Investigation on Evolutionary Computing Based Approach for Optimal Power Flow Solution

A Thesis Submitted in Partial Fulfillment of the Requirements for the Award of the Degree of

DOCTOR OF PHILOSOPHY

Submitted by

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DECLARATION

I hereby certify that the work which is being presented in this thesis entitled **"Investigation on Evolutionary Computing Based Approach for Optimal Power Flow Solution"** submitted in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in the Department of Electrical Engineering, Delhi Technological University, Delhi. This is an authentic record of my own work carried out under the supervision of Dr. Narendra Kumar and Dr. Laxmi Srivastava. The matter presented in this thesis has not been submitted elsewhere for the award of a degree.

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CERTIFICATE

On the basis of candidate's declaration, I hereby certify that the thesis entitled **"Investigation on Evolutionary Computing Based Approach for Optimal Power Flow Solution"** submitted to the Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirements for the award of degree of Doctor of Philosophy, is an original contribution with the existing knowledge and faithful record of the research work carried out by him under my guidance and supervision.

To the best of my knowledge, this work has not been submitted in part or full for the award of any degree elsewhere.

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Dedicated to my beloved parents

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ABSTRACT

Electrical energy has become an essential part of modern human life. The power and energy industries have undergone significant transformations in recent years. Electric utilities are increasingly being privatized, restructured, and deregulated. With the current trend of deregulation, privatization, and restructuring in power systems, operating an electric power system has become more difficult. In order to deal with these difficulties, the optimal power flow (OPF) methodology is required by power engineer's / utility companies as the key tool for operation planning, and control of power systems.

OPF is a highly nonlinear, multimodal, non-convex, and non-differential optimization problem, which includes a large number of complex constraints, decision variables, and non-linear power flow equations. To solve the optimal power flow problem, several conventional and intelligent algorithms were used in recent years. Some of the conventional algorithms have outstanding convergence properties, and are often used in the industry. However, conventional algorithms depend on convexity to find the global best solution and are required to simplify relationships to achieve convexity. These approaches are normally limited to particular cases of OPF and do not have much flexibility in terms of different kinds of objective functions or constraints that could be employed. Except for linear programming and convex optimization, most of the conventional optimization algorithms cannot be guaranteed to find globally optimal solutions for complex constrained optimization problems.

Nowadays, numerous Evolutionary Computing (EC) based optimization or meta-heuristic algorithms have been developed by researchers, which are found to be powerful tools for handling difficult optimization problems. These random search, population-based

algorithms are highly flexible, which means that they are appropriate to solve various types of optimization problems, including linear as well as non-linear problems, and complex constrained optimization problems. Due to the stochastic nature of the EC algorithms, evaluating the performance of Evolutionary Computing algorithms for addressing the OPF problem is a challenging task. However, it has been logically proved that any single optimization algorithm does not have the potential to solve various types of engineering and complex optimization problems, thus, the "No Free Lunch" theorem supports, and encourages the scientists and researchers to improve the performance of existing algorithms and developed new algorithms. Hence, the main objective of this research is to develop an efficient optimization method for the OPF problem.

To begin, the optimal power flow problem is solved using two meta-heuristic algorithms: bat search optimization and bird swarm algorithms. These algorithms have been used in IEEE 30-bus test systems for fuel cost minimization, total voltage deviation minimization, emission minimization, power losses minimization, and voltage stability enhancement under the normal condition as well as during line outage contingency. Based on OPF outcomes, it was concluded that both the proposed algorithms for the OPF problem are competitively better and have competitive nature compared to other reported methods.

Evolutionary Computing algorithms are population-based random search techniques. Despite their advantages, these meta-heuristic algorithms have some drawbacks. These algorithms require parameter tuning to find the optimum results and for parameters tuning, they require multiple trials and a significant computing time. Moreover, the best solutions achieved by such algorithms cannot be replicated exactly, and thus several trials should be performed to ensure accuracy and meaningful statistical results. In this thesis, the Rao algorithms, a recently developed algorithm-specific parameter-less optimization algorithms have been proposed to solve the OPF problem. The Rao algorithms have been applied to the standard IEEE 30-bus system, IEEE 57-bus system, and the IEEE 118-bus test system to demonstrate their efficacy and ability to solve OPF problems. Various objectives for solving the OPF problem are fuel cost minimization, total voltage deviation minimization, enhancement of voltage stability under normal and under contingency conditions, real power loss minimization, and emission minimization. As noted from the OPF results, the performance of the proposed Rao algorithms has been better than the other reported algorithms mentioned in the recent literature.

When used to solve complex real-world engineering optimization problems, standard versions of some of the EC-based algorithms have been found to have some limitations, as some algorithms are good in exploration, while others are in exploitation. To overcome this problem a hybrid algorithm is proposed, which is based on a sine-cosine mutation operator and a modified Jaya (SCM-MJ) algorithm, to solve the OPF problems in this work. The efficacy of the SCM-MJ algorithm is primarily evaluated using thirteen (unimodal and multimodal) mathematical benchmark functions. Later, the SCM-MJ algorithm is applied to the Algerian 59-bus system and IEEE 118-bus test system to handle the OPF problems. The SCM-MJ algorithm successfully provided a minimum value of the objective function over several runs than other modern meta-heuristic optimization approaches in all the thirteen mathematical benchmark functions as well as in OPF case studies. The comparison of OPF outcomes demonstrates that the suggested SCM-MJ algorithm dominates over other approaches for solving the OPF problem. The SCM-MJ algorithm has provided better results for mathematical benchmark functions and OPF problems quickly and efficiently.

Due to the increase in demand for electrical energy over limited reserves of fossil fuels and environmental concerns, renewable energy-based distributed generation is a highly concerned area in the modern power industry. Hence, in modern power systems, integration of distributed generation (DGs) is becoming increasingly essential day by day. This opens up new opportunities for the formulation of the OPF problem considering DG units in sub-transmission and distribution systems. As a result, the next work included in this thesis is to solve the OPF problem including DG units. A hybrid EC-based approach Jaya-PPS, which is the combination of the Jaya and Powell's Pattern search (PPS) method, is proposed in this work to solve the optimal power flow problem for fuel cost minimization, emission minimization, real power losses minimization, and total voltage deviation minimization simultaneously. The recently developed Jaya algorithm has been applied for the exploration of search space, while the excellent local search capability of the PPS method has been used for exploitation purposes. Integration of the local search procedure into the classical Jaya algorithm has been carried out in three different ways, which resulted in three versions, namely, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3. These three versions of the proposed hybrid Jaya-PPS approach were developed and implemented to solve the OPF problem in the standard IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems. The obtained results of the three versions are compared to the dragonfly algorithm (DA), grey wolf optimization (GWO) algorithm, Jaya algorithm, and other reported methods. A comparison of the results demonstrates the superiority of the proposed Jaya-PPS1 algorithm over different versions of proposed algorithms and the reported methods.

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviations

ABBPPO	Adaptive Biogeography Based Predator–Prey Optimization
ALC-PSO	Particle Swarm Optimization with Aging Leader and Challengers
ARCBBO	Adaptive Real-Coded Biogeography-Based Optimization
AVR	Automatic Voltage Regulator
BB-MPSO	Bare Bones Multi-Objective PSO
BBO	Biogeography-Based Optimization
BFA	Bacteria Foraging Algorithm
BHBO	Black-Hole-Based Optimization
BS	Bat Search
BSA	Bird Swarm Algorithm
BSOA	Backtracking Search Optimization Algorithm
CDMC	Centroid Decision Making Concept
COA	Chaos Optimization Algorithm
COF	Combine Objective Function
COT	Classical Optimization Technique
CSA	Cuckoo Search Algorithm
CV	Control Variables
DA	Dragonfly Algorithm
DE	Differential Evolution

DG	Distributed Generation
DSA	Differential Search Algorithm
DV	Decision Variables
EC	Evolutionary Computing
ECHT-DE	Ensemble of Constraint Handling Techniques—Differential Evolution
EFO	Electromagnetic Field Optimization
EGA	Enhanced Genetic Algorithm
ELD	Economic Load Dispatch
EP	Evolutionary Programming
ESADE	Enhanced Self-Adaptive Differential Evolution
FACTS	Flexible Alternating Current Transmission System
FCM	Fuel Cost Minimization
FFA	Firefly algorithm
FPA	Flower Pollination Algorithm
FPNLP	Fletcher-Powell Non-Linear Programming
GA	Genetic Algorithm
G-best	Global Best
GBICA	Gaussian Bare-Bones Imperialist Competitive Algorithm
GOA	Grasshopper Optimization Algorithm
GPC	Giza Pyramids Construction
GPM	Gradient Projection Method
GPU	Graphics Processing Units
GPU-PSO	Graphics Processing Unit's Particle Swarm Optimization

GSA	Gravitational Search Algorithm
GSO	Glowworm Swarm Optimization
GWO	Grey Wolf Optimization
HS	Harmony Search
HVDC	High-Voltage Direct Current
ICA	Imperialist Competitive Algorithm
IEEE	Institute of Electrical and Electronics Engineers
IEP	Improved Evolutionary Programming
IGSO	Improved Group Search Optimization
IMFO	Improved Moth-Flame Optimization
ISSO	Improve Social Spider Optimization
Jaya-PPS	Jaya- Powell's Pattern Search
KH	Krill Herd
kW	Kilowatt
LCA	League Championship Algorithm
LM	Levy Mutation
MDE	Modified Differential Evolution
MFO	Moth Flame Optimization
MFPA	Modified Flower Pollination Algorithm
MGBICA	Multi-Objective Gaussian Bare-Bones Imperialist Competitive Algorithm
MGOA	Modified Grasshopper Optimization Algorithm
MH	Meta-heuristic
MHBF	Multi-Hive Bee Foraging

MJ	Modified Jaya
MOABC	Multi-Objective Artificial Bee Colony
MOEA	Multi-Objective Evolutionary Algorithm
MOHES	Multi-Objective Hybrid Evolutionary Strategy
MOICA	Multi-Objective Imperialist Competitive Algorithm
MOPSO	Multiple Objective Particle Swarm Optimization
MPSO	Modified Particle Swarm Optimization
MSA	Moth Swarm Algorithm
MSCA	Modified Sine Cosine Algorithm
MSO	Moth Search Optimization
MW	Megawatt
NFL	No Free Lunch
NISSO	Novel Improved Social Spider Optimization
NKEA	Neighborhood Knowledge-Based Evolutionary Algorithm;
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NSGA-III	Non-dominated Sorting Genetic Algorithm III
OBL	Oppositional Based Learning
OPF	Optimal Power Flow
PA	Photosynthetic Algorithm
PCPDIP	Predictor-Corrector Primal-Dual Interior Point
PPS	Powell's Pattern Search
PSO	Particle Swarm Optimization
PSOGSA	Hybrid Particle Swarm Optimization and Gravitational Search Algorithm

QO	Quasi-Oppositional
QOJA	Quasi-Oppositional-Based Jaya algorithm
RCBBO	Real-Coded Biogeography-Based Optimization
RPLM	Real Power Losses Minimization
SA	Simulated Annealing
SCA	Sine Cosine Algorithm
SCM	Sine-Cosine Mutation
SF-DE	Superiority of Feasible Solutions–Differential Evolution
SI	Swarm Intelligence
SKH	Stud Krill Herd Algorithm
SOS	Symbiotic Organisms Search
SP-DE	Self-Adaptive Penalty–Differential Evolution
SPSO	Self-Adaptive Particle Swarm Optimization
SSA	Salp Swarm Algorithm
TLBO	Teaching Learning-Based Optimization
TSO	Tree-Seed Optimization
TVDM	Total Voltage Deviation Minimization
VPLE	Valve Point Loading Effects
VSE	Voltage Stability Enhancement
WSCC	Western System Coordinating Council

Parameters/variables

A	Loudness
A_i, B_i, C_i	Fuel cost coefficients of the i^{th} generating unit
A^t	Average loudness

a_1 and a_2	Positive constants between 0 and 2
B_{ij}	Susceptance between bus *i* and bus *j*,
C	Cognitive accelerated coefficients
f	Frequency
F(x,u)	Objective function
FL	Following factor between 0 and 2
f_k	Frequency of the k^{th} bat
f^{min} and f^{max}	Minimum and maximum values of frequency
G_K	Conductance of K^{th} line is connected between *i* and *j* buses
G_{ij}	Conductance between bus *i* and bus *j*,
g_j	Best previous position shared by the swarm
G (x,u)	Equality constraint
$H_k^{(L)}$	Lower bounds of inequality constraint
$H_k^{(U)}$	Upper bounds of inequality constraint
H (x,u)	Inequality constraint
$iter$	Iterations
$iter_{max}$	Maximum number of iterations
$J_{i,j,k_{c1}}$ $J_{i,j,k_{c2}}$ and $J_{i,j,k_{c3}}$	Three random solutions in the i^{th} iteration
$J_{i,j,B}$	Best candidate value of variable j^{th}
$J_{i,j,W}$	Worst candidate value of variable j^{th}
$J_{i,j,k}$	Value of the j^{th} variable for k^{th} candidate during the i^{th} iteration
$J_{i+1,j,k}$	Updated value of $J_{i,j,k}$

$J_{new(i+1,j,k)}$	k^{th} candidate's new position value during $(i+1)^{th}$
$K_{1,}\ K_{2,}\ K_{3,}\ K_4$	Penalty factor
k	Random positive integer ($k \neq i$)
L_J	Static voltage stability index
meanj	j^{th} element of the average position of the whole swarm
NO_x	Nitrogen oxides
NB	Number of load buses
NC	Number of VAR compensators
NG	Number of generators
NLB	Number of load buses
NT	Number of regulating transformers
ntl	Number of transmission lines
P_{g_1}	Slack bus generated active power
P_{di}	Active power load demand at bus i
P_{gi}	Generators' active power outputs at bus i,
$pFit_i$	Best fitness value of the bird b_i
$p_{i,j}$	Best previous position of the i^{th} bird
p_r	Pulse emission rate
Pop.	Population size
Q_G	Generator reactive power output
Q_{di}	Reactive power load demand at bus i
Q_{gi}	Reactive power generation at bus i,
Q_{sh}	Shunt VAR compensation

