Chapter 5

Optimum Integration of Wind and Solar Units using Levy Flight PSO.

5.1 Introduction

Technological advancement and digitalization of the electrical power grid are going to transform the convectional grid into a smartgrid. The microgrid is part of smartgrid. The microgrid environment is concerned with projects that involve optimal planning, operation, maintenance, and demand resource management in order to provide reliable, stable, and secure power. The planning procedure of combining natural power Distributed Generators (DG) with storage devices while considering economic and environmental issues is critical for the existing power distribution grid to optimize the positive impact of natural power distributed generators on a microgrid. This chapter describes a novel Levy Flight Particle Swarm Optimization (LFPSO) method for achieving the optimal combination of natural power distributed generators with a storage device and conventional DG while accounting for economic and technical factors. The levelised cost of renewable electricity and the cost of uncertainty for hourly estimated natural resources are included in the economic factor. Technical key considerations tend to involve grid losses, power generation management, and control variables such as nodal voltage and phase angle. The optimal integration of natural power resources is achieved for the efficient and reliable operation of the microgrid. The optimal operation of the grid is investigated at various load levels. It demonstrates that the levelised cost of hybrid generation and grid losses have been decreased. As a microgrid, the IEEE-13 node distribution system has been used.

The world's current demand is intended to bring nature into balance by reducing the emission of greenhouse gas production. Renewable energy generation is one of the best alternatives for the world of electrical energy. Decentralization of the power grid is an effective way to incorporate natural energy resources into the grid. Decentralization opens the door to the creation of microgrids, which can boost the flexibility and reliability of power networks. The importance of a microgrid application can be evaluated by its economic benefits, stability and reliability, and cost savings for users and owners. Power society must plan the finest microgrid architecture to combine natural power resources and other distributed energy source technologies, so that it is able to deal with demand and supply balance while ensuring buoyancy against what appear to be escalating natural and man-made disturbances. [100]. A microgrid must maintain a balance between the available output power of renewable energy resources with storage devices and the load in order to be reliable. The article [101] proposes an algorithm for renewable energy management. In this article, an energy management algorithm has been implemented by designing a Microgrid central controller based on the multi-agent system concept. A business model for determining the most cost-effective capacity and operation of distributed energy resources in microgrids has been examined, and technological and policymaker variables have been resolved [102]. The finding of this article has focused on potential deployment of renewable distributed energy sources in microgrid which radically reduce consumer energy cost.

Many researchers from different fields have developed various algorithms for accurate planning and operation of micro - grids with integration of renewable/non-renewable distributed generators, energy storage devices, control strategy based on load response, and availability of natural power sources in order to promote the microgrid concept throughout the world. A combined method based on Genetic Algorithm (GA) and Intelligent Water Drops (IWD) and a Genetic Algorithm (GA) method combined with PSO have been proposed to find place and capacity of DG in Microgrid for optimizing network power losses with improving voltage regulation and rising the voltage stability within system.[52][50]. An eagle strategy with particle swarm optimization has been implemented for allocation of distributed generators in the microgrid considering power system losses as objective function [103]. In the article [104], symbiotic Organism Search approach has been applied to determine optimal number of Distributed Generators and loss sensitivity factors have been used to locate the place of DG in the distribution system. The effect of integration of distributed generators on power system has been investigated. The virus colony search (VCS) algorithm has been employed to improve reliability indices as a prominent parameter to determine the optimal placement and size of distributed generators [105]. The author has proposed a hybrid optimization technique based on the Ant Bee Colony and Cuckoo Search algorithms to choose position of multiple DGs in distribution grids and suggested that the above method has superior performance provision over GA-PSO, PSO and GA in terms of optimum power loss, percentage loss reduction, DG cost and energy cost [106]. A meta heuristics cuckoo search algorithm has been tested on a 33 bus radial distribution system to determine optimal capacity and positions of capacitors involving DG units in addition to reduce annual cost/year, improve voltage profile and reliability [107].

All of these above researchers mainly focused on DG cost, allocation and technical effectiveness, but not considered the type of renewable DG and its uncertainty. The output power of renewable energy sources is robustly associated to the weather, time, temperature, and location [107]. The potential benefits, challenges and progress of RE-DGs and their operational scheduling in electrical grids have been thoroughly investigated in [108]. The PSO has been applied to resolve a multi objective optimization problem as optimal cost and dispatch strategy for integration of renewable-based DG and natural gas DG in microgrid. The optimal planning and impacts of RE-based DG units particularly wind power generation and solar units have been addressed for techno-economic benefits. [109]. A new Harris Hawks Optimizer using Particle Swarm Optimization algorithm has been presented for the optimal allocation and sizing of RE-DG units in the distribution system. Uncertainty behavior of wind power and solar power generation has been considered using appropriate probability distribution in [110]. The schostatics behavior of wind speed and solar irradiation has been considered in the planning procedure of renewable DG location with load growth. The proposed method has been tested on a 31-bus radial system [111]. The energy management strategy has been proposed for economical operation of the microgrid on the basis of forecasting data and dispatch power of controllable units on the basis of real data in [112]. While the multi criteria wind and solar power generation planning has presented to maximize a use of natural energy and minimize cost and a statistical quality control criterion has been implemented for developing meta heuristic algorithm and tested on 13-node distribution system [113]. The Economic power dispatch problem has been solved by distributed replicator dynamics algorithm, considering network losses coefficient and uncertainty in load and wind generation [114]. The same dynamic economic dispatch strategy has been proposed by considering variation in load and power generation of conventional and renewable energy sources and network cost analysis has been done [114]. Under consideration of variation in load power generation activity, optimal power dispatch strategies has been addressed for reduction in cost in AC-DC hybrid microgrid. For optimal solution A combination of particle swarm optimization and fuzzy max-min technique is then employed [115].

