operated in order to improve their efficiency. Thus, the current study proposes a new methodology for reconfiguration of radial MV networks with the existence of renewable energy based DG units. Since the main concept of the proposed methodology is to minimize the energy loss, definition of a typical network, based on a real life urban network, will be handled. In this regards, the optimization algorithm was formulated using a combination of Tabu Search (TS) and Branch Exchange (BE). The utilized algorithm was based on C++ and NEPLAN – power system analysis software. Whereas, the load profiles of residential and commercial loads were used through the implementation of the algorithm. Two phases were conducted in the implementation of the proposed algorithm. In the first phase, the DG power has been assumed to be constant at different percentages of the rated power of each unit. In the second phase, the DG with generation profiles has been considered. At that end, the current methodology demonstrated a high performance in minimizing the energy loss, improving the voltage profiles and relieving the bottlenecks in the lines.

1. Introduction

Recently, the interest in Distribution Automation (DA) leading to Smart Grids has been widely grown as an important issue. The network reconfiguration process, which is one of the DA functions, improves the load flow of the distribution networks by changing the status of the switches without violating the operating constraints. Therefore, the reconfiguration is exploited for loss reduction, relief of overloads (load balancing), Volt/Var support (maximizing loadability), and system restoration [1]. The reconfiguration algorithms can be identified by the solution methods that employ: algorithms based upon a blend of heuristics and optimization methods, algorithms based solely on heuristics, and Artificial Intelligence (AI) based techniques [2]. Based on the reported studies, the introduction of DG in power distribution networks will increase the complexity of the reconfiguration problem. Reconfiguration of distribution networks can be conducted considering the load profile, generation profile, hybrid (i.e. load and generation profiles), constant load, or constant generation. In the previous studies, the optimal reconfiguration of distribution networks was illustrated to include system operation, planning, and DG placement. Briefly, the influence of DG on the distribution networks using a time variant load and a constant output power of DG was investigated by Agustoni et al. [3]. While, the distribution networks graphic simulator, developed with reconfiguration functions and a special focus on loss allocation, both considering the presence of DG was discussed by Oliveria et al. [4]. The Genetic Algorithm (GA) for reconfiguration of a distribution network with the existence of DG units, which was considered as a constant supplying power at a

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http://dx.doi.org/10.1016/j.epsr.2014.07.007
0378-7796/

certain power factor, was used by Choi et al. [5]. Calderaro et al. [6] implemented the reconfiguration of distribution networks for maximizing the capacity of DG which can be interconnected while the operating constraints were kept within their limits. The TS was used by Rugthaicharoencheep et al. [7,8] for optimal reconfiguration of distribution systems with the existence of DG units to minimize the power loss. Mishima [9] exploited the TS for reconfiguration of distribution networks. The authors have developed their methods dealing with equally distributed loads. The algorithm was implemented in different cases, such as the system without DG, only one DG is existed, and multiple DGs were connected. Consequently, with a different output power of wind energy, Zhang et al. [10] showed a method to get the optimal network reconfiguration scheme of distribution networks. Kargar and Maleki [11] introduced a reconfiguration method of distribution networks with DG based on Imperialist Competitive Algorithm (ICA) with objectives of minimizing the loss and increment the load balance. Syahputra et al. [12] developed a reconfiguration methodology based on a fuzzy multi-objective approach. A methodology for distribution networks reconfiguration based on Simulated Annealing (SA) using Open Distribution Simulator Software (Open DSS) was modified by Nie et al. [13]. Random characteristics of wind power generation were considered for the distribution network reconfiguration [14]. The optimization was performed based on multiple objective Particle Swarm (PS) algorithm. In this regards, the wind power was utilized based on two scenarios; a single and multiple wind farm scenarios. The optimum operation of a distribution network in the presence of DG and capacitors using system reconfiguration was demonstrated [15]. Based on Ant Colony (AC) algorithm, a reconfiguration methodology was established [16]. Therefore, in the current study, a new switching state optimization method for radial MV distribution network is proposed. The main concern of our study was based on the BE and TS for minimizing the energy loss of distribution networks in the presence of renewable energy based DG units. In terms of that purpose, minimizing the energy loss, a nonlinear optimization problem was formulated. Thus, the current method enables an easy way to identify the time horizon for conducting the optimization process. As a result, selection of 1 h, one day, one week, month, or a year will be possible. Moreover, the proposed method offers the use of load and generation profiles. At that end, the profiles can be measured, standardized, or forecasted. Forecasting approaches of the renewable energy based resources generation profiles such as wind and PV will be evolved into the new concept of the Smart Grid [17,18]. These approaches will provide the proposed methodology with generation and load profiles to be exploited in the switching optimization process. Hence, the optimum switching state of a day ahead can be identified. The structure of the current study will be presented in several sections. Introduction to the TS will be shown in the next section. While in Sections 3 and 4 the problem formulation and the solution mechanism will be illustrated, respectively. Sections 5 and 6 represents the typical distribution network and the implementation phases of the proposed approach. The results will be carefully explained in Section 7. Finally, the conclusions will be summarized in Section 8.

2. Tabu Search

"Tabu Search (TS) is basically a gradient-descent search with memory. The memory preserves a number of previously visited states along with a number of states that might be considered undesired. This information is stored in a tabu list" [19]. The most important parameters in the TS are the definition of the state, the area around the state, and finally the length of the tabu list [19]. Moreover, there are two extra parameters which are often used, aspiration and diversification. "Aspiration is used when all the neighboring states of the current state are also included in the tabu list. In that case, the tabu obstacle is overridden by selecting a new state while; diversification adds randomness to this otherwise deterministic search. If the Tabu Search is not converging, the search is reset randomly" [19]. Using the TS, the optimum solution is approached by searching the solution of the neighbor state. In the tabu list every exchange step is stored; it called a "tabu" and cannot be turned around again. Through the tabu list the local and global solution space can be covered and this is one of the advantages of the TS method. The computational cost in the TS methods is lower than that of the GA method [9]. Therefore, the TS can achieve the optimal or suboptimal solution within a reasonably short time. In terms of initial conditions the TS is straightforward and deterministic so that it is more robust than GA. In the TS method the search for the optimal solution is performed in a more aggressive way compared to the case of SA and GA. Based on these advantages, the TS method since 1999, is used in different optimization applications in power system [20]. One of these applications is the reconfiguration of distribution networks with distributed power generation [9]. In the current work the TS has been selected because it depends on an initial solution, and this is valid for the networks under study, while both GA and TS are applied to the reconfiguration optimization of distribution networks with the existence of DG units [5,9].

3. Problem formulation

In the reported studies two types of switches in the distribution networks are always implemented in the reconfiguration process: tie switches and sectionalizing switches. Tie switches are the switches which are used to connect different branches or feeders, while the sectionalizing switches are utilized to switch between the MV substations through the feeder. In the current study the switches at the two ends of the branches are only used in the reconfiguration process as has been identified by the network operator because only these switches can be automatically switched. Therefore, each branch is summarized between these two switches through the optimization process. The main concern of the proposed reconfiguration methodology is the minimizing of the energy loss with turning the switches on/off. To that end, the reconfiguration problem has the following constrains:

1. Power flow equations.
2. Voltage magnitudes at each node in the system must be within the acceptable limits, which are provided by the network operator (±3%).
3. Line currents in all branches has to be within their acceptable limits.
4. The radial structure of the system must be maintained.
5. No interconnection between the HV stations.
6. All nodes have to be energized.

