Chapter 7

ESHADE in Optimization of Islanded Microgrids

7.1 Introduction

This chapter presents a method to determine optimal droop settings of DGs in a DCIMG. Minimization of system losses are considered as objective function while droop characteristics and power balance is considered as operational constraints of the DCIMG. The resultant optimization problem is solved using ESHADE and CINR. Here, ESHADE is an enhanced version of SHADE algorithm [217]. SHADE [217] is an acronym for Success-History based Parameter Adaption for Differential Evolution. CINR is used to calculate the objective function and ESHADE is used to calculate the optimal droop setting for all DGs.

An islanded MG is a low or medium voltage distribution system where electrical boundaries are clearly defined and a group of DGs and loads are interconnected without the support of the main grid [84,85,218]. In MG, the group of DGs supports local demands fully or partially of electricity and heat within the electrical boundaries [84,85]. MGs can be seen as a single controllable unit with respect to the main grid. In MGs, the system can operate in islanded or grid-connected mode, or it can operate in a smooth transition state between these two modes [84,85,219]. Islanded mode provides following benefits to the utilities as well as customers 1) improved power quality, 2) improved the system reliability, 3) overloads prevention, 4) maintenance of components of systems without interruption of power supply to the customers [220]. In the near future, microgrids are likely to be operated in an islanded mode for longer time durations due to above-mentioned potential benefits.

For the successful operations of a DCIMG, microgrid's local loads must be shared among the DGs within the limits of the bus voltages and operating frequency. Besides, the line flows should be within acceptable limits. In the literature, several droop control schemes are introduced for power-sharing among the DGS in DCIMG [169, 221, 222]. However, it is essential to operate the microgrids in an islanded mode not only in a stable state but also with optimal settings. From the customer perspective, the system should be operated at a low operating cost without compromising with its performance.

Nowadays, researchers focus on the optimal operation of DCIMG. In [223], an energy management system is proposed for DCIMG to operate stably with low fuel consumption. In [224], an optimization process is proposed to dispatch DGs and storage systems optimally for medium -voltage DCIMG with low operating cost and low emission. In a DCIMG, the operating frequency and bus voltages are been determined by the droop characteristics of DGs and loading conditions of the system. Moreover, the power output of a droop-controlled DGs are not known before the power flow analysis. In [225], a multistage algorithm is proposed to minimize fuel cost by considering constraints on voltage, frequency, and stability for a VSC-based microgrid.

In this thesis, a multi-operator variant of DE, ESHADE, is proposed to calculate the optimal droop settings of DGs for minimizing the operating cost and system losses in DCIMG. The proposed approach integrates the CINR method to perform the power flow analysis calculating the objective function values for each combination of droop settings of DGs. In ESHADE, four mutation strategies are employed with the same self-adaptation scheme of control parameters, but strategies are selected for individuals independently using a probability-based selection. To update the said probability, the success rate of each mutation strategy is utilized. Thus, the larger part of the population will get enrolled gradually in the better performing strategy.

7.2 Problem Formulation

In this work, we presume the existence of a Microgrid Central Controller (MGCC) and a noncritical low-bandwidth communication infrastructure to complement the droop control scheme. In this paradigm, the optimization of the islanded microgrid operation is performed centrally by a higher level coordinated management function at the MGCC. Using periodic measurements of the islanded microgrid generation and loads, the MGCC updates the DG unit droop settings (i.e., characteristics) in order to optimally dispatch the different DG units in the Islanded microgrids.

The main objective of this chapter is to find an optimal setting for droop controllers to minimize active power losses and reactive power losses.

