Chapter 6

EBOwithCMAR in Optimization of Grid-connected Microgrids

6.1 Introduction

In this part, a technique is proposed to reduce the active and reactive power loss with phase balancing at the main transformer simultaneously in the system by using Single-Phase Distributed Generators (SPDGs) with capacitors. An optimization algorithm, Effective Butterfly Optimizer with Covariance Matrix Adapted Retreat Phase (EBOwithCMAR), is proposed and applied to optimally size and site the SPDGs in power distribution systems for reducing the active and reactive system losses with minimal load unbalance at the primary transformer.

DGs with capacitor banks may be set up locally adjacent to the consumer points. which can significantly support the extra load demand, cut down operational cost, minimize losses, enhance voltage profile and power capability of the system. DGs can be a micro-turbine operated on natural gas, a light synchronous generator driven on diesel, fuel cells, and wind turbines, etc. Several renewable sources such as wind turbine and solar units have further added advantages of low direct emissions. In addition, the evolvement of compact DGs is the principal reason to take advantage of cheaper investment and low space requirement. Although DGs provide many improvements, there are various challenges when these are consolidated with the power distribution system. DG can set up a bidirectional flow of power through the line of the distribution system. If a DG has not been accurately sited and sized, it may substantially increase system losses and overvoltages at the end of buses.

On the contrary, loads like high rated induction motors, system lines, transformers, and cables are highly inductive. These kinds of loads use VAR as the primary source of power and establish a lagging power factor at the buses which further increases losses and degrades the behaviors of the system. Several DG technologies such as fuel and PV cells can only deliver active power to the systems, while some alternative DG technologies such as wind turbines can operate as a reactive and active power source. Capacitors are simple static devices that can be utilized to provide reactive power support to the system for compensating the lagging VAR. In several studies, it has been established that the shunt capacitors can be utilized to reduce system losses, raise feeder strength and enhance the reliability of the system.

Optimal siting and sizing of DGs are important in enhancing performances of the distribution systems. Several research efforts focused on optimal siting and sizing of DGs to reduce active power losses. Several numerical algorithms [203] and nature-inspired meta-heuristics like GA [204], PSO [205,206], modified PSO (mPSO) [207], modified Ant Colony Optimization and Artificial Bee Colony [208] have been investigated for different types of DGs. While the impact of size and site of the DG has broadly been investigated, a system containing both elements requires more consideration. Naik et al. [209] took an analytical approach to optimally site and size both DG and capacitor. In [210], PSO is adopted with improved results. In most recent studies, heuristic techniques such as Hybrid Harmony Search method and Particle Artificial Bee Colony [211], Intersect Mutation Differential Evolution [212] and Backtracking Search Algorithm [213] have all been used for optimal size and site of both DGs and capacitors. All the above-mentioned methods aim towards minimizeing active losses without properly addressing other system parameters, such as voltage profile, reactive losses, etc.To reduce search space of the method and hence the computational burden, Naik et al. [209] and Muthukumar et al. [211] approached location optimization based on active power loss sensitivity factors of buses. The bus with largest sensitivity of active power loss is preferred as candidate bus for DG placement.

In this chapter, an optimization method, EBOwithCMAR, is proposed and has been applied to minimize the active and reactive power losses with minimal unbalance at the end of the primary transformer in the distribution network. This study utilizes the unbalanced distribution systems such as CASE11, CASE25, and CASE37 for demonstrating the effectiveness of the proposed approach. As an optimization algorithm, EBOwithC-MAR has several advantages over other popular algorithms and it is the winner of IEEE CEC 2017's competition on bound-constrained optimization problems.

6.2 Problem Formulation

The main objective of this study is to determine the appropriate location and size of SPDGs in the power distribution system that will provide minimal power loss with low phase unbalance at the main transformer. Though, the placement of SPDGs and sizing of SPDGs are long term problem which considers reliability, cost and other aspects, these were not in the scope of the thesis.

The active and reactive power losses in the line connecting buses i and j are computed as follows.

$$P_{loss}(i,j) = R_{ij}\frac{P_i^2 + Q_i^2}{|V_i|^2}, \tag{6.1}$$

$$Q_{loss}(i,j) = X_{ij}\frac{P_i^2 + Q_i^2}{|V_i|^2}, \tag{6.2}$$

where P_{loss} and Q_{loss} represent active and reactive power loss. Total power loss of the system can be determined by summing up all the lines losses of the system as follows.

$$\mathbf{P}_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{loss}(i,j), \tag{6.3}$$

and,

$$\mathbf{Q}_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} Q_{loss}(i,j) \tag{6.4}$$

where $\mathbf{P}_{loss}$ and $\mathbf{Q}_{loss}$ represent the total active and reactive power loss, respectively. N is the total number of buses in the network.

Current injection at the root node (bus connected to main transformer) can be calculated using the following equations.

$$I_1^s = \left(\frac{S_1^s}{V_1^s}\right)^* \tag{6.5}$$

where I_1^s is current injection at phase s of root node (bus 1), S_1^s is total power transformed at phase s of main transformer, and $s \in \{a,b,c\}$.

Negative-sequence and zero-sequence current injection at main transformer can be calculated as follows.

$$I_1^- = \frac{I_1^a + \alpha^2 I_1^b + \alpha I_1^c}{3}, \tag{6.6}$$

$$I_1^0 = \frac{I_1^a + I_1^b + I_1^c}{3} \tag{6.7}$$

where, I_1^- and I_1^0 are negative-sequence and zero-sequence current injections at main transformer, respectively and $\alpha = 1\angle 120°$.

In this study, SPDGs with capacitor bank are considered to supply single-phase active and reactive power. When an SPDG is connected to s-th phase of i-th bus for delivering power, S_{dg}, the load in that phase changes from S_i^s to $S_i^s - S_{dg}$. To test proposed formulation, a representative distribution system having SPDGs of fixed size at fixed bus locations was needed. However, to have a system with fixed SPDG sizes (capacities) at specified bus locations, we have developed such systems considering the loss minimization and negative- and zero-sequence current minimization for peak loading conditions of the system. The resulting system with fixed SPDG sizes (capacities) at pre-specified locations is considered to be a representative distribution system of the above problem. For creating a representative distribution system, the optimization algorithm must check all possible locations of SPDGs with a different capacity at peak loading condition for minimum losses with minimal phase unbalance at the root node. Therefore, this optimization problem can be defined as follows.

$$\text{Minimize } f(\mathbf{k}, \mathbf{s}, \mathbf{Pdg}, \mathbf{Qdg}) = w_1 \mathbf{P}_{loss} + w_2 \mathbf{Q}_{loss} + w_3 \sqrt{(I_1^-)^2 + (I_1^0)^2} \tag{6.8}$$

where $\mathbf{k} = \{k_1, k_2 ..., k_n\}$ represents the bus location of SPDGs, $\mathbf{s} = \{s_1, s_2 ..., s_n\}$ represents the phase location of SPDGs. Similarly, $\mathbf{S}_{dg} = \mathbf{P}_{dg} + j\mathbf{Q}_{dg} = \{S_{dg,1}, S_{dg,1} ..., S_{dg,n}\}$ represents the power capacity of SPDGs. Parameters w_1, w_2, and w_3 $(w_1 + w_2 + w_3)$are the weighing factor for different objectives to transform multi-objective optimization problem into single objective optimization problem. This optimization problem is a non-convex, non-linear, and mixed integer bound-constrained optimization problem.

Once the locations and SPDG sizes (capacities) are fixed on a peak loading scenario, then the generation scheduling of SPDG (within the said capacities) and phase switching at the pre-specified buses are determined on hourly basis. For this case, the new optimization problem can be defined as

$$\text{Minimize } f(\mathbf{s}, \mathbf{Pdg}, \mathbf{Qdg}) = w_1 \mathbf{P}_{loss} + w_2 \mathbf{Q}_{loss} + w_3 \sqrt{(I_1^-)^2 + (I_1^0)^2} \tag{6.9}$$

6.3 Proposed Methodology

To solve above-discussed optimization problems, an optimization algorithm, EBOwith-CMAR, is proposed in this section. Objective function of these problems can not be directly calculated as bus voltages of the system are not available for different locations of SPDGs. Therefore, power flow analysis is required for calculating bus voltages to evaluate the objective function. In this work, CINR (proposed in chapter 2) is employed for power flow analysis.

6.3.1 EBOwithCMAR

EBOwithCMAR is an optimization algorithm which incorporates Effective Butterfly Optimizer (EBO) with a powerful local search technique, Covariance Matrix Adapted Retreat Phase (CMAR) to improve local search capability of EBO. Before describing the framework of EBOwithCMAR, main steps of EBO and CMAR are presented in following subsections.