Mathematically, the problem can be formulated as follows:

$$\text{Min}Z = \sum_{m=1}^{m=24} \sum_{k \in B} |I_k^m|^2 R_k \quad (1)$$

Subject to

$$g(x) = 0 \quad (2)$$

$$V_i^{\min} < V_i < V_i^{\max} \quad (3)$$

$$I_k^{\min} < I_k < I_k^{\max} \quad (4)$$

where Z is the objective function (Wh), I_k^m is the branch k current during m hour obtained by running the load flow, therefore the number of points per day is 24. R_k is the branch resistance, B is the set of all the network branches, m is the number of time intervals per day, and k is the branch number. The reconfiguration process will be performed for the whole day after performing the load flow with load profiles with a time interval of 1 h and then summarized for the whole energy loss of the day. $g(x)$ is the load flow equations. The variable x represents the algebraic variables of the voltage and its angle at each node in the system and g are the algebraic equations for the active and the reactive power balances at each node in the system. V_i is the node voltage. For more explanation different inputs and outputs are presented in this section.

3.1. Inputs

3.1.1. Load profiles

The maximum power for each load connected at the LV side of the transformer is assigned. Then the standard load profiles combinations are given. The active and reactive powers are given at each node based on the maximum power and the accompanied profile. In the current work the standard households and commercials load profiles were used through the optimization.

3.1.2. Generation profiles

The DG power was taken in the first phase of the optimization, as constant percentages of the rated of each unit. While in the second phase the DG was used with the generation profiles (which have been provided by the utility as measured generation data for one year). A variable is also defined in the code to identify the percentage of the rated DG power.

3.1.3. Network topology

The network structure has been built into NEPLAN platform. To identify a switch state, a binary identification was used, where 0 was taken for off switches and 1 was taken for on switches. The initial switching state of the network has to be given in binary manner in the C++ code.

3.1.4. Time

Using the load flow with load profile simulation, the time interval has to be specified. In the current study, to reduce the time consumption points, time interval was taken as 1 h. Thus, 24 points for each load and each generator are used through the whole day.

3.1.5. Tabu list length

One of the main inputs which affect the optimization process is the long of the tabu list.

3.1.6. Maximum number of Iterations

Different numbers of iterations were tested. In the current work 30 was selected to be the maximum number of iterations.

3.1.7. Optimization function

As the proposed approach was used to minimize and maximize the energy losses, a variable was identified which is 0 for minimization and 1 for maximization.

3.2. Outputs

3.2.1. Energy loss

The energy loss minimization is the objective of the proposed methodology. The minimum and maximum energy loss are obtained and compared in order to specify the potential of using the new approach.

3.2.2. Voltage

The voltages at all nodes through the studied day are given at the end of the optimization process.

3.2.3. Line loadings

The loadings of all lines in the networks are also one of the outputs.

4. Solution mechanism

In order to identify the optimum switching state of the network, an algorithm was developed and implemented in C++ which is coupled to the power system analysis software NEPLAN. For this purpose, NEPLAN software and its C++ interface is being used. Fig. 1 describes the fundamental solution mechanism. The power flow

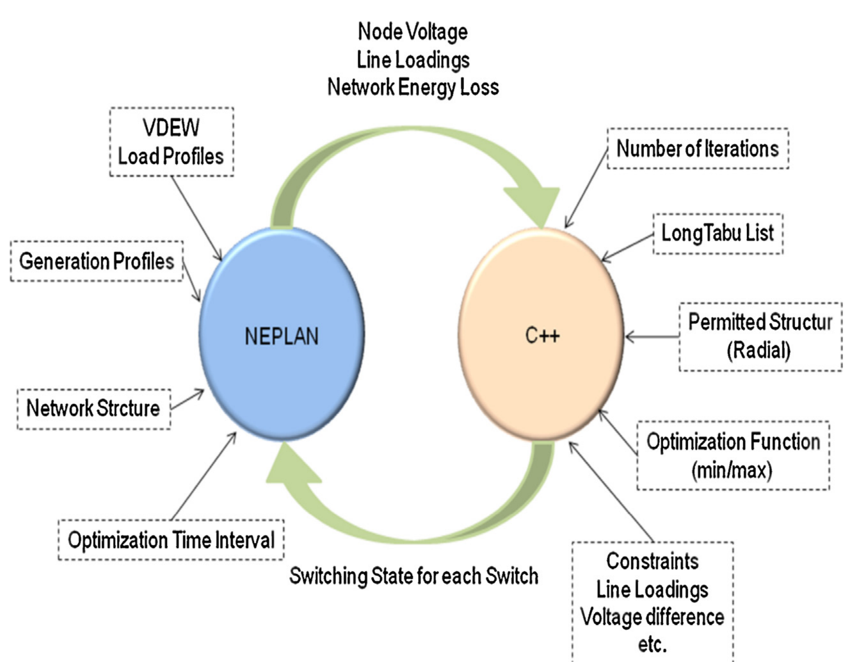

Fig. 1. Solution mechanism.

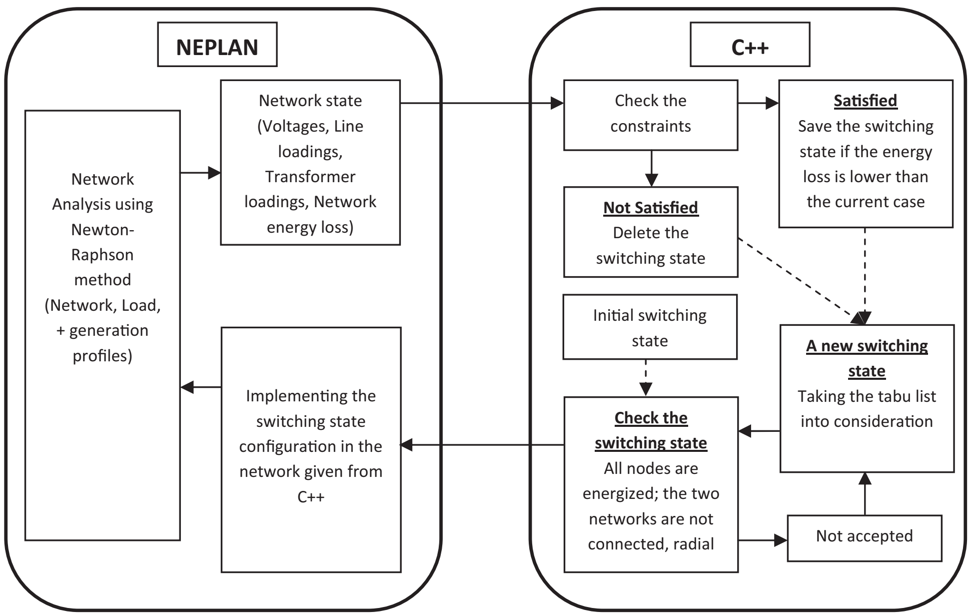

Fig. 2. Interaction between NEPLAN and C++.