The active and reactive power losses in the line connecting buses i and j can be calculated using following equations.

$$P_{loss}(i,j) = R_{ij}\frac{P_i^2 + Q_i^2}{|V_i|^2} \tag{7.1}$$

$$Q_{loss}(i,j) = X_{ij}\frac{P_i^2 + Q_i^2}{|V_i|^2} \tag{7.2}$$

where P_{loss} and Q_{loss} are active and reactive power loss. Total power loss of the system can be calculated by summing up all the lines losses of the system, i.e.,

$$\mathbf{P}_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{loss}(i,j), \tag{7.3}$$

$$\mathbf{Q}_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} Q_{loss}(i,j) \tag{7.4}$$

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.

In this study, the optimal values of the droop setting are obtained to calculate for minimizing the active and reactive losses. This problem can be formulated as a bound-constrained optimization problem. During the optimization process, the algorithm must evaluate all feasible settings of droop controllers to provide the minimum losses. For this purpose, the following optimization problem is considered in this study.

$$\text{Minimize } f(\mathbf{m}_p, \mathbf{n}_q) = w_1\mathbf{P}_{loss} + w_2\mathbf{Q}_{loss} \tag{7.5}$$

where $\mathbf{m}_p = \{m_{p1}, m_{p2}..., m_{pn}\}$ and $\mathbf{n}_q = \{n_{q1}, n_{q2}..., n_{qn}\}$ represent the droop settings of active and reactive power of DGs. Index n represents the number of DGs in islanded microgrids. Parameters w_1, and w_2 are the weighing factor for different objectives to represent multi-objective optimization problem into single objective optimization problem. This optimization problem is a non-convex, and non-linear continuous unconstrained optimization problem.

7.3 Proposed Methodology

To solve the above-discussed optimization problem, an optimization algorithm, ESHADE, is proposed in this section. The objective function of this problem can not be directly calculated because bus voltages of the system are not available for a different setting of droop controllers. Therefore, power flow analysis is required for calculating bus voltages to evaluate the objective function. In this work, CINR (proposed in chapter 4) is considered for power flow analysis.

7.3.1 ESHADE

In this section, the procedures and steps of ESHADE are discussed in detailed form. The self-adaptation mechanism for control parameters is also discussed which is an improved version of success history based parameter adaptation scheme proposed in [217]. The main step of ESHADE Algorithm is shown in Algorithm- 8. Steps, which is not described in Algorithm -8, is discussed in following subsections:

Initialization

In order to start the optimization process, an initial population P^0 should be generated uniformly within the upper and lower bound of the search-space. The Population, P^0 is represented using the following equation:

$$P^0 = [\bar{x}_1^0, \bar{x}_2^0.....\bar{x}_{N_p}^0], where \tag{7.6}$$

$$\bar{x}_i^0 = [x_{i1}^0, x_{i2}^0....x_{iD}^0]'$$

where, N_p and D are the size of population and dimension of search-space respectively. Here, x_{ij}^0 is initialized randomly as follows:

$$x_{ij}^0 = x_{Lj} + rand(0,1]. \times (x_{Uj} - x_{Lj}) \tag{7.7}$$

where x_{Lj} and x_{Uj} are the lower and upper bound of j^{th}-dimension of search-space. Operator $rand(0,1]$ stands for random number generator from uniform distribution.