EBO

EBO is a dual population-based global optimization algorithm based on the mate-locating behaviors of male butterflies. Two mate-locating behaviors, *Perching* and *Patrolling*, are used in EBO to update the solutions. In EBO, the following rules are utilized to implement mate-locating behaviors of male butterflies.

1. Male butterflies are attracted to the object with the highest UV radiation/reflection.

2. Male butterflies memorize the best perching position by using different cues of the surrounding.

3. Population size is kept constant during the algorithmic process.

4. Position of all male butterflies is updated using one of the mate-locating behaviour viz. *Perching* and *Patrolling*.

Algorithm begins with randomly initialized solutions that form two populations ($X1 = \{\hat{x}1_1, \hat{x}1_2, ...\hat{x}1_{NP_1}\}$, $X2 = \{\hat{x}2_1, \hat{x}2_2, ...\hat{x}2_{NP_2}\}$), where NP_1 and NP_2 are the sizes of the population of the primary and secondary population, respectively. A new set of updated solutions, $Y = \{\hat{y}_1, \hat{y}_2, ...\hat{y}_{NP_1}\}$, is calculated using "towards-best" or "criss-cross" modification operators.

Modification Operators:

In the case of criss-cross modification operator, $\hat{y}_i$ is calculated using the following equation.

$$\hat{y}_i = \hat{x}1_{cc_i} + F * (\hat{x}1_{r1_i} - (X1 \cup X2)_{r2_i}), \tag{6.10}$$

and in case of towards-best modification operator, $\hat{y}_i$ is calculated using the following equation.

$$\hat{y}_i = \hat{x}1_{best_i} + F * (\hat{x}1_{cc_i} - (X1 \cup X2)_{r2_i}), \tag{6.11}$$

where ($\hat{x}1_{cc_i}$, $\hat{x}1_{r1_i}$, and $(X1 \cup X2)_{r2_i}$) are distinct from each other and $r1_i$ and $r2_i$ are randomly chosen index from 1 to NP_1 and 1 to $(NP_1 + NP_2)$, respectively. $\hat{x}1_{best_i}$ represents a best-neighbor of individual i and F is a parameter used to control the evolving rate of solutions. $X1 \cup X2$ represents the combination of both the populations of solutions.

Here, $\hat{x}1_{cc_i}$ is a criss-cross neighbor of the i^{th} solution and cc_i is calculated using Equation 6.12.

$$\{cc_1, cc_2, ...cc_{NP_1}\} = randp(1, NP_1) \tag{6.12}$$

where $randp(1, NP_1)$ is a random permutation of integers between 1 and NP_1. To update each solution, the selection of modification operator is decided using probabilities, P_{perch} and P_{pat}.

Hanging Binomial Crossover:

Hanging Binomial Crossover is a modified version of Binomial Crossover. Crossover rate of each elements j, cr_j, is calculated using equations (6.13) and (6.14).

$$n_j = Rem(D + j - j_{rand}, \frac{D}{2}) \tag{6.13}$$

where D is the total number of decision variable of the problem and $Rem(x, y)$ is a remainder function operator which produces the remainder to the division of x and y. Parameter j_{rand} is randomly selected index from 1 to D.

$$cr_j = CR * e^{-\frac{t}{D} * n_j} \tag{6.14}$$

where t represents a parameter within the range of $[0, 0.5]$. If $t = 0$, then this crossover method is reduced to binomial crossover.

Selection:

Selection of solutions in both the populations for the next iteration is done by the following equations.

$$\hat{x}1_i^{k+1} = \begin{cases} \hat{y}1_i^k, & \text{if } f(\hat{x}1_i^k) > f(\hat{y}1_i^k) \\ \hat{x}1_i^k, & \text{otherwise} \end{cases}, \tag{6.15}$$

and

$$\hat{x}2_i^{k+1} = \begin{cases} \hat{x}1_i^k, & \text{if } f(\hat{x}1_i^k) > f(\hat{y}1_i^k) \\ \hat{x}2_i^k, & \text{otherwise} \end{cases}, \tag{6.16}$$

where, $f(\hat{x}1_i)$ represents the objective function value of solution $\hat{x}1_i$. Note that the objective function value of solution $\hat{x}2_i^{k+1}$ is not evaluated because the objective function value of solution $\hat{x}2_i^{k+1}$ is not utilized in optimization steps of EBO. Step-by-step procedure of EBO is shown in Algorithm-6.

CMAR

CMAR is population based iterative optimization techniques which sample new solutions from probabilistic models. For generating a new sample of the solution, it is essential to calculate the mean and the covariance matrix of the distribution of the probabilistic model. The parameter adaptation procedure of CMAR is adopted from [214]. A brief description of the main steps used to generate new samples is as follows.

1. *Probabilistic Model*: Two probabilistic models are used in CMAR to sample the new solution with a probability of 0.5. The distribution of these two models are individually controlled by its mean m and covariance matrix C. The distribution of these models can be described using the following ways.

$$M1(m, C) \sim m + C^{\frac{1}{2}}.M1(0, I), \tag{6.17}$$

$$M2(m, C) \sim m + C^{\frac{1}{2}}.M2(0, I), \tag{6.18}$$

   where $M1$ and $M2$ represent the distribution of probabilistic models, I is an identity matrix, and m and C represent the mean and covariance matrix of the distribution, respectively.

Algorithm 6: Effective Butterfly Optimizer

Initialization;
Fitness evaluation;
while *stopping criteria is not met.* **do**
    /*Modification Operator*/;
    $\{cc_1, cc_2, ..., cc_{NP_1}\} \leftarrow randp(1, NP_1)$;
    for $i = 1$ *to* NP_1 **do**
        $r2_i \leftarrow$ randomly selected solution from $X1 \cup X2$;
        if $rand < P_{perch}$ **then**
            /*Generate $\hat{y}_i$ using criss-cross modification operator8/;
            $r1_i \leftarrow$ randomly selected solution from $X1$;
            $\hat{y}_i \leftarrow \hat{x}1_{cc_i} + F(\hat{x}1_{r1_i} - (X1 \cup X2)_{r2_i})$;
        else
            /*Generate $\hat{y}_i$ using towards-best modification operator*/;
            $\hat{y}_i \leftarrow \hat{x}1_{best_i} + F * (\hat{x}1_{cc_i} - (X1 \cup X2)_{r2_i})$;
        end
    end
    /*Hanging Binomial Crossover*/;
    for $i = 1$ *to* NP_1 **do**
        /*crossover between $\hat{y}_i$ and $\hat{x}1_i$*/;
        $j_{rand} \leftarrow$ randomly selected index from 1 to D;
        for $j = 1$ *to* D **do**
            $n_j \leftarrow Rem(D + j - j_{rand}), \frac{D}{2}$;
            $cr_j \leftarrow CR \times e^{-\frac{t}{D} n_j}$;
            $rand \leftarrow$ randomly generated number from uniform distribution;
            if $(rand \geq cr_j)||(j \ = j_{rand})$ **then**
                $y_{i,j} \leftarrow x1_{i,j}$;
            end
        end
    end
    Evaluate fitness value on newly updated positions;
    /* Selection*/;
    for $i = 1$ *to* NP_1 **do**
        if $f(\hat{x1}_i^k) > f(\hat{y1}_i^k)$ **then**
            $\hat{x1}_i^{k+1} \leftarrow \hat{y1}_i^k$;
            $\hat{x2}_i^{k+1} \leftarrow \hat{x1}_i^k$;
        end
    end
    $k \leftarrow k + 1$;
end
Result: Best Solution having lowest objective function

2. *Sampling*: The i-th new sample of a solution is generated at k-th iteration by using

following equation.

$$x_i^{(k+1)} \sim \begin{cases} m^{(k)} + \sigma^{(k)} C^{\frac{1}{2}(k)} M1(0, I), & \text{if rand} \leq 0.5 \\ m^{(k)} + \sigma^{(k)} C^{\frac{1}{2}(k)} M2(0, I), & \text{otherwise} \end{cases} \tag{6.19}$$

where, σ is the step-size value and rand is the random number generated from uniform distribution within the range $(0, 1)$.

3. *Mean Calculation*: The mean, m, for the next iteration is calculated using a weighted average of half of the best solutions from the current N samples, $\{x_1, x_2, ..., x_N\}$, as shown in Equation 6.20.

$$m^{(k+1)} = \sum_{i=1}^{\frac{N}{2}} w_i x_{i:N}^{(k)}, \tag{6.20}$$

where $x_{i:N}$ represents the i-th best solution of N samples of solutions. Here, $\sum_{i=1}^{\frac{N}{2}} w_i = 1$ and w_i is calculated by following equation.

$$w_i = \frac{ln(\frac{N}{2} + 1) - ln(i)}{\sum_{j=1}^{\frac{N}{2}} ln(\frac{N}{2} + 1) - ln(j)}, \tag{6.21}$$

where $f(*)$ represents the objective function value at $*$ solution.