calculation is mapped using NEPLAN, whereas the optimization algorithm is implemented in the programming language C++. In the current study, the calculation of the network state data within NEPLAN was passed to C++, and the algorithm determines the optimal switching state and passes the new switch configuration to NEPLAN again. Fig. 1 shows the input variables and the exchange of data between NEPLAN and C++. The investigated network is stored in NEPLAN, containing cable lengths, cable types, MV/LV transformers, as well as nodes information. At each node, the load is connected at the LV side. The mapping of the load profiles was represented as a combination of standard load profiles of VDEW, as will be described in the next section. In addition, DG units are integrated into the grid. The generation profiles are also stored in NEPLAN. The states of the switch (open or closed) are taken from the C++ program and they are previously tested for admissibility. From NEPLAN, the results are returned to the C++ code. These include the power losses, line loading and the voltages at all nodes. The maximum number of iterations, the long of the tabu list, the optimization function, the constraints, and the evaluation criterion of the accepted network topology which in this case radial are given in the C++ code. Fig. 2 shows the principal interaction between NEPLAN and C++. The method works iteratively, so that each switching state found in C++ is passing within the maximum number of iterations to NEPLAN for load flow with load profiles calculation. Then the evaluation of the network losses and constraints were carried out or completed in C++.

The optimization starts with an initial switching state for the network to be examined. This is passed to NEPLAN and adjusts the switching states of all switches in the network for investigation. Here, the power flow calculation for the current state is conducted. Consequently, the data is passed to the C++ algorithm. The algorithm verifies the compliance with the constraints of the node voltages and line loadings and compares the network energy losses with the best solution. If the value is better, the switching state is saved, otherwise discarded. A switching state is also discarded if the constraints were not achieved. In the next step, a new switching combination was determined and their validity, according to the Tabu Search conditions, was tested. A switching combination was only accepted when each node was supplied by exactly one substation. Therefore, supplying of one node by two substations is not permitted, as applied in the real networks. Then the new switching state was handled to the network calculation software, and the process is repeating until reaching the number of the maximum iterations. The switching state with the lowest energy losses in compliance with the constraints is the output and it will be the optimum switching state. The choice of the input parameters is dependent on the requirements of the implementation phases; therefore it will be demonstrated in Section 5. Different initial solutions with different iteration number were tested to evaluate the robustness of the algorithm and the algorithm was found to be robust.

4.1. Optimization algorithm

This section describes the operation of the algorithm, which has been implemented in the language C++. Fig. 3 illustrates the proposed algorithm. The TS method, as explained in Section 2, the heuristic method which has been selected for the task to search for optimal switching combination and thus to determine a new network structure for each iteration step. The change of a switch depends on the chosen objective function. In the proposed methodology, choosing between minimizing and maximizing the network energy losses could be possible. To minimize the energy loss, the switches and their neighbors are modified in which the voltage difference between the two adjacent nodes is the greatest. Thus, the aim is to minimize the voltage difference. To maximize the energy loss, maximizing the voltage difference is desirable or needed. The determination of the reliability of the new network structure is adjoined by the change of the switching states. These will be checked during the change of the switching state, if this operation is allowed. If the operation is permitted, it is executed and the switch is set to the tabu list, and is therefore locked in the next exchange processes. If the exchange transaction inadmissible, the next switch is changed. A change is not permitted if one of the following constraints is violated:

1. A switch adjacent nodes is no longer supplied by the switching action, i.e. not associated with a one of the two main transformers.
2. A switch adjacent nodes which will be supplied from the two substations if the switching action is performed.

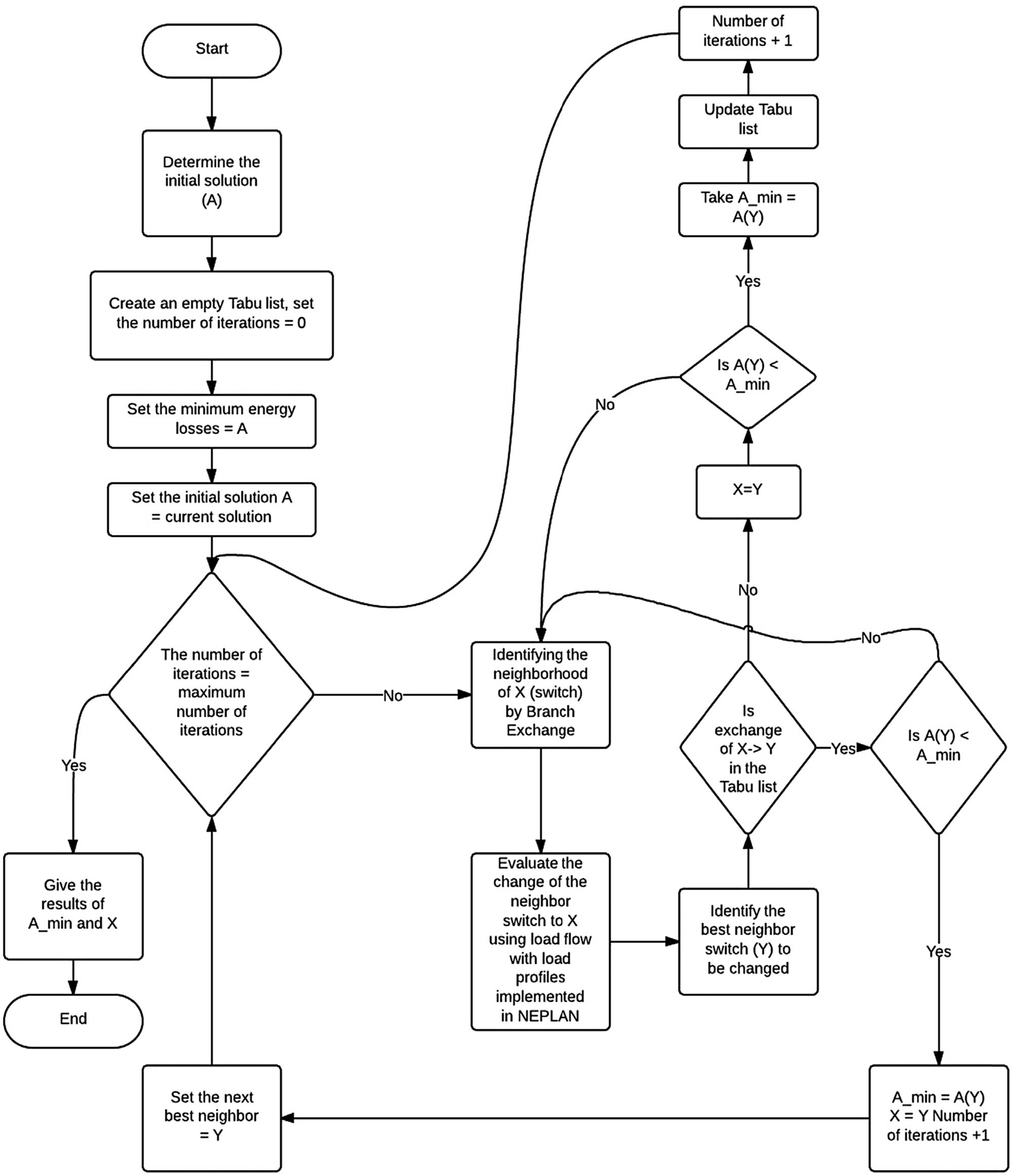

Fig. 3. Proposed algorithm.

