# Chapter 8
# Optimal Distributed Generation Placement Problem for Power and Energy Loss Minimization

**Aggelos S. Bouhouras, Paschalis A. Gkaidatzis and Dimitris P. Labridis**

**Abstract** This chapter introduces the Optimal Distributed Generation Placement problem towards power and energy loss minimization. Several solving methods are applied in order for the most suitable to emerge. Apart from technical and DG constraints, recent raised issues due to high Distributed Generation penetration like the reverse power flow effect is considered as well. The load and generation variability and their impact in integrating Renewable Energy Sources are examined, aided by the use of Capacity Factors implementation. In addition, the impact of Optimal Distributed Generation Placement problem in conjunction with Network Reconfiguration and Optimal Energy Storage Systems Placement is introduced aiming to examine how joined management schemes could be efficiently combined in order to maximize the potential loss and energy reduction.

**Keywords** ODGP · Loss minimization · Distributed generation
Optimization · Heuristics · Reverse power flow · Capacity factors
Load/generation variability · ESS · Network reconfiguration

---

A. S. Bouhouras (✉) · P. A. Gkaidatzis · D. P. Labridis
School of Electrical and Computer Engineering,
Aristotle University of Thessaloniki, AUTH, Thessaloniki, Greece
e-mail: abouhou@ece.auth.gr; abouchou@teiwm.gr

P. A. Gkaidatzis
e-mail: pgkaidat@ece.auth.gr

D. P. Labridis
e-mail: labridis@auth.gr

A. S. Bouhouras
Department of Electrical Engineering, University of Applied Sciences,
TEIWM, Kozani, Greece



F. Shahnia et al. (eds.), *Electric Distribution Network Planning*,
Power Systems, https://doi.org/10.1007/978-981-10-7056-3_8

## 8.1 Introduction

The penetration of Distributed Generation (DG) units in Electric Distribution Networks has been considered as an efficient way to exploit the benefits of sustainable energy, promoted by distributed energy resources. In most cases, appropriate consideration of DG installation can highly benefit the electric distribution networks in terms of loss reduction, voltage-profile, and reliability improvement [1, 2]. However, high penetration of DG units could potentially cause problems to several operational characteristics, especially due to reverse power flow, leading to excessive losses and feeder overloading [3, 4]. Regarding DG placement, the final decision lies on the owners and investors, depending on site and fuel availability or climatic conditions. Notwithstanding the merits of installing DG and exploiting it in order to solve networks problems, the fact remains that, in most cases, the Distribution Network Operator (DNO) has neither significant control, nor influence over the DG location and size. Still, DG placement affects critically the operation of a network, below a certain limit. Thus, optimization tools which provide both optimal locations and capacity of DG units to be installed should be highly appreciated by DNOs. The Optimal Distributed Generation Placement (ODGP) problem generally deals with the determination of the location and appropriate sizing of DG units to be installed into existing electric distribution networks, subject to networks' and DG operational, as well as investment constraints.

In this chapter, a comparative analysis of several promising methods is initially presented, such as analytical or heuristic ones and their merits and drawbacks are pointed out, when contemplating power loss reduction via ODGP approach. The DG units are considered capable of both active and reactive power production. Secondly, using the most suitable of them, the ODGP towards *power loss reduction* is solved by taking into consideration a possible reverse power flow effect [5, 6]. Thirdly, as a first step for the integration of an optimal combination of Renewable Energy Resources (RESs) into an electric distribution network, a method is demonstrated, considering concurrently the geographical characteristics of the area, where the examined network is placed, the different weather conditions and the availability of RESs, by the introduction of Capacity Factors (CFs), while trying to keep problem complexity at a minimum.

Furthermore, the ODGP towards *energy loss reduction* is coped, initially taking into account the impact of load composition variation while considering the DG units having constant power output, and then with variable power output resembling the function of several RESs such as Wind Turbines, or Photovoltaics. Finally, the cooperation of ODGP with Network Reconfiguration (NR) towards power loss reduction is presented and an initial effort regarding the cooperation of ODGP with the Optimal Energy Storage System Placement (OESSP) problem.

## 8.2 ODGP Towards Power Loss Minimization—Problem Formulation

### 8.2.1 Objective Function—Constraints

The ODGP problem is a mixed-integer-non-linear-constrained (MINLC) optimization problem; mixed integer because both the power of the DGs installed (sizing) and their position (siting) are requisites; non-linear, due to the power flow equations needed to solve the problem. As an optimization problem, various objectives can be found in literature, such as cost minimization, benefit maximization, greenhouse gas emission reduction, either solved individually, or as a multi-objective approach [7–9]. In this section, power loss minimization is to be contemplated, formulated as

$$F_{loss} = \min \sum_{k=1}^{n_l} g_{i,j}\left[V_i^2 + V_j^2 - 2V_iV_j\cos\left(\theta_i - \theta_j\right)\right] \tag{8.1}$$

where:

$g_{i,j}$ is the conductance between buses $i$ and $j$, respectively,
$n_l$ is the total number of branches of the network,
$V_i$, $V_j$ are the voltage magnitudes of buses $i$ and $j$, respectively, and
$\theta_i$, $\theta_j$ are the voltage angles of buses $i$ and $j$, respectively.

The constraints of the problem can be separated to obligatory and occasional. As *obligatory constraints*, the power flow Eqs. (8.2a), (8.2b) and the technical constraints of the electric distribution network (8.3), (8.4) are considered, as they must always be met. They are expressed as:

Power Flow Constraints:

$$P_{G,i} - P_{D,i} - \sum_{j=1}^{n_b} |V_i||V_j||Y_{i,j}|\cos\left(\varphi_{i,j} - \theta_i + \theta_j\right) = 0 \tag{8.2a}$$

$$Q_{G,i} - Q_{D,i} + \sum_{j=1}^{n_b} |V_i||V_j||Y_{i,j}|\sin\left(\varphi_{i,j} - \theta_i + \theta_j\right) = 0 \tag{8.2b}$$

DN Contraints:

$$V_i^{min} \le V_i \le V_i^{max} \tag{8.3}$$

$$S_k \le S_k^{max} \tag{8.4}$$

where:

| | |
|---|---|
| $P_{G,i}$, $Q_{G,i}$ | is the active and reactive power generation at bus $i$, respectively, |
| $P_{D,i}$, $Q_{D,i}$ | is the active and reactive power demand at bus $i$, respectively, |
| $n_b$ | is the total number of buses of the network, |
| $Y_{i,j}$ | is the magnitude of bus admittance element $i$,$j$, |
| $\varphi_{i,j}$ | is the angle of bus admittance element $i$,$j$ |
| $V_i^{min}$, $V_i^{max}$ | are the voltage lower and upper limits of bus $i$, respectively, and |
| $S_k^{max}$ | is the thermal limit of line $k$, by terms of apparent power. |

As *occasional constraints*, technical constraints regarding DG units and/or their penetration level are considered. They are classified as occasional because they can be present on occasion, defined by the aspect of the problem examined and not necessarily mandatory, as the previous ones. They can be expressed as:

DG constraints:

$$S_{min}^{DG} \leq S_m^{DG} \leq S_{max}^{DG} \tag{8.5}$$

$$pf_{min}^{DG} \leq pf_m^{DG} \leq pf_{max}^{DG} \tag{8.6}$$

Penetration Constraints:

$$\sum_{m=1}^{n_{DG}} S_m^{DG} \leq \eta \cdot S_{Total}^{Load} \tag{8.7}$$

where:

| | |
|---|---|
| $S_m^{DG}$ | is the power of a DG unit, |
| $pf_m^{DG}$ | is the power factor of a DG unit, |
| $S_{min}^{DG}$, $S_{max}^{DG}$ | are the limits of power for a DG unit, respectively, |
| $pf_{min}^{DG}$, $pf_{max}^{DG}$ | are the limits of power factor of a DG unit, respectively, |
| $n_{DG}$ | is the total number of DG units to be installed, |
| $\eta$ | is a percentage indicating the desired DG penetration level, and |
| $S_{Total}^{Load}$ | is the total load installed in the DN. |

## *8.2.2 Penalty Function—Terms*

In general, constrained problems can be solved using deterministic, or stochastic algorithms. However, deterministic approaches such as feasible direction and generalized gradient descent, require strong mathematical properties of the objective function, such as continuity and differentiability. Moreover, solving the ODGP problem by analytical methods could prove to be complex and time-consuming [10], or be restrained to solutions including only one DG unit. In cases, where these properties are absent, evolutionary computation offers reliable alternative methods. Since most evolutionary approaches were primarily designed to address unconstrained problems, constrained handling techniques are usually required to detect only feasible solutions. The most common of those techniques is the use of a penalty function. In spite of its drawbacks, it performs rather efficiently, provided a proper calibration of the penalty parameters is undertaken [11, 12]. According to this approach, the constraints expressed via penalty terms are incorporated into the objective function in order to formulate the penalty function that penalizes any infeasible solutions as:

$$P(x) = f(x) + \Omega(x) \tag{8.8}$$

$$\Omega(x) = \rho\left\{g^2(x) + [max(0, h(x))]^2\right\} \tag{8.9}$$

where:

$P(x)$ is the Penalty function,
$f(x)$ is the objective function, in this case the $F_{loss}$, as expressed in (8.1),
$\Omega(x)$ is the penalty term,
$\rho$ is the penalty factor,
$g(x)$ refers to the equality constraints, in this case as defined in (8.2a), (8.2b), and
$h(x)$ refers to the inequality constraints, in this case as defined in (8.3)–(8.7).

Thus, in case of the ODGP problem and using, for the sake of argument, only the obligatory constraints, the updated Penalty Function could be expressed as:

$$P(x) = \min(F_{loss} + \Omega_P + \Omega_Q + \Omega_V + \Omega_L) \tag{8.10}$$

where $\Omega_P$ and $\Omega_Q$ refer to the equality constraints of

$$\Omega_P = \rho_P \sum_{i=1}^{n_b}\left\{P_{G,i} - P_{D,i} - \sum_{j=1}^{n_b}|V_i||V_j||Y_{i,j}|\cos\left(\varphi_{i,j} - \theta_i + \theta_j\right)\right\} \tag{8.11a}$$

$$\Omega_Q = \rho_Q \sum_{i=1}^{n_b}\left\{Q_{G,i} - Q_{D,i} + \sum_{j=1}^{n_b}|V_i||V_j||Y_{i,j}|\sin\left(\varphi_{i,j} - \theta_i + \theta_j\right)\right\} \tag{8.11b}$$

and $\Omega_V$ and $\Omega_L$ to inequality constraints of

$$\Omega_V = \rho_V \sum_{i=1}^{n_b}\left\{\max\left(0, V_i^{min} - V_i\right)\right\}^2 + \rho_V \sum_{i=1}^{n_b}\left\{\max\left(0, V_i - V_i^{max}\right)\right\}^2 \tag{8.12}$$

$$\Omega_L = \rho_L \sum_{k=1}^{n_l}\left\{\max\left(0, S_k - S_k^{max}\right)\right\}^2 \tag{8.13}$$

As can be easily deduced, any other constraints such as (8.5), (8.6) or (8.7) can be incorporated in (8.10) via the same process.