Algorithm 8: Framework of ESHADE

Data: Define N_P^0 and all other parameters required

Result: X

Generate an initial population, P^0 of N_P^0 individual;
Objective function evaluation at each individual of population;
$nfes \leftarrow N_P^0$, $g \leftarrow 0$;
$\mu_{sF} \leftarrow 0.5$, $\mu_{cr} \leftarrow 0.5$, $\mu_{prob} \leftarrow 1$, $k \leftarrow 1$;
while *termination condition is not satisfied* **do**
    $g \leftarrow g + 1$;
    for i = *1:*N_P **do**
        % calculation of parameter starts;
        $sF_i \leftarrow$ using Equations 7.14 and 7.15;
        $cr_i \leftarrow$ using Equations 7.16;
        $prob \leftarrow$ using Equations 7.18;
        % Mutation;
        if $rand < 0.5$ **then**
            $r \leftarrow rand()$;
            if $r < prob(1)$ **then**
                $\bar{v}_i \leftarrow$ using **DE1**;
            else if $prob(1) < r < prob(1) + prob(2)$ **then**
                $\bar{v}_i \leftarrow$ using **DE2**;
            else
                $\bar{v}_i \leftarrow$ using **DE3**;
            end
        else
            $\bar{v}_i \leftarrow$ using **DE4**;
        end
        % Crossover;
        $\bar{u}_i \leftarrow$ **BinomialCrossover**($\bar{x}_i$, $\bar{u}_i$, cr_i);
        % Selection;
        objective function evaluate at $\bar{u}_i$;
        $nfes \leftarrow nfes + 1$;
        $\bar{x}_i \leftarrow$ **Selection**($\bar{x}_i$, $\bar{u}_i$);
    end
    Update the k^{th} element of μ for all parameter;
    $\sigma \leftarrow$ describe as in [226];
    $C \leftarrow$ describe as in [226];
    $k \leftarrow rem(k + 1, h)$;
    Resize the Population and Archive using EPSR;
end

Mutation

For each individual, a mutant vector has been generated. In ESHADE, four mutation strategies (modified version of mutation strategies reported in [217, 226, 227]) are used to generate mutant vectors and are as follows:

- DE1: current-to-$p$best with archive [217]:

$$\bar{v}_i^g = \bar{x}_i^g + sF_i \times (\bar{x}_{\text{pbest}}^g - \bar{x}_i^g + \bar{x}_{r_1}^g - \hat{x}_{r_2}^g) \tag{7.8}$$

- DE2: current-to-$\phi rand$ [226]:

$$\bar{v}_i^g = \bar{x}_i^g + sF_i \times (\bar{x}_{r_\phi}^g - \bar{x}_i^g + \bar{x}_{\phi\text{best}}^g - \bar{x}_{\phi\text{worst}}^g) \tag{7.9}$$

- DE3: Modified DCMA-ES with archive [227]:

$$\bar{v}_i^g = \mathcal{N}(\bar{x}_m^g, \sigma^2 C^g) + 0.1sF_i \times (\bar{x}_{r_1}^g - \hat{x}_{r_2}^g) \tag{7.10}$$

- DE4: $\phi rand$ [226]:

$$\bar{v}_i^g = \bar{x}_{r_\phi}^g + sF_i \times (\bar{x}_{\phi\text{best}}^g - \bar{x}_{\phi\text{worst}}^g) \tag{7.11}$$

where, $r_1 \neq r_2 \neq i$ are integer with $\bar{x}_{r_1}$ is randomly selected from population P, $\hat{x}_{r_2}$ is randomly selected from union of population and archive. While $p\bar{\text{best}}$ is selected from $p\%$ individuals from best individuals of P. In order to select $\bar{x}_{r_\phi}$, $\bar{x}_{\phi\text{best}}$, and $\bar{x}_{\phi\text{worst}}$; entire population is divided into three clusters, ϕbest, ϕ, and ϕworst (best, better, and worst) of size $p\%$, $(1-2p)\%$ and $p\%$ of N_p respectively. $\bar{x}_{r_\phi}$, $\bar{x}_{\phi\text{best}}$, and $\bar{x}_{\phi\text{worst}}$ are randomly selected from cluster ϕ, ϕbest, and ϕworst respectively. The calculation procedures of σ and C used in equation (7.10) are discussed in Section 6.3.1 in previous chapter.

In ESHADE, all mutation strategies are classified into two classes. In the first class, the three mutation strategies: DE1, DE2, and DE3 are applied with probability $prob(1)$, $prob(2)$, and $prob(3)$ respectively to generate a mutant vector. While in the second class, a mutant vector is generated using DE3. In every iteration, a mutant vector is calculated for every individual of the population using one of the above-mentioned mutation class with equal probability.