An admissible switching combination of the network is passed to NEPLAN, which calculates the power flow within the selected time window and the objective function value and the constraints returns to the algorithm. For the urban network which is selected in the current study a time frame of 24 h, which means that a switch state for the entire 24 h is optimized. The returned values are then checked whether the voltage constraints of ±3% at each node are complied with, and whether the line loading is more 100% for no line. As these constraints are satisfied, the energy loss value and the switch combination are stored if the objective function value is better than the best so far.

As the algorithm in our paper was implemented for identifying the optimal switching state within a time horizon of one day, it consumes approximately 4 h to find the solution. That is because the time was consumed for load flow with load profile. We have proposed to the utility that a switching catalog can be identified based on the classification of the generated power, i.e. high or low. Moreover, it can be used based on a forecasting tool for day ahead.

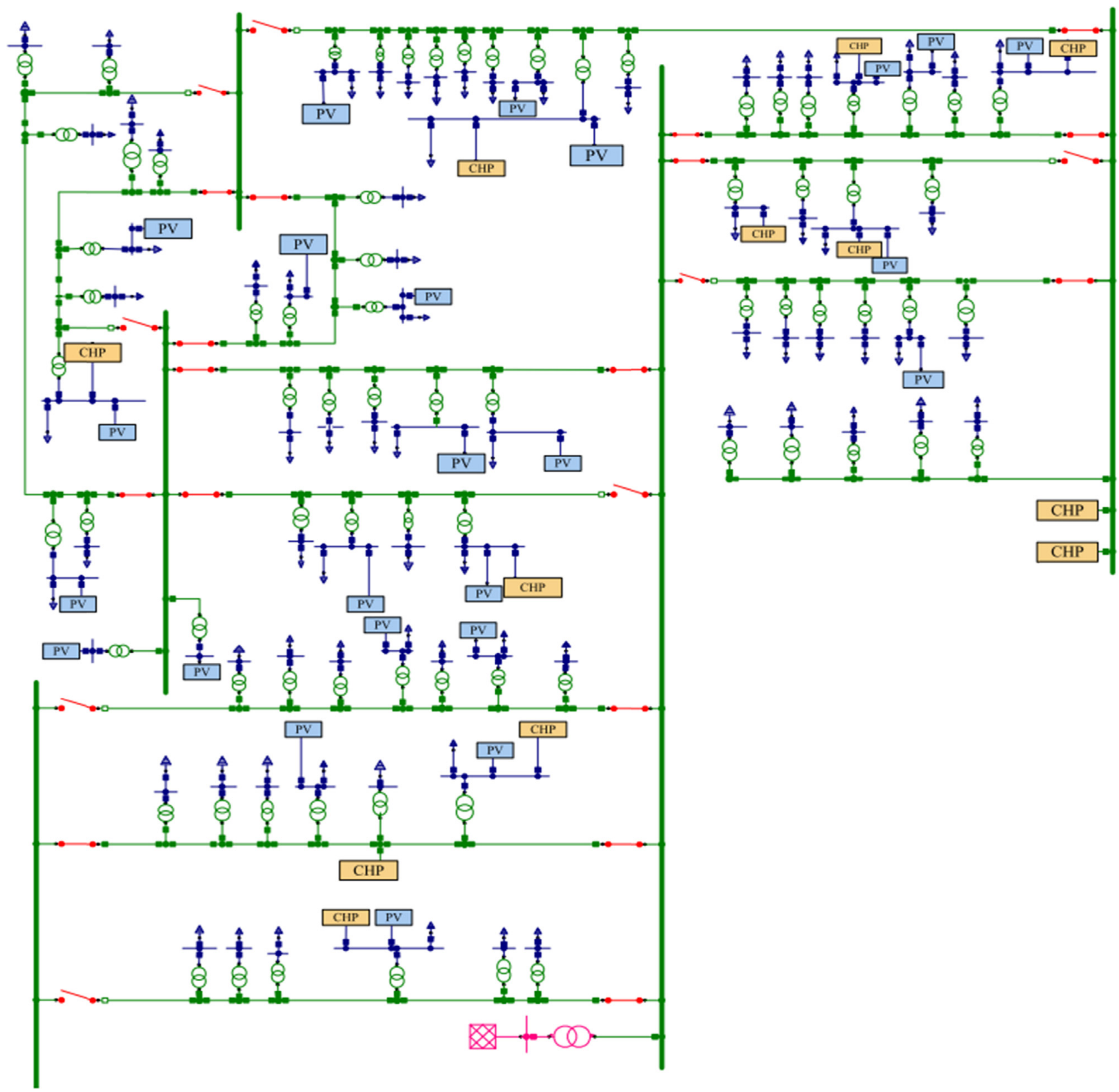

Fig. 4. Real urban network. (For interpretation of the references to color near the citation of this figure, the reader is referred to the web version of the article.)

5. Typical urban network

Fig. 4 presents a real urban MV network, which is operated at 20 kV. The main buses are numbered as given in the figure. In this network, the available switches are colored in red. The 15 MVA HV/MV transformer is connected at the main bus. A schematic diagram of the typical MV urban network is given in Fig. 5. This network has been built based on the network shown in Fig. 4. That means the real urban network given in Fig. 4 is copied three times and then the four parts are connected in order to build the typical network. The connections between the different parts were performed at the main buses of each part. In Fig. 5, it can be seen that part 1 and part 3 are supplied through the HV/MV transformer connected in part 1, while parts 2 and 4 are supplied through the HV/MV transformer connected at part 4.The DG technologies in this network are PV and CHP which are used with the given rated power at the given locations for the first part (original part) of the network. While for the other three parts, the locations are changed randomly for more realistic operation of the network. All of the PV units are connected at the LV side of MV/LV transformers, while there are some CHP units are connected at the MV side and the others at the LV side. Two high voltage power stations using two transformers of 110/20 kV are used for supplying the power to the typical network. Parts 1 and 3 are supplied through the HV/MV transformer connected in part 1. Parts 2 and 4 are supplied from the HV/MV transformer existing in part 4. Table 1 illustrates the

Table 1
Network data for the typical network with 622 nodes.

