OPTIMAL SIZING AND PLACEMENT OF ENERGY STORAGE IN COORDINATION WITH RENEWABLE DISTRIBUTED GENERATION

Ph.D. Thesis

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This thesis is submitted as a partial
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CERTIFICATE

This is to certify that Ph.D. candidate Mr. **Vaiju Nago Kalkhambkar** (*2012 RCV 9019*) presented and defended his thesis work orally before the oral board of examiners and satisfactorily answered all the queries. The candidate has satisfactorily incorporated all the suggestions and comments of the examiners. Therefore, the board recommends the award of Ph.D. degree in Centre for Energy and Environment of Malaviya National Institute of Technology, Jaipur to **Vaiju Nago Kalkhambkar**.

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This is to certify that the thesis entitled, **"Optimal Sizing and Placement of Energy Storage in Coordination with Renewable Distributed Generation"** submitted by **Vaiju Nago Kalkhambkar** (2012 RCV 9019) to Malaviya National Institute of Technology, Jaipur for the award of the degree of ***Doctor of Philosophy*** in Centre for Energy and Environment is a bonafide record of original research work carried out by him under my supervision.

It is further certified that:

1. The results contained in this thesis have not been submitted in part or in full, to any other University or Institute for the award of any degree.
2. Mr.Vaiju Nago Kalkhambkar has fulfilled the requirement for the submission of this thesis.

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ABSTRACT

Renergy sources, such as solar and wind, are considered as future energy sources due to their sustainability and environmental friendliness. High penetration of solar and wind RDG in the grid is targeted by several countries. However, it is difficult to maintain grid stability and reliability with high penetration of these sources, due to their high variability and weak predictability. Energy storage (ES) helps to address these challenges and support the evolution of a stable and green power grid. ES consists a broad range of technologies that include batteries, flywheels, pumped storage, heat storage and compressed air, including electric vehicles. Battery ES systems are easily scalable and can be deployed almost anywhere in the system, and thus find wider acceptability. ES offers several technical and economic benefits. The main technical benefits offered by ES include voltage support, frequency support, load leveling/peak shaving, spinning reserve, power quality improvement and power reliability. Economic benefits of ES include reduction in demand charges, reliability-related financial losses, and power quality-related financial losses. Strategic placement of ES offers multiple ways to enhance and optimize power system operation and planning.

RDG connection at non-optimal places with improper sizing increases power losses. Hence, a suitable allocation strategy of RDG and ES with the distribution system is required. Optimally sized and placed solar and wind RDGs employed in distribution networks reduce energy losses. Optimal allocation of RDGs in a distribution system for loss minimization is a challenging issue due to their intermittency. Hence, it is necessary to identify optimal sizing and placement of RDG in a distribution network. Further, hybrid RDG, i.e., combined placement of solar and wind RDG, enhances utilization of available energy resources and provides consistent energy generation.

Research work in this thesis is initiated by developing an optimal solution methodology, for sizing and placement of RDG, to minimize energy losses. A probabilistic generation model is developed. Load is modeled as per IEEE-RTS load model, where the hourly load is expressed as a percentage of daily peak load. Thus, a generation-load model is obtained. The number of states involved in generation-load state model are reduced with the proposed methodology to reduce involved complexity. The developed hourly generation-load model is used for optimal power flow. Then a generation-load model is developed for hybrid RDG allocation using expected generation of solar and wind RDG.

The proposed nonlinear, constrained optimization problem of optimal RDG allocation is solved with a robust and competitive Grey Wolf Optimizer (GWO) algorithm. The results are compared with another set of algorithms, i.e., GA, PSO, SOS, and FFA. This proposed methodology provide optimal solutions for allocation of single RDG as well as hybrid RDG. In the present study, optimal sizing and placement of wind RDG improve loss minimization, as compared to solar RDG and hybrid RDG. GWO offers a better solution than other algorithms, i.e., GA, PSO, SOS, and FFA. This optimal allocation technique can be applied to RDG planning.

Optimally allocated ES helps to reduce power losses in the distribution system. An effective way to reduce distribution losses with ES is peak shaving. Peak shaving is a process of shaving peak load and filling load valley. It shifts a part of the load from peak period to off-peak period, thus minimizing losses. The line flows are affected while integrating ES in the presence of RDG. Hence, it is essential to propose optimal sizing and placement of ES in the presence of RDG. In the proposed work, optimal sizing and placement of ES is obtained in the presence of RDGs, for energy loss minimization. It is observed that the proposed methodology minimizes energy losses.

Optimal allocation of ES, as well as the RDG, affect the line flows and hence the line losses. Therefore, a combined optimal allocation of ES and RDG is necessary to achieve significant energy loss minimization. The proposed methodology considers joint optimal allocation of solar RDG-ES, wind RDG-ES, and hybrid RDG-ES combinations. Joint optimal placement and sizing of ES and RDG provide significant loss minimization.

The thesis finally, proposes a joint optimal allocation methodology for ES and RDG to economize benefits. The joint optimal allocation of RDG and ES minimizes Distribution Company's (DISCOM's) cost, reduces DISCOM's network losses and increases revenue of RDG owner. DISCOMs purchase the renewable energy based on the long-term contract price. The contract price of renewable energy is a critical parameter that decides the economic benefits of RDG owner and DISCOM. The contract price of renewable energy needs to be considered in the joint allocation of ES and RDG, to achieve economic benefits. Hence, a methodology is proposed for joint optimal allocation of RDG and ES considering contract price of renewable energy. This joint optimal allocation of ES and RDG offers significant cost minimization for DISCOM. The proposed joint allocation methodology provides size and location of RDG and ES, considering the contract price of renewable energy. The RDG owner is encouraged to invest in RDG, by providing an assured economic benefit.

Thus, considering the environmental challenges and sustainable energy needs, the thesis addresses optimal sizing and placement of RDG and ES. The major objectives addressed in the thesis include i) Optimal sizing and placement of RDG for energy loss minimization. ii) Optimal sizing and placement of ES in-coordination with RDG for energy loss minimization. iii) Joint optimal sizing and placement of ES and RDG for energy loss minimization and iv) Joint optimal sizing and placement of RDG and ES for economic benefit. v) Application of GA, PSO, SOS, FFA and GWO algorithms for the proposed methodologies.

Significant finding of the thesis includes i) Energy loss minimization is obtained with optimal sizing and placement of solar RDG, wind RDG and hybrid RDG in the distribution network. ii) Optimal sizing and placement of ES at multiple sites in coordination with RDG provides energy loss minimization and also helps in peak shaving. iii) Joint optimal allocation of RDG and ES further improves energy loss minimization as compared to earlier two cases. iv) It is found that joint optimal sizing and placement of ES and RDG provides significant cost benefits to the DISCOM and RDG owner. vii) Comparing with all cases, i.e., solar RDG, wind RDG and hybrid RDG; wind RDG provides significant energy loss minimization. The Grey Wolf Optimizer (GWO) provides optimal solutions, as compared to other optimization methods, i.e., GA, PSO, SOS and FFA.

LIST OF ABBREVIATIONS

RES	Renewable energy sources
RDG	Renewable Distributed Generation
DISCOM	Distribution Company
ES	Energy Storage
RDGO	Renewable Distributed Generation Owner
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
SA	Simulated Annealing
ACO	Artificial Bee Colony
FFA	Firefly Algorithm
ACO	Ant Colony Optimization
GSA	Gravitational Search Algorithm
PV	Photovoltaic
GWO	Gray Wolf Optimizer
cdf	Cumulative Distribution Function
pdf	Probability Distribution Function
IEA	International Energy Agency
SOS	Symbiotic Organisms Search
SD	Standard Deviation
SOC	State of Charge

LIST OF SYMBOLS

F_β	Beta pdf
s	Solar irradiance
$\mathit{\Gamma}$	Gamma function
s	Random variable of solar irradiance kW/m^2
$\alpha\ and\ \beta$	Shape parameters of beta distribution function
μ	Mean deviation of s
σ	Standard deviation of s
I_y	Cell current at state y
V_y	Cell voltage at state y
T_{cy}	Cell temperature °C at state y
T_a	Ambient temperature °C
K_v	Voltage temperature coefficient V /°C
K_i	Current temperature coefficient A /°C
N_{OT}	Nominal operating temperature °C
f_f	Fill factor
I_{sc}	Short circuit current A
V_{oc}	Open circuit voltage V
s_{ay}	Average solar irradiance of state y
I_{MPP}	Current at maximum power point A
V_{MPP}	Voltage at maximum power point V
$F_w(v)$	Weibull pdf for wind turbine
k	Shape index
c	Scale index
v	Wind speed m/s

ρ	Air density
A	Rotor area in m^2
$p(v)$	Power generated by the wind turbine
$C_p(v)$	Power coefficient of wind turbine
v_{ci}	Cut-in speed of wind turbine m/s
v_{co}	Cut-off speed of wind turbine m/s
v_r	Rated speed of wind turbine m/s
v_{av}	Average speed of wind turbine m/s
$P_o(w)$	Power of wind turbine at state 'y'
$P(W)$	Expected power of wind turbine at state 'y'
P_{WG}	Total expected wind power at any time interval
P_{loss}	Power losses
P_i	Active at node i
Q_i	Reactive load at node i
I_i	Current through branch i
β_i	Set of branches connected to node i
P_{G1}	Injected active at substation
Q_{G1}	Reactive power at substation
P_{RDGEi}	RDG's forecasted power
P_i	Total active loads at i^{th} node
Q_i	Reactive loads at i^{th} node
$P_{Loss,b}$	Active power losses at branch b
$Q_{Loss,b}$	Reactive power losses at branch b
nb	Total number of branches.
$c_{s,i}$	Number of solar panels at i^{th} bus
P_{SG}	Solar PV generation
P_{SDGR}	Rating of solar PV module
D	Candidate bus
$c_{w,i}$	Number of wind turbines at i^{th} bus
P_{WG}	Wind power
P_{WDGR}	Rating of wind turbine

$c_{sh,i}$	Number of solar panels at i^{th} bus for hybrid combination
$c_{wh,i}$	Number of wind generators at i^{th} bus for hybrid combination
P^t_{load}	System load at time t
$P^{t,min}_{grid}$	Minimum power supplied by all the generators in the power system
$P^{t,max}_{grid}$	Maximum power supplied by all the generators in the power system
T	Total time period
dt	Time interval
η_c	Charge efficiencies of the battery
η_d	Discharge efficiencies of the battery
T_{dis}	Total peak time period
T_{ch}	Off-peak time period
$P_{B,ch}$	Optimal charging power for loss minimization
$P_{B,dis}$	Optimal discharging power for loss minimization
I_{Li}	Load current of node i
P_i	Active power of load at node i
Q_i	Reactive power of load at node i
β_i	All branches connected to node i
SOC_{min}	Minimum state of charge of battery
$P_{msh,t}$	Maximum power to shave
$T_{dis,t}$	Discharge time
C_{INVST}	Total investment cost
C_{IS}	Investment cost of solar RDG in $Rs.perMW$
C_{IW}	Investment cost of wind RDG in $Rs.perMW$
P_{ISG}	Total installed capacity of solar RDG MW
P_{IWG}	Total installed capacity of wind RDG MW
C_{OMS}	Operation and maintenance cost of solar RDG $RsperMW$
C_{OMW}	Operation and maintenance cost of wind RDG $RsperMW$
N_Y	Total number of years
R_{inf}	Inflation rate
R_{int}	Interest rate or discount rate
IN_{RDGO}	RDGO's profit from selling the generated electricity

CP_{RDG}	Contract price in Rs. per unit of electricity
P_{SDG}	Solar generated power
P_{WDG}	Wind generated power
$P_{RDGE,i}$	Expected power of RDG
C_E	Cost of energy in Rs. per unit
C_{IBE}	Total investment cost of battery
C_{OMBE}	Operation and maintenance cost of battery
C_{IBE}	Investment cost of Battery in $Rs.perMWh$
E_B	Total installed capacity of battery MWh
C_{OMB}	Operation and maintenance cost of battery $Rs.perMW$
P_{LS}	Annual energy loss minimization by solar RDG MWh
P_{LW}	Annual energy loss minimization by wind RDG MWh
C_{SEL}	Cost of energy losses for solar RDG $Rs.perkWh$
C_{WEL}	Cost of energy losses for wind RDG $Rs.perkWh$
P_{G1}	Active power injected at substation
Q_{G1}	Reactive power injected at substation
P_i	Total active power loads at ith node
Q_i	Total reactive power loads at ith node
$P_{Loss,b}$	Active power losses at branch b
$Q_{Loss,b}$	Reactive power losses at branch b
$n_{s,i}$	Number of solar RDGs
$n_{w,i}$	Number of wind RDGs
P_{SDGR}	Rated discrete size of solar RDG
$n_{w,i}$	Number of wind RDG at i^{th} bus
P_W	Expected wind power
P_{WDGR}	Rated discrete size of wind RDG
$n_{sh,i}$	Number of solar RDG in hybrid combination
$n_{wh,i}$	Number of wind RDGs in hybrid combination

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CHAPTER 1

INTRODUCTION

1.1 General

Renewable energy sources (RES) are the future of supply systems due to increasing concerns about air pollution, global warming, and reduction in fossil fuels. Market concerns of liberalization and governments incentives have further accelerated the growth of renewable energy sector. Over the last few decades, there has been a keen interest in many countries in renewable energy. As the energy demand is increasing rapidly, a transition from the traditional fossil-fueled generation to the generation based on renewable resources (e.g., solar and the wind) becomes crucial for future grid [1]. The potential of RES is to supply a large-scale electric power demand. It has been a growing area of research over the last decade because of energy independence, sustainability, and low-carbon technologies [2].

Integration of Renewable sources at distribution network is termed as renewable distributed generation (RDG). The utility has more concern about the high penetration of RDG in distribution systems. They are more concerned about network stability, voltage regulation, and power quality. Therefore, the RDGs have to fulfill technical and regulatory issues to ensure safe and efficient operation of the network [3]. RDGs such as solar and the wind are considered as promising energy resources due to the sustainability and environmental friendliness [4]. Also, the technical and economic benefits have led to the increased interest in RDG. RDG can be strategically placed in power systems for reducing power losses, improving voltage profiles, deferring system upgrades and improving system efficiency [5].

The renewable sources are variable energy resources which affect the reliable operation of power system. The effect of the variability can be mitigated by using i) demand-side management, ii) generators with high ramp rates, and iii) energy storage devices. If demand is managed efficiently so that the net injection remains close to the energy of forecast, the power system operation is not affected by the variability of renewable energy resources. For a system with a high penetration of renewable energy resources, demand-side management alone is enough to mitigate the resource variability. Hydroelectric power plants have a high ramp rate, but they are built in limited locations and their operation is limited due to environmental constraints. The other types of generators using gas fuel have high ramp rates. If the number of these generators are increased according to the penetration of renewable generators, then the resulting system becomes highly inefficient. Energy Storage (ES) devices provide enough flexibility to mitigate the impact of variable output of the variable generations. ES devices are attractive candidates to control the resource variability [6]. There are two significant challenges in integrating the wind and solar power into the power system. First, their output fluctuates widely, rapidly and randomly that creates operational problems. Secondly, the geographical locations of the wind and solar farms are certainly far from the load centers. These two problems demand the large-scale storage that can absorb short-term fluctuations and enhance transmission capacity. It also provides spatial diversity in the generation to mitigate intermittency of renewable sources [7].

1.2 Motivation for the Present Work

The benefits of RDG mainly depend on its size and location into the distribution network. Despite its RDG benefits, installing the RDG into the distribution network is not to simply place and operate issue. The placement of RDG requires a careful consideration of interaction with the power network. They have to consider stability, reliability, power quality issues, energy losses, etc. First of all, it is important to determine the optimal location and size of a given RDG before it is connected to a power system. With the increased penetration of RDG into the network, the power losses minimization also become the main issue. However, the systematic and paramount rule for optimal sizing and placement of RDG is still an open question.

The inherent intermittency of RDG requires the support of Energy Storage [8]. Optimal sizing and placement of Energy Storage provides economic benefits and energy support to the system [9, 10, 11, 12, 13, 14]. In addition to the energy support, the integration of Energy Storage in distribution system also provides voltage support, distribution loss reduction, capacity support and deferral of distribution investment [15, 16]. Storage related problems such as, increasing the capacity of the storage device, efficiently allocating energy storage to minimize curtailment of renewables has also been studied. However, it is necessary to address the potential and limitations of large-scale energy storage [17].

The optimal sizing and placement of the energy storage in the distribution system is an important aspect to maximize the benefits of the system. The inappropriate energy storage sizing and placement cause under or over voltages in the distribution network. Energy storage also affects the system energy losses due to its proximity to the load centers. Therefore, it is necessary to get an appropriate location in the distribution system to install energy storage to obtain the optimal effects. The energy storage should be located on a bus, where they provide a higher reduction in the losses without violating the system constraints such as the bus voltages [18].

The benefits of energy storage for energy loss minimization is also little addressed. Significant energy loss minimization and hence corresponding economic benefits can be obtained by optimal sizing and placement of Energy Storage in the distribution network. The previous works mainly address the optimal sizing and placement of renewable distributed generation. Also, a few has dealt with the optimal sizing or placement of energy storage for energy loss minimization. The combined integration of RDG and ES into the systems affects the system power flows hence their combined effect must be considered while considering the energy losses. Hence joint optimal allocation of RDG and ES for energy loss minimization is an important planning issue. Similarly, the joint optimal allocation of RDG and ES should be addressed while considering the economic analysis. The economic analysis should consider the benefits of RDG Owner and Distribution Company (DISCOM). While considering the cost benefits of the DISCOM, RDGO must get some assured benefits to encourage the RDG owner for the investment in Renewable Distributed Generation.

Considering the above facts, there is a need for optimal sizing and placement methodology for Renewable Distributed Generation and Energy Storage. The joint optimal allocation of Renewable Distributed Generation and Energy Storage must be addressed to obtain significant energy loss minimization. Also, a methodology for joint optimal allocation of Renewable Distributed Generation and Energy Storage must be proposed to achieve economic benefits of both, RDG owner and DISCOM.

1.3 Contribution of the Present Work

The ultimate goal of the work adopted in this thesis is to tackle the problem of distribution system planning with Renewable Distributed Generation and Energy Storage for energy loss minimization and economic cost benefits.

Following is a summary of the contribution of the present work

1. From the critical survey of literature about optimal allocation of distributed generation, an overview of optimal sizing and placement of ES and RDG is presented. The detailed study helps to understand the issues associated with optimal sizing and placement of ES and RDG for energy loss minimization and economic benefits.

2. Initial part of this thesis work develops a methodology for optimal sizing and placement of RDG for energy loss minimization. The proposed methodology uses a probabilistic approach to obtain the expected RDG generation considering the seasonal variation of the generation. The expected generation for hybrid

RDG (*i.e.*, solar RDG and wind RDG operated in combination) is also proposed using the generations of solar RDG and wind RDG. The robust and competitive algorithm is applied for the proposed methodology to obtain optimal solutions for the sizing and placement of RDG.

3. The ES technology has been enough matured and it is available in grid scale rating. Hence, energy storage can be viewed as an opportunity for energy loss minimization. The optimal sizing and placement of energy storage are proposed for energy loss minimization. Significant energy loss minimization is obtained with the proposed methodology.

4. The placement of RDG and ES affects the power flows in the network. Therefore, optimal sizing and placement of the RDG and ES should consider the joint allocation of these two energy sources. Considering this fact, a methodology for joint optimal allocation (*i.e.*, sizing and placement) of RDG and ES for energy loss minimization is presented.

5. The optimal sizing and placement of grid-scale energy storage are addressed by many researchers to achieve economic benefits. Similarly, the cost-benefit analysis for RDG is also presented by various methodologies. Considering the effect of combined placement of RDG and ES in the network, economic analysis must take into account their combined placement. The thesis develops a methodology to achieve economic benefits by joint optimal sizing and placement of RDG and ES. The proposed methodology considers the cost minimization of DISCOM while assuring the benefits to the RDG owner.

1.4 Organization of the Thesis

The Ph.D. thesis consists of seven chapters, including introduction and conclusions. The research approach is to formulate first, optimal sizing and placement of RDG for energy loss minimization. Thus the size and location of RDG are kept as decision variables in the optimization. Next, optimal sizing and placement of ES for energy loss minimization is analyzed in the presence of the optimally allocated RDG. The size and location of ES are the decision variable. Afterward, the joint optimal allocation of RDG and ES is presented where size and location of RDG and ES are decision variables. Thus, in the joint optimal allocation of RDG and ES, four decision variables are included in the optimization problem. Finally, the economic benefit of RDG owner and distribution company (DISCOM)is analyzed by a joint optimal allocation of RDG and ES.

This chapter presents mainly the motivation of current work and contribution of the thesis. The rest of the chapters of this thesis are organized as follows:

Chapter 2 presents a literature survey on optimal sizing and placement of energy sources for energy loss minimization. It mainly provides the literature review on optimal sizing and placement of RDG for energy loss minimization, optimal sizing and placement of ES for energy loss minimization, optimal sizing and placement of combined RDG and ES for energy loss minimization. Finally the literature review on optimal sizing and placement of RDG and ES to obtain cost-benefit analysis is presented.

Chapter 3 proposes an optimal sizing and placement methodology for RDG for energy loss minimization. It includes the modeling of solar RDG, wind RDG and load modeling. A robust and competitive grey algorithm called grey-wolf optimizer is applied to the proposed methodology. The results of optimal allocation are discussed in details.

Chapter 4 presents optimal sizing and placement of Energy Storage for energy loss minimization. In this Chapter, the modeling of battery energy storage is performed. The detail results are presented on optimal sizing and placement of energy storage for energy loss minimization.

Chapter 5 proposes a joint optimal allocation methodology of RDG and ES. The size and location of both RDG and ES are optimized to achieve energy loss minimization. The proposed methodology is applied to three cases, *i.e.,* solar RDG-ES, wind

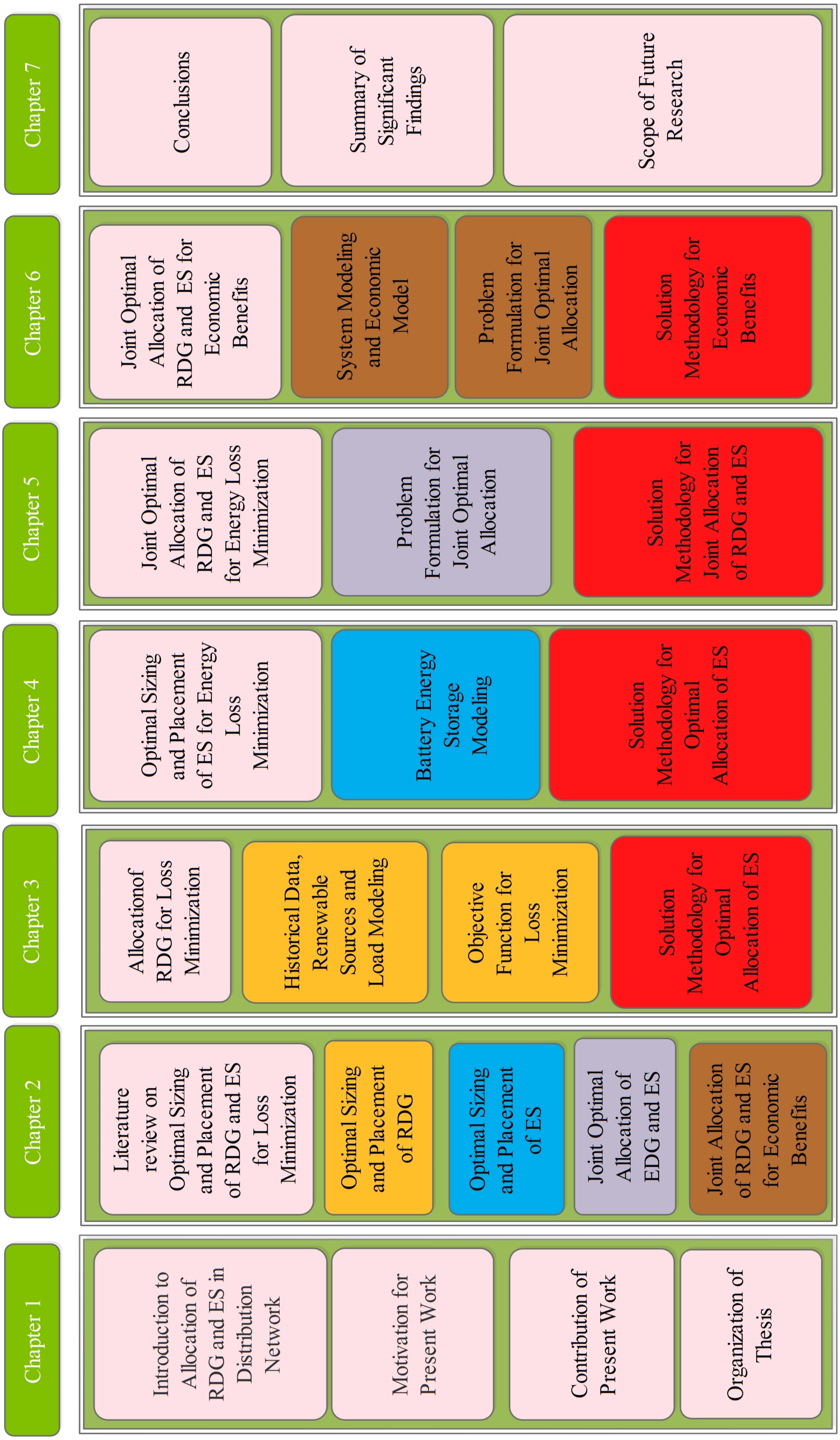

Figure 1.1: Thesis organization.

RDG-ES, and hybrid RDG-ES combinations. The results highlight the significance of joint optimal allocation technique.

Chapter 6 proposes cost-benefit based joint allocation of RDG and ES. The RDG and ES are jointly placed and sized to obtain economic benefits to RDG owner and DISCOM. The economic model mainly includes the RDG owners costs and benefits, DISCOM's costs and benefits. The sizing and location of RDG and ES are obtained such as the cost of DISCOM gets minimized.

Chapter 7 summarizes the main findings of the work presented in this thesis and suggests directions for a future scope in this area.

Finally, *AppendixA* provides the publications obtained from the thesis.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

The traditional approach of power generation by centralized power plants with extensive transmission and distribution network is changing to dispersed generation. These generators are integrated into power systems at the distribution level. Modern electric power distribution utilities are under the pressure of expansion of networks to fulfill the load growth of their consumers. To meet these objectives, there is a need for distributed energy sources. Distributed generation includes renewable and non-renewable energy sources. The recent technological progress resulted into many advantages of distributed generation that includes low capital cost, environment friendliness, easy to place, modular size, short lead. Distributed generation mainly serves one large customer or several customers close to each other. Therefore, it reduces distribution losses, improves system voltage profile, relieves heavily loaded feeders and extends equipment life [19, 20]. Table 1. shows the various benefits of distributed generation.

Incentive-based regulation for the network with higher performance is the another driver for power loss minimization in distribution networks. Traditionally, loss minimization is achieved by network reconfiguration or reactive power support through capacitor placement. However, the transition from passive distribution networks to

Table 2.1: Benefits of distributed generation.

Reliability improvement	Voltage profile/ quality improvement	Line loss/ energy reduction	Security enhancement
1. Improved power system reliability 2. Reduced capacity release 3. Improved generation diversity 4. Peak power reduction	1. Voltage quality improvement 2. Voltage profile improvement 3. Reduced voltage flicker 4. Voltage support and better regulation	1. Reduced line losses 2. Better control of reactive power	1. Enhanced security of the critical loads 2. Reduced security risks to grid 3. Improved utilities security 4. Reduced cyber attacks, terrorist-attacks

active provides an opportunity for energy loss minimization. Optimal sizing, placement and operation of distributed generation to minimize energy losses has attracted the interest of research community in the last 15 years [21].

This chapter provides a comprehensive literature review on optimal sizing and placement of RDG and ES. First, the literature review on optimal sizing and placement of RDG for energy loss minimization is presented. Then the literature on grid scale ES and distributed ES optimal sizing and placement is presented. Next, the literature review on the joint optimal allocation of RDG and ES is presented. Finally, the joint optimal allocation of RDG and ES for economic benefit is presented. The major limitations and gaps found from the literature review are also highlighted at appropriate places of the literature review.

2.2 Renewable Generation Technologies

RDGs are power generation resources connected to the distribution systems. The RDG technologies mainly includes solar power, wind power, geothermal power, biomass, small-hydro, mini-hydro and micro-hydro power. RDG power can be supplied to the grid or to serve a local load. World Energy Council have predicted that the global power output from RES will increase from 23% in 2010 to about 34% in 2030 [22].

Two prominent RDG technologies *i.e.*, solar PV and wind are discussed in the next section. The thesis considers the optimal sizing and placement of these two sources and their hybrid combination.

i) **Wind Power Generation system:**

Wind energy system converts wind power to electrical power. Ti mainly consists generator, rotor, blades and an control circuit interface [23]. The output power of wind sturbine depends on the wind speed and the height of the wind turbine above the ground [24, 25].The wind speed is proportional to the kinetic energy of the wind [26]. Site having good wind resources produces electricity at the optimal cost. The power system planners must go for proper wind resource assessment and environmental impact assessment [27]. The wind systems have no green hose gas (GHG) emission, low cost of installation, no fuel cost and maintenance costs and supply of reactive power [28]. Renewable generation owner should consider the availability of land, availability of distribution lines and understand the wind energy economics. Power outage mitigation and GHG effect lead to rapid acceptance of wind energy systems. Global generation of wind power is supposed to reach about 2000 GW by 2030 with emissions reduction of 3 billion tons per year by 2030 [29].

ii) **Solar PV generation systems:**

The PV generation consists an arrays of photovoltaic cells that converts solar energy into electrical energy [30]. The output of PV cell depends mainly on the solar insolation. It is is a potential source of energy due to the environmental friendly nature of solar PV generation. Solar PV systems can independently supply a specific load or it can operate in parallel with the utility grid to shave the peak load [31]. The main advantages of solar PV generation for a power system includes easy installation, energy independence, environment friendliness, longer life and minimum O & M costs [32]. It is widely accepted that solar energy can reduce the dependence on the fossil fuel based power generation. The solar PV system also improves the security of power supply as it is not affected by the variation in fuel prices. International Energy Agency (IEA) has predicted that the global power output from solar PV will increase from 140 GW in 2014 to about 872 GW in 2030 [33].

2.3 Optimal Sizing and Placement of Renewable Distributed Generation

The increased power demand has set the trends towards the utilisation of renewable energy. Utilities are using decentralised energy sources so that RDG can be directly connected into distribution network. RDG provide environmental, technical and economic benefits to the distribution system and consumers. Also, RDG integration is increased due to the deregulation of the electricity market [34]. The benefits achieved by RDG integration depend on the optimal sizing and placement of RDG [21]. To achieve the maximum benefits from RDGs penetration, strategic approaches must be carried out for optimal sizing and location of RDG [35]. The loss minimization with optimal sizing and placements obtained with two broad approaches: minimization of power losses and minimization of energy losses.

1. Minimization of Power Losses

   This approach is extensively used when considering passive networks , *i.e.*, without RDG. With this approach it is not possible to determine the actual impact of variable forms of RDG (*i.e.*, wind RDG and solar RDG). The reduction of losses brought by the optimal sizing and location of RDG during maximum demand might not occur at other loading levels, resulting in non-optimal energy losses. This effect is mainly observed due to the inherent variability of loads. This power loss minimization approach has been addressed using analytical methods [36, 37, 38, 39], classical methods [40, 41, 42], metaheuristics [43, 44], impact indices [20, 45], and other techniques [46, 47, 48].

2. Minimization of Energy Losses

   Loss minimization with optimal allocation should consider energy losses due to the variability of both; demand and generation for a given horizon [49]. Modeling

RDG is adopted for energy loss analyses using tabu search [50], genetic algorithm based multi-objective approaches [51, 52] and impact indices [53]. GA-based multiobjective technique is applied for active network management and energy loss minimization. Energy loss minimization was also studied through the optimal mix of renewable sources [13]. RDG on energy losses depend on the network topology, and the location of generation sources. (*i.e.* firm or variable). These involved complexities into an optimization makes the optimal allocation of RDG as a challenging task [21].

Analytical methods, results in increased computational efforts with sub-optimal solutions [54, 55, 56]. Weighing factors method offer optimal solutions; however quality of solutions are affected by choice of weighing factors [57]. Probabilistic methods with large 'generation-load' states involves clustering methods. Clustering obtained by an iterative process may converge to local minima, to produce sub-optimal solutions [58]. Intermittent generation of hybrid RDG is obtained probabilistically using convolution process. [13]. A large number of states involved in convolution and 'generation-load state' models affects the quality of optimal solutions. This underscores the necessity of optimal sizing and placement methodology of RDG to provide optimal solutions. The optimal allocation problem having very large search space requires a methodology to explore the search space for obtaining optimal solutions [59]. This motivates to propose an optimal sizing and placement methodology of RDG for energy loss minimization.

The heuristic search methods are extensively used in power system problems that involve optimal sizing and placement methodologies. These methods mimic the behaviors of the natural phenomenon to find a solution for problems which are difficult to solve by classical methods [60]. The optimal allocation of RDG mainly mixed integer and the nonlinear problem that can be solved using heuristic search methods. The optimization algorithms used for optimal placement and sizing of DG mainly includes genetic algorithm (GA) [61, 62, 63, 64, 65] particle swarm optimization (PSO) [66, 67], Simulated Annealing (SA) [68], Artificial Bee Colony (ABC) [69] and Firefly Algorithm [70]. The hybrid combination of algorithms such as GA and Tabu search [71], Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) [72], (PSO) and Gravitational Search Algorithm (GSA) [73] are also used for optimal allocation of RDGs. In this thesis, a robust and competitive algorithm called Gray Wolf Optimizer(GWO), is applied to the proposed optimal sizing and placement methodology.

2.4 Grid Scale Energy Storage(ES)

ES forms an integral part of modern power systems. It can be placed at various locations in the distribution network and at the customers side. The traditional electricity value chain system is changed with the integration of ES systems as shown in Figure 2.1 [74].

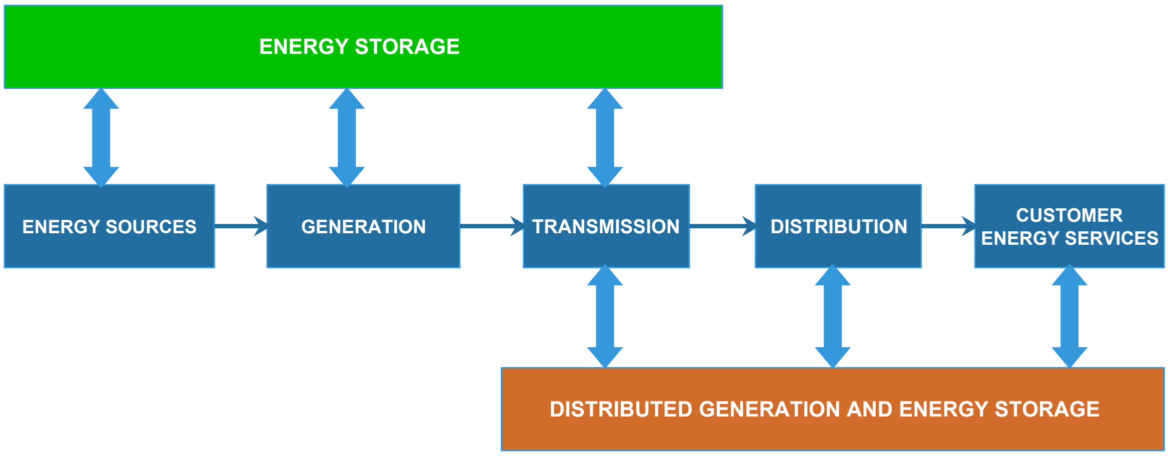

FIGURE 2.1: Classification of ES technologies based on form of stored energy.

The increased penetration of RDG in deregulated power system necessitates the use of ES. It makes a balance between generation and demand improving the performance of whole power system. Also, in collaboration with RDGs, the ES can be integrated into distribution networks to bring ancillary services for the power system and hence enables an increased penetration of RDG[75]. Afterward, the stored energy is converted back into electrical energy [76]. The following section gives the classification of various ES technologies.