Using one optimization technique or a combination of one and more optimization techniques, these researchers presented optimal design of non-renewable/renewable distributed generators, optimal operation, and power dispatch strategy for the microgrid. For improved solutions, the majority of researchers have adopted particle swarm optimization approaches. The main goal of optimization is to maximise the technological and economic benefits of DG in the microgrid. The smart grid optimization competitions have been held using a modern heuristics optimization strategy as described in [116], [117].

In this chapter integration of natural power sources and micro turbine has been presented for optimal and stable operation of microgrid emphasizing on control variables. The operation of storage devices is also incorporated in the microgrid by considering theory that the energy storage devices help to reduce power losses and adjust power flow in distribution network. The optimization algorithm has been developed using meta heuristics- levy flight particle swarm optimization method in which, the obtained solution reduces levelised cost of electricity, grid losses and substation dependency index keeping control variables within stable limits. Most researchers have presented an independent cost model for economic dispatch of the power system. In this chapter, the cost model is included with the levelised cost of electricity of renewable units and penalty for uncertain power generation. The levy flight particle swarm optimization method presents in first part for optimal operation of microgrid. This method gives global optimal solution without trapped in local minima and consumes less time. In the second part objective function formation is represented, which has been formulated by two-step method. First step shows objective function related to economic factors which have been formulated including levelised cost and uncertainty cost of natural sources. The concept of levelised cost is given in [118]. Second step represents formation of optimized function based on technical factor which has been formulated including network losses and substation dependency factor. The steps in solving the problem have been outlined in detail, along with a flowchart of the algorithm. The proposed technique is tested on an IEEE 13-node radial distribution system, and the results indicate that the proposed method is effective.

5.2 An Enhanced Particle Swarm Optimizer Algorithm with Levy Flight

Particle swarm optimization(PSO)is one of the well-known nature inspired evolutionary algorithms for solving many scientific and real-world engineer- ing problems involving nonlinear function, many variables and complex constraints. The attraction towards PSO is due to ease implementation and less parameters setting to reach optimal solution. However trapping of local minima and law convergence rate for multimodal problems are the main drawback of PSO. These drawbacks cause unbalance between local search and global search. To recover this poor performance a lot of hybrid algorithms which enhanced PSO have been developed for multi model optimization problems in mathematics and engineering. Author in [119] has presented that the PSO (Particle Swarm Optimization) combined with the self-adaptation power of Evolutionary Algorithms (EA) gave better performance to solve optimization problems. he has also developed DE+EA+PSO as improved version of EPSO. In [120]the ABC-PSO are combined to solve high dimensional optimization problems and have achieved excellent results. Ref [121] presents Quantum Particle Swarm Optimization(QPSO) and the Hybrid Differential Search Algorithm (HDSA) to obtain a solution of energy sources planning in the power system. On the same path an Optimized algorithm to get an enhanced version of PSO with LEVY flight distribution has been proposed and performed on Twenty one benchmark test functions in [122]. These algorithms have also given best results to solve optimization problems. The recently developed optimization technique such DEEPSO, CDEEPSO, LEVYPSO have been used in 2017, 2018, 2019 Grid Optimization Competition.[116][117], Improved Differential Evolution (IDE) and Firefly algorithms, Particle Swarm Optimization with Global Best Perturbation(PSO- GBP), Improved Chaotic Differential Evolutionary Particle Swarm Optimization (IC-DEEPSO), Unified PSO (UPSO), a Chaotic Evolutionary Particle Swarm Optimization Algorithm (CEPSO), are applied to solve such complex and non-linear optimization problem. In [123] Enhanced Velocity Differential Evolutionary

Particle Swarm Optimization(EVDEPSO) algorithm has been proposed to tackle the Energy resources management problem in the microgrid. The rise in Velocity by the terms is named as Enhanced Velocity by mutation of inertia weight and normal distribution N [0,1]. The author has compared the result with other methods and proved robustness and efficiency of EVDEPSO. Here the Enhanced PSO algorithm with levy flight distribution presents to achieve optimal planning of microgrid with Dg integration. This method finds global optimal solution without trapping on local minima and reduces execution time compare to conventional PSO.

5.2.1 Levy Flight Distribution

The conventional particle swarm optimization approach is population-based and mimics the behaviour of flocks of birds and fish swarms. Each particle behaves as a separate swarm. The position and velocity of each particle for a D-dimensional value are represented as $X_i = X_{i1}, X_{i2}, X_{i3}, .., X_{iD}$, and $V_i = V_{i1}, V_{i2}, V_{i3}, ..., V_{iD}$ respectively. Each particle moves in the search space using its personal experience-pbest and the group experience-gbest. Particles use the p_{best} and g_{best} memory to reach the next optimum solution. The update of velocity and position is carried out using eq:(5.1) as ;

$$V_{i,D}^{t+1} = w_t V_{i,D}^t + c_1 \times rd_1 * \left(p_{best_{i,D}}^t - X_{i,D}^t\right) + c_2 \times rd_2 * \left(gbest_{i,D}^t - X_{i,D}^t\right) \tag{5.1}$$

$$X_{i,D}^{t+1} = X_{i,D}^t + V_{i,D}^{t+1} \tag{5.2}$$

c_1 is the cognitive weight factor, and c_2 is the social weighting factor, both are used to ensure that particles are more affected. The inertia coefficient weight(w) balances local and global search. It is set as a constant or according to the following equation: $w =$ Uniform $(0.5, 1.0)$. At iteration t, It is expressed according to eq:(5.3)

$$w_t = w_{max}\frac{(t_{max} - t)}{t_{max}} - w_{min}\frac{t}{t_{max}} \tag{5.3}$$