$R_{i,j,k}$	the j^{th} variable value for the k^{th} candidate
$R_{j,best,i}$	Value of the j^{th} variable for the best candidate
$R_{j,worst,i}$	Value of the j^{th} variable for the worst candidate
r, φ	Random numbers (0, 1)
Randn(0,1)	Gaussian distributed random number with mean (μ) zero
SO_x	Sulphur oxides
S_g^l	Search direction for l^{th} coordinate for g^{th} dimension
S_l	Transmission line loading (line flow)
S	Social accelerated coefficients
sumFit	Sum of the best fitness value of the whole swarms
T_r	Tap settings of regulating transformer
u	Set of control Variables
V_L	Load (PQ) bus voltage
V_i	Voltage magnitudes of bus i
VAR	Volt-amp reactive
V_g	Generator bus voltages
V_j	Voltage magnitudes of bus j
v_k	Random flying velocity of bats at the position X_k
v_k^t	Velocity of the K^{th} bat at t^{th} time step
W_{RPLM}, W_{TVDM}, W_{VSE} and W_{EM}	Weight factors
X_*	Global best solution
X_j^{min} and X_j^{max}	Lower and upper boundaries for dimension j,

X_{kj}	j^{th} component position vector of X_k
X_k^t	Position of the K^{th} bat at t^{th} time step
x	Set of dependent Variables
Y_{ij}	Admittance between bus i and bus j,
$\alpha_{i,j,1}$ and $\alpha_{i,j,2}$	Two random numbers between 0 and 1
$\alpha_i, \beta_i, \gamma_i, \lambda_i, \xi_i$	Emission coefficients of i^{th} generating unit
$\gamma_{i,j,1}$ and $\gamma_{i,j,2}$	Two random numbers between 0 and 1
δ_i	Voltage angles at bus i
δ_j	Voltage angles at bus j
λ_g^*	Step length
λ_g^{min} and λ_g^{max}	Minimum and maximum step length for g^{th} decision variable
ϵ	Smallest constraint which is used to avoid zero-division error
σ	Standard deviation
β	Random number between 0 and 1
Ψ	Uniformly distributed random number (-1 to 1)

CHAPTER 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

A power system is the largest interconnected electrical system on the earth having numerous generating sources, transmission and distribution systems, loads, and controlling devices like transformers, AVRs and governors, relays, circuit breakers, and other modern controlling devices, etc. to ensure its reliable, stable and unceasing operation. In the last few decades, the power and energy industries have undergone remarkable advancements. Earlier, power systems were structured as a centralized vertically integrated utility that comprises three unidirectional levels of operation via generation, transmission, and distribution. There have been growing trends of restructuring and deregulation of electric utilities. It has evolved the system from vertically integrated utilities to decentralized control, which led to the growth of multiple power producers on the scale of small to large power generation. The operation of electric power systems is now becoming more challenging with the present trend of deregulation, and restructuring in power systems[1], [2]. The main goal of these changes is to increase the operating efficiency of power plants, reduce system losses and consequently electricity costs.

With the integration of different kinds of power electronic appliances and renewable energy sources in the sub-transmission and distribution system in the existing electrical power system, the operation and control of the power systems have become complex and challenging. The efficient planning for a power system to utilize the best possible use of existing capacity is of prime importance and key input to the process of economic development. Therefore, the importance of solving the optimum power flow (OPF) problem has increased many folds. OPF results are needed for planning, economic operation, and control of existing electrical power systems as well as for its future expansion planning.

Due to the increase in demand for electrical energy over limited reserves of fossil fuels and environmental concerns, renewable energy generation is a highly concerned area in the modern power industry. At present, the continuously increasing global energy demand is currently unable to be met by centralized generation. Approximately 16% of the world's people still do not have access to electricity [3]. Therefore, the growing inclination of penetration of distributed generation (DG) units in inter-connected restructured power systems has increased the importance of solving optimum power flow many times.

1.2 OPTIMAL POWER FLOW

The main aim of solving an OPF problem is to find the optimal set of control variables that optimizes a certain objective function, at the same time satisfying various operating constraints and power balance equations. Optimal power flow results are needed for economic operation, planning, and control of the existing electrical grid and future expansion planning [4]. For the OPF problem, the control variables used are V_g (generator bus voltages), P_g (generators' active power outputs excluding slack bus), phase shifters, T_r (tap settings of regulating transformer) and Q_{sh} (injected reactive power using capacitor banks, FACTS devices etc.). Some of these variables are discrete, e.g., tap settings of regulating transformer, injected reactive power source output, and phase shifters, while others are continuous (e.g., P_g and V_g). The discrete nature of the control variable poses a challenge for the optimization techniques and makes OPF a non-convex problem. At the beginning of the 1960s, Carpentier addressed the OPF problem as an extension of economic load dispatch for the first time in history [5]. Since then, researchers have contributed significantly to this crucial issue.

The OPF is an essential tool that regulates the control or decision variables set in the feasible region to find the optimal control variables setting, which can minimize a pre-specified objective functions [6]. In the formulation of the OPF problem, fuel cost minimization (FCM) is frequently used as a primary objective function in addition to other objectives like voltage stability enhancement (VSE), total voltage deviation minimization (TVDM), real power losses minimization (RPLM), and emission minimization (EM) via readjustment of control variables, taking into account both operational and physical constraints. OPF is a complex optimization problem, which associates several constraints and decision or control variables. It is a highly non-linear, high-dimensional, non-differential, multi-modal, and non-convex problem with discrete and continuous control variables[7].

1.3 DISTRIBUTED GENERATION

DG is defined in various ways. The IEEE defines DG [8]as:

"the generation of electricity by facilities that are sufficiently smaller than central generating plants so as to allow interconnection at nearly any point in a power system, a subset of distributed resources".

On-site generation, dispersed generation, decentralized generation, district/distributed energy, embedded generation, and redistributed energy are all terms used to describe distributed generation. In general, distributed generation is a method of producing electricity near the consumer side by using small-scale technologies. These generations rely on technologies that are mostly renewable, such as wind turbines, photovoltaic cells, geothermal energy, and micro hydropower plants. In addition, now a day's hybrid DGs system is also used which is a combination of renewable and conventional energy sources (Fuel cells, Micro turbine and gas turbines, etc.) or renewable and storage devices (like batteries, ultra-capacitor, Flywheels, etc).

DGs are decentralized, modular, and flexible technologies that are located close to the load. Their capacities are ranging typically from 1 kW to 10,000 kW or less. Fig. 1 depicts the classification of DGs. The DGs are classified as micro, small, medium, or large based on their power ratings[9].

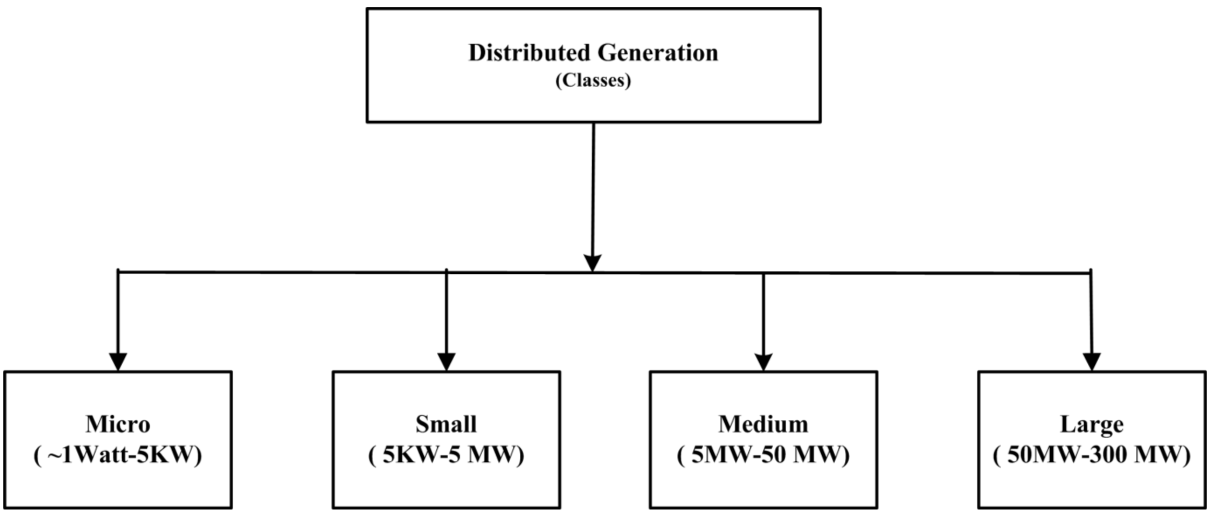


Fig 1.1: Distributed generation classification

1.3.1 Distributed generation technology

The DGs include a variety of technologies such as renewable energy generation like wind, PV, wave, and geothermal, as well as non-renewable resources such as fuel cells, micro turbines, and internal combustion engines. The characteristics of the various DGs and studying the behaviour of these technologies can improve system design and analysis. The following section discusses the major DG technologies. Fig.2 shows the different types and technologies of distributed generations.

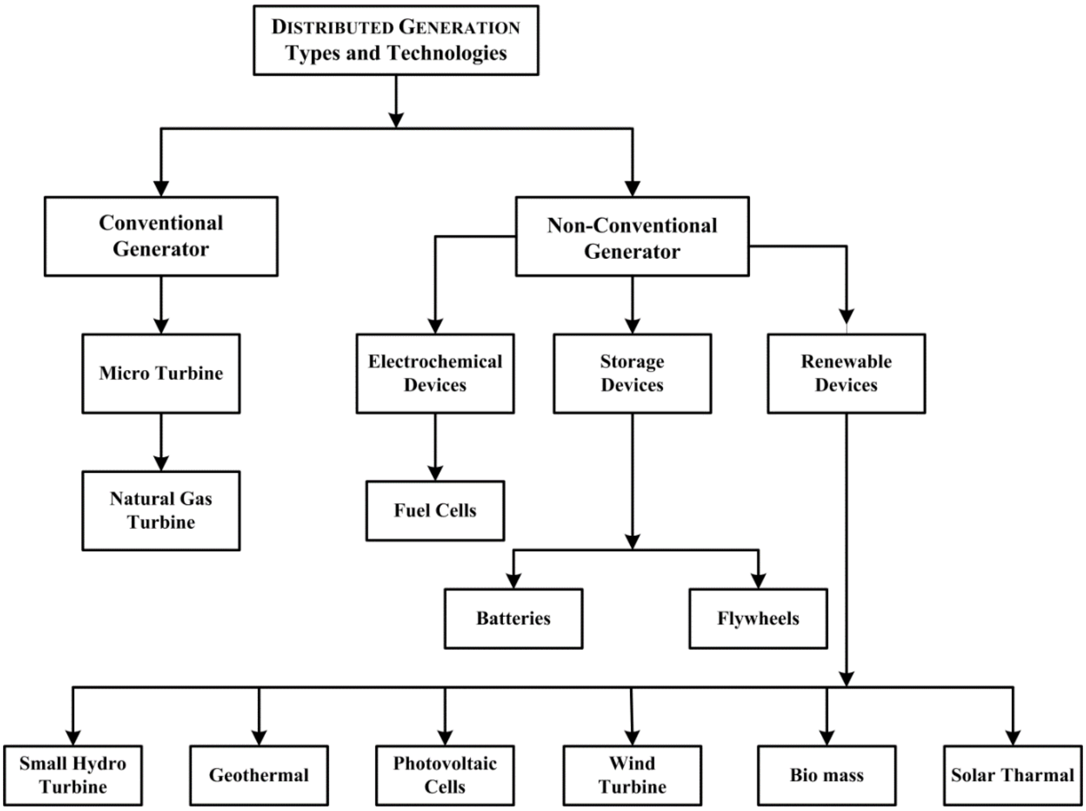


Fig 1.2: Types and technologies of distributed generation

The DGs may also be classified into four major types based on terminal characteristics in terms of real and reactive power delivering capability as described in [10]. Four common types of DG power injection are described here

Type 1: DG capable of supplying real power only (P)

Type 2: DG capable of supplying reactive power (Q) only

Type 3: DG capable of supplying real power (P) and reactive power (Q) both

Type 4: DG capable of supplying active power (P) but consuming reactive power (Q).

1.3.2 Purpose of integration of DGs

The inclusions of DG units in modern electrical power system have numerous economic and technical advantages. The following are some of the benefits of DGs[11]–[13]:

- **From the economical point of view:**

i) It opens the door to reforms in the power sector.

ii) It encourages the use of clean energy and the exploration of renewable energy sources.

iii) Installing DGs in optimum locations is improve the available transfer capacity of transmission lines that reduces the expansion of the transmission and distribution network at the time of future planning of the power system.

iv) The DGs installation process is very easy and cost-effective. Thus, it can be set up in a short period of time in any location.

v) The DGs unit is operated independently and separately from the other DGs units which mean it is not controlled by central operators. Consequently, it is added or removed from the electrical grid as per power demand.

vi) By supplying power to the grid at the peak hour, DGs are reducing the cost of electricity to end-users. In addition, the construction of new power plants, transmission, and distribution lines can be reduced.

vii) In many circumstances, supplying power to remote places becomes too expensive or impracticable. The DG can be installed close to the load and operated on-site. In such circumstances, hybrid distributed generation is typically used to provide service to a single large client or a group of small customers.

- **From the operational point of view:**

i) DGs have a positive impact on the voltage profile, system stability, and power quality of the distribution and sub-transmission systems.

ii) The optimum location and size of DG can reduce the real power losses of transmission and distribution networks.

iii) DGs can be used as a backup power source on-site in the event of a power outage or a system failure.

iv) DGs keep the system stable and provide the spinning reserve.

v) The DGs capacity varies from a few kW to MW that allows them to be installed on medium and/or low voltage distribution and sub-transmission networks. It provides flexibility and is placed near to various small and big consumers.

vi) Renewable energy base DGs reduce or eliminate emissions, thus it is good for the environment and society.

vii) DGs help to reduce the congestion of transmission and distribution networks.

viii) For industries that require uninterrupted service, DG technologies may provide benefits in the form of a more reliable power source.

ix) DGs help to reduce the load demand during peak hour times of the grid or minimise congestion of the transmission network, because they produce power locally for users.

x) DGs technologies can provide emergency power for a wide range of public services, and communications station while remaining grid-independent.

xi) It provides a solution for rural electrification in a country like India.