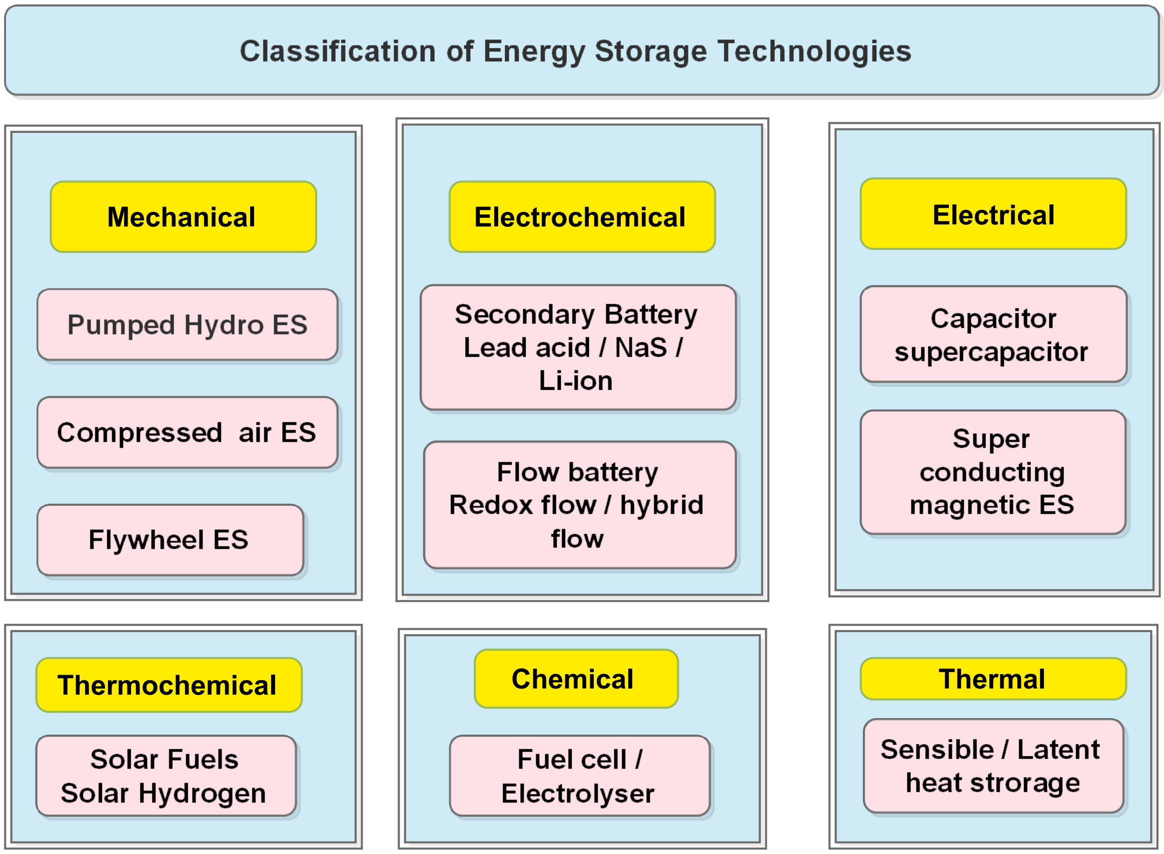

FIGURE 2.2: Classification of ES technologies based on form of stored energy.

ES technologies are mainly classified in terms of their functions and storage durations [76, 77]. The most widely used classification is based on the form of energy stored in the ES system as shown in Figure 2.2 [78, 79].

Based on the form of energy stored, ES can be classified into mechanical (pumped-hydro ES, compressed air ES and flywheel ES), electrical (super conducting, capacitors and magnetic energy storage), electrochemical (rechargeable battery ES and flow battery ES), thermo-chemical, chemical and thermal energy storage. A brief description of each type of ES technology is given in the next section.

A. **Pumped Hydroelectric Storage (PHES):**

PHES is a technology with high technical maturity and large energy capacity. With an installed capacity of 127.129 GW in 2012, PHES contributes to about 3% of global generation [26,28,29]. A typical PHES plant uses two water reservoirs.

During off-peak hours, the water is pumped into the upper level reservoir and during peak hours, the water is released back into the lower level reservoir. The energy stored depends on the difference between the heights of reservoirs [80]. The PHES plants have power ratings from 1 MW to 3003 MW, and efficiency about 85% [76, 81].

B. **Flywheel Energy Storage (FES):** FES system consists a flywheel, bearings, a reversible electrical motor/generator set, power electronic unit and a vacuum chamber [82]. Electricity is used to accelerate or decelerate the flywheel through an integrated motor/generator set. For reducing wind shear and energy loss from air friction, the FES system is placed in a high vacuum environment. The amount of energy stored dependents on the speed and inertia of the flywheel. FES is classified into low-speed FES (below 6000 rpm) and high-speed FES (up to 100000 rpm) [83]. Low-speed FES is used for short-term and medium/high power applications whereas high-speed FES are used in high power quality applications [84]. FES is used to supply power for a short time and can not be used as standalone backup power. The FES devices suffer from idling losses [85].

C. **Compressed Air Energy Storage (CAES):**

CAES is a commercialized ES technology producing power output of over 100 MW. A reversible motor/generator is driven to run a compressors to inject air into a storage vessel. Thus energy is stored in the storage vessel in the form of high-pressure air. During high power demand, the stored compressed air is released and heated. CAES applications involve load shifting, peak shaving, and voltage and frequency control. Also, CAES mainly works with RDG to smooth the output power [86, 87, 88, 89]. The major limitations to implement large-scale CAES is to get suitable geographical locations and low round-trip efficiency.

D. **Capacitor and Super-capacitor Energy Storage:**

In a capacitor, energy is stored in an electrostatic field [76, 90]. They are suitable for storing the small amount of energy. Capacitor storage have high power density and low charging time compared to battery energy storage [91]. They have low energy density and high self-discharge losses [76, 90]. Capacitors are used mainly for power quality applications.

Supercapacitors are named as ultracapacitors or electric double-layer capacitors. They have two electrodes, an electrolyte and a porous membrane [92]. Supercapacitors have both the characteristics of capacitors and battery ES. Their power and energy densities are between batteries and capacitors [93, 94]. Supercapacitors are suitable for short-term storage applications e.g. UPS devices.

E. **Superconducting Magnetic Energy Storage (SMES):** SMES consists a superconducting coil, a power conditioning system, and a refrigeration and vacuum system [92, 95]. The SMES stores electrical energy in the magnetic field created by the DC current in the superconducting coil cooled to a temperature below its superconducting temperature. A commonly used superconducting material is Niobium-Titanium having a superconducting critical temperature of 9.2 K [76]. SMES releases the stored energy back to the AC system, using power converter whose magnitude depends on the self-inductance of coil [96]. SMES has relatively high power density, fast response time, quick discharge time, high cycle efficiency and longer lifetime [97, 98]. The drawbacks include high capital cost and high daily self-discharge. SMES is suitable for short-term power and energy applications. It is a more suitable ES with intermittent RDGs [95].

F. **Thermal Energy Storage (TES):**

A TES consists of a storage medium in a reservoir, refrigeration system, pump, and controls. TES are classified into low-temperature TES and high- temperature TES [99, 100, 101]. Low-temperature TES normally uses water cooling and reheating processes. This is more suitable for peak shaving applications [76]. TES have different features depending on the applications e.g. latent heat storage provides relatively high storage density and used in buildings [102]. TES has been used in load shifting and electricity generation for heat engine cycles.

G. **Hydrogen Storage and Fuel Cell:** Hydrogen ES uses two separate processes for storing energy and producing electricity. Generally, water electrolysis is used to produce hydrogen which is stored in high pressure containers. The stored hydrogen is used for electricity generation with the help of the fuel cell. Fuel cells convert chemical energy into hydrogen and oxygen to electrical energy [92, 103] . The electricity generation using fuel cells is a less polluting and more efficient approach [104]. It has a compact design and easy scaling (*i.e.*, from 1 kW to hundreds of MW) [105]. Fuel cells combined with hydrogen storage can provide stationary or distributed power and transportation power [106].

H. **Battery Energy Storage (BES):**

BES is most widely used energy storage technology. Batteries are used for various applications such as used in different applications like power quality and energy management systems [97]. The location for installation of ES are flexible *i.e.*, it can be located close to the load but they have low cycling times and high maintenance costs. The various types of BES includes Leadacid batteries, Lithium-ion (Li-ion) batteries, Sodiumsulfur (NaS) batteries, and Nickelcadmium (NiCd) batteries.

A redox flow battery is a secondary rechargeable battery in which energy is stored chemically in liquid electrolytes (*i.e.*, sulfuric acid) containing different redox couples. There is also a separate storage tank which pumps the electrolyte into flow cells across a proton exchange membrane. The power of the flow battery is determined by the electrodes size and the number of cells ; whereas the storage capacity is determined by the amount and concentration of electrolyte [107]. The various types of flow batteries, *i.e.*, vanadium redox, zinc bromine and polysulfide bromine are potentially used for utility ES applications. The other applications of flow batteries include enhancing power quality, improving load leveling, power security and supporting intermittent generation of RES.

Currently, research on leadacid batteries focuses on performance improvement and battery technology applications for wind and photovoltaic power integration. Amongst all battery types, the lead-acid battery is the oldest and mature technology. It has been widely used for a majority power system applications [76]. Lead acid battery storage is considered in the proposed problem formulation of this thesis.

2.5 Application & Selection of ES in Power System

This sections explains the application and selection criteria of ES in power system.

2.5.1 Application of ES in Power System

ES in the power system has diverse and multiple applications. ES is very important in growing renewable energy penetration level, frequency control, voltage uctuations mitigation and power quality improvement. The important application of energy storage to the power system is briefly explained here.

1. **Increasing penetration of RDG:** RESs are environment friendly but the intermittent nature of some RESs such as solar and wind results in the voltage and frequency oscillations. Thus, the integration of RESs creates new challenges in the operation of the power system [108, 109]. The intermittent RDG can be supported by ES integration to smooth the intermittencies [105, 110, 111]. A large and reliable ES can provide an opportunity to tackle intermittent RDG in collaboration with power grids to meet the requirements for a more sustainable future [112].

2. **Emergency power:** ES can supply power to important users in case of power failures [113]. Emergency power requires instant response and longer power discharge [113, 114, 115]. The telecommunications back-up applications instant response time is required [116].

3. **Ramping and load following:** ES provides support in following load changes to electrical demand [117, 118]. ES trial project with battery storage are build that offers load following and voltage support [119].

4. **Peak shaving and load levelling:** In peak shaving ES supplies energy during peak hours and it get chargeded during off peak period and provide economic benefits by avoiding use of energy during peak hours [120].

Load leveling balances the fluctuations associated with energy demand. The benefits of ES in peak shaving and load following requires reduction in overall cost and increased cycling times competitiveness [121, 122, 123, 124].

5. **Black-start:** ES can provide system start up from a shutdown without taking power from the grid. A typical example is to provide black-start power to a nuclear power plant [125, 126].

6. **Voltage regulation and control:** The changes in active and reactive power affect the voltage profile in networks [127]. ES technologies are used for voltage control solutions [128]. Flywheel ES is used to regulate DC voltage on a network [129].

7. **Spinning reserve:** When a fast increase in generation results in a contingency, ES functions as spinning reserve. The ES responds immediately and maintain the outputs for few hours [92, 130, 131] .

8. **Transportation applications:** ES provides power to transportation applications, *i.e.*, hybrid electric vehicles (HEVs) and electric vehicles (EVs). The ES should have high energy density, modular and light weight and fast response [132, 133, 134, 135]. In an another application, ES using a fuel cell, battery, and supercapacitors is used for power train [132].

9. **Uninterruptible Power Supply (UPS):** ES provides uninterruptible power to maintain electrical power during the power interruption. A typical UPS offers instantaneous power by supplying energy stored in batteries flywheels or supercapacitors [85, 136, 137, 138].

10. **Standing reserve:** Standing reserve balances the supply and demand of electricity for a stipulated time. ES provides extra generation to the grid for a short duration. Also, it can be used when the actual demand exceeds the forecast demand [139, 140].

ES integration provides potential benefits to power system. Integration of ES has some significant challenges that include, selection of suitable ES technology to match the power system applications, evaluation of technical and economic benefits of ES and cutting down the cost of ES technology to an acceptable level [79]. To achieve these benefits, optimal sizing and placement of ES is an important task. The various methods of optimal sizing and placement of ES to achieve these applications are discussed in the next section.

2.5.2 Selection Criteria of ES in Power System

The criteria for energy storage device selection is as given below [141]:

- **Unit Size:** Scale of technology decides the storage system, e.g. large storage technology can support grid-connected renewable energy sources.
- **Storage Capacity:** Storage capacity is the total available energy after charging ES.
- **Available Capacity:** Average value of output power based on SOC.
- **Self-discharge Time:** It is the time to reach a certain depth of discharge for a fully charged and idle, (i.e., nonconnected) storage device. This decides the operational condition of system.
- **Efficiency:** This affects the energy input issue of conversion technology and energy storage.
- **Life-cycle:** Number of charge-discharge cycles a storage can undergo, while maintaining other specifications within its limits.
- **Autonomy:** It is the maximum number of time for which the system can continuously release energy. Autonomy is the ratio of energy capacity to maximum discharge power.
- **Mass and Volume Density:** It is energy stored per unit mass or volume of the energy storage.
- **Cost:** It is the O&M Cost and installation cost of energy storage technology.

- **Reliability:** It is guarantee of service provided by energy storage.

Additional information required for the selection of ES include monitoring and control equipment, operational constraints, environmental impacts, simplicity of design, operation flexibility and response time.

2.6 Optimal Sizing and Location of Energy Storage

There is no unique solution or application for sizing and placement of ES due variety of ES technologies with different technical and economic constraints. ESS are mostly selected and optimized based on their power rating (MW), energy rating (MWh) and location in the distribution network. The sizing and placement of ES determined by many methods. It can be classified into four main groups as based on literature review found *i.e.,* analytical methods, mathematical programming methods, exhaustive search methods and heuristic methods.

2.6.1 Analytical Methods

Analytical methods use predefined network and operational constraints. Analytical methods are used for the optimal sizing of ES to balance the generation of RES [142, 143, 144]. These methods are generally used to capture benefits of energy arbitrage using historical load demand curves [145, 146, 147, 148, 149]. or statistical data analysis [150, 151, 152, 153]. These methods do not include network constraints.

2.6.2 Mathematical Programming

Mathematical programming uses different numerical methods to find optimal solutions. In ES sizing and placement, mathematical programming is used to solve operational issues such as unit commitment and optimal power flow problems. Linear programming, is a special case of mathematical programming. It is an efficient method that provides single global optimum solution keeping the objective function and constraints linear.

Optimal sizing and location problems require combinatorial effort which makes sizing and siting problems NP hard (Non-deterministic Polynomial time hard). Mathematical programming becomes impractical for large power systems. Using LP methods improvements in islanded systems is obtained with pumped storage and system constraints [154]. Mixed Integer Linear Programming (MILP) is used to solve Unit Commitment(UC) problem. Diesel generator with ES backup can provide additional savings in the system [155].

2.6.3 Exhaustive Search Methods

Exhaustive search method provides optimal solution in a limited discrete search with large computational time. Simultaneous sizing and placement problem are unsolvable by exhaustive search method due to the its NP hard nature. Exhaustive search method is used to determine ES power and energy capacity [156]. Exhaustive search method is used to find solar PV and ES size for cost minimization[157]. Exhaustive search is used to determine battery power and energy capacity in frequency support application [158]. ES charging discharging power is obtained to minimise battery charge discharge cycles [159]. UC problem is solved with exhaustic search to obtain power and energy rating of ES [9]. Costbenefit based optimal size of ES is obtained with exhaustive search method [160]. ES size is obtained to provide primary frequency control [161]. Optimal ES size is determined with stochastic UC and MILP optimisation [156].

2.6.4 Heuristic Search Methods

Heuristic search methods have become very popular for computational methods. They are robust and widely accepted methods. The work using heuristic search methods are highlighted here. GGA combined with optimal power flow maximise wind power utilisation and enables large penetration of RDG [162]. PSO is used for network expansion problem to minimize operational costs. [163]. Better energy procurement and loss minimisation is obtained with ES using Fuzzy PSO method [164]. Optimal sizing and placement of vehicle charging stations are obtained with artificial bee colony (ABC) method [165]. Bat algorithm (BA) is used to minimise ES investment cost and, microgrid generation and operation costs [166].

2.6.5 Optimal Sizing and Placement of ES for Energy Loss Minimization

ES when optimally allocated helps to reduce power losses in distribution networks [167]. The placement of ES at non-optimal places increases system losses. Hence, optimal sizing and placement of Energy Storage is an essential planning aspect for energy loss minimization [18, 168]. Planning the best allocation of ES has a significant impact on the power system including minimizing energy losses [169]. One of the effective ways to reduce distribution losses is peak shaving. Peak shaving is a process of shaving the peak load and filling the load valley. It shifts some of the current from the peak period to off-peak period and decreases the net ohmic losses [170, 171, 172]. A limited literature is available on optimal sizing and placement of Energy Storage for energy loss minimization. The paper [173] addresses the problem of power loss minimization to obtain the installed capacity of ES. The papers [18, 174, 175, 176, 177] present methodologies for optimal location of ES for minimizing system energy losses. An analytical approach is proposed to obtain optimal size and location of ES units to reduce energy losses at peak load level [178].

The above sizing or placement of ES methodologies mainly consider the placement of ES in the power system without considering the optimal allocation of RDG. The line flows are affected while integrating the ES in presence of RDG. Hence it is essential to propose the optimal sizing and placement of ES in presence of RDG. This thesis proposes an optimal sizing and placement methodology of ES for energy loss minimization in the presence of optimally allocated RDG. Optimal sizing and location of ES is a non-deterministic polynomial-time (NP) hard problem and needs to solve efficiently.

2.7 Joint Optimal Allocation of RDG and ES

Significant literature is available on optimal sizing and placement of ES and RDG but they address it separately [13, 21, 170, 171, 179, 180, 181, 182, 183]. ES is optimally allocated to reduce the energy losses of distribution systems with RDG of fixed size and location in [164]. A significant annual energy loss minimization is obtained with ES [184]. This energy loss minimization is obtained with optimal allocation of ES with pre-sized RDG at selected locations. Considerable loss minimization is achieved with optimal allocation of ES, in coordination with pre-sized RDG at a selected locations [185].

Hybrid RDG (*i.e.*, solar RDG and wind RDG) with ES forms a complementary system. The solar RDG provides energy during periods of sunshine and the wind RDG provides energy during little or no sunshine periods. ES allows the shifting of the energy by storing it during the favorable time and then using it whenever necessary. This complementary feature of hybrid RDG system is beneficial to system reliability [186]. Also, the hybrid combination of the renewable RDG provides a significant reduction in the annual energy losses by providing continuous power supply [13]. Existing studies related to solar RDG, wind RDG and ES are mainly focused on modeling [187], capacity allocation [164], optimal design [188], economic evaluation [189], reliability evaluation [190], and optimal operation aspects [191].

From the literature it can be found that optimal ES allocation methodologies for energy loss minimization, optimize size and location of either ES or RDG but not the both. However, joint optimal allocation of ES and RDG affects the line currents and hence it affects on the line losses. Therefore a combined optimal sizing and location of RDG and ES is necessary to provide significant loss minimization. This significant aspect of loss minimization by joint optimal sizing and placement is addressed in the proposed methodology.

2.8 Joint Optimal Allocation of ES and RDG for Economic Benefits

RDG offers several benefits to utilities, customers, and society. Therefore, it is necessary to develop suitable methods for sizing and placement RDG that can provide economic, environmental and technical benefits [192, 193]. Optimal sizing and placement decisions for RDG are obtained through cost-benefit analysis [194]. Along with the economic benefits of RDG owner, proper placement of RDG allows distribution network operators to capture the benefits of network deferral [195, 196]. Optimum RDG allocation minimizes investment cost, operating cost and costs of system losses [41]. It also minimizes the Distribution Company's (DISCOM's) cost, reduces the power flow in the DISCOM's primary distribution feeders, minimizes the DISCOM's system network loss and maintains positive profit for the RDG owner [197].

The distribution planner has to maximize the profit of the investments and improve the performance of the system [198]. The optimal allocation of RDGs affects the economic performance of the system [199]. Thus optimally allocated RDG units in the distribution system maximize the savings in system upgrades, the cost of energy losses, the cost of interruption and achieve overall economic benefits [13]. Hence optimally assessed RDG benefits both the RDGOs and DISCOMs [200, 201].

Integration of ES into the distribution network helps to mitigate the intermittency, provides system security, reliability and energy arbitrage, thus it provides economic benefits [202]. Optimal sizing of ES and its economic analysis is presented in paper [9]. Paper [13], presents sizing of ES in a distribution system with large penetration of RDG to maximizes the benefits of both the RDGO and the utility. In [11], an approach is proposed to minimize the power system cost by sitting and sizing of ES in RDG penetrated power system. In [164], the optimal sitting and sizing of ES are obtained through a cost-benefit analysis, which maximizes the DISCOM's profit from energy transactions and operation cost savings. In a few works, ES is allocated in a co-optimized market to maximize the profits [203, 204]. Also, ES and RDG controls are implemented to achieve economic benefits [205, 206].

From the above literature, it is evident that sufficient work has been done in the area of sizing and location of RDG as well as sizing and location of ES to obtain economic benefits. Also, ES is allocated in a co-optimized market to maximize the profits. Recently, a few has also addressed the simultaneous sizing of RDG and ES. However, the problem of simultaneous sizing and placement of both, RDG and ES for the cost benefits analysis remains un-addressed. The placement of RDG and ES has a significant impact on the network power losses and affects the energy costs. Hence, the simultaneous allocation problem should consider the sizing as well as placement of RDG and ES.

In a power system, the distributed generation owner can sell the generated electricity to DISCOM with a fixed contract price. This contract price is a key parameter that decides the benefit or distributed generation owner. Similarly, in RDG scenario the contract price plays an important role to decide the benefit of RDG owner and cost of DISCOM. Hence, the contract price of renewable energy needs to be addressed along with the allocation of RDG and ES to achieve economic benefits. The thesis address this novel issue.

2.9 Relevance to Indian Power Sector

During the year 2016-17, India has installed generation capacity of 315.4 GW and Peak Demand is about 138 GW primarily consisting Thermal (68.2%), Hydro (14.1%), Renewable (15.9%) and Nuclear (1.8%) [251]. Indian power sector is modernizing to provide sustainable, secure and affordable energy to the growing population. A sustainable renewable energy mix is required to reduce the carbon footprint and increase energy availability. India plans to increase renewable generation capacity to 170 GW by 2022, adding of 100 GW solar, 70 GW of wind power. Such a large addition of renewable energy needs to address RDG integration challenges [252, 253, 254]. Considering these facts, planning issues for renewable energy sources and energy storage are relevant in Indian context. The proposed methodology would help to address following challenges in Indian power sector.

- **Renewable Energy Sources and Distributed Generation Integration:** India has strong solar resources with an average of 300 sunny days per year and an average yearly irradiation of 200 W/m^2. The total onshore wind energy potential in the country is 302 GW as per National Institute of Wind Energy. The National Institute of Solar Energy in India has determined the country's solar power potential at 750 GW. Thus, there is a strong potential of renewable energy sources and distributed generation. Considering this potential of renewable sources, the proposed work aims to model the optimal sizing and placement of the major renewable energy sources, i.e., solar RDG and wind RDG. This planning can help DISCOM and RDG owner to identify placement sizing of RDGs in the distribution network.

- **Integration of Energy Storage:** The mismatch in demand supply can be matched by storing excess energy, and supplying it when required. Large integration of renewable energy sources can be achieved by developing grid-scale energy storage. Research is required for developing large-scale energy storage. The thesis addresses the integration of ES in the distribution network, that could help the planning of energy storage.

- **Technical & Commercial (AT&C) Loss Minimization :** Large AT&C losses have adversely affected DISCOM's working conditions. Increased cost of power generation due to low fuel availability, poor financial conditions and high power losses have contributed to reduced demand fulfillment by DISCOMs. Indias AT&C losses are as high as 25 %. Also, there are considerable losses in distribution lines due to geographical spread of network. During peak load period, the losses exceed due to overloading. Thus loss minimization is the key challenge for Indian power utilities. This thesis addresses this critical issue with optimal allocation of RDG and ES for energy loss minimization. The proposed methodology can be applied to similar networks of Indian utilities.

- **Peak Demand Mitigation:** India has large peak demand and measures to manage peak demand are essential. Daily peak demand can be managed by peak shifting. Energy storage can charge during the off-peak period and discharge during the peak period. The thesis addresses the placement of multiple ES at optimal locations for peak shifting, along with energy loss minimization. The proposed methodology can be extended for the purpose of peak shaving exclusively, without considering energy loss minimization.

- **Large Integration of Customer Owned RDG:** Customers have their own renewable generation, into the grid. Currently, subsidies are provided to encourage renewable generation. If suitable contract prices are formulated considering the benefits of both, i.e., RDG owner and DISCOM, subsidies can be done away. This work includes the Contact price as a variables in the economic-benefit analysis of DISCOM and RDG owner.

- **Optimal Generation Mix Development:** Indian power sector needs to develop conventional and renewable forms of energy. The mix should consider the energy demand pattern and available energy. The optimal resources mix for the next 20-25 years should focus on solar and wind power. The solar and wind mix can be complementary to each other and enhance energy reliability. This thesis addresses this issue by formulating the planning of hybrid RDG. This hybrid resources allocation methodology of solar RDG and wind RDG can be extended to other optimal resource mix planning.

Large integration of RDG is an urgent need for Indian power sector. The regulators need to focus on framing policies to encourage integration of RDG into the grid. The framed policies must benefit economically to RDG owner and DISCOM. Integration of ES with proper framework should considered to support the large integration of RDG. Also, optimal planning of ES and RDG should support ancillary services like loss minimization for energy saving and economic benefits.

2.10 Summary

In this chapter, a detailed literature review on optimal sizing and placement of RDG and ES is presented. The optimal sizing and placement of two main renewable sources, *i.e.*, solar RDG and wind RDG is reviewed. The literature on ES is presented to highlight the need for optimal sizing and placement of ES in coordination with RDG for energy loss minimization. Also, from the literature review, it is found that the optimal allocation of RDG and ES has been separately addressed, that shows the need of joint optimal allocation methodology for energy loss minimization. Finally, the literature on cost-benefit based optimal allocation of RDG and ES is presented. The need for cost-benefit based joint optimal allocation of RDG and ES is shown from the existing literature.

CHAPTER 3

Optimal Sizing and Placement of Renewable Distributed Generation

3.1 Introduction

One of the major reasons of integrating RDG units in a distribution network is to reduce the electrical power losses in the system. Line loss depends on the line length and current through it. The line loss has a significant impact on the economic dispatch [207, 208]. In some cases the consumers are charged for the losses and they have to pay large energy costs [20]. The distribution line loss can be minimized by reducing the line current in the distribution system. In another way, if RDG are strategically integrated into the distribution network that improves the node voltage. This contributes to power loss minimization and also helps to defer the network upgrading [209]. Size and location of RDG, system load and network configuration impacts the energy losses. [21, 49, 210]. Integration of RDG units into the distribution network produces many technical challenges that have not yet been fully addressed. Energy loss minimization with integration of RDG has attracted the attention of researches for a long time. [13, 54].

This chapter presents a methodology for optimal sizing and placement of RDG to minimize energy losses. A probabilistic generation model for RDG (*i.e.*, solar RDG and wind RDG) is developed and load is modeled using IEEE-RTS load modeling method. IEEE-RTS load modeling express the hourly load as percentage of daily peak load. The generation-load model is integrated with optimal power flow to provide optimal solutions. Similarly, generation-load model is also obtained for hybrid RDG using the expected generation of solar RDG and wind RDG. The optimal allocation of RDG is a nonlinear, constrained optimization due the power flow with non-linear equations. This non-linear, constrained optimization problem is solved with a newly developed nature inspired optimization algorithm called as Gray Wolf Optimizer (GWO). Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Firefly Algorithm (FFA) and Symbiotic Organisms Search (SOS) are also used to obtain the results. GA and PSO are popular and well proven algorithms while FFA and SOS are representative of recently developed heuristic optimization algorithms. Comparative results from the standard heuristic optimization algorithms, *i.e.,* GA, PSO, SOS and FFA highlight the efficiency of GWO algorithm to offer better solutions for energy loss minimization for the proposed allocation methodology.

3.2 Historical Data Processing

Solar and wind energy are mainly non-dispatchable and site dependant sources. To accurately assess these sources at specified site for production of electrical energy, historical records of the wind speed or solar radiation data are being used. The historical approach is time consuming, expensive and it's difficult to get accurate data. Recently, the statistical methods have gained more popularity. They are economic, less time consuming and predicts system behaviour accurately [211]. Various probability distribution functions (*pdf*) are used to model solar radiation and wind speed. Two such pdfs that are widely used beta and Weibull distributions. The soar PV data is modeled with beta pdf and wind speed data is modeled with Weibull pdf.

Historical data is used to predict solar power generation and wind power generation using cumulative distribution function (cdfs). The hourly solar irradiance and wind speed are taken for the selected site to obtain hourly power generation. Hourly data for five years is taken to develop the pdfs. Each year is divided into three seasons *i.e.*, summer, monsoon and winter considering average temperatures of these seasons for the selected site. Each season is represented by any day within that season. Historical data is used to generate a typical days frequency distribution of the solar irradiance and wind speed. The day that represents the season is further divided into 24 hour segments, thus each hour refers to a particular hour of entire season. Considering a month to be 30 days, each time segment has 120 irradiance and wind speed data points for a season (i.e., 30 days * 4 season). Thus for 5 years each hour of a season has 600 data points (*i.e.*, 120 * 5 years). To obtain cdfs with reasonable accuracy each hour is further segmented into small states 'y' (i.e. steps) depending on maximum solar irradiance and wind speed. As an example, a hour with maximum solar irradiance of 700 W/m^2 will be segmented into 7 steps, considering each step of 100 W/m^2. Using these data points of each season, parameters of beta *cdf* for solar RDG and Rayleigh *cdf* for wind RDG are obtained. *cdf* shows the probability which is greater than or less than a certain value associated with climate changes. These *cdf*s are used to obtain expected generation of solar RDG and wind RDG.

3.3 Solar Power Modeling

A stochastic model of Solar PV is developed based on beta distribution function. It is considered as the most suitable model for statistical representation of probability density function(*pdf*). Solar PV generation is intermittent and random function of solar irradiance. Randomness of solar irradiance is expressed by beta pdf F_β [13, 212]. The F_β indicates the probability or fraction of time for which solar irradiance is at a given irradiance s.

The general form of the beta probability density function is as given below.

$$F_\beta(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)(b-a)^{\alpha+\beta-1}}(s-a)^{(\alpha-1)}(b-s)^{(\beta-1)} & a \leq s \leq b, \alpha, \beta \geq 0 \\ 0 & otherwise \end{cases} \tag{3.1}$$

where, Γ is gamma function; s is solar irradiance in kW/m^2; α and β are the shape parameters of beta distribution function; a, b are lower and upper bounds of s. The case where $a = 0$ and $b = 1$ is called the standard beta distribution. Equation for the standard beta distribution is,

$$F_\beta(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha-1)}(1-s)^{(\beta-1)} & 0 \leq s \leq 1, \alpha, \beta \geq 0 \\ 0 & otherwise \end{cases} \tag{3.2}$$

For the beta *pdf* solar irradiance is considered in kW/m^2, i.e if the solar irradiance is 100 W/m^2 then it is taken as 0.1 kW/m^2, if 200 W/m^2 then 0.2 kW/m^2 and so on.

The shape parameters α and β are as given below.

$$\beta = (1-\mu)\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right) \tag{3.3}$$

$$\alpha = \frac{\mu\beta}{1-\mu} \tag{3.4}$$

where, μ, σ are mean and standard deviation of s respectively. The cumulative distribution function (*cdf*) is used for estimating the time for which solar irradiances 's' is within a certain irradiance interval (*i.e.*, s_1 and s_2).

$$f_\beta(s) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \int_0^t s^{(\alpha-1)}(1-s)^{(\beta-1)} dt \tag{3.5}$$

Probability of solar irradiance being between s_1 and s_2 is obtained by the difference of corresponding *cdfs*.

$$f_\beta(s_1 < s < s_2) = f_\beta(s_2) - f_\beta(s_1) \tag{3.6}$$

The power output $P_o(s)$ of PV cell at any state y is as given below.

$$T_{cy} = T_a + s_{ay}\left(\frac{N_{OT} - 20}{0.8}\right) \tag{3.7}$$

$$I_y = s_{ay}\left[I_{sc} + K_i\left(T_c - 25\right)\right] \tag{3.8}$$

$$V_y = V_{oc} - K_v * T_{cy} \tag{3.9}$$

$$f_f = \frac{V_{MPP} * I_{MPP}}{V_{oc} * I_{sc}} \tag{3.10}$$

$$P_o(s) = N * f_f * V_y * I_y \tag{3.11}$$

where, I_y & V_y are cell current and cell voltage respectively at state y ; T_{cy} is cell temperature °C at state y; T_a is ambient temperature °C ; K_v is voltage temperature coefficient V /°C ; K_i is current temperature coefficient A /°C ; N_{OT} is nominal operating temperature °C ; f_f is fill factor; I_{sc} is short circuit current A; V_{oc} is open circuit voltage V; s_{ay} is average solar irradiance of state y; I_{MPP} is current at maximum power point A; V_{MPP} is voltage at maximum power point V;

Expected solar PV output power $P(s)$ of any state at irradiance 's' is given as below.

$$P(s) = P_o(s) * f_\beta(s) \tag{3.12}$$

Total expected output power P_{SG} at any hour is given as below.

$$P_{SG} = \int_0^\infty P_o(s) * f_\beta(s).ds \tag{3.13}$$

This hourly expected output of solar PV is used to obtain the optimal size and location of the solar RDG for energy loss minimization.

3.4 Wind Power Modeling

Wind speed variation is modeled with Weibull *pdf* due to it's simplicity and best fit to experimental data [213]. Weibull *pdf* is accepted as one of the best models and widely used in wind energy analysis. The pdf indicates the probability of time for which wind is at a given speed v. Total energy available from a turbine over a period is estimated by integrating energy within the limits of the cut-in and cut-out velocities and multiplying it with time factor. The Weibull *pdf* $F_w(v)$ for wind turbine is as given below [214].

$$F_w(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \qquad for\ 0 < v < \infty \tag{3.14}$$

Here, k, c and v are the shape index, scale index and wind speed respectively.

Average wind speed of a regime, is given as,

$$v_m = \int_0^{\infty} v f_w(v) dv \quad or \quad v_m = c\ \Gamma\left(1 + \frac{1}{k}\right) \tag{3.15}$$

Substituting for $f_w(v)$ in above equation and simplifying we get,

$$V_m = c\ \Gamma\left(1 + \frac{1}{k}\right) \tag{3.16}$$

Rayleigh distribution is a simplified case of Weibull distribution where shape factor 'k is assumed as 2 [215]. The sites with annual average wind speeds greater than 4.5 m/s tend to have a near-Rayleigh cumulative wind distribution [216]. Under Rayleigh based approach, *pdf* is as given below.

$$F_w(v) = \left(\frac{2v}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^{2}\right] \tag{3.17}$$

The average wind speed is obtained by substituting k=2, in equation (3.16).

$$v_m = c\ \Gamma\left(\frac{3}{2}\right) \tag{3.18}$$

Above expression can be rearranged and evaluated to get c.

$$c = \frac{2}{\sqrt{\pi}}\ v_m \tag{3.19}$$

From above equation, value of c is found as 1.128 v_m. The *cdf* is used for estimating the time for which wind is within a certain velocity interval (e.g. v_1 & v_2) . The *cdf* for wind speed interval v_1 & v_2) are given as below.

$$f_w(v) = 1 - e^{-\left[\frac{\pi}{4}\left(\frac{v}{vm}\right)\right]} \tag{3.20}$$

Probability of wind speed being between v_1 and v_2 is obtained as,

$$f_w(v)(v_1 < v < v_2) = f_w(v_2) - f_w(v_1) \tag{3.21}$$

The available power $p_w(v)$ of the wind having speed v with air density ρ that crosses the rotor of a wind turbine having area A is given as,

$$p_w(v) = \frac{1}{2}\ A\ \rho\ v^3 \tag{3.22}$$

Where v is wind speed in in m/s, A is the rotor area in m^2 and ρ is the air density. This power generated by the wind turbine gets modified as $p(v)$ due to a power coefficient $C_p(v)$, which is given as,

$$p(v) = C_p(v)\ p_w(v) \tag{3.23}$$

C_p depends on the blade design, tip angle and relationship between wind speed and rotor speed. The power coefficient value includes mechanical and electrical losses and aerodynamic behavior of blades. Power coefficient is obtained from the manufacturer data. Power delivered by a wind turbine $P_o(w)$ is usually represented through its power curve, where a relation between wind speed and power is established. The wind output power for various states is calculated as,

$$P_o(w) = \begin{cases} 0 & 0 \leq v_{av} \leq v_{ci} \\ P_r * \left(\frac{v_{av}-v_{ci}}{v_r-v_{ci}}\right) & v_{ci} \leq v_{av} \leq v_r \\ P_r & v_r \leq v_{av} \leq v_{co} \\ 0 & v_{co} \leq v_{av} \end{cases} \tag{3.24}$$

Where, v_{ci}, v_{co}, v_r, v_{av} and P_r represent the cut-in speed, cut-off speed, rated speed, average speed and rated power of wind turbine respectively.

Expected wind turbine output power $P(w)$ at speed 'v' for any state is as given below.

$$P(w) = P_o(w) * f_w(v) \tag{3.25}$$

Total expected wind power P_{WG} at any time interval is obtained as given below.

$$P_{WG} = \int_0^\infty P_o(w) * f_w(v).dv \tag{3.26}$$

This hourly expected output of wind power is used to obtain optimal size and location of wind RDG for energy loss minimization.

3.5 Load Modeling

The load profile follows IEEE-RTS system load modeling [217]. In this load modeling the hourly peak load is obtained by expressing it as percentage of daily peak load. Hourly loads for three different seasons *i.e.*, summer, monsoon and winter are considered to get the seasonal variation into the load. A 34-bus network is considered in the proposed methodology [218]. This 34-bus system is as shown in Figure 3.1.