4. *Calculation of square root of covariance matrix*: In CMAR, square root of the covariance matrix is adapted in each iteration by using the evolution path, $P_c^{(k)}$, and random numbers, $z_i^{(k)} (= M1(0, I)$ or $M2(0, I))$, used to genrate samples at k-th iteration.

$$P_c^{(k)} = (1 - c_c) P_c^{(k-1)} + hs^{(k)} \sqrt{c_c(2 - c_c)\mu_{eff}}.z_m^{(k)}, \tag{6.22}$$

$$C^{\frac{1}{2}(k+1)} = (1 - c_{cov} - c_1(1 - (1 - hs^{(k)})c_c(2 - c_c)))C^{\frac{1}{2}(k)} \tag{6.23}$$

$$c_1 C^{\frac{1}{2}(k)} \left(P_c^{(k)} (P_c^{(k)})^T\right) + c_{cov} C^{\frac{1}{2}(k)} \sum_{i=1}^{\frac{N}{2}} w_i z_{i:N}^{(k)} \left(z_{i:N}^{(k)}\right)^T, \tag{6.24}$$

where,

$$z_m^{(k)} = \sum_{i=1}^{\frac{N}{2}} w_i z_{i:N}^{(k)}. \tag{6.25}$$

The control parameters N, c_c, c_1, c_{cov}, and μ_{eff} are set by using following equations.

$$N = 4 + \lfloor 3ln(D) \rfloor, \tag{6.26}$$

$$\mu_{eff} = \frac{(\sum_{i=1}^{\frac{N}{2}} w_i)^2}{\sum_{i=1}^{\frac{N}{2}} w_i^2}, \tag{6.27}$$

$$c_c = \frac{4D + \mu_{eff}}{D^2 + 4D + 2\mu_{eff}}, \tag{6.28}$$

$$c_1 = \frac{1}{(D+1.3)^2 + \mu_{eff}}, \tag{6.29}$$

$$c_{cov} = \min\left(0.5 - c_1, \frac{\mu_{eff}^2 - 2\mu_{eff} + 1}{\mu_{eff}^2 + \mu_{eff}(D+2)^2}\right). \tag{6.30}$$

5. *Step-size adaptation*: The adaptation of step-size are done by using following equation.

$$P_s^{(k+1)} = (1 - c_s)P_s^{(k)} + \sqrt{c_s(2 - c_s)\mu_{eff}}.z_m^{(k)}, \tag{6.31}$$

$$\sigma^{(k+1)} = \sigma^{(k)}.exp\left(\frac{c_s}{d_s}\left(\frac{||P_s^{(k+1)}||}{E_x} - 1\right)\right) \tag{6.32}$$

where, c_s, d_s, and E_x are the control parameters. These parameters can be calculated by using following equations.

$$c_s = \frac{\mu_{eff} + 2}{\mu_{eff} + D + 5}, \tag{6.33}$$

$$d_s = 1 + 2.max\left(0, \sqrt{\frac{\mu_{eff} - 1}{D+1}} - 1\right) + c_s, \tag{6.34}$$

$$E_x = \sqrt{D}\left(1 - \frac{1}{4D} + \frac{1}{21D^2}\right) \tag{6.35}$$

The parameter hs used in Equation 6.22 is updated in each iteration by using following equation.

$$hs^{(k+1)} = \begin{cases} 1, & \text{if } \frac{||P_s||^2 D}{(1-(1-c_s)^{2(k+1)})} < 2 + \frac{4}{D+1}, \\ 0, & \text{otherwise} \end{cases} \tag{6.36}$$

In the following sections, the framework of EBOwithCMAR is discussed.

Framework of EBOwithCMAR

In EBOwithCMAR, an initial population of size N is randomly generated from the uniform distribution within the bound of solution-space. This population is split into three different populations, X_1, X_2, and X_3 of sizes, N_1, N_2, and N_3, respectively, where the first two populations are used in EBO and the last population is used in CMAR. Algorithms EBO and CMAR are utilized to update the solutions with probabilities $prob_{EBO}$ and $prob_{CMAR}$, respectively, at a particular iteration. A cycle, cy, of a fixed number of iteration is initialized at the beginning of the optimization process where both of the algorithms are utilized parallelly ($prob_{EBO}$ and $prob_{CMAR}$ are set to 1) for the half of the cycle. At the end of the half cycle, the new values of $prob_{EBO}$ and $prob_{CMAR}$ are updated for the next half of the cycle. The new value of probabilities $prob_{EBO}$ and $prob_{CMAR}$ depends upon the following criteria.

1. Based on the superiority of the best solution obtained using EBO and CMAR, and

2. Based on the diversity of solutions of the populations, X_1 and X_3.

A data sharing between the populations X_1 and X_3 are done at the last of each cycle. Whenever EBOwithCMAR will enter into the next cycle, and similar steps are replicated. To improve the local search potential of EBOwithCMAR, sequential quadratic programming is utilized at the later phases of the optimization process (75% of the optimization process is completed) with a probability of $prob_{ls}$. In case of failure of the SQP algorithm, probability $prob_{ls}$ is reduced to a very small value.

In EBOwithCMAR, some components of EBO are modified. The modified components of EBO are described in the following sections.

Modified component of EBO:

A brief description of the main steps of EBO is discussed earlier. In EBOwithCMAR, modification operators are modified to improve the diversity of the populations X_1 and X_2, and a self-adaptive approach is utilized for the different parameters of EBO.

1. *Modified modification operators*: A modified criss-cross and towards-best modification operators used in EBOwithCMAR are shown in Equation (6.37) and Equation (6.38), respectively.

$$\hat{y}_{i,j} = \begin{cases} \hat{x}1_{i,j} + F_i(\hat{x}1_{cc_i,j} - \hat{x}1_{i,j} + \hat{x}1_{r1_i,j} - (X_1 \cup X_2)_{r2_i,j}), \\ \text{if } (rand_j(0,1) \leq cr_{i,j} \text{ or } j = j_{rand}) \\ \hat{x}1_{i,j}, \\ \text{otherwise.} \end{cases} \tag{6.37}$$

$$\hat{y}_{i,j} = \begin{cases} \hat{x}1_{i,j} + F_i(\hat{x}1_{best_i,j} - \hat{x}1_{i,j} + \hat{x}1_{cc_i,j} - (X_1 \cup X_2)_{r2_i,j}), \\ \text{if } (rand_j(0,1) \leq cr_{i,j} \text{ or } j = j_{rand}) \\ x1_{i,j}, \\ \text{otherwise.} \end{cases} \tag{6.38}$$

where ($cc_i, r1_i,$ and $r2_i$) are distinct integers.

2. *Selection of $best_i$*: The $best_i$ is the best solution among the randomly selected D solutions from population X_1. When the size of the population X_1 is less than the $2D$, $best_i$ is randomly selected from the 10% of best solutions.

3. *Calculation of P_{perch} and P_{pat}*: The probabilities P_{perch} and P_{pat} are initially set to 0.5. The improvement rate of objective function values is utilized to modify the value of these probabilities. The improvement rate is estimated using the following equation.

$$I_i^{(k+1)} = \frac{\sum_{z \in S_i}^{PS_1} max(0, f_z^{(k+1)} - f_z^{(k)})}{\sum_{z \in S_i}^{PS_1} f_z^{(k)}}$$

$$\text{where } S_i \text{ is a set of solutions updated by } \begin{cases} perching, & \text{if } i = 1 \\ patrolling, & \text{if } i = 2. \end{cases} \tag{6.39}$$

Now, P_{perch} and P_{pat} are modified using following equation.

$$P_{perch} = max\left(0.1, min\left(0.9, \frac{I_1}{I_1 + I_2}\right)\right), \tag{6.40}$$

$$P_{pat} = 1 - P_{perch} \tag{6.41}$$

4. *Linear Reduction of Size of N_1 and N_2*: Reduction in the size of populations X_1 and X_2 at the end of each iteration is done by using a linear reduction mechanism proposed in [215]. In this approach, the size of X_1 is reduced by eliminating the worst solutions, while the size of X_2 is reduced by eliminating random solutions from the population. The reduced sizes of populations are calculated using the following equations.

$$N_1^{(k+1)} = round\left(\left(\frac{N_{1,min} - N_{1,max}}{FE_{max}}\right) * FEs\right) + N_{1,max} \tag{6.42}$$

$$N_2^{(k+1)} = round\left(\left(\frac{N_{2,min} - N_{2,max}}{FE_{max}}\right) * FEs\right) + N_{2,max} \quad (6.43)$$

where $(N_{1,max}, N_{2,max})$ and $(N_{1,min}, N_{2,min})$ are the maximum and minimum values allowed for N_1 and N_2 respectively. FE_{max} and FEs represent the maximum allowed function evaluation and current function evaluation, respectively.