1.4 MOTIVATION

In the early decades, many classical methods [14], [15], like quadratic programming, interior point method, linear programming, non-linear programming and mixed-integer non-linear programming, etc. have been applied to solve the OPF problems. But the conventional algorithms depend on convexity to find the global best solution and are required to simplify relationships to achieve convexity. However, since the OPF problem is non-convex in general, several local minima can exist. If the valve point loading effects of thermal generators are taken into account, the non-convexity increases even further.

Some conventional optimization techniques have outstanding convergence properties, and are often used in the industry. Because of the nonlinear, non-differential, multimodal, non-smooth, and non-convex nature of the OPF problem, the conventional optimization techniques are less efficient for solving the optimal power flow problem [16]. In other words, the conventional optimization methods are less efficient, particularly, when the constraints and objective functions are non-linear, non-convex, and have multiple local optima.

To overcome the demerits of classical optimization methods and to handle such difficulties, several Evolutionary Computing (EC) based or meta-heuristic algorithms came into being as alternatives to the classical optimization methods[17]. As a result, EC-based algorithms have recently got a lot of attention and are being applied to solve various real-world optimization problems in science and engineering fields. Some of these are genetic algorithm (GA), particle swarm optimization (PSO), differential Evolution (DE), gravitational search algorithm (GSA), moth swarm algorithm (MSA), black-hole-based optimization (BHBO) approach, salp swarm optimizer algorithm (SSA), league championship algorithm (LCA), teaching learning-based optimization (TLBO) etc.

When used to solve complex real-life engineering optimization problems, standard versions of some of the more common meta-heuristic approaches have been found to have some limitations. For example, premature convergence or local optima trapping is a common occurrence in GA and moth search optimization (MSO) algorithms. Similarly, the simulated annealing (SA) and PSO algorithms are relatively ineffective in searching for optimal global solutions [18]. In addition, poor communication in the TLBO algorithm during the second phase (Learning Phase) may result in insufficient knowledge sharing, therefore may get trapped in the local solution. Furthermore, the Jaya algorithm has a strong capacity to explore the search space for optimization, but occasionally it suffers from premature convergence [19]. The stud krill herd (SKH) algorithm was used to overcome the sluggish convergence of the krill herd (KH) algorithm and to find an optimum solution to solve the OPF problem[20]. Various modifications and hybridization of meta-heuristic algorithms have been proposed in the literature to address the shortcomings of the poorly performing standard versions of meta-heuristic approaches.

It was found that all EC-based algorithms have some advantages and disadvantages through the literature survey. Two main parts of any EC-based algorithm are exploration and exploitation or intensification and diversification. Some algorithms have good exploration capability but poor exploitation, and vice versa. Some algorithms are more suitable to solve certain types of problems than others. It is logically proved that any single EC based optimization algorithm does not have the potential to solve various types of engineering and complex optimization problems, thus, the "No Free Lunch" theorem encourages the development of new algorithms and modified the existing algorithms [21].

To enhance the global search ability for solving the OPF problem, many improved variants have been explored in recent years. Some of these are, quasi-oppositional TLBO, novel improved social spider optimization algorithm, improved evolutionary programming, enhanced genetic algorithm, adaptive biogeography based predator–prey optimization, levy mutation TLBO algorithm, G-best guided ABC algorithm, improved group search optimization, enhanced self-adaptive differential evolution (ESDE), and modified sine cosine algorithm (MSCA) etc.

A hybrid meta-heuristic algorithm is the most recent research trend to solve practical optimization problems. Recently, hybridization of meta-heuristic or EC-based algorithms has become more popular because of its improved ability to deal with complex optimization problems. In recent literature, a large number of hybrid EC-based algorithms have been proposed to solve complex optimization problems successfully.

Despite their advantages, EC-based algorithms have some drawbacks. To find the near-global optimal solution, they require parameter tuning. The parameters' tuning needs multiple trials and hence takes a long time to get the optimal solution. Moreover, the best solution achieved by such algorithms cannot be replicated exactly, thus several trials should be performed to ensure accuracy and meaningful statistical results. From that context, to alleviate this problem of the meta-heuristic or EC based algorithms and make them more effective, a set of modified and hybrid versions of parameter-less optimization algorithms are proposed in this thesis.

1.5 CONTRIBUTIONS

Developing hybrid optimization methods and improving the computation performance of existing optimization algorithms is the main focus of this research work.

The application of these modified and hybrid algorithms to solve OPF problems with and without distribution generation were examined.

The main contribution in this thesis work is as follows:

- To evaluate the performance of two meta-heuristic algorithms namely, bat search and bird swarm algorithms to solve the optimal power flow problem.
- To apply three easy-to-use metaphor-less optimization algorithms, Rao algorithms, to solve the optimal power flow problem.
- To develop and propose a modified Jaya algorithm for solving the optimal power flow problem.
- To develop a novel sine-cosine mutation-based modified Jaya algorithm for solving the optimal power flow problem.
- To develop a hybrid meta-heuristic Jaya-Powell's Pattern Search (Jaya-PPS) method to solve the optimal power flow problem integrated with and without distributed generating units.

1.6 LAYOUT OF THESIS

The current chapter begins with an overview and background of OPF problems, followed by the motivation for conducting research in the field of OPF. This thesis is divided into eight chapters, including an introduction and conclusion. The remaining chapters of the thesis are organized as follows:

Chapter 2 depicts a literature survey on numerous classical and meta-heuristic algorithms for the OPF problem. Based on the literature survey, significant research gaps are recognized. The difficulties encountered in OPF solution methods, as well as the need for numerous modifications in classical and meta-heuristic algorithms are also included.

Chapter 3 presents the mathematical modelling of the OPF problem with and without DG in a power system. The power flow equations as well as their operational constraints are thoroughly discussed. In addition, based on the critical review, certain essential objectives functions are identified and suggested.

Chapter 4 presents a detailed study of two meta-heuristic algorithms, bat search (BS) optimization, and bird swarm algorithm (BSA), for optimizing the optimal power flow problem. These algorithms have been employed in IEEE 30-bus test system for fuel cost minimization, total voltage deviation minimization, emission minimization, real power losses minimization, and voltage stability enhancement under the normal condition as well as during line outage contingency. The comparative analysis of BS optimization with BSA on OPF problem is carried out.

Chapter 5 introduces Rao algorithms, which are newly proposed algorithm-specific parameter-less optimization approach for solving the OPF problem. The Rao algorithms have been applied to the standard IEEE 30-bus, IEEE 57-bus system and the IEEE 118-bus test system to demonstrate the efficacy and ability of Rao algorithms to solve OPF problems. Various objectives for solving the OPF problem were considered in this chapter namely: fuel cost minimization, total voltage deviation minimization, voltage stability enhancement under normal and under contingency conditions, real power loss minimization, and emission minimization. Because the Rao algorithms do not require adjustment of algorithm-specific parameters, the proposed algorithms were found to be better to other reported methods. The simulation results achieved by the proposed Rao algorithms were compared with recently developed optimization algorithms, which proved the superiority of the Rao algorithms, particularly Rao-2 and Rao-3 algorithms in terms of robustness and quality of solutions.

Chapter 6 applies a hybrid algorithm, which is based on a sine-cosine mutation operator and a modified Jaya (SCM-MJ) algorithm to solve the OPF problems. The efficacy of the SCM-MJ algorithm is primarily evaluated using thirteen mathematical benchmark functions. Later, the SCM-MJ algorithm is applied to the Algerian 59-bus system and IEEE 118-bus test system to handle the OPF problems. The SCM-MJ algorithm has provided better solutions for mathematical benchmark functions and OPF problems quickly and efficiently. The comparison of numerical outcomes demonstrates that the suggested SCM-MJ algorithm dominates over other approaches for solving the OPF problem.

Chapter 7 presents the hybrid meta-heuristic Jaya-Powell's Pattern Search method to solve the optimal power flow problem integrated with and without DG units. Powell's Pattern Search method has been incorporated into the Jaya algorithm in three different ways, resulting in three variants namely; Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3. To demonstrate the efficacy of the proposed algorithm and its potential to solve OPF problems, it is tested on the standard IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems for fuel cost minimization, emission minimization, real power loss minimization, and total voltage deviation minimization. Over several runs, Jaya-PPS1 consistently provided a lower objective function value in all the case studies regardless of the complexities and size of the power system.

Chapter 8 summarizes the conclusions and key contributions of the thesis work. Finally, the scope of future study in the field of optimal power flow has been highlighted.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

A large number of optimization techniques have been applied to solve OPF problems. These optimization techniques are categorized into two major categories. The first category is classical or traditional optimization algorithms[14], [15], which cover both calculus-based and numerical methods. Further, another category is EC-based or meta-heuristic optimization algorithms [17], [22], which includes the evolutionary computing based, nature-inspired, chemistry-based, human behaviour based, plant-based and physics-based algorithms, etc. In general, the classification of optimization techniques is shown in Fig. 2.1. This chapter systematically presents an inclusive literature review on the several optimization techniques used for optimal power flow solutions.

2.2 CLASSICAL OPTIMIZATION ALGORITHMS FOR OPTIMAL POWER FLOW

Many classical optimization techniques (COTs) such as linear programming [23]–[30], non-linear programming [30]–[32], gradient based method [33]–[36], hessian matrix based method [37], [38], interior point method [39]–[43], Newton method [44]–[50], quadratic programming method [51]–[57], semi definite programming method [58]–[61], and chance-constrained method [62]–[65] etc. were employed during the early decades to solve the OPF problems.

M. Sasson [66] presented the solution to the OPF problem using the Fletcher-Powell Non-Linear Programming (FPNL) algorithm. The proposed FPNL algorithm is an improved version of the Powell method. The FPNL algorithm has claimed better performance to find global solutions in comparison to the Powell method. The proposed algorithm was applied in the IEEE 30-bus system to solve the OPF problem.

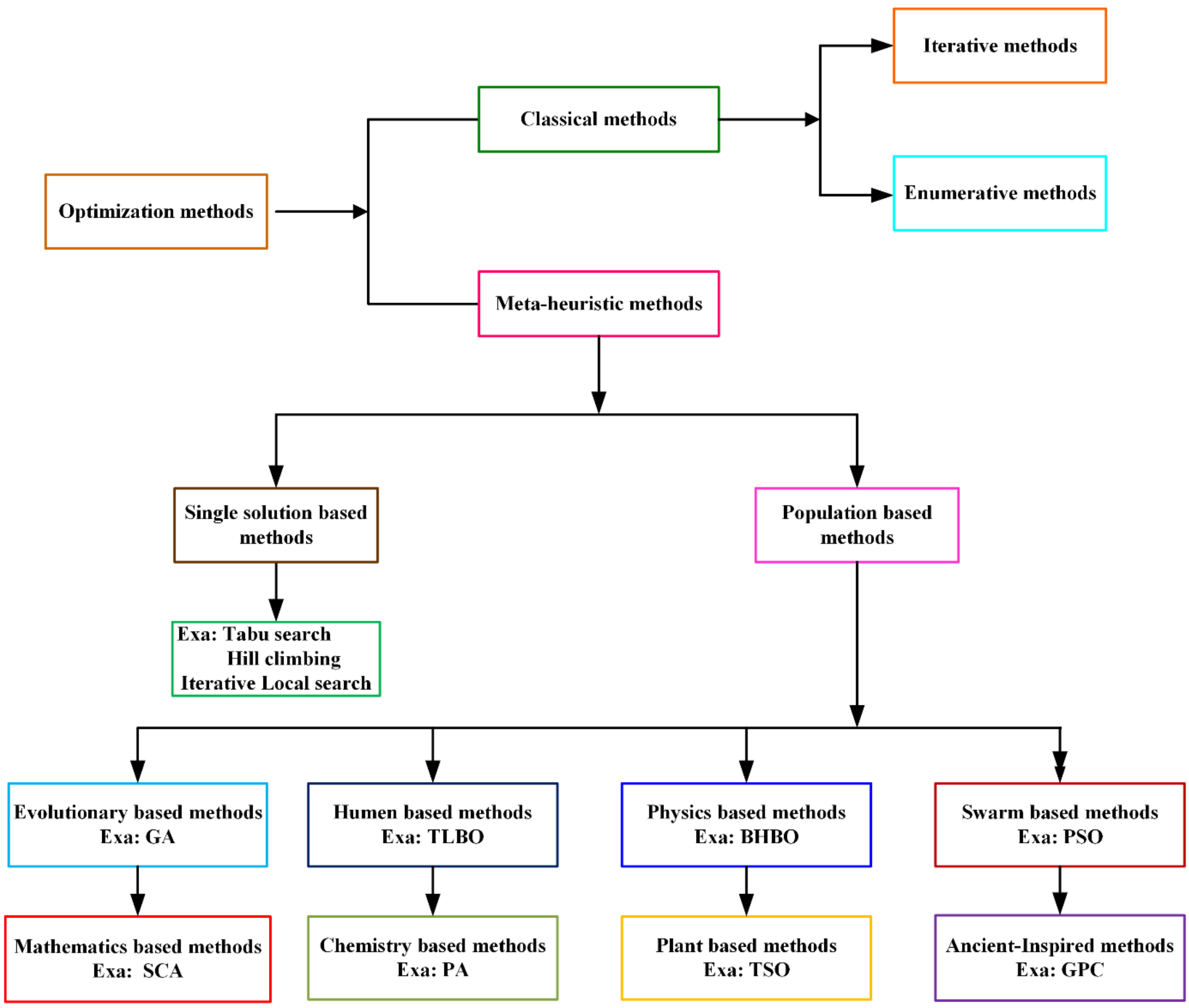


Fig 2.1: Classification of optimization algorithms

F. Capitanescu and L. Wehenkel [67] presented the solution to the OPF problem using a sensitivity-based method. C. H. Jolissaint, N.V. Arvanitidis and D. G. Luenberger [68] applied the decomposition method for online applications of real and reactive power flows.