## 8.3 ODGP Towards Power Loss Minimization—Solving Methods

According to a literature survey on the subject, a great amount of scientific research has been undertaken with the aim of solving the ODGP problem [13]. Several promising methods have emerged such as analytical ones [14–17], heuristics [5, 6, 18–33], or combination of the above, solving siting and sizing individually, but in a sequential order [34–36].

However, as stated earlier, ODGP is a MINLC optimization problem. The conventional approaches utilizing analytical methods could be intricate and time-consuming in this case, or restricted to solving for just one DG unit being placed. Therefore, over the last few decades, Heuristics such as Particle Swarm Optimization (PSO) [5, 6, 18], Genetic Algorithm (GA) [9, 19, 20], Artificial Bee Colony (ABC) [21–23], Cuckoo Search (CS) [24–27], and Harmony Search (HS) [28–30] have been implemented. Moreover, they have proved quite promising and still evolving in this field. Some additional mentions could be, for example, Bacterial Foraging Optimization Algorithm (BFOA) [31], Ant-Lion Optimization (ALO) [32], Grey Wolf Optimization (GWO) [33], and many more [13], noting more advancement in solving the ODGP problem. In this section, a small comparative analysis will take place in order to determine the most suitable method to solve the ODGP problem. Three versions of PSO, namely, the Local, Global and Unified PSO, GA, ABC, CS and HS methods is compared and evaluated. As analytical methods, the ones presented in [15], namely, Improved Analytical (IA) method, Loss Sensitivity Factor (LSF) method and Exhaustive Load Flow (ELF) method is also demonstrated.

### *8.3.1 Analytical Methods*

For calculating the losses for those methods, instead of (8.1) the exact loss formula is utilized, expressed as:

$$F_{loss} = \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} \left[ \alpha_{ij} \left( P_i P_j + Q_i Q_j \right) + \beta_{ij} \left( Q_i P_j - P_i Q_j \right) \right] \tag{8.14}$$

where:

$$\alpha_{ij} = \frac{r_{ij}}{V_i V_j}\cos\left(\theta_i - \theta_j\right), \quad \beta_{ij} = \frac{r_{ij}}{V_i V_j}\sin\left(\theta_i - \theta_j\right) \tag{8.15a, b}$$

where:

| | |
|---|---|
| $r_{ij} + jx_{ij} = Z_{ij}$ | is the $ij$th element of the impedance matrix, |
| $P_i$ and $P_j$ | are the active power injections at $i$th and $j$th buses, respectively, and |
| $Q_i$ and $Q_j$ | are the reactive power injections at $i$th and $j$th buses, respectively. |

#### 8.3.1.1 IA Method

In IA different formulas are formed according to the DG type to be used, i.e. injecting only active, and/or reactive, or both. The advantage of the method is that load flow is required only twice: once at the initial state of the electric distribution network and once the DG is in place. The drawback is that only a single DG unit is placed at a time.

#### 8.3.1.2 LSF Method

LSF is based on the linearization of the power flow Eqs. (8.2a), (8.2b). It is most appropriate for locating the most suitable buses to host DG units by ranking them according to their LSF values. Then, a DG unit is placed at the bus with the highest priority and its size is calculated by increasing it in small steps and running load flow. The merits of the method are its simplicity and directness. However, as in IA method, only a single DG unit is placed at a time and naturally after the first time, the solution is biased since some DG units have been already installed.

#### 8.3.1.3 ELF Method

ELF method, also known as repeated load flow solution, requires excessive computational time since all buses are considered in calculation; however, it can lead to a completely optimal solution. Also, as the number of DG units to be installed increases to more than one, so does the computational load and indeed does so in an exponential rate.

## 8.3.2 Heuristic Methods

### 8.3.2.1 GPSO, LPSO, UPSO Methods

PSO was introduced by Eberhart and Kennedy [37]. It was inspired by the social behavior of bird flocking. A swarm of particles is assigned to explore the solution space in order to retrieve the optimal solution. Their movement in the solution space is defined by three key elements:

1. their personal knowledge of the solution space, represented by the Personal Best parameter,
2. the social knowledge gained by exchanging information among a group of particles, represented by the Social Best parameter, and finally,
3. their current movement on the solution space, represented by the previous gained velocity.

Regarding the Social Best, when the information exchange takes place amongst all particles within the swarm, it is called Global Best, and the respective algorithm Global PSO (GPSO), whereas if it takes place among smaller formations, called neighborhoods, it is called Local Best and the respective algorithm Local PSO (LPSO).

Concerning GPSO, because the particles are instantly aware of the swarm's best position, rapid convergence is achieved, therefore better exploitation of the knowledge gathered regarding the solution space. However, this happens at the expense of exploration of the solution space, thus resulting in probable local minima entrapment and therefore not achieving a near-optimal solution.

In contrast, in LPSO the formation of overlapping particle neighborhoods and the information exchange within them enables for better exploration of the solution space [38]. However, this happens at the expense of exploitation, thus longer convergence, since the information exchange is distilled among the various neighborhoods, instead of the whole swarm.

Therefore, under GPSO, or LPSO, the algorithm is biased towards exploitation, or exploration, respectively. UPSO, introduced by Parsopoulos and Vrahatis [39], has been developed as an attempt to harness their merits and, at the same time, aiming to neutralize their flaws. In this chapter, the UPSO's Swarm Partitioning scheme is applied for merging the two versions of PSO, as the most promising [40]. A generic flowchart for PSO is presented in Fig. 8.1.

### 8.3.2.2 GA Method

GA was introduced by Holland [41]. A simulation of the three fundamental genetic processes comprises the technique, namely selection, crossover and mutation. A group of chromosomes is designated in the solution space, here considered a genetic pool. The most fitted are selected as parents to form the next generation.

**Fig. 8.1** PSO flowchart

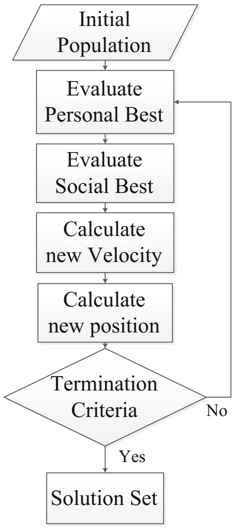
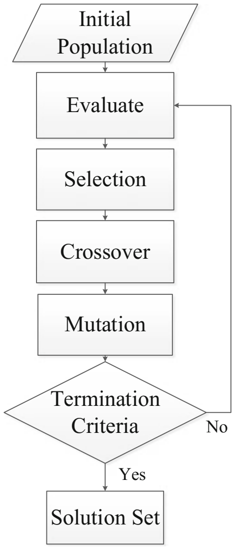



**Fig. 8.2** GA flowchart




In this chapter, the roulette-wheel selection scheme is applied. The parents are stochastically combined to breed offspring that bear combinations of their chromosomes. In addition, a mutation process takes place, where stochastically several parts of the offspring's chromosomes are altered. Finally, the best among both parents and offspring are chosen to constitute the next generation of chromosomes, as presented in Fig. 8.2.

#### 8.3.2.3 ABC Method

ABC method was proposed by Karaboga [42]. It was inspired by the intelligent way bee swarms locate and harness their food. The candidate solution space in that case is represented by places of potential food sources. The bee colony, divided into employed, onlooker and scout bees, spreads across it. Employed bees target and exploit potential food position and inform the onlookers for more potential food sites. The employed bees then are trying to determine the food potential of those positions. If an employed bee's position does not represent a good solution, then the bee turns into a scout and starts exploring the solution space. The number of the employed bees is equal to the number of food sources, each of which also represents a site, being exploited at the moment or to the number of solutions in the population, as presented in Fig. 8.3.

#### 8.3.2.4 CS Method

CS method was first introduced by Yang and Deb [43]. It was inspired by the way some cuckoo species lay their eggs in the nests of other host birds (of other species), to be nurtured. Each egg in the nest represents a solution, and cuckoo eggs represent new solutions. The aim is to use the new and potentially better solutions (cuckoos) to replace the least suitable solutions in the nests. In each iteration, one cuckoo egg is laid randomly in a selected nest; The nests with high quality eggs will carry over to the nest generation; Then, in the remaining least suitable nests, a discovery

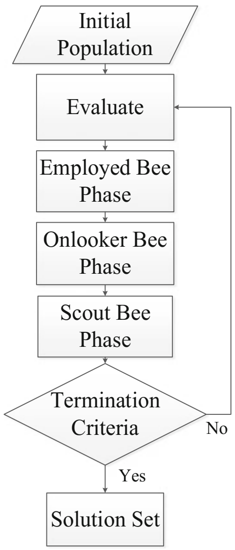
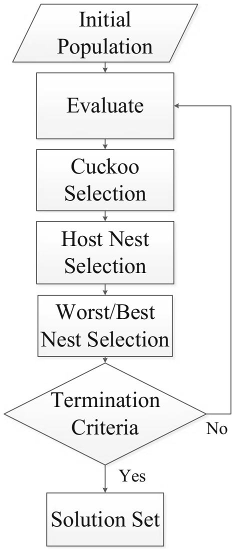



**Fig. 8.3** ABC flowchart

**Fig. 8.4** CS flowchart




operation takes place by the host birds, stochastically retrieving cuckoo laid eggs and discarding them, therefore ignoring them from further calculations. A generic flowchart is presented in Fig. 8.4.

#### 8.3.2.5 HS

HS method, introduced in [44], is inspired by the improvisation process of jazz musicians. Improvisation is a process of searching for the most appropriate harmony by trying various combinations of rhythms, under the following three rules:

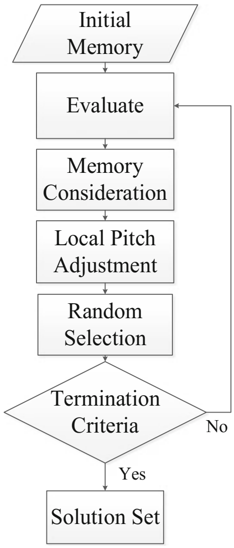
1. playing any existing rhythm from the memory;
2. playing an altered rhythm from the memory;
3. playing a random rhythm from the possible range.

HS simulates this procedure as:

1. choosing any value from the HS memory;
2. choosing an altered value from the HS memory;
3. choosing a random value from the possible value range.

A generic flowchart is presented in Fig. 8.5.