5. *Adaptation of F, $freq$, CR and T*: In EBOwithCMAR, a parameter adaptation technique is utilized to auto-tune the parameters F, $freq$, CR, and T at each iteration. The following steps are performed to adapt the parameters.

   - A matrix of size $(4 \times H)$, M, is initialized at their default values. The default value of parameters F, CR, $freq$, and T are 0.7, 0.5, 0.5, and 0.1, respectively.
   - The new value of parameters CR_i, F_i, $freq_i$, and T_i associated with solution $\hat{x}1_i$ is calculated by following equations.

$$CR_i = M2(M_{3,r}, 0.1), \quad (6.44)$$

$$freq_i = randci(M_{2,r}, 0.1), \quad (6.45)$$

$$F_i = \begin{cases} \frac{1}{2}\left(\tan(\pi(FEs+1))\frac{FE_{max}-FE}{FE_{max}} + 1\right), & \text{if } FEs \le FE_{max} \;\&\; rand \le 0.5 \\ \frac{1}{2}\left(\tan(2\pi freq_i * FEs)\frac{FEs}{FE_{max}} + 1\right), & \text{if } FEs \le FE_{max} \;\&\; rand > 0.5 \\ randci(M_{1,r}, 0.1), & \text{otherwise} \end{cases}, \quad (6.46)$$

$$T_i = M2(M_{4,r}, 0.05), \quad (6.47)$$

   where r represents a integer from $[1, H]$, and $randci$ provides the random number from cauchy distribution.

   - The value of $M_{i,d}$ is updated by using the following equation at the end of each iteration.

$$M_{i,d} = \frac{\sum_{\gamma=1}^{4} w_\gamma S_{i,\gamma}^2}{\sum_{\gamma=1}^{4} w_\gamma S_{i,\gamma}}, \quad (6.48)$$

   where, $S_{i,1:\gamma} = (F_i, CR_i, freq_i, T_i)$ and $1 < d < H$ is the index of the memory to be updated. It is initialized to 1, and then increased by 1 whenever an index of memory is updated and if it is greater than H, it is reset to 1. w_γ is calculated by using following equation.

$$w_\gamma^{(k+1)} = \frac{\triangle f_\gamma^{(k+1)}}{\sum_{i=1}^{N_1} \triangle f_\gamma^{(k+1)}} \quad (6.49)$$

and $\triangle f_\gamma = |f_\gamma^{(k)} - f_\gamma^{(k+1)}|$.

- *CMAR*: CMAR starts with a randomly generated initial population of size N_3 ($X_3 = \{x_1, x_2 ... x_{N_3}\}$ from uniform distribution within the solution-space. Initial mean, $m^{(0)}$, is calculated by the arithmetic mean of X_3.

Update of $prob_{EBO}$ ***and*** $prob_{CMAR}$***:***

Two factors are considered to update the probabilities $prob_{EBO}$ and $prob_{CMAR}$. They are the diversity of the population and quality of solutions.

Two quality values, $\hat{Q}_{EBO}$ and $\hat{Q}_{CMAR}$, are calculated at the end of half of cycle by using the following equation.

$$\hat{Q}_i = \frac{f_{best,i}^{\frac{CS}{2}}}{f_{best,EBO}^{\frac{CS}{2}} + f_{best,CMAR}^{\frac{CS}{2}}} \; \forall\, i \in \{EBO, CMAR\}, \tag{6.50}$$

where $f_{best,i}^{\frac{CS}{2}}$ is the best objective function value at the end of half of cycle, $\frac{CS}{2}$ by i-th algorithm.

At the same time, the diversity of the populations X_1 and X_3 are calculated using the following equation.

$$\hat{div}_i = \frac{div_i}{div_{X_1} + div_{X_3}} \; \forall\, i \in \{EBO, CMAR\}, \tag{6.51}$$

where div_i is the diversity rate of population with respect to best solution at the end of half of cycle, $\frac{CS}{2}$ by i-th algorithm.

A progress index, PI_i is calculated by using equation (6.52).

$$PI_i = (1 - \hat{Q}_i) + \hat{div}_i, \; \forall\, i \in \{EBO, CMAR\} \tag{6.52}$$

Now, the probability, $prob_i$ is calculated as shown in equation (6.53).

$$prob_i = max\left(0.1, min\left(0.9, \frac{PI_i}{PI_{EBO} + PI_{CMAR}}\right)\right), \; \forall\, i \in \{EBO, CMAR\} \tag{6.53}$$

If the sum of PI is equal to zero, $prob_{EBO}$ and $prob_{CMAR}$ are set to 1.

Data Sharing:

At the end of every cycle, CS, algorithm having a greater value of probability is considered to be best algorithm of that cycle. If EBO is considered as the best, then population X_3 is replaced by the random solution of population X_1. Parameters of CMAR is also

Algorithm 7: EBOwithCMAR

Define $N \leftarrow N_1 + N_2 + N_3$, $cy \leftarrow 0$, $prob_{EBO} = prob_{CMAR} \leftarrow 1$ and all other parameters required;
for $i = 1$ *to* N **do**
    $X_i \leftarrow$ uniformly distributed D random numbers within the bounds of search-space;
end
Randomly assign N_1, N_2, and N_3 individuals from X to $X_i, \forall i = 1, 2, 3$;
while *termination condition is not satisfied* **do**
    $cy \leftarrow cy + 1$;
    if $cy == \frac{CS}{2}$ **then**
        Calculate $prob_{EBO}$ and $prob_{CMAR}$ using Equation (6.53);
    end
    if $cy == CS$ **then**
        Share Data;
        $prob_{EBO} = 1$, and $prob_{CMAR} = 1$;
        $cy \leftarrow 0$;
    end
    if $rand \leq prob_1$ **then**
        Apply EBO;
        $FEs \leftarrow FEs + N_1$;
    end
    if $rand \leq prob_2$ **then**
        Apply CMAR;
        $FEs \leftarrow FEs + N_3$;
    end
    if $rand \leq prob_{ls}$ & $FEs \geq 0.75 * FE_{max}$ **then**
        Apply SEQ;
        $FEs \leftarrow FEs + FE_{seq}$;
        if *best solution is improved* **then**
            $prob_{ls} \leftarrow 0.1$;
            update X_1 and X_2;
        else
            $prob_{ls} \leftarrow 0.0001$;
        end
    end
    $k \leftarrow k + 1$;
end
Result: Best Solution having lowest objective function

reinitialized at default value except the step size, σ, where σ is calculated as $\sigma = \sigma_{initial} * (1 - cFE/FE_{max})$.

On the other hand, if CMAR emerges as the best, the worst individual in X_1 is replaced by the best individual in X_3. After data sharing, new cycle is again started and process repeated. The step-by-step procedure of EBOwithCMAR is shown in Algorithm-7. The performance of EBOwithCMAR in comparison of state-of-the-art algorithms are reported in the Appendix.

6.3.2 Evaluation of Objective Function

In any optimization algorithm, objective function for each generated solution needs to be evaluated for improving the solutions. The objective function of the optimization problem discussed in the section 6.2 cannot be evaluated directly. Power flow analysis is needed to obtain the steady-state voltage at each bus of the system because these voltages are used to calculate the objective function defined in Equation 7.5.

CINR algorithm is employed to calculate the steady-state voltage at each bus for every solution of the optimization problem. Each solution contains the location (bus and phase) and power capacity of SPDG. First of all, loads of the system are updated according to the solution (location and capacity of SPDGs). Loads are modified by using following equations.

$$P_{L,i}^{t} = \begin{cases} P_{L,i}^{t} - P_{dg,j}, & \text{if } i == k_j \ \& \ t == s_j \\ P_{L,i}^{t}, & \text{else} \end{cases} \tag{6.54}$$

and,

$$Q_{L,i}^{t} = \begin{cases} Q_{L,i}^{t} - Q_{dg,j}, & \text{if } i == k_j \ \& \ t == s_j \\ Q_{L,i}^{t}, & \text{else} \end{cases} \tag{6.55}$$

where $P_{L,i}^{t}$ and $Q_{L,i}^{t}$ represent the active and reactive load at t-th phase of i-th bus. $\{K_j, s_j, P_{dg,j}, Q_{dg,j}\}$ represents the bus-location, phase-location, active power capacity, and reactive power capacity of j-th SPDG.