A.M. Sasson [69] solved the load-flow problem using the decomposition technique. In the 19th century, the main drawback of the conventional method required huge storage and computation time to solve the OPF problems for the large power system. The beauty of the decomposition technique is the reduced computation time as well as efficiently use of memory storage. The proposed method reduced 90% of computation time for IEEE 57-bus system. The decomposition method is formulated for solving the OPF problem in the IEEE 14-bus, IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems. The proposed technique efficiently solved the 500-node power system problem without external storage. F. Capitanescu and L. Wehenkel [70] solved the corrective security-constrained OPF problem using the new iterative method. H. Y. Yamin, K. Al-Tallaq, and S. M. Shahidehpour [71] have applied benders decomposition to solve the dynamic OPF problem of deregulated electrical market. J. E. Van Ness and J. H. Griffin [72] presented a load-flow study using the elimination method. M. Vanti and C. Gonzaga [73] solved the OPF problem using the Newton interior-point method.

G. Tognola, and R. Bacher [74] solved the OPF problem using an unlimited point algorithm. The proposed method has conceptually similar to the interior point method. The unlimited point algorithm was applied to minimize of real power loss up to 700-bus system successfully. N. Alguacil and A. J. Conejo [75] proposed the benders decomposition method to solve the multi-period OPF problem. S.H. Low [76] presented convex relaxation of OPF Part I and Part II. S. N. Talukdar and T.C. Giras [77] solved the optimal power flow problem using a fast and robust variable metric method.

G. Torres and V. Quintana [78] solved optimal power flow using the nonlinear complementarity method. To demonstrate the efficacy of the proposed algorithm and its potential to solve OPF problems, it is tested on the different IEEE benchmark test systems including IEEE 30-bus, IEEE 57-bus, IEEE 118-bus, and IEEE 300-bus systems and the Brazilian power network. The Brazilian power network is a practical power system, which is considered to demonstrate the validity of the proposed algorithm to solve a practical power system problem. S.-Y. Lin, Y.-C. Ho and C.-H. Lin [79] presented the solution to the OPF problem using an ordinal optimization theory-based algorithm. L. P. M. I. Sampath et al. [80] solved the AC OPF problem using the trust-region based sequential linear programming method. A. S. Jr, S. M. Deckmann and S. Soares [81] solved the active and reactive OPF problem using the dual augmented Lagrangian approach.

G. Verbic, and C. A. Cañizares [82] proposed a two-point estimate method to solve the OPF problem considering competitive electrical market-based uncertainty. The main benefit of the suggested technique is that; it does not need derivatives of the nonlinear function which is employed in probability distribution computations. The proposed algorithm has been applied on 3-bus and 129-bus test systems for supply-side bidding and inelastic demand. N. Grudinin [83] solved the OPF problem for economic dispatch and security control using a combined quadratic-separable programming algorithm. Q. Wang et al. [84] presented the Lagrangian relaxation and benders decomposition method to solve the corrective risk-based security-constrained OPF problem. R. A. Jabr [85] presented the solution to the OPF problem using the primal-dual interior-point based semi-definite programming. R. R. Shoults and D. T. Sun [86] applied the P-Q decomposition technique to solve the OPF problem.

D. Phan, and J. Kalagnanam [87] proposed the Lagrangian duality method to solve the security-constrained OPF problem. To check the efficiency and supremacy of the proposed algorithm, Lagrangian duality method has been applied to three standard IEEE test systems 30-bus, 57-bus and 118-bus test systems and two practical (New England system and Polish network) power systems. The proposed algorithm solved the OPF problem under normal and stress conditions. In addition, the Polish network (PL 3012) is considered to validate the scalability of the proposed algorithm to handle large dimensional OPF problems, as in this system the numbers of buses are 3012.

The classical methods have outstanding convergence properties, many of them are often used in the industry. In addition, most of the classical methods have used slop of objective function with respect to optimization variables. Therefore, most of the time, they stuck local minima that prevent the algorithm from searching actual global optimal solution. Moreover, they are facing the problem to deal with the system having non-convex, non-differentiable, multi-modal optimization functions and constraints. Also, these approaches are normally limited to particular cases of OPF and do not have much flexibility in terms of different kinds of objective functions or constraints that could be employed [88]. Therefore, conventional optimization algorithms are not efficiently solving the all kinds of OPF problem.

2.3 INTELLIGENT OR META-HEURISTIC ALGORITHMS FOR OPTIMAL POWER FLOW

To overcome the demerits of classical optimization methods like dependency of nature of problem, constraints and initial starting point etc., various meta-heuristic algorithms came into being as alternatives to the classical optimization methods. As a result, meta-heuristic or EC-based optimization algorithms have recently got a lot of attention and are being applied to solve various types of optimization problems. It is worth noting that continuous research in the soft computing area has led to the development of more than

100 algorithms present in the latest literature [89]. A. Saha, P. Das, and A. K. Chakraborty [90] presented the solution to the OPF problem using the water evaporation method. The conventional IEEE 30-bus and IEEE 118-bus test systems were used to demonstrate the effectiveness of the water evaporation algorithm. A comparison of the optimization results acquired from this algorithm with those of modern meta-heuristic optimization approaches published in recent literature demonstrates that the water evaporation algorithm is highly efficient and robust over other recently developed optimization algorithms. A. Barzegar et al. [91] suggested a water cycle algorithm to find the solution OPF problem. [92]–[94] have presented some extensive research work on the usage of an artificial bee colony algorithm for optimal power flow.

A.A. El-Fergany, and H.M. Hasanien [95] solved optimal power flow using a salp swarm optimizer. The proposed algorithm is applied to IEEE 57-bus and IEEE 118-bus systems considering four objective functions namely, minimization of fuel cost, minimization of voltage deviation, minimization of real power loss and voltage stability enhancement. The simulation outcomes obtained by the salp swarm algorithm are compared to other meta-heuristic algorithms and it is observed that the proposed algorithm produces better results than its competitors for both the test systems. B. Allaoua and L. Abdellah [96] have applied the ant manners algorithm to solve the OPF problem. C. A. Roa-Sepulveda and B. J. Pavez-Lazo [97] presented a simulated annealing algorithm to solve the optimal power flow problem. [98]–[100] present a collection of comprehensive research papers on the application of an ant colony optimization algorithm for optimal power flow problems.

G. Chen, X. Yi, Z. Zhang, and H. Wang [101] proposed a firefly algorithm to solve the optimal power flow problem. The proposed algorithm was implemented in the IEEE

30-bus, IEEE 57-bus and IEEE 118-bus systems for solving the multi-objective OPF problems for minimization of fuel cost, minimization of emission and for real power loss minimization. The OPF results of the firefly algorithm were compared with NSGA-II, NSGA-III, and MOPSO algorithms and the reported results available in recent literature. Based on the results it is found that the firefly algorithm provided the minimum value of the objective function in most of the cases. H. A. Hassan and M. Zellagui et al. [102] solved the OPF problem using the grey wolf optimizer algorithm. The grey wolf optimizer algorithm is inspired nature of grey wolves. To test the efficacy of the suggested GWO method, it is applied to WSCC 9-bus and modified 5-bus test systems for optimal power flow of two-terminal HVDC transmission networks. In addition, bacterial foraging algorithm [103]–[106], biogeography-based optimization algorithm [107]–[109], backtracking search algorithm [110]–[112] have been used to solve the OPF problems.

H. Chen, M. L. Bo, and Y. Zhu [113] presented the solution to single and multi-objective optimal power flow problems using the multi-hive bee foraging (MHBF) algorithm. To show the effectiveness of the suggested MHBF algorithm, this algorithm has been applied to six benchmarks functions as well as to the OPF problem. The obtained results of the MHBF algorithm were compared to the NSGA-II, MOABC, and MOPSO algorithms. A comparison of the results clearly demonstrates the superiority of the proposed MHBF algorithm over the reported methods.

H. R. E. H Bouchekara, M. A. Abido, and M. Boucherma [114] suggested teaching-learning-based optimization (TLBO) algorithm for the OPF problem. The TLBO algorithms are parameter-less optimization algorithms. As a result, algorithm-specific parameter tuning is not required at all. To demonstrate the efficacy of TLBO algorithms, the proposed TLBO algorithm has been employed in two standard IEEE test systems (30-

bus, and 118-bus) to solve the OPF problem. The OPF results of TLBO algorithms and the results provided by other swarm intelligence (SI)/ evolutionary computing-based algorithms published in recent literature have been compared.

H.R.E.H Bouchekara [115] applied a black-hole-based optimization algorithm to solve the OPF problem. The proposed black-hole-based algorithm was implemented in the IEEE 30-bus and Algerian 59-bus systems for solving the OPF problem. Furthermore, differential evolution algorithm [116]–[124], evolutionary programming [125]–[130], genetic algorithm [131]–[139], particle swarm optimization algorithm [140]–[146] were applied to solve the optimal power flow problem.

H.R.E.H Bouchekara et al. [147] have applied the league championship algorithm (LCA) to solve the OPF problem in the Algerian power system. The Algerian 59-bus system is a practical power system used to demonstrate the validity and scalability of the proposed LCA algorithm to solve the OPF problem. I. N. Trivedi et al. [148] presented a moth-flame optimizer algorithm to solve the OPF problem. K. Abaci and V. Yamacli [149] solved the OPF problem using a differential search algorithm. The proposed algorithm was applied in IEEE 9-bus, IEEE 30-bus, and IEEE 57-bus test systems to solve the OPF problem for minimization of fuel cost, minimization of emission, voltage stability enhancement, and minimization of total voltage deviation.

M. Basu [150] solved optimal power flow problem using group search optimization. P.K. Roy and C Paul [151]proposed a krill herd algorithm to solve the optimal power flow problem. S. S. Reddy, and C. S Rathnam [152] applied the glowworm swarm optimization (GSO) method to solve the optimal power flow problem. To check the efficacy of the GSO algorithm, it was applied for solving the OPF problem in the standard IEEE 30-bus and Indian 75-bus systems. The Indian 75-bus system is a practical power system used to demonstrate the validity of the GSO algorithm for solving the real-world OPF problem. A comparison of the optimization results acquired from the proposed GSO algorithm with those of modern meta-heuristic optimization approaches published in recent literature demonstrates that the proposed algorithm is highly efficient and robust over other well-known algorithms.

S. Sivasubramani, and K. S. Swarup, [153] addressed the OPF problem using a multi-objective harmony search algorithm. V. Roberge, M. Tarbouchi, and F. Okou [154] applied graphics processing units for the OPF problem. W. Warid et al. [155] proposed the Jaya algorithm to solve the OPF problem with and without distribution generation (DG) source. The proposed algorithm handles the OPF problem considering DG units with three objectives functions simultaneously, namely, minimization of fuel cost, minimization of real power losses and voltage stability enhancement. To demonstrate the efficacy of the Jaya algorithm and its capacity to solve OPF problems, the proposed algorithm was applied to the standard IEEE 30-bus system and IEEE 118-bus test system. Y. T. K. Priyanto, and L. Hendarwin [156] proposed a wolf algorithm to find the solution to the multi-objective OPF problem.

B. Bentouati, S. Chettih, and L. Chaib [157] presented the solution to the OPF problem using the interior search algorithm. Moreover, gravitational search algorithm [158]–[160], moth swarm algorithm [161], [162], tree-seed algorithm [163] and symbiotic organisms search algorithm [164], [165] have been employed to solve the OPF problem.

When used to solve complex real-life engineering optimization problems, standard versions of some of the more common meta-heuristic approaches have been found to have some limitations. For example, premature convergence or local optima trapping is a common occurrence in GA and MSO algorithms.

2.4 VARIANTS OF INTELLIGENT ALGORITHMS FOR OPTIMAL POWER FLOW

To encounter the shortcoming of meta-heuristic algorithms and enhance the global search ability for solving the OPF problem, many improved variants have been explored in recent years. A. M. Al-Attar et al. [166] presented the modified grey wolf optimizer to solve optimal power flow problem. The proposed modified GWO algorithm was applied in IEEE 30-bus system considering two objective functions namely, minimization of fuel cost and pollution gasses emission. Simulation outcomes obtained by modified grey wolf optimizer were better compared to classical GWO algorithm and other competitors.

A. R. Bhowmik, and A. K. Chakraborty [158] have applied an opposition-based gravitational search algorithm (GSA) to solve single and multi-objective OPF problems. To overcome the drawback of the classical GS algorithm, the oppositional based learning (OPL) strategy has been used. The IEEE 30-bus system is used to demonstrate the validity and scalability of the proposed OPL- GSA to solve the OPF problem.

Artificial bee colony (ABC) [167] is another population-based stochastic optimization algorithm. It has good global search ability but sometime it is suffering from premature convergence problem. To overcome the drawbacks of the classical ABC algorithm, several variants of the ABC algorithm have been proposed to solve the optimal power flow problem. Some notable ones are: modified ABC algorithm [168], chaotic ABC algorithm [169], new enhanced ABC algorithm [170], g-best guided ABC algorithm [171], [172], improved ABC algorithm based on orthogonal learning[173], improved ABC algorithm[174], new quantum-inspired chaotic ABC algorithm [175] and many more. Moreover, several improved variants of the biogeography-based optimization (BBO) techniques were also used to solve the OPF problem. These are adaptive biogeography based predator–prey optimization technique [176], adaptive real coded BBO algorithm [177] and quasi-oppositional BBO algorithm [178] and others.

The Particle swarm optimization (PSO) algorithm [179] is a nature-inspired optimization technique developed by Kennedy and Eberhart in the year 1995. Like most swarm intelligence based optimization algorithms, the PSO algorithm is suffering premature convergence. Thus, recently several modified or improved versions of PSO have been developed to efficiently solve the OPF problem. Some of these are: non-dominated sorting PSO algorithm [180], improved PSO algorithm [181]–[183], modified PSO algorithm [184], [185], chaotic improved PSO algorithm[186], parallel PSO algorithm [187], comprehensive learning PSO algorithm [188], PSO with an aging leader algorithm [189], evolutionary PSO algorithm [190], new constriction PSO algorithm [191], mixed-integer PSO algorithm [192] and many more.