The value of the inertia coefficient weight decreases between ($wmax = 0.9$) and ($wmin = 0.4$). The fitness value is computed after updating the velocity and position of the particle. The p_{best} and g_{best} updates are continued until the stop criteria are met. The levy distribution has been obeyed to choose the direction and generation of random numbers[122][124], which is described as

$$L(y) \sim |y|^{-1-\gamma},\ where\ 0 < \gamma < 2$$

Levy distribution is defined in simple mathematics form as,

$$L(y,\beta,\mu) = \sqrt{(\frac{\beta}{2\pi})} \times \exp(-\frac{\beta}{(2s-\mu)}) \times (\frac{1}{(s-\mu)^{\frac{3}{2}}})\forall 0 < \mu < y < \infty$$

$$= 0 \qquad Otherwise;$$

Here (β) is scale parameter and (μ)is location parameter. When we consider the levy distribution for any stochastic variable, it becomes larger due to the heavy tail kind of distribution. Here for Levy PSO inertia weight is set as stochastic variable, which follows:

$$w_t \sim Levy_{pdf}(w,\mu,\beta)$$

In this suggested LEVY-PSO, the larger value of w has been attained on occasion. So, the global search ability of particles improves, and they move toward the optimum route in the global area rather than trapping in the local area.

However,Due to larger value of w, the increased velocity and distance travelled may be excessive. Therefore, limits are established in order to avoid extended travelling distances as per eq:(5.4)and (5.5).

$$V_{i,D}^{t+1} = B_V\left(w_t V_{i,D}^t + c_1 \times rd_1 * \left(p_{best_{i,D}}^t - X_{i,D}^t\right) + c_2 \times rd_2 * \left(g_{best_{i,D}}^t - X_{i,D}^t\right)\right) \tag{5.4}$$

$$X_{i,D}^{t+1} = B_X\ \left(\ X_{i,D}^t + V_{i,D}^{t+1}\right) \tag{5.5}$$

$$B_V = \begin{cases} \sin(V) & if \quad |V| < V_{\max} \\ V_{max}, & otherwise \end{cases}$$

$$B_X = \begin{cases} X_{min} – X|X_{min}| & if \quad X_{min} > X \\ X_{max} – X|X_{max}| & if \quad X_{max} > X \\ X & if \quad X_{min} \leq X \leq X_{max} \end{cases}$$

X_{min} and X_{max} are minimum and maximum limits of position of particles in the search domain.

V_{max} is the critical velocity in search domain.

5.3 IEEE-13 node Distribution System as Microgrid

In order to apply the Levy Flight particle swarm optimization technique for optimal and stable microgrid operation, the 13 bus IEEE network, as described in Chapter 4, is also considered a microgrid. To plan microgrid structure form the existing grid, the no of distributed generators units are considered based on geographical situation. The number of wind and solar units has been determined based on a geographical constraint assumption. The deployment of Natural power dg is mostly preferred in high-loaded nodes. Different nCr combinations were attempted for the location of DG and the best placement has been found.

5.4 Problem Formation

5.4.1 Nomenclature

p_{dg_i} = power generation of Distributed Generator

$p_{dg_i}^{emin}$ = expected minimum real power generation of wind/solar power DG

$p_{dg_i}^{emax}$ = expected maximum real power generation of wind/solar power DG

F_e = economy based objective function

F_T = Technical based objective factor

n_{dg} = No of dg

n_{sdg} = No of solar dg

n_{mtdg} = No of microturbine dg

n_{wdg} = No of wind dg

SD = storage device

C_O = Operating cost of DG which is a function of no. of actual unit generated.

U_{wdg_i} = actual unit generated of wind power DG

U_{sdg_i} = actual unit generated of solar power DG

U_{mtdg_i} = actual unit generated of microturbine DG

C_U = cost of uncertainty

p_{dg}^{mt} = power generation of microturbine

P_{WG_i} = probable power generation of i_{th} wind unit in KW

P_{SG_i} = probable power generation of i_{th} solar power unit

$C_{O_{SD}}$ = operating cost of storage devices

$p_{dg\frac{w}{s}i}^{\frac{eava}{h}}$ = estimated hourly average power generation of solar/wind unit per day

$p_{dg\frac{w}{s}i}^{\frac{aava}{h}}$ = actual hourly average power generation of solar/wind unit per day

$\alpha_w, \alpha_s,$ = levelised cost of electricity of wind and solar unit respectively

α_{mt} = cost- coefficient of microturbine
W_e = weightage of economic factor
W_t = weightage of Technical Factor
C_{ui} = cost coefficient of underestimation and over estimation of renewable power generation
SOC = State Of Charge of energy storage devices
$E_{SD_{r_i}}$ = rated energy storage capacity of SD unit i
$C_{char/dis}$ = charging discharging cost coefficient
$P_{SD_{w/s_i}}^{\frac{cha}{dis}}$ = Charging discharging power of storage unit attached with wind/solar unit
$P_{blosses}$ = branch losses
V_i, V_j =volt at node i and j
$SBDI$ = substation dependency index
CON = number of constraints
P_{L_i} =load at each bus
SOC =actual energy stored/rated energy storage capacity

5.4.2 Objective Function

The objective function, which has been made up of economic and technical functions, can be expressed as follows:

$$min(F_e, F_T),\ p_{dg_i} \in [\frac{p_{dg_i}^{\min}}{day}\ \frac{p_{dg_i}^{max}}{day}] \tag{5.6}$$

Where, i = 1, 2, 3 … ..n number of distributed generators F_e is a cost function that has been developed for the most economical operating model of a microgrid with the integration of renewable and nonrenewable DG, and it is stated as;

$$F_e = We\left(C_O(U_{dg}) + C_U(p_{dg_i}^{\frac{aava/h}{eava/h}}) + C_{O_{SD}}(P_{SD}^{\frac{cha}{dis}})\right) \tag{5.7}$$

The operational costs of renewable DGs are calculated using the weighted-average Levelized cost of electricity. The concept of the average Levelized cost of electricity is presented in [118]. It comprises the capital cost, variable and fixed operation and maintenance costs, a depreciation charge, renewable unit life, and so on. It is a linear function of the number of units produced. The cost function of renewable DG and microturbine is considered as per eq:(5.8);

$$C_O(U_{dg}) = \alpha_w * \sum_{i=1}^{n_{wdg}} U_{wdg_i} + \alpha_s * \sum_{i=1}^{n_{sdg}} U_{sdg_i} + C_O(U_{mtdg_i}) \tag{5.8}$$