Crossover

In this chapter, binomial crossover is employed. In the binomial crossover, the target vector, $\bar{x}_i$, is crossed over with the mutated vector,$\bar{v}_i$, using the binomial experiment scheme, to generate the trial vector, $\bar{u}_i$ for target vector.

$$u_{ij}^g = \begin{cases} x_{ij}^g, & \text{if } (rand_{ij} > cr_i), \\ v_{ij}^g, & \text{if } (rand_{ij} < cr_i) \text{ or } (j == j_{rand}) \end{cases} \tag{7.12}$$

Selection

After trial vector, $\bar{u}_i$, has been calculated, a selection operator is applied to find out the survivor for the next generation [132]. In selection operator, $\bar{x}_i$ is compared with the $\bar{u}_i$ on the basis of their objective function value and the better one is stored in population for the next generation.

$$\bar{x}_i^{g+1} = \begin{cases} \bar{x}_i^g, & \text{if } (f(\bar{x}_i^g) < f(\bar{u}_i^g)), \\ \bar{u}_i^g, & \text{otherwise} \end{cases} \tag{7.13}$$

Parameter adaptation of population size (N_p), scaling factor (sF), and crossover rate (cr)

The performance of DE is highly influenced by the parameter setting. Parameter setting is problem dependent and each problem has its own set of parameter values. In order to resolve this issue, self-adaptation procedures for parameters are proposed in this subsection.

Adaptation procedure for scaling factor, sF***:***

In order to perform an adaptation for sF, the procedure is composed of two sections. The first section is activated during the initial evolutionary process, while the other section is activated later part of the evolutionary process.

Here, the first section uses the condition : $nfes < 0.2 \times max_n fes$ to activate. In first section of adaptation of scaling factor, sF_i is generated within the range of [0.45, 0.5] using following mathematical equation:

$$sF_i = \begin{cases} 0.5, & \text{if } (\mu_{sF}(j) > 0.5), \\ 0.45 + rand(0, 0.1], & \text{otherwise} \end{cases} \tag{7.14}$$

where $\mu_{sF}(j)$ is the j^{th} element of μ_{sF}. Here, μ_{sF} is a memory where Lehmer mean of successful scaling factor's value of previous generations are stored [217]. Index j is randomly selected for each individual independently from the range $[1, H]$ where H is memory size.

During the second section, the adaptation of scaling factor is done using following equation:

$$sF_i = randc(\mu_{sF}(j), 0.1) \tag{7.15}$$

where *randc* stands for random number generator from Cauchy distribution.

Adaptation procedure for crossover rate, cr:

In ESHADE, the crossover rate, cr_i, is adapted according following equation:

$$cr_i = randn(\mu_{cr}(j), 0.1) \tag{7.16}$$

where, μ_{cr} has similar function of μ_{sF}, but it stores the weighted mean of successful crossover rate's values of previous generations and *randn* stands for normal distribution [217].

Exponential population size reduction for population size, N_p:

In order to improve the performance of ESHADE, exponential population size reduction (EPSR) technique is employed to reduce the population exponentially. In EPSR, the following equation is used:

$$N_p^{g+1} = N_p^0 \times round\left(1 - \gamma \frac{N_p^0 - N_{p,min}}{max_{nfes}}\right)^g \tag{7.17}$$

where γ is a parameter to control the exponential curve, N_p^0 is the initial population size and $N_{p,min}$ is minimum allowed population size which is equal to 4.

The calculation and adaptation procedure of the parameters associated with DE3, σ and C, have already been discussed in Section 6.3.1.