A.F. Attia, R. A. El Sehiemy and H. M. Hasanien [193] proposed a modified sine-cosine algorithm to solve the OPF problem. The sine-cosine algorithm (SCA) has a strong capacity to explore search space globally, but sometimes it suffers from getting stuck in local optima. In order to overcome this problem and to make this algorithm more efficient, a modified sine-cosine algorithm (MSCA), which combines the SCA and levy flights algorithm, is proposed in this paper. B. Mahdad and K. Srairi [194] suggested an adaptive partitioning flower pollination algorithm to solve the OPF problem. The conventional IEEE 30-bus and IEEE 57-bus test systems were used to demonstrate the effectiveness of the proposed algorithm to solve security constrained OPF problems. B. S. Rao, and K. Vaisakh [195] presented solution to the optimal power flow problems integrated with

FACTS devices using an adaptive clonal selection algorithm. D. Nualhong et al. [196] solved optimal power flow using a reactive tabu search algorithm.

Differential Evolution (DE) is a powerful evolutionary algorithm and has a strong exploitation search capability. To enhance the global search capability of the DE algorithm, many improved or modified variants of DE were applied to solve the OPF problem. Some of these are: forced initialized DE algorithm [197], enhanced self-adaptive DE [198], evolving ant direction DE algorithm [199], DE integrated with effective constraint handling techniques [200], improved adaptive DE algorithm [201], modified DE algorithm [202], multi-agent based DE algorithm [203] and improved DE algorithm [204].

E. Barocio et al. [205] used a modified flower pollination algorithm (MFPA) to solve multi-objective optimal power flow. The centroid decision making concept (CDMC) has been used to select the best solutions for the Pareto fronts. The CDMC concept is simple as compared to entropy criterion, and fuzzy membership methods and has provided better results for multi-objective OPF problems. To check the efficacy of the MFPA algorithm, it was applied for solving the multi-OPF problem in the IEEE 30-bus system considering bi and tri objective functions namely, fuel cost, voltage deviation and real power loss. G. Chen et al. [206] solved optimal power flow using a modified pigeon-inspired optimization method.

Evolutionary programming (EP) is a powerful evolutionary algorithm developed by L. J. Fogel. The working principle of the EP method is similar to that of genetic algorithm. Like GA, EP is also suffering from premature convergence or local optima trapping. Thus, the various modified version of EP has been developed to efficiently solve the complex power system problem. Some of these are, parallel evolutionary programming [207], modified MOEA/D approach [208], wheeling using EA algorithm [209], EA with constraint handling technique [125], faster EA algorithm [210], efficient evolutionary algorithm [211], improved evolutionary programming [212], improved strength Pareto EA algorithm [213]. Furthermore, improved variants of the symbiotic organisms search (SOS) algorithm has also been used to solve the OPF problem [214].

H.R.E.H. Bouchekara [215] has applied a modified electromagnetic field optimization algorithm to find the solution to the OPF problem. A versatile combination of chaotic maps concept and EFO algorithm may overcome their common weaknesses while taking advantage of the strengths of the two algorithms. The performance of the proposed algorithm was evaluated by solving optimal power flow in IEEE 30-bus, IEEE 57- bus, and IEEE 118-bus systems. The numerical results obtained by the proposed algorithm are better than the EFO algorithm and other well-known optimization algorithms in all three systems. In addition, several improved variants of the krill herd algorithm have also been used to solve the OPF problem. These are oppositional krill herd algorithm[216], chaotic krill herd algorithm[217], [218], and novel oppositional krill herd algorithm [219]. Furthermore, several improved variants of the teaching–learning based optimization have also been used to solve OPF problems. These are modified TLBO algorithm [220], quasi-oppositional TLBO algorithm [221] and Lévy mutation based TLBO algorithm [222].

An improved colliding bodies optimization algorithm for solving the OPF problem has been proposed by H.R.E.H. Bouchekara et al. [223]. The suggested algorithm's performance was assessed by solving the optimal power flow problems for three different IEEE benchmarked (IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus) systems considering 16 objective function cases. K. Srilakshmi, P. R. Babu and P. Aravindhababu [224] solved the OPF problem using the enhanced most valuable player algorithm. M. A. Taher et al.

[225] solved optimal power flow using an improved moth-flame optimization algorithm. M. A. Taher et al. [226] presented an optimal power flow problem using a modified grasshopper optimization method. M. Ghasemi et al. [227] have applied the chaotic invasive weed optimization algorithm to solve the OPF problem. M. H. Hassan et al. [228] addressed the OPF problem with a DG source using a modified Rao-2 algorithm. In addition, improved variants of the Jaya algorithm (JA) namely, Quasi-Oppositional JA [229], has also been used to solve the OPF problem.

John Holland proposed a population-based stochastic optimization algorithm named genetic algorithm in 1975, which was motivated by the survival of fitness and natural selection. To make new children from parent chromosomes, GA uses genetic operators (mutation, crossover, and selection) the same as the DE algorithm. GA is a well-known and efficient global optimization algorithm but sometimes suffers local optima trapping or premature convergence. Therefore, the last couple of years numerous modified or improved versions of GA have been developed to overcome this problem and to make this algorithm more efficient. Some of these are, enhanced GA [230]–[232], linear adaptive GA [233], adapted GA with adjusting population size [234], efficient parallel GA [235], dynamic strategy based fast decomposed GA [236], parallel non-dominated sorting GA-II [237], GA with a new multi-parent crossover [238], improved non-dominated sorting GA-III [239], modified simple GA [240], non-dominated sorting GA-II [241], improved GA [242], refined GA [243], modified non-dominated sorting GA-II algorithm [244], [245], mixed integer GA with arithmetic operators [246], real-coded mixed-integer GA [247] and many more.

The multi-objective OPF problem was solved using an adaptive group search optimization by N. Daryani, M. T. Hagh, and S. Teimourzadeh [248]. T. Niknam et al.

[249] presented a modified shuffle frog leaping algorithm to find the solution OPF problem. The OPF problem was solved using an improved salp swarm algorithm by S. A. El-sattar et al. [250]. Moreover, several improved variants of the bacteria foraging algorithm (BFA) were used to solve the OPF problem. These are: modified BFA [251], [252] and enhanced BFA [253].

T. Niknam et al. [254] solved the dynamic optimal power flow problem using a modified honey bee mating optimization. The proposed algorithm solved the OPF problem by taking into account practical issues of generator units like prohibited operating zones and valve loading effects. The performance of the proposed algorithm was evaluated by solving optimal power flow considering three IEEE test systems namely, IEEE 14-bus, IEEE 30-bus, and IEEE 118-bus systems. V. Raviprabakaran and R.C. Subramanian [255] solved the OPF problem using enhanced ant colony optimization. Moreover, several improved variants of the harmony search method have been used to solve the OPF problem. These are the improved harmony search (HS) method [256], chaotic self-adaptive differential HS algorithm [257] and differential HS algorithm [258].

T. T. Nguyen [259]proposed improved social spider optimization (ISSO) algorithm to solve optimal power flow. The proposed ISSO algorithm has been modified in three different ways, resulting in three variants namely; ISSO1, ISSO2, and ISSO3. The performance of the proposed algorithm is evaluated by solving optimal power flow for IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems. Y. Tan et al. [260]suggested an improved group search optimization algorithm for solving optimal power flow problem.

2.5 HYBRID ALGORITHMS FOR OPF

Various types of hybridization of meta-heuristic algorithms have been proposed in the literature to address the shortcomings of the poorly performing standard versions of meta-heuristic approaches. A. Gacem, and D. Benattous [261] proposed a hybrid algorithm, which was based on genetic algorithm and particle swarm optimization algorithm. The IEEE 30-bus test system was used to demonstrate the effectiveness of the proposed algorithm to solve OPF problem. The numerical results obtained by the proposed algorithm were superior as compared to GA and PSO algorithms. A. Khelifi, B. Bentouati, and C. Saliha [262] applied a hybrid firefly krill herd algorithm to solve the OPF problem. To improve the local search performance of the hybrid algorithm, a light intensity operator was employed in the krill herd algorithm. To examine the efficacy of the proposed algorithm, it was applied in IEEE 30-bus system considering various single and multi-objective functions. M. Kaur and N. Narang [263]proposed a hybrid invasive weed optimization method to solve the OPF problem. The proposed hybrid method is a combination of Powell's pattern search and invasive weed optimization algorithm.

B. Mahdad, and K. Srairi [264]solved the OPF problem considering four objectives: minimization of fuel cost, real power loss, total voltage deviation, and power system security with loading margin stability enhancement using a hybrid firefly pattern search algorithm. The IEEE 14-bus and IEEE 30-bus systems were used to examine the effectiveness of the proposed algorithm. C.-M. Huang, and Y.-C. Huang [265] presented optimal power flow problems integrated with FACTS devices using a hybrid optimisation method. The proposed hybrid algorithm is a combination of the harmony search algorithm and the ant system algorithm. To check the efficacy of the algorithm, it has been applied to the IEEE 30-bus to solve OPF problems considering real power loss, and voltage deviation as the main objective functions. The numerical results obtained by the proposed algorithm were compared with DE and PSO algorithms. The comparison of numerical outcomes demonstrates that the proposed hybrid algorithm dominates over other methods reported in the recent publications for solving the OPF problem.

D. B. Das, and C. Patvardhan [266] solved the OPF problem using multi-objective hybrid evolutionary strategy (MOHES). The proposed hybrid algorithm was applied to IEEE 30-bus and IEEE 118- bus systems considering fuel cost, emission cost, real power loss, and total voltage deviation as the main objective functions to be minimized. The results obtained by the proposed method were more robust and competitive as compared to those of the reported algorithms. E. Naderi et al. [267] presented the solution to single- and multi-objective optimal power flow problems using self-adaptive particle swarm optimization (SPSO) and differential evolution algorithms. J. Radosavljevic et al. [268] applied particle swarm optimization and gravitational search algorithm (GSA) to find the solution to the OPF problem. The hybrid method utilized the social thinking of the PSO algorithm and the exploitation quality of the GSA algorithm.

K.-H. Kim et al. [269] presented hybrid evolutionary programming incorporating sequential quadratic programming to find the solution to the OPF problem. The proposed hybrid algorithm was applied in modified IEEE 14-bus system to solve the OPF problem taking into account generation unit and transmission line outage as main objective functions. L. Shengsong, H. Zhijian and W. Min [270]proposed a hybrid algorithm, which is based on a chaos optimization algorithm (COA) and linear predictor-corrector primal-dual interior point (PCPDIP) algorithm to solve the OPF problem. The proposed hybrid approach is primarily concerned with balancing the exploration and exploitation steps of the optimization procedure. PCPDIP technique has good search space exploitation capability, while COA is able to explore the search space very well. The goal of incorporating PCPDIP with COA is to combine the benefits of both algorithms. The OPF problem was solved using an evolving ant direction hybrid DE algorithm by K. Vaisakh, L. Srinivas, and K. Meah [271].

L. Shengsong, H. Zhijian and W. Min [272] used hybrid chaos optimization and successive linear programming to find the solution of the OPF problem. The conventional IEEE 14-bus, 30-bus and 57-bus test systems were used to demonstrate the effectiveness of the proposed algorithm to solve OPF problems. M. Ghasemi et al. [273]solved the OPF problem using a hybrid imperialist competitive algorithm (ICA) and teaching-learning algorithm (TLA). M. R. Narimani et al.[274] solved the optimal power flow problem using a hybrid PSO and the shuffle frog leaping algorithm. The proposed algorithm was applied in IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus test systems to solve the OPF problem taking into account practical issues of generator units like valve point effect and multi-fuel type of generation units, and many others. M. R. Al Rashidi, and M. E. El-Hawary [275] solved the discrete optimal power flow problem considering valve-point loading effects using a hybrid particle swarm optimization. P. Bhasaputra and W. Ongsakul [276] solved an OPF problem using hybrid tabu search and simulated annealing algorithms. T. Niknam, M. R. Narimani, and R. Azizipanah-Abarghooee [277] presented a hybrid algorithm, which is based on shuffled frog leaping algorithm and simulated annealing (SA) to find the solution to the OPF problem. The proposed hybrid algorithm solved the OPF problem taking into account practical issues of generator units like prohibited operating zones and valve loading effects. T. S. Chung and Y. Z. Li, [278] solved the optimal power flow problem using a hybrid genetic algorithm. Y. Xu et al. [279] applied a hybrid evolutionary algorithm to solve transient stability based OPF problem and many more.

2.6 RESEARCH CHALLENGES AND OBJECTIVES

From the aforementioned critical literature review relating to methods that have been used for optimal power flow, the following research challenges are identified:

- OPF is a complex optimization problem, which associates several constraints and decision variables. Conventional optimization methods are less efficient for solving OPF problems particularly, when the constraints and objective functions are non-linear, non-convex, and have multiple local optima.

- Various evolutionary computing based algorithms were proposed in recent literature to overcome the shortcomings of classical optimization techniques to solve the OPF problem.

- When used to solve complex real-life engineering optimization problems, standard versions of some of the more common EC based approaches were found to have some limitations. For example, premature convergence or local optima trapping is a common occurrence in meta-heuristic algorithms.

- Despite their advantages, EC based algorithms have some drawbacks. To find the near-global optimal solution, they require parameter tuning. The parameters' tuning needs multiple trials and hence take a long time to get the optimal solution. Moreover, the best solutions achieved by such algorithms cannot be replicated exactly thus several trials should be performed to ensure accuracy and meaningful statistical results.

- It is observed that most of the evolutionary computing based and nature inspired algorithms have some advantages and disadvantages through the literature survey. Two main parts of these algorithms are exploration and exploitation. Some algorithms have good exploration capability but poor exploitation, and vice versa. Some algorithms are more suitable to solve certain types of problems than the others.

The following objective functions are considered on the basis of the aforementioned challenge and critical review.

- To apply the parameter-less optimization algorithm for the OPF problem.
- Develop hybrid algorithm(s) to balance the exploration and exploitation capability of the algorithm during the search process. Validation of the modified / hybrid algorithm(s) using several standard mathematical benchmark functions.
- To assess the robustness of the modified / hybrid algorithm(s) algorithms for solving the OPF problem with and without DG, statistical analysis was performed.
- To illustrate the proposed work through realistic case studies.

2.7 SUMMARY

This chapter presents a comprehensive and critical overview of optimal power flow. Further, various solution methodologies for the OPF problem are also discussed in detail. Based on the literature survey, research gaps are recognized and research objectives have been framed for the present research work. Apart from presenting various methodologies for optimal power flow reported in the literature, this chapter also discusses the pros and cons of these optimization techniques.