Fig. 8.5 HS flowchart




### 8.3.3 Heuristic Methods Evaluation

For the evaluation of all aforementioned solution techniques, the typical 33-bus system [45] has been employed, as depicted in Fig. 8.6. It is a radial electric distribution network and has a total load of 3.72 MW and 2.38 MVAr, presenting initial power loss of 211 kW. Due to their stochastic nature, the methods have been

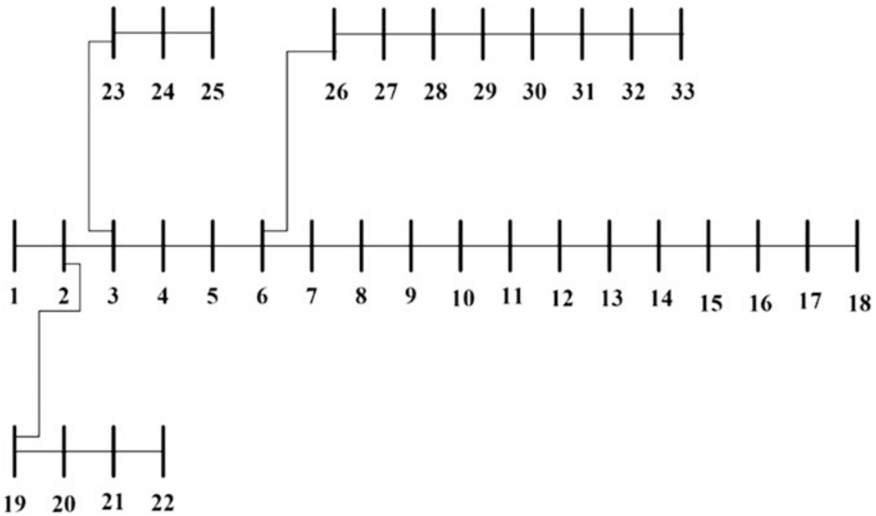



Fig. 8.6 The 33-bus system

applied 1000 times each, and within an ample time of 1000 iterations. Also, they have been let unrestrained in terms of number of DG units, so as to deduce how close the optimal solution they could arrive; with the actual optimal solution being the one with DG units installed in all nodes with nominal capacity equal to the nodes' respective load. The installed DG units are considered capable of injecting active power and injecting/consuming reactive power. Similar results have been extracted from implementation on other networks, such as the typical 16, 30 and 69-bus systems.

In Table 8.1 solution-related properties for all examined heuristic techniques are presented: the minimum loss achieved by each technique, the loss reduction percentage, the number of DG units installed along with the total DG installation size in MVA, as provided by the best solution among the 1000 trials that each technique has reached. Due to the ample time given, every technique has achieved a significant loss reduction in both systems and the differences are virtually slim, though, GA seems to be slightly in a bit of a disadvantage, as also confirmed by Fig. 8.7, where the mean Bus Voltage profile for all the examined heuristic techniques is shown.

In Table 8.2 convergence related properties are presented, i.e. the average execution time of one trial, the iteration number required for each technique to

**Table 8.1** Heuristics' solution performance comparison

| Method | Minimum power loss (kW) | Power loss reduction (%) | Total DG no. | Total size of installed DG units (MVA) P + *j*Q |
|---|---|---|---|---|
| GPSO | 0.34 | 99.84 | 20 | 3.64 + *j*2.32 |
| LPSO | 0.22 | 99.89 | 20 | 3.55 + *j*2.21 |
| UPSO | 0.13 | 99.94 | 22 | 3.66 + *j*3.26 |
| GA | 10.77 | 94.89 | 21 | 3.00 + *j*0.71 |
| ABC | 0.52 | 99.75 | 17 | 3.73 + *j*2.28 |
| CS | 0.48 | 99.77 | 20 | 3.82 + *j*2.32 |
| HS | 2.67 | 98.74 | 19 | 3.30 + *j*2.08 |

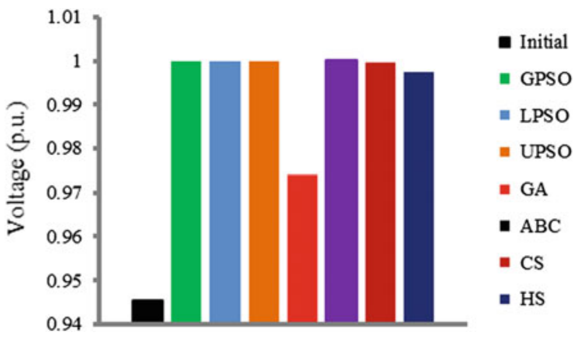



**Fig. 8.7** Average voltage

**Table 8.2** Heuristics' convergence performance comparison

| Method | 10% tolerance iteration | 1% tolerance iteration | 0.1% tolerance iteration | 93.22% loss reduction iteration | Average execution time (min) |
|---|---|---|---|---|---|
| GPSO | 832 | 983 | 999 | 6 | 6.7 |
| LPSO | 845 | 983 | 999 | 7 | 6.9 |
| UPSO | 339 | 839 | 900 | 5 | 6.9 |
| GA | 747 | 975 | 999 | 900 | 7.3 |
| ABC | 846 | 987 | 999 | 19 | 13.7 |
| CS | 909 | 992 | 999 | 43 | 12.5 |
| HS | 684 | 945 | 996 | 9 | 3.8 |

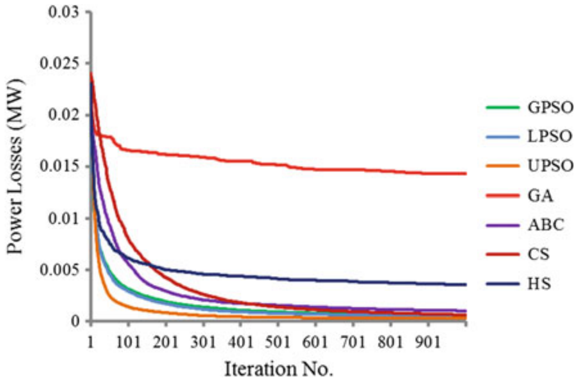



**Fig. 8.8** Average convergence

reach in average within 10, 1 and 0.1% tolerance of its final optimal solution, respectively, e.g. for UPSO given that its optimal solution is 0.133 kW, the 10% tolerance is 0.146 kW power loss.

In terms of execution time, evidently HS proves to be the fastest with less than four minutes execution time. Moreover, the iteration number needed for each technique to reach a certain amount of loss reduction is also presented in Table 8.2. It is set to 93.22%, regarding the average loss reduction achieved by the least performing technique, namely being GA. Although all the techniques perform rather well, it seems, the PSO versions, and especially UPSO, performs better than the rest, regarding convergence and iteration steps, reaching their final solution in the least amount of iterations. Therefore, although UPSO is not as efficient as HS in terms of execution time, it can be argued that it can be applied for less iterations, thus overcoming this drawback.

This is illustrated in Fig. 8.8, where each technique's average convergence of the 1000 trials is presented. This is also confirmed by Fig. 8.9, where again each technique's average convergence of the 1000 trials is presented, but in a margin of

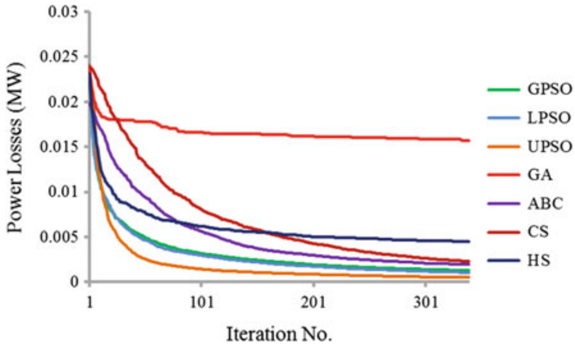



**Fig. 8.9** Average convergence zoom-in

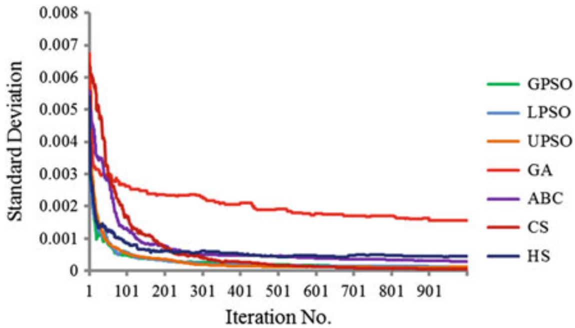



**Fig. 8.10** Convergence's deviation

less than 1000 iterations, and specifically, within the 10% iteration tolerance of the best performing technique, being UPSO.

In addition, as shown in Fig. 8.10, the PSO versions, and especially UPSO, have the lowest convergence of standard deviation along 1000 iterations, meaning that their 1000 trials do not deviate far from each other, ensuring the robustness of their solution process and even that less trials are possible.

### *8.3.4 Heuristic Versus Analytical Methods Evaluation*

For a more direct evaluation comparison of the most prominent Heuristic technique, i.e. UPSO, with the analytical methods presented in this section (IA, LSF, ELF) again the typical 33-bus system is employed. Three DG units are considered for installation and capable of injecting only active power. In Table 8.3 the solutions reached by the four methods are presented.

Based on the results of the previous section, UPSO has been applied 50 times and with 400 iterations. As can be deduced, UPSO performs rather better than the analytical ones, in terms of optimal solution, but rather poorly in terms of execution time. However, as evidenced in the precious section, a Heuristic method is able to

**Table 8.3** Heuristics versus analytical methods solution comparison

| Method | Minimum power loss (kW) | Power loss reduction (%) | DG position | DG size (kW) | Total DG installed (MW) | Time (s) |
|---|---|---|---|---|---|---|
| UPSO | 77.9 | 65.50 | 13<br>24<br>30 | 802<br>1092<br>1054 | 2.95 | 70 |
| IA | 81.05 | 61.62 | 6<br>12<br>31 | 900<br>900<br>720 | 2.52 | 0.4 |
| LSF | 85.07 | 59.72 | 18<br>25<br>33 | 720<br>900<br>810 | 2.43 | 0.23 |
| ELF | 74.27 | 64.83 | 13<br>24<br>30 | 900<br>900<br>900 | 2.7 | 3.06 |

perform with the same efficiency, regardless of the considered number of DGs for installation, whereas the analytical ones would be either restricted to a small number of DGs, as in this case, or be biased since installing one DG unit at a time alters the electric distribution network every time. Moreover, since, the ODGP problem addresses primarily network planning and operational issues, it can be argued that time is not considered as important as finding the optimal solution, resulting in giving priority to the latter.

In conclusion, it is indicated that when contemplating ODGP towards power loss with a small amount of DG units to be installed, an analytical method might prove a better option than a heuristic one, in terms of time with only a minor setback in terms of optimal solution. When, an optimal or near optimal solution is required and more DG units should be considered for installation, a heuristic method would prove more suitable.

## 8.4 ODGP Towards Power Loss Minimization—Reverse Power Flow

Integration of DG in existing electric distribution networks has been discussed and studied thoroughly during the last years as a measure of reducing grid's power loss. However, the possible impacts of Reverse Power Flow (RPF), caused by extended DG penetration, on solving the ODGP have not been fully considered.

While reaching optimal solutions for the ODGP problem, recent and forthcoming massive DG integration brings to light RPF considerations, i.e. power flow pushed upstream of the network and on neighbouring networks. So far, literature solves the ODGP problem, towards different optimization functions, either without considering possible RPF to adjacent grids, or by simply not allowing it.

However, this solution approach could be proved inadequate; on the one hand, if RPF is ignored, unfair power displacement to neighbouring grids may occur, or not recognised; on the other hand, if it is strictly prohibited, it might lead to biased and sub-optimal solutions, since there are indications that when RPF is included during the planning process, it could lead to different ODGP solutions that can further reduce power loss [46–49].