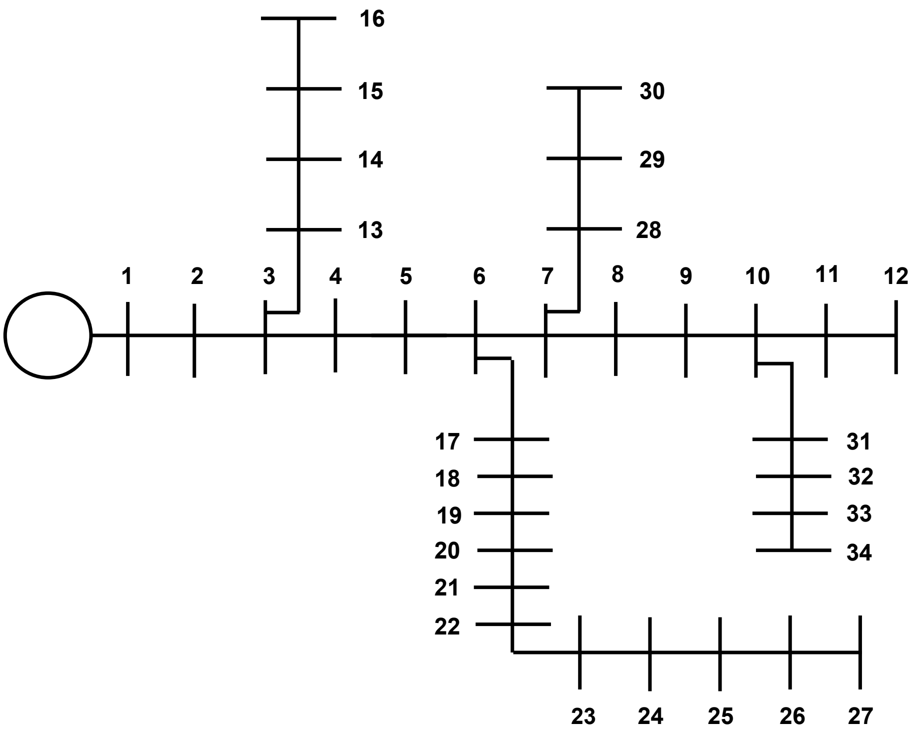

FIGURE 3.1: 34 bus system

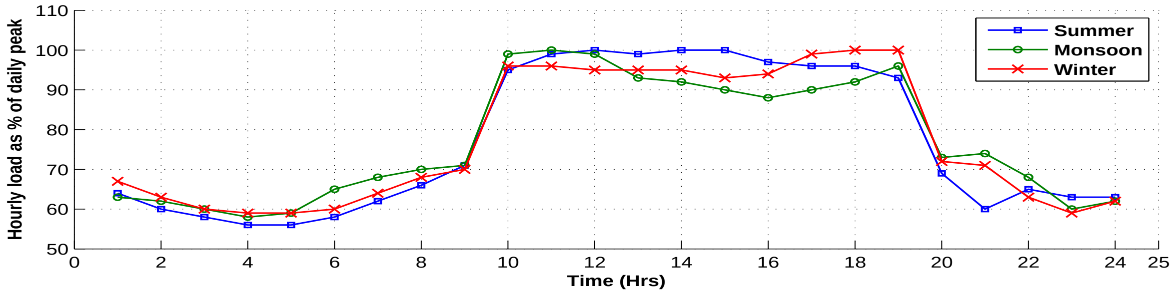

FIGURE 3.2: Hourly load variation for different seasons

TABLE 3.1: Bus Load

Bus No	Peak Load kW	Peak Load kVAR	Load % of total load
1	0	0	0
2	150	86.16	3
3	150	86.16	3
4	150	86.16	3
5	161	100.52	3.5
6	161	100.52	3.5
7	150	86.16	3
8	150	86.16	3
9	150	86.16	3
10	153	100.52	3.5
11	153	71.8	2.5
12	150	86.16	3
13	150	86.16	3
14	150	86.16	3
15	150	86.16	3
16	151	100.52	3.5
17	150	71.8	2.5
18	150	86.16	3
19	153	100.52	3.5
20	153	71.8	2.5
21	153	71.8	2.5
22	150	86.16	3
23	150	86.16	3
24	150	86.16	3
25	150	100.52	3.5
26	150	86.16	3
27	155	100.52	3.5
28	155	86.16	3
29	150	71.8	2.5
30	150	86.16	3
31	150	86.16	3
32	150	86.16	3
33	151	100.52	3.5
34	151	71.8	2.5
Total	5000	2872	100

TABLE 3.2: Hourly Peak Load as % Daily Peak

Hour	Summer	Monsoon	Winter
12–1 am	64	63	67
1–2	60	62	63
2–3	58	60	60
3–4	56	58	59
4–5	56	59	59
5–6	58	65	60
6–7	62	68	64
7–8	66	70	68
8–9	71	71	70
9–10	95	99	96
10–11	99	100	96
11–12 pm	100	99	95
12–1	99	93	95
1–2	100	92	95
2–3	100	90	93
3–4	97	88	94
4–5	96	90	99
5–6	96	92	100
6–7	93	96	100
7–8	69	73	76
8–9	60	74	71
9–10	65	68	63
10–11	63	60	59
11–12 am	63	62	62

Table 3.1, gives the total peak load on the system on the 34-buses of the network. It mainly represents the bus numbers, peak active and reactive load on the various buses and load percentage with total peak load on the system. Table 3.2 shows the hourly peak load expressed as percentage of daily peak load. The percentage of load each hour is given for three seasons i.e., summer, monsoon and winter. Thus, load modeling provides hourly variation of load on each bus for 24 hours. The load modeling also includes the seasonal variation of load.

3.6 Distribution System Power Flow

The expected hourly generation and load are used for load flow calculation. Power losses P_{loss} are calculated with backward/forward method [219, 220]. Backward/forward method is one of the effective methods for load-flow analysis for radial distribution systems [221]. Hourly RDG generation and hourly load is used to get hourly power losses and annual energy losses are calculated. The system is assumed balanced and represented on per phase basis. In a radial system, the number of buses n are related with number of branches n_b as,

$$n = n_b + 1 \tag{3.27}$$

The node numbering generally starts with '0' for source node and increases thereafter. Advantage of numbering is that the number of nodes and upstream branches are always same and this is utilized in the load flow process. Based on this numbering process, voltage of ith node is given as,

$$V_i = V_{(i-1)} - I_i Z_i \tag{3.28}$$

where V_i and $V_{(i-1)}$ are voltages of node i and $(i-1)$ respectively, I_i is current flow in line i and Z_i is the impedance of the line. Since the voltage of slack bus is known, equation (3.28) is used to determine the voltages of other nodes in forward sweeps. Load current I_{Li} of node i, is expressed as,

$$I_{Li} = \frac{P_i - Q_i}{V_i^*} \tag{3.29}$$

where, P_i and Q_i are active and reactive power of load at node i, respectively. Current through branch i, *i.e.* I_i is the load current of node i plus branch currents connected to this line.

$$I_i = I_{Li} + \sum_{j \in U_i} I_j \tag{3.30}$$

where, U_i are the all branches connected to node i. Thus for calculating branch currents, all branches connected to the node must be determined. Also, equation (3.30) is utilized in backward sweeps from all end nodes towards the source node.

Initially, a constant voltage of $(1p.u.\angle 0)$ for all nodes is assumed. Then all load currents are computed by using equation (3.29) and branch currents are computed by using equation (3.30) in backward sweep. Thereafter, voltage of each node is calculated by equation (3.28) in forward sweeps. When new values of voltages at all nodes are calculated, the convergence criterion for voltage is checked. Load currents are computed using most recent values of voltages and the whole process is repeated till the convergence is achieved.

Total real power loss in the system is given as,

$$P_{Loss} = \sum_{i=0}^{n-1} I_i^2 \ \ r_i \tag{3.31}$$

Integration of RDG supplies the active power and modifies the load power P_i in equation (3.29). Considering RDG power ($P_{RDGE,i}$) at node i, active power P_i gets modified to $(P_i - P_{RDGE,i})$. This results in minimization of power losses.

3.7 Objective Function for Loss Minimization

The problem is formulated as optimization problem. The objective function is to minimize annual energy losses by optimal sizing and placement of solar RDG and wind RDG. Generation and load is obtained for three seasons *i.e.*, summer, monsoon and winter considering the seasonal variation of generation and load. This provides a reasonable accuracy and fast numerical evaluation. Each season is represented by a day in that season. loss minimization is obtained for 24 hrs of a day. Considering each season has 120 days (*i.e.*, 30 $days \times 4$ months), the objective function is as shown below. Annual energy losses are obtained by summation of losses for three seasons.

$$F = min\left[120\left(\sum_{t=1}^{24} P_{loss,summer,t} + \sum_{t=1}^{24} P_{loss,monsoon,t} + \sum_{t=1}^{24} P_{loss,winter,t}\right)\right] \tag{3.32}$$

The constraints includes active power balance, feeder current limits, bus voltage limits and maximum penetration of RDG. The constraints are as given below.

i) **Active power balance:** Assuming RDG sources are operating at unity power factor and supplying only active power, the active powers balance is given as:

$$P_{G1,t} + \sum_{i=1}^{n} P_{RDGEi,t} - \sum_{i=1}^{n} P_{i,t} - \sum_{b=1}^{n} P_{loss,b,t} = 0 \tag{3.33}$$

Where, P_{G1} is active power at the grid. $P_{RDGEi,t}$ is RDG's forecasted power at time t, $P_{i,t}$ is total load during time t at i^{th} bus, $P_{Loss,b,t}$ is active power loss during time t at branch b, nb is the total number of branches and n is total number of buses.

ii) **Bus voltage limit:** Bus 1 is assumed as slack bus. Voltage at each bus should be within upper and lower limits.

$$V_1 = 1.0 \qquad \delta_1 = 0.0 \tag{3.34}$$

$$V_{min} \leq V_i \leq V_{max} \qquad \forall i \notin \text{substation bus} \tag{3.35}$$

iii) **Feeder current limit:** With the placement of RDG, feeder current I_{ij} should be within the feeder current capacity $I_{ij_{max}}$.

$$0 \leq I_{ij} \leq I_{ij_{max}} \tag{3.36}$$

iv) **Maximum penetration of RDG:** RDG penetration affects design and operation of distribution system. Also, they increase cost of distribution system and consumer payments [222]. Therefore RDG penetration is always a few percent (e.g. $k\%$) of system's total peak load (P_{Lmax}). As per IEA study, 25 to 40 % penetration of renewable energy sources put a little additional cost on the system in the long run, and hence it is an acceptable penetration limit [223]. The summation of power injected by all RDGs should be equal to the allowed maximum penetration of RDGs. Maximum penetration limits for solar RDG, wind RDG and hybrid RDG are given by equations (3.37), (3.38) and (3.39) respectively.

$$\sum_{i=1}^{n} c_{s,i} \times P_{SG} = k \times P_{Lmax} \qquad \forall i \in D \tag{3.37}$$

where $c_{s,i}$, P_{SG}, and D give integer variables representing number of solar panels at i^{th} bus, expected solar PV generation and candidate bus respectively.

$$\sum_{i=1}^{n} c_{w,i} \times P_{WG} = k \times P_{Lmax} \qquad \forall i \in D \tag{3.38}$$

where, $c_{w,i}$ and P_{WG} give integer variables representing number of wind turbines at i^{th} bus and expected wind power respectively.

$$\sum_{i=1}^{n} c_{s,i} \times P_{SG} + \sum_{i=1}^{n} c_{w,i} \times P_{WG} = k \times P_{Lmax} \qquad \forall i \in D \tag{3.39}$$

3.8 Optimal Sizing and Location of RDG

The network power loss minimization depends on size of RDG and their location. The size of RDG at any location can be obtained in terms of the number of RDGs. Once the number of RDGs to provide expected power P_{SDGE} (*i.e.*, forecasted output power) at optimal location are obtained then rated optimal size of RDG is obtained. The mathematical equations for obtaining the expected optimal size and rated optimal size of RDG are as given below.

i) **Solar RDG:** The expected optimal size (P_{SDGE}) and rated optimal size (P_{SDG}) of SDG at optimal location can be given by Equations (3.40) and (3.41) respectively.

$$P_{SDGE,i} = c_{s,i} \times P_{SG} \qquad \forall i \in D \tag{3.40}$$

$$P_{SDG,i} = c_{s,i} \times P_{SDGR} \qquad \forall i \in D \tag{3.41}$$

where $c_{s,i}$, P_{SG}, P_{SDGR} and D give the integer variables representing number of solar panels at i^{th} bus, expected solar PV generation, rating of solar PV module and candidate bus respectively.

ii) **Wind RDG:** The expected optimal size (P_{WDGE}) and rated optimal size (P_{WDG}) of wind RDG at optimal location can be given by equation (3.42) and (3.43) respectively.

$$P_{WDGE,i} = c_{w,i} \times P_{WG} \qquad \forall i \in D \tag{3.42}$$

$$P_{WDG,i} = c_{w,i} \times P_{WDGR} \qquad \forall i \in D \tag{3.43}$$

where, $c_{w,i}$, P_{WG}, and P_{WDGR} give the integer variables representing number of wind turbines at i^{th} bus, expected wind power and rating of wind turbine respectively.

iii) **Hybrid RDG:** The expected optimal size (P_{HDGE}) and rated optimal size (P_{SDGH}, P_{WDGH}) of hybrid RDG at optimal location are given by equation (3.44) and (3.45-3.46) respectively.

$$P_{HDGE,i} = c_{sh,i}\ P_{SG} + c_{wh,i}\ P_{WG} \qquad \forall i \in D \tag{3.44}$$

$$P_{SDGH,i} = c_{sh,i}\ P_{SDGR} \qquad \forall i \in D \tag{3.45}$$

$$P_{WDGH,i} = c_{wh,i}\ P_{WDGR} \qquad \forall i \in D \tag{3.46}$$

where, $c_{sh,i}$ and $c_{wh,i}$, give the integer variables representing the number of solar panels and wind generators at i^{th} bus for hybrid combination.

3.9 Optimization Algorithms

The power system problems of load flows and loss minimization are nonlinear problems. Conventional linear programming (LP), quadratic programming (QP), and mixed integer linear programming (MILP) can solve the power flow problems with assumptions of convexity and continuity, which affect the actual solution. MILP can solve these problems but causes inaccuracy in optimal solutions[224]. MILP can be applied to simplified models. MILP takes more time as compared to heuristic algorithms when the system becomes complex. These drawbacks can be mitigated by heuristic optimization algorithms, such as genetic algorithm (GA) and particle swarm optimization (PSO). Results obtained from heuristic methods are found promising for power system applications [225].

The proposed RDG allocation is a complex, mixed integer, non-linear, constrained optimization problem. Heuristics approaches are efficient in finding global optima with higher success rates for better solutions [226]. The proposed optimal sizing and placement is a constrained, nonlinear optimization problem having large number of variables. Considering large search space and complexity of this problem, it is suggested to use heuristic methods to solace it. In this thesis, five heuristic algorithms of different category are used. These algorithms are briefly explained as below.

3.9.1 Genetic Algorithm (GA)

Genetic algorithm is a search technique based on the principles of genetics. GAs operate on a population of candidate solutions and apply principle of survival of the fittest to evolve the candidate solutions. Invention of genetic algorithms is credited to John Holland. He developed the basic ideas of GA in the late 1960s and early 1970s. GA is used widely used in programming and artificial intelligence[227, 228].

The candidate solutions are referred to as *individuals*. Properties of these individuals are encoded to chromosomes. The chromosome consist of a string of genes. A gene can be represented by a binary number, an alphabet, an integer, real-value, etc.

A Group of individuals is referred as *population*. The $fitness$ of an individual gives idea about how good a individual is as the solution to given problem. Using a fitness function, Individuals are assigned fitness values using a fitness function. Individuals with better fitness are more like to survive and reproduce.

An initial population is randomly generated with the fitness function for the given optimization problem and fitness values are also generated. Then a pair of chromosomes (*i.e.*, parent) is selected from the population. The probability of selection gets increased with increased fitness. Crossover and mutation operations are applied to parent chromosomes to generate children. The children create a new population, for which fitness values are assigned. The process of selection, crossover, mutation and assigning fitness is repeated until a stopping criterion is attained. The iteration of this procedure is called as generation. Thus GA is different from the classical optimization methods as follows:

- GA operate encodings of parameter values and not the actual parameter values
- GA operate on a population of solutions rather than single solution
- GA only uses the fitness values and do not require derivative information.
- GA uses probabilistic computations and not the deterministic ones.
- GA efficiently handles problems with a discrete search space

The flowchart of GA is as shown follows:

GA begins with an initialization, followed by fitness evaluation, selection, crossover and mutation.

i) **Initialization:** In this step, initial solutions are randomly generated as binary strings of the true variables or encodings that are selected to mimic the natural data structure of the problem. The generation number k is set to 0 and the initial population is denoted P_0.

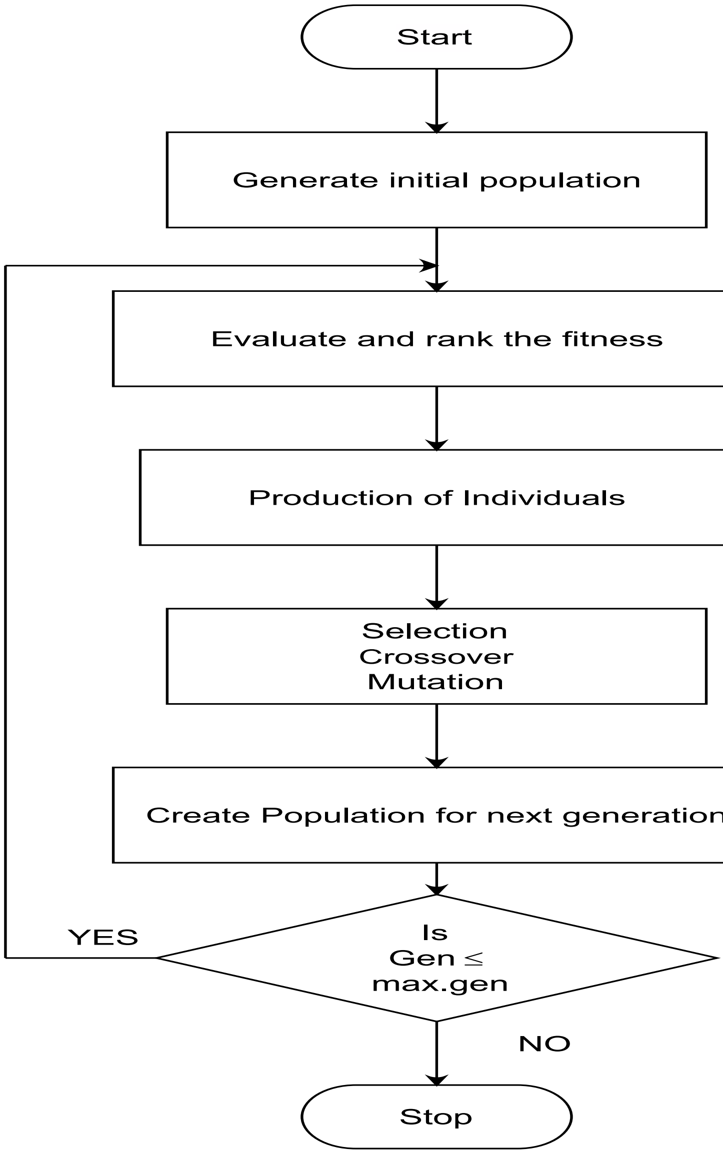

FIGURE 3.3: Flowchart of GA

ii) **Fitness Evaluation:** In this step, each individual is assigned with its fitness value. Fitness is a figure of merit for an individual. Higher fitness value means a more optimal individual.

iii) **Selection:**

Individuals that are more suitable to the environment are likely to survive and reproduce. Selection operator ensures that the individuals with larger fitness values are likely to survive to reproduce. Among the several selection methods, the roulette wheel selection is one of the most popular selection methods used to form a mating pool.

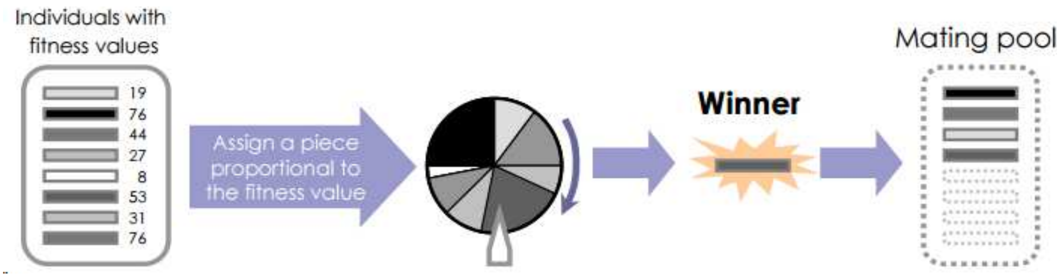

FIGURE 3.4: Roulette wheel selection

In this selection method all individuals are evaluated and assigned with their fitness. One can imagine a roulette wheel with different sections whose number is same as the number of individuals. The areas of these sections are proportional to the fitness values of the individuals. Then the wheel is turned and a chromosomes are selected and placed to the mating pool M_k. The selection process is repeated till mating pool is full.

iv) **Crossover:** Crossover exchanges information of solutions in a way similar to the natural organism undergoing reproduction. In crossover new individuals are generated that share the characteristics of their parents. Crossover is performed on the mating pool M_k to form population P_{k+1} as a first step in forming next generation. The single-point crossover and the multiple-point crossover operators are list below. In single

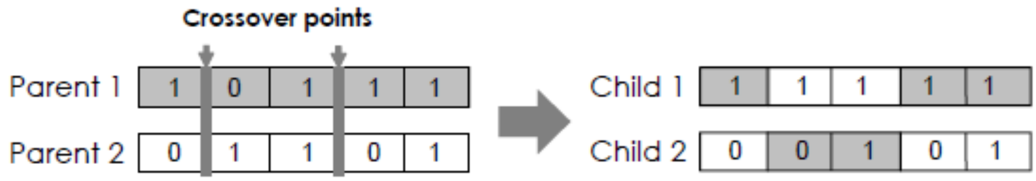

FIGURE 3.5: Crossover in Genetic Algorithm

crossover, a crossover point is randomly selected and genes of parents are exchanged after the crossover point whereas several crossover points are chosen and genes of parents are exchanged in between the crossover points as shown below.

v) **Mutation:** In nature, mutation occurs as a result of an error in trnsforming the gene information. In a similar way, mutation is a process of changing some genes in chromosomes randomly. Mutation maintains genetic diversity of the population by preserving diversity in the initial generation. GA using binary representation, mutation operator flips the selected bit value as shown Figure.

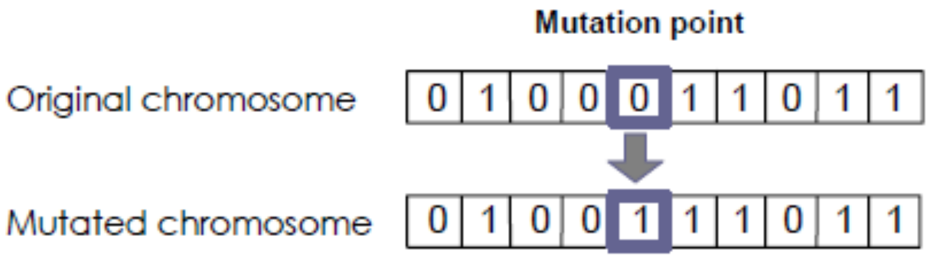

FIGURE 3.6: Mutation in Genetic Algorithm

Algorithm 1 Genetic Algorithm (GA)

1: Start with a randomly generated population of nlbit chromosomes
2: Calculate the fitness (x) of each chromosome x in the population.
3: Repeat the following steps until n offspring have been created:
   i. A pair of parent chromosomes are selected from current population, probability of selection is a function of fitness.
   ii. Do Selection 'with replacement', meaning that the same chromosome can be selected more than once to become a parent.
   iii. cross over the pair at a randomly chosen point to form two offspring.
   iv. If no crossover takes place then form two offspring which are exact copies of their respective parents.
   iv. Mutate the two offspring at each locus with probability pm (mutation probability) and place the resulting chromosomes in new population.
   v. When n is odd, one new population member is discarded at random.
4: Replace the current population with new population.
5: Go to step 2

A new population is formed after applying selection, crossover and mutation to the initial population, and generational counter is increased by one. This process of selection, crossover and mutation is continued for a fixed number of generations or some form of convergence criterion has been met. GA is as shown in above Algorithm 1. GA forms the basis of a general and highly effective search algorithm.

3.9.2 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization developed by Dr. Russell Eberhart, an electrical engineering professor at Purdue University and Dr. James Kennedy, a social psychologist with the US Department of Labor in 1995 [229, 230, 231]. The algorithm is inspired by social behavior of bird flocking or fish schooling. Afterwards it was subsequently developed in various scientific papers and applied to many diverse problems. Similar to GA, it is a population-based method, that represents the state of the algorithm by a population.

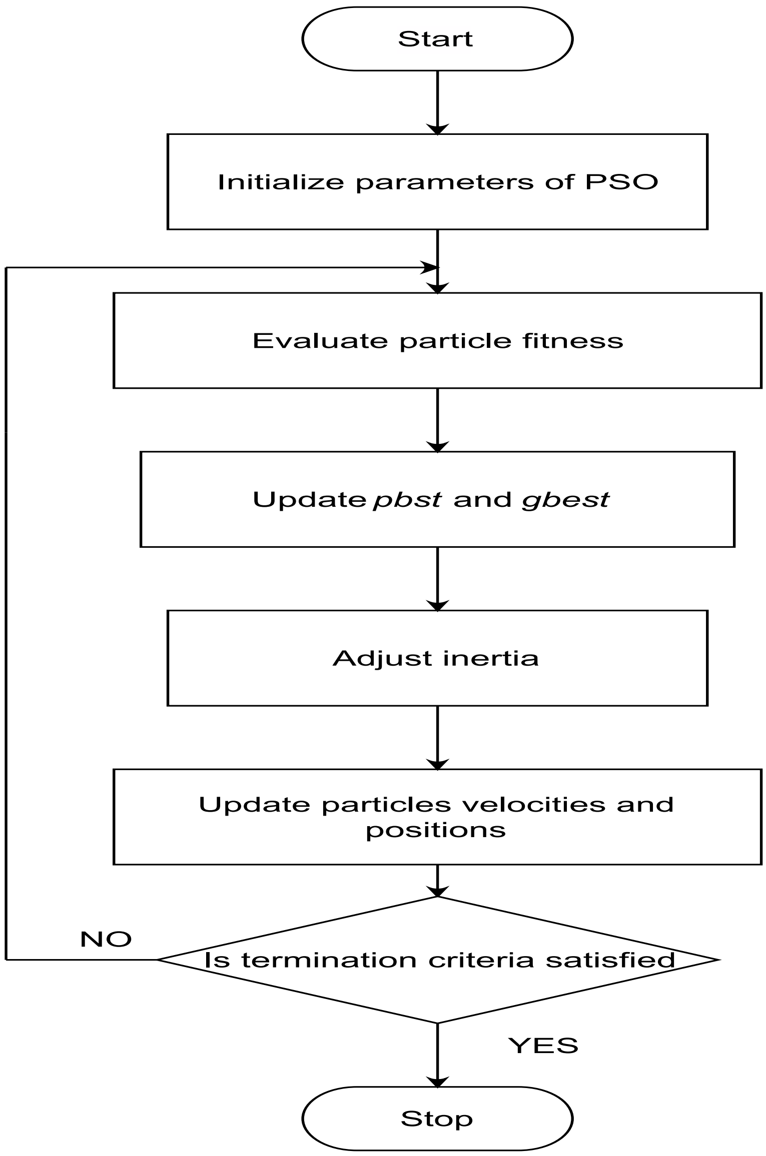

FIGURE 3.7: Flowchart of PSO

The behavior of swarms of birds can be modeled with simple rules but of each individual of the swarm is complex. Reynolds utilized the following three simple rules in the researches on boid *i.e.*, simulating the flocking behaviour of birds.

- Step away from nearest agent
- Go toward the destination
- Go to the center of swarm

These behavior of each agent of swarm can be modeled with simple vectors. Reynolds research forms one of the basic backgrounds of PSO. Kennedy and Eberhart developed PSO in a two-dimensional space through the simulation of bird flocking. Each agent's position is represented by its x, y axis position. Its velocity of x axis is expressed by vx and its velocity of y axis is represented by vy. The modification of agent position is obtained by the position and velocity information. The swarm optimizes a certain objective function. Each agent knows its best value (*pbest*) and its x, y position. Also, each agent knows the best value so far in the group (*gbest*) among *pbest*s. Each agent modifies its position using following information:

i) Current positions (x, y),

ii) Current velocities (vx, vy),

iii) Distance between current position and *pbest*

iv) Distance between current position and *gbest*

The modification is represented by the concept of velocity. Velocity of each agent is modified by using following equation.

$$v_i^{k+1} = wv_i^{k+1} + c_1\ rand_1 \times (pbest_i - s_i^k) + c_2\ rand_2 \times (gbest - s_i^k) \tag{3.47}$$

where v_i^k is velocity of agent i at iteration k, c_1, c_2 are weighting coefficients, w is weighting function, $rand$ is random number between 0 and 1,s_i^k is current position of agent i, $pbest_i$ is $pbest$ of agent i, and $gbest$ is gbest of group. The weighting function used in above equation is as given below.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{3.48}$$

where w_{min} and w_{max} are initial and final weights respectively, $iter_{max}$ is maximum iteration count, and $iter$ is current iteration number. The inertia weights w is very important in convergence behaviour of the PSO

The right-hand side of Equation (3.52) consists of three vectors (terms) The first term indicates previous velocity of the agent. The second and third terms are used to change the velocity of agent. Without second and third terms, agent keeps on 'flying' in same direction until it reaches the boundary. The first term corresponds with diversification in the search procedure. Without first term, velocity of the agent is only determined by using its current position and best positions in history.

The searching point in the solution space (*i.e.* current position) can be modified by using following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{3.49}$$

In PSO each potential solution is assigned a randomized velocity and potential solutions called particles are then flown through the problem space. Each particle keeps track of its coordinates in the problem space which are associated with the best solution. This value is called $pbest$. Another best value called $gbest$ is the overall best value obtained by any particle in the population. The process of implementing the global version of PSO is as follows: Particles velocities on each dimension are fixed to a maximum velocity $vmax$. It determines the fitness or resolutins with which the regions between the present position and the target are searched . The acceleration constant c_1 and c_2 in equating (1) represent the acceleration terms that pull each particle towards $pbest$ and $gbest$ positions. In local versions of PSO particles have information only of their own and their neighbours bests, instead of entire group. The neighbours are

Algorithm 2 Particle Swarm Optimization (PSO)

1: Initialize a population or particles with random positions and velocities on d dimensions in the problem space
2: For each particle , evaluate the desired optimization fitness function in d variables
3: Compare particles fitness with evaluation with particles pbest. If current value is better than *pbest* then set *pbest* value equal to current value.
4: Compare fitness evaluation with the populations overall previous best. If current value is better than *gbest*, then reset *gbest* to the current particles array index and value.
5: Change the velocity and and position of the particle according to following equations. equations

$$v_i^{k+1} = wv_i^{k+1} + c_1\ rand_1 \times (pbest_i - s_i^k) + c_2\ rand_2 \times (gbest - s_i^k) \tag{3.50}$$

$$s_i^{k+1} = s_i^k) + v_i^{k+1} \tag{3.51}$$

6: Loop to step 2 until criterion is meet, usually a sufficiently good fitness or a maximum number of iterations

topological and neighborhoods do not change during a run. PSO is simple, easy to implement and computationally efficient algorithm.

3.9.3 Firefly Algorithm (FFA)

Fireflies are one of the wonderful creations whose life style of living is quite different from other creature. Based on their behaviour, Yang and Xingshi developed Firefly Algorithm (FFA) in 2008 [23]. Fireflies are characterized by their flashing lights. Flashing lights has two purposes, one is to attract breeding partners and subsequent is to prevent beast of prey . The flashing light obeys rule of physics that intensity (I) of light decreases with increase of distance (r), which is governed by the equation $I = 1/r2$. Generally, the first signallers are flying males, who attempt to fascinate female fireflies. Females fireflies respond to these signals in terms of emitting blinking lights. Distance between fireflies affects the attraction between the breeding partners as light intensity decreases with distance. Both partners produce discrete signal patterns to code information like identity of species and sex [232, 233].

The FFA algorithm has three rules:

1. All fireflies are unisexual, so one firefly will be attracted by all other fireflies. 2. Attractiveness is proportional to their brightness, the less bright one will be attracted by the brighter one and the brightness decreases as the distance between the fireflies increases. 3. If there are no fireflies brighter than a given firefly, it will move randomly.

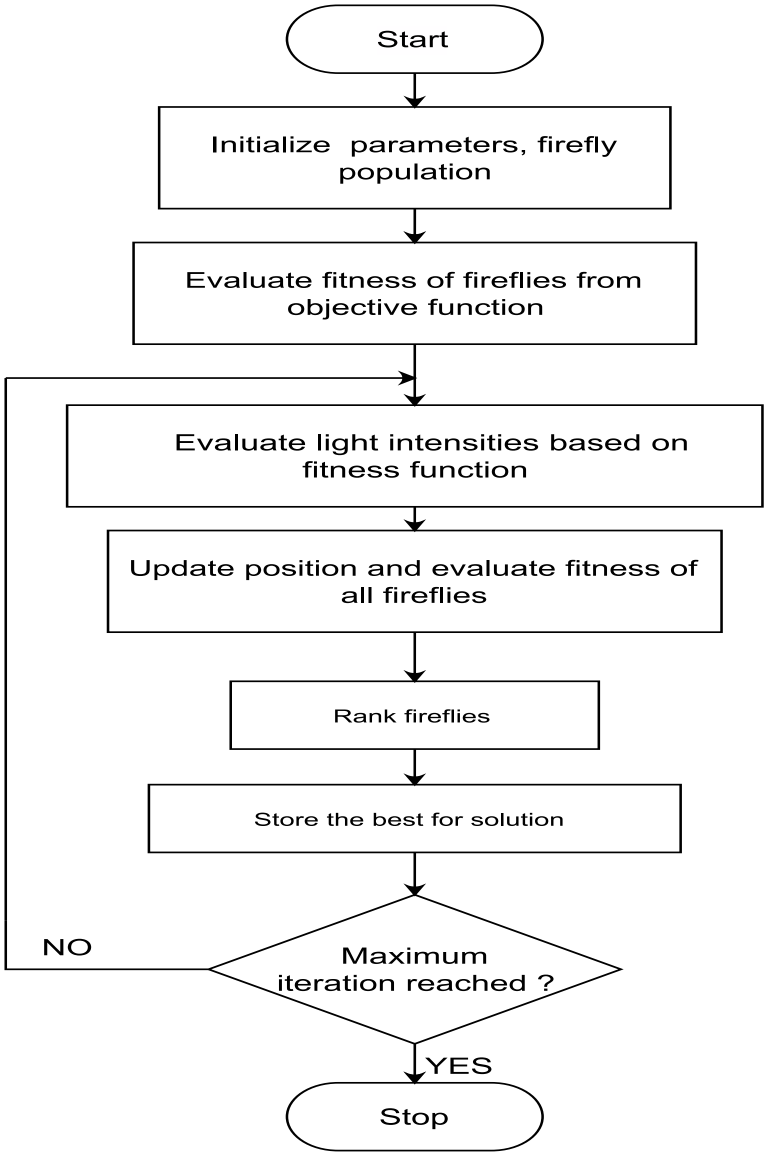

FIGURE 3.8: Flowchart of Firefly Algorithm (FFA)

Thus, brightness of flash is associated with fitness function. The light intensity that obeys inverse square law is as given below.

$$I(r) = \frac{I_0}{r^2} \tag{3.52}$$

where $I(r)$ is light intensity at distance r and I_0 is source intensity. For a given medium with fixed absorption coefficient γ, light intensity I varies with distance r as given in below.

$$I(r) = I_0 \ e^{\ \gamma \ r^2} \tag{3.53}$$

Where, I_0 is original light intensity, γ is absorption coefficient and r is distance between fireflies. The attractiveness β of fireflies is proportional to their light intensities I. Therefore, an equation similar to Equation 3.53 is defined for the attractiveness.

$$\beta = \beta_0 \ e^{\ \gamma \ r^2} \tag{3.54}$$

where, β_0 is the attractiveness at distance $r = 0$. The space between the fireflies i and j with position S_i and S_j is expressed as the Euclidean distance as given below.

$$r_{ij} = \sqrt{\sum_{k=1}^{n} (S_{ik} - S_{jk})^2} \tag{3.55}$$

where, n represents dimension of model. Less attractive fireflies (ith) will move towards most attractive firefly (j). Thus, FA parameters will be updated as below.

$$S_i(t+1) = S_i(t) + \beta_0 e^{-\gamma \ r_{ij}^2} (S_j(t) - S_i(t)) + \alpha \ \epsilon_i \tag{3.56}$$

where,ϵ_i is a random number and α is randomization constraint.