CHAPTER 3

OPTIMAL POWER FLOW

CHAPTER 3

OPTIMAL POWER FLOW

3.1 INTRODUCTION

The motive of solving an optimal power flow problem is to determine the optimal set of control variables in a given power system network that optimizes some objective functions. The objective functions to carry out OPF are fuel cost minimization, total voltage deviation minimization, real power losses minimization, voltage stability enhancement and emission minimization via optimal adjustment of the power system independent variables, while at the same time it takes care of various network physical operating constraint. The control variable used for the OPF problem are generator bus voltages, generator's active power outputs (except slack bus), transformer tap settings, phase shifters and other sources of reactive power such as shunt capacitor or some shunt FACTS controllers. Some of them are discrete (e.g. reactive injections, and transformer tap settings) and others are continuous (e.g. generator real power outputs and generator voltages) in nature.

The presence of the discrete nature of the variables provides a challenge to optimization techniques and makes the OPF problem become a non-convex one. The power system equality and inequality constraints such as generator constraints, shunt VAR constraints, transformer constraints, line-flows and bus voltages are effectively handled in the OPF problem by implementing the penalty factor approach. OPF problem formulation yields a highly non-linear, multi-modal, non-convex, non-differential objective function having discrete and continuous control variables and it has been introduced by Carpentier in the early 1960's [280].

3.2 PROBLEM FORMULATION

A set of objective functions and constraints are used to construct the OPF problem. Either each objective is optimized individually or all of them are combined, at the same time all the system constraints (limits) need to be satisfied. In general, the OPF problem can be mathematically formulated as follows [281]:

$$\text{Minimize} \quad F(x, u) \tag{3.1}$$

$$\text{Subject to;} \quad \begin{cases} G(x,u) = 0 \\ H_k^{(L)} \leq H(x,u) \leq H_k^{(U)} \end{cases} \tag{3.2}$$

Where,

$F(x, u)$: objective function,

$G(x, u)$, $H(x, u)$: equality and inequality constraints,

x, u: set of dependent and control variables,

$H_k^{(L)}, H_k^{(U)}$: lower and upper bounds of inequality constraint

The 'x' is the vector of dependent variables in a power system network that includes:

- Slack bus generated active power P_{g_1}.
- Load (PQ) bus voltage V_L.
- Generator reactive power output Q_g .
- Transmission line loading (line flow) S_l.

Hence, x can be expressed as:

$$x^T = [P_{g_1}, V_{L_1} \dots V_{L_{NLB}}, Q_g \dots Q_{g_{NC}}, S_{l_1} \dots S_{l_{ntl}}] \tag{3.3}$$

Where *NLB*, *NG* and *ntl* are the number of load buses, the number of generators and the number of transmission lines, respectively.

In Eqs (3.1) and (3.2), *u* denotes the independent or control variables of a power system network that includes:

- Generator active power output P_g except at slack bus P_{g_1}.
- Generator bus voltage V_g.
- Transformer taps setting T_r.
- Shunt VAR compensation Q_{sh}.

Hence, *u* can be expressed as:

$$u^T = [P_{g_2} \dots P_{g_{NG}}, V_{g_1} \dots V_{g_{NG}}, Q_{sh_1} \dots Q_{sh_{NC}}, T_1 \dots T_{NT}\ ] \tag{3.4}$$

Where *NG*, is the number of generators, *NC* is the number of VAR compensators, and *NT* is the number of regulating transformers respectively.

3.3 CONSTRAINTS

The optimal power flow problem has two types of constraints namely equality and inequality constraints, as given below [282].

3.3.1 Equality Constraints

These constraints can be divided into real power and reactive power static load flow equations as:

$$0 = \mathrm{P_{gi}} - \mathrm{P_{di}} - \mathrm{V_i} \sum_{j=1}^{NB} \mathrm{V_j}\, [\mathrm{G_{ij}} \cos(\theta_{ij}) + \mathrm{B_{ij}} \sin(\theta_{ij})] \tag{3.5}$$

$$0 = \mathrm{Q_{gi}} - \mathrm{Q_{di}} - \mathrm{V_i} \sum_{j=1}^{NB} \mathrm{V_j} \left[\mathrm{G_{ij}} \sin(\theta_{ij}) - \mathrm{B_{ij}} \cos(\theta_{ij})\right] \tag{3.6}$$

Where, $\theta_{ij} = \theta_i - \theta_j$, the voltage magnitudes at bus *i* and bus *j* are V_i and V_j respectively, NB is the number of buses, P_{gi} and Q_{gi} are the active and reactive power output of generator at bus *i*, P_{di} and Q_{di} are the active and reactive load demand at bus i, G_{ij} and B_{ij} are the elements of the admittance matrix ($Y_{ij} = -G_{ij} + jB_{ij}$) representing the conductance and susceptance between bus *i* and bus *j*, respectively.

3.3.2 Inequality Constraints

These constraints can be categorized into four types, namely, generation constraints, shunt VAR compensation constraints, transformer constraints and security constraints [283].

- Generator Constraints:

The voltage V_{g_k}, active power output P_{g_k} and reactive power output Q_{g_k} should be regulated by their lower and upper limits for all the generators including slack bus generator:

$$\mathrm{V_{g_k}^{min}} \le \mathrm{V_{g_k}} \le \mathrm{V_{g_k}^{max}} \quad , \mathrm{k} = 1 \ldots \ldots \mathrm{NG} \tag{3.7}$$

$$\mathrm{P_{g_k}^{min}} \le \mathrm{P_{g_k}} \le \mathrm{P_{g_k}^{max}} \quad , \ \mathrm{k} = 1 \ldots \ldots \mathrm{NG} \tag{3.8}$$

$$\mathrm{Q_{g_k}^{min}} \le \mathrm{Q_{g_k}} \le \mathrm{Q_{g_k}^{max}} \quad , \mathrm{k} = 1 \ldots \ldots \mathrm{NG} \tag{3.9}$$

- Transformer Constraints:

Transformer taps-settings (T_r) are regulated to their lower and upper limits:

$$\mathrm{T_{r_k}^{min}} \le \mathrm{T_{r_k}} \le \mathrm{T_{r_k}^{max}} \quad \mathrm{k} = 1 \ldots \ldots \mathrm{NT} \tag{3.10}$$

- Shunt VAR compensator constraints:

Controllable *VAR* sources (Q_{sh}) are maintained within the maximum and minimum limits:

$$Q_{sh_k}^{min} \leq Q_{sh_k} \leq Q_{sh_k}^{max} \quad k = 1 \ldots \ldots NC \tag{3.11}$$

- Security Constraints:

The voltage at load buses V_L and power flow in transmission lines S_l should vary within their minimum and maximum limits.

$$V_{L_j}^{min} \leq V_{L_j} \leq V_{L_j}^{max} \qquad j = 1 \ldots \ldots NLB \tag{3.12}$$

$$S_{l_k} \leq S_{l_k}^{max} \qquad k = 1 \ldots \ldots ntl \tag{3.13}$$

Where, *NG*, *NT*, *NC*, *NLB* and *ntl* are the number of generators, numbers of regulating transformers, numbers of shunt compensation, the number of load buses and number of transmission lines respectively. The corresponding lower and upper limits are represented by scripts “min” and “max” in Eqs. (3.7) - (3.13) respectively.

3.4 INCORPORATION OF CONSTRAINTS

The penalty factor approach is used in the OPF problem to efficiently include the working limits of the operating constraints, such as load bus voltage constraints, transmission line-flows, and generator constraints [284]. The penalty factor approach penalizes each violation by multiplying it by a large number, so that infeasible solutions are rejected and only feasible solutions are considered. To find feasible solutions, the above mentioned inequality constraints are included and the augmented objective function is obtained by Eq. (3.14).

$$F_{aug} = F(.) + K_1\left(P_{g_1} - P_{g_1}^{lim}\right)^2 + K_2 \sum_{k=1}^{NG}\left(Q_{g_k} - Q_{g_k}^{lim}\right)^2 + K_3 \sum_{j=1}^{NLB}\left(V_{L_j} - V_{L_j}^{lim}\right)^2 + K_4 \sum_{k=1}^{ntl}\left(S_{l_K} - {S_{l_K}}^{lim}\right)^2 \tag{3.14}$$

Where, K_1, K_2, K_3, and K_4 are the penalty factors. In this work, K_1, K_2, K_3, and K_4 are all set equal to 10^5.

3.5 OBJECTIVE FUNCTIONS

In the formulation of the OPF problem, fuel cost minimization (FCM) is frequently used as a primary objective function in addition to other objectives like voltage stability enhancement (VSE), total voltage deviation minimization (TVDM), real power losses minimization (RPLM), and emission minimization (EM) via readjustment of control variables, taking into account both operational and physical constraints. Either each objective is optimized individually or all of them are combined, at the same time, all the system constraints need to be satisfied. This section represents details of these objective functions [285], [286].

3.5.1 Fuel cost minimization (FCM)

The first objective function, namely, minimization of generators' fuel cost can be expressed as:

$$F_{FCM}(x, u) = \sum_{i=1}^{NG} f\left(P_{gi}\right)\left(\$/h\right) \quad = \sum_{i=1}^{NG} A_i + B_i P_{gi} + C_i P_{gi}^2 \; \left(\$/h\right) \tag{3.15}$$

where $A_{i,}B_i$ and C_i are the quadratic fuel cost coefficients of the i^{th} generating unit and P_{g_i} is the active power output of i^{th} generating unit.

3.5.2 Total Voltage Deviation Minimization (TVDM)

All bus voltages close to the rated voltage are required for the steady-state operating condition of a power system. The main motive of the second objective function i.e. Voltage profile improvement can be attained by minimization of the voltage variation in all load buses from 1.0 pu. The objective function can be described in this case as follows:

$$\mathrm{F_{TVDM}}(\mathrm{x},\mathrm{u}) = \sum_{\mathrm{i}\epsilon\mathrm{NLB}}\left|\mathrm{V}_{\mathrm{L}_i} - 1\right| \tag{3.16}$$

where V_L is the voltage magnitude in pu at i^{th} load bus.

By employing weighted sum method, the two objective functions namely fuel cost and voltage profile can be combined and transformed into a single objective function as fellow:

$$\mathrm{COF} = \mathrm{F_{FCM}}(\mathrm{x},\mathrm{u}) + W_{TVDM} \times \mathrm{F_{TVDM}}(\mathrm{x},\mathrm{u}) \tag{3.17}$$

where W_{TVDM} is a weight factor, and it is to be selected by the user.

3.5.3 Voltage Stability Enhancement (VSE)

At present, the need for electricity in an interconnected power system is constantly increasing; sometimes this requirement may not be fulfilled by the utilities. This leads to the problem of voltage stability issues and poor voltage profile on the load side. For the stable operation of a power system, the bus voltage of all the load buses must be maintained within acceptable limits during a sudden change in load and in normal operating conditions. By checking the L-index value for all the PQ buses, the power system voltage stability can be monitored.

Consider the Ng generators in an N-bus system. The following equation expresses the relationship between voltage and current:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \tag{3.18}$$

The complex currents and voltages at the generator and load buses are denoted by I_G, V_G, I_L, and V_L respectively.

By rearranging the equation above, we get:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{3.19}$$

Where,

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}] \tag{3.20}$$

The j^{th} node's line (L)-index is given by the following expression:

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \angle(\theta_{ji} + \delta_i - \delta_j) \right| \quad j = 1,2,3\ldots\ldots\ldots\ldots\ldots\ldots..NLB \tag{3.21}$$

Where V_i is the voltage magnitude of i^{th} generator bus i: V_j is the voltage magnitude of j^{th} load bus : δ_i is the voltage angles of i^{th} generator unit: δ_j is the voltage angles of j^{th} generator unit. The phase angle of the term F_{ji} is θ_{ji}.

The L-index is described below:

$$F_{VSE}(x, u) = \max[L_j] \quad j = 1,2 \ldots \ldots NLB \tag{3.22}$$

where L_j is the static voltage stability index or L-index at j^{th} load bus.

The L-index values vary between 0 and 1. The most insecure bus in a power network is the bus with the highest value of the L-index. The L-Index assessment of the load-bus provides information on its closeness to voltage unstable / failure state. By reducing the L-index, voltage stability can be increased.

By employing the weighted sum method, the two objective functions namely fuel cost and voltage stability can be combined and transformed into a single objective function as follows:

$$\mathrm{COF} = \mathrm{F}_{\mathrm{FCM}}(\mathrm{x}, \mathrm{u}) + W_{VSE} \times \mathrm{F}_{\mathrm{VSE}}(\mathrm{x}, \mathrm{u}) \tag{3.23}$$

where W_{VSE} is a weight factor, and it is to be selected by the user.

3.5.4 Emission minimization (EM)

In the present case, two types of emission gasses mainly the oxides of SO_x (Sulphur) and NO_x (nitrogen) are taken as the main pollutants. The emission gasses are considered as a combination of quadratic and an exponential function of the generator's active power output. The total emission is defined as below:

$$\mathrm{F}_{\mathrm{EM}}(\mathrm{x}, \mathrm{u}) = \sum_{\mathrm{i}=1}^{\mathrm{NGN}} \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} \mathrm{P}_{\mathrm{g_i}} + \gamma_{\mathrm{i}} \mathrm{P}_{\mathrm{g_i}}^2 + \xi_{\mathrm{i}} \exp\left(\lambda_{\mathrm{i}} \mathrm{P}_{\mathrm{g_i}}\right) \quad (\mathrm{ton/h}) \tag{3.24}$$

where α_i, β_i, γ_i, ξ_i, λ_i are the emission coefficients of i^{th} generating unit.

3.5.5 Real power losses minimization (RPLM)

The real power losses of the electrical network can be computed using the following expression:

$$\mathrm{F}_{\mathrm{RPLM}}(\mathrm{x}, \mathrm{u}) = \sum_{\mathrm{k}=1}^{\mathrm{ntl}} \mathrm{G}_{\mathrm{k}} \left| \mathrm{V}_{\mathrm{i}}^2 + \mathrm{V}_{\mathrm{j}}^2 + 2|\mathrm{V}_{\mathrm{i}}||\mathrm{V}_{\mathrm{j}}| \cos(\delta_{\mathrm{i}} - \delta_{\mathrm{j}}) \right| \tag{3.25}$$

Where G_k the conductance of k^{th} line is connected between i^{th} and j^{th} buses: *ntl* is the number of transmission lines: V_i is the voltage magnitude at bus *i*: V_j is the voltage magnitude at bus *j*: δ_i is the voltage angles at bus *i*: δ_j is the voltage angles at bus *j*.