In this section, it is shown that the RPF effect can be integrated into the ODGP problem as an occasional constraint imposed on the Slack Bus itself. As an alternative, an intermediate bus between the Slack Bus and the rest of the electric distribution network might be inserted, and imposing the constraint on the total power that flows through it, via its adjacent branches, modifying the network slightly [50]. The constraint and the corresponding penalty term can be expressed as

$$P_{perm} \leq \eta_{RPF}^{\%} \cdot P_{init} \tag{8.16}$$

$$\Omega_{RPF} = \rho_{RPF} \left[ \max\left(0, \left|P_{perm}\right| - \eta_{RPF}^{\%} \cdot \left|P_{init}\right|\right)\right]^2 \tag{8.17}$$

where:

| | |
|---|---|
| $P_{init}$ | is the initial power flowing through the Slack to the network |
| $P_{perm}$ | is the permitted power flowing through the Slack Bus to/from the network |
| $\eta_{RPF}^{\%}$ | is the percentage of the allowed RPF, with respect to the initial Slack Bus flowing power. |

Results from implementation on the typical 30 and 33-bus systems [51], a radial and a meshed electric distribution network, respectively, are shown in Figs. 8.11, 8.12, 8.13 and 8.14. Power loss reduction is the objective function, while gradually increasing RPF percentages are considered, and therefore the total permitted DG capacity to be installed is accomplished. A total number of seven DG units capable only of active power was considered for both examined networks. Furthermore, it should be stressed that the 30-bus system has already a 100% DG penetration with respect to installed load, whereas the 33-bus system has none. Overall, increasing the RPF results in reduced power loss savings, as can be deduced by Figs. 8.11

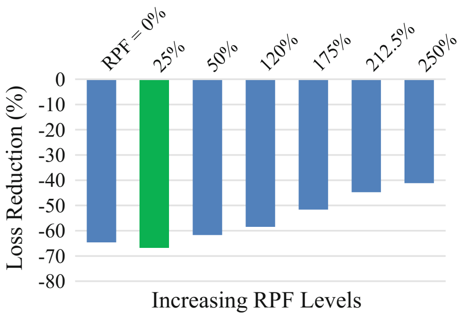



**Fig. 8.11** RPF impact on loss reduction (%) in the 33-bus system

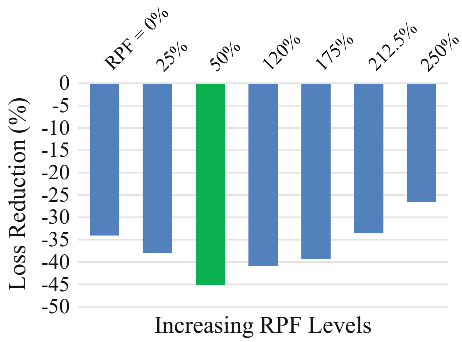



**Fig. 8.12** RPF impact on loss reduction (%) in the 30-bus system

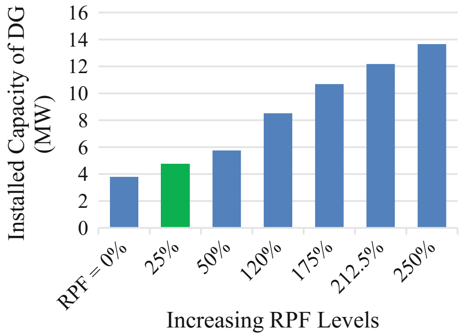



**Fig. 8.13** Installed DG capacity in the 33-bus system

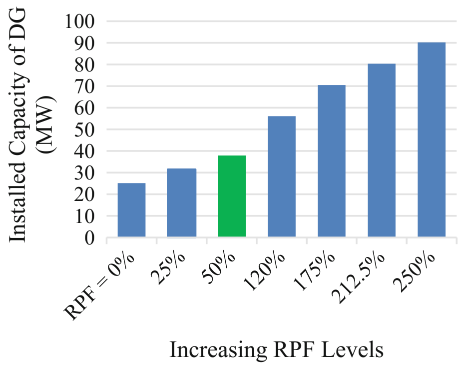



**Fig. 8.14** Installed DG capacity in the 30-bus system

and 8.12. The RPF ranges from 0% (no RPF allowed) up to equal to 250% of the initial downstream power flow. However, it is also deducted that regardless of the network's topology (radial or meshed) and with RPF percentage from 25 to 50% of the initial downstream power flow, an even better loss reduction is achieved, when compared to the one with RPF 0%. Moreover, for these RPF percentages the total DG installed reaches over 100% penetration in both networks, as shown in

Figs. 8.13 and 8.14; in the 33-bus system, for the best loss reduction for 25% RPF a total over 4 MW DG is installed, whereas its total installed load is 3.72 MW and in the 30-bus system, a nearly additional 40 MW DG is installed, in spite of already having achieved 100% DG penetration.

In conclusion, RPF existence up to a certain level will not necessarily affect negatively the ODGP, when considering power loss reduction. Additionally, it might lead to solutions with greater loss reduction and DG penetration over than 100%. This could benefit other operational aspects of the network, e.g. reliability improvement and environmental benefits under the installation of Renewable Energy Sources.

## 8.5 ODGP Towards Power Loss Minimization—Renewable Energy Sources

When examining ODGP towards power loss minimization, it is rather difficult to examine Renewable Energy Sources (RESs) directly and their installation in an electric distribution network, while keeping problem complexity at minimum, since their most distinctive feature, stochasticity, is dependent on time. In ODGP towards power loss minimization only a single state or snapshot of the network is taken into account. In examining different types of DGs, the most direct distinction from the network's point of view are:

- type 1: DG injecting only active power,
- type 2: DG injecting only reactive power,
- type 3: DG injecting active power and injecting/consuming reactive power.

With that in mind, apart from optimal site and size, an aspect of optimal mix of DG types can be added in the problem formulation. However, the question remains if it would be possible to examine the integration of RESs in an electric distribution network even in the current stage, without integrating on time, in other words if an Optimal Renewable Energy Sources Placement (ORESP) problem can be contemplated. To that end, several alternatives are offered.

More specifically, one alternative refers to solving the problem separately, i.e., to find the optimal siting and sizing of DG units in a network, as an ordinary ODGP problem, and then to determine the RES type, e.g. Photovoltaic or Wind Turbine [52]. However, no mix of RESs is examined for penetration and an impartial solution might not be achievable. If an optimal mix is required, an investigation regarding the different impacts of DGs on power quality and reliability must be performed; the DG penetration level could be limited by harmonic distortion because of the nonlinear current injected by inverter-based DG units, as well as by protection coordination constraints because of the variation in fault current caused by synchronous-based DG units [53]. Another approach is to implement the ELFs concept for each bus and each technology of DG [54], though either a possible needless computational effort would take place, or the solution could just rely on approximations. A considerable contribution at this field has been accomplished in [55], in which the optimal mix of DGs of different technologies has been achieved, via stochastic models of wind speed and solar irradiance. The candidate nodes for DG installation are predefined however and thus, only their size is estimated. Additionally, the different DG technologies could be divided according to their power output, i.e. whether they can control active/reactive power independently (PQ mode, or constant power factor mode), or active power and voltage (PV mode, or variable reactive power mode) [56]. In this latter approach, a simultaneous solution regarding number, siting and sizing is achieved, under a multi-objective function that includes active/reactive power loss minimization and voltage profile improvement. However, the aforementioned distinction between different DG technologies might not be quite so accurate.

Finally, in this section, the concept of Capacity Factors is implemented [57]. The basic issue in ORESP is the variations regarding RESs' power output; it is related to their technology and the natural resources' potential and they have to be taken into account. For example, solar irradiance, wind speed and water availability are expected to vary among candidate nodes within an electric distribution network, and these variations could have a significant impact on the optimal siting and sizing of such RESs, especially when a mix of different RESs is examined. The network's nodes are divided into groups, representing different areas with different natural characteristics and resources, and hence with different CFs. The values of these CFs express the potential of the respective natural resources available in that node. Thus, according to their positions, all RESs are assigned their CFs. These CFs are then included as an additional occasional constraint in the problem formulation, as

$$\Omega_{CF} = \rho_{CF} \sum_{l=1}^{n_{res}} CF_l \tag{8.18}$$

where $n_{res}$ the number of RESs, and $\rho_{CF}$ the corresponding penalty factor.

For example, let three RESs technologies to be considered, e.g. Photovoltaic (PV), Wind Turbine (WT) and Hydro-Plant (HP), for installation in the typical 69-bus system [58]. In order to assign potential for the local natural resources at each node, the electric distribution network in question has been divided into three areas, as depicted in Fig. 8.15. At each area, each of the nodes is assigned a value for the CFs of the three technologies examined, i.e. PV, WT, and HP, respectively. Assuming that each area is relatively small, it is evident that the nodes within that area share the same value of the CFs of their respective technologies.

In Table 8.4 a set of typical CFs values for each technology is assigned to each area, whereas in Tables 8.5 and 8.6 the results of the proposed method are presented. The results of the ODGP implementation on the same electric distribution network are also presented for comparison and LPSO was used in both approaches. Five DG units were considered for installation for the ODGP problem, whereas 5 RESs units for each technology in the ORESP problem. It can be concluded that via

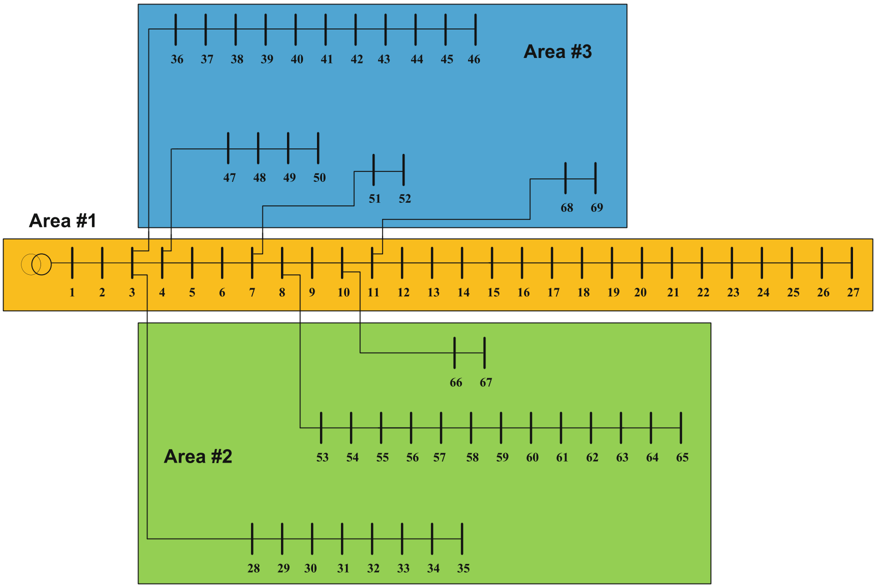



**Fig. 8.15** The 69-bus system divided into CF areas

**Table 8.4** CFs values

| Area | RES type | | |
|---|---|---|---|
| | PV | WT | HP |
| #1 | 0.10 | 0.00 | 0.42 |
| #2 | 0.10 | 0.25 | 0.00 |
| #3 | 0.15 | 0.12 | 0.00 |

**Table 8.5** Overall results

| | Initial losses (kW) | Minimum losses (kW) | Loss reduction (%) |
|---|---|---|---|
| ODGP | 602.2 | 148.4 | 75.357 |
| ORESP | 602.2 | 169.4 | 71.8698 |

this method the different geographical characteristics of an area and different weather conditions leading to availability of RESs, can be taken into account all at once, by the aid of CFs. Moreover, the corresponding ORESP problem can be solved while keeping its complexity at minimum and an optimal solution, in terms not only of siting and sizing, but also of RES type, is achievable.