Calculation of *prob*

In order to calculate *prob*, an index, j, is generated randomly within the range $[1, h]$ for every individual. Then, j^{th} element of the historical memory, μ_{prob}, is used to calculate prob using following equation:

$$prob(k) = \frac{\mu_{prob}(j,k)}{\sum_{n=1}^{3} \mu_{prob}(j,n)}, \text{ where } k = 1, 2, 3. \tag{7.18}$$

Updation of historical memory, μ

Elements of the historical memory, μ, is updated using the *success* of the individuals at the end of every iteration. Here at g iteration, the *success* of i^{th} individual is calculated using the following equation:

$$success_i^g = f(\bar{x}_i^g) - f(\bar{x}_i^{g+1}) \tag{7.19}$$

where, $f(.)$ stands for objective function value.

For parameters cr, and sF, k^{th} element of historical memory μ_{cr} and μ_{sF} respectively are calculated using following equations:

$$\mu_{cr}(k) = \frac{\sum_{n=1}^{N_p} w_n^2 cr_n}{\sum_{n=1}^{N_p} w_n cr_n} \tag{7.20}$$

$$\mu_{sF}(k) = \frac{\sum_{n=1}^{N_p} w_n^2 sF_n}{\sum_{n=1}^{N_p} w_n sF_n} \tag{7.21}$$

where,

$$w_i = \frac{success_i}{\sum_{n=1}^{N_p} success_n} \tag{7.22}$$

In case of $prob$, k^{th} elements of historical memory μ_{prob} are calculated using following equation:

$$\mu_{prob}(k,m) = (1-c)\mu_{prob}(k,m) + c\triangle_m \tag{7.23}$$

where c is the learning rate, and $\triangle_m$ is calculated using Equation-(7.24)

$$\triangle_m = \frac{\sum_{n \epsilon S_m} success_n}{\sum_{n=1}^{N_p} success_n} \tag{7.24}$$

where S_m is the set of individuals which are selected for m^{th} mutation strategy (here m can be 1, 2, and 3 which are stand for for DE1, DE2, and DE3 respectively).

7.3.2 Evaluation of Objective Function

In optimization algorithms, evaluation of objective function at each iterations for all the solutions is required for improving the solutions. The objective function considered in this chapter cannot be evaluated directly. Power flow analysis is to be perform 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 utilized to calculate the steady-state voltage at each bus for every solution of the optimization process. Each solution contains the droop settings of all DGs. First of all, power capacity of the DGs are updated according to the solution (droop settings of DGs). Power generation are modified by using following equations.

$$P_{dg,i} = \frac{1}{n_{pi}}(w_i^* - w) \tag{7.25}$$

and,

$$Q_{dg,i} = \frac{1}{m_{qi}}(|V_i|^* - |V_i|) \tag{7.26}$$

where $P_{dg,i}$ and $Q_{dg,i}$ represent the active and reactive power at i-th bus. $\{n_{pi}, m_{qi}\}$ represent the droop characteristics of i-th DG.

After modifying the power capacity equations, power flow analysis is performed using CINR to calculate the voltage at each bus. Further these voltages are used to calculate the objective function values.

7.3.3 Proposed Algorithm

The above-discussed optimization problem considers droop settings (related to active and reactive power output) of DGs as the problem variables. Each solution vector has $2 * M$ elements where M is the total number of DGs in the systems.

The purpose of this problem is to find the optimum droop settings for all the DGs so that the objective function is minimized.

The following steps are utilized to solve the optimization problem.

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

2. **Step 2:** Power flow analysis is performed at each solution of current population.

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

4. **Step 4:** Solutions of population are updated using ESHADE (proposed algorithm)

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 set the droop controllers of DGs within the system.

7.4 Results and Discussion

In this section, the proposed optimization algorithm is applied to solve the optimal power flow problem of droop-controlled islanded microgrids through optimal setting of droop parameters.

Before applying this method for optimal power flow problem, the proposed algorithm is validated on standard benchmark problem used in 100-digit challenge at IEEE CEC 2019 [228]. The results corresponding to all problems are given in Appendix III

7.4.1 Parameter Setting

For ESHADE, the parameter are set as follows: $N_p^0 = 18 \times D$, $N_{p,min} = 4$, $\gamma = 5$, and $c = 0.8$.