After modifying the loads, power flow analysis is performed on this loading condition using CINR to calculate the voltage at each bus. Further these voltages are used to calculate the objective function values.

6.3.3 Proposed Algorithm

The above-discussed optimization problem considers location (in terms of phase and bus) and size (in terms of active and reactive power) of SPDGs as the problem variables. Each solution vector has $4 * M$ elements where M is the total number of SPDGs used in the systems.

The purpose of this problem is to find the optimum location and rating for all the SPDGs so that the objective function is minimized. It is worth mentioning here that the solution variables related to location must be an integer value. Therefore, during the calculation of objective function value, these variables are rounded off to its adjacent integer value.

The following steps are utilized to solve the optimization problem.

1. **Step 1:** Initialization of population of N_p solutions is done as uniformly distributed random points within the bound of each variables.

2. **Step 2:** Power flow Analysis is performed using each solution of current population.

3. **Step 3:** Objective function is evaluated using each solution of current population

4. **Step 4:** Solutions of population are updated using EBOwithCMAR

5. **Step 5:** Check the stopping criteria. If stopping criteria is met, go to **Step 6**, otherwise go to **Step 2**

6. **Step 6:** Best solution on the basis of minimum objective function value is extracted from population to locate and schedule the SPDGs within the system.

6.4 Results and Discussion

In this section, the performance of the proposed approach, as well as comparative analysis are discussed.

In this analysis, three test systems, CASE13, CASE25, and CASE37, are considered. The details of these systems are reported in the Appendix I. Details of the experimental setup are given in Table 6.1. The performance of proposed algorithm has been compared with state-of-the-art algorithms reported in literature. The algorithms chosen for comparative analysis are IMDE [212], Analytical Approach (AA) [209], PSO [210], BSA [213], and IPSO [216].

Four scenario are studied in this work. In first case, only phase-balancing is done i.e. negative-sequence and zero-sequence currents are minimized at root node. In second scenario, minimization of active power loss is considered as objective function. Similarly, reactive power loss is considered as objective function in third scenario. In last scenario,

Table 6.1: The detail of experimental setup

S.N.	Test System	Number of SPDGs	P_{max}	Q_{max}
1.	CASE13	3	2 p.u.	2 p.u.
2.	CASE25	5	2 p.u.	2 p.u.
3.	CASE37	7	2 p.u.	2 p.u.

the weighted objective function with equal weighing factor is considered to minimize all the objective function simultaneously.

6.4.1 Parameter Settings

For EBO, $N_{1,max} = 18D$, $N_{1,min} = 4$,$N_{2,max} = 46.8D$, $N_{2,min} = 10$ $H = 6$. For CMAR, $N_3 = 4 + (3log(D))$ [214], and $\sigma = 0.3$. $CS = 100$. For local search, $prob_{ls} = 0.1$ and $FE_{ls} = 0.25 * FE_{max}$ function evaluations. Here, $D = 4 * M$.

6.4.2 Case Studies

The proposed algorithm with other state-of-the-art algorithms has been run for all the test cases.

CASE13

The best site and size of SPDGs obtained after 100 independent runs using all algorithms are recorded for the weighted objective function. The parameters (negative-sequence current, zero-sequence current, active loss and reactive loss) at the optimal solution obtained from all algorithms are reported in Table 6.2. This table shows that the optimal solutions obtained from all algorithms are different from each other. The proposed algorithm provides better solutions as compared to solutions obtained from other competitive algorithms. From this analysis, it can be concluded that the proposed approach is a better option to solve the optimization problem in case of CASE13.

Further, proposed algorithm is utilized for analyzing the system for all the objective function cases. The optimal size and site of SPDGs for different objective functions (scenarios) are depicted in Table 6.3. From table 6.3, the site of SPDGs for scenario-2,

Table 6.2: Simulation results for CASE13 test system.

Index	EBOwithCMAR	IMDE	AA	PSO	BSA	IPSO
I_1^0	**2.08E-09**	6.72E-06	8.24E-06	7.45E-05	8.25E-06	1.87E-08
I_1^-	**9.23E-10**	2.41E-05	4.21E-05	1.06E-05	5.87E-05	6.83E-09
$\mathbf{P}_{loss}$	7.23E-02	6.23E-02	**5.34E-02**	1.07E-01	8.43E-02	7.54E-02
$\mathbf{Q}_{loss}$	1.51E-01	1.48E-01	**1.45E-01**	1.83E-01	1.73E-01	1.76E-01

scenario-3 and scenario-4 are same, while the size of SPDGs are different to minimize objective functions of these scenarios.

Table 6.3: Results for CASE13 for scenario-4

scenario-1	location	2-b	7-a	10-c
	P_{dg}	3.24E-01	4.73E-01	5.48E-01
	Q_{dg}	2.26E-01	2.04E-01	2.93E-01
scenario-2	location	7-c	8-a	9-b
	P_{dg}	1.02E+00	7.68E-01	3.24E-01
	Q_{dg}	4.28E-01	2.03E-01	3.13E-02
scenario-3	location	7-c	8-a	9-b
	P_{dg}	1.02E+00	9.11E-01	3.16E-01
	Q_{dg}	4.03E-01	3.37E-01	7.40E-02
scenario-4	location	7-c	8-a	9-b
	P_{dg}	7.06E-01	5.83E-01	4.75E-01
	Q_{dg}	1.18E-01	1.00E-02	4.33E-02

Table 6.4: Value of main parameters of system for different cases of CASE13

Index	scenario-1	scenario-2	scenario-3	scenario-4
I_1^0	4.72E-12	8.77E-02	8.87E-02	2.08E-09
I_1^-	2.05E-12	9.17E-02	1.52E-01	9.23E-10
$\mathbf{P}_{loss}$	1.04E-01	4.70E-02	5.04E-02	7.23E-02
$\mathbf{Q}_{loss}$	2.10E-01	6.10E-02	5.40E-02	1.51E-01

CASE25

From 100 independent runs, the best size and site of SPDGs are selected for comparative analysis on CASE25. The parameters of CASE25 at the optimal solution are reported in Table 6.5 for all algorithms. This table shows that the proposed algorithm performs better than other algorithms for this test system. These outcomes conclude that the proposed algorithm provides a better option for solving this optimization problem in this test system.

Table 6.5: Simulation results for CASE25 test system for scenario-4

Index	EBOwithCMAR	IMDE	AA	PSO	BSA	IPSO
I_1^0	**2.65E-11**	1.32E-06	3.56E-06	2.93E-05	2.85E-06	5.85E-06
I_1^-	**2.69E-11**	4.23E-05	3.83E-05	3.08E-05	9.75E-05	4.86E-06
$\mathbf{P}_{loss}$	**2.93E-01**	3.01E-01	3.28E-01	3.18E-01	3.87E-01	2.98E-01
$\mathbf{Q}_{loss}$	**3.35E-01**	3.37E-01	3.85E-01	4.01E-01	4.01E-01	3.38E-01

In addition, EBOwithCMAR is employed to further analyze the CASE25 for different scenarios having different objective function. The experimental outcomes are depicted in Table 6.6. From this table, the site and size of SPDGs are different from each other to minimize all objective functions. Negative-sequence current and zero-sequence current at root node with active and reactive power loss are also reported in Table 6.7 at the optimal solution of all cases of the objective function.

CASE37

The performance of the proposed algorithm is also analyzed on CASE37. Similarly to CASE13 and CASE25, the best solution from 100 independent runs is selected for analysis. Negative-sequence and zero-sequence with active and reactive power loss are reported in Table 6.8 for all solutions obtained by all algorithms. As shown in Table 6.8, the performance of EBOwithCMAR is superior to other algorithms. Therefore, for further analysis only the proposed algorithm is utilized for all objective functions (scenarios).