	Part 1 (original network)	Part 2	Part 3	Part 4	Typical network
Load (kVA)	12,138	11,252	11,864	10,148	45,402
CHP (kW)	1600	1600	1600	1600	6400
PV (kW)	150	150	150	150	600
No. of switches	24	24	24	24	96 + 9 = 105
Tr. 110/20	Yes	No	No	Yes	2

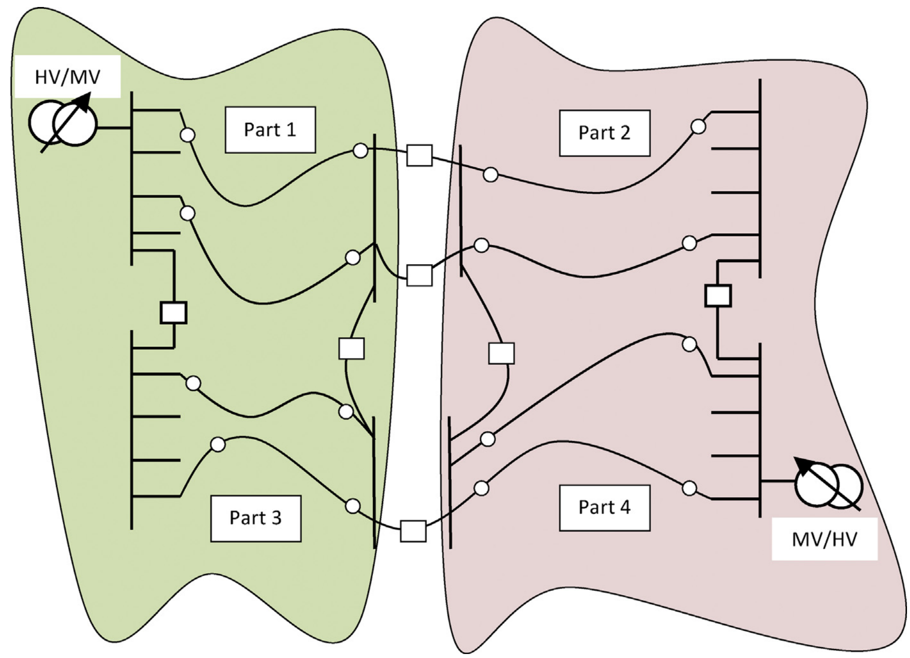

Fig. 5. Schematic diagram of the typical network.

loads, CHP power, PV power, and number of switches in each part of the network. Nine switches are used to connect the four parts in the networks. The loads in Table 1 display the sum of the maximum load at all MV/LV transformers in each part. The MV/LV transformers which are used were with the power of 630, 400, 250, 160, 100, and 50 kVA rated. The operators of distribution networks need to apply simple methods to estimate the power flow to the end customers for the inquiry of the power demand balance. Hence, for this customer group with less than 100,000 kWh of annual consumption or less than 50 kW of connection, standardized load profiles were provided. For small customer's groups, the installation of a load meter is not economic due to the technical and organizational expenditure, furthermore the substantial costs [21,22]. In the first phase of the liberalized market, the standard load profiles defined by the VDEW (Verband der Elektrizitätswirtschaft, which became BDEW Bundesverband der Energie- und Wasserwirtschaft) are applied in Germany since the first of October 2001 according to VDEW publication "Repräsentative VDEW-Lastprofile" (M-28/99) [23]. The households (H0) standard load profiles as discussed [21,22] are used in the current work. The VDEW households and

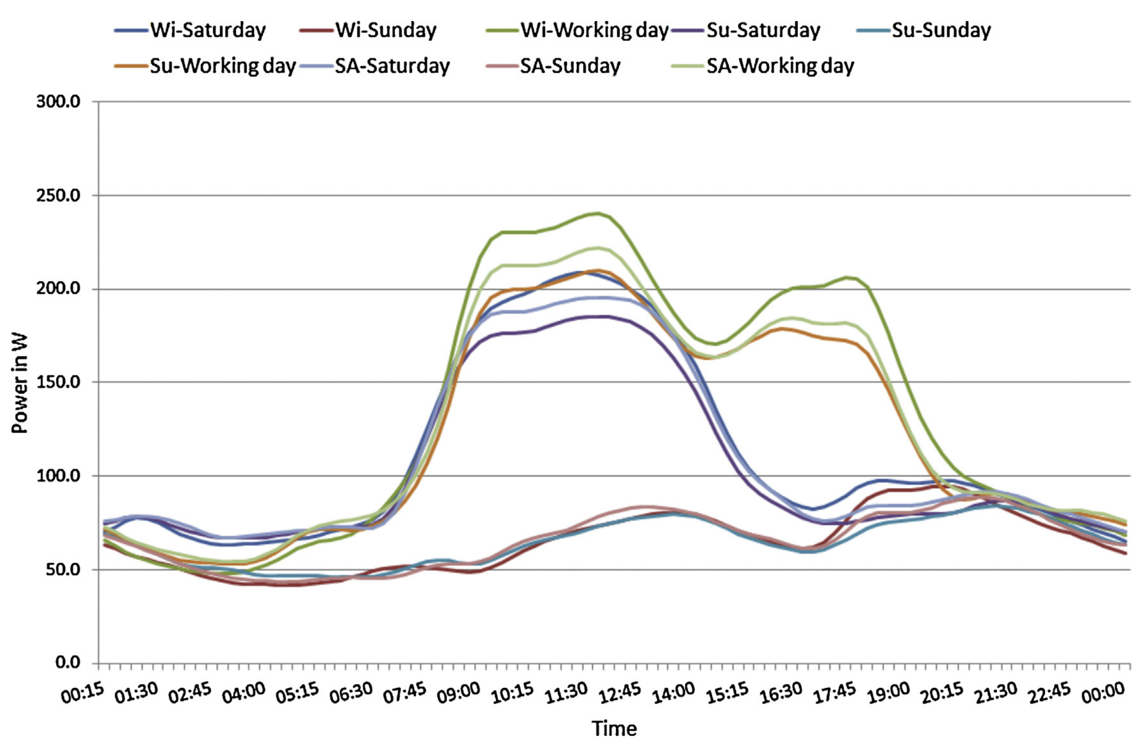

Fig. 6. VDEW load profiles of commercials (G0).

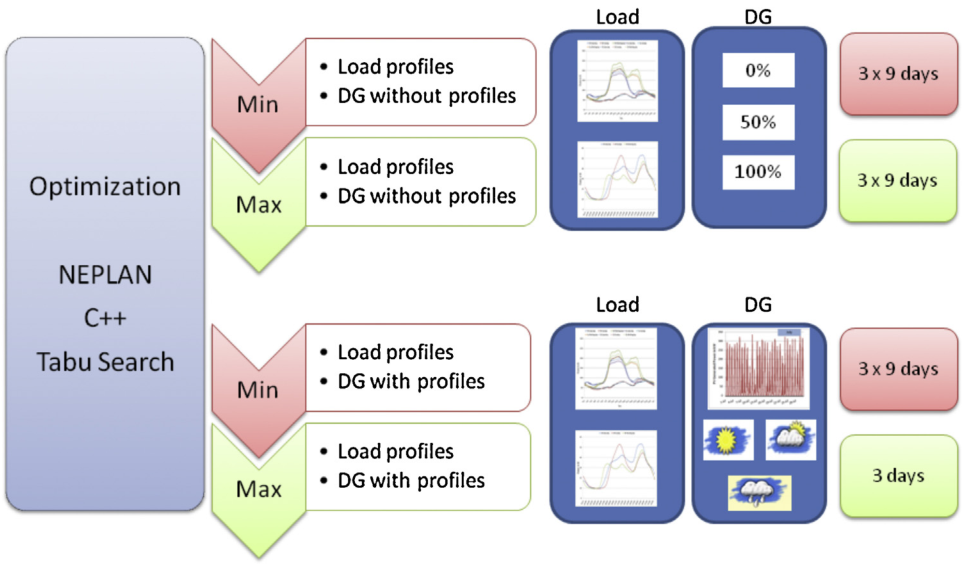

Fig. 7. Implementation of the proposed methodology.

commercials (G0) load profiles have been selected and implemented in different combinations in the simulation of the typical network. For example, 80% H0 with 20% G0, 60% H0 with 40% G0, and 100% H0 with 0% G0 have been used. The load profiles for different days of G0 are given in Fig. 6.