Where,

$$C_O\left(U_{mtdg_i}\right) = \alpha_{mt} * \sum_{i=1}^{n_{mtdg}} U_{mtdg_i} + \alpha_{mt_1} * \sum_{i=1}^{n_{mtdg}} \left(U_{mtdg_i}\right)^2 + \alpha_{mt_0}$$

Another aim of the optimal microgrid operation model is to reduce the cost of other resources such as main grid usage and microturbine generation under unpredictable conditions. The mathematical model of uncertain cost function because of underestimation and overestimation of probable power generation of solar and wind units for various scenarios has been proposed and analyzed in [125]. Here the uncertainty penalty cost is the function of underestimation or overestimation of RES-DG output power is formulated as;

$$C_U\left(p_{dg_i}^{\frac{aava/h}{eava/h}}\right) = C_{u_i} \sum_{i=1}^{n_{w/sdg}} \left(p_{dg\frac{w}{s}i}^{\frac{eava}{h}} \pm p_{dg\frac{w}{s}i}^{\frac{aava}{h}}\right) \tag{5.9}$$

The profit of a distribution firm has been maximised as a result of energy transaction planning and operational cost savings. This goal has been met by locating and sizing energy storage devices. An operational strategy of battery storage devices has been proposed in [126]. The main purpose of energy storage devices is to balance generation and consumption of the microgrid, to diminish transfer of power from subgrid and to lower substation dependency index. The operation and maintenance cost of energy storage devices are influenced by the device's strategy and charging discharging frequency. To avoid frequent switching, it is expected that storage devices are permitted to function within maximum charging and discharging limitations. The charging and discharging energy of a storage device is calculated as follows;

$$P_{SD}^{Char/dis} = \pm \frac{\left(SOC^{t_2} - SOC^{t_1}\right)\ E_{SD_{r_i}}}{t_2 - t_1} \tag{5.10}$$

$$C_{O_{SD}}\left(P_{SD}^{\frac{cha}{dis}}\right) = C_{char/dis} * \sum_{i=1}^{n_{w/sdg}} \left(p_{SD_{w/s_i}}^{\frac{cha}{dis}}\right) \tag{5.11}$$

The F_t is formulated for optimal technical operation model of microgrid with integration of renewable and non renewable DG expressed as;

$$F_t = Wt\left(\sum_{ij=1}^{nb} P_{blosses_{ij}}\left(V_i, V_j\right) + |SBDI|\right) \tag{5.12}$$

The SBDI is an index that reflects the amount of power exchanged from substation to microgrid to balance generation-load demand when RES-DG + storage devices provide inadequate or surplus power. When power generation exceeds load demand, electricity is transmitted to the substation, resulting in a negative SBDI. The SBDI is defined as follows:

$$SBDI = \left(\sum_{i=1}^{n_{dg}} P_{dg_i(w,s,mt)} \pm P_{SD_i} - \sum_{i=1}^{nb} P_{Li} \right) / \sum_{i=1}^{nb} P_{Li} \tag{5.13}$$

The formula for branch current losses is stated as;

$$P_{blosses_{ij}}\left(V_i, V_j\right) = \left(\hat{V}_i - \hat{V}_j\right)^2 * G_{ij};\ \forall\ \hat{V}_i = V_i < \delta_i\ \hat{V}_j = V_j < \delta_j \tag{5.14}$$

5.4.3 System constraints

1. Power balance at each node:

   The microgrid operation should ensure that active power (P_i) and reactive power (Q_i) balances are maintained at each node (i). Nodal voltage and load angle are viewed as controlled variables in terms of the microgrid's stability and optimal performance. As a consequence, the power balance has been calculated as a function of nodal voltage and load angle. It is a nonlinear equation that appears like this;

$$\begin{array}{llll} P_i\ (V_i, \delta_i) = 0 & \forall\, V_i \epsilon\, [V_{max}\ ,\ V_{min}\ ] & \forall\, \delta_i \epsilon\, [\delta_{max}\ ,\ \delta_{min}\ ] \\ Q_i\ (V_i, \delta_i) = 0 & \forall\, V_i \epsilon\, [V_{max}\ ,\ V_{min}\ ] & \forall\, \delta_i \epsilon\, [\delta_{max}\ ,\ \delta_{min}\ ] \end{array}$$

2. Branch current flow constraint:

   The microgrid should be built to allow bidirectional branch current flows within the limits of feeder thermal efficiency. The greatest capability of the feeder to flow current in each direction determines the thermal efficiency of the feeder. This constraint is denoted as: $-I_{\min} \leq I_{ij} \leq I_{\max}$

3. DG unit and size constraint:

The number of DG units is determined by the intended or current location of the microgrid. The number of units is determined by the availability of natural resources, the type of consumer demand, and the rate of load growth. To ensure optimal operation, one or more units can be installed on each bus or on a subset of buses. The following is the power generation limits for wind and solar renewable DG units:
Wind DG Unit:

$$P_{WG} = \sum_{i=1}^{nb} n_{wdg_i} * P_{WG_i}$$

Where $P_{WG_i} = F\left(u_m, P_{wrated}\right)$, u_m = mean wind speed; P_{wrated} = rated capacity of wind power unit. The unpredictability of wind power output has been modelled as a function of mean wind speed for the time period under consideration and wind turbine rated capacity. Wind speed is believed to follow the Weibull distribution function.
Solar DG Unit:

$$P_{SG} = \sum_{i=1}^{nb} n_{sdg_i} * P_{SG_i}$$

Where $P_{SG_i} = F\left(S_m, P_{Sratedi}\right)$ Where,S_m= mean solar irradiation; ;$P_{Sratedi}$s = available rated capacity of solar unit in KW.
The unpredictability of solar power output has been modelled as a function of mean solar irradiation for the time period under consideration and solar panel rated capacity. The behaviour of solar irradiation is expected to follow the beta distribution function. The estimated power generation for the day by wind unit/solar unit has been calculated according to method discribed in chapter-2 and 3
Micro turbine DG Unit:

$$P_{MTG} = \sum_{i=1}^{nb} n_{mtdg_i} * P_{MTG_i} \qquad Where, \quad P_{MTG}^{\max} \leq P_{MTG_i} \leq P_{MTG}^{\min}$$