FFA is applied in spatial fields with different dimensions with promising efficiency. FFA is a metaheuristic algorithm, which assumes that a solution of an optimization problem is associated with the location of firefly and objective function is encoded as the light intensity. In FFA there are two important factors; first, variations in light

Algorithm 3 Firefly Algorithm (FFA) [233]

Objective function $f(x)$, $x = (x_1, ..., x_d)^T$
Initialize a population of fireflies $x_i (i = 1, 2, ..., n)$
Define light absorption coefficient γ
while (t < MaxGeneration)
for i = 1 : n all n fireflies
  for j = 1 : i all n fireflies
    Light intensity I_i at x_i is determined by $f(x_i)$
    if $(I_j > I_i)$
      Move firefly i towards j in all d dimensions
    end if
    Attractiveness varies with distance r via exp [γ r^2]
    Evaluate new solutions and update light intensity
  end for j
 end for i
Rank the fireflies and find the current best
 end while
Postprocess results and visualization

intensity, and second formulation of attractiveness that is based on brightness function, which in turn is associated with objective function. Attractiveness of a firefly is directly proportional to the objective function.

3.9.4 Symbiotic Organisms Search (SOS)

The SOS algorithm is proposed by Cheng and Prayogo [234]. The SOS algorithm works on the cooperative behavior observed between organisms in nature. Some organisms do not live alone. They are interdependent on each other for survival and food. The interdependency between two species is known as symbiotic. The most common symbiotic relations found in the nature are mutualism, commensalism, and parasitism. When the relation between two different species results in mutual benet, it is called mutualism. A relationship between two organisms that offers benets to only one of them is called commensalism. Finally, relationship between two different organisms that offers benets to one and harms to the other is called parasitism.

In SOS, new solution generation is governed by imitating biological interaction between two organisms of the ecosystem *i.e.*, mutualism, commensalism, and parasitism. Organism interacts with each other randomly through all phases. The process is repeated until termination criteria is achieved. The outline of the algorithm is as follows:

- Initialization
- REPEAT
  i) Mutualism phase
  ii) Commensalism phase
  iii) Parasitism phase
- UNTIL (termination criterion criteria achieved)

SOS algorithm algorithm is explained in following Section.

i) **Mutualism Phase:** The mutualism phase of SOS mimics a mutualistic relationships between two organisms e.g. bees and flowers. If X_i is an organism matched to i_{th} member of the ecosystem, then organism X_j is randomly selected from ecosystem to interact with X_i. New candidate solutions for X_i and X_j are calculated based on mutualistic symbiosis between them. The benefit factors (BF_1, BF_2) represent level of benefit to each organism. A vector called 'Mutual_Vector' represents relationship between organism X_i and X_j. Mutualistic effort to achieve their goal in increasing their survival is given by $(Xbest - Mutual\_Vector * BF_1)$. The X_{best} represents highest degree of adaptation.

ii) **Commensalism Phase:** This is observed in remora fish and shark. The remora attaches itself to shark and eats food leftovers, thus receiving a benefit, while shark is unaffected by remora fish. Here an organism X_j, is randomly selected to interact with X_i. Organism X_i attempts to benefit from the interaction. However, organism X_j itself neither benefits nor suffers. New candidate solution of X_i is calculated according to commensal symbiosis between organism X_i and X_j.

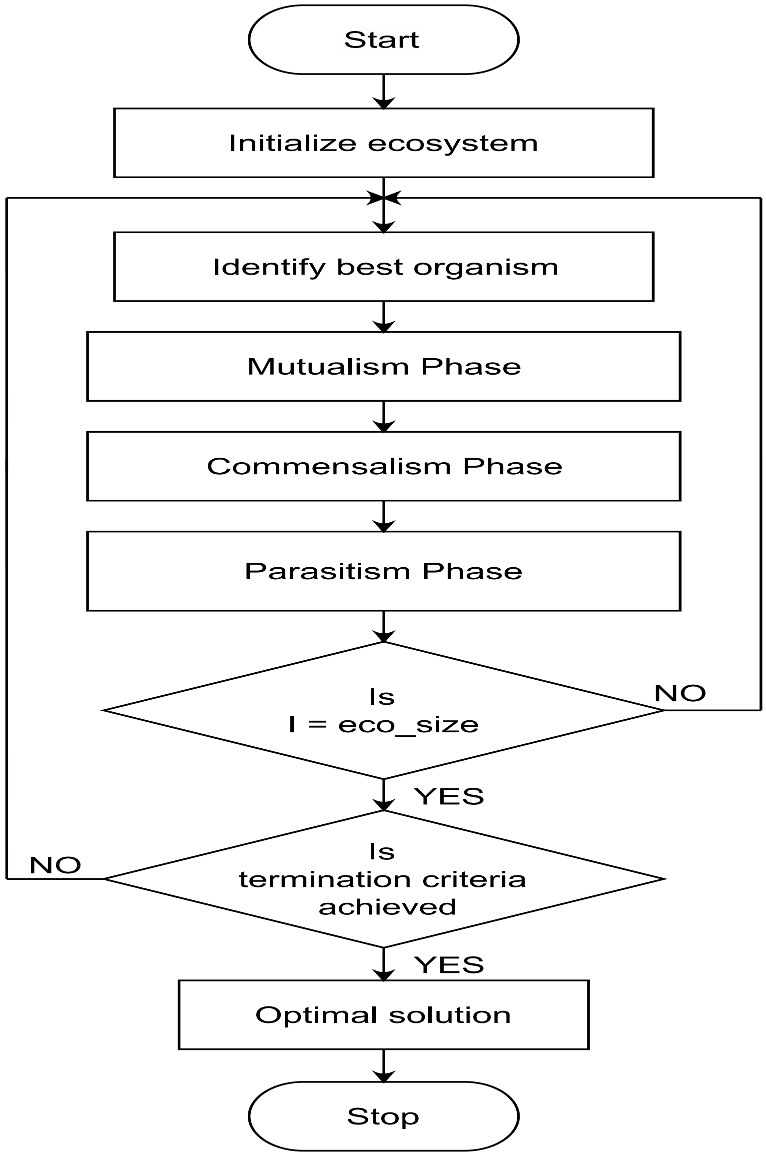

FIGURE 3.9: Flowchart of Symbiotic Organisms Search (SOS)

iii) **Parasitism Phase:** This is observed in mosquito and human body. Here a parasite vector is created by duplicating organism X_i. The randomly selected organism X_j serves as a host to parasite vector. Parasite vector tries to replace X_j in the ecosystem. Parasite_Vector having better fitness value kills organism X_j and fixes its position in the ecosystem. If fitness value of X_j is better, it will have immunity from the parasite and Parasite_Vector will be discarded from the ecosystem.

Algorithm 4 Symbiotic Organisms Search (SOS) [234]

1: **Ecosystem Initialization**
i Number of organisms (eco_size), initial ecosystem, termination criteria, num_iter = 0 num_fit_eval= 0, max_iter, max_fit_eval.
2: **Go to the next iteration**
3: **Identify the best solution** X_{best}
4: **Mutualism Phase**
i. Select one organism randomly, Xj, where $Xj \neq Xi$
ii. Determine mutual relationship vector ($Mutual\_Vector$) and benefit factor (BF)
iii. Mutual _Vector = $(Xi + Xj)/2$
BF_1 = random number either 1 or 2; BF_2 = random number either 1 or 2
iv. Modify organism Xi and Xj based on their mutual relationship
v. $Xi\ new = Xi + rand(0,1) * (Xbest - Mutual\_Vector * BF_1)$ $Xj\ new = Xj + rand(0,1) * (Xbest - Mutual\_Vector * BF_2)$
vi. Select Fitter organisms as solutions for the next iteration.
5: **Commensalism Phase**
i. Select one organism randomly, Xj, where $Xj \neq Xi$
ii. Modify organism Xi with the assist of organism Xj
iii.$Xi\ new = Xi + rand(-1,1) * (Xbest - Xj)$
iv. Select Fitter organisms as solutions for the next iteration
6: **Parasitism Phase**
i. Select one organism randomly, Xj, where $Xj \neq Xi$
ii. Create a Parasite ($Parasite\_Vector$) from Organism Xi
iii. Select Fitter organisms as solutions
7: Go to step 2 (Mutualism) if the current Xi is not the last member of the ecosystem otherwise proceed to next step
8: Stop if one of the termination criteria is reached
otherwise return to step 2 and start the next iteration

3.9.5 Grey Wolf Optimizer (GWO)

This algorithm is inspired by grey wolves and it is based on the leadership hierarchy and hunting mechanism [235]. Four types of grey wolves *viz.,* alpha, beta, delta, and omega are used in the algorithm. Also, three main phases of grey wolf hunting strategy *viz.,* searching for prey, encircling prey, and attacking prey are used in the algorithm. Grey wolves are considered at top of the food chain. Grey wolves mostly prefer to live in a pack with a group size of 5-12 on average and have a very strict social dominant hierarchy as shown in Figure 3.1.

First level in the hierarchy of grey wolves are alphas. They are leaders and consists of male and female wolves. The alphas are responsible for making decisions about

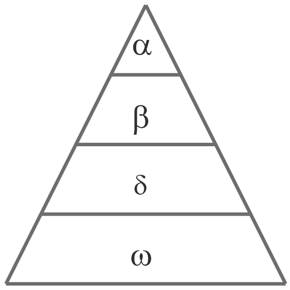

FIGURE 3.10: Hierarchy of grey wolves

hunting, searching sleeping place, time to wake *etc.* Alpha's decisions are mandatory to the whole group. Beta wolf are into the second level of hierarchy. They are subordinate wolves who help alphas in decision-making. The beta wolves can be either male or female. They are are selected as alpha when any alfa passes away. The omega take the blame for others wolves. They always always obey to all other wolves. Omega are less individual in the pack. They help to relive violence and frustration in the pack.

If a wolf is not an alpha, beta, or omega, he/she is called as delta. Delta wolves have to obey to alphas and betas. Scouts, sentinels, elders, hunters, and caretakers belong to this category. Scouts warn the pack in case of any danger. Sentinels protect and guarantee safety to all. Elders are experienced wolves who can be promoted to alpha or beta. Hunters help the alphas and betas when hunting a prey. The caretakers are responsible for caring for the weak, ill, and wounded wolves.

Social behavior of group hunting is another characteristics that includes:

- Tracking, chasing, and approaching the prey.
- Pursuing, encircling, and harassing the prey until it stops moving.
- Attack towards the prey.

This hunting technique and the social hierarchy of grey wolves can be mathematically modeled in order to design GWO algorithm.

i) **Social hierarchy:** In the mathematically modeling of GWO the fittest solution is considered as the alpha (α). The other solutions are named as beta (β) and

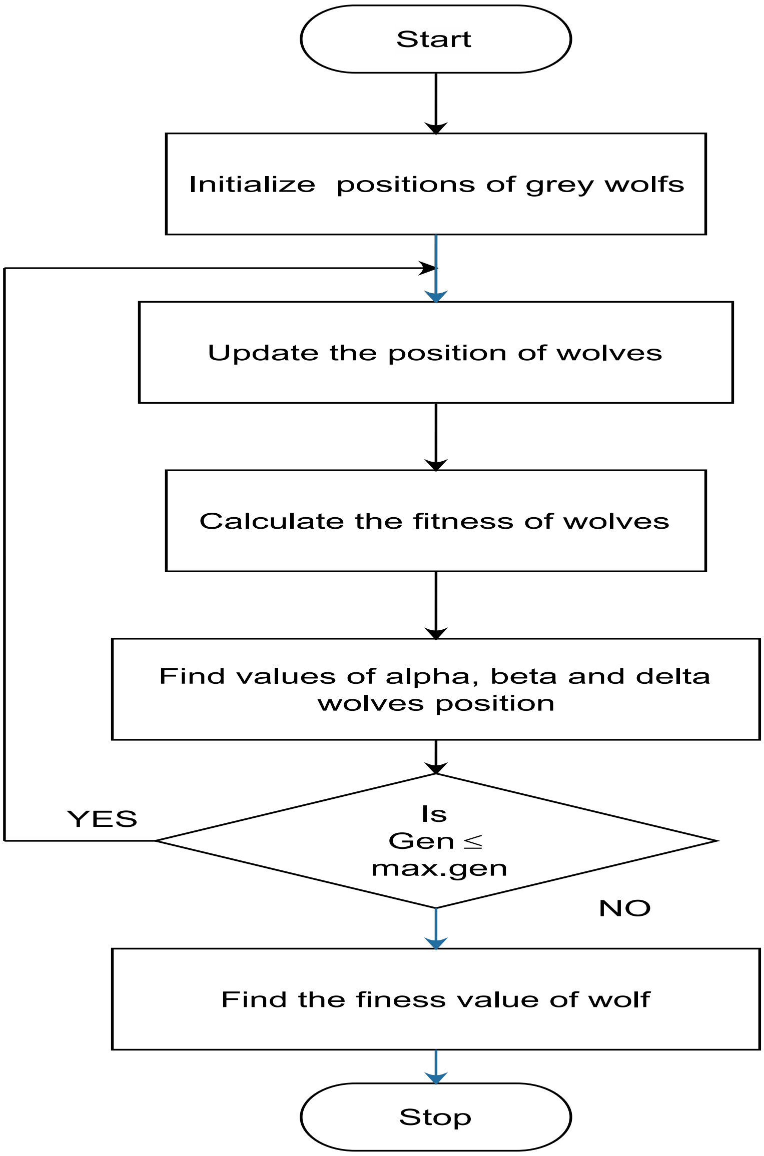

FIGURE 3.11: Flowchart of GWO

delta (δ) respectively. The remaining candidate solutions are omega (ω). In GWO algorithm the optimization is guided by α, β, ω and δ.

ii) **Encircling prey:** Grey wolves encircle prey during the hunt. Mathematically encircling behavior is modeled as shown below.

$$\vec{D} = |\ \vec{C}.\vec{X}_p(t) - \vec{X}(t)| \tag{3.57}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\ \vec{D} \tag{3.58}$$

Algorithm 5 Grey Wolf Optimizer (GWO) [235]

Initialize the grey wolf population X_i (i= 1, 2,...,n)
Initialize *a*, A and C
Calculate the fitness of each search agent
X_α= the first best search agent
X_β=the second best search agent
$X\delta$=the third best search agent
while (t < Max. number of iterations)
    for each search agent
        Update the position of the current search agent using equation (3.63)
    end for
    Update a, A and C
    Calculate the fitness of all search agents
    Update X_α, X_β and $X\delta$
    $t = t + 1$
end while
return X_α

where t indicates the current iteration, $\vec{X}_p$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf. The coefficient vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2.\vec{a}.\vec{r_1} - \vec{a} \tag{3.59}$$

$$\vec{C} = 2.\vec{r_2} \tag{3.60}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0, 1]. The equation (3.57) and equation (3.58) is represented by a two-dimensional position vector. A grey wolf in the position of (X, Y) updates its position according to position of the prey (X^*, Y^*). Different places around the best agent can be reached with respect to current position by adjusting the value of $\vec{A}$ and $\vec{C}$ vectors. Random vectors r_1, r_2 allow wolves to reach any position between around the prey.

iii) **Hunting:** Mathematically, hunting behavior of grey wolves is simulated assuming that alpha (*i.e.*, best candidate solution), beta and delta have better knowledge about the potential location of prey. Thus, the first three best solutions obtained so far are saved and other search agents are ignored and asked to update their positions according to the position of best search agents. This is represented as below.

$$\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha - \vec{X}|,\ \vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}|,\ \vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}| \tag{3.61}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha),\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta),\ \vec{A}_3 = \vec{X}_\delta - \vec{X}_3.(\vec{D}_\delta) \tag{3.62}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{3.63}$$

Thus alpha, beta, and delta wolves estimate position of the prey, and other updates their positions randomly around the prey.

iv) **Attacking and search for prey :** Grey wolves finish hunt by attacking the prey when it stops moving. Approaching the prey is mathematically modelled by decreasing the value of $\vec{a}$. The $\vec{A}$ has a random value in the interval [-2a, 2a] where a is decreased from 2 to 0. The $|A| < 1$ condition forces the wolves to attack the prey.

Search for prey or divergence is mathematically modelled by utilizing $\vec{A}$ with random values greater than 1 or less than -1. The $|A| > 1$ condition forces the grey wolves to diverge from the prey to find a another best prey.

3.10 Solution Methodology

The flowchart of optimal sizing and placement methodology is as shown in Fig. 3.12. Optimal sizing and placement of RDG is obtained by GA, PSO, SOS, FFA and GWO algorithm. The energy losses are calculated by backward forward sweep method. The population size for GA, fixed as 20. The values of C_1, C_2 and population size for PSO is initializes as 1, 2 and 20 respectively. The *eco_size* for SOS, firefly population for FFA and grey wolf population is fixed as 20 for each. The termination criteria are fixed to 100 iterations or a tolerance value of 10^{-6}, whichever is met first.

The initialization mainly includes system data, bus data, expected solar RDG generation and wind RDG generation, and the total number of RDGs. The initialization

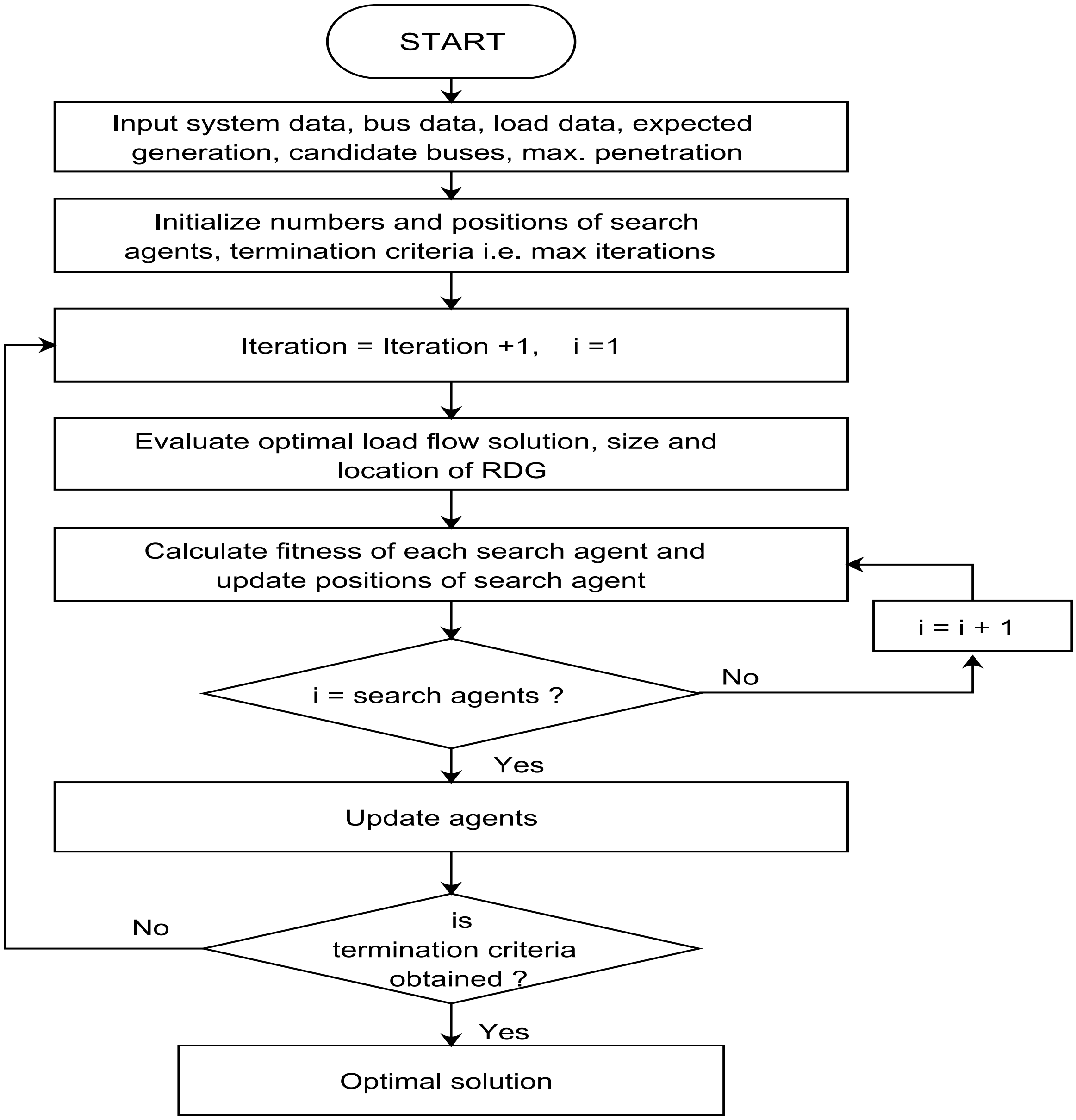

FIGURE 3.12: Solution methodology for RDG allocation

of algorithm includes the number of search agents, initial states and termination criteria. Fitness of search agents is calculated considering the objective function *i.e.,* loss minimization by optimal sizing and placement of RDG. The positions of the search agents are updated. If termination criterion is reached, then optimal values are stored otherwise the process is repeated.

3.11 Economic analysis

Economic analysis is carried out highlight the economic benefit of energy loss minimization. The costs include investment, operation and maintenance cost. Quantum benefits can be achieved in terms of energy generation and loss minimization from optimal allocation of RDG and ES. The total investment cost C_{INVST} and operation & maintenance (O&M) cost C_{OM} can be given as,

$$C_{INVST} = P_{ISG}\, C_{IS} + P_{IWG}\, C_{IW} \tag{3.64}$$

$$C_{OM} = \sum_{j=1}^{N_Y} (P_{ISG}\, C_{OMS} + P_{IWG}\, C_{OMW}) \left(\frac{1 + R_{inf}}{1 + R_{int}}\right)^j \tag{3.65}$$

Where, C_{IS} investment cost of solar RDG in $Rs./MW$; C_{IW} investment cost of wind RDG in $Rs./MW$; P_{ISG} total installed capacity of solar RDG MW; P_{IWG} total installed capacity of wind RDG MW; C_{OMS} O&M cost of solar RDG $Rs./MW$; C_{OMW} O&M cost of wind RDG $Rs./MW$; N_Y total number of years; R_{inf} inflation rate; R_{int} interest rate or discount rate; Revenue is obtained from generation of renewable energy. The total benefit by the production of renewable generation can be obtained as below,

$$B_{EG} = \sum_{j=1}^{N_Y} (P_{SG}\, C_{SE} + P_{WG}\, C_{WE}) \left(\frac{1 + R_{inf}}{1 + R_{int}}\right)^j \tag{3.66}$$

Where, C_{SE} cost of solar energy $Rs./kWh$; C_{WE} cost of wind energy $Rs./kWh$; With the optimal allocation of RDG, significant loss minimization is attained. The cost of this saved energy due to loss minimization is given as,

$$B_{EL} = \sum_{j=1}^{N_Y} (P_{LS}\, C_{SEL} + P_{LW}\, C_{WEL}) \left(\frac{1 + R_{inf}}{1 + R_{int}}\right)^j \tag{3.67}$$

Where, P_{LS} annual energy loss minimization by solar RDG MWh; P_{LW} annual energy loss minimization by wind RDG MWh; C_{SEL} cost of energy losses for solar RDG $Rs./kWh$; C_{WEL} cost of energy losses for wind RDG $Rs./kWh$;

Various indices used for economic analysis of RDGs include net present value (NPV), aggregate benefit cost ratio (ABCR) and discounted payback period (DPBP).

NPV is the net value of all benefits (i.e. cash inflows) and costs (i.e. cash outflows) of the project. The project with NPV greater than 0 is economically acceptable as it brings profit to investors. While comparing investment options, project with higher NPV is selected.

$$NPV \ = \ cash\ inflows \ - \ cash\ outflows \tag{3.68}$$

While comparing two projects with different initial investments, judging them merely on NPV basis may be misleading. The project with large investment shows an impressive NPV than projects with lower capital. Under such conditions, Benefit Cost Ratio (BCR) is a better tool to judge the economic viability.

ABCR is the ratio of the accumulated present value of all the benefits, to the accumulated present value of all costs, including the initial investment.

$$ABCR = \frac{Present\ value\ of\ benefits}{Present\ value\ of\ costs} \tag{3.69}$$

The project with higher $ABCR$ is most preferable.

DPBP indicates the minimum period over which the investment for the project is recovered considering the time value of money. At payback period,

$$Present\ value\ of\ costs = present\ value\ of\ benefits \tag{3.70}$$

The project with lower pay back period is most preferable.

3.12 Results and Discussions

3.12.1 System under Study

The proposed optimal sizing and placement methodology is applied to a 34 bus test system as shown in Figure 3.1 [218]. The system load is modeled as specified in IEEE-RTS system. Hourly solar and wind data of 5 years is taken for Satara (Longitude:74.05 E, Latitude:17.75 N) Maharashtra state, India. The selected site of Satara district in

Maharashtra has a strong potential for solar and wind generation. Abundant land is available for installation of solar and wind power plants. Also, the site equally suitable for the placement of hybrid RDG, due to the availability of both types of renewable generation. Thus, Satara is considered as representative region for the renewable generation, considering the progressive renewable generation of Govt. of India. To obtain the expected generation for the case studies, five-year data for wind speed and solar irradiance from National Renewable Energy Laboratory (NREL) is considered [236].

Table 3.3: KD325GX-LFB solar panel

	STC	NOCT	Temp.Coeff.
V_{MPP}(V)	40.3	36.2	-0.47
I_{MPP}(A)	8.07	6.47	0.025
V_{oc}(V)	49.7	45.5	-0.36
I_{sc}(A)	8.69	7.04	0.060

Table 3.4: WES100 wind turbine

Rated Power	100 kW
Cut-in wind speed	3 m/s
Rated wind speed	13 m/s
Cut-off wind speed	25 m/s
Survival wind speed	60 m/s

Table 3.5: Parameters of solar and wind *pdf*s

Solar PV generation		Wind generation	
Parameter	Values	Parameter	Values
μ	0.378	k	2
ρ	0.077	V_m	8.6380
α	33.217	c	9.7437
β	54.584		

The solar PV module used is 325 W [237] and wind turbine is 100 kW [238]. These specifications of SPV module and wind turbine are shown in Table 3.3 and Table 3.4. The *cdf*s are generated selecting different states per hour for β *cdf* and Reilaygh *cdf* respectively. The states are selected based on maximum solar irradiance and maximum wind speed. A state of 100 W/m_2 is selected for solar irradiance. Thus, there will be 10 sates for solar irradiance of 1000 W/m_2. A state of $1m/s$ is selected for wind speed. Thus, there will be 10 sates for wind speed of 10 m/s. The values of various parameters of solar RDG and wind RDG are shown in Table 3.5.

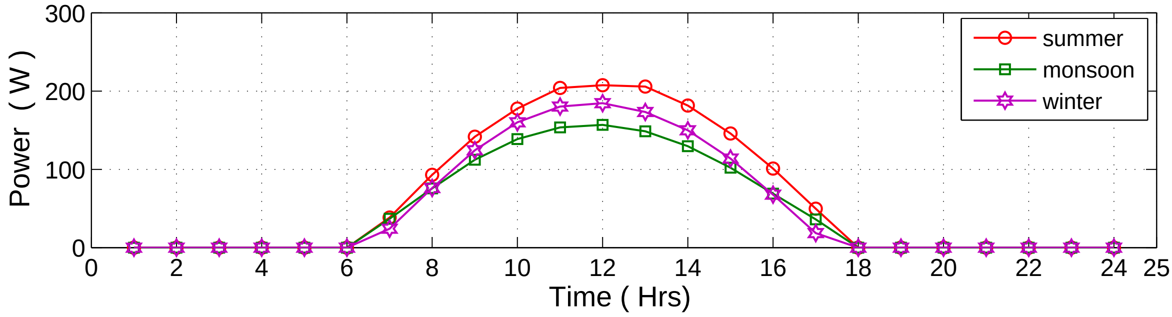

FIGURE 3.13: Expected solar power generation

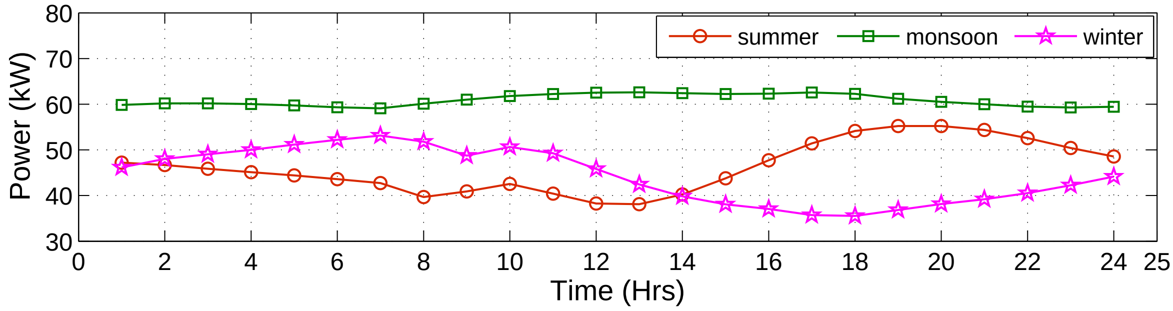

FIGURE 3.14: Expected wind power generation

TABLE 3.6: Probability & output power of states for solar RDG

s_1	s_2	s	$f_\beta(s)$	$P_o(s)$	$P(s)$
0	0.1	0.05	0.00000	12.863	0.00
0.1	0.2	0.15	0.00000	38.133	0.00
0.2	0.3	0.25	0.06111	62.712	3.83
0.3	0.4	0.35	0.60617	86.507	52.44
0.4	0.5	0.45	0.32201	109.421	35.23
0.5	0.6	0.55	0.01063	131.360	1.40
0.6	0.7	0.65	0.00001	152.227	0.00
0.7	0.8	0.75	0.00000	171.929	0.00
0.8	0.9	0.85	0.00000	190.369	0.00
0.9	1	0.95	0.00000	207.453	0.00

TABLE 3.7: Probability & output power of states for wind RDG

v_1	v_2	v	$f_w(v)$	$P_o(w)$	$P(w)$
0	1	0.5	0.0159	0	0.00
1	2	1.5	0.0463	0	0.00
2	3	2.5	0.0724	0	0.00
3	4	3.5	0.0920	5	0.46
4	5	4.5	0.1041	15	1.56
5	6	5.5	0.1084	25	2.71
6	7	6.5	0.1057	35	3.70
7	8	7.5	0.0975	45	4.39
8	9	8.5	0.0855	55	4.70
9	10	9.5	0.0716	65	4.65
10	11	10.5	0.0575	75	4.31
11	12	11.5	0.0442	85	3.76
12	13	12.5	0.0327	95	3.11
13	14	13.5	0.0233	100	2.33
14	15	14.5	0.0160	100	1.60
15	16	15.5	0.0106	100	1.06
16	17	16.5	0.0067	100	0.67
17	18	17.5	0.0041	100	0.41
18	19	18.5	0.0025	100	0.25
19	20	19.5	0.0014	100	0.14

Probability and output for different states of a typical hour (*i.e.* 8 am) for solar RDG and wind RDG are shown in Table 3.6 and Table 3.7. For solar PV, probabilistic generation for 10 states is obtained considering the maximum irradiance of that hour state as 1 kW/m^2 The summation of output of each state gives the expected generation of a particular hour. Similarly for wind, probabilistic generation for 20 states is obtained considering the maximum wind speed that hour state as 20 m/s. The summation of output of each state gives the expected generation wind RDG for a particular hour.

Total system peak load is 5.0 MVA. RDG penetration is considered as 2 MW *i.e.*, 40% of system's total peak load (P_{Lmax}) at unity power factor. The base case annual energy losses in the distribution network are 815.630 MWh.

The candidate buses selected for RDG placement are randomly selected ten buses as D {5, 15, 18, 22, 25, 27, 28, 29, 30, 32}. However in practice, any number of candidate buses can be selected depending on renewable potential and space availability. Allocation of RDG can be obtained on any of these buses by the optimization. The discrete size of RDG is considered as 100 kW. Solar RDG's minimum size is considered as 100 kW and maximum size is considered as 500 kW. Maximum size of RDG at any bus is limited by the feeder current. Here, the maximum current limit is 50 A. Optimal sizing and placement of RDG is discussed in the following sub-sections.

3.12.2 Optimal Allocation of Solar RDG

A solar model considered is of 325 W hence a solar RDG of 100 kW requires 308 rated solar PV modules. Thus, 20 solar RDGs has to be optimally placed on the candidate buses with their optimal size (*i.e.*, number) for 2 MW penetration (*i.e.*, 40 % penetration).

Table 3.8 shows annual energy loss minimization by optimal sizing and placement of solar RDG using various optimization algorithm *i.e.*, GWO, PSO, SOS, GA and FFA. Heuristic algorithms is a random search method. They do not produce unique solution for the optimization function, hence it is optimized for multiple runs. Ten runs of each optimization algorithm are taken to get optimal solution and best solution is

Table 3.8: Energy losses for solar RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	726.278	727.476	730.858	733.320	733.13
2	726.238	727.521	728.719	735.755	732.98
3	726.268	727.422	727.737	731.886	733.63
4	726.514	727.567	734.340	736.849	731.57
5	726.268	728.673	729.513	732.647	732.74
6	726.238	727.047	732.459	730.008	733.94
7	726.279	727.439	730.754	732.830	733.65
8	726.946	728.678	731.369	736.308	735.36
9	726.571	727.954	730.359	734.599	734.71
10	726.556	727.973	729.910	735.627	733.63
Mean	726.416	727.775	730.6018	733.983	733.534
SD	0.23068	0.543544	1.873077	2.20085	1.047316
Best	726.268	727.0472	727.737	730.008	731.570
Worst	726.946	728.678	734.340	736.849	735.360

Table 3.9: Optimal sizing and location of solar RDG

Location	Size (kW)				
(Bus no)	GWO	PSO	SOS	GA	FFA
5	-	-	-	-	100
15	-	-	-	100	100
18	-	-	100	200	100
22	400	200	300	300	300
25	400	300	400	300	200
27	400	400	400	300	400
28	200	300	200	200	100
29	-	-	200	100	100
30	200	400	100	300	200
32	400	400	300	200	400
Losses (MWh)	726.27	727.05	727.74	730.01	731.57
Loss reduction (MWh)	89.36	88.5828	87.893	85.622	84.06

picked from it. Mean value, Standard Deviation (SD), Best value and worst value for each algorithm are calculated as shown in Table 3.8. The mean value provide good indication about the convergence of the algorithm. The standard deviation indicate the stability of algorithm.

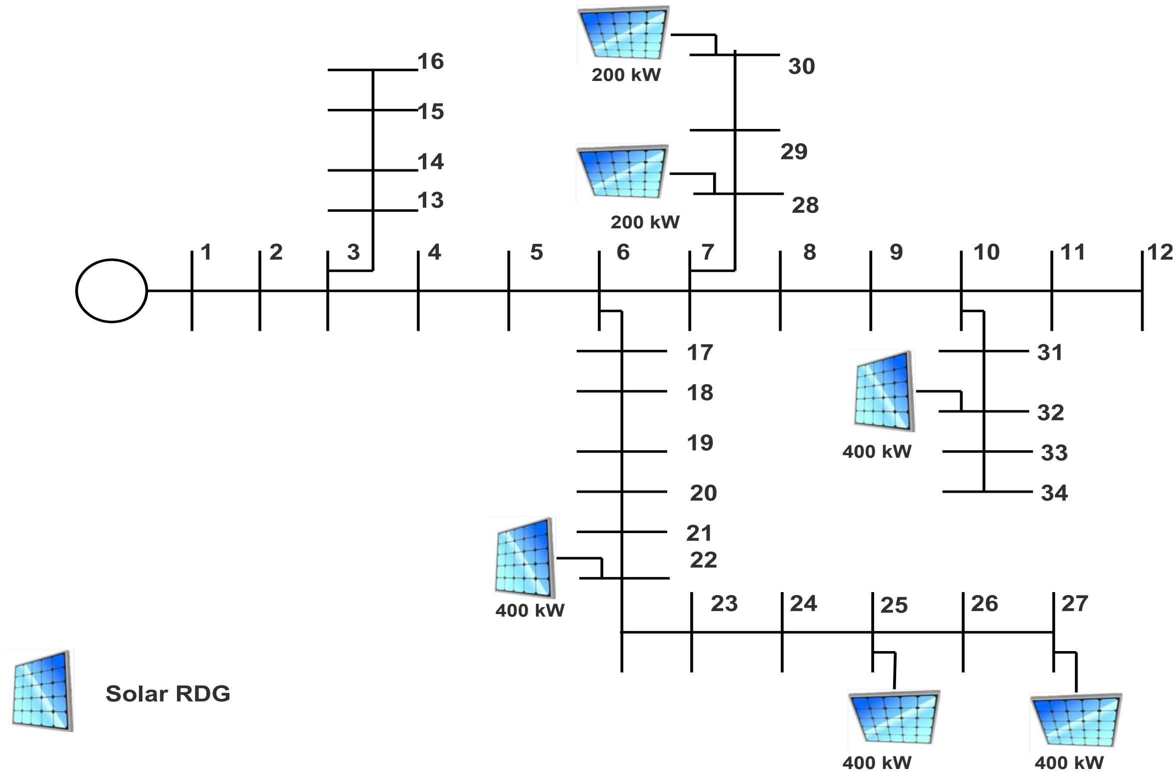

FIGURE 3.15: Optimal location of solar RDG in 34 bus system

GWO provides best optimal results as compared PSO, SOS, GA and FFA. Also, GWO has least SD. Optimal sizing and locations of solar RDG corresponding to the best optimal values are shown in Table 3.9. The GWO obtains optimal locations as {22, 25, 27, 28, 30, 32} with corresponding sizes in kW as {400, 400, 400, 200,200, 400}. Energy losses obtained by GWO are 726.27 MWh. Loss minimization is obtained by subtracting the losses obtained after placement of RDG from the base case losses of the system (*i.e.* 815.630 MWh). Loss minimization obtained by GWO is 89.36 MWh. PSO obtains the optimal locations at {22, 25, 27, 28, 30, 32} with corresponding sizes in kW as {200, 300, 400, 300, 400, 400}. Energy losses and loss minimization obtained by PSO are 727.05 MWh and 88.5828 MWh respectively. Similarly SOS obtains optimal locations as {18, 22, 25, 27, 28, 29, 30, 32} with corresponding sizes in kW as {100, 300, 400, 400, 200, 200, 100, 300 }. Energy losses and loss minimization obtained by SOS are 727.74 MWh and 87.893 MWh respectively. Optimal sizing and location, energy losses, and loss minimization provides by other algorithms *i.e.*, GA and FFA are shown in Table 3.9. The optimal placement of solar RDG is shown in Figure 3.15. The solar RDGs are placed on optimal locations that reduces ohmic losses in the network and provides energy loss minimization.