Moreover, the network operator can apply some forecasting models for predicting the loads in different zones of the network which will play an important role in short term and long term operation of the network. These forecasted load profiles can be also exploited in the reconfiguration algorithms.

6. Implementation of the optimization algorithm

Fig. 7 presents the implementation phases of the proposed algorithm. Two phases have been conducted, in the first phase only the load profiles are taken into account, while the DG power, at different percentages of its rated power (e.g. 0%, 50%, and 100%) was constant. As the initial switching state was randomly selected, the objective function, i.e. the energy loss was minimized and then maximized. Therefore the potential of implementing the new methodology in reducing the energy losses can be evaluated through the year. Three seasons have been considered, winter, summer, and the two other were immerged to be one season. Three working days per each season were investigated, in addition to Saturday, and Sunday. Like this for three different penetration levels (i.e. 0%, 50%, and 100%) the optimization was conducted for 27 days for minimization and 27 days for maximization. In the second phase the load and DG profiles are taken into consideration. The two DG technologies which exist in the network under study are CHP and PV. The CHP units are considered to supply its rated power all over the day as it has been informed by the utility company, while the PV profiles are taken into consideration. Therefore, the days are classified into sunny, cloudy and rainy. The optimization was conducted in three seasons in different day types. The results of each phase will be presented and discussed in the next section.

7. Results and discussion

7.1. DG with constant power generation

The switching state of the typical network in nine days for each penetration level has been optimized; these days are identified as follows: (1) Wi-Working day, Wi-Saturday, Wi-Sunday; (2) Su-Working day, Su-Saturday, Su-Sunday; (3) SA-Working day, SA-Saturday, SA-Sunday.

The minimization and maximization were performed starting from the initial switching state. The results of the reconfiguration on the variation of the energy losses were introduced in the next subsections.

7.1.1. Optimal configuration

The numbers of switches which their states are changed for different constant power generation (i.e. 0%, 50%, and 100%) are given in Table 2. As an example, the optimal configuration of typical network with 50% DG power for a summer Saturday has been checked. It has been observed that after changing the state of 34 switches in the network three branches in part 2 are supplied from the main transformer located at part 1. Moreover, that the large CHP unit which is connected at the left side of part 4 is switched to supply its power to part 3. Also, CHP unit which is connected at part 2 is switched to supply its power to part 1. This means, the reconfiguration with the existence of DG units did not only affect the direction of power flow to the load but also affect the power flow from the connected generators. As one of the constraints that each main transformer has to be separated from the other one, and it can be said that the optimum switching state is not occurred through the switching inside the region supplied by a certain main transformer, but by interconnection between them.

Table 2
Number of switched switches for each day type.

	0%	50%	100%
Winter			
Working day	34	34	32
Saturday	34	36	32
Sunday	34	34	34
Summer			
Working day	34	34	34
Saturday	34	34	32
Sunday	42	34	34
Spring–Autumn			
Working day	34	36	36
Saturday	34	36	34
Sunday	40	30	34

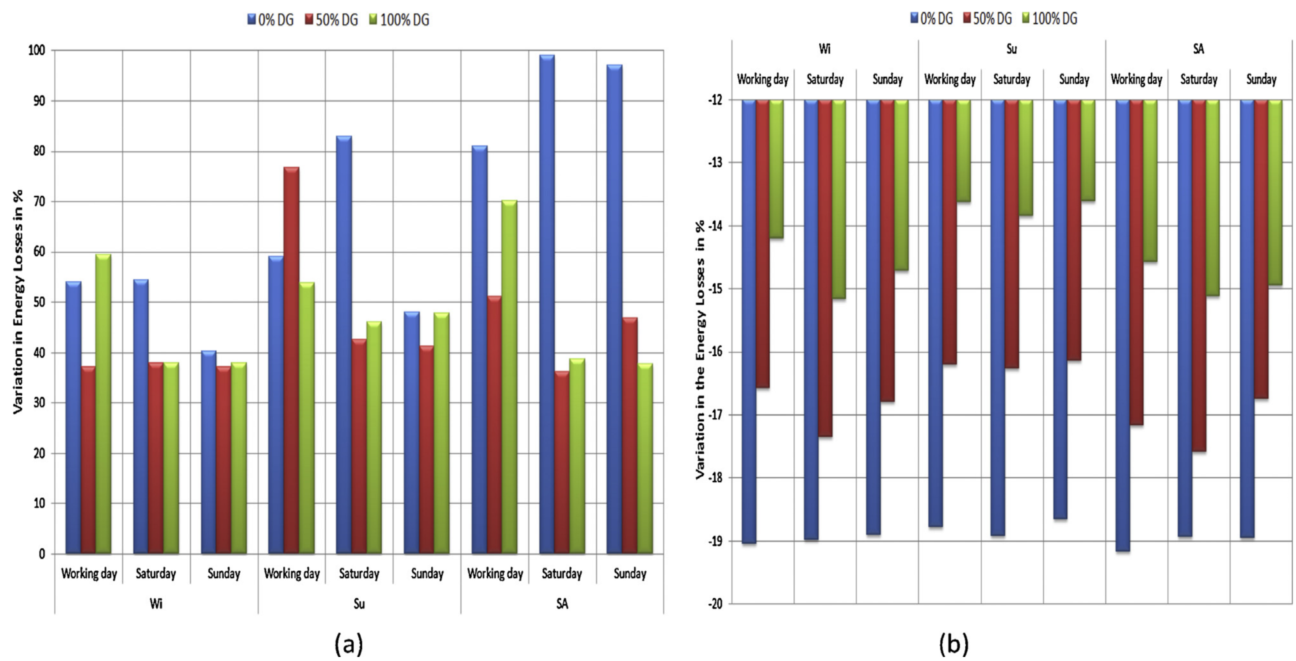

Fig. 8. Variation in the energy losses in percentage for different investigated days using (a) maximization and (b) minimization.

7.1.2. Variation in the energy loss

Fig. 8 shows the variation in the energy losses for the investigated days using maximization (Fig. 8a) and minimization (Fig. 8b), respectively. The minimization and maximization process were conducted for all DG percentages, 0%, 50%, and 100%. Without DG, i.e. 0% DG, the energy losses were reduced within the range of 18.6–19.2%, while, with 50% DG, the losses were decreased within the range of 16.2–17.6%. Furthermore, with 100% DG, the energy losses were minimized within the range of 13.6–15.2%. As the same initial switching state was used for all DG penetrations, it was observed that the availability for minimizing the losses through the switching optimization was decreased as the DG penetration was increased. This can be explained as the DG units were dispersed through the network giving the chance for the DG power to be consumed locally and therefore the losses were decreased. For example, the energy losses of the initial switching state for a Wi-Working day are 5.6, 4.64, and 3.9 MWh with 0%, 50%, and 100% DG power, respectively. These values are minimized to 4.6, 3.87, and 3.33 with 0%, 50%, and 100% DG power, respectively. However, with 100% and optimal switching the energy loss can be minimized by approximately 40%, compared to 0% DG and no optimal switching states.