Energy storage device operation constraint:

$$P_{SD_{min}}^{char/dis} \leq P_{SD}^{Char/dis} \leq P_{SD_{max}}^{char/dis}$$

$$SOC^{t_{min}} \leq SOC^{t} \leq SOC^{tmax}$$

4. Fitness function:

It is structured as;

$$FF = F_e + F_T + \sigma \sum_{j=1}^{CON} max[0, K_j] \tag{5.15}$$

K_j is the value of j^{th} constraint.

5.5 Steps to Solve Optimization Problem using LF-PSO for 12-node Grid connected Microgrid

1. For the selected system, read essential data such as bus data, line data, and load data. Determine the discrete number of solar and wind units and the average expected generation of each unit based on geographical conditions.

2. Define control variables and examine their lower and upper bounds for the steady functioning of the microgrid. Set up a total of 24 variables, including 12 bus nodal voltages and 12 phase angles. The population 'm' is assumed to be 100.

3. Set up power generation of DG units (in this study -4 units chosen)as state variables. The 100 random values of wind and solar power generation units within expected power production limits for best combination of four DG has been loaded for program execution.

4. Because there are 28 variables and 100 population sizes, a matrix of 100 X 28 is generated for iteration step one.

5. program execution start with iteration step (iter) one and current position as per row = 1 of the matrix , which equals to current-p_{best}.

6. Evaluate fitness function as per eq:(5.15) for each particle.

7. Find the optimal value of the objective function for iteration step one. Then, update the memory.update row of the matrix.

8. Examine random uniform distribution to see if it indicates local or global exploitation. Update particle velocity and location using the levy flight distribution as described in eq: (5.4) and (5.5).

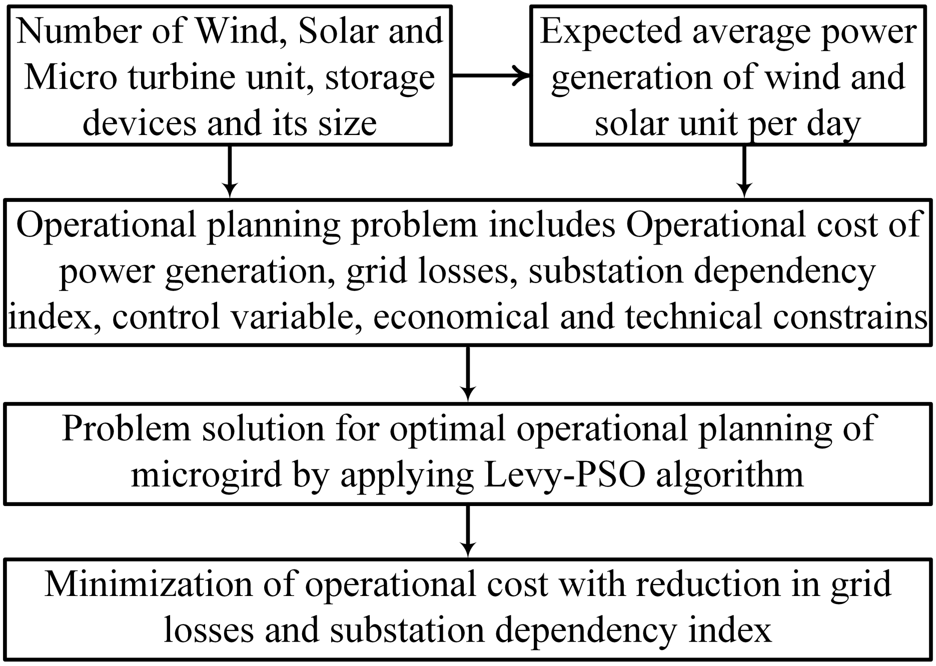

Figure 5.1: Block diagram of proposed optimal operation of Microgrid

9. Check the p_{best} and location parameter within domain. if they are within domain evaluate fitness function for each particles and update the g_{best}.

10. Update iteration step (iter= iter+1),

11. Repeat steps 6 to 9 and record the the g_{best},

12. Load natural power unit generation again as per step (3) and repeat steps 5 to 11 for Iteration steps for 100 times,

13. Record all solution for the expected unit generation of wind and solar resources.

14. Find best solution out of these 100 iteration steps, which gives minimized grid losses, minimized levelised operating cost, SBDI with optimized controlled variables and expected average value of natural resources.

The block representation of the optimal operational planning of microgrid with integration of renewable-non renewable DG and storage devices is shown in Fig. 5.1. The flow chart of problem solution is shown in Fig.5.2.