The optimal site and size of SPDGs for all case of the objective function are reported in Table 6.9. From this table, it can be seen that the location and size of SPDGs are different in all cases. Obtained active and reactive loss with zero-sequence and negative-

Table 6.6: Obtained results for CASE25

scenario-1	location	4-a	5-c	12-c	16-a	17a
	P_{dg}	1.32E+00	1.15E+00	9.02E-01	1.36E+00	1.06E+00
	Q_{dg}	5.65E-01	6.68E-01	5.76E-01	1.03E+00	1.03E+00
scenario-2	location	9-b	10-c	11-a	14-a	15-a
	P_{dg}	2.00E+00	2.00E+00	2.00E+00	2.00E+00	1.26E+00
	Q_{dg}	2.00E+00	2.00E+00	1.63E+00	1.76E+00	4.36E-02
scenario-3	location	11-a	13-b	14-c	23-a	25-c
	P_{dg}	2.00E+00	1.99E+00	2.00E+00	2.00E+00	2.00E+00
	Q_{dg}	2.00E+00	1.90E+00	2.00E+00	2.00E+00	1.12E+00
scenario-4	location	5-c	8-a	10-b	11-c	13-a
	P_{dg}	3.02E-01	2.00E+00	2.45E-01	2.00E+00	2.00E+00
	Q_{dg}	1.15E+00	2.00E+00	1.78E+00	1.86E+00	2.00E+00

Table 6.7: Value of main parameters of system for different cases of CASE25

Index	scenario-1	scenario-2	scenario-3	scenario-4
I_1^0	1.23E-20	9.63E-01	9.30E-01	2.65E-11
I_1^-	9.98E-21	2.06E+00	8.57E-01	2.69E-11
$\mathbf{P}_{loss}$	4.00E-01	2.29E-01	2.48E-01	2.93E-01
$\mathbf{Q}_{loss}$	4.37E-01	2.82E-01	2.68E-01	3.35E-01

sequence current at root node are also shown in Table 6.8 for all cases of the objective function.

6.4.3 24-hour loading scenario

In this loading scenario the optimal SPDG locations obtained in case studies of CASE25 have been fixed. Using these sites for SPDGs along with reactive supports, the optimization for 24-hour load scenarios for objective function stated in equation 6.9 has been considered.

For each of the 24-hour loading scenario the optimal phase and sizes of the SPDGs have been obtained using EBOwithCMAR algorithm. In the following paragraphs the re-

Table 6.8: Simulation results for CASE37 test system of scenario-4

Index	EBOwithCMAR	IMDE	AA	PSO	BSA	IPSO
I_1^0	3.20E-12	6.87E-06	5.90E-06	4.88E-07	3.95E-07	3.94E-06
I_1^-	1.82E-12	4.56E-05	8.36E-05	3.87E-06	2.95E-06	4.69E-06
$\mathbf{P}_{loss}$	8.98E-02	1.05E-01	9.87E-02	1.15E-01	1.13E-01	1.04E-01
$\mathbf{Q}_{loss}$	4.89E-02	8.48E-02	7.84E-02	1.09E-01	1.14E-01	9.25E-02

Table 6.9: Obtained results for CASE37

scenario-1	Location	30-c	31-a	31-b	31-c	32-a	32-b	33-a
	P_{dg}	1.81E-01	5.06E-02	3.91E-02	1.19E-01	5.36E-02	3.73E-02	5.39E-02
	Q_{dg}	1.03E-01	4.61E-02	5.07E-02	1.07E-01	4.67E-02	4.76E-02	4.67E-02
scenario-2	Location	26-a	28-c	30-a	31-a	34-b	35-a	35-c
	P_{dg}	6.38E-02	2.55E-01	1.37E-01	1.22E-01	1.52E-01	1.27E-01	2.19E-01
	Q_{dg}	5.48E-02	9.99E-02	9.35E-02	1.00E-02	9.87E-02	1.18E-01	7.55E-02
scenario-3	Location	5-b	8-a	10-c	12-c	24-c	25-a	34-b
	P_{dg}	2.53E-01	4.49E-01	2.40E-01	1.94E-01	1.70E-01	1.00E-02	8.48E-02
	Q_{dg}	1.02E-01	2.41E-01	1.29E-01	1.38E-01	3.71E-02	1.00E-02	3.66E-02
scenario-4	Location	8-c	12-c	21-a	22-a	25-c	34-b	35-a
	P_{dg}	2.99E-01	1.40E-01	3.01E-02	4.20E-02	4.20E-02	2.55E-01	2.88E-01
	Q_{dg}	1.81E-01	4.88E-02	1.68E-02	2.10E-02	2.10E-02	1.44E-01	1.61E-01

Table 6.10: Value of main parameters of system for different cases of CASE37

Index	case-1	case-2	case-3	case-4
I_1^0	3.94E-22	9.82E-03	1.62E-03	3.20E-12
I_1^-	6.26E-23	3.23E-02	2.00E-03	1.82E-12
$\mathbf{P}_{loss}$	6.96E-02	4.67E-02	6.28E-02	8.98E-02
$\mathbf{Q}_{loss}$	4.39E-02	2.51E-02	3.08E-02	4.89E-02

sults obtained in terms of sequence and phase currents, voltages, losses (real and reactive), and phase utilization index are discussed.

Sequence Currents: The hourly negative- and zero-sequence currents for 24-hours without SPDG and with SPDG are shown in Fig. 6.1. It is observed from the figure that, without SPDG the amount of negative- and zero-sequence currents lie in the range 0.66 pu to 1.90 pu and with DG the negative- and zero-sequence currents are found to be almost negligible.

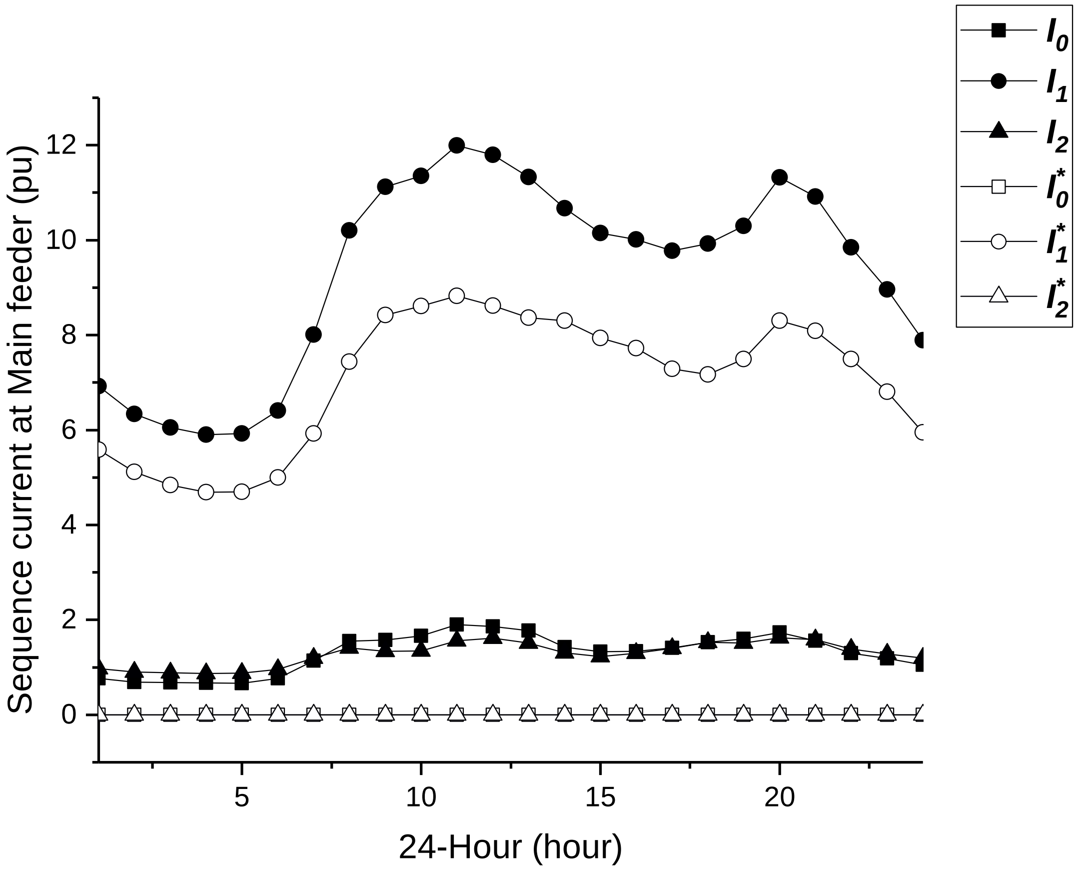

Figure 6.1: Hourly positive-, zero-, negative-sequence currents without and with SPDGs. I_0, I_1, and I_2 indicate sequence currents for the case when SPDGs are not placed. I_0^*, I_1^*, and I_2^* indicate sequence currents for the case when SPDGs are placed.

Phase currents: The effect of reduction in zero- and negative-sequence currents is also reflected in the phase currents at main-substation as shown in Fig. 6.2. Fig. 6.2 shows that the SPDGs provide currents in such a manner that currents in three phases at the main substation get balanced. An important observation made from the figure is that the balanced phase currents of all the three phases at the main-substation are reduced to the minimum of three phase currents under unbalance (without SPDG). It is to be noted that I_b (minimum of phase current) overlaps with I_a^*, I_b^*, I_c^*. This results in increased MVA margins on the other two phases.