7.4.2 Case Studies

Three test systems viz. CASE6, CASE22, and CASE38, are considered to analyze the performance of proposed algorithm. The detail of these test systems are reported in Appendix-II.

Proposed algorithm is applied on CASE6 test system to obtained the optimal droop settings for minimal active and reactive power losses.

Table 7.1: Results of optimal power flow problem of CASE6

Without Optimization				Min of $\mathbf{P}_{loss}$				Min of $\mathbf{Q}_{loss}$				Min of $(0.5 * \mathbf{P}_{loss} + 0.5 * \mathbf{Q}_{loss})$			
w	0.9991			w	0.9961			w	0.9941			w	0.9945		
$\mathbf{P}_{loss}$	0.0080			$\mathbf{P}_{loss}$	0.0063			$\mathbf{P}_{loss}$	0.0064			$\mathbf{P}_{loss}$	0.0063		
$\mathbf{Q}_{loss}$	0.0062			$\mathbf{Q}_{loss}$	0.0026			$\mathbf{Q}_{loss}$	0.0025			$\mathbf{Q}_{loss}$	0.0025		
Voltage	Bus	$\lvert V \rvert$	$V_\angle$	Voltage	Bus	$\lvert V \rvert$	$V_\angle$	Voltage	Bus	$\lvert V \rvert$	$V_\angle$	Voltage	Bus	$\lvert V \rvert$	$V_\angle$
	1	0.9600	0.0000		1	0.9481	0.0000		1	0.9495	0.0000		1	0.9505	0.0000
	2	0.9725	-0.5214		2	0.9646	-0.3301		2	0.9690	-0.3961		2	0.9682	-0.3772
	3	0.9639	-2.6710		3	0.9568	-0.3260		3	0.9686	-0.3515		3	0.9653	-0.3466
	4	0.9872	-0.0740		4	0.9723	-0.2379		4	0.9714	-0.2098		4	0.9738	-0.2121
	5	0.9901	-0.4461		5	0.9746	-0.5212		5	0.9790	-0.5033		5	0.9778	-0.5185
	6	0.9693	-2.8542		6	0.9645	-0.4217		6	0.9768	-0.4736		6	0.9733	-0.4599
Power	Bus	P	Q	Power	Bus	P	Q	Power	Bus	P	Q	Power	Bus	P	Q
	1	-0.1487	-0.0984		1	-0.1451	-0.0960		1	-0.1455	-0.0963		1	-0.1458	-0.0965
	2	0.0000	0.0000		2	0.0000	0.0000		2	0.0000	0.0000		2	0.0000	0.0000
	3	-0.1993	-0.1409		3	-0.1964	-0.1388		3	-0.2013	-0.1422		3	-0.1999	-0.1413
	4	0.1187	0.0587		4	0.0985	0.0638		4	0.0894	0.0572		4	0.0957	0.0603
	5	0.1187	0.0457		5	0.0546	0.0508		5	0.0591	0.0420		5	0.0548	0.0445
	6	0.1187	0.1411		6	0.1946	0.1228		6	0.2046	0.1418		6	0.2015	0.1355
m_p	0.0075	0.0075	0.0075	m_p	0.0713	0.0200	0.0395	m_p	0.1000	0.0289	0.0661	m_p	0.1000	0.0272	0.0573
n_q	0.2173	0.2173	0.2173	n_q	0.5000	0.2888	0.4343	n_q	0.5000	0.1637	0.5000	n_q	0.5000	0.1971	0.4352

Table 7.1 shows the results of CASE6 after solving the optimal power problem using ESHADE. It can be concluded from Table 7.1 that the active and reactive power losses are reduced by 21.25% and 59.68%, respectively after using the optimal setting of droop

coefficients. In Table 7.1, results of single objective optimal power flow is also reported and these results show that these objectives are also able to reduce the active and reactive power losses with sufficient margins.