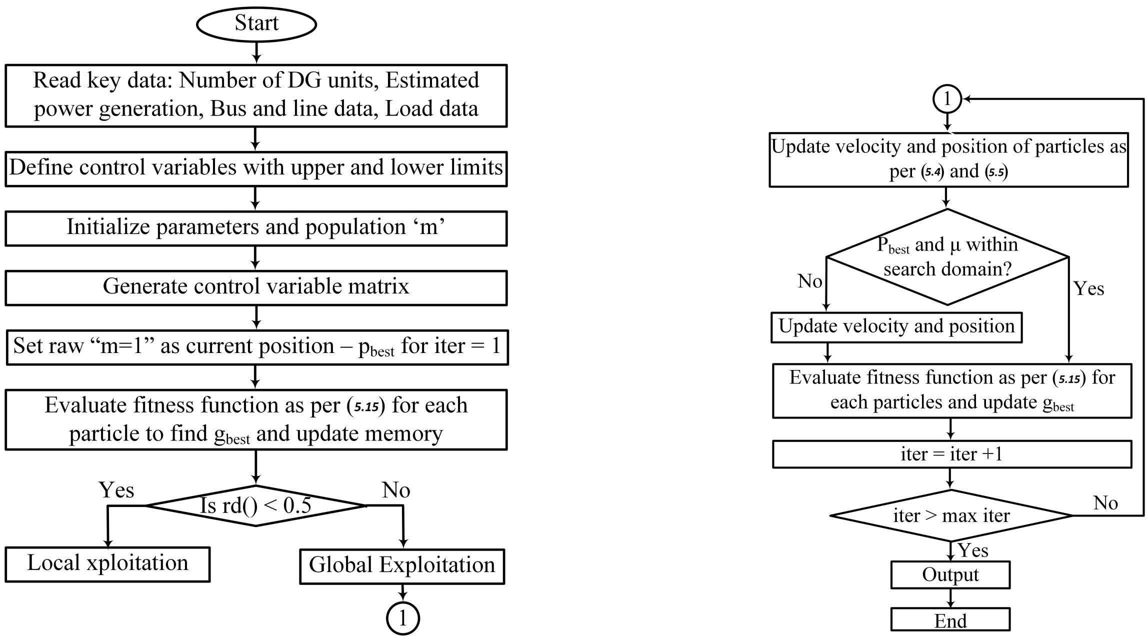

Figure 5.2: Flow chart represents proposed algorithm for optimal operation of Microgrid with Levy PSO

5.6 Simulation Result and Discussion

A Matlab code has been developed to simulate the proposed technique. As shown in Table:5.1, the discrete number of wind units and solar units, the daily solar irradiation range, and the probable mean wind speed range have been taken into account. The maximum and minimum limits of natural sources such as wind speed and solar irradiation for specific periods have been established by observing such data in the region near the Gulf of Cambay through [`http://niwe.res.in/`]and website [`https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html`].

For simulation, two mean wind speed ranges have been counted: 4m/s to 6m/s and 6m/s to 9m/s. During the execution of a program, the actual average power generation is obtained by creating random wind speeds ranging from zero to the upper range of the expected range of wind speeds.

The solar power generation limits have been predicted for the morning and evening hours when there is very little sun irradiation available, whereas a high value of solar irradiation has been recorded during the midday hour, and power calculations have been

Table 5.1: Renewable DG unit and estimated power generation data.

Type of DG Unit	Solar unit	Wind unit	Micro turbine unit
No of units and rating	1 unit of 100 Kw	2 units,each-2MW	1 unit 500 kw.
Estimated Hourly Average power generation kw/h/day	19-26 kw/h (Low irradiation range)	228-540 kw/h (wind speed range-4m/s to 6m/s)	Max 500Kw/h
	50-70 kw/h (High irradiation range)	540-700 kw/h (wind speed range-6m/s to 9m/s)	

Table 5.2: Cost data of natural power resources and storage devices.

Type of DG Unit/storege Device	cost coefficient
Wind turbine DG Unit	$\alpha_w = 0.0115$ \$/KWh
Solar panel DG Unit	$\alpha_s = 0.068$ \$ /kwh
Micro turbine DG Unit	α_{mt_1} =1.6e-6\$/kwh, $\alpha_{mt} = 0.2$ \$/kwh, $\alpha_{mt_0} = 1e-6$ \$/kwh
Storage charging and discharging	$C_{(char/dis)}$ =0.375\$/kwh
Penalty for under/over estimation	0.03 \$/KWh

performed by it. During programme execution, random solar irradiation between estimated ranges is generated to acquire the real average solar power output. The solar and wind generating units for the minimum and maximum estimated mean values of have been calculated using the approach described in chapter 2,3and 4. The details of the data are mentioned in Table:5.1.

The levelised cost of energy for a PV cell and an offshore wind turbine is taken into consideration, as specified in[118]. The cost co-efficient of a microturbine DG unit is shown in Table: 5.2 has been taken from [127]. The optimization problem has been solved for various scenarios predicated on renewable resource availability for the specified period, as seen in Table: 5.3. The program is executed by placing the DG into all possible

Table 5.3: Various Scenario of combination of solar and wind unit as per probable power generation.

	Scenario	Estimated Solar power Generation	Estimated wind power Generation
1	Solar unit lower range of irradiation period and wind unit with estimated mean wind speed-4-6 m/s available	19-26 kwh	220-540 kwh
2	Solar unit morning/evening period(lower range of irradiation) and wind unit with estimated mean wind speed- 6-9 m/s available	19-26 kwh	540-700 kwh
3	Solar unit at higher range of irradiation period and wind unit with estimated mean wind speed– 6-9 m/s available	50-70kwh	540-700 kwh
4	Solar unit at higher range of irradiation period and wind unit with estimated mean wind speed-6 to 8 m/s available	50-70 kwh	220-540 kwh

bus combinations (ncr). After attempting all possibilities of DG placement, the optimal result is determined when DG is placed at the combination of bus nos. 4, 6, 9, and 12. The problem has been solved for all possible scenarios and load circumstances. For a specific scenario (Table: 5.3), the solution of the fitness function has been determined.