The multi-objective function which consists of four contradictory objective functions i.e. fuel cost minimization, emission minimization, real power losses minimization and total voltage deviation minimization is transformed into a single objective function by using weighing factors to combine the four objective functions as given below.

$$\mathrm{COF} = \mathrm{F_{FCM}}(\mathrm{x},\mathrm{u}) + W_{TVDM} \times \mathrm{F_{TVDM}}(\mathrm{x},\mathrm{u}) + W_{EM} \times \mathrm{F_{EM}}(\mathrm{x},\mathrm{u}) + W_{RPLM} \times \mathrm{F_{RPLM}}(\mathrm{x},\mathrm{u}) \tag{3.26}$$

Where W_{ECM}, W_{RPLM} and W_{TVDM} are weight factors and COF is a combined objective function.

3.6 SUMMARY

This chapter discusses the mathematical formulation of the optimal power flow problem of a power system. Furthermore, the power flow equations and several operating constraints related to OPF problem are then explained in detail. The various technical and economic objective functions associated with the OPF problem namely, fuel cost minimization, emission minimization, voltage stability enhancement, real power losses minimization and total voltage deviation minimization are thoroughly discussed.

CHAPTER 4

SWARM INTELLEGENT ALGORITHMS FOR OPTIMAL POWER FLOW

CHAPTER 4

SWARM INTELLEGENT ALGORITHMS FOR OPTIMAL POWER FLOW

4.1 INTRODUCTION

The OPF is a well-known complex constrained optimization problem, which associates several constraints and control variables. Nowadays, researchers and scientists are used to solving complex science and engineering problems using intelligent algorithms. These random search, population-based algorithms are highly flexible and are appropriate to solve various types of optimization problems, including linear problems, non-linear problems and complex constrained optimization problems.

This chapter presents the application of two renowned swarm-based optimization algorithms namely, bat search and bird swarm algorithms to solve the optimal power flow problem. These algorithms are population-based random search techniques. The bat search (BS) algorithm is based on the echolocation capability of bats responsible for their unique foraging behaviours. However, the bird swarm algorithm (BSA) is a recently developed bio-inspired evolutionary algorithm. It uses swarm intelligence derived from the social interactions and social behaviours in bird swarms for searching the near global optimal solution. The objective functions to carry out OPF are fuel cost minimization, total voltage deviation minimization, emission minimization, real power losses minimization and voltage stability enhancement under normal as well as under contingency conditions. The effectiveness of the proposed algorithms has been demonstrated by applying these algorithms to solve the OPF problem in the standard IEEE 30-bus system with the above-mentioned objectives. The results obtained using both the algorithms are compared with the results obtained using other evolutionary computing techniques reported in the literature.

4.2 BAT SEARCH (BS) OPTIMIZATION ALGORITHM

Bat search optimization algorithm is a nature inspired optimization technique, developed by Xin She Yang in the year 2010 [287]. This algorithm is based on the echolocation capability of bats responsible for their unique foraging behavior. Most the bats are using sonar echoes to recognize, detect or sense different types of obstacles. The species including bats using sonar echoes ability, emit sound pulses of frequencies in the range of 10 kHz to 200 kHz. These pulses when hitting the objects or the prey around a bat produce echoes. The bats listen to the echo and then analyze and evaluate the distance of prey from them. Yang developed a basic bat search algorithm by considering the following approximation and ideal rules:

- Echolocation is used by all the bats to sense the distance and the difference between food/prey and background barriers.
- The bats have a random flying velocity v_k at the position X_k with a frequency f^{min}, changing the wavelength and loudness A^O to find prey.
- Bats have capability to regulate automatically the wavelength of their emitted pulses and adjust the pulse emission rate $p_r \in [0, 1]$ according to the proximity of the object.
- Even though the loudness of the emitted pulses can vary in several ways, it is assumed to lie within a large positive value A^O to some minimum value A^{min}.

The basic steps used in the bat search optimization algorithm can be summarized as follows [287], [288]:

4.2.1 Initialization of bats

The initial population of bats N is randomly generated with dimension d by taking into account upper and lower boundaries. The j^{th} component X_{kj} of the position vector X_k can be written as:

$$X_{kj} = X_j^{min} + \varphi\left(X_j^{max} - X_j^{min}\right) \tag{4.1}$$

Where $k = 1, 2 \ldots N$, $j = 1, 2 \ldots d$, X_j^{min} and X_j^{max} are the lower and upper boundaries for the dimension j, respectively. φ is a random number and it lies within range of 0 to 1.

4.2.2 Movement of bats

The frequency(f_k), velocity (v_k) and position of the bat (X_k) are updated according to Eqs. (4.2)- (4.4)

$$f_k = f^{min} + \beta(f^{max} - f^{min}) \tag{4.2}$$

$$v_k^t = v_k^{t-1} + (X_k^{t-1} - X_*)f_k \tag{4.3}$$

$$X_k^t = X_k^{t-1} + v_k^t \tag{4.4}$$

Where, f^{max} and f^{min} are the maximum and minimum values of frequency, f_k represents the frequency of the k^{th} bat, β is a number that is randomly generated between 0 to 1, vector X_* is current global best location (solution) obtained on comparison of all the N number of solutions and v_k^t and X_k^t are the velocity and position of the k^{th} bat at t^{th} time step.

BS optimization algorithm uses the benefit of the local search for maintaining the solutions diversity of the population. The local search follows the random walk strategy to generate a new solution.

$$X_{new} = X_{old} + \Psi A^t \tag{4.5}$$

Where, Ψ is a random number uniformly distributed ranging from -1 to 1 and A^t is average loudness value of all bats at t^{th} time step.

4.2.3 Loudness and Pulse Emission Rate

The loudness (A) and pulse emission rate (p_r) can be updated according to Eqs. (4.6) - (4.7) respectively.

$$A_k^{t+1} = \alpha A_k^t \tag{4.6}$$

$$p_{r_k}^{t+1} = p_{r_k}^{0}(1 - e^{-\gamma t}) \tag{4.7}$$

Where γ and α are constants, $p_{r_k}^{0}$ is the initial pulse emission rate value of the k^{th} bat. Flowchart of BS algorithm has been shown in Fig. 4.1.

The solution algorithm for solving OPF using bat search optimization algorithm can be summarized in following steps:

i) Set the bat population size (N), loudness (A), and pulse emission rate p_r, the maximum number of iterations ($iter_{max}$) and the number of decision variables (d).

ii) Initialize bat position X_k of N individuals randomly in the feasible area and their velocities v_k.

iii) For each bat, run load flow (e.g. NRLF) program, to find the fitness for each individual as per the objective functions of various cases mentioned above.

iv) Adjust the frequency, and update velocities and position using Eqs (4.2) to (4.4) to produce new solutions.

v) If *rand* is greater than p_{r_k} select the best solution among various solutions and generate new solution using local search. Otherwise create a new solution randomly.

vi) If *rand* > p_r (pulse emission rate) and $f(X_i) < f(X_*)$, accept the created new solution and increase the value of p_r and decrease the loudness A_i using Eqs. (4.6) - (4.7).

vii) Ranking of bats (solutions) based on fitness value and find the current best solution.

viii) If *iter* < $iter_{max}$, increase *iter* by 1 i.e. *iter* =*iter*+1 and go to step iv., Otherwise go to step iii).

ix) Stop the process and display the best solution. If the stopping criterion is satisfied.

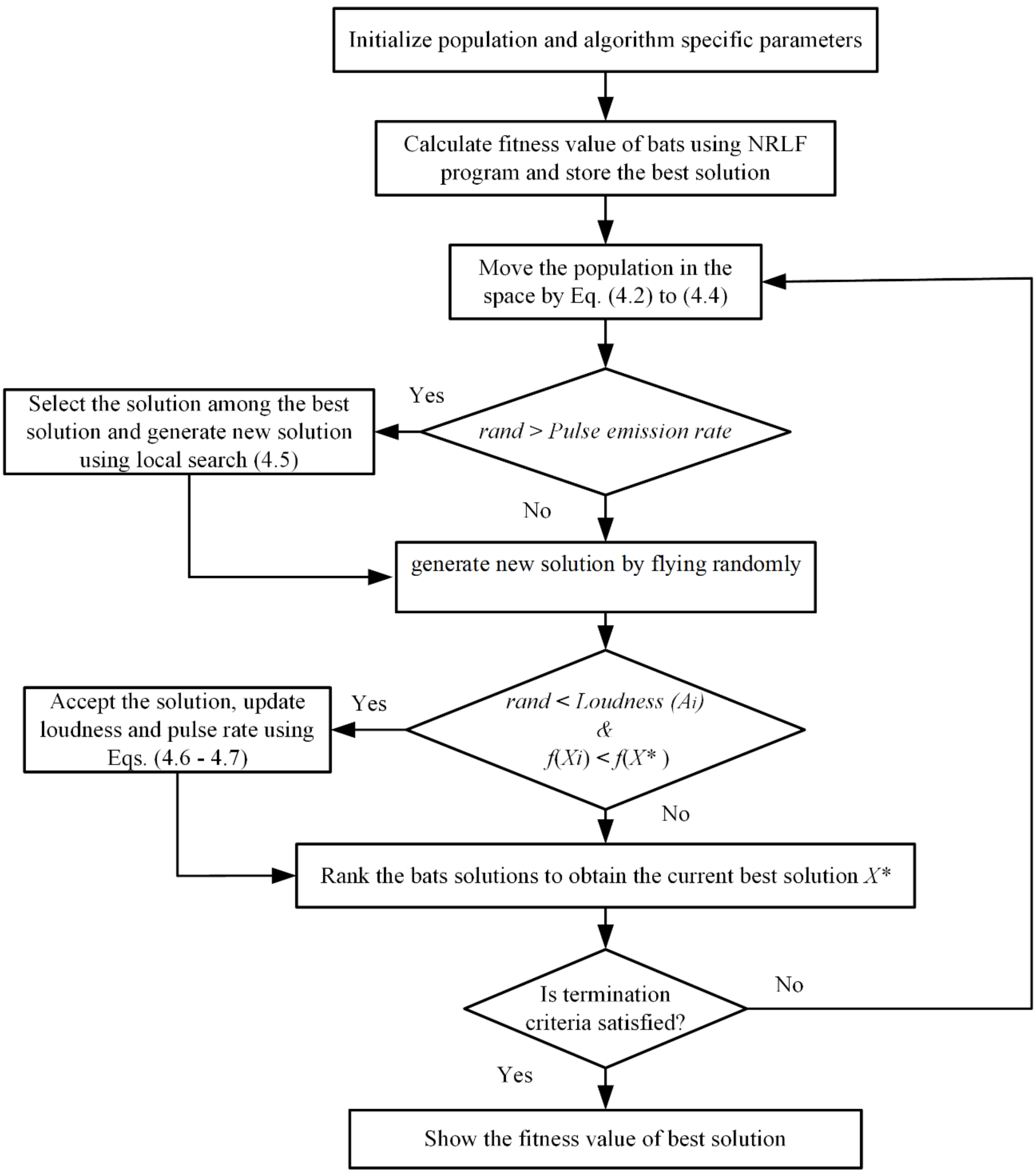


Fig. 4.1: Flowchart of bat search optimization algorithm

4.3 BIRD SWARM ALGORITHM (BSA)

The bird swarm algorithm is a recently developed bio-inspired algorithm. It is based on the social interactions and social behaviors of bird swarms. Three kinds of behaviors are mainly possessed by all birds. These are foraging behavior, vigilance behavior and flight behavior. For survival and searching for good forage, birds use their sense and move in the flock. Each bird shares its experience with the rest of the birds in a flock. If it finds food, it frequently raises its head and scans near the surrounding area which is called vigilance behavior. All the birds have a competition to achieve their positions at the center of the flock because of more chances of being attacked at the periphery of the group. Birds may move from one location to another to escape from the hunter and to find their food. Two different breeding groups in flock birds exist namely, producers and scroungers.

All *N* virtual birds, depicted by their position $x_i^t (i \in [1, \dots N])$ time step *t*, forage for food and fly in *D*-dimensional space. The main steps used in bird swarm algorithm can be described as follows [289]:

4.3.1 Foraging behaviour

All the birds search for food as per their own and swarm experience. The mathematical expression of the foraging behavior can be written as below:

$$x_{i,j}^{t+1} = x_{i,j}^t + (p_{i,j} - x_{i,j}^t) \times C \times \mathrm{rand}(0,1) + (g_j - x_{i,j}^t) \times S\, \mathrm{rand}(0,1) \quad (4.8)$$

Where$(j \in [1, \dots D])$, *rand* (0, 1) represents a random number. It is uniformly distributed between (0, 1). *S* and *C* are two positive constants, which can be respectively called as social and cognitive accelerated coefficients. $p_{i,j}$ represents the best previous position of the i^{th} bird and g_j is the best previous position shared by the swarm.

4.3.2 Vigilance behaviour

Each bird tries to attain its position at the center of the swarm to save itself from the predators, and they inevitably compete with each other. Thus, each bird would not directly move toward the center of the swarm. These motions can be formulated as given below:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A1\left(\mathrm{mean}_j - x_{i,j}^{t}\right) \times \mathrm{rand}(0,1) + A2\left(p_{k,j} - x_{i,j}^{t}\right) \times \mathrm{rand}(-1,1) \quad (4.9)$$

$$A1 = a1 \times \exp\left(-\frac{\mathrm{pFit}_i}{\mathrm{sumFit}+\epsilon} \times N\right) \quad (4.10)$$

$$A2 = a2 \times \exp\left(\left(\frac{\mathrm{pFit}_i - \mathrm{pFit}_k}{|\mathrm{pFit}_k - \mathrm{pFit}_i + \epsilon|}\right) \frac{N \times \mathrm{pFit}_k}{\mathrm{sumFit}+\epsilon}\right) \quad (4.11)$$

Where, *k* is a random positive integer, having its value between 1 and *N*, but not equal to *i*. *a1* and *a2* are positive constants between 0 and 2. $pFit_i$ is the best fitness value of the bird b_i and *sumFit* denotes the sum of the best fitness value of the whole swarms. ϵ is the smallest constant in the computer which is used to avoid zero-division error. *meanj* represents the j^{th} element of the average position of the whole swarm.