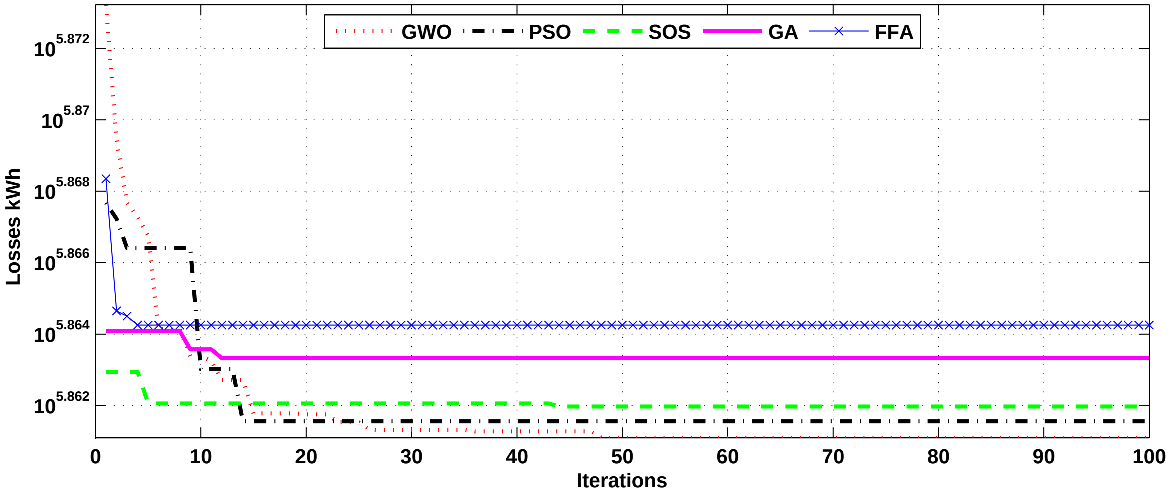

FIGURE 3.16: Convergence plot for solar RDG

Convergence plots for GWO, PSO, SOS, GA and FFA for solar RDG are shown in Figure 3.16. The convergence results specify a time limit within which the algorithm is guaranteed to converge. For all algorithms, population size and maximum iteration count is fixed to 20 and 100 respectively. The convergence values for GWO, PSO, SOS, GA and FFA are 48, 14, 6, 11 and 6 respectively. GWO offers best fitness value with slow convergence. Convergence of SOS and FFA are better with less optimal solutions as compared other algorithms.

3.12.3 Optimal Allocation of Wind RDG

Table 3.10 shows the annual energy loss minimization by optimal sizing and placement of wind RDG using various optimization algorithms *i.e.*, GWO, PSO, SOS, GA and FFA. Ten runs of each optimization algorithm are taken to get optimal solution. Mean value, standard deviation, best value and worst value for each algorithm is shown in

Table 3.10. After 10 runs, the mean value, SD, best and worst value of the objective function *i.e.*, loss minimization is 563.39,0.481,563.213 and 564.766 respectively. GWO provides best optimal results with best SD indicating the best stability of this algorithm. The optimal sizing and locations corresponding to the best optimal values for wind RDG are shown in Table 3.11.

TABLE 3.10: Energy losses for wind RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	563.225	565.514	566.925	575.286	582.200
2	563.261	566.873	579.019	577.854	575.563
3	564.766	567.587	580.048	575.771	580.855
4	563.261	570.151	579.237	574.148	575.879
5	563.273	571.406	572.423	580.399	577.052
6	563.273	568.239	579.846	572.011	577.052
7	563.213	569.432	569.891	577.487	575.987
8	563.227	567.293	580.494	573.321	578.888
9	563.273	567.470	578.325	578.749	580.134
10	563.213	566.854	573.019	576.694	580.908
Mean	563.399	568.082	575.923	576.172	578.452
SD	0.481	1.763	4.918	2.578	2.446
Best	563.213	565.514	566.925	572.011	575.563
Worst	564.766	571.406	580.494	580.399	582.200

GWO algorithm provides optimal locations at {22, 25, 27, 28, 29, 30, 32} with corresponding sizes in kW as {400, 400, 300, 200, 100, 200, 400}. Energy losses and loss minimization obtained by GWO are 563.213 MWh and 252.417 MWh respectively. PSO obtains the optimal locations as {18, 22, 25, 27, 28, 30, 32} with corresponding sizes in kW as {100, 400, 100, 400, 200, 400, 400}. Energy losses and loss minimization obtained by PSO are 565.514 MWh and 250.116 MWh respectively. The optimal sizing and location, energy losses, and loss minimization obtained with other algorithms is shown in Table 3.11. Figure 3.17 shows the optimal placement of wind RDGs on the 34-bus network.

Table 3.11: Optimal sizing and location of wind RDG

Location (Bus no)	Size (kW) GWO	PSO	SOS	GA	FFA
5	-	-	-	100	-
15	-	-	-	-	100
18	-	100	-	100	200
22	400	400	300	200	200
25	400	100	300	300	200
27	300	400	200	300	300
28	200	200	200	300	300
29	100	-	300	200	300
30	200	400	300	200	100
32	400	400	400	300	300
Losses (MWh)	563.213	565.514	566.925	572.011	575.563
Loss Reduction (MWh)	252.417	250.116	248.705	243.619	240.067

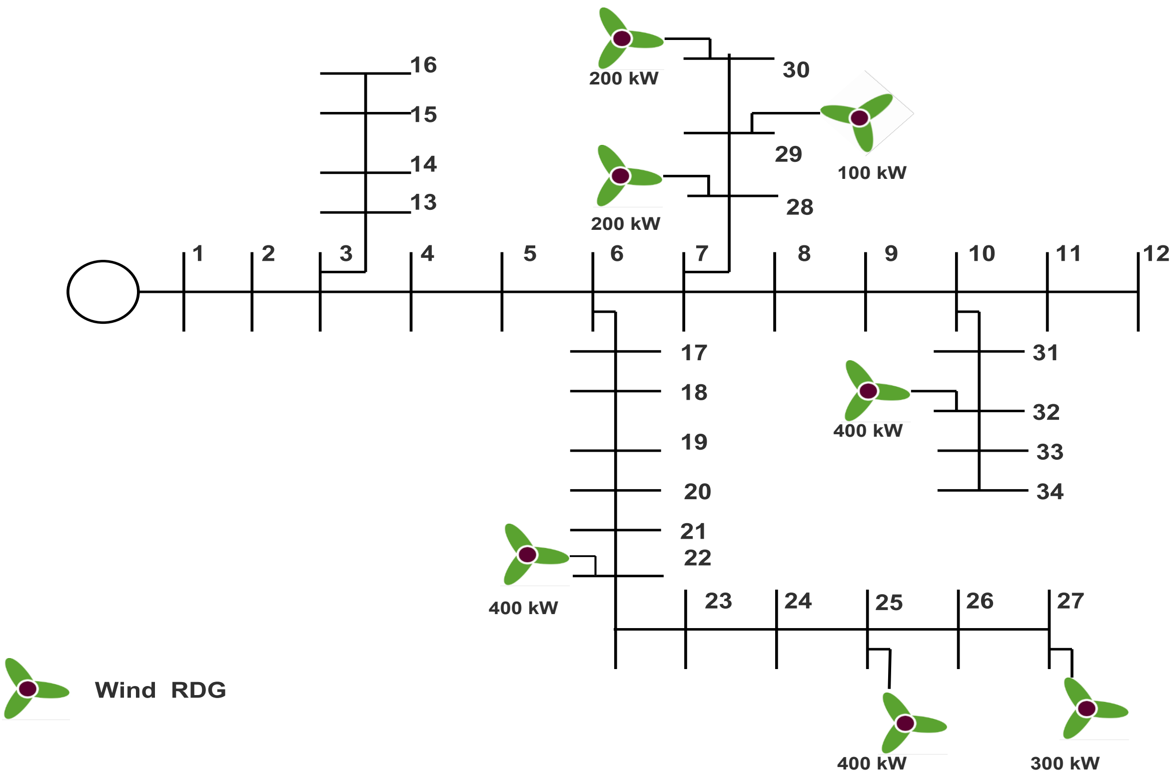

Figure 3.17: Optimal location of wind RDG in 34 bus system

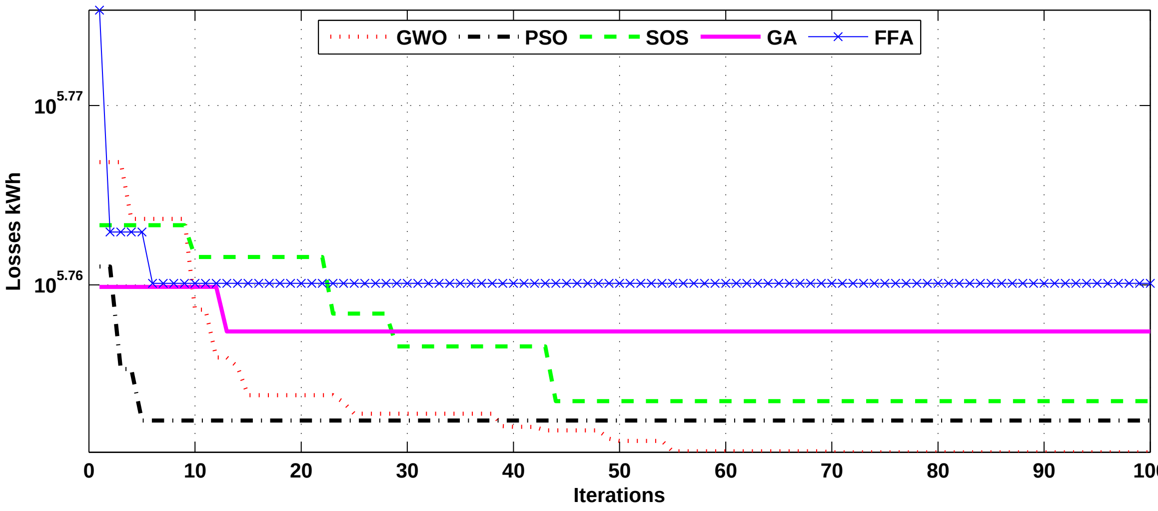

FIGURE 3.18: Convergence plot for wind RDG

The convergence plots for solar RDG with various algorithms is shown in Figure 3.18. The convergence values for GWO, PSO, SOS, GA and FFA are 55, 6, 10, 13, and 6 respectively. GWO offers best fitness value.

3.12.4 Optimal Allocation of Hybrid RDG

In hybrid RDG allocation solar RDG and wind RDG are optimally allocated. The combined maximum penetration for hybrid RDG (*i.e.*, solar RDG and wind RDG) is considered as 2 MW. Thus, solar RDG and wind RDG each contributes a 50 % penetration. Maximum 10 solar RDGs and 10 wind RDGs are optimally sized and placed on the candidate buses.

Table 3.12 shows the annual energy loss minimization by optimal sizing and placement of hybrid RDG. Mean value, standard deviation, best value and worst value for each algorithm are shown in the Table 3.12. The optimal sizing and placement of hybrid RDG corresponding to the best optimal values are shown in Table 3.13. The optimal placement or hybrid RDG is shown in Figure 3.19.

GWO obtains optimal placement of solar RDG on buses { 18, 22, 27, 30, 32} with corresponding sizes in kW as {100, 200, 200, 100, 400} and placement of wind RDG

Table 3.12: Energy losses for hybrid RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	622.114	632.427	648.409	656.795	650.320
2	627.316	631.549	654.674	655.719	654.439
3	621.705	638.759	646.523	648.549	647.084
4	623.334	630.941	662.970	653.644	645.740
5	621.133	639.259	662.857	645.890	647.971
6	624.342	637.840	645.535	652.692	652.422
7	625.576	641.985	640.008	645.528	655.108
8	620.769	643.932	665.200	655.658	652.064
9	625.794	634.613	644.448	648.851	649.032
10	620.869	637.543	640.713	652.651	648.313
Mean	623.295	636.885	651.134	651.598	650.249
SD	2.347	4.410	9.574	4.126	3.162
Best	620.769	630.941	640.008	645.528	645.740
Worst	627.316	643.932	665.200	656.795	655.108

Table 3.13: Optimal sizing and location of hybrid RDG

Location	Size (kW)									
	GWO		PSO		SOS		GA		FFA	
(Bus no)	S	W	S	W	S	W	S	W	S	W
5	-	-	100	-	100	100	-	-	-	-
15	-	-	-	-	100	-	-	-	-	100
18	100	-	200	-	-	-	-	-	100	200
22	200	100	-	400	100	100	-	-	100	100
25	-	400	-	-	100	200	100	400	100	200
27	200	100	300	100	400	200	100	200	100	100
28	-	-	-	-	-	-	-	-	200	100
29	-	-	-	-	-	300	100	-	200	-
30	100	-	100	200	-	-	300	-	100	100
32	400	400	300	300	200	100	400	400	100	100
Losses (MWh)	620.769		630.941		640.008		645.528		645.740	
Loss Reduction	194.861		184.689		175.622		170.102		169.890	
S - Solar W - Wind										

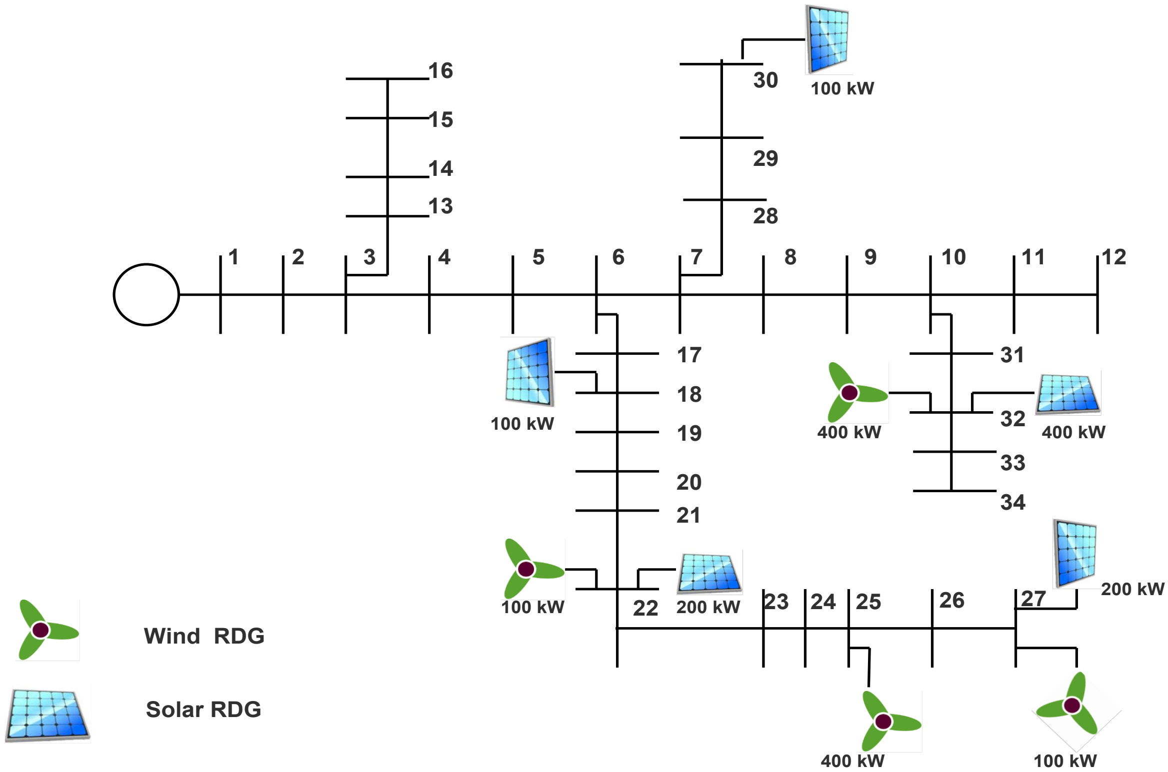

FIGURE 3.19: Optimal location of hybrid RDG in 34 bus system

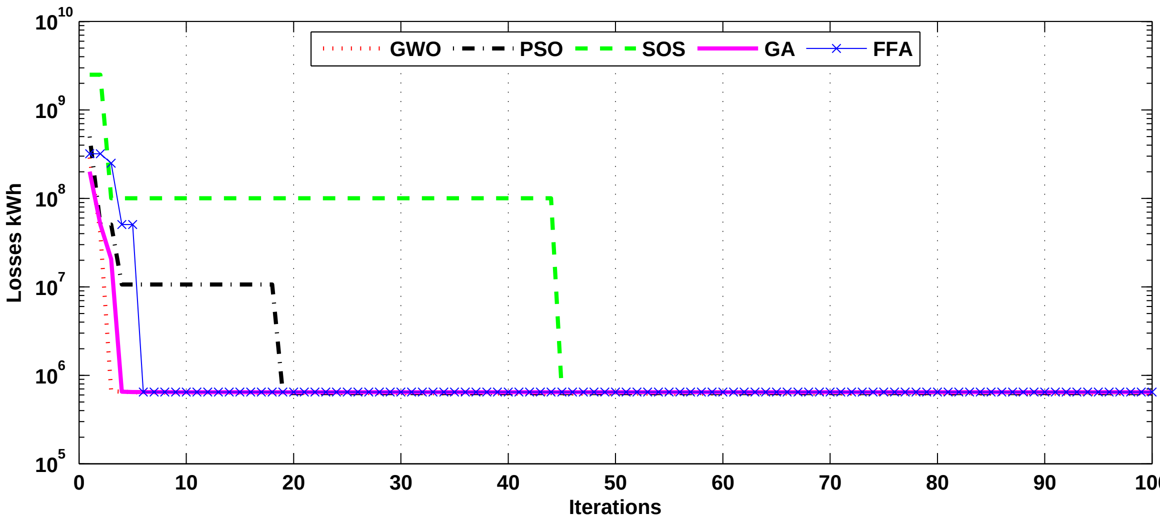

FIGURE 3.20: Convergence plot for hybrid RDG

on buses { 22, 25, 27, 32} with corresponding sizes in kW as {100, 400, 100, 400}. Energy losses and loss minimization obtained by GWO are 620.769 MWh and 194.861 MWh respectively. PSO obtains optimal placement of solar RDG on buses {5, 18, 27, 30, 32} with corresponding sizes in kW as {100, 200, 300, 100, 300} and placement of wind RDG on buses { 22, 27, 30, 32} with corresponding sizes in kW as {400, 100, 200, 300}. Energy losses and loss minimization obtained by PSO are 630.941 MWh and 184.689 MWh respectively. The optimal sizing and location, energy losses, and loss minimization provided by other algorithms are shown in Table 3.13. Figure 3.20 shows the optimal allocation of hybrid RDG in 34-bus system. The convergence plots for hybrid RDG with various algorithms is shown in Figure 3.20. The convergence values for GWO, PSO, SOS, GA and FFA are 59, 19, 45, 9 and 6 respectively.

Above results shows that proposed methodology gives significant results for loss minimization by optimal sizing and placement of renewable Distributed Generation. Among the three Renewable Distributed Generations, Wind RDG offers higher loss minimization. A moderate loss minimization is obtained with solar RDG. Hybrid RDG provides improved loss minimization as compared to solar RDG due to the support of wind RDG with continuous generation. GWO provides best optimal solutions for loss minimization for all the cases *i.e.*, solar RDG, wind RDG and hybrid RDG allocation as compared to other optimization methods *i.e.*, GA, PSO, SOS and FFA. Also optimization results of GWO are found to be more consistent. Hence GWO is more suitable for these type of optimization problems.

3.12.5 Economic Study Results

Economic benefits of solar RDG, wind RDG and hybrid RDG is analyzed using NPV, ABCR and DPBP. Investment cost for solar RDG and wind RDG in Rs./MWh is 58733000 and 61916000 respectively and O&M cost in Rs./MWh is 1300000 and 1063000 respectively. The inflation rate and discount rate are considered as Rs. 6.10 and Rs. 10.81. The cost of energy for solar RDG and wind RDG in Rs./kWh is 6.86 and 6.58 respectively [239]. The cost of energy for hybrid RDG is considered as an average of costs of generation form solar RDG and wind RDG.

The cost of energy losses are 6.86 Rs./kWh for solar RDG, 6.58 Rs./kWh for wind RDG and 6.72 Rs./kWh for hybrid RDG. Table 1 shows the NPV, ACBR and DPBP

Table 3.14: Economic Analysis

RDG	Loss reduction benefit	NPV	ABCR	DPBP
Solar	RS. 10373830.95	Rs. 133051107.8	1.896	9.6
Wind	RS. 26613985.35	Rs. 622508841.6	4.312	4.5
Hybrid	RS. 20613173.20	Rs. 427152618.2	3.481	5.7

for solar RDG, wind RDG and hybrid RDG. The useful life of renewable project is considered as 20 years. Higher NPV Rs. 622508841.6, higher ABCR 4.312 and lowest DPBP 4.5 years is obtained for wind RDG. Thus, wind RDG is more economical than solar RDG and hybrid RDG. After observing NPV, ACBR and DPBP for RDG, It can be concluded that energy saving by loss minimization over the life period of RDG is worth to cover capital and running costs.

3.13 Summary

RDGs are viewed as sustainable energy solution for future energy generation. In addition to energy generation, optimally sizing and placement of solar RDG and wind RDGs in distribution networks provides energy loss minimization. The purposed work considers the optimal sizing and placement of solar RDG, wind RDG and hybrid RDG for energy loss minimization. The historical data is used to obtain *cdf*s for the RDGs. The solar RDG, wind RDG and load is modeled to obtain generation-load models. The proposed methodology provides optimal solutions for sizing and placement of single RDG as well as hybrid RDG. In this case, allocation of wind RDG provides better loss minimization as compared to solar and hybrid RDG. GWO provides best optimal solution compared to other algorithms *i.e.*, GA PSO, SOS and FFA. Thus, GWO is suitable for this non-linear constrained RDG allocation problem. This optimal allocation technique can be applied for planning of RDGs.

CHAPTER 4

Optimal Sizing and Placement of Energy Storage

4.1 Introduction

Energy storage (ES) provide various applications to power system. A few important applications are in growing renewable energy penetration, voltage fluctuations mitigation and power quality improvement. Energy loss minimization with the help of ES is viewed as one of the important application of ES to power system. Optimal sizing and placement of ES in distribution network provides energy loss minimization in addition to energy supply to the system.

An optimal sizing and placement methodology of ES to obtain energy loss minimization in the presence of RDG is presented here. ES is optimally allocated in presence of the optimally allocated RDGs. The size and locations of optimal set of RDGs are selected from Chapter 3. Thus, the delusion variables are the size and location of ES. Battery ES sizing is modeled by considering the generation and load profile. This storage is suitably divided into multiple storage units and optimally placed at multiple sites. GA, PSO, SOS, FFA and GWO algorithms are applied to proposed methodology. The proposed methodology is illustrated by various case studies on a 34-bus test system.

The optimal sizing and placement solar RDG and wind RDG is obtained as explained in Chapter 3. Also, load modeling is obtained as given in previous chapter. ES modeling is explained in the next section.

4.2 Battery Energy Storage Modeling

Battery modeling is the basis for battery design, control and management. The common battery models are classified as electrochemical models and equivalent circuit models. The electrochemical models address the fundamental and physical aspects of batteries. They mainly analyze the complexity of electrochemical processes of the battery. The electric circuit models are lumped-parameter models developed for long-time studies. Electrical engineers prefer electric circuit models of battery for design and simulation studies [240].

In this thesis, a generic model proposed by the Western Electricity Coordinating Council (WECC) has been considered. It represents a single plant connected to distribution systems and an explicit ES model as shown in Fig 4.1 [241, 242].

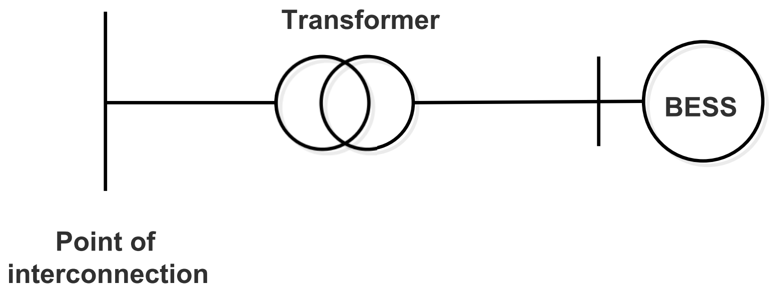

FIGURE 4.1: Single Generator Equivalent Representation for a BESS.

Battery ES plant is considered in a modular form. Therefore, its single generator equivalent model is sufficient for power flow analysis. ES charging or dis-charging condition are represented by setting an equivalent machine's output to positive or negative generation.

The lead acid battery converts chemical energy into electrical energy and vice versa. The current flows in external circuit conventionally from positive to negative electrode. Charging-discharging modes can be written as follows [243, 244]:

During discharging the reactions are,

Positive electrode:

$$PbO_2 + 4H^+ + SO_4^{2-} + 2e^- \longrightarrow PbSO_4 + 2H_2O \tag{4.1}$$

Negative electrode:

$$Pb + SO_4^{2-} \longrightarrow PbSO_4 + 2e^- \tag{4.2}$$

During charging the reactions are:

Positive electrode:

$$PbSO_4 + 2(OH)^- \longrightarrow PbO_2 + H_2SO_4 + 2e^- \tag{4.3}$$

Negative electrode:

$$PbSO_4 + 2H^+ + 2e^- \longrightarrow Pb + H_2SO_4 \tag{4.4}$$

In the proposed methodology, battery operates in charging mode during off-peak period and dis-charging mode during the peak period.

The important battery characteristics are [245, 246]:

- **Ampere-hour Capacity:** It is the total charge that can be discharged from a battery in fully charged state under specified conditions.
- **C-rate:** It represents a charge or discharge rate of a battery in one hour. For a 1 Ah battery, C equals to charge or discharge the battery at 1 A. Correspondingly,

0.1C is equivalent to 0.1 A, and 2C for charging or discharging the battery at 2 A.

- **State of Charge (SOC):** It is defined as the remaining capacity of a battery. It is mainly affected by operating conditions like temperature and load current.

$$SOC = Remaining\ \ Capacity\ /\ Rated\ \ Capacity \tag{4.5}$$

SOC is a critical condition parameter for battery management. Accurate measurement of SOC is challenging but important for healthy and safe of battery operation.

- **Depth of Discharge (DOD):**. It indicates the percentage of total battery capacity that has been discharged. Deep-cycle batteries can be discharged to 80% or higher.

$$DOD = 1 - SOC \tag{4.6}$$

- **State of Health (SOH):** It is ratio of the maximum charge capacities of an aged battery to a new battery. SOH helps to indicate the performance degradation and battery remaining lifetime.

$$SOH = Aged\ Energy\ Capacity\ /\ Rated\ Energy\ Capacity \tag{4.7}$$

- **Cycle Life:** It is the number of dis-charge charge cycles the battery can handle before it fails to meet specific performance at a specific DOD. The operating life of the battery is affected by DOD, charging and discharging rates, and temperature. Higher DOD reduces cycle life of a battery."

In a power system renewable energy sources are supposed to supply electric power to load for all the time. When power supplied by RDG exceeds the load, it is stored in the ES and when renewable energy is not sufficient, energy is supplied by the ES. The charging and discharging power of battery ES at each hour is expressed as given [247].

$$P_{ch}^{min} = P_{grid}^{t,min} - P_{load}^{t} \qquad P_{grid}^{t,min} \geqslant P_{load}^{t} \qquad \forall\ \ t \tag{4.8}$$

$$P_{dis}^{min} = P_{load}^{t} - P_{grid}^{t,max} \qquad P_{load}^{t} \geqslant P_{grid}^{t,max} \qquad \forall \;\; t \tag{4.9}$$

where, P_{load}^{t} is system load at time t, $P_{grid}^{t,min}$ and $P_{grid}^{t,max}$ represents minimum and maximum power supplied by all the generators in the power system. The minimum power rating of battery will be same as the maximum value of charging or discharging power as given below.

$$P_{BES} = max\left(P_{ch}^{min}, P_{dis}^{min}\right) \tag{4.10}$$

Also minimum energy charged into battery is,

$$E_{ch}^{min} = \int_{0}^{T} (P_{grid}^{t,min} - P_{load}^{t})\; dt, \qquad P_{grid}^{t,min} \geqslant P_{load}^{t} \tag{4.11}$$

and minimum energy supplied during discharging of battery is,

$$E_{dis}^{min} = \int_{0}^{T} (P_{load}^{t} - P_{grid}^{t,max})\; dt, \qquad P_{load}^{t} \geqslant P_{grid}^{t,max} \tag{4.12}$$

where T is total time period, which is one day, dt is time interval which is one hour. The minimum energy rating of battery will be the maximum value of charging or discharging energy as given below [160].

$$E_{batt}^{min} = max\left(\frac{E_{dis}^{min}}{\eta_d}, \eta_c\; E_{ch}^{min}\right) \tag{4.13}$$

where η_c and η_d are the charge and discharge efficiencies of the battery respectively.

Considering the seasonal renewable generation for summer (sum), monsoon (mon), winter (win) and seasonal load variation of the system, the minimum energy rating of battery ES is obtained as given below.

$$E_{batt}^{min} = max\left[\left(\frac{E_{dis}^{min}}{\eta_d}, \eta_c\; E_{ch}^{min}\right)_{sum}, \left(\frac{E_{dis}^{min}}{\eta_d}, \eta_c\; E_{ch}^{min}\right)_{mon}, \left(\frac{E_{dis}^{min}}{\eta_d}, \eta_c\; E_{ch}^{min}\right)_{win}\right] \tag{4.14}$$

The battery ES ratings obtained with equation (4.10) and (4.14) is taken as the maximum battery rating E_{BEG} in grid connected mode. This single large sized storage is split into N_d multiple storage units. Improved loss minimization is obtained if these multiple storage units are optimally allocated [172]. The maximum number of multiple storage units depends on the required loss minimization and economic constraints. The energy rating of multiple storage units is as given below.

$$E_{BEGD} = \frac{E_{BEG}}{N_d} \tag{4.15}$$

By observing the total peak time period T_{dis} and off-peak time period T_{ch} from load pattern, maximum charge / discharge power is obtained as,

$$P_{B,dis}^{max} = \frac{E_{BEGD}}{T_{dis}} \tag{4.16}$$

$$P_{B,ch}^{max} = \frac{E_{BEGD}}{T_{ch}} \tag{4.17}$$

With these maximum charge discharge power as upper limits, optimal charging power $P_{B,ch}$ and discharging power $P_{B,dis}$ for loss minimization is obtained by optimization techniques as given below.

$$P_{B,ch,i} = \eta_c \quad c_{B,ch,i} \quad P_{B,ch}^{max} \qquad \forall \quad i \tag{4.18}$$

or

$$P_{B,dis,i} = c_{B,dis,i} \quad \frac{P_{B,dis}^{max}}{\eta_d} \qquad \forall \quad i \tag{4.19}$$

The integer variable $c_{B,ch}$ or $c_{B,dis}$ represents an integer value obtained by optimization method. This is a percentage value that vary between 0-100%. This optimal charge / discharge power is utilized to calculate optimal energy rating of battery storage as given below.

$$E_B = P_{B,ch}, i \times T_{ch} \tag{4.20}$$

or

$$E_B = P_{B,dis,i} \times T_{dis} \tag{4.21}$$

Now, there must remain some minimum energy in the battery *i.e.,* minimum state of charge (SOC_{min}). Considering (SOC_{min}), each battery rating will be,

$$E_B = E_B + SOC_{min} \ E_B \tag{4.22}$$

Power loss P_{Loss} at each hour is calculated with backward / forward sweep method. Now considering RDG power and charging discharging power of battery at node i, active power P_i will get modified as shown below.

During charging,

$$P_i = P_{Li} - P_{RDGE,i} + P_{B,ch,i} \tag{4.23}$$

During discharging,

$$P_i = P_{Li} - P_{RDGE,i} - P_{B,disch,i} \tag{4.24}$$

The energy supplied by RDG at the ith node a fixed parameter but the value of $P_{B,ch,i}$ and $P_{B,disch,i}$ depends on the optimal size and location of battery ES.

Battery management system (BMS) is considered responsible for SOC and other related controls. BMS can use a various methods available for calculation of battery SOC [248]. These methods include i) Measuring electrolyte physical properties like acid density, viscosity, conductivity and refractive index ii) Measurement of open circuit voltage iii) Electrical charge / discharge characteristics measurement to calculate SOC iv) Impedance spectroscopy method to study the electrochemical processes in battery for SOC as well as SOH calculation. v) Internal resistance method to calculate battery SOC vi) Kalman Filter algorithm to find battery SOC vii) Ampere hour method to determine battery SOC

The SOC in ampere hour method is given by equation,

$$SOC = SOC_0 - \frac{1}{C_N}\int_{t_0}^{t} \delta_I I_{Batt} dt \tag{4.25}$$

where, SOC_0 nominal SOC of battery; C_N rated capacity of battery; δ_I current loss coefficient (Generally taken as 0.98); I_{Batt} Battery Current;

4.3 Objective Function of Loss Minimization by Allocation of ES

The objective function is to minimize annual energy losses by optimal sizing and placement of battery ES. Considering each season of four months and each month has 30 days, objective function is as given below.

$$F = min\left[120\left(\sum_{t=1}^{24} P_{loss,summer,t} + \sum_{t=1}^{24} P_{loss,monsoon,t} + \sum_{t=1}^{24} P_{loss,winter,t}\right)\right] \tag{4.26}$$

- **Constraints** All constraints related to RDG i.e., active and reactive power balance, feeder current and maximum penetration of RDG are explained in Chapter 3. The battery ES constraints are as given below.

  Battery ES charging discharging power should be within the upper and lower battery charge limits. Battery ES constraints are as given below.

$$\begin{aligned} 0 \leq P_{B,dis,t} &\leq P_{B,dis,t}^{max} \\ 0 \leq P_{B,ch,t} &\leq P_{B,ch,t}^{max} \\ P_{B,t,min}(t) \leq P_{B,t} &\leq P_{B,t,max} \end{aligned} \tag{4.27}$$

The last constraint in this equation indicate the storage power limits.

4.4 Solution Methodology

The optimal sizing and placement of ES in presence of RDG is obtained by GA, PSO,SOS, FFA and GWO algorithm. The energy losses are calculated by backward forward sweep method. The search agents are initialized as 20, and termination criteria is fixed to 100 iterations or a tolerance of 10^{-6}. The flowchart of proposed methodology is as shown in Fig 4.2.