For each scenario, random particles with $m = 100$ controllable variables within limits, solar and wind power generation between estimated ranges have been provided as input parameters at each level of the optimization program. The voltage magnitude and phase angle of each bus are considered controlled variables; hence, 24 are controlled variables, while the power generation of four DGs is put on bus nos. 4, 6, 9, and 12 (one optimal combination) are considered state variables. A matrix ($[mX28]$) has been formed. This

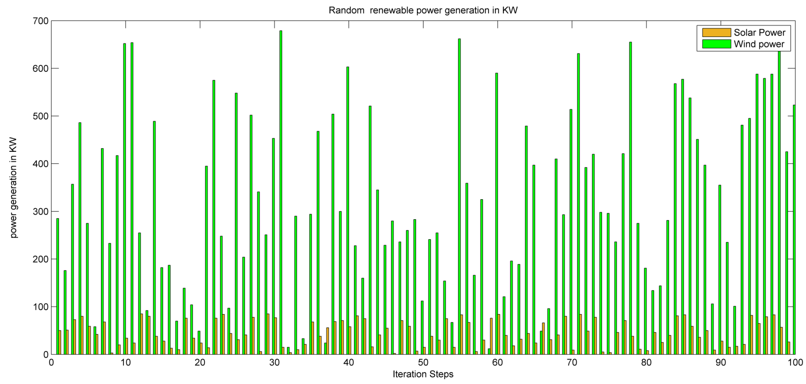

Figure 5.3: Actual wind and solar power generation by randomization

iteration step is repeated 100 times, resulting in a total of 10000 inputs used to find the best solution. Fig: 5.3 depicts the hourly average renewable power at the end of each step. The results of each step have been noted and verified. For each iteration step, a solution of the optimized function is obtained. The fig.5.4 shows g_{best} at each iteration step. For the given load conditions, the gbest corresponding to solar and wind power generation is within a narrow range for scenarios 1 to 4. Table:5.4 shows the mean g_{best} of fitness function for the 100 iteration steps, mean SBDI, system losses, and operating cost of electricity with optimum combination of natural power resources for efficient operation of the microgrid.

According to the results, operation costs and system losses have been lowered while maximizing the utilization of available natural resources. If the controlled variables received after running this software are preset and configured according to the loading situation and estimated natural resources, an optimum operation is attainable for every load condition. In this case, the operational cost per unit of hybrid power is greater than the levelised cost of solar and wind generating for any possible resource scenario. It is due to the cost of estimation error and the charging and discharging of storage devices, as well as the generation of microturbine.

It can be seen that the operating cost at peak load varies from 0.14474 USD/unit to 0.14144 USD/unit based on the situation of renewable source availability; this is a very small variance in operational cost. At peak load, the substation dependence index is positive, indicating that electricity would be sent to the microgrid from the substation. While for other loading conditions, power is fed to the main grid. It has been demonstrated

Table 5.4: Mean of Optimum fitness function, system operating cost, system losses and SBDI at various loading condition.

	Scenario	25% peak load KW	50% Peak load KW	75% Peak load KW	peak load KW
Best fitness function	1	16.2918	19.7538	22.0854	122.7594
	2	19.8265	12.5894	21.5289	130.6470
	3	15.2040	18.1925	24.0895	120.0811
	4	13.6568	23.0399	27.4478	118.1541
Operating cost of electricity ($/Kwh)	1	0.054636	0.106705	0.13753	0.14415
	2	0.046256	0.096204	0.1427	0.14474
	3	0.055300	0.093176	0.13430	0.142686
	4	0.13656	0.108511	0.139999	0.1414472
system active power losses(kw)	1	10.7457	8.97576	8.11740	13.4042
	2	5.14882	9.19587	6.8825	4.2434
	3	9.17070	8.40789	9.97642	2.6991
	4	7.60829	10.7179	5.9984	7.396
SBDI	1	−5.43266	−4.29652	17.771280	19.17176
	2	−13.8414	−9.9656	−2.2471	19.223
	3	−13.8141	−3.57017	−7.0972	19.46049
	4	−5.5533	−10.9262	−4.2965	17.77

that the most efficient use of natural resources,

The graph of the optimal value of these regulated voltages at the g_{best} point for a 25% load is presented in Fig: 5.5. At peak load, the system's total active power losses are reduced from 19.63 KW to 2.6991 KW (Table:5.4), and losses are reduced during the period of Scenario 3. Also, for all load conditions and scenarios, system's, total active losses are reduced.