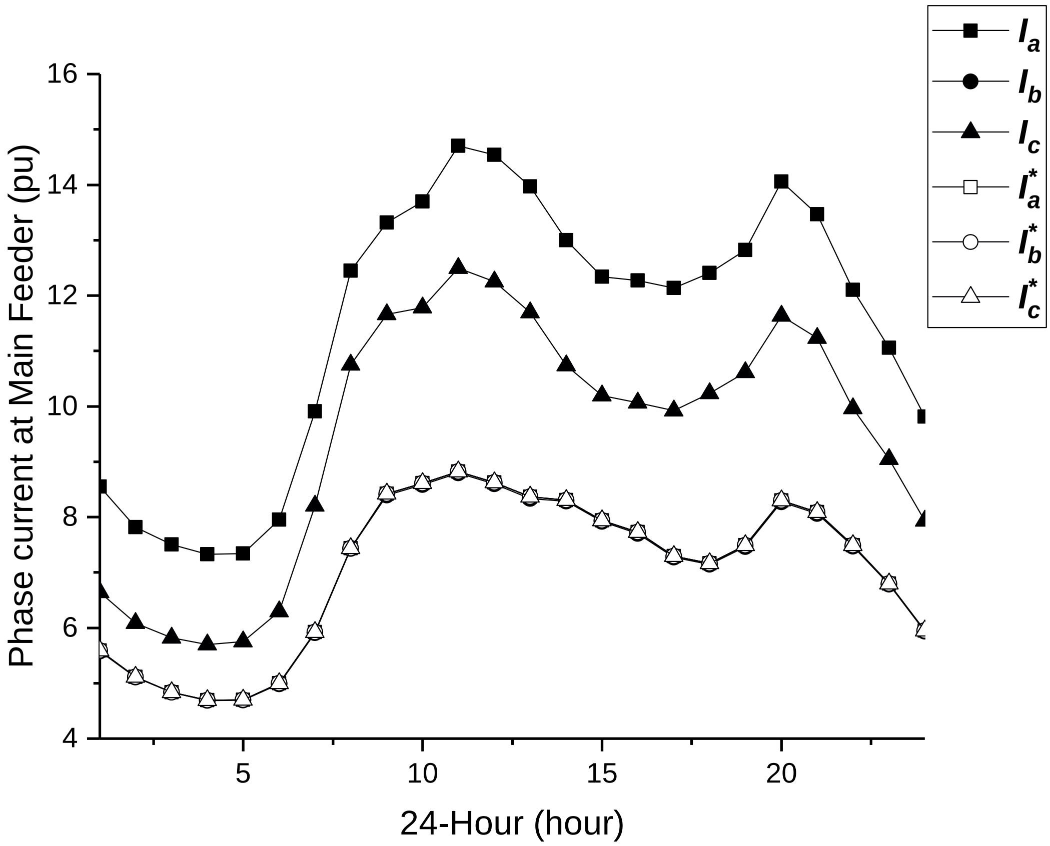

Figure 6.2: Hourly phase currents without and with SPDGs. I_a, I_b, and I_c indicate phase currents for the case when SPDGs are not placed. I_a^*, I_b^*, and I_c^* indicate phase currents for the case when SPDGs are placed.

Voltages: The bus-wise phase voltages for the peak load condition are plotted in Fig. 6.3. From this figure, it is observed that with the use of SPDGs, voltage profile improves and voltages become more balanced as compared to the case without SPDG. It is observed that phase voltages after scheduling SPDGs get pulled up towards the highest phase voltage of the case when SPDGs are not used. Comparison of minimum bus voltage before and after placing the SPDGs at every hour is shown in Fig. 6.4. From Fig. 6.4, minimum bus voltages of the system considerably improve when SPDGs are optimally placed in the system.

Losses: Scheduling of SPDGs in the system also affect the line losses. If SPDGs are

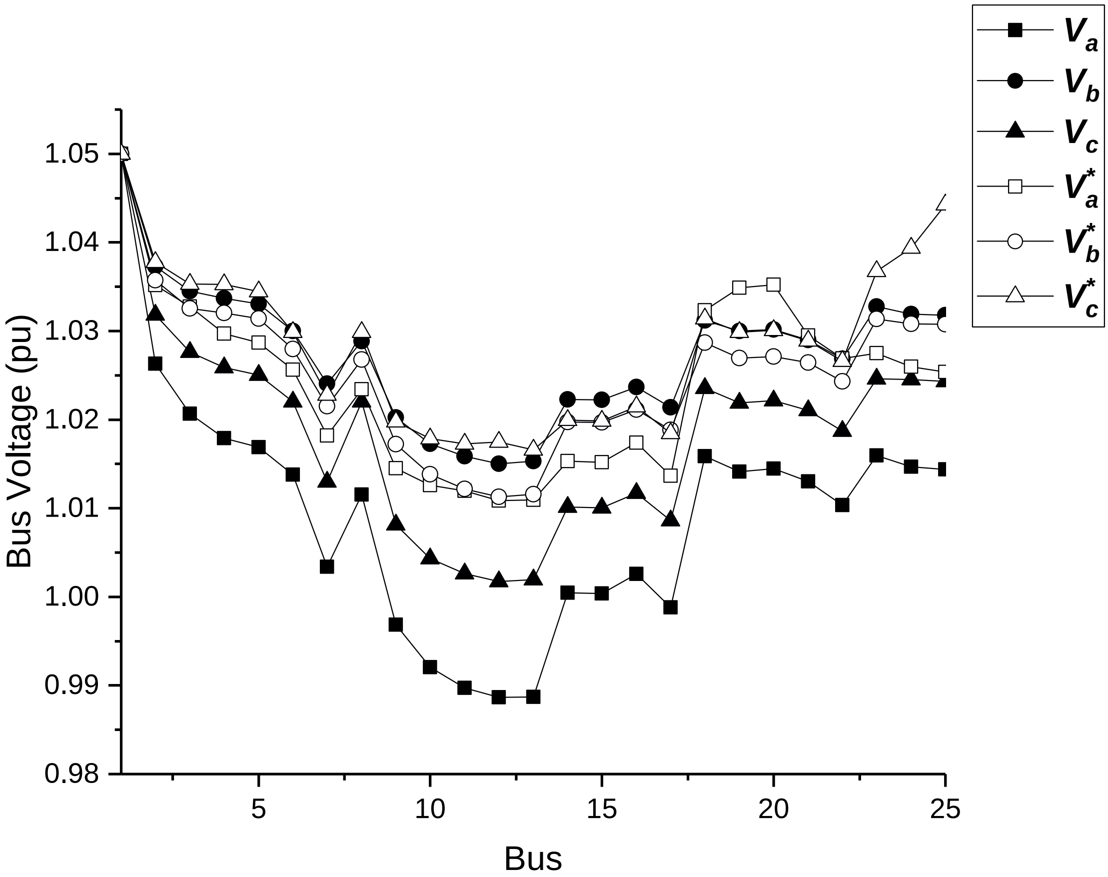

Figure 6.3: Bus voltages without and with SPDGs. V_a, V_b, V_c indicate bus voltages without SPDGs. V_a^*, V_b^*, V_c^* indicate bus voltages with SPDGs.

not suitably placed, losses may increase dramatically. Effect of placement of single-phase SPDGs on the active and reactive line losses is also studied. Active and reactive line losses before and after placing SPDGs for 24-hour are shown in Fig. 6.5. It is clear from Fig. 6.5 that the active and reactive line losses also reduce. Hence, the placement of SPDGs to balance the currents at main feeder does not increase the line losses, instead losses will come down.

Phase Utilization Index (PUI): PUIs before and after placing the SPDGs for 24-hour are shown in Fig. 6.6. Fig. 6.6 clearly shows that the PUIs are negligible when the SPDGs are optimally placed.