On the other hand, the comparison between minimization and maximization showed that the initial switching state lies at

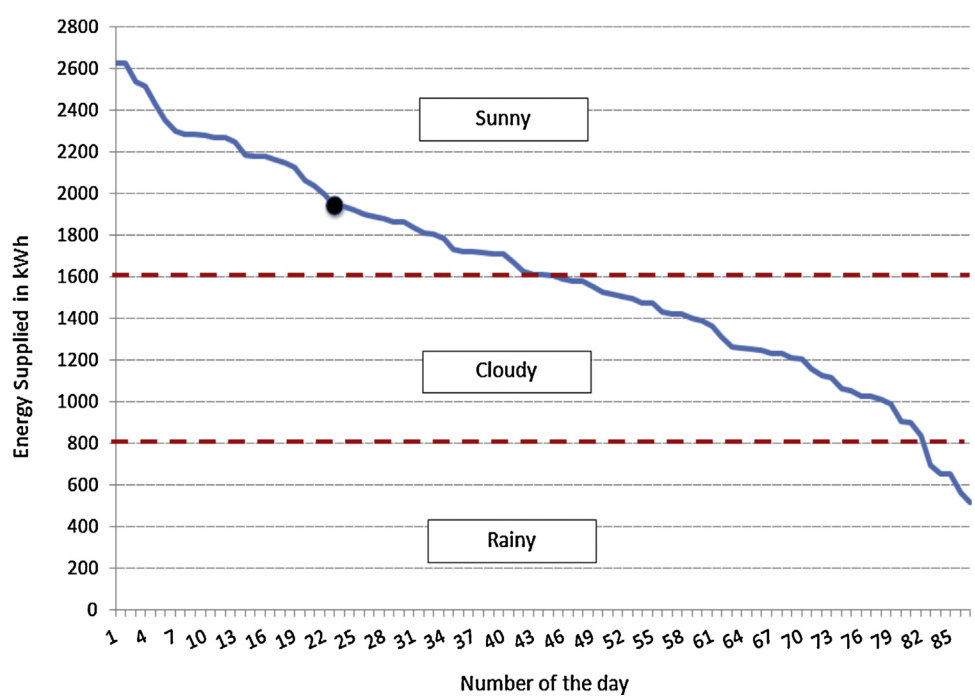

Fig. 9. Day specification based on the supplied energy for summer working days.

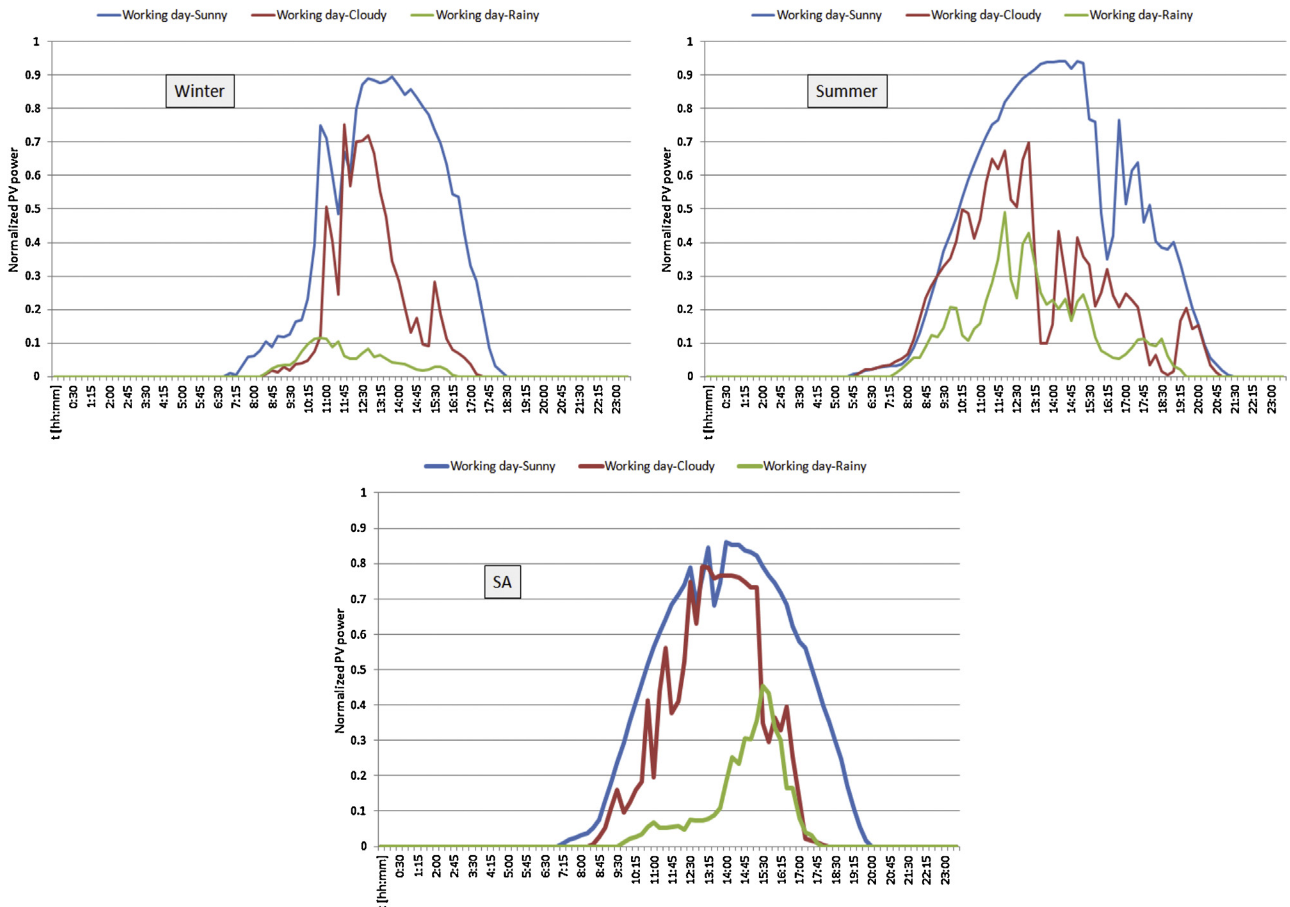

Fig. 10. Normalized PV generation profile for working days in winter, summer, and SA.

different distances from the minimum and maximum energy for each day and different DG penetrations. Therefore, for each DG power and load value, there is a certain optimum switching state. This clarifies the importance of taking the load and generation profiles into consideration through the optimization process. The annual potentials for different scenarios were evaluated based on the number of each investigated day in the year 2009. These potentials were also evaluated related to the maximum energy losses. As a result, based on the proposed algorithm, an annual minimization of approximately −51.4%, −44%, and −44.4% can be obtained for 0%, 50% and 100% DG power, respectively.