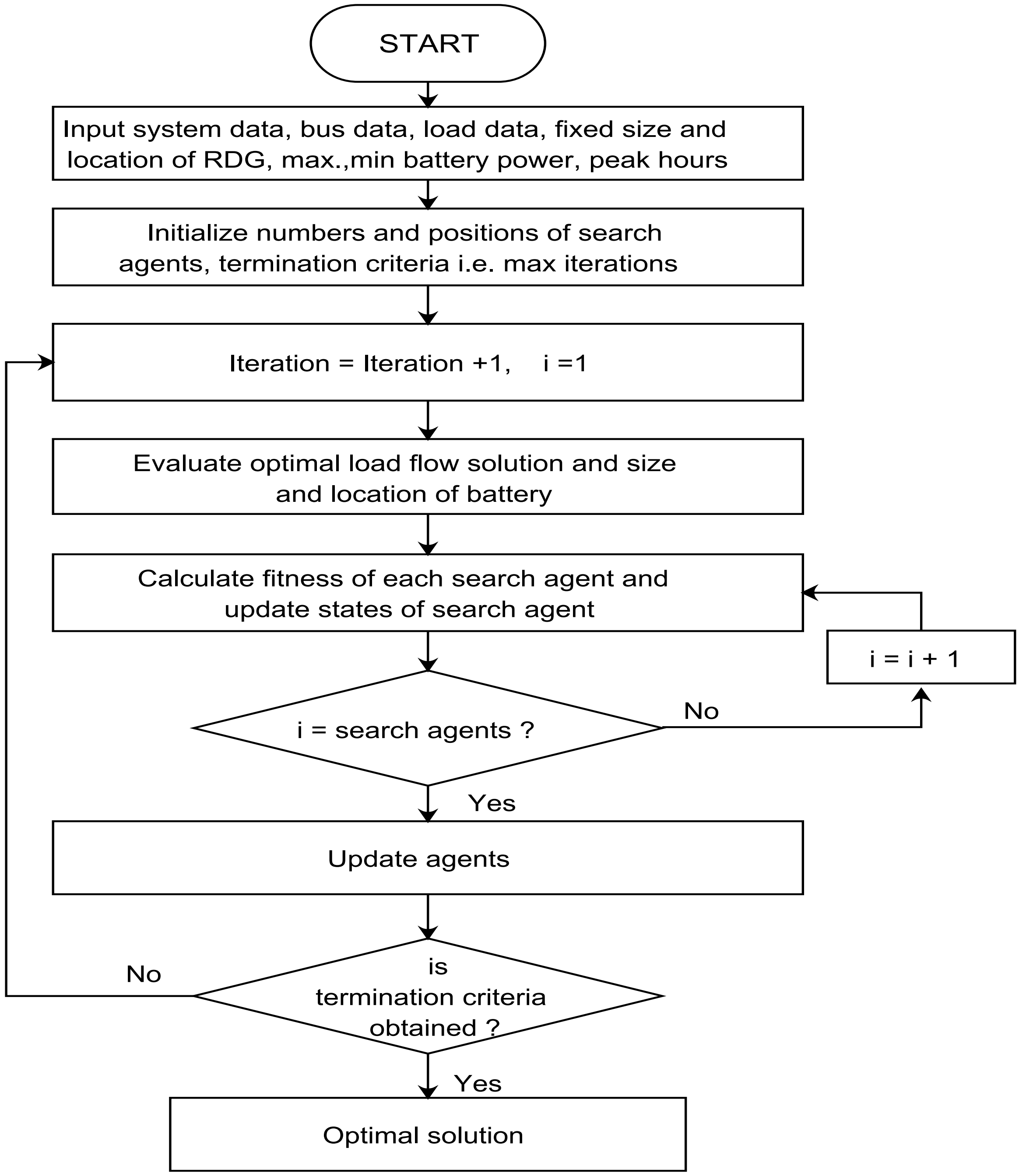

FIGURE 4.2: Solution methodology for ES allocation

The initialization mainly includes system data, bus data, expected solar and wind generation, charge discharge time *i.e.,* peak and off-peak time, the fixed sizing and locations RDGs. Initialization for GWO includes the number of search agents, initial positions and termination criteria. Fitness of search agents is calculated considering the objective function *i.e.,* loss minimization by optimal sizing and placement of ES in presence of RDG. The positions of the search agents are updated. If termination criterion is reached, optimal values are stored otherwise the process is repeated.

4.5 Results and Discussion

The storage units are optimally placed on any of the 34 buses except the source bus (i.e. bus number 1). The main approach is to optimally place the RDG in presence of RDG. The RDGs best optimal set of size and locations is selected from Chapter 3. These sizes and locations of RDG are taken from Chapter 3. These optimal sets are provided by GWO. Maximum penetration of RDG is considered as 2 MW (i.e., 40% penetration). The charging discharging efficiency of ES is assumed as 90% and minimum SOC is limited to 20%. The load peak is from 10 a.m. to 5 p.m. The battery ES discharges during peak load and get charged during off-peak period. ES allocation methodology is applied to three case studies i.e., ES sizing and placement in presence of solar RDG, wind RDG and hybrid RDG.

4.5.1 Allocation of Energy Storage in presence of solar RDG

Considering the renewable generation and load profile, maximum power rating of the ES is obtained as explained in Section 4.2. Power rating of ES is 4.89 MW. The ES is equally split into four units Sizing and placement of these four storage units is obtained in presence of RDGs. The optimal size and location of solar RDG is taken from chapter 3. The locations for solar RDG are {22, 25, 27, 28,30, 32} with corresponding sizes in kW as {400, 400, 400, 200, 200, 400}. These solar RDGs are fixed into the distribution network.

Table 4.1 shows the annual energy loss minimization by optimal sizing and placement of ES in presence of RDG. The mean value, standard deviation, best value and worst value are shown in the Table 4.1. The best optimal solutions provided by GWO, PSO, SOS, GA and FFA are 672.756 MWh,674.664 MWh,682.023 MWh,683.016 MWh and

TABLE 4.1: Energy losses by optimal allocation of ES with Solar RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	672.755	674.650	682.098	682.810	683.609
2	672.755	674.768	682.040	683.367	684.073
3	672.810	674.486	682.258	683.170	683.520
4	672.755	674.450	681.847	682.926	684.950
5	672.690	674.503	681.815	682.803	683.533
6	672.699	674.516	682.100	683.450	683.520
7	672.832	674.724	682.179	683.054	683.645
8	672.755	675.165	681.980	682.687	683.518
9	672.755	674.804	681.928	683.029	684.068
10	672.755	674.574	681.987	682.863	683.522
Mean	672.756	674.664	682.023	683.016	683.796
SD	0.043	0.216	0.141	0.250	0.461
Best	672.690	674.450	681.815	682.687	683.518
worst	672.832	675.165	682.258	683.450	684.950

683.796 MWh respectively. The optimal sizing and locations of ES corresponding to these optimal solutions are shown in Table 4.2.

TABLE 4.2: Optimal sizing and placement of Energy Storage with solar RDG

Algorithm	Battery location (bus no.)				Battery size		Losses (MWh)	Loss reduction (MWh)
					Power kW	Energy kWh		
GWO	3	10	13	17	242	2325	672.690	142.940
PSO	8	10	16	19	178	1705	674.450	141.180
SOS	7	10	13	17	197	1891	681.815	133.815
GA	8	11	13	18	193	1851	682.687	132.943
FFA	7	10	14	18	211	2024	683.518	132.112

GWO obtains optimal locations of Energy Storage on buses {3, 10,13, 17 } and the size of Energy Storage is 242 kW and 2325 kWh. This gives optimal power and energy rating of Energy Storage. With this optimal sizing and placement the annual energy loss minimization obtained 142.940 MWh respectively. PSO obtains optimal locations of Energy Storage on buses {8, 10, 16, 19} and the size of Energy Storage is 178 kW and 1705 kWh. The annual energy loss and loss minimization obtained is 674.450 MWh and 141.180 MWh. The optimal sizing and location, energy losses, and

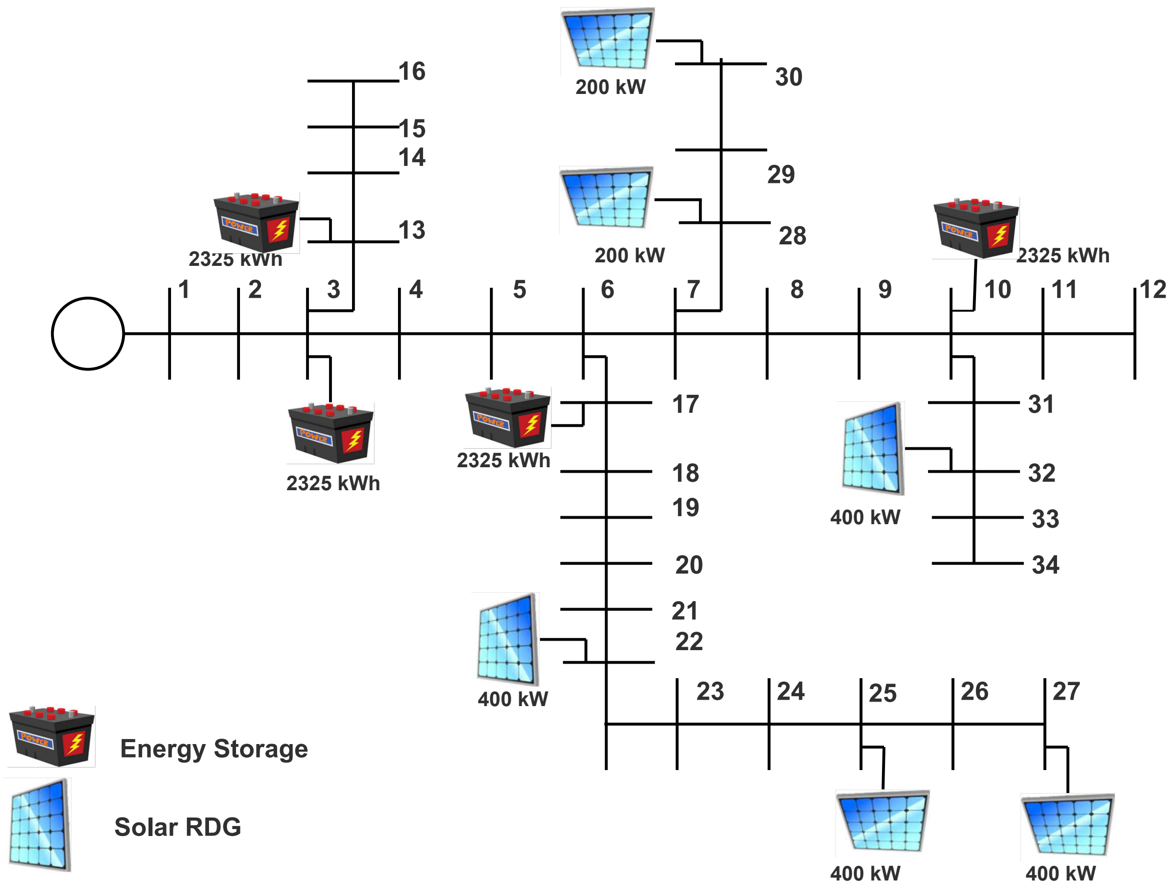

FIGURE 4.3: Allocation of ES in 34-bus system with solar RDG

loss minimization provided by other algorithms i.e., SOS, GA and FFA are shown in Table 4.2. The optimal placement of ES is in 34-bus network is shown in Figure 4.3. It can be observed that the battery ES is usually placed at node junction from where multiple nodes originates. Thus the line flows from the grid are minimized providing energy loss minimization.

The convergence plots for GWO, PSO, SOS, GA and FFA is shown in Figure 4.4. For all algorithms, the population size and maximum iteration count is fixed to 30 and 100 respectively. The convergence values for GWO, PSO, SOS, GA and FFA are 13, 37, 38, 8, and 17 respectively. The convergence of PSO and SOS are close to each other i.e., 37 and 38 iterations. GWO provides best optimal solutions. Also, it has best SD value that shows the stability of the algorithm.

The base case losses for the 34-bus test system are 815.63 MWh. Optimal placement

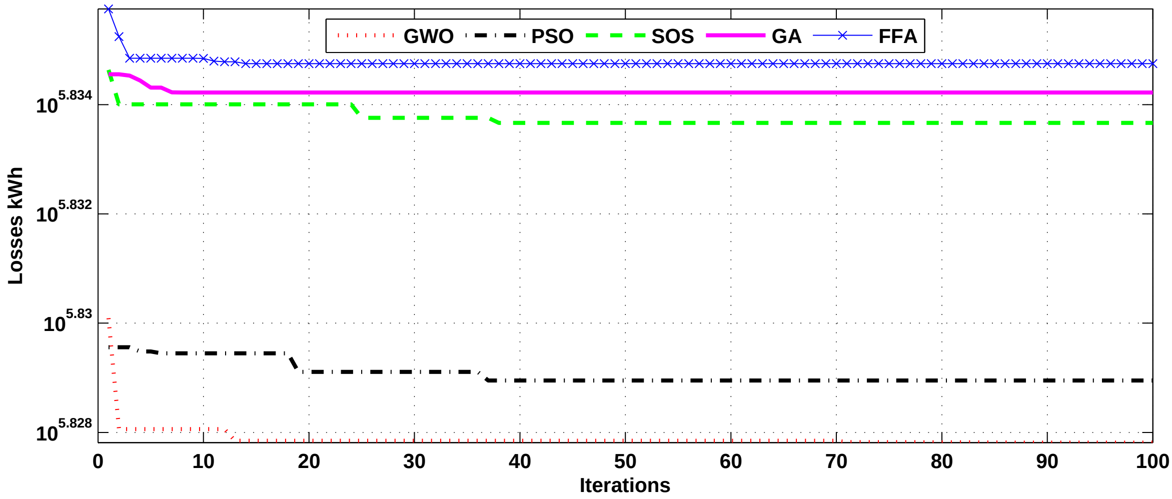

FIGURE 4.4: Convergence plot for allocation of ES with solar RDG

of solar RDG into the system energy provides energy losses for the optimal case (i.e., GWO) as 726.46 MWh and the loss minimization is 89.36 MWh as shown in Chapter 3 (Table 3.2). Further, optimal sizing and placement of ES in presence of solar RDG, provide energy losses as 672.690 MWh and loss minimization as 142.940 MWh. Thus, improved loss minimization is obtained by optimal sizing and placement of ES in presence of optimally allocated RDG.

4.5.2 Allocation of Energy Storage in presence of wind RDG

Energy Storage is optimally sized and placed in presence of wind RDG. In this case,

the maximum power rating of ES is 4 MW. This storage unit is split into four storage units. Sizing and placement of these ES units are obtained in presence of RDG. These fixed locations for wind RDG are {22,25,27,28,29,30,32} with corresponding sizes in kW as {400,400,300,200,100,200,400}.

Table 4.3 shows the optimal sizing and placement of ES in presence of RDG with GWO, PSO, SOS, GA and FFA. The results from this table shows that GWO provides best optimal results. The optimal sizing and locations of Energy Storage corresponding to these best optimal values are shown in Table 4.4.

Table 4.3: Energy losses by optimal allocation of ES with wind RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	534.588	541.603	546.296	549.697	550.336
2	534.393	541.604	547.232	549.233	549.734
3	534.269	541.244	547.224	549.789	549.437
4	534.393	541.568	546.466	548.513	550.619
5	534.269	541.770	546.715	548.170	549.444
6	534.418	541.359	546.663	548.500	549.369
7	534.738	541.395	546.223	548.117	549.978
8	534.269	541.548	546.843	548.393	549.621
9	534.393	541.487	546.042	547.193	549.874
10	534.550	541.151	546.991	548.792	550.205
Mean	534.428	541.473	546.670	548.640	549.862
SD	0.155	0.186	0.413	0.781	0.422
Best	534.269	541.151	546.042	547.193	549.369
worst	534.738	541.770	547.232	549.789	550.619

Table 4.4: Optimal sizing and placement of Energy Storage with wind RDG

Algorithm	Battery location (bus no.)				Battery size		Losses (MWh)	Loss reduction (MWh)
					Power (kW)	Energy (kWh)		
GWO	7	13	24	31	342	2959	534.269	281.361
PSO	3	6	24	31	325	2804	541.151	274.479
SOS	6	10	14	23	358	3095	546.042	269.588
GA	7	13	24	31	356	3073	547.193	268.437
FFA	10	14	24	28	317	2741	549.369	266.261

GWO obtains optimal locations of Energy Storage on the buses {7, 13, 24, 31 } and the size of Energy Storage is 342 kW and 2959 kWh. This size gives the power and energy rating of the Energy Storage. With this optimal sizing and placement the annual energy losses and loss minimization obtained is 534.269 MWh and 281.361 MWh respectively. PSO obtains optimal locations of Energy Storage on buses {3, 6, 24, 31} and the size of Energy Storage is 325 kW and 2804 kWh. The annual energy loss and loss minimization obtained is 541.151 MWh and 274.479 MWh. The optimal sizing and location, energy losses, and loss minimization provided by other algorithms i.e., SOS, GA and FFA are shown in Table 4.4. Figure 4.5 shows allocation of ES in 34-bus system with wind RDG.

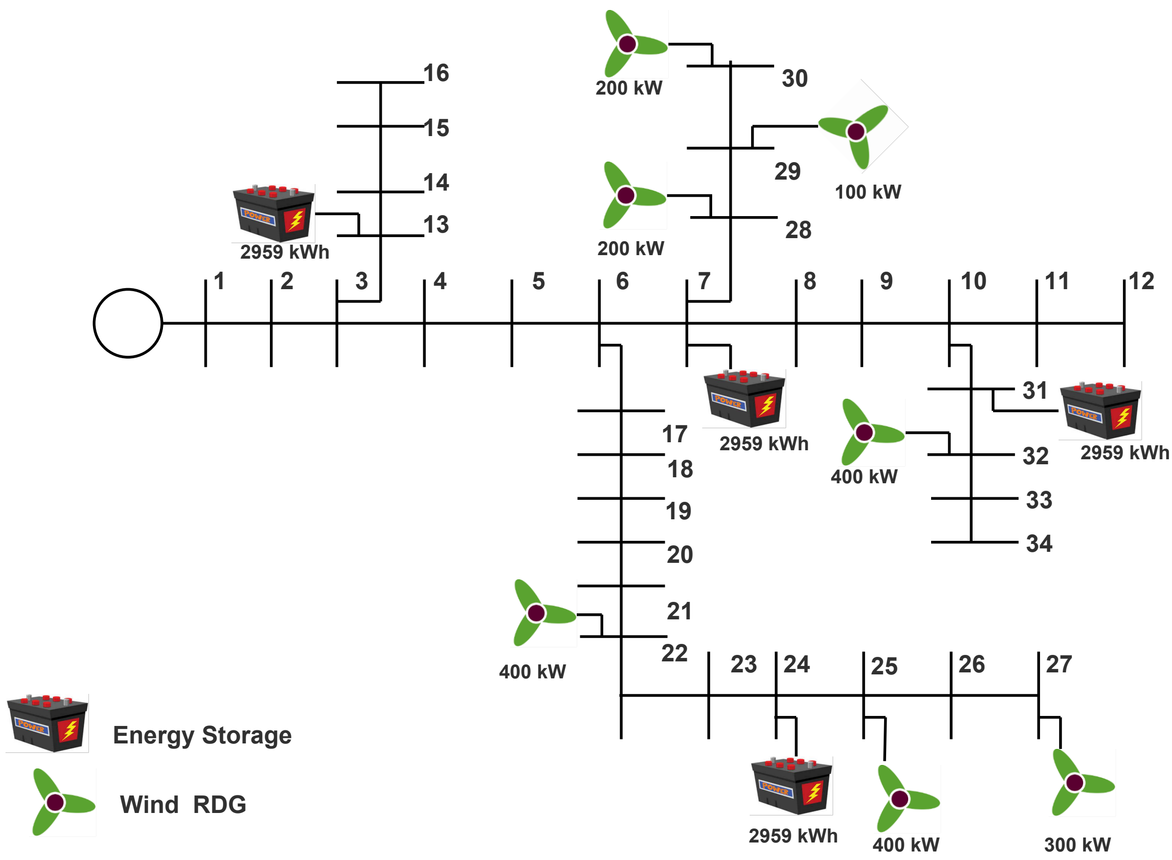

FIGURE 4.5: Allocation of ES in 34-bus system with wind RDG

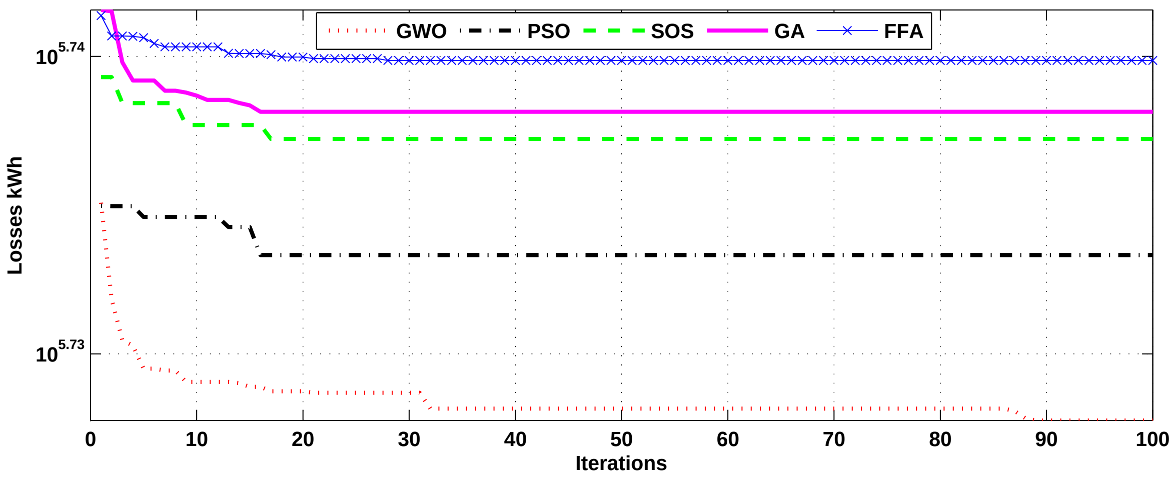

FIGURE 4.6: Convergence plot for allocation of ES with wind RDG

The convergence plots for GWO, PSO, SOS, GA and FFA is shown in Figure 4.6. For all algorithms, the population size and maximum iteration count was fixed to 30 and

100 respectively. The convergence values for GWO, PSO, SOS, GA and FFA are 32, 16, 17, 16 and 28 respectively. GWO offers best fitness value with slow convergence. The convergence of PSO, SOS and GA are close to each other i.e., 16 and 17. Converges of FFA is relatively slow as compared to PSO, SOS and GA.

It can be observed that the optimal placement of wind RDG provides energy losses for the optimal case as 653.399 MWh with 252.417 MWh energy loss minimization as shown in Chapter 3 (Table 3.4). Energy loss minimization is further improved with optimal sizing and placement of ES in presence of wind RDG. ES placement provide energy losses as 534.428 MWh and loss minimization as 281.361 MWh as shown in Table 4.4. Thus, improved loss minimization is obtained by optimal sizing and placement of ES in presence of optimally allocated wind RDG.

4.5.3 Allocation of Energy Storage in presence of hybrid RDG

In this case Energy Storage is optimally sized and placed in presence of hybrid RDG. The obtained maximum power rating of the storage is 4 MW. This storage unit is split

TABLE 4.5: Energy losses by optimal allocation of ES with hybrid RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	596.720	612.183	615.217	614.918	621.979
2	596.768	611.775	615.088	615.423	621.852
3	596.720	611.717	615.060	615.505	622.081
4	596.768	611.776	614.932	615.110	621.913
5	596.720	611.733	615.708	615.100	621.839
6	596.720	612.611	614.752	615.749	622.125
7	596.720	612.189	614.789	616.039	622.337
8	596.720	611.926	614.682	615.575	621.939
9	596.720	611.975	614.684	615.533	622.176
10	596.768	612.112	614.478	615.533	622.016
Mean	596.734	612.000	614.939	615.448	622.026
SD	0.023	0.281	0.351	0.332	0.156
Best	596.720	611.717	614.478	614.918	621.839
Worst	596.768	612.611	615.708	616.039	622.337

into multiple storage units. Sizing and placement of these storage units are is obtained in presence of Renewable Distributed Generation. The fixed locations and size of solar RDG are taken from chapter 3. These fixed locations for solar RDGs are on buses {18, 22, 27, 30, 32} with corresponding sizes in kW as {100, 200, 200, 100, 400} and placement of wind RDGs are on buses { 22, 25, 27, 32} with corresponding sizes in kW as {100, 400, 100, 400}.

TABLE 4.6: Optimal sizing and placement of Energy Storage with hybrid RDG

Algorithm	Battery location (bus no.)				Battery size Power (kW)	Battery size Energy (kWh)	Losses (MWh)	Loss reduction (MWh)
GWO	7	10	13	23	259	2486	596.720	218.91
PSO	13	23	29	31	237	2280	611.717	203.91
SOS	7	10	14	20	287	2756	614.478	201.15
GA	12	15	23	28	265	2545	614.918	200.71
FFA	10	14	23	29	248	2379	621.839	193.79

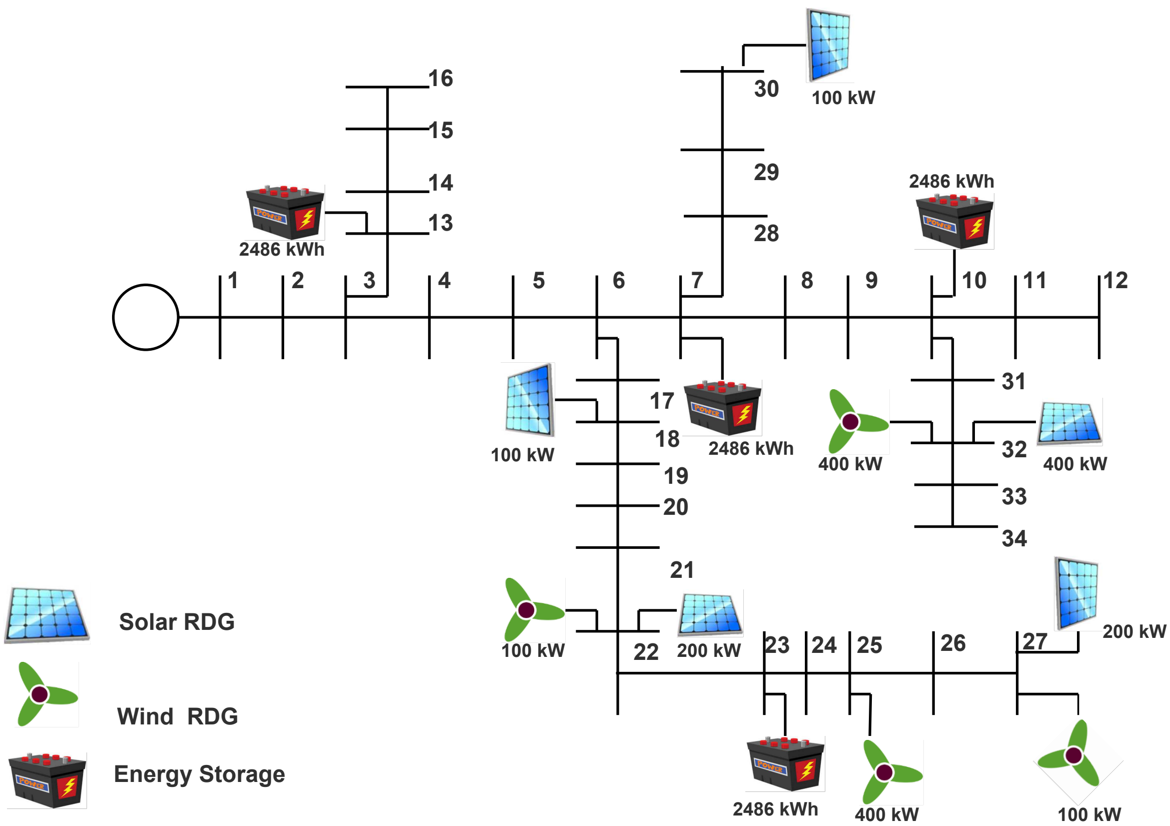

FIGURE 4.7: Allocation of ES in 34-bus system with hybrid RDG

Table 4.5 shows the annual energy loss minimization by optimal sizing and placement of ES in presence of hybrid RDG with Mean value, standard deviation (SD), best value and worst value. After GWO, optimal results are provided by PSO, SOS, GA and FFA. The optimal sizing and locations of ES corresponding to the best optimal values are shown in Table 4.6.

GWO obtains optimal locations of Energy Storage on the buses {7, 10, 13, 23 } and the size of Energy Storage is 259 kW and 2486 kWh. This size gives the power and energy rating of the Energy Storage. With this optimal sizing and placement the annual energy losses and loss minimization obtained is 596.720 MWh and 218.91 MWh respectively. PSO obtains optimal locations of Energy Storage on buses {13, 23, 29, 31 } and the size of Energy Storage is 237 kW and 2280 kWh. The annual energy loss and loss minimization obtained is 611.717 MWh and 203.91 MWh. The optimal sizing and location, energy losses, and loss minimization provided by other algorithms i.e., SOS, GA and FFA are shown in Table 4.6. Figure 4.7 shows allocation of ES in 34-bus system with wind RDG.

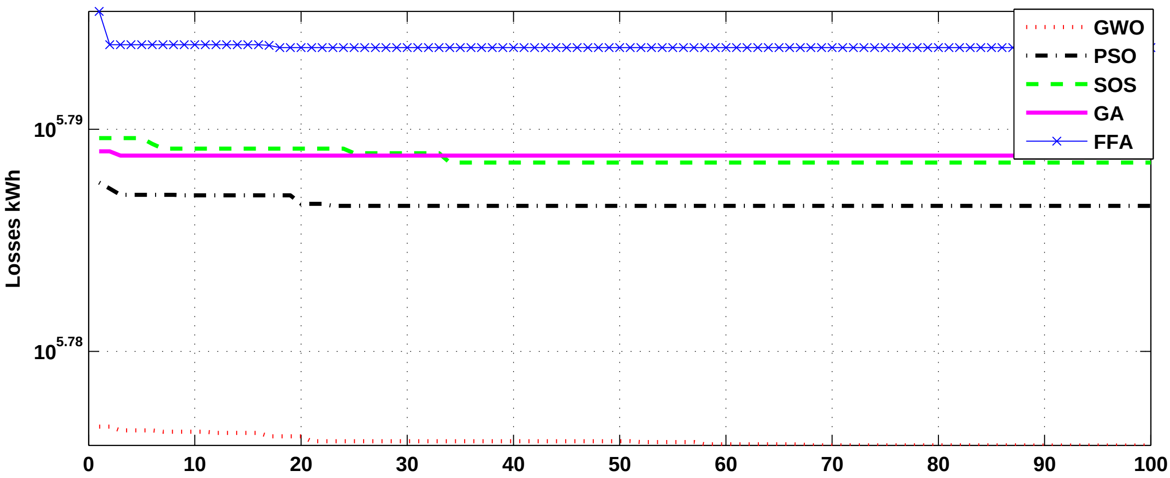

FIGURE 4.8: Convergence plot for allocation of ES with hybrid RDG

Convergence plots for GWO, PSO, SOS, GA and FFA are shown in Figure 4.8. The convergence values for GWO, PSO, SOS, GA and FFA are 21, 23, 34, 6, and 18 respectively. GWO offers best fitness value with relatively slow convergence.

The result shows that optimal allocation of ES in presence of hybrid RDG enhance the energy loss minimization. The loss minimization with hybrid RDG is 194.861 MWh as shown in Chapter 3 while the placement of ES provides loss minimization as 218.91 MWh as shown in Table 4.6. From above discussions it can be observed that, optimal sizing and placement of ES in coordination with RDG provides improved energy loss minimization.

4.6 Summary

The proposed allocation methodology shows that optimal allocation of ES provides energy loss minimization in the distribution network. The presence of RDG in the network is considered while planing allocation of ES. The Battery ES size is modelled considering the generation and load profile. This ES is divided into multiple storage units and optimally sizing and placement is obtained for energy loss minimization. ES is optimally allocated in presence of solar RDG, wind RDG and hybrid RDG. Significant loss minimization is obtained by optimal placement of ES at multiple locations. The ES is generally placed at the junction node from where multiple node starts in the network. In the present study, location of ES in presence of wind RDG provides better loss minimization as compared to solar RDG and wind RDG. Also, GWO provides best optimal solutions for energy loss minimization.

CHAPTER 5

Joint Optimal Allocation of RDG and ES

5.1 Introduction

Energy loss minimization is obtained by optimal sizing and placement of RDG and ES. In the literature, allocation of RDG and ES is addressed separately but RDG and ES allocation should be allocated a combined way as their placement affects the power flows and energy losses. In this Chapter, a method for joint optimal sizing and placement of RDG and ES for energy loss minimization is presented. A probabilistic generation model for solar RDG, wind RDG and hybrid RDG is used. The joint ES and RDG model, storage model and load model are integrated into an optimal power flow to obtain energy loss minimization. GA, PSO, SOS FFA and GWO algorithms are used to solve this nonlinear constrained optimization problem. Comparitive results of these algorithms for loss minimization is also presented. A study on 34-bus test system is presented for joint optimal sizing and placement of solar RDG-ES, wind RDG-ES, and hybrid RDG-ES.

5.2 Problem Formulation for Joint Optimal Allocation of RDG and ES

The problem formulation for joint optimal allocation of RDG and ES mainly includes:

1. Historical data processing
2. Solar PV modeling to obtain expected generation
3. Wind power modeling to obtain expected generation
4. Load modeling to get hourly load profile
5. Energy storage modeling

The above modeling is explained in Chapter 3 and Chapter 4 in subsequent Sections.

The objective is to find joint optimal size and location of energy storage, and RDG such that annual energy losses of distribution network are minimized. The power loss P_{Loss} at each hour is calculated with backward / forward sweep method. Now considering RDG power and ES charging discharging power at ith node, active power P_i is as given below.

During charging,

$$P_i = P_{Li} - P_{RDGE,i} + P_{B,ch,i} \tag{5.1}$$

During discharging,

$$P_i = P_{Li} - P_{RDGE,i} - P_{B,disch,i} \tag{5.2}$$

The energy supplied by RDG at ith node and value of $P_{B,ch,i}$ and $P_{B,disch,i}$ depends on optimal size and location of RDG and battery ES.

Considering 120 days for each season, loss minimization is obtained for the whole year. The objective function to minimize annual energy losses by joint optimal allocation of RDG and ES is as given below.

$$F = min \left[120 \left(\sum_{t=1}^{24} P_{loss,summer,t} + \sum_{t=1}^{24} P_{loss,monsoon,t} + \sum_{t=1}^{24} P_{loss,winter,t} \right) \right] \tag{5.3}$$

The constraints for RDG and ES are given in Chapter 3 and Chapter 4 respectively.

Decision variables in the optimization are :

i) Size of RDG

ii) Location of RDG

iii) Size of battery ES

iv) Location of battery ES

5.3 Solution Methodology

The solution methodology for joint optimal sizing and placement of RDG and battery ES is presented here. Energy losses are calculated by the same backward forward sweep method. The four parameters that are to be optimized are size and location of both, battery ES and RDG. Search agents for each algorithm are fixed as 20, and termination criteria is fixed to 100 iterations and tolerance value of 10^{-6}. A general Flowchart for the proposed methodology using GA, POS, SOS, FFA and GWO is as shown in Fig. 5.1.

Initialization includes, system data, bus data, expected solar and wind generation, charge discharge time *i.e.,* peak and off-peak time, total number of RDGs and storage units that are to be placed. Initialization for algorithms includes the number of search agents, initial states and termination criteria. Fitness of search agents is calculated considering the objective function *i.e.,* optimal size and location of ES and RDG for

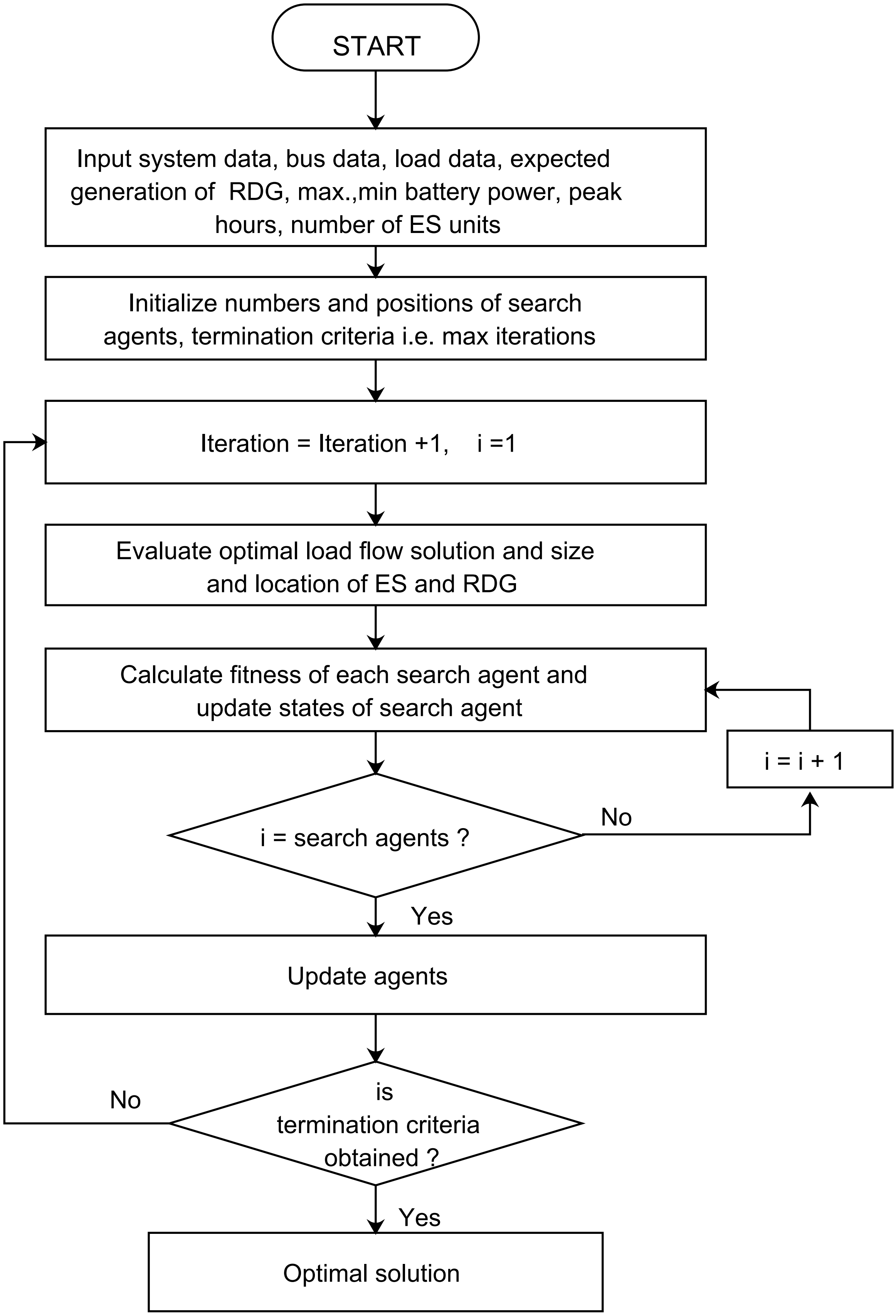

Figure 5.1: Solution methodology for joint RDG-ES allocation

loss minimization. Afterwards, positions and fitness of the search agents are updated. When termination criteria is reached, optimal values are stored.