**Table 8.6** Detail results

| ODGP | | ORESP | | |
|---|---|---|---|---|
| Bus no. | P (kW) | Type | Bus no. | P (kW) |
| 12 | 503.2 | PV | 20 | 420.3 |
| 19 | 376.0 | | 61 | 23.0 |
| 40 | 718.5 | WT | 40 | 723.2 |
| 53 | 1718.8 | | 45 | 580.8 |
| 61 | 29.48 | | 53 | 1458.1 |
| | | | 56 | 226.0 |
| | | | 59 | 57.7 |
| | | HP | 12 | 283.5 |
| Total no. | Total P (kW) | | Total no. | Total P (kW) |
| 5 | 3346.5 | | 8 | 3778.2 |

## 8.6 ODGP Towards Energy Loss Minimization—Load/Generation Variation

Although many issues can be examined in ODGP, such as power loss minimization or reduction, reverse power flow, voltage stability and reliability improvement, the approach remains incomplete without the time variable. If time is taken into account though, the problem becomes more complex and time-consuming, than it already is. Thus, a solving method able to prove the Golden Section between quick convergence time and optimal solution will become more than useful, as that examined in Sect. 8.3. Thus, the analysis of ODGP towards power loss minimization is useful and important and also a significant step before examining ODGP towards energy loss minimization.

Still, an electric distribution network's load does not remain constant, but varies over time. Furthermore, the stochasticity of RESs' generation, and their impact on a network cannot be examined, when only a single snapshot of the latter is considered.

For the ODGP towards energy loss, an energy loss minimization objective function could be

$$F_{eloss} = \sum_{\Delta t=1}^{t} \sum_{k=1}^{n_l} g_{i,j}\left[V_i^2 + V_j^2 - 2V_iV_j\cos\left(\theta_i - \theta_j\right)\right] \tag{8.19}$$

where $\Delta t$ is the time interval and $t$ is the time period examined.

Regarding the constraints, they remain the same, with the following exception: the single constraint value retrieved from the single snapshot's load flow analysis in power loss minimization approach, now in the energy loss minimization approach, is replaced by the maximum absolute value retrieved from the time period examined $t$, in order to maintain the same order of magnitude in the penalty function.

The impact of DG units on energy losses depends on the specific characteristics of the network, such as demand profile, topology, as well as the relative location of the generators and whether their output is considered constant or variable. Incorporating these complexities into an optimization framework for energy loss minimization is a challenge that has only been partially addressed by a few studies [59]. In [47] the analysis regarding load and DG power output variations relies on uniformly distributed loads while these variations refer to a typical daily pattern for both. Moreover, only the optimal siting of DG units is examined, and one DG unit is considered for installation. In [60] the case of one wind power unit under both power output and load demand variations is examined. The analysis yields the optimal node for the wind power unit installation by considering a sequential analysis with only one candidate node for DG installation at a time and concludes that subject to load variations, the optimal location is different when compared to the operational snapshot. In [55] a probabilistic technique is proposed for optimally allocating different types of DG technologies. The technique is based on generating a probabilistic generation-load model. Beta and Rayleigh Probability Density Functions (PDFs) are used for simulating solar irradiance and wind speed uncertainty, respectively, while IEEE-RTS for the load profile. However, the positions of the DGs are predetermined, as the number of DGs as well. Other approaches incorporating load or DG power variations, as in [61], may provide biased solutions since the installation nodes are predetermined. Furthermore, the analysis in [62] concludes that the power analysis of one load snapshot is not necessarily adequate for the overall operation of the electric distribution network in [63] a two-stage method of optimal siting and sizing of DG units is proposed. Finally, in [64], a method to address and evaluate the economic benefits of RESs is proposed, when applied to networks, but the candidate buses are predetermined and the number of DGs for each type is limited and predefined.

### *8.6.1 Load Variation*

In electric distribution networks, the loads are highly distributed and quite variable. Thus, detailed modelling is not possible, as yet, and even more difficult due to the absence of available real data. Thus, mathematical methods are resorted to formulate the load variations. In a first approach, the load of a test network, like the ones examined so far in this chapter, could be stochastically altered, in order to create different snapshots of a network, or even more, the load in each node could be stochastically altered, regarding the current/original load value of the network, either as its average, or its maximum value.

If the load of an electric distribution network, or even its load composition, is considered as an average snapshot of the network, then load variations or even load composition variations could be constructed via a uniform distribution, within a 20 and 50% range of the original snapshot. The loading condition of the IEEE-24 bus Reliability Test System [65] can be studied as a base case, in order to justify the

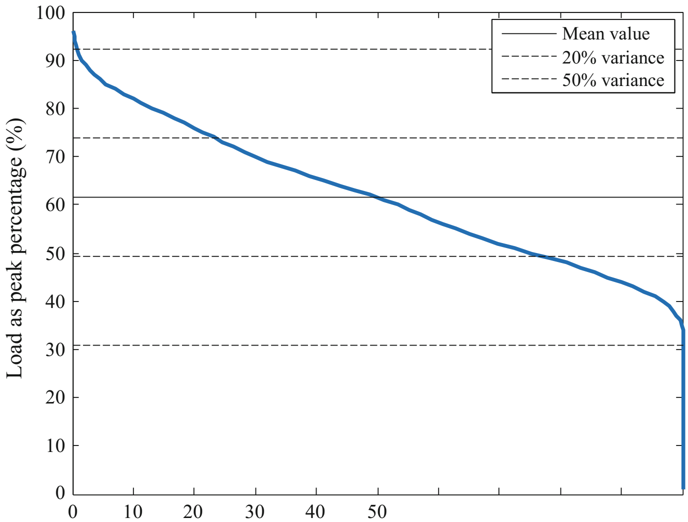



**Fig. 8.16** Load duration curve for the typical IEEE-24 bus reliability test system

load variations modelling for the present analysis. Its hourly, daily, and weekly peak load factors were used to construct the annual load curve. These peak load factors have been selected in order to capture the loading conditions that yield the highest annual energy losses and moreover in order to justify the upper limit for the load variations (i.e. 50%) adopted in this analysis. This selected variance could cover a loading composition for the network that refers to the highest load demands that are expected within a one year time period. Subsequently, the annual load curve is transformed into a cumulative power curve, as shown by the blue line in Fig. 8.16 to investigate the loading variability. In the same figure, the mean annual power, 61.45% of the annual peak power, along with the 20 and 50% variance limits are also marked in continuous, dotted, and dashed grey lines, respectively. It is calculated that the 20 and 50% variance cover the 55.08 and 99.40% of the total annual loading levels, respectively. As proved by Fig. 8.16, the majority of loading conditions of the network during a one year time period could be captured by load variations up to 50% of the average load composition of the network.

If the ODGP towards power loss minimization is solved for every snapshot created, then it would provide an optimal solution for each and every snapshot. When examining the overall results, it is deduced that some buses appear more frequently than others, i.e. appear in most of the snapshot's solutions. This suggests that some buses emerge as the most critical for siting DG units. Moreover, this means that the siting stage of the ODGP is insensitive to the load variations, or even to the load composition variations. Thus, the two stages of ODGP, siting and sizing, can be examined separately. In Fig. 8.17 the results from the implementation on the 33-bus system are presented, for 2000 snapshots within 20%, and 6000 snapshots within 50% range of the original load composition solved. The related frequency of

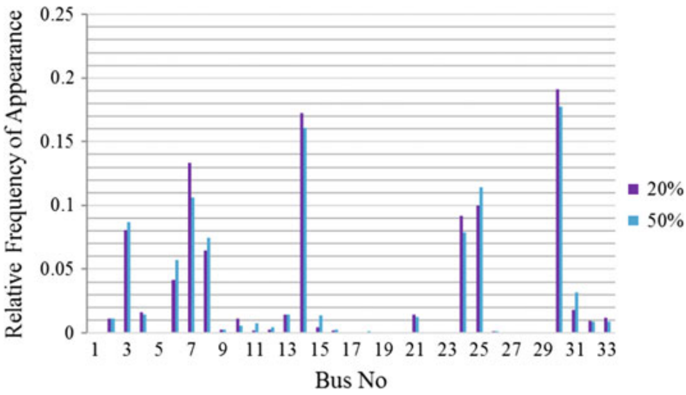
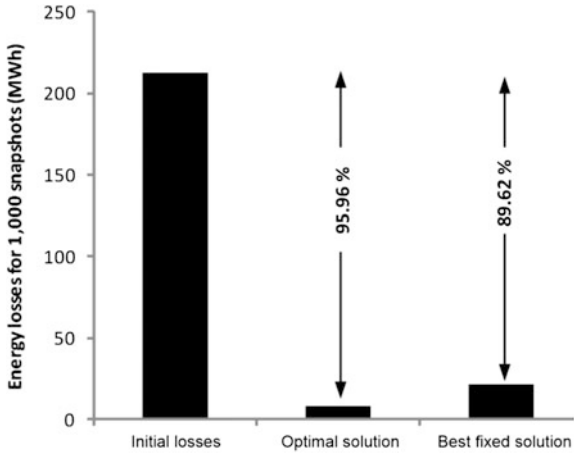



**Fig. 8.17** Relative frequency of appearance of buses in the 33-bus system

**Fig. 8.18** Energy loss reduction comparison for 1000 snapshots on the 33-bus system




appearance of each bus for each case (20 and 50%, respectively) is shown. It appears that buses No. 3, 7, 14, 24, 25 and 30 for both 20 and 50% range variations emerge as the most prominent for DG installation.

In addition, if their average active and reactive power from the snapshot solutions are to be taken into account for these prominent/critical buses, then they can present a fixed but adequate solution for the ODGP problem towards energy loss minimization [66]. In Fig. 8.18, for instance, results from 1000 snapshots within 20% range applied to the 33-bus system are presented. The total energy losses for the 1000 snapshots without any DG installed is compared to the losses obtained from the optimal solutions of every snapshot and the fixed solution from the most prominent buses along with their respective average active and reactive power. It is demonstrated that the fixed solution's energy loss reduction is very close to the loss reduction sum of the optimal solutions of all the snapshots, diverging only slightly

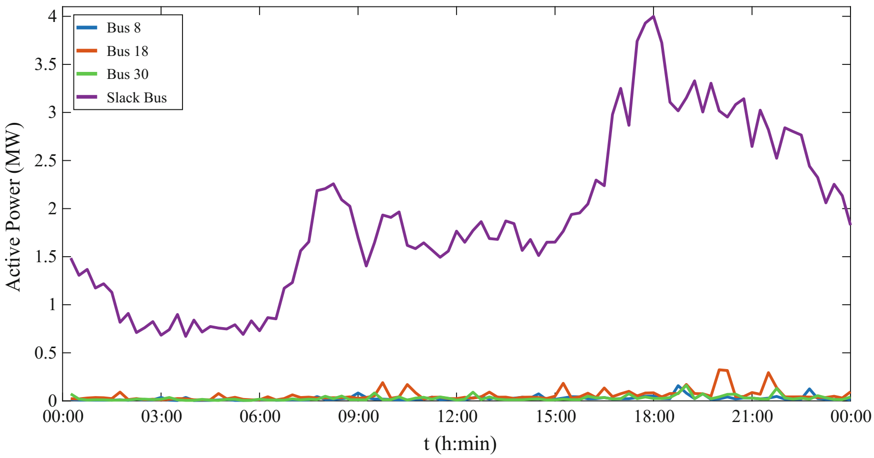



**Fig. 8.19** Daily load profile of various buses of the 33-bus system

by 6% from it. Hence, a very first estimation, if not an adequate solution, regarding the ODGP towards energy loss is provided.