7.2. DG with generation profiles

7.2.1. Day's classification

In this phase of the study, the reconfiguration process was conducted by taking the DG generation profiles into consideration. For the CHP units, the generated power was constant at its rated values, as was provided from the utility company. While the PV generation profiles were considered and the measured generation profile of PV generations was implemented. These profiles were integrated into the NEPLAN model. Without the DG profiles, the investigated days were only classified according to the day type and the season of the year. However, with DG profiles the investigated days were determined according to the day type, the season, and the energy supplied from the DG unit. Regarding the DG energy supplied, for each day type within a certain season, there were three available scenarios, sunny, cloudy, and rainy. This criterion was illustrated in Fig. 9, where the different generation scenarios were defined according to the total energy supplied from the PV units. The number of the investigated days in this case was 27 and the following are some examples which clarify the day's classifications:

(1) Wi-Working day – Sunny, Wi-Working day – Cloudy, Wi-Working day – rainy.
(2) Wi-Saturday – Sunny, Wi-Saturday – Cloudy, Wi-Saturday – rainy.
(3) Wi-Sunday – Sunny, Wi-Sunday – Cloudy, Wi-Sunday – rainy.

In Fig. 10, normalized PV generation profiles for working days in different seasons are given. The investigated day for each scenario is always selected to be at the middle of the number of the selected type. For example, for the summer working days there are 45 sunny days, so that 12 June is selected to represent the Su-Working day-Sunny because it was the day number 23 of 45 days. This day is illustrated in Fig. 9 by a black point.

7.2.2. Optimal configuration

Table 3 illustrates the number of switches which their states are changed for different seasons and different day types. The optimal switching state of the network for a Wi-Saturday-Rainy as an example has been checked and it has been observed that four branches in part 2 are switched to be supplied from the main transformers in part 1. An interesting observation is that the two large CHP units in parts 2 and 4 are switched to supply their power into part 2 where the main transformer is connected. Therefore, the CHP unit, which is connected in part 2, is switched to supply its power to part 3 through a node in part 4.

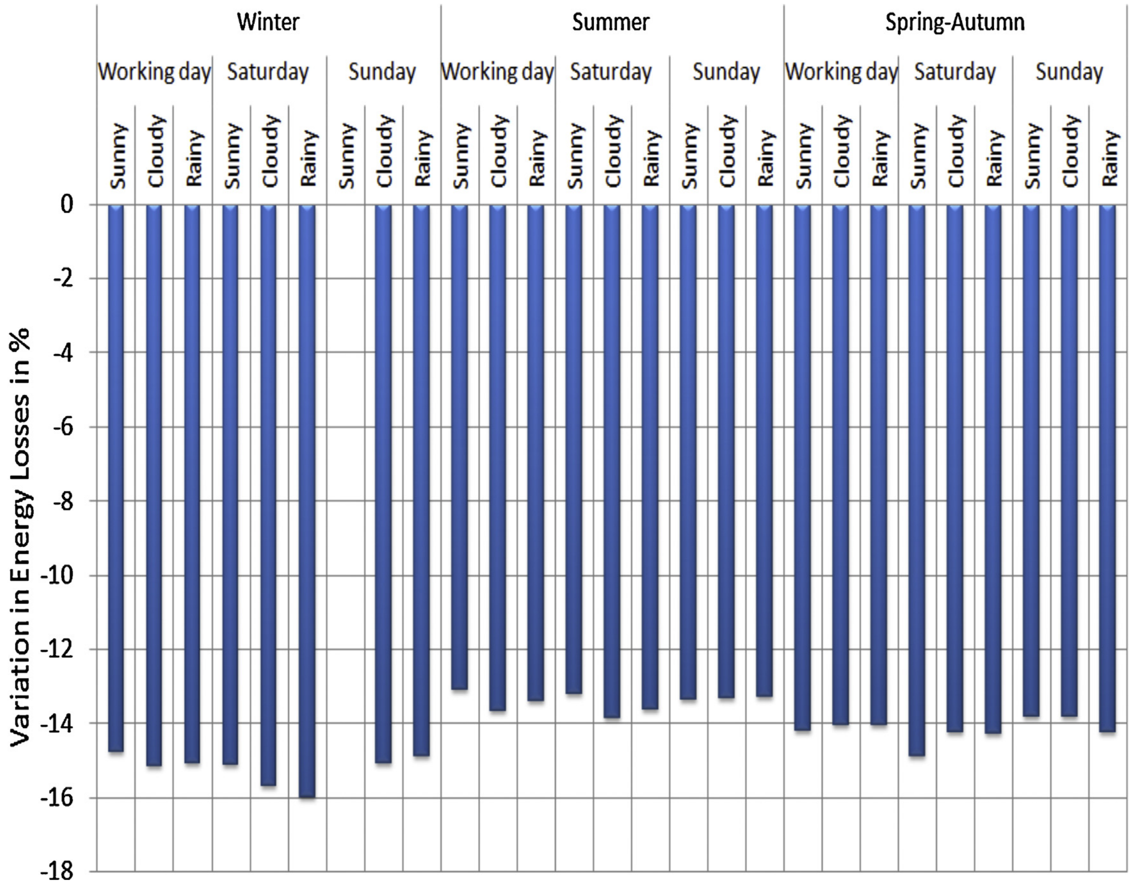

Fig. 11. Variation in the energy losses for different investigated days.

7.2.3. Variation in the energy losses

The results of the energy variation relative to the initial switching state in percentage are shown in Fig. 11. By applying the classification criterion it has been found that there is no sunny Wi-Sunday, so that no results can be found for that day. The results show that relative to the initial energy losses, the presented algorithm can minimize the energy losses within the range between 13 and 16% related to the initial switching state. The energy losses were then maximized starting from the initial switching state. In this case only three days were selected to perform the maximization. These three days have the maximum energy losses among the nine days in each season. The results of the maximization in percentage are 23.4%, 46.3% and 40.2 for Wi-Saturday-Rainy, Su-Saturday-Cloudy, and SA-Saturday-Sunny, respectively. The annual reduction in the energy losses based on the initial and maximum energy losses have been evaluated based on the number of each specified day in the year of 2009. It has been found that the energy losses can be reduced by approximately 49% relative to the maximum energy losses.

Table 3
Number of switched switches for each day type.

	Winter	Summer	Spring-Autumn
Working day			
Sunny	38	36	35
Cloudy	38	36	38
Rainy	33	38	36
Saturday			
Sunny	30	36	40
Cloudy	32	36	34
Rainy	34	40	38
Sunday			
Sunny	0	34	34
Cloudy	34	34	34
Rainy	34	38	36

8. Conclusions

In this paper, a new algorithm for switching state optimization of typical MV networks was introduced. A typical MV network was built and presented based on a real MV network. Here, the main findings:

1. The proposed methodology provides the availability of using different load profiles. Therefore, measured or forecasted load profiles can be considered. Moreover, generation profiles of renewable energy based distributed resources can be implemented. The availability to identify the time frame (hour, day, and week) for performing the switching state optimization.
2. As the penetration of DG units increased the availability to minimize the energy losses through reconfiguration decreases.
3. Reconfiguration of distribution networks with the presence of DG will not only enhance the branches interconnections into the network but also alter the connection of the DG resources.
4. The proposed method can be used with a forecasting tool of loads and DG power profiles and therefore an optimal switching state of a day ahead can be specified.

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