5.4 Results and Discussions

This section presents case studies for the proposed methodology. Expected generation is calculated from historical data of the selected site. Proposed placement and sizing methodology is applied to the same 34 bus radial system with solar PV module KD325GX-LFB and wind turbine WES 100. Expected generation of RDG is obtained as explained in Chapter 3.

Total peak load on the system is 5 MW and hourly peak load is expressed as a percentage of the daily peak as explained in Chapter 3. The candidate buses selected for RDG placement are {5,15,18,22,25,27,28,29,30,32}. Maximum penetration of the solar RDG and wind RDG is considered as 2 MW assuming 40% penetration. The minimum RDG size on any bus is taken as 100 kW, hence total 20 RDGs need to be optimally allocated. The size of storage units is 4.89 MW. ES is split into four storage units and placed into the network to provide energy loss minimization. Three cases are presented to discuss the proposed methodology.

5.4.1 Joint Optimal Allocation solar RDG and ES

Table 5.1 shows annual energy loss minimization by joint optimal sizing and placement of ES and RDG using GWO, PSO, SOS, GA and FFA. Mean value, standard deviation, best value and worst value for GA, PSO, SOS, FFA and GWO algorithm are shown in the Table 5.1. Comparative results from this table shows that GWO provides best optimal results for joint allocation of RDG and ES. The optimal sizing and placement corresponding to best optimal values are shown in Table 5.2.

GWO obtains optimal locations as {22, 25, 27, 29, 30, 32 } with corresponding sizes in kW as {400, 400, 400, 100, 300, 400}. PSO obtains the optimal locations as {22, 25, 27, 29, 30, 32 } with corresponding sizes in kW as {400, 400, 300, 400, 100,

Table 5.1: Energy losses by joint optimal allocation of ES and Solar RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	669.661	672.919	686.942	691.962	685.012
2	669.395	671.449	680.383	688.579	687.510
3	669.366	673.065	682.158	696.075	687.440
4	670.027	672.237	684.284	683.444	684.890
5	672.402	672.050	680.833	680.578	683.710
6	675.067	673.556	684.860	693.090	684.340
7	669.633	673.455	684.151	681.030	685.394
8	669.972	672.413	682.149	682.548	686.950
9	669.971	673.588	681.364	697.300	686.440
10	669.477	672.581	680.499	682.778	685.174
Mean	670.497	672.731	682.762	687.738	685.686
SD	1.834	0.712	2.194	6.450	1.322
Best	669.366	671.449	680.383	680.578	683.710
Worst	675.067	673.588	686.942	697.300	687.510

Table 5.2: Optimal sizing and placement of solar RDG

Location	Size (kW)				
(Bus no)	GWO	PSO	SOS	GA	FFA
5	-	-	100	100	200
15	-	-	100	100	100
18	-	-	300	200	200
22	400	400	300	100	200
25	400	400	400	400	200
27	400	300	200	200	200
28	-	-	100	200	200
29	100	400	200	200	100
30	300	100	100	200	300
32	400	400	200	300	300

400}. The sizing and placement of provided by other algorithms i.e., SOS, GA and FFA are shown in Table 5.2.

GWO obtains optimal locations of Energy Storage on buses {3, 4, 6, 10 } and the size of Energy Storage is 241 kW and 2315 kWh. This size gives the power and energy rating of the Energy Storage. Annual energy losses and loss minimization obtained are 669.367 MWh and 146.263 MWh respectively. PSO obtains optimal locations of Energy Storage on buses {16, 19, 33, 34} and the size of Energy Storage is 127 kW

TABLE 5.3: Optimal sizing and placement of Energy Storage

Algorithm	Battrey location (bus no.)				Battry size Power (kW)	Battry size Energy (kWh)	Losses (MWh)	Loss reduction (MWh)
GWO	3	4	6	10	241	2315	669.367	146.263
PSO	16	19	33	34	127	1215	671.449	144.181
SOS	3	10	13	34	172	1651	680.383	135.247
GA	3	19	21	33	155	1486	680.578	135.052
FFA	11	16	17	24	202	1941	681.780	133.850

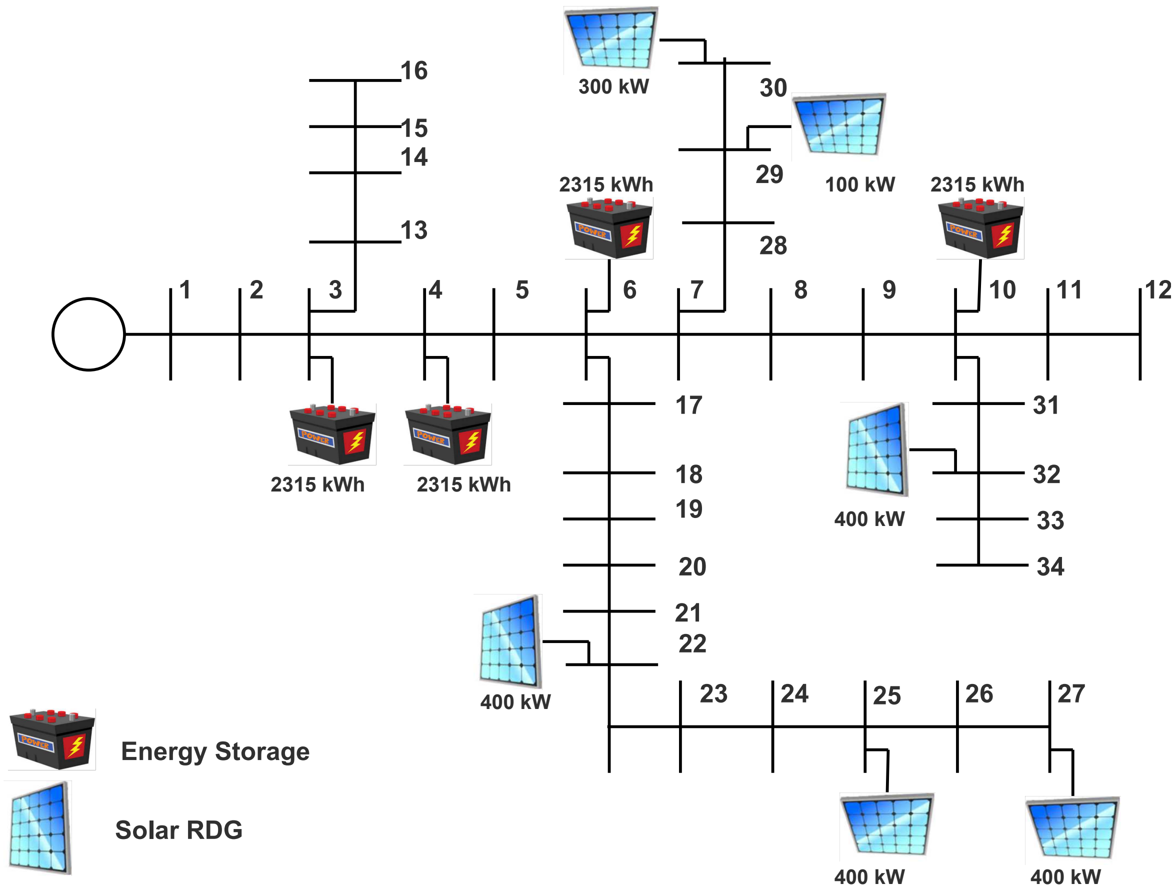

FIGURE 5.2: Joint allocation of solar RDG and ES on 34 bus system

and 1215 kWh, annual energy losses and loss minimization obtained are 671.449 MWh and 144.181 MWh respectively. The optimal sizing and location, energy losses, and loss minimization provided by other algorithms i.e., SOS, GA and FFA are shown in Table 5.3. The optimal sizing and placement of solar RDG and ES in 34-bus network by joint allocation is shown in Figure 5.2.

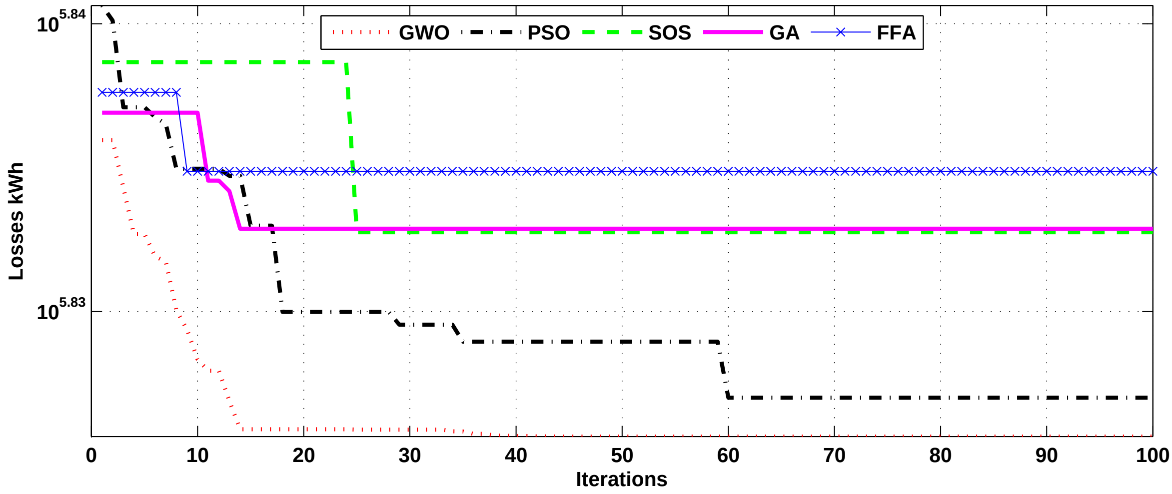

FIGURE 5.3: Convergence plot for solar RDG

The convergence plots for GWO, PSO, SOS, GA and FFA is shown in Figure 5.3 For all algorithms, the population size and maximum iteration count was fixed to 30 and 100 respectively. The convergence values for GWO, PSO, SOS, GA and FFA are 44, 60, 25, 14, and 9 respectively. GWO offers best fitness value with relatively slow convergence of 44 iterations. The convergence of FFA is fast (9 iterations) with less optimal solutions.

The base case losses for the system are 815.63 MWh. The loss minimization is improved as compared to previous two cases i.e., allocation of RDG only and allocation ES in presence of RDG due to the increased decision variables. It can be observed that optimal placement of solar RDG provides energy losses as 726.46 MWh and loss minimization as 89.36 MWh as shown in Chapter 3 (Table 3.2). Optimal allocation of ES in presence of solar RDG, provide energy losses and loss minimization as 672.690 MWh and 142.940 MWh respectively as shown in Chapter 4. Further, joint allocation of solar RDG and ES provides loss minimization as 146.263 MWh. Thus, improved loss minimization is obtained by joint optimal allocation of solar RDG and ES.

5.4.2 Joint allocation of wind RDG and ES

Table 5.4 shows the annual energy loss minimization by joint optimal sizing and placement of Energy Storage and Renewable Distributed Generation using various optimization algorithms i.e., GWO, PSO, SOS, GA and FFA. Ten runs of each optimization algorithm are taken to get best optimal solution. Mean value, Standard Deviation (SD), Best value and Worst value for each algorithm from these ten runs is calculated as shown in the Table 5.4.

Table 5.4: Energy losses by joint optimal allocation of ES and wind RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1	529.519	541.046	552.621	546.552	558.119
2	529.927	541.080	547.958	551.354	550.124
3	531.016	540.231	554.529	558.803	551.619
4	529.527	541.056	544.398	546.604	548.193
5	530.173	541.273	545.557	553.450	554.240
6	529.218	542.794	545.504	551.366	548.455
7	529.519	540.135	555.936	553.833	550.366
8	529.927	538.086	546.516	552.962	548.455
9	531.016	540.509	556.086	557.099	548.386
10	529.527	541.046	545.305	559.538	549.007
Mean	529.937	540.726	549.441	553.156	550.696
SD	0.631	1.184	4.787	4.494	3.222
Best	529.218	538.086	544.398	546.552	548.193
Worst	531.016	542.794	556.086	559.538	558.119

The comparative results from this table shows that GWO provides best optimal results with least SD. After GWO, optimal results are provided by PSO, SOS, GA and FFA. The optimal sizing and locations corresponding to the best optimal values are shown in Table 5.5.

The GWO obtains optimal locations as {22, 25, 27, 28, 29, 30, 32 } with corresponding sizes in kW as {400, 400, 300, 100, 300, 100, 400}. PSO obtains the optimal locations on buses {5, 18, 22, 27, 29, 30, 32 } with corresponding sizes in kW as {100, 100, 400, 400, 300, 300, 400}. Similarly SOS offers the placement of wind RDG on buses {5, 18, 22, 25, 27, 28, 29, 32 } with corresponding sizes in kW as {200 300 300

Table 5.5: Optimal sizing and placement of wind RDG

Location	Size (kW)				
(Bus no)	GWO	PSO	SOS	GA	FFA
5	-	100	200	100	100
15	-	-	-	100	-
18	-	100	300	100	300
22	400	400	300	200	200
25	400	-	100	300	100
27	300	400	400	400	300
28	100	-	200	200	200
29	300	300	200	100	300
30	100	300	-	300	200
32	400	400	300	200	300

100 400 200 200 300}. The sizing and placement of provided by other algorithms i.e., GA and FFA are shown in Table 5.5.

Table 5.6: Optimal sizing and placement of Energy Storage

Algorithm	Battery location (bus no.)				Battery size Power (kW)	Battery size Energy (kWh)	Losses (MWh)	Loss reduction (MWh)
GWO	3	7	10	24	348	3007	529.218	286.41
PSO	7	15	25	34	377	3257	538.086	277.54
SOS	2	8	25	33	334	2887	544.398	271.23
GA	8	21	22	34	252	2178	546.552	269.08
FFA	12	12	13	20	272	2351	548.193	267.44

GWO obtains optimal locations of Energy Storage on buses {3, 7, 10, 24 } and the size of Battery Energy Storage is 348 kW and 3007 kWh, annual energy losses and loss minimization obtained are 529.218 MWh and 286.41 MWh respectively. PSO obtains optimal locations of battery ES on buses {7, 15, 25, 34} and the size of Energy Storage is 377 kW and 3257 kWh. The annual energy losses and loss minimization obtained is 538.086 MWh and 277.54 MWh respectively. The optimal sizing and location, energy losses, and loss minimization provided by other algorithms i.e., SOS, GA and FFA are shown in Table 5.6. The optimal sizing and placement of solar RDG and ES in 34-bus network by joint allocation is shown in Figure 5.4.

The convergence plots for GWO, PSO, SOS, GA and FFA is shown in Figure 5.5 For all algorithms, the population size and maximum iteration count was fixed

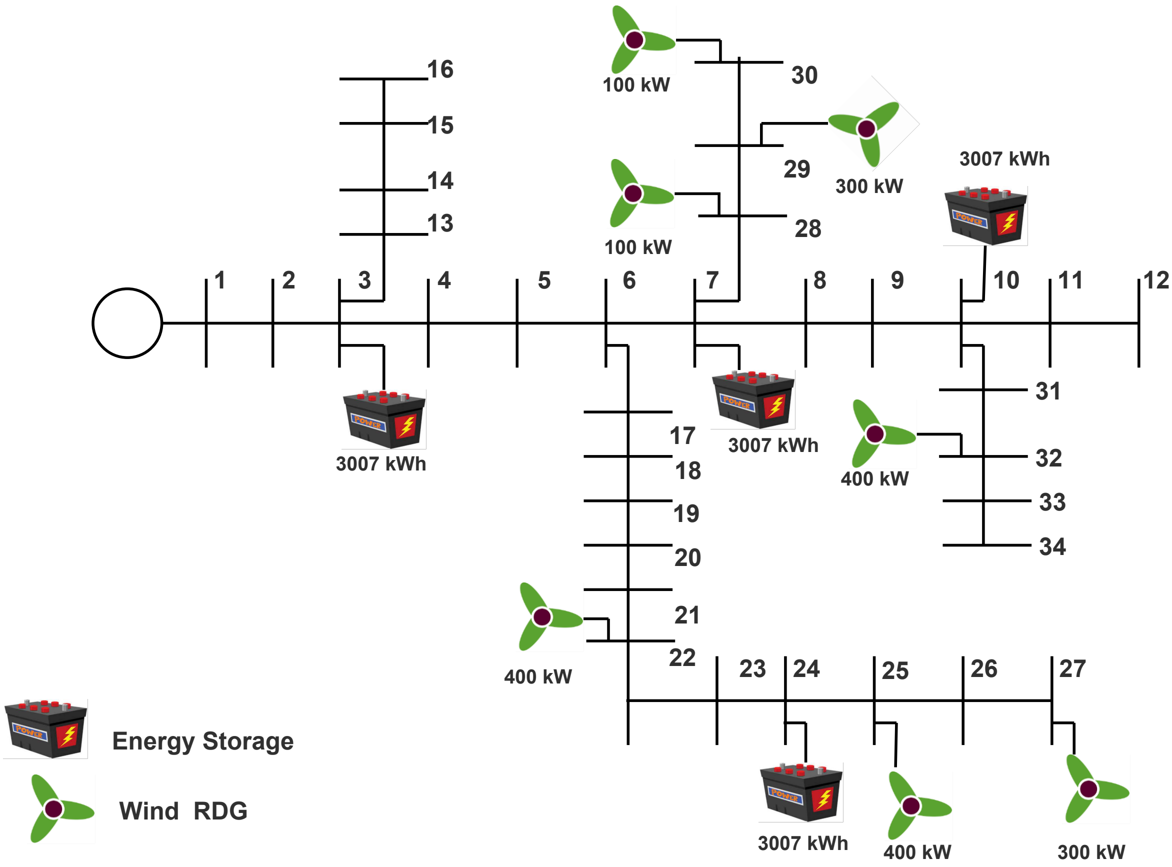

FIGURE 5.4: Joint allocation of wind RDG and ES on 34 bus system

to 30 and 100 respectively. The convergence values for GWO, PSO, SOS, GA and FFA are 89, 14, 50, 16 and 4 respectively. GWO offers best fitness value with slower convergence. Convergence of FFA is faster with less optimal solutions as compared other algorithms. The convergence of GA and PSO are closer to each other with 14 and 16 iterations.

Optimal placement of only wind RDG provides energy losses and energy loss minimization as 653.399 MWh and 252.417 MWh respectively as discussed in Chapter 3 (Table 3.4). Optimal sizing and placement ES placement in presence of wind RDG provide energy losses as 534.428 MWh and loss minimization as 281.361 MWh as shown in Chapter 4 (Table 4.4. Thus enhancement in loss minimization is obtained. It can be observed that joint allocation of wind RDG and ES provide energy losses and loss minimization as 529.2418 and 286.41 respectively. Thus, improved loss minimization

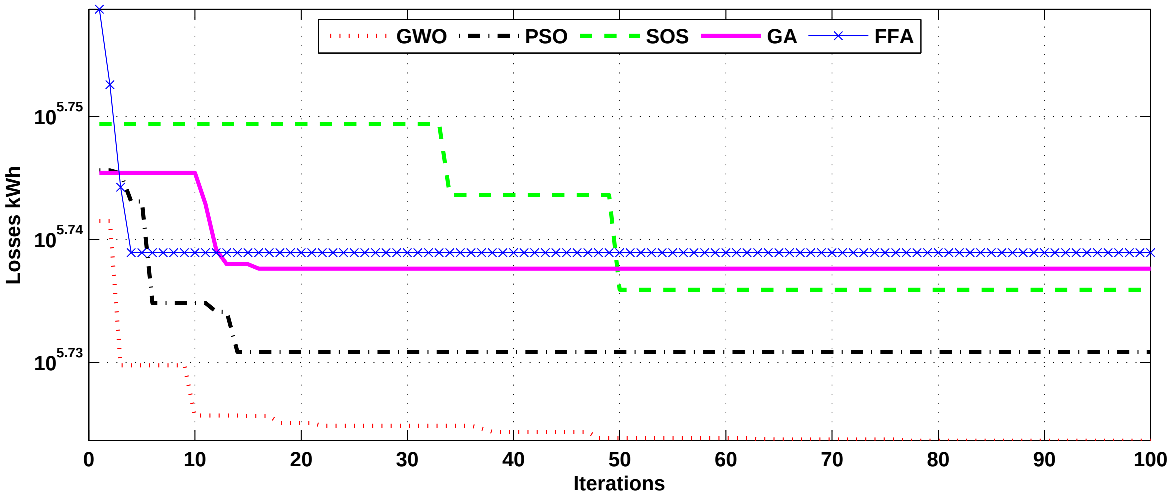

FIGURE 5.5: Convergence plot for wind RDG

is obtained by joint optimal allocation of RDG and ES as compared to only RDG placement or only ES placement in presence of RDG.

5.4.3 Joint allocation of hybrid RDG and ES

The joint optimal allocation of hybrid RDG and ES is presented here. Table 5.7 shows the annual energy loss minimization by joint optimal sizing and placement of ES and hybrid RDG using various optimization algorithms i.e., GWO, PSO, SOS, GA and FFA.

Mean value, standard Deviation, best value and worst value for each algorithm is calculated as shown in the Table 5.7. The comparative results from this table shows that GWO provides best optimal results with least SD. After GWO, optimal results are provided by PSO, SOS, GA and FFA. The optimal sizing and locations corresponding to the best optimal values are shown in Table 5.8.

GWO obtains optimal placement of solar RDG on buses { 18, 22, 25, 32} with corresponding sizes in kW as { 100, 200, 300, 400} and placement of wind RDG on buses { 25, 27, 32} with corresponding sizes in kW as {200, 400, 400}. PSO obtains obtimal placement of solar RDG on buses {15, 18, 30, 32} with corresponding sizes in

TABLE 5.7: Energy losses by joint optimal allocation of ES and hybrid RDG

Runs	Losses (MWh)				
	GWO	PSO	SOS	GA	FFA
1.000	581.121	612.513	637.786	612.207	621.591
2.000	579.199	610.374	629.961	618.614	622.221
3.000	589.443	627.106	633.445	624.003	641.341
4.000	599.014	610.473	641.281	616.462	627.179
5.000	590.697	622.168	610.757	626.229	627.949
6.000	595.906	611.972	619.148	616.015	620.804
7.000	600.662	625.228	617.768	624.595	622.442
8.000	588.585	614.645	620.361	623.688	629.317
9.000	583.136	627.145	618.194	617.302	619.187
10.000	587.102	619.836	631.327	614.035	622.864
Mean	589.487	618.146	626.003	619.315	625.490
SD	7.310	6.927	10.065	4.930	6.486
Best	579.199	610.374	610.757	612.207	619.187
Worst	600.662	627.145	641.281	626.229	641.341

TABLE 5.8: Optimal sizing and placement of hybrid RDG

Location	Size (kW)									
	GWO		PSO		SOS		GA		FFA	
(Bus no)	S	W	S	W	S	W	S	W	S	W
5	-	-	-	-	-	-	-	-	-	200
15	-	-	400	-	100	-	100	-	-	100
18	100	-	300	-	100	100	-	-	200	100
22	200	-	-	100	0	200	-	300	100	100
25	300	200	-	100	200	200	300	-	200	100
27	-	400	-	200	100	-	300	200	100	100
28	-	-	-	200	300	100	-	-	100	-
29	-	-	-	100	100	200	-	100	100	100
30	-	-	200	100	100	100	300	-	100	100
32	400	400	100	200	-	100	-	400	100	100

S - Solar
W - Wind

kW as {400, 300, 200, 100 } and placement of wind RDG on buses { 22, 25, 27, 28, 29, 30, 32} with corresponding sizes in kW as {100, 100, 200, 200, 100, 100, 200}. The optimal sizing and placement provided by other algorithms i.e., SOS, GA and FFA are shown in Table 5.8.

TABLE 5.9: Optimal sizing and placement of Energy Storage with hybrid RDG

Algorithm	Battery location (bus no.)				Battery size		Losses	Loss reduction
					Power (kW)	Energy (kWh)	(MWh)	(MWh)
GWO	3	7	10	21	266	2302	579.199	236.43
PSO	2	23	31	32	320	2765	610.374	205.26
SOS	3	3	12	29	171	1474	610.757	204.87
GA	3	4	10	20	326	2821	612.207	203.42
FFA	11	14	19	21	232	2002	619.187	196.44

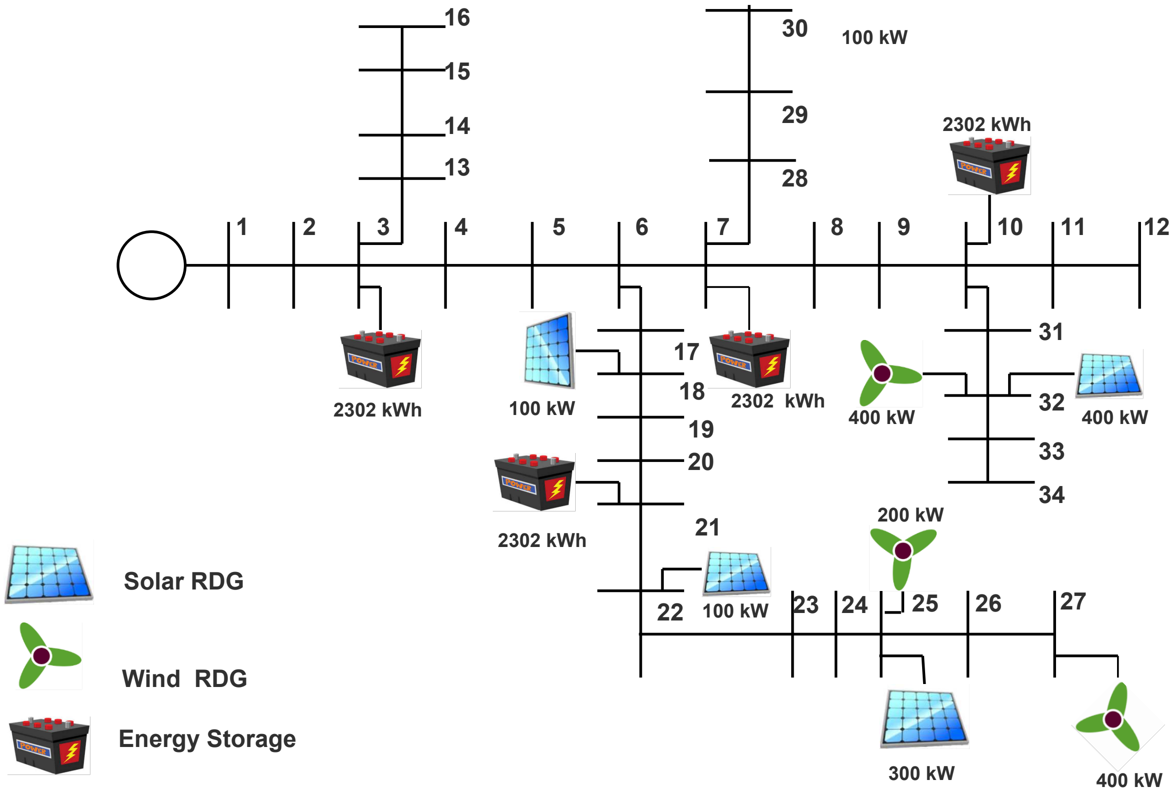

FIGURE 5.6: Joint allocation of hybrid RDG and ES on 34 bus system

GWO obtains optimal locations of ES on the buses {3, 7, 10, 21 } and the size of ES is 266 kW and 2302 kWh, annual energy losses and loss minimization obtained is 579.199 MWh and 236.43 MWh respectively. PSO obtains optimal locations of ES on buses {2, 23, 31, 32 } and the size of Energy Storage is 320 kW and 2765 kWh respectively. PSO obtains annual energy loss and loss minimization as 610.374 MWh and 206.26 MWh respectively. The optimal sizing and location, energy losses, and loss minimization provided by other algorithms i.e., SOS, GA and FFA are shown in Table

5.9. The optimal sizing and placement of solar RDG and ES in 34-bus network by joint allocation is shown in Figure 5.6.

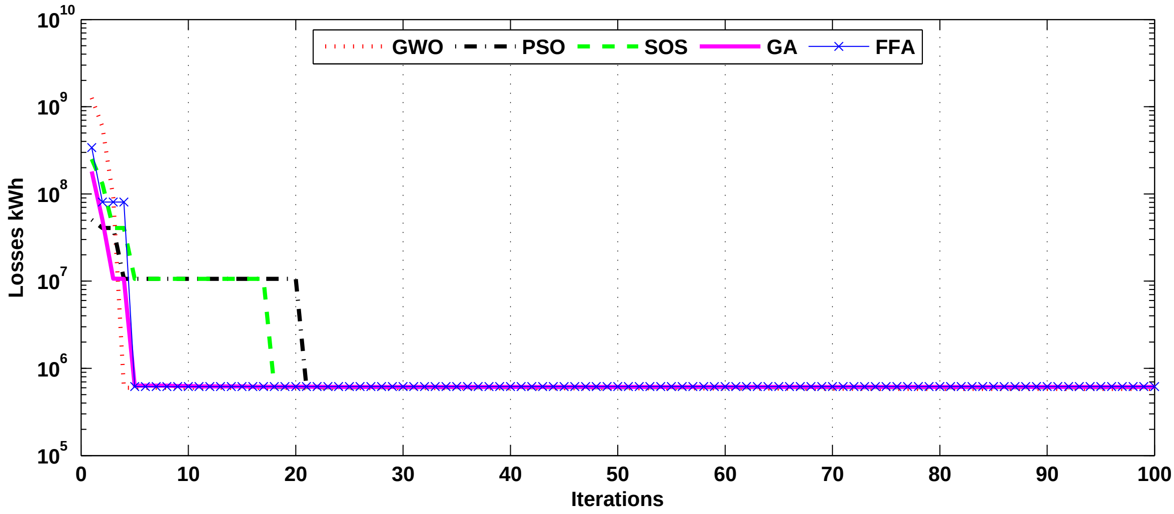

FIGURE 5.7: Convergence plot for hybrid RDG

The convergence plots for GWO, PSO, SOS, GA and FFA is shown in Figure 5.7 For all algorithms, the population size and maximum iteration count was fixed to 30 and 100 respectively. The convergence values for GWO, PSO, SOS, GA and FFA are 98, 21, 18, 23, and 5 respectively. GWO offers best fitness value. FFA has fast convergence with 5 iterations and less optimal solutions. The convergence values of PSO, SOS and GA are closer to each other.

The loss minimization with only hybrid RDG is 194.861 MWh as shown in Chapter 3, loss minimization with ES in presence of hybrid RDG is 218.91 MWh as shown in Chapter 4. The loss minimization with joint optimal allocation of hybrid RDG and ES are 236.43 MWh. The results shows joint optimal allocation of hybrid RDG and ES provides improved energy loss minimization as compared the cases:only hybrid RDG and ES in presence of hybrid RDG. Significant loss minimization can be obtained by joint optimal sizing and placement of RDG and multiple ES units. Wind RDG and ES provides better loss minimization as compared to other optimization algorithms. In this case, the GWO algorithm provides optimal results for loss minimization as compared to other optimization algorithms *i.e.,* GA, PSO, SOS, and FFA.

5.5 Summary

This chapter proposes a joint optimal allocation methodology for ES and RDG *i.e.,* solar RDG, wind RDG and hybrid RDG. The joint optimal sizing and placement of ES and RDG provides significant loss minimization. The wind RDG-ES combination provides optimal solutions for energy loss minimization. This nonlinear, constrained optimization problem is solved with GA, PSO, SOS, FFA and GWO algorithms. GWO optimization algorithm provides improved loss minimization as compared to other competitive algorithms.

CHAPTER 6

Joint Allocation for RDG and ES for Economic Benefits

6.1 Introduction

RDG and ES offers economic benefits to utilities and customers. Joint optimal allocation of RDG and ES can further enhance the economic benefits. This chapter presents a joint optimal allocation methodology of RDG and ES to achieve economic benefits. The proposed method minimizes costs of distribution company (DISCOM). Also, benefit of RDG owner is ensured by adding suitable constraint in objective function. Cost of DISCOM mainly includes the cost of renewable energy, cost of energy purchased from grid and energy storage cost. The RDG owner obtains benefit by selling the renewable energy to DISCOM at a mutual contract price. Thus, the contract price is a key parameter in the cost benefit analysis of the DISCOM and RDG owner. This work formulates the contract price of renewable energy along with allocation of RDG and ES to achieve cost-benefits of RDG owner and DISCOM. Also, the generation model, storage model and load model are combined into an optimal power flow to obtain energy loss minimization. This constrained nonlinear problem is solved using Grey Wolf Optimizer (GWO).

6.2 System Modeling

The system modeling includes, renewable sources modeling to obtain expected generation, load modeling, battery storage modeling and economic model. The renewable resources modeling (i.e., solar power and wind power modeling), load modeling is explained in Chapter 3. Here, the battery battery size is obtained considering the peak shaving application. The obtained ES size is taken for joint allocation with RDG.In this Section, the battery ES model and economic model is explained.

6.2.1 Battery Storage Model

Battery ES size is obtained considering the amount of peak shaving. Thus, ES contributes for peak shaving. Power peaks on load curves are area above the reference value P_R as shown in Figure 6.1.

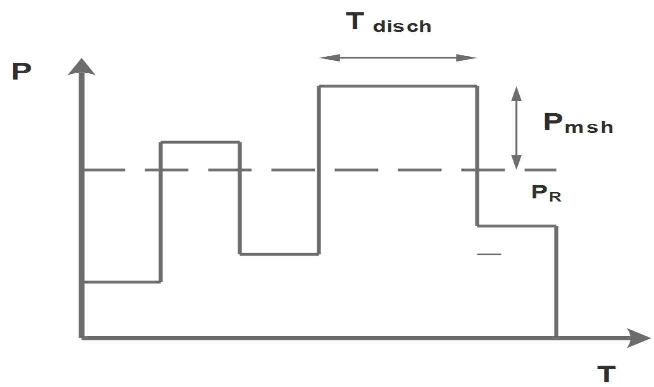

FIGURE 6.1: Power peak and peak shaving

If $P_{msh,t}$ is required maximum power to shave and $T_{dis,t}$ is discharge time then area above P_R gives battery capacity (E_{BE}) as given below [123].

$$E_{BE} = \sum_{t=1}^{T} P_{msh,t} \; T_{dis,t} \tag{6.1}$$

This battery size is modified according to minimum state of charge (*i.e., SOC*) and efficiency of battery ES. Loss minimization is improved by splitting the large sized storage into multiple storage units (N_d) obtaining load shifting at multiple sites rather than at single site [172]. The energy rating of these multiple ES units is as given below.

$$E_{BES} = \frac{E_{BE}}{N_d} \tag{6.2}$$

Considering a minimum state of charge (i.e, SOC_{min}), energy rating of battery is given as,

$$E_B = E_B + SOC_{min}\ E_B \tag{6.3}$$

Observing the total peak time period T_{dis} and off-peak time period T_{ch} from load pattern, maximum charge discharge power is obtained as,

$$P_{B,dis}^{max} = \frac{E_{BES}}{T_{dis}} \quad or \quad P_{B,ch}^{max} = \frac{E_{BES}}{T_{ch}} \tag{6.4}$$

The battery power rating P_B is obtained form the charge discharge power as shown below.

$$P_B = max\left[P_{B,dis}^{max}, P_{B,ch}^{max}\right] \tag{6.5}$$

DC bus voltage regulation system in battery energy storage provides a constant DC bus voltage to grid side converter. This results in efficient power conversion and protection of DC bus against voltage stress [249]. The variation in DC bus voltage is mitigated by controlling duty cycle with suitable controllers [250]. In the proposed work it is assumed that the DC bus voltage is maintained and controlled by the system controller at desired level.

6.2.2 Economic Model

Economic model includes the costs and benefits of RDG owner and DISCOM. DISCOM is responsible for the placement of RDG and ES and achieves corresponding benefits. The cost minimization of DISCOM is achieved while considering the benefits of RDG owner. Thus, economic model includes the costs and benefits of RDG owner and DISCOM. Equations shown in economic model are for hybrid RDG and Energy Storage combination.