An alternative approach to load variations would be to consider that the electric distribution network's snapshot at hand is the peak load for the time period examined. Moreover, instead of stochastically reproducing load snapshots to create a load profile, the network itself can be combined with time-series of standard load profiles, either real, or synthesized via load forecasting techniques. Thus, in a straightforward approach, each bus's load could be multiplied with a normalized standard load profile and so creating the desired snapshots. However, since the loads in a network do not necessarily change simultaneously or present the same pattern, and most importantly the standard load profiles are more or less measurements of the DNO on the substations within its purview and not on the load buses themselves, a more elaborate scheme can be contemplated. It could be theorized that the total network's load follows the standard load profile's pattern and each bus's load changes in such a way, so that this can be achieved. An example can be seen in Fig. 8.19, where the load profile of three buses is shown along the total load profile of the network, as seen from the Slack Bus for a daily time period of hourly quarter's intervals, from the implementation of this method on the 33-bus system. The buses' load follow their own individual patterns, while the total network load profile is seen from the Slack Bus, and that is observed by the DNO. Thus, a more realistic approach of the problem has been achieved.

**Table 8.7** ODGP of different technologies—energy loss reduction results

| Technology | Energy loss reduction (%) |
|---|---|
| DG | 82.9874 |
| PV | 36.5701 |
| WT | 50.2236 |

**Table 8.8** ODGP of different DG technologies—detailed solution results

| DG | | | PV | | | WT | | |
|---|---|---|---|---|---|---|---|---|
| Bus no | P (kW) | Q (kVar) | Bus no | P (kW) | Q (kVar) | Bus no | P (kW) | Q (kVar) |
| 3 | 248 | 78.4 | 3 | 281.6 | 81.5 | 3 | 395.8 | 78.6 |
| 6 | 281 | 94 | 6 | 550 | 204.3 | 6 | 358.7 | 71.9 |
| 11 | 222.6 | 59.1 | 9 | 96.8 | 22.2 | 11 | 312.7 | 64.1 |
| 16 | 217.6 | 50.9 | 11 | 214.8 | 46.7 | 16 | 387.7 | 63.2 |
| 31 | 206.1 | 109.2 | 16 | 262.5 | 52.2 | 30 | 388.9 | 152.3 |
| Total no. | Total P (kW) | Total Q (kVar) | Total no. | Total P (kW) | Total Q (kVar) | Total no. | Total P (kW) | Total Q (kVar) |
| 5 | 1175.5 | 391.6 | 5 | 1405.7 | 406.9 | 5 | 1843.8 | 430.1 |

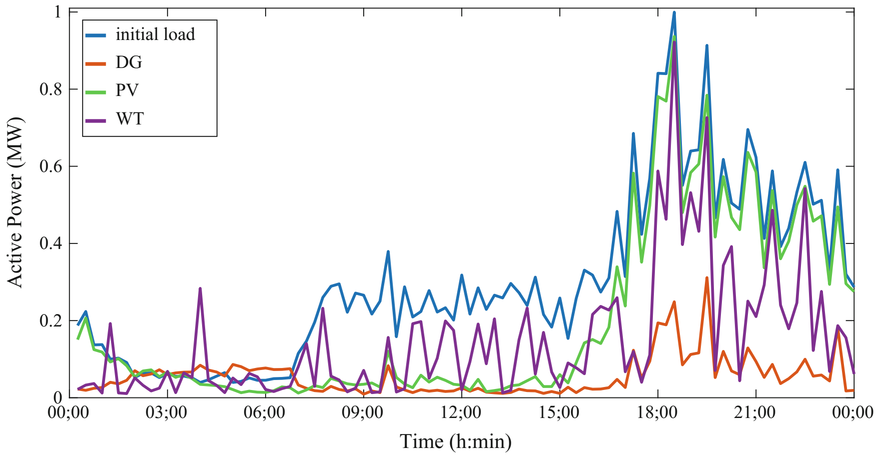



**Fig. 8.20** Daily load curve without any DG (initial load), and with generic DG, PV and WT

## *8.6.2 Load/Generation Variation*

With respect to RESs' generation, there are data available both from DG stations and mathematical tools, such as the Weibull distribution for wind speed, or a

Beta PDF for solar irradiance modelling. In spite of the more realistic approach of the problem, it is of interest that still the siting stage of the ODGP is insensitive to the load variation, load composition variation and perhaps DG technology, indicating that it is more network-topology oriented. Furthermore, as expected, the energy loss reduction is DG technology dependent. These can be seen in Tables 8.7 and 8.8, where results from an application on the 33-bus system are presented. A daily period of hourly quarter's intervals is considered and five DG units capable of injecting active power with a maximum power factor of 0.95 leading/lagging. DG units of constant power output, PVs and WTs as renewable technologies have been applied. In case of PVs real data were used, whereas for WTs synthesized data were obtained. The corresponding load curves can be seen in Fig. 8.20.

Additionally, with respect to an optimal mix of DG technologies, e.g. PVs and WTs, it can be argued that the approach proposed in 8.5, is not that far from reality.

**Fig. 8.21** The 33-bus system divided into three CF areas

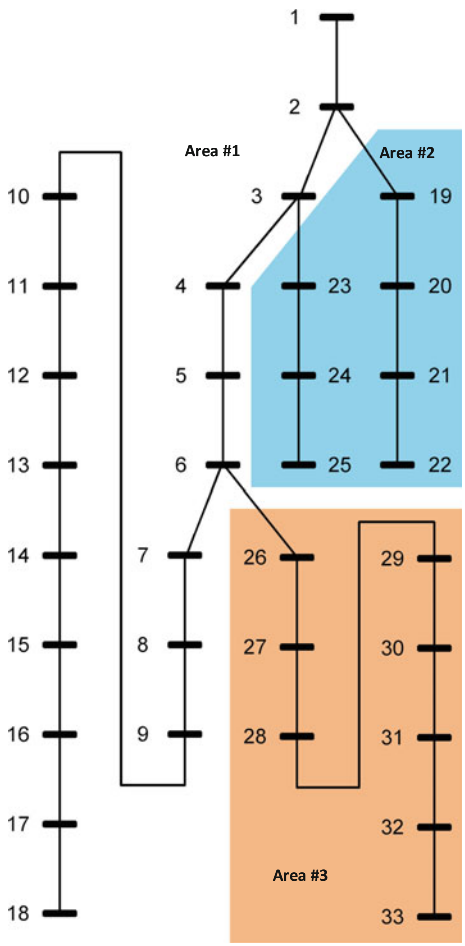


**Table 8.9** ORESP towards energy loss minimization using a realistic approach and CF method

| ORESP—realistic approach | | | ORESP—CF on peak load | | |
|---|---|---|---|---|---|
| Energy loss reduction (%) | 45.1869 | | Energy loss reduction (%) | 28.102 | |
| PV | | | PV | | |
| Bus no. | P (kW) | Q (kVar) | Bus no. | P (kW) | Q (kVar) |
| 3 | 40.4 | 33.9 | | | |
| 6 | 440.9 | 73.1 | 6 | 725.7 | 321.4 |
| 11 | 265.1 | 66.9 | 11 | 424.5 | 124.3 |
| 16 | 270.7 | 55.2 | 16 | 514.7 | 82.6 |
| Total no. | Total P (kW) | Total Q (kVar) | Total no. | Total P (kW) | Total Q (kVar) |
| 4 | 1017.1 | 229.1 | 3 | 1664.9 | 528.3 |
| WT | | | WT | | |
| Bus no. | P (kW) | Q (kVar) | Bus no. | P (kW) | Q (kVar) |
| 2 | 0 | 63.8 | | | |
| 23 | 667 | 41.1 | 23 | 193.6 | 25.2 |
| 30 | 1046.5 | 149 | 30 | 239.7 | 95.7 |
| Total no. | Total P (kW) | Total Q (kVar) | Total no. | Total P (kW) | Total Q (kVar) |
| 3 | 1713.5 | 253.9 | 2 | 433.3 | 120.9 |

More specifically, the 33-bus system is divided in three areas of different weather and geographical potentials, as depicted in Fig. 8.21, where in area #1 and #2 sun and wind potential are dominant, respectively, and in area #3 they are competitive. As earlier, same DG operation regarding active/reactive power and load profile is assumed. As can be deduced from Table 8.9, if the method developed in Sect. 8.5 is performed for the peak load of the network, the solutions reached are a bit different, though comparable. It should be stressed, however, that the analysis is performed in a short time scale, i.e. a daily load curve. However, if the time scale is extended to a whole year, or years, the solutions might bear more resemblance.

## 8.7 Combination of ODGP with Other Problems

### *8.7.1 ODGP and NR*

In ODGP the siting and sizing of DG units is the objective whereas in Network Reconfiguration (NR) an alternative layout is the objective in order to redistribute the power flow. Both techniques are established as efficient, regarding power loss reduction.

Despite the significant contribution of each technique towards loss reduction, when applied individually, it seems that there are quite few studies that try to examine the potentials of a combined approach under an efficient application order for them [67–69]. Both power loss reduction techniques, when applied individually, affect either the load composition of the electric distribution network (the net power of the nodes that host DG units is altered in ODGP) or its layout (a reconfigured topology after the NR application). Thus, when both techniques are applied, the application order is highly possible to have an impact on the final solution regarding the overall amount of loss reduction. If it is assumed that the highest possible loss reduction refers to the ideal 100%, then the contribution of each technique towards such a solution is affected by the order of their application. For instance, ODGP could theoretically yield a solution with 100% power loss reduction in the ideal case with one DG unit with power injection equal to the local load installed at each node. In this latter case, the further application of NR would be meaningless. On the other hand, if the ODGP problem refers to the more realistic case of limited available DG units to be optimally sized and sited, then the application of the NR technique could yield additional loss reduction and further improve the solution.

If the opposite application order is examined then it is interesting to investigate how both the siting and sizing of the available DG units to be penetrated in the electric distribution network would be affected, given that the ODGP problem will now be applied to an altered network, i.e. with a reconfigured topology while keeping the same load composition.

Let us consider the following three scenarios of the solving order of ODGP and NR:

- scenario-1: NR solved first, then ODGP,
- scenario-2: ODGP first, then NR, and,
- scenario-3: both ODGP and NR are concurrently solved.