The Voltage profile of system is reduced in the system after including optimal droop settings. The main reason behind this issue is that the droop coefficient related to reactive power are increased to minimize the losses. Similarly system operating frequency is also reduced due to increase of droop coefficient related to active power.

Table 7.2: Results of optimal power flow problem of CASE22

Normal		Min of $\mathbf{P}_{loss}$		Min of $\mathbf{Q}_{loss}$		Min of $(0.5 * \mathbf{P}_{loss} + 0.5 * \mathbf{Q}_{loss})$	
w	0.9996	w	0.9994	w	0.9865	w	0.9994
$\mathbf{P}_{loss}$	0.0053	$\mathbf{P}_{loss}$	0.0022	$\mathbf{P}_{loss}$	0.0022	$\mathbf{P}_{loss}$	0.0022
$\mathbf{Q}_{loss}$	0.0027	$\mathbf{Q}_{loss}$	0.0011	$\mathbf{Q}_{loss}$	0.0011	$\mathbf{Q}_{loss}$	0.0011
m_p	0.0051	m_p	0.0043	m_p	0.1000	m_p	0.0041
	0.0015		0.0043		0.1000		0.0041
	0.0045		0.0027		0.0623		0.0025
	0.0015		0.0033		0.0766		0.0031
n_q	0.0500	n_q	0.0103	n_q	0.0100	n_q	0.0103
	0.0300		0.0135		0.0132		0.0135
	0.0100		0.0100		0.0100		0.0100
	0.0200		0.0114		0.0112		0.0113

The outcomes of CASE22 and CASE38 are reported in Tables 7.2 and 7.3, respectively. From these tables, it can be concluded that the active and reactive power losses are reduced after implementing the optimal droop settings into the systems. It is worthwhile to note that the outcomes of all types of objective functions are almost similar in all case studies. This outcome implies that the minimizing of active power and minimizing of reactive power are not conflicting objectives in case of droop controlled islanded microgrids.

7.5 Summary

In this chapter, a new optimization algorithm, ESHADE, is proposed to solve the optimal power flow problem of droop-controlled islanded microgrids where minimization of power losses are the objectives. The proposed algorithm is validated on the standard benchmark

Table 7.3: Results of optimal power flow problem of CASE38

Normal		Min of $\mathbf{P}_{loss}$		Min of $\mathbf{Q}_{loss}$		Min of $(0.5 * \mathbf{P}_{loss} + 0.5 * \mathbf{Q}_{loss})$	
w	0.9982	w	0.9772	w	0.9555	w	0.9579
$\mathbf{P}_{loss}$	0.0053	$\mathbf{P}_{loss}$	0.0841	$\mathbf{P}_{loss}$	0.0845	$\mathbf{P}_{loss}$	0.0842
$\mathbf{Q}_{loss}$	0.1269	$\mathbf{Q}_{loss}$	0.0700	$\mathbf{Q}_{loss}$	0.0685	$\mathbf{Q}_{loss}$	0.0686
	0.0051		0.0291		0.0618		0.0569
	0.0015		0.0452		0.0994		0.0868
m_p	0.0045	m_p	0.0586	m_p	0.1000	m_p	0.1000
	0.0023		0.0565		0.1000		0.1000
	0.0023		0.0153		0.0295		0.0281
	0.0500		0.0684		0.0830		0.0775
	0.0300		0.1000		0.1000		0.1000
n_q	0.0500	n_q	0.1000	n_q	0.1000	n_q	0.1000
	0.0100		0.1000		0.1000		0.1000
	0.1000		0.0423		0.0405		0.0422

problems and obtained results show that the proposed algorithm is effective and robust in comparison to state-of-the-art algorithms.

The results of the optimal power flow show that active and reactive power losses of the system are reduced, while the voltage profile is also reduced to adjust the new setting of droop coefficients related to reactive power generation.