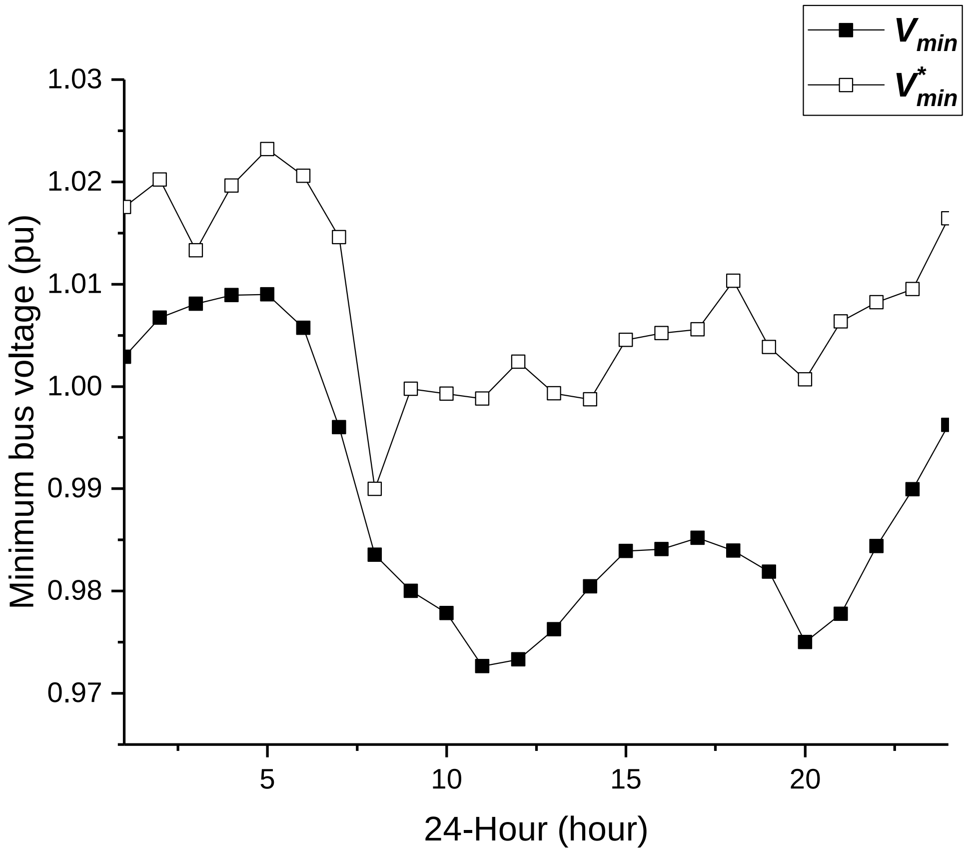

Figure 6.4: Minimum of the all bus Voltages without SPDGs and with SPDGs for 24 hour. V_{min} and V^*_{min} indicate the minimum bus voltage in case of Without SPDGs and with SPDGs respectively.

6.5 Summary

Planning of SPDGs for the purpose of phase balancing and a loss minimization is proposed in this chapter. EBOwithCMAR with CINR algorithm is utilized to solve this problem. CINR is utilized to calculate objective function at each solution. The planning is approached for different objectives. In the first objective function, the optimal SPDG locations (phase and bus) and sizes are obtained for minimum negative-sequence and zero-sequence current at the root node. The location and size are then evaluated for the minimization of active and reactive loss. Also, hourly scheduling of SPDG (in term of phase and size) for 24-hour loading scenario to obtain the phase balancing with minimum active and reactive losses is performed. It has been established that EBOwithCMAR with CINR is an effective algorithm for solving phase balancing and loss minimization problem.

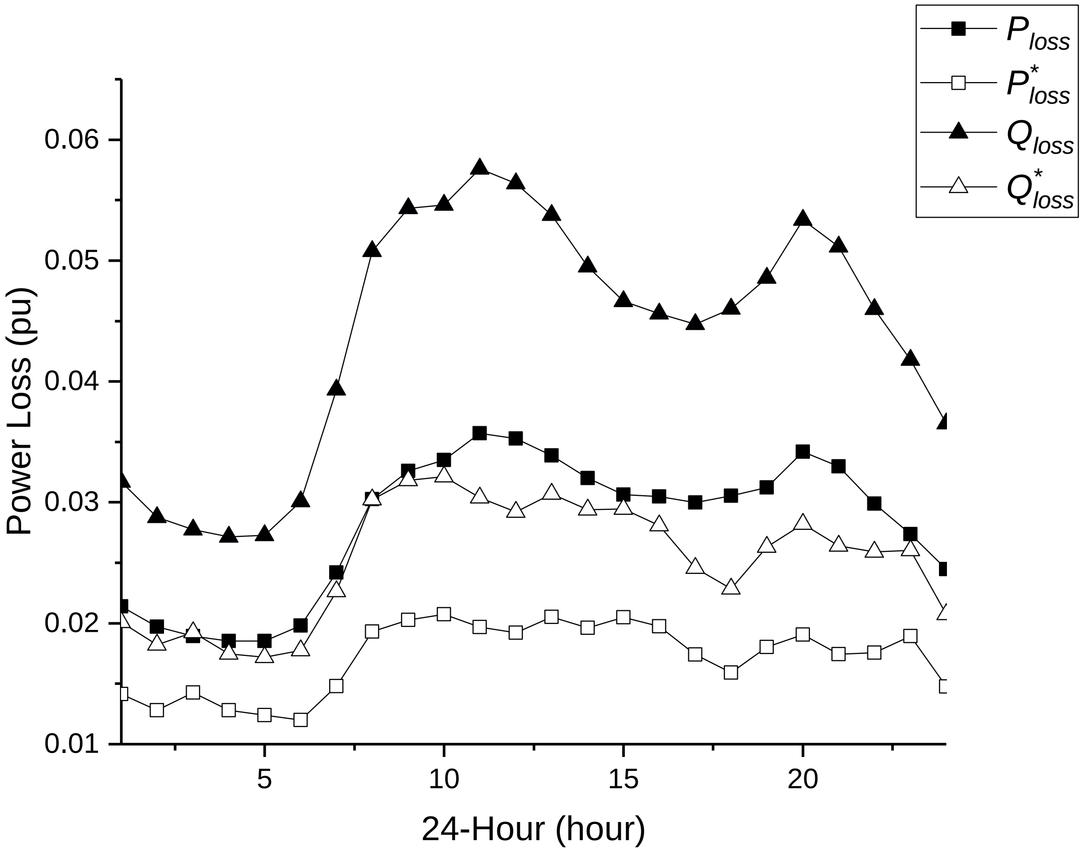

Figure 6.5: Total active and reactive power line loses for 24-hours. P_{loss} and Q_{loss} indicate total active and reactive line losses for the case when SPDGs are not placed. P^*_{loss} and Q^*_{loss} indicate total active and reactive power line loss for the case when SPDGs are placed.

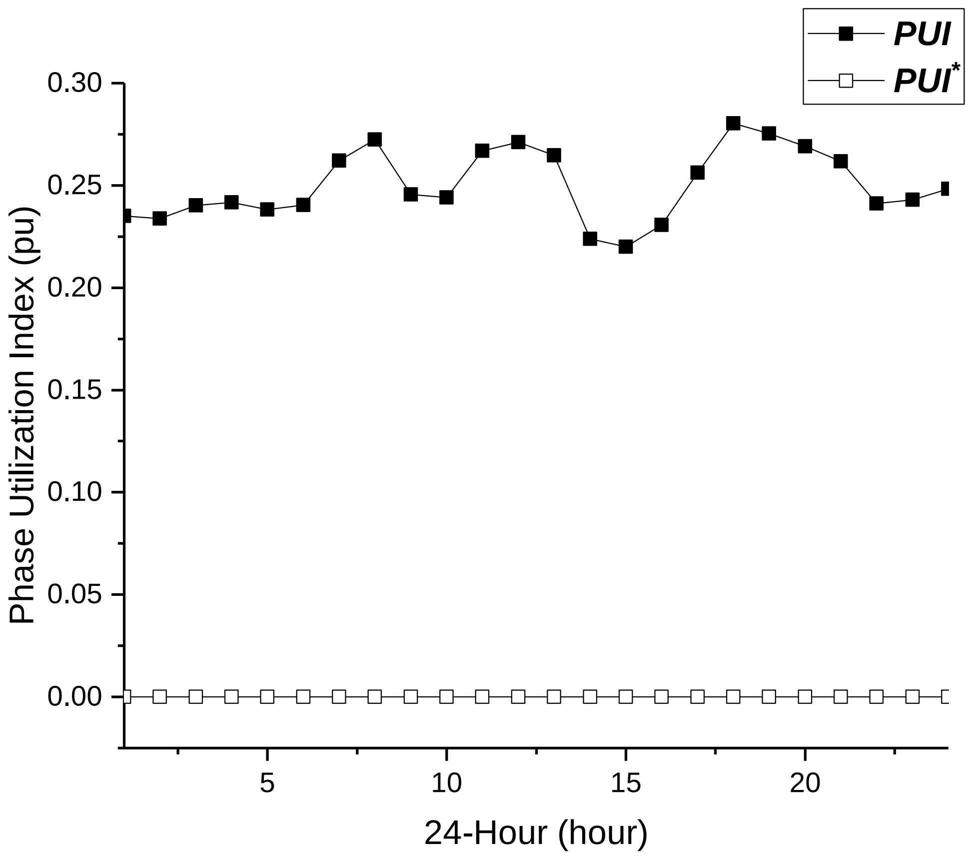

Figure 6.6: Phase Utilization Index at main feeder for 24 hours. PUI and PUI^* indicates the phase utilization index in case of without SPDGs and with SPDGs respectively.