The results, when implemented in the 69-bus system are presented in Tables 8.10, 8.11, and 8.12, whereas in Fig. 8.22 the 69-bus system along with its tie-switches is depicted. Seven DG units are considered for installation and capable

**Table 8.10** Scenario-1: NR 1st, ODGP 2nd

| NR applied | Initial losses (kW) | Sectionalizers open | Tie switches closed | Loss reduction % | Final losses (kW) |
|---|---|---|---|---|---|
| | 229.8 | 14,58,62 | Tie3-Tie5 | 54.7 | 104.1 |
| ODGP applied | 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) |
| | 104.1 | 5<br>9<br>12<br>22<br>40<br>53<br>56 | 901.7<br>241.6<br>427.4<br>338.3<br>0<br>1416.1<br>318.5 | 189.2<br>177.2<br>299.6<br>226.6<br>536.4<br>938.2<br>226.7 | 93.65%<br>6.6 |

**Table 8.11** Scenario-2: ODGP 1st, NR 2nd

| ODGP applied | 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) |
|---|---|---|---|---|---|
| | 229.8 | 2<br>3<br>9<br>12<br>19<br>40<br>53 | 0<br>539<br>0<br>501.2<br>380.8<br>717<br>1674 | -53.2<br>340<br>184.9<br>279.8<br>251.7<br>512<br>1178.8 | 97.35%<br>6.1 |
| NR applied | Initial losses (kW) | Sectionalizers open | Tie switches closed | Loss reduction % | Final losses (kW) |
| | 6.1 | – | – | 0 | 6.1 |

**Table 8.12** Scenario-3: ODGP NR concurrently

| Candidate node to host DG units | Active power of each DG unit (kW) | Reactive power of each DG unit (kVar) | Sectionalizers open | Tie switches closed | Loss reduction %—final losses (kW) |
|---|---|---|---|---|---|
| 57 | 2021.5 | 849.8 | 20,42,46,58,61 | Tie1-tie5 | 68.28%<br>72.9 |

of both active and reactive power generation. The UPSO algorithm, as presented in Sect. 8.3, is utilized. The first scenario seems to be advantageous since the switching operations rely on the already existent tie-switches and that results in lower required DG capacity for power loss minimization. In the second scenario, it is highly possible to be unable to apply the NR technique, especially if the ODGP technique performs quite well under high power loss reduction by the installation of the proposed DG units. Finally, in the third scenario since both techniques are considered concurrently, the problem's complexity increases exponentially, thus the algorithm seems unable to provide an adequate solution. It is yet to be investigated, whether the worth of a better solution in this case is overweighted by the increased computational burden [70–72].

### 8.7.2 *ODGP and OESSP*

ODGP can be targeted towards energy loss reduction, due to the nature of DG units since they produce electricity even for a certain time period. ESSs, though, present an entirely different complexion. Moreover, because ESSs' integration in a more massive or industrial scale is still in its infancy, cost is still and a more important

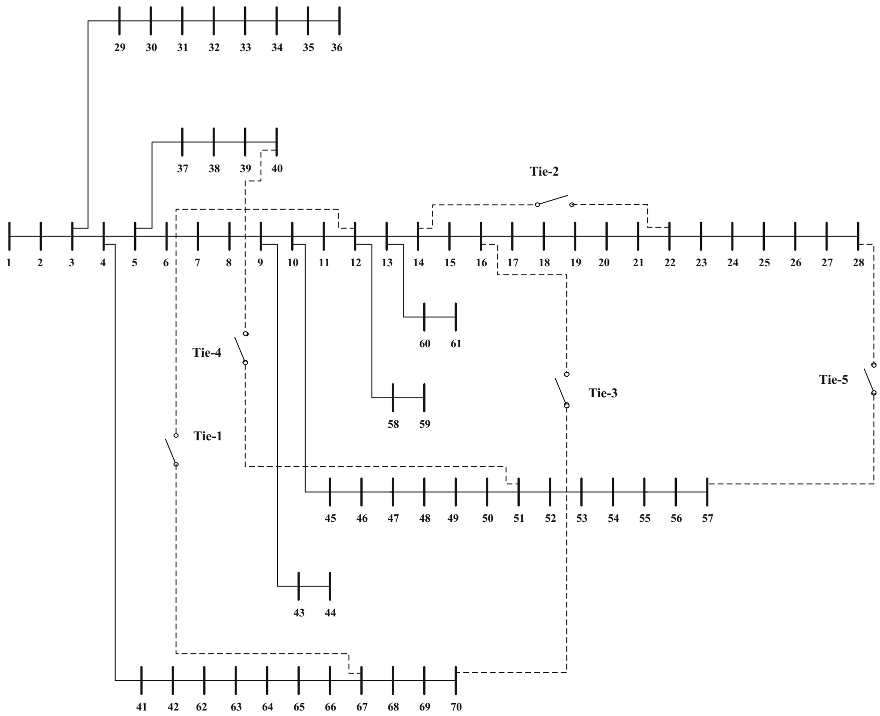



**Fig. 8.22** The 69-bus system depicted with its tie-switches

**Table 8.13** Energy loss reduction from installing DG units along with ESSs

| | Energy loss (MWh) | Energy loss reduction (%) |
|---|---|---|
| Initial | 2.7647 | – |
| DG | 1.5593 | 43.5997 |
| LS | 1.5606 | 43.5526 |
| EM = 1 MWh | 1.5532 | 43.8203 |
| EM = 2.5 MWh | 1.5449 | 44.1205 |
| EM = 5 MWh | 1.5353 | 44.4678 |

issue. Thus, when dealing with the OESSP problem, cost or profit objective functions are considered [73]. Furthermore, it might not be of significant aid towards energy loss reduction. For example, using the load/generation tools available from Sect. 8.6.2, two modes of ESSs can be added: load smoothing (LS) and energy management (EM). The former is used in order to smooth out any abrupt spikes in load curves and the latter in storing energy during one time period and providing it at another. PVs and WTs have also been utilised, for a more thorough approach, provided from the example in Sect. 8.6.2. For LS, the ESSs are considered to be installed in the buses where the PVs and WTs have been installed,

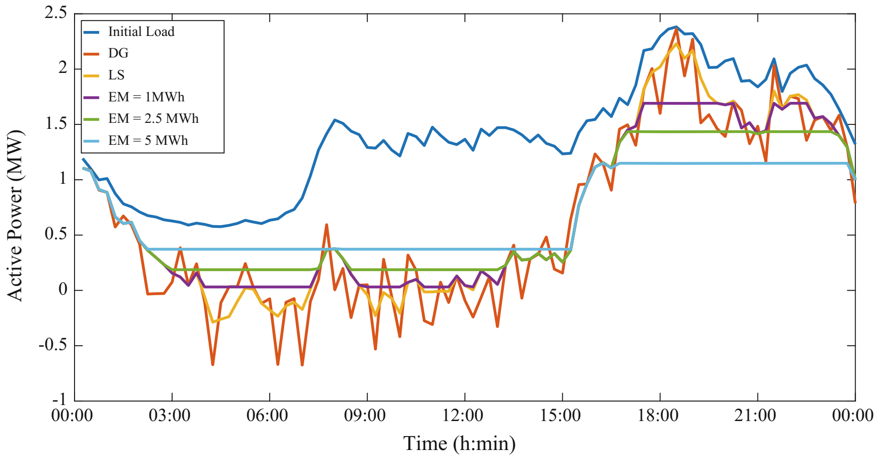



**Fig. 8.23** Load curves for integrating DGs along ESS in LS and EM mode

and for EM near the Slack Bus, since it is theorized that it will be installed by the DNO. In Table 8.13 the energy losses are presented and in Fig. 8.23 the load curves for a time period of one day are illustrated. As can be seen, in this configuration the impact in energy losses of ESS is limited, regardless of mode or size, although great benefits have been provided for the DNO, from both modes, regarding the load curves. It should be emphasized though, that OESSP might prove promising in the field of energy loss minimization over a more extended and elaborate analysis. For instance, both sizing and siting could be examined concurrently, and ESSs systems capable of LS and EM operation, or even Frequency Regulation, as well.

## References

1. T. Ackermann, V. Knyazkin, Interaction between distributed generation and the distribution network: operation aspects, in *IEEE/PES Transmission and Distribution Conference and Exhibition* (2002), pp. 1357–1362
2. N. Mohandas, R. Balamurugan, L. Lakshminarasimman, Optimal location and sizing of real power DG units to improve the voltage stability in the distribution system using ABC algorithm united with chaos. Int. J. Electr. Power Energy Syst. **66**, 41–52 (2015)
3. V.H. MendezQuezada, J. RivierAbbad, T. GomezSanRoman, Assessment of energy distribution losses for increasing penetration of distributed generation. IEEE Trans. Power Syst. **21**(2), 533–540 (2006)
4. K.O. Oureilidis, E.A. Bakirtzis, C.S. Demoulias, Frequency-based control of islanded microgrid with renewable energy sources and energy storage. J. Mod. Power Syst. Clean Energy **4**(1), 54–62 (2016)
5. P.A. Gkaidatzis, D.I. Doukas, A.S. Bouhouras, K.I. Sgouras, D.P. Labridis, Impact of penetration schemes to optimal DG placement forlossminimisation. Int. J. Sustain. Energy **36** (5), 473–488 (2017)

6. A.S. Bouhouras, K.I. Sgouras, P.A. Gkaidatzis, D.P. Labridis, Optimal active and reactive nodal power requirements towards loss minimization under reverse power flow constraint defining DG type. Int. J. Electr. Power Energy Syst. **78**, 445–454 (2016)
7. M. Esmaili, Placement of minimum distributed generation units observing power losses and voltage stability with network constraints. IET Gener. Transm. Distrib. **7**(8), 813–821 (2013)
8. S. Ge, L. Xu, H. Liu, J. Fang, Low-carbon benefit analysis on DG penetration distribution system. J. Mod. Power Syst. Clean Energy **3**(1), 139–148 (2015)
9. A. Soroudi, M. Ehsan, R. Caire, N. Hadjsaid, Hybrid immune-genetic algorithm method for benefit maximisation of distribution network operators and distributed generation owners in a deregulated environment. IET Gener. Transm. Distrib. **5**(9), 961 (2011)
10. Y. del Valle, G.K. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, R.G. Harley, Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Trans. Evol. Comput. **12**(2), 171–195 (2008)
11. K.E. Parsopoulos, M.N. Vrahatis, *Particle Swarm Optimization and Intelligence: Advances and Applications* (IGI Global, Hershey, 2010)
12. U. Leeton, D. Uthitsunthorn, U. Kwannetr, N. Sinsuphun, T. Kulworawanichpong, Power loss minimization using optimal power flow based on particle swarm optimization, in *2010 IEEE International Conference on Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON)* (2010), pp. 440–444
13. P.S. Georgilakis, N.D. Hatziargyriou, A review of power distribution planning in the modern power systems era: models, methods and future research. Electr. Power Syst. Res. **121**, 89–100 (2015)
14. D.Q. Hung, N. Mithulananthan, R.C. Bansal, Analytical expressions for DG allocation in primary distribution networks. IEEE Trans. Energy Convers. **25**(3), 814–820 (2010)
15. D.Q. Hung, N. Mithulananthan, Multiple distributed generator placement in primary distribution networks for loss reduction. IEEE Trans. Ind. Electron. **60**(4), 1700–1708 (2013)
16. D.Q. Hung, N. Mithulananthan, Loss reduction and loadability enhancement with DG: a dual-index analytical approach. Appl. Energy **115**, 233–241 (2014)
17. P. Prakash, D.K. Khatod, An analytical approach for optimal sizing and placement of distributed generation in radial distribution systems, in *1st IEEE International Conference on Power Electronics. Intelligent Control and Energy Systems (ICPEICES-2016)* (2016), pp. 1–5
18. T. Kumar, T. Thakur, Comparative analysis of particle swarm optimization variants on distributed generation allocation for network loss minimization, in *2014 First International Conference on Networks & Soft Computing (ICNSC2014)* (2014), pp. 167–171
19. A.A. Abou El-Ela, S.M. Allam, M.M. Shatla, Maximal optimal benefits of distributed generation using genetic algorithms. Electr. Power Syst. Res. **80**(7), 869–877 (2010)
20. K.-H. Kim, Y.-J. Lee, S.-B. Rhee, S.-K. Lee, S.-K. You, Dispersed generator placement using fuzzy-GA in distribution systems, in *IEEE Power Engineering Society Summer Meeting*, vol. 3 (2002), pp. 1148–1153
21. F.S. Abu-Mouti, M.E. El-Hawary, Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm. IEEE Trans. Power Deliv. **26**(4), 2090–2101 (2011)
22. A.A. Seker, M.H. Hocaoglu, Artificial Bee Colony algorithm for optimal placement and sizing of distributed generation, in *2013 8th International Conference on Electrical and Electronics Engineering (ELECO)* (2013), pp. 127–131
23. N. Taher, I.T. Seyed, A. Jamshid, T. Sajad, N. Majid, A modified honey bee mating optimization algorithm for multiobjective placement of renewable energy resources. Appl. Energy **88**(12), 4817–4830 (2011)
24. W.S. Tan, M.Y. Hassan, M.S. Majid, H.A. Rahman, Allocation and sizing of DG using Cuckoo search algorithm, in *2012 IEEE International Conference on Power and Energy (PECon)* (2012), pp. 133–138
25. M. Zahra, A. Amir, A novel approach based on cuckoo search for {DG} allocation in distribution network. Int. J. Electr. Power Energy Syst. **44**(1), 672–679 (2013)