6.2.3 RDG Owner's Costs and Benefits

RDG owner's costs mainly includes the investment cost and operation & maintenance cost and they get profit by selling the renewable energy.

i) **Investment Cost:** The investment cost for solar RDG mainly includes cost of land, solar panel cost, inverter cost and installation cost. Investment cost for wind RDG mainly includes cost of land, wind turbine cost, foundation cost, and grid connection cost. Total investment cost C_{INVST} for hybrid RDG is as given below.

$$C_{INVST} = P_{ISG}\, C_{IS} + P_{IWG}\, C_{IW} \tag{6.6}$$

Where, C_{IS} investment cost of solar RDG in $Rs./MW$; C_{IW} investment cost of wind RDG in $Rs./MW$; P_{ISG} total installed capacity of solar RDG MW; P_{IWG} total installed capacity of wind RDG MW;

ii) **Operation and Maintenance (O&M) Cost:** This cost includes regular maintenance cost, repair cost, cost of spare parts and administration cost. The discounted total O& M cost is given as,

$$C_{OM} = \sum_{j=1}^{N_Y} (P_{ISG}\, C_{OMS} + P_{IWG}\, C_{OMW}) \left(\frac{1+R_{inf}}{1+R_{int}}\right)^j \tag{6.7}$$

where, C_{OMS} O&M cost of solar RDG $Rs./MW$; C_{OMW} O&M cost of wind RDG $Rs./MW$; N_Y total number of years; R_{inf} inflation rate; R_{int} interest rate or discount rate;

iii) **RDG Owner Benefit:** RDG owner earns profit by selling renewable energy to DISCOM. The energy is sold on the contract price decided between them.

$$IN_{RDGO} = \sum_{j=1}^{N_Y} (P_{SDG} + P_{WDG})\, CP_{RDG} \left(\frac{1+R_{inf}}{1+R_{int}}\right)^j \tag{6.8}$$

Where, IN_{RDGO} RDGO's profit from selling the generated electricity, CP_{RDG} contract price in Rs. per unit of electricity, P_{SDG} and P_{WDG} Solar and wind generated power. The net benefit of RDGO is as given below.

$$BEN_{RDGO} = IN_{RDGO} - C_{INVST} - C_{OM} \tag{6.9}$$

6.2.4 Distribution Company's Costs

DISCOM purchases renewable energy from RDG owner. Also, DISCOM takes into account the allocation of RDGs and ES. Thus, DISCOM's profit is affected by optimal allocation of RDGs and ES.

i) **Renewable Energy Cost:** DISCOM purchases power from RDG owner at the contract price. Contract price creates a coupling between DISCOM's cost and RDGO's benefit. The cost of renewable energy purchased from RDG owner is as given below.

$$RDG_{COST} = \sum_{j=1}^{N_Y} (P_{SDG} + P_{WDG})\ CP_{RDG} \left(\frac{1 + R_{inf}}{1 + R_{int}} \right)^j \tag{6.10}$$

ii) **Grid Energy Cost:** The power requirement beyond RDG's capacities is purchased from substation by DISCOM. The power to be purchased and its cost is obtained as given below.

$$P_{SUB,i} = \sum_{i=1}^{N} P_{L,i} + P_{Loss,i} - P_{RDGE,i} - P_{B,disch,i} \tag{6.11}$$

where $P_{L,i}$ is active power load, $P_{Loss,i}$ real power loss, $P_{RDGE,i}$ epected power of RDG and $P_{B,disch,i}$ is battery discharge power. The cost of energy purchased from grid is given by the following equation.

$$SUBE_{COST} = \sum_{j=1}^{N_Y} \sum_{t=1}^{24} P_{SUB}\ C_E \left(\frac{1 + R_{inf}}{1 + R_{int}} \right)^j \tag{6.12}$$

Where, C_E gives cost of energy in Rs. per unit.

iii) **Battery Storage Cost:** The total investment cost C_{IBE} and operation & maintenance cost C_{OMBE} of battery ES is given by Equation (6.13) and Equation (6.14) respectively.

$$C_{IBE} = E_B \; C_{IB} \tag{6.13}$$

$$C_{OMBE} = \sum_{j=1}^{N_Y} (E_B \; C_{OMB}) \left(\frac{1 + R_{inf}}{1 + R_{int}} \right)^j \tag{6.14}$$

Where, C_{IBE} investment cost of Battery in $Rs./MWh$; E_B total installed capacity of battery MWh; C_{OMB} O&M cost of battery $Rs./MW$; The total cost of battery ES is given as,

$$BES_{COST} = C_{IBE} + C_{OMBE} \tag{6.15}$$

iv) **Loss Minimization Benefits:** The cost benefit achieved by loss minimization is as given as below.

$$B_{EL} = \sum_{j=1}^{N_Y} (P_{LS} \; C_{SEL} + P_{LW} \; C_{WEL}) \left(\frac{1 + R_{inf}}{1 + R_{int}} \right)^j \tag{6.16}$$

Where, P_{LS} annual energy loss minimization by solar RDG MWh; P_{LW} annual energy loss minimization by wind RDG MWh; C_{SEL} cost of energy losses for solar RDG $Rs./kWh$; C_{WEL} cost of energy losses for wind RDG $Rs./kWh$;

6.3 Problem Formulation

A) **Objective Function:** The objective is to minimize the costs of DISCOM. The benefit of RDG owner is formulated as one of the constraints. The objective function 'f' for cost minimization of DISCOM is as given below.

$$f = min \left[\sum_{j=1}^{N_Y} \sum_{t=1}^{24} (RDG_{COST} + SUBE_{COST} + BES_{COST}) \right] \tag{6.17}$$

B) **Decision Variables:** Following are the decision variables in the optimization problem.

i.) Size of RDG (i.e., number of RDGs) and location of RDG (i.e., optimal bus number.)

ii.) Location of battery storage (i.e., optimal bus number.)

iii.) Contract price that minimizes the costs of DISCOM and the RDGO gets an assured benefit.

C) **Constraints:** The constraints includes; technical constraints and economic constraints. All the technical constraints related to RDG i.e., active and reactive power balance, feeder current and maximum penetration of RDG are explained in Chapter 3. The economic constraints are as given below.

i) **Owner Benefit:** The RDG owner should be assured with a minimum benefit (BEN_{RDGO}^{min}). He may get get more than this assured benefit.

$$BEN_{RDGO} \geq BEN_{RDGO}^{min} \tag{6.18}$$

ii) **Contract price:** The contract price is decided depending on market electricity price and economic considerations. This constraint is as given as below.

$$CP_{RDG}^{min} \leq CP_{RDG} \leq CP_{RDG}^{max} \tag{6.19}$$

CP_{RDG}^{min} and CP_{RDG}^{max} are the minimum and maximum amount of contract price.

6.4 Solution Methodology

Joint allocation of RDG and ES for cost minimization of DISCOM is optimized by GWO algorithm. The energy losses are calculated by backward forward sweep method. The search agents for GWO are initialized as 20, and termination criteria are fixed to 150 iterations or a tolerance value of 10^{-6}. The flowchart of the proposed methodology is as shown in Fig 6.2. The initialization mainly includes system data, bus data, expected solar and wind generation, charge-discharge power and time *i.e.,* peak and

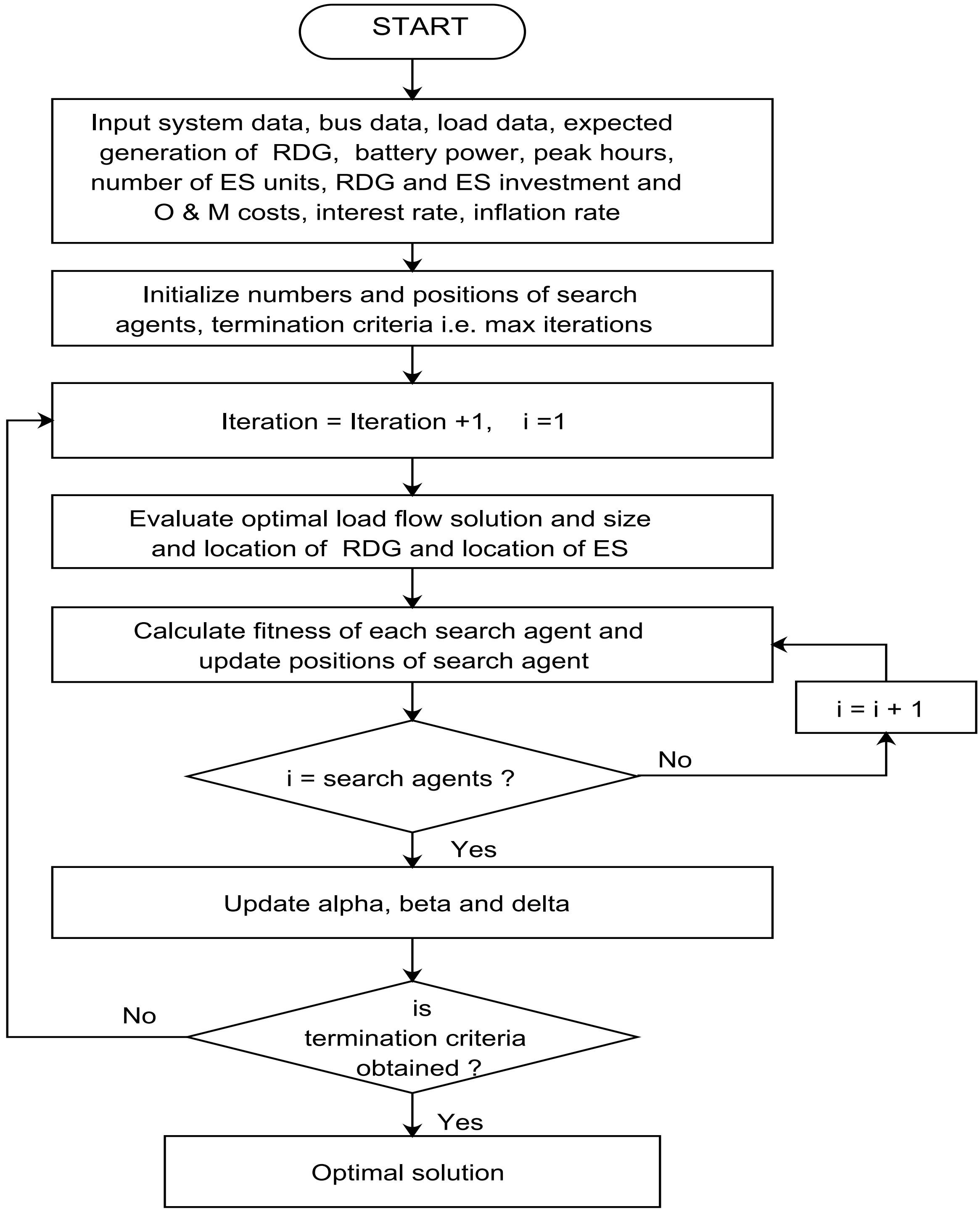

Figure 6.2: Solution methodology for cost-benefit based allocation of RDG-ES

off-peak time, total number of RDGs, storage units and range of contract price. The initialization for algorithms includes number of search agents, initial states and termination criteria. The fitness of search agents is calculated considering the objective function *i.e.,* cost minimization of DISCOM by joint optimal allocation of RDG and ES. If termination criterion is reached, the optimal values are stored otherwise the process is repeated.

6.5 Results and Discussions

The proposed joint allocation methodology for economic benefits is applied to a 34-bus radial distribution system.The solar PV module and wind turbine considered in this study are KD325GX-LFB and WES 100 respectively. Hourly solar irradiance and wind speed data of 5 years is taken from the same site named, Satara Maharashtra state, India. Probability of each state is calculated using β *cdf* and Reilaygh *cdf*. The product of probability and power output of each state provides the expected generation of that state. The summation of entire states provides the expected generation of the particular hour. The values of various parameters of *cdf* of solar RDG and wind RDG with the expected generation is given in Chapter 3. The total peak load on the system is 5 MW and maximum penetration of the solar RDG and wind RDG is considered as 2 MW assuming 40% penetration. The candidate buses selected for RDG placement are randomly selected ten buses as D {5,15,18,22,25,27,28,29,30,32}.

The RDG is optimally placed with a size of multiple of 100 kW and a maximum size of 500 kW. The maximum size of RDG at any location is limited by the feeder current capacity which is 50 A. Thus, ES contributes loss minimization through peak shaving [172]. Four number of storage units considered for optimal placement for economic benefits. The charging-discharging efficiency of the storage is assumed as 95% and minimum *SOC* is limited to 20%.

Table 6.1: Commercial information of RDG

Cost parameters	SDG	WDG
Investment cost (Rs/MW.)	58,733,000	61,916,000
O & M cost (Rs./MW)	1,300,000	27,801,127

The proposed methodology is applied to three case studies, i.e., solar RDG, wind RDG and hybrid RDG. The investment cost for solar RDG and wind RDG in Rs./MWh

Table 6.2: Commercial information of battery ES

Cost parameters	Value
Capital energy cost (Rs./kWh)	37,000
Annual O&M cost (Rs./kW)	1,000
Capital replacement cost (Rs./kWh)	11100

is taken as 58733000 and 61916000 respectively and the O&M cost in Rs./MWh is 1300000 and 1063000 respectively as shown in Table 6.1 . The battery ES capital cost, O& M cost and capital replacement cost in Rs. is taken as 37000, 1000 and 11100 respectively as shown in Table 6.2. The inflation rate and discount rate is considered as Rs. 6.10 and Rs. 10.81 respectively. The life of solar, wind and battery storage project is considered as 20 years.

The results for optimal allocation of solar RDG-ES, wind RDG-ES and hybrid RDG-ES are presented here. Table 6.3 shows the optimal allocation of these RDGs. Figure 6.3, Figure 6.4, and Figure 6.5 shows the optimal allocation of of solar RDG-ES, wind RDG-ES and hybrid RDG-ES in a 34-bus system.

Table 6.3: Sizing and location of RDGs

Location	SDG (kW)	WDG (kW)	HDG (kW)	
			SDG	WDG
5	200	100	-	-
15	100	100	100	100
18	300	300	-	100
22	-	100	200	100
25	400	100	-	200
27	200	100	100	200
28	-	300	200	-
29	300	200	200	-
30	300	300	100	200
32	200	400	100	100

The optimal locations for solar RDG are buses {5 15 18 25 27 29 30 32} and optimal size in kW are found as {200 100 300 400 200 300 300 200 }. The wind RDG is located on all the candidate buses with optimal sizes as { 100 100 300 100 100 100 300 200 300 400 }. For hybrid RDG, the solar RDG and wind RDG of 100kW each are placed on bus no. 15, on bus number 18, a wind DG of 100kW is placed. Similarly, optimal allocation of hybrid RDG is as shown in Table 6.3.

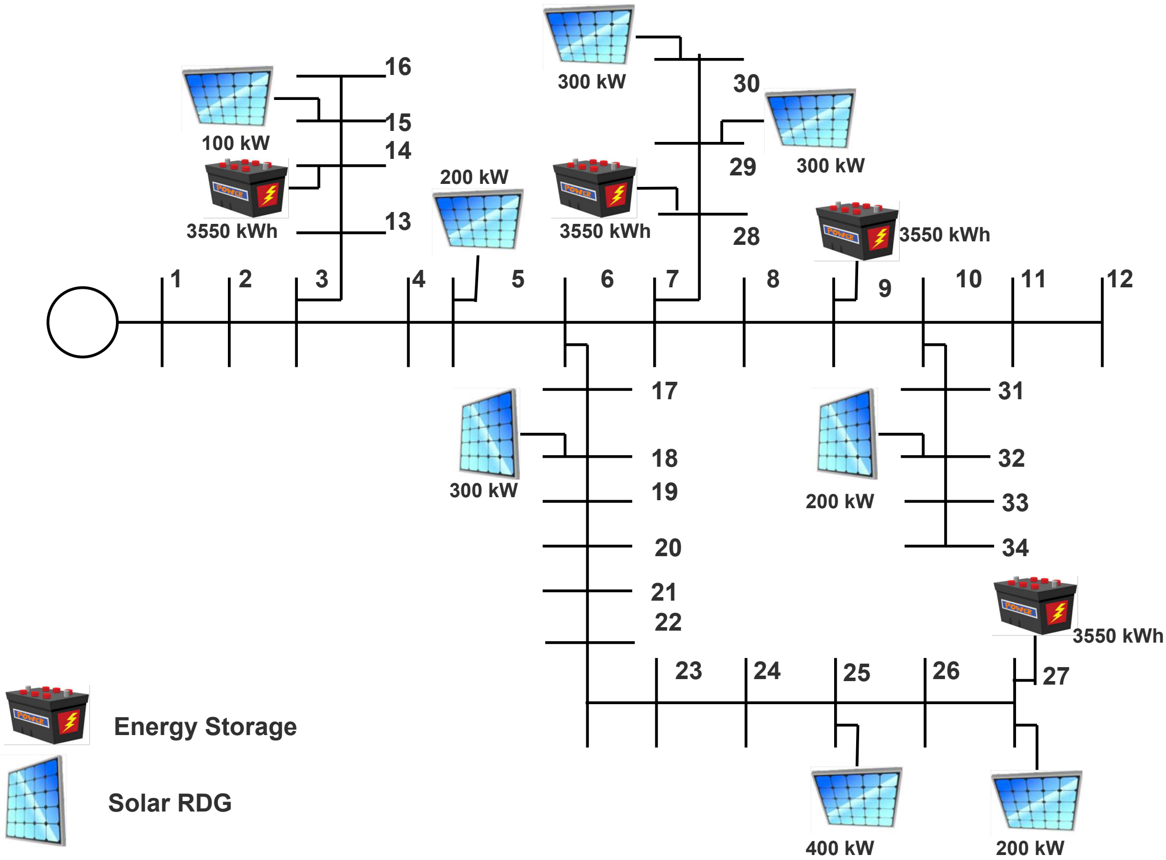

FIGURE 6.3: Allocation of solar RDG-ES on 34 bus system for economic benefits

The battery is rated to shave peak load that is above 75 % of daily load. The battery rating obtained is 280 kW and 3.55 MWh. Considering peak and off peak hours, charging and discharging power is obtained as 280 kW and 200 kW respectively. The allocation of battery ES with various types of RDGs is shown in Table 6.4. The optimal location of battery storage with solar RDG is on buses { 9, 14, 27, 28 }. The optimal location of battery storage with wind RDG is at locations { 3, 7, 10, 24 } and optimal location of battery storage with hybrid RDG is at locations { 4, 7, 10, 24 }.

The energy contract price between RDGO and DISCOM is also given in Table 6.4. Contract price for solar RDG-ES, wind RDG-ES and hybrid RDG-ES cases are 20000 Rs./MW, 7000 Rs./MW and 10000 Rs./MW respectively. A minimum contract price

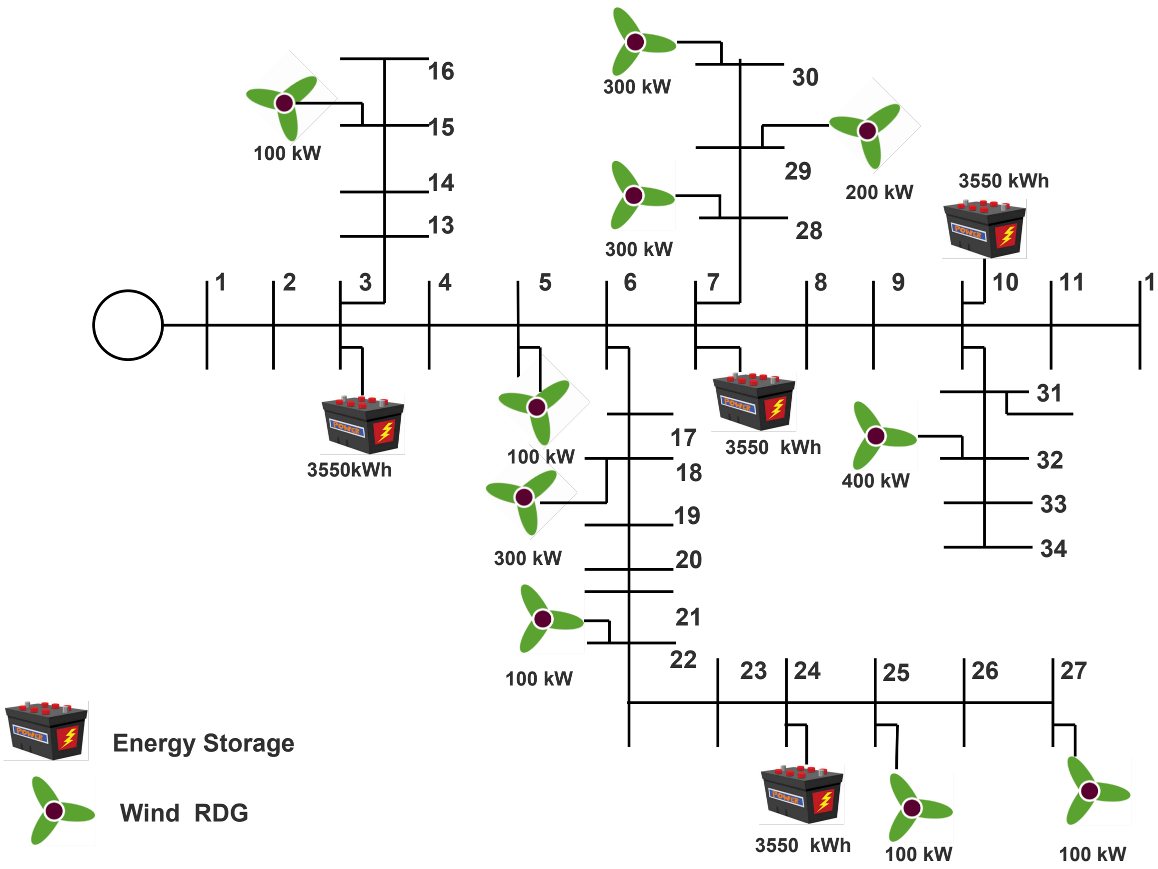

FIGURE 6.4: Allocation of wind RDG-ES on 34 bus system for economic benefits

TABLE 6.4: Location of Energy storage and contract price

RDG Type	Battery storage location				Contract energy price (Rs./MW)
SDG	9	14	27	28	20000
WDG	3	7	10	24	7000
HDG	4	7	10	24	10000

is offered by the wind RDG and maximum contract price is offered by solar RDG. The contract price is mainly affected by potential of RDG at the selected site.

Table 6.5 shows the costs and benefits of RDGO and DISCOM. The solar RDG owner gets a benefit of Rs. 617407472. Cost of energy purchased from solar RDG is Rs. 768872969 and cost of energy purchased from the grid is 987610387. DISCOM gets a benefit of 7186204 by loss minimization. Similarly, RDGO benefit, costs and benefits of DISCOM are shown in Table 6.5 for other cases, i.e., wind RDG and hybrid

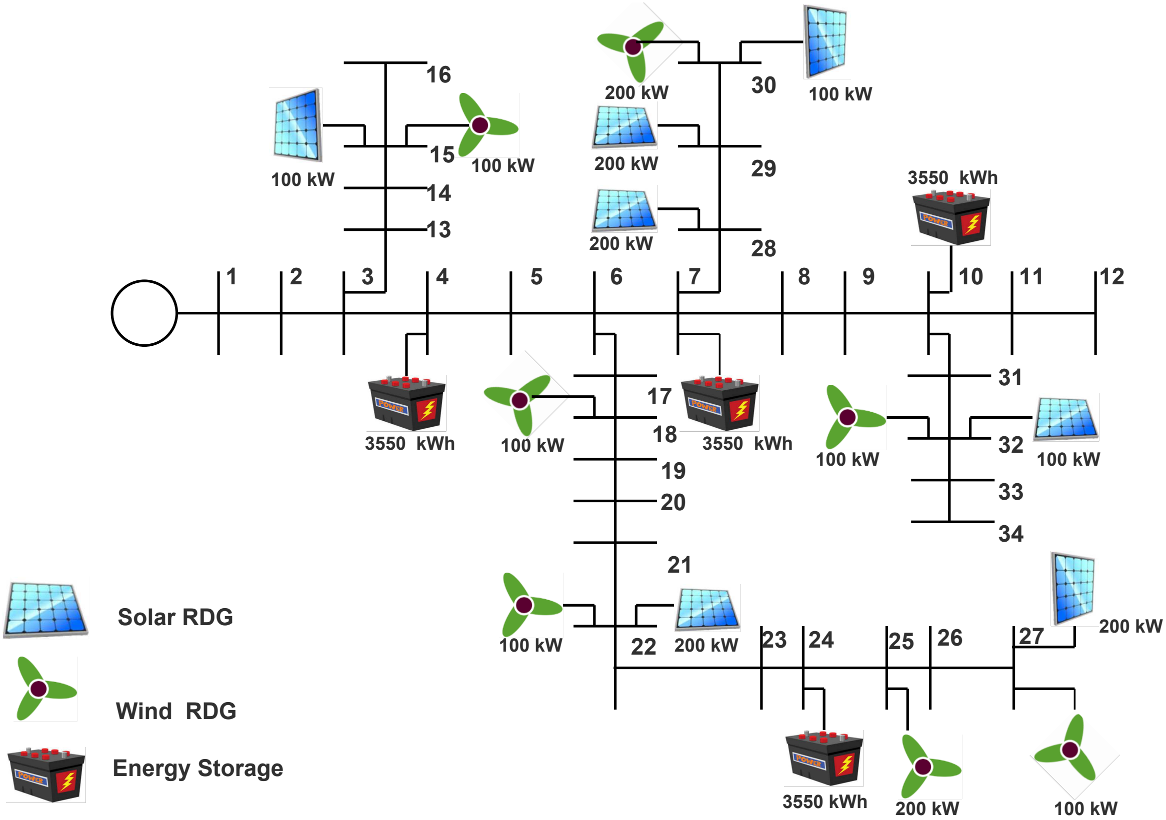

FIGURE 6.5: Allocation of hybrid RDG-ES on 34 bus system for economic benefits

TABLE 6.5: Benefits and costs of RDGO and DISCOM

RDG type	RDG owner benefit (Rs.)	RDG energy cost (Rs.)	Grid energy cost (Rs.)	Loss reduction benefit (Rs.)
SDG	617407472	768872969	987610387	7186204
WDG	646993707	798626834	804804886	15255361
HDG	606757631	762665981	899628832	7799586

RDG.

From the above discussions, it is observed that proposed joint allocation methodology of RDG and ES provides benefits to DISCOM by cost minimization and also RDGO achieves economic benefits. Significant loss minimization is obtained by the optimal allocation of multiple RDG units and multiple ES units. The methodology provides an optimal contract price of renewable energy for both; RDGO and DISCOM.

6.6 Summary

Allocation of RDG and ES offers significant cost minimization benefits to DISCOM. This chapter shows a joint allocation methodology for ES and RDG *i.e.,* solar RDG, wind RDG and hybrid RDG. The proposed methodology provides size and location of both, RDG and ES along with a contract price of the renewable energy. The RDG owner is encouraged for the investment in RDG by providing an assured economic benefit. Significant loss minimization benefits are also obtained by the joint RDG and ES allocation methodology. This nonlinear, constrained optimization problem is solved with a robust and competitive optimization algorithm called Grey Wolf Optimizer (GWO). The effectiveness of the methodology is tested with a comprehensive case study on a 34-bus test system. In this case, wind RDG-ES joint allocation provides significant economic benefits compared to other RDG-ES combinations. The proposed methodology can be useful to check the economic viability of various grid integrated energy technologies.

CHAPTER 7

CONCLUSIONS AND FUTURE SCOPE

Integration of RDG is considered as one of the significant contributions to the world energy considering future perspectives of them. The power utilities are more concerned with the high penetration RDGs due to increased energy demand and diminishing fossil-fuel based resources. Solar and the wind are promising RDG technologies due to the stainability and environment friendliness. Also, they can be strategically placed in power systems for reducing power losses, improving voltage profiles and improving system efficiency. Incentive-based regulation for the network and improved system performance are major concerns of energy loss minimization. Loss minimization by optimal allocation of RDGs is addressed by meany researchers in last few years. Optimal sizing and placement become complex due to variable nature of RDG as well as load. Loss minimization with optimal sizing and placement is obtained with either minimization of power losses or minimization of energy losses. Loss minimization methodology should consider energy losses due to the variability of both; demand and generation. This research work considers optimal sizing and placement of RDG for energy loss minimization

ES has become an integral part of modern power systems due to the increased penetration of RDGs into distribution networks. It has multiple applications into the power system. ES helps in growing renewable energy penetration level, frequency control, voltage uctuations mitigation and power quality improvement. Optimal sizing and placement of ES have a significant impact on energy loss minimization in power system. The research formulates an optimal placement and sizing methodology of ES in the presence of RDG.

The optimal sizing and placement of RDGs affect the economic performance of power system. Optimally allocated RDG units in the distribution system maximize savings in system upgrades, the cost of energy losses, the cost of interruption and achieve overall economic benefits. The cost-benefit problem by the joint allocation of RDG and ES should minimize DISCOM's cost and provide significant profit to RDG owner. RDG owner sells the energy to the DISCOM at a contract price. Thus, Cost of DISCOM and profit of RDG owner are lined with each other by contract price of renewable energy. Hence, the research work considers the contract price in the cost-benefit formulation.

7.1 Summary of Significant Findings

The research in this thesis has addressed the problem of distributed generation planning with RDG and ES. A planning methodology is proposed for optimal sizing and placement of Renewable Distributed Generation that mainly includes the solar RDG, wind RDG and hybrid RDG (i.e., combined solar RDG and wind RDG). A probabilistic generation model is used for solar PV generation and wind power generation. The developed generation load model is integrated into optimal power flow to obtain energy loss minimization with optimal sizing and placement of RDGs, i.e., solar RDG, wind RDG and Hybrid RDG. GA, PSO, SOS, FFA and GWO algorithms are applied to the proposed methodology. Significant loss minimization is obtained with proposed methodology. GWO provides best optimal solutions with significant loss minimization. The wind RDG provides improved energy loss minimization as compared to other RDG techniques as compared to the other RDGs.

Secondly, optimal sizing and placement of Energy Storage in the presence of Renewable Distributed Generation is proposed to minimize energy losses. The size of Battery Energy Storage is obtained from the generation -load profile of the system. This energy storage is split into multiple Energy Storage units and it is optimally sized and placed in the distribution system. Significant loss minimization obtained by optimal placement of multiple Energy Storage units at multiple sites. The loss minimization with ES in the presence of RDG is improved as compared to the only optimal RDG placement approach.

Considering the effect of allocation of RDG and ES on line flows of the system a joint optimal sizing and placement of RDG and ES is presented. Three cases i.e., solar RDG-ES, wind RDG-ES and hybrid RDG-ES are presented for joint allocation methodology. Four storage units are jointly allocated with RDGs to obtain energy loss minimization. The non-linear constrained optimization problem is solved with GA, PSO, SOS, FFA and GWO algorithms. Significant loss minimization is obtained with the proposed joint optimal allocation methodology. GWO provides best optimal solutions as compared to other optimization algorithms. The wind RDG-ES combination provides a significant energy loss minimization. It can be observed that improved loss minimization is obtained with joint allocation methodology as compared to RDG allocation and ES in the presence of RDG allocation approach.

Finally, this work presents a joint optimal sizing and placement methodology of ES and RDG for economic benefits. The joint optimal allocation methodology minimizes the cost of DISCOM. It also provides ensured benefits to RDG owner. In the proposed formulation various costs and benefits of both DISCOM and RDGO are considered. The contract price of renewable energy is included in the problem formulation to benefit both; DISCOM and RDG owner.

The work proposed in this thesis provides optimal sizing and placement method for solar RDG, wind RDG hybrid RDG for energy loss minimization. An optimal sizing and placement methodology for ES in the presence of RDG is addressed to minimize energy losses. Considering the combined effect of RDG and ES on power flows, a joint optimal allocation methodology for RDG and ES is presented for energy loss minimization. The cost-benefit based joint optimal allocation of RDG and ES is presented which also includes contract price of renewable energy. The subject matter addressed in this thesis is relevant for optimal planning of RDG and ES including economic benefits.

7.2 Practical Application of the Proposed Research

The proposed methodology can be practically implemented for the optimal allocation RDG and ES.

The first task is to select a potential site for RDG. The site should have land availability to place the RDGs. Depending on these information decide the candidate buses for RDG. Collect the historical data for solar irradiance and wind speed for the selected region.

Forecast the renewable generation on hourly and seasonal basis by applying probabilistic approaches. Precise forecasting is essential to obtain accuracy in the planning of RDG. Next, obtain hourly load profile of the selected network using suitable load forecasting.

Decide total penetration limit of RDG considering the feeder capacities and stability of the system. Overall stability with increased renewable generation needs to be checked. Select appropriate energy storage technology. ES should provide required energy and power requirement.Then, decide the design variables, constraints of the proposed scheme. Obtain the optimal sizing and placement using the proposed methodology.

Next, to obtain economic benefits, provide various costs of DISCOM and RDG owners. Provide minimum economic benefit value that RDG owner should achieve. Obtain optimal size and locations of RDG and ES along with contract price using proposed methodology.

Important factors that impact the successful implementation of proposed methodology to Indian power sector include accurate forecasting of load and renewable energy sources. Energy forecasting in Indian electricity market has multiple challenges, as compared to advanced markets like Pennsylvania-New Jersey-Maryland (PJM). PJM plays an important role in U.S. electric system and it is the largest electrical system in North America [255]. It has following features:

i) It provides a secure, efficient and economic operation by using locational marginal prices (LMP). ii) PJM incorporates user input to a create functional, practical and complete market. iii) PJM has advanced solar and wind forecasting mechanisms [256, 257].

As compared to electricity markets like PJM, forecasting for Indian utilities has following challenges:

i) Manual load forecasting based on previous years data is found at several places. ii) External load forecasting tools are not applied. iii) Accuracy of available load forecasting is below expectation. iv) Inaccurate load forecasting is primarily responsible for improper scheduling rather than inaccurate renewable energy forecasting. v) Renewable generation forecasting in India is at its developing stage. vi) Renewable energy forecasting should be accompanied by load forecasting of equivalent accuracy.

Considering the extreme seasonal variations in renewable generation and load in Indian utility, optimal planning of RDG requires high quality renewable and load forecasting. Currently, renewable energy forecasting is mainly provided by India Meteorological Department (IMD) with traditional weather forecasting [258]. However, reliable and robust forecasting systems are required for optimal planning of large scale integration of RDGs.

The 34 bus test network is a three phase radial distribution feeder and is used as a representative network of Indian utilities, to validate the proposed algorithms [218]. The similarities include,

i) It is a radial distribution network with a main substation and multiple feeders.

ii) It is long length feeders.

iii) System voltage is 11 kV.

iv) The feeder has spot loads.

The main difference in the feeder characteristic is that the 34 bus test feeder is considered as balanced and represented on per phase basis, while the real feeder has three phase unbalanced loads. Also, in the real feeder, it is necessary to consider transformers, voltage regulators and capacitors. With these considerations, the 34-bus test feeder can be considered as representative of Indian distribution utilities.

7.3 Future Scope for Research

Research is a continuous process and always there is a scope. Optimal sizing and placement of RDG and ES for energy loss minimization and economic benefits is presented in this research work. As a path forward, some of the identified areas and research directions are given as follows.

1. Joint optimal allocation of ES and RDG can be used in a co-optimized market. In a co-optimized market, a portion of energy from being dispatched in the energy market is reserved for providing regulation services in the ancillary market and carry over the remaining energy to the next period to sell it in the energy market. ES can make revenues from a co-optimized electricity market than just energy only market.

2. RDG, distributed ES and demand-side management are recognized as main facilitators for the smart grid. The optimal allocation methodology can be extended with the demand side management. The combination of RDG, ES and demand-side management results in a system of diverse generation sources with possibilities for improved energy efficiency, local generation and controllable loads.

3. ES technology has various technical benefits, however, the high cost of ES technology is a problem. It is necessary to understand cost and benefits of various ES

technologies. Operation and application of large-scale ES should be associated with efficient use of it.

4. Wind RDG and solar RDG can cause voltage fluctuations and affects voltage stability of the grid. ES can provide reactive power support and it can assist other reactive power compensation equipment. Thus, ES and RDG allocation can be extended with reactive power panning.

5. Micro-grids are making better use of renewable energy. The study of the allocation of RDG and ES can be extended to an interconnected network of multiple micro-grids, with local energy generation and inter-grid energy transmission.

6. Ancillary services brings additional benefits and improves ES feasibility. Various ancillary services can be addressed in ES and RDG planning and operation.

Thus, optimal allocation problem RDG and ES can be associated with promising research areas some of these includes co-optimized electricity market, demand side management, reactive power support and ancillary services.

Appendix A

Publications from the Thesis

Journal Publications

1. Vaiju Kalkhambkar, Rajesh Kumar, Rohit Bhakar, Joint Optimal Allocation Methodology for Renewable Distributed Generation and Energy Storage for Economic Benefits, **IET-Renewable Power Generation**, 10.9 (2016): 1422-1429.

2. Vaiju Kalkhambkar, Rajesh Kumar, Rohit Bhakar, Optimal Allocation of Renewable Energy Sources for Energy Loss Minimization, **Journal of Electrical Systems**, 113.1 (2017): 115-130

3. Vaiju Kalkhambkar, Rajesh Kumar, and Rohit Bhakar, Energy Loss Minimization through Peak Shaving using Energy Storage, **Perspectives in Science**, 8 (2016): 162-165.

Conference Publications

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