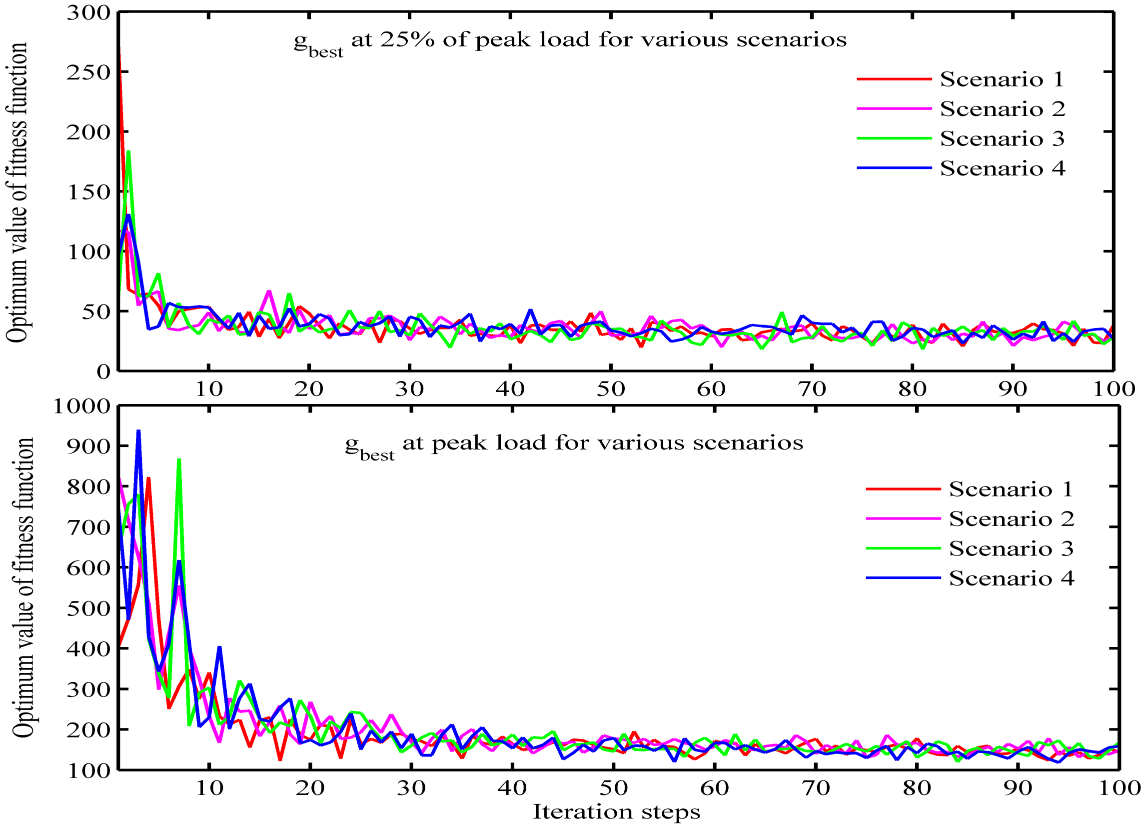

Figure 5.4: g_{best} at 25 % of peak load and peak load with various scenario

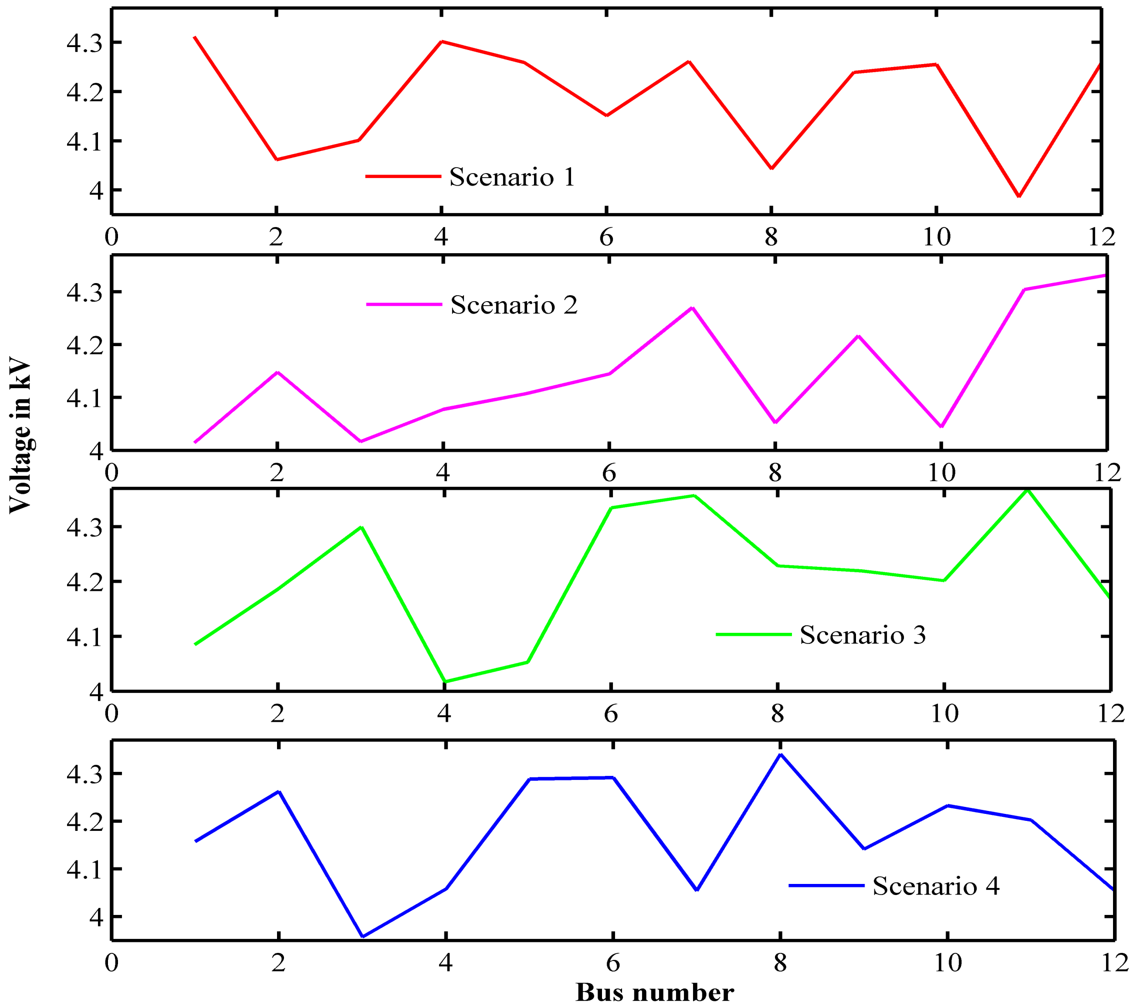

Figure 5.5: voltage at 25 % load with various scenario

5.7 Conclusion

The optimum integration of wind, solar, and microturbine units associated with storage devices is depicted in this study for optimal functioning. The Levy flight PSO has been used to determine the optimal solution of variables for maximum usage of renewable sources based on expected power generation. Especially compared to traditional PSO, this technique is much faster and simpler. This paper is mainly focused on the operation and maintenance cost of DG units and technical factors like losses, substation dependency, and stability, by determining the optimum value of bus voltage and phase angle within a limit. As a consequence, it may be adjusted to the optimal value to turn in the least amount of operation cost, power losses, and maximum use of renewable sources. Costs associated with controlling devices are not included in this study. it is possible to incorporate the cost of voltage and phase-controlled devices for improved microgrid operation in the same algorithm. The proposed technique will be used to deploy small-scale wind and solar power units in off-grid and grid-connected microgrid in diverse regions where resource availability is low to medium. This will be used to optimize the operation of off-grid and grid-connected microgrid in real-time.