26. W. Buaklee, K. Hongesombut, Optimal DG allocation in a smart distribution grid using Cuckoo search algorithm, in *2013 10th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)* (2013), pp. 1–6
27. S. Roy, S. Sultana, P.K. Roy, Oppositional cuckoo optimization algorithm to solve DG allocation problem of radial distribution system, in *2015 International Conference on Recent Developments in Control, Automation and Power Engineering (RDCAPE)* (2015), pp. 44–49
28. A.Y. Abdelaziz, R.A. Osama, S.M. Elkhodary, Using the harmony search algorithm for reconfiguration of power distribution networks with distributed generation units. J. Bioinform. Intell. Control **2**(3), 237–242 (2013)
29. S.I. Kumar, N.P. Kumar, A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems. Int. J. Electr. Power Energy Syst. **45**(1), 142–151 (2013)
30. R.S. Rao, K. Ravindra, K. Satish, S.V.L. Narasimham, Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. IEEE Trans. Power Syst. **28**(1), 317–325 (2013)
31. A. Mohamed Imran, M. Kowsalya, Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization. Swarm Evol. Comput. **15**, 58–65 (2014)
32. M.J. Hadidian-Moghaddam, S. Arabi-Nowdeh, M. Bigdeli, D. Azizian, A multi-objective optimal sizing and siting of distributed generation using ant lion optimization technique. Ain Shams Eng. J. 1–9 (2017)
33. A. Sobieh, M. Mandour, E.M. Saied, M.M. Salama, Optimal number size and location of distributed generation units in radial distribution systems using Grey Wolf optimizer. Int. Electr. Eng. J. **7**(9), 2367–2376 (2017)
34. M.H. Moradi, M. Abedini, A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. Int. J. Electr. Power Energy Syst. **34**(1), 66–74 (2012)
35. A.J.G. Mena, J.A.M. Garcia, An efficient approach for the siting and sizing problem of distributed generation. Int. J. Electr. Power Energy Syst. **69**, 167–172 (2015)
36. R. Viral, D.K. Khatod, An analytical approach for sizing and siting of DGs in balanced radial distribution networks for loss minimization. Int. J. Electr. Power Energy Syst. **67**, 191–201 (2015)
37. R. Eberhart, J. Kennedy, A new optimizer using particle swarm theory, in *Proceedings of the Sixth International Symposium on Micro Machine and Human Science MHS'95* (1995), pp. 39–43
38. A.P. Engelbrecht, *Computational Intelligence: An Introduction*, vol. 115, 2nd edn. (Wiley, Chichester, 2008), pp. 3–78
39. K.E. Parsopoulos, M.N. Vrahatis, Parameter selection and adaptation in unified particle swarm optimization. Math. Comput. Model. **46**(1–2), 198–213 (2007)
40. P.A. Gkaidatzis, A.S. Bouhouras, D.I. Doukas, K.I. Sgouras, D.P. Labridis, Application and evaluation of UPSO to ODGP in radial distribution networks, in *2016 13th International Conference on the European Energy Market (EEM)*, vol. 2016, July (2016), pp. 1–5
41. J.H. Holland, Genetic algorithms. Sci. Am. **267**(1), 66–72 (1992)
42. D. Karaboga, B. Basturk, Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems, ed. by P. Melin, O. Castillo, L.T. Aguilar, J. Kacprzyk, W. Pedrycz, in *Proceedings of the Foundations of Fuzzy Logic and Soft Computing: 12th International Fuzzy Systems Association World Congress (IFSA 2007)*, Cancun, Mexico, 18–21 June 2007 (Springer, Berlin, Heidelberg, 2007), pp. 789–798
43. X.S. Yang, S. Deb, Cuckoo search via levy flights, in *World Congress on Nature Biologically Inspired Computing (NaBIC 2009)* (2009), pp. 210–214
44. Z.W. Geem, J.H. Kim, G.V. Loganathan, A new heuristic optimization algorithm: harmony search. Simulation **76**(2), 60–68 (2001)

45. M. Kashem, V. Ganapathy, G. Jasmon, M. Buhari, A novel method for loss minimization in distribution networks, in *International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT2000). Proceedings (Cat. No.00EX382)*, no. 603 (2000), pp. 251–256
46. S. Ghosh, S.P. Ghoshal, S. Ghosh, Optimal sizing and placement of distributed generation in a network system. Int. J. Electr. Power Energy Syst. **32**(8), 849–856 (2010)
47. C. Wang, M.H. Nehrir, Analytical approaches for optimal placement of distributed generation sources in power systems. IEEE Trans. Power Syst. **19**(4), 2068–2076 (2004)
48. M.F. Akorede, H. Hizam, I. Aris, M.Z.A. Ab Kadir, Effective method for optimal allocation of distributed generation units in meshed electric power systems. IET Gener. Transm. Distrib. **5**(2), 276 (2011)
49. R.K. Singh, S.K. Goswami, Optimum siting and sizing of distributed generations in radial and networked systems. Electr. Power Components Syst. **37**(2), 127–145 (2009)
50. D.I. Doukas, P.A. Gkaidatzis, A.S. Bouhouras, K.I. Sgouras, D.P. Labridis, On reverse power flow modelling in distribution grids, in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016)* (2016), p. 65 (6.)
51. R. Yokoyama, S.H. Bae, T. Morita, H. Sasaki, Multiobjective optimal generation dispatch based on probability security criteria. IEEE Trans. Power Syst. **3**(1), 317–324 (1987)
52. P. Kayal, C.K. Chanda, Placement of wind and solar based DGs in distribution system for power loss minimization and voltage stability improvement. Int. J. Electr. Power Energy Syst. **53**, 795–809 (2013)
53. V.R. Pandi, H.H. Zeineldin, W. Xiao, Determining optimal location and size of distributed generation resources considering harmonic and protection coordination limits. IEEE Trans. Power Syst. **28**(2), 1245–1254 (2013)
54. A. Keane, M. O'Malley, Optimal distributed generation plant mix with novel loss adjustment factors, in *2006 IEEE Power Engineering Society General Meeting* (2006), 6 pp
55. Y.M. Atwa, E.F. El-Saadany, M.M.A. Salama, R. Seethapathy, Optimal renewable resources mix for distribution system energy loss minimization. IEEE Trans. Power Syst. **25**(1), 360–370 (2010)
56. C. Yammani, S. Maheswarapu, S. Matam, Optimal placement of multi DGs in distribution system with considering the DG bus available limits. Energy and Power **2**(1), 18–23 (2012)
57. P.A. Gkaidatzis, A.S. Bouhouras, K.I. Sgouras, D.I. Doukas, D.P. Labridis, Optimal distributed generation placement problem for renewable and DG units: an innovative approach, in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016)* (2016), p. 66 (7.)
58. S. Soudi, Distribution system planning with distributed generations considering benefits and costs. Int. J. Mod. Educ. Comput. Sci. **5**(October), 45–52 (2013)
59. L.F. Ochoa, G.P. Harrison, Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation. IEEE Trans. Power Syst. **26**(1), 198–205 (2011)
60. L.F. Ochoa, A. Padilha-Feltrin, G.P. Harrison, Evaluating distributed time-varying generation through a multiobjective index. IEEE Trans. Power Deliv. **23**(2), 1132–1138 (2008)
61. G.N. Koutroumpezis, A.S. Safigianni, Optimum allocation of the maximum possible distributed generation penetration in a distribution network. Electr. Power Syst. Res. **80**(12), 1421–1427 (2010)
62. Y.M. Atwa, E.F. El-Saadany, Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems. IET Renew. Power Gener. **5**(1), 79 (2011)
63. F. Rotaru, G. Chicco, G. Grigoras, G. Cartina, Two-stage distributed generation optimal sizing with clustering-based node selection. Int. J. Electr. Power Energy Syst. **40**(1), 120–129 (2012)
64. M.F. Shaaban, Y.M. Atwa, E.F. El-Saadany, DG allocation for benefit maximization in distribution networks. IEEE Trans. Power Syst. **28**(2), 939–949 (2013)
65. P. Subcommittee, IEEE reliability test system. IEEE Trans. Power Appar. Syst. **PAS-98**(6), 2047–2054 (1979)

66. A.S. Bouhouras, C. Parisses, P.A. Gkaidatzis, K.I. Sgouras, D.I. Doukas, D.P. Labridis, Energy loss reduction in distribution networks via ODGP, in *International Conference on the European Energy Market (EEM)*, vol. 2016–July (2016)
67. B. Pawar, S. Kaur, G.B. Kumbhar, An integrated approach for power loss reduction in primary distribution system, in *2016 IEEE 6th International Conference on Power Systems (ICPS)* (2016), pp. 1–6
68. W.M. Dahalan, H. Mokhlis, Network reconfiguration for loss reduction with distributed generations using PSO, in *2012 IEEE International Conference on Power and Energy (PECon)* (2012), pp. 823–828
69. W. Mohd Dahalan, H. Mokhlis, R. Ahmad, A.H. Abu Bakar, I. Musirin, Simultaneous network reconfiguration and DG using EP method. Int. Trans. Electr. Energy Syst. **25**(11), 2577–2594 (2015)
70. A.S. Bouhouras, P.A. Gkaidatzis, D.P. Labridis, Optimal application order of network reconfiguration and ODGP for loss reduction in distribution networks, in *17 IEEE International Conference on Environment and Electrical Engineering (EEEIC 2017)* (2017), pp. 1–6
71. A.S. Bouhouras, G.T. Andreou, D.P. Labridis, A.G. Bakirtzis, Selective automation upgrade in distribution networks towards a smarter grid. IEEE Trans. Smart Grid **1**(3), 278–285 (2010)
72. A.S. Bouhouras, D.P. Labridis, Influence of load alterations to optimal network configuration for loss reduction. Electr. Power Syst. Res. **86**, 17–27 (2012)
73. N.D. Hatziargyriou, D. Skrlec, T. Capuder, P.S. Georgilakis, M. Zidar, Review of energy storage allocation in power distribution networks: applications, methods and future research. IET Gener. Transm. Distrib. **10**(3), 645–652 (2016)