4.3.3 Flight behaviour

Birds fly to another location for searching food and to save themselves against the predators' attack. A bird can be a producer or a scrounger and its behaviors can be expressed as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \mathrm{rand}(0,1) \times x_{i,j}^{t} \quad (4.12)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + (x_{k,j}^{t} - x_{i,j}^{t}) \times FL \times \mathrm{rand}(0,1) \quad (4.13)$$

Where, *randn* (0, 1) is expressed as Gaussian distributed random number with μ (mean) = 0 and σ (standard deviation) = 1, $k \in [1, \ldots N]$, $(k \neq i)$. *FL* ($FL \in [0, 2]$) is a following factor which means scrounger would follow producer to search their food. For simplicity, it is assumed that each bird moves to one site to another site every FQ unit interval. The basic flowchart of the BSA is shown in Fig. 4.2.

The solution algorithm for OPF using the BSA algorithm can be summarized in the following steps:

Pseudo code of bird swarm algorithm (BSA)

Input: *N*: birds or population size, *P*: the probability of foraging for food, *FQ*: frequency of bird's flight behavior, *C, S, a1, a2, FL*: five constant parameters, *M*: the maximum number of iterations and the control /decision variables (*D* = 24 here). The minimum and maximum value of the control variable in vector form $X_{Min} = [\ \mathrm{X}_1^{\min} \ldots\ldots\ \mathrm{X}_\mathrm{D}^{\min}]$ and $X_{Max} = [\ \mathrm{X}_1^{\max} \ldots\ldots\ \mathrm{X}_\mathrm{D}^{\max}]$. Initialise the load flow data.

Set count *G* = 0 and define algorithm parameters, Population (*P*): Initialise the population randomly with uniformly distributed amongst $[X_{Min}, X_{Max}]$. For each bird, run load flow (e.g. NRLF) program and evaluate the fitness of each bird.

While (G < M)

If (G % FQ ≠ 0)

For i = 1: N

If rand (0, 1) < P

Birds forage for food (Equation 4.8)

Else

Birds keep vigilance (Equation 4.9)

End if

End for

Else

Divide the swarm into two parts: producers and scroungers.

For i=1: N

If *i* is a producer

Producing (Equation 4.12)

Else

Scrounging (Equation 4.13)

End if

End for

End if

Evaluate new solutions

If the new solutions are better than their previous ones, update them

Find the current best solution

G=G+1;

End while

Output: the individual with the best objective function value in the population.

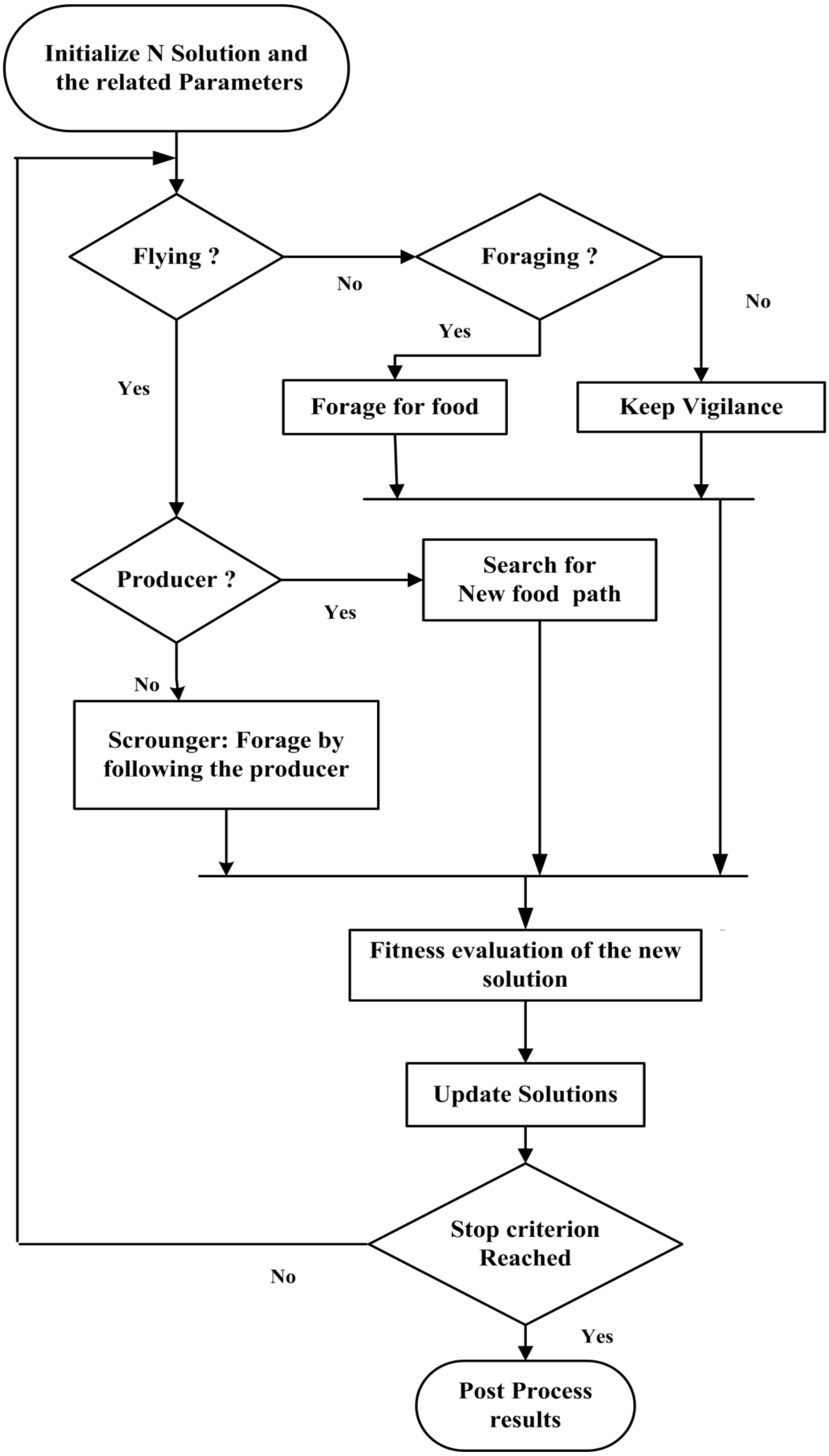


Fig. 4.2: Flowchart of bird swarm algorithm

4.4 RESULTS AND DISCUSSION

To demonstrate the efficacy of the proposed algorithms, these algorithms have been applied standard IEEE 30-bus test system to solve the OPF problem. For the IEEE 30-bus system under study, the control variables limit, line data, bus data along with their initial settings are given in *Appendix A*. For this system, 30 runs were taken using both the algorithms to solve the OPF problem with different objective functions and the best results are given here.

4.4.1 Minimization of Fuel Cost

In this case, minimization of fuel cost was considered an objective function as defined in Eq. (3.15). Here, the cost characteristics of all the generators were assumed to be quadratic. The fuel cost offered by the BS optimization algorithm is 800.5087 $/h, which is the lesser as compared to other reported results, while Bird Swarm algorithm provided the minimum fuel cost as 800.8374 $/h. The fuel cost obtained using the BS optimization algorithm is compared with the BSA and other reported methods and given in Table 4.1. This OPF outcome demonstrates the potential of the proposed BS optimization algorithm to solve the OPF problem. Fig. 4.3 shows the convergence characteristics of both the algorithms for the minimization of total fuel cost.

Table 4.1: Comparison of OPF results for Case 1

Method	**Fuel cost (pu)**	**Computation Time (sec)**
Base Case	902.004	0.08
BS	**800.500**	**98.34**
BSA	800.837	102.83
ABC [93]	800.66	-
GWO [123]	801.4100	-
DE [123]	801.2300	-
GPU-PSO [154]	800.5300	-

MSA [162]	800.509	-
MPSO [162]	800.516	-
MDE[162]	800.839	-
MFO [162]	800.686	-
FPA [162]	802.79	-
ARCBBO [177]	800.51	-
RCBBO[177]	800.87	-
BBO [177]	801.05	-
HSFLA-SA [277]	801.79	-
MSFLA [249]	802.28	-
SFLA [249]	802.50	-

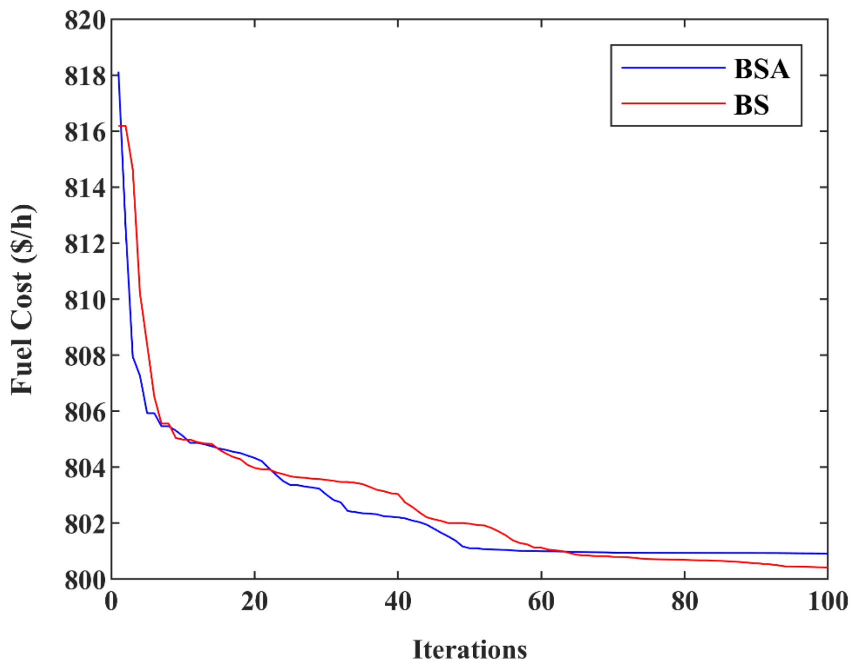


Fig 4.3: Convergence characteristics for IEEE 30-bus system, Case 1

4.4.2 Total Voltage Deviation Minimization

The objective function chosen in Case 2 was minimization of the total fuel cost and improvement of voltage profile by minimizing the total voltage deviation simultaneously. The OPF results attained using the BSA has been compared with the BS optimization algorithm and other reported results in Table 4.3. The minimum fuel cost and total voltage deviation obtained by the BSA were 804.5222 $/h and 0.1000 pu, which is least among other reported results. The OPF results confirm the potential of the proposed BSA compared to the BS optimization algorithm and other reported algorithms. The voltage profile is significantly improved in this case 2 as compared to that of case 1, as the total voltage deviation is reduced from 1.0762 in case 1 to 0.1000 in case 2. The voltages of load buses of both the algorithms are displayed in Fig. 4.4.

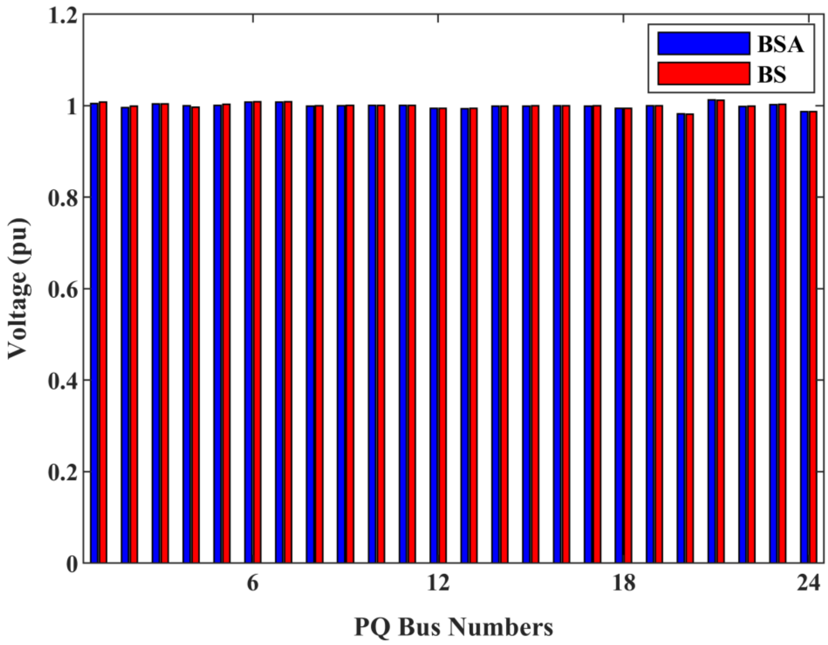


Fig. 4.4: Load bus voltage profile for IEEE 30-bus system, Case 2

Table 4.2: Comparison of OPF results of case 2

Method	**Fuel cost ($/h)**	**TVDM (pu)**	**Computation Time (sec)**
Base Case	902.004	1.1601	0.08
BSA	**804.5222**	**0.1000**	**108.23**
BS	803.7503	0.1052	123.83
DE [124]	805.2619	0.1357	-
MSA [162]	803.3125	0.1084	-
MPSO [162]	803.9787	0.1202	-

MDE [162]	803.2122	0.1264	-
MFO [162]	803.7911	0.1056	-
FPA [162]	803.6638	0.1365	-

4.4.3 Voltage Stability Enhancement

The objective function for minimization of the total fuel cost and enhancement of voltage stability simultaneously was selected in case 3. The minimum fuel cost and L-index as obtained by the BS optimization algorithm were 801.8202 \$/h and 0.1259 respectively. The OPF outcome attained using the BS algorithm is compared with the BSA and results are obtained using the reported algorithms. The comparison of numerical results is given in Table 4.3. The optimal setting of control variables is given in Table 4.4. As depicted in Table 4.3, the BS optimization algorithm has provided better results as compared to the BSA and other reported algorithms.

Table 4.3: Comparison of OPF results of Case 3

Method	Fuel cost ($/h)	L-index	Computation Time (sec)
Base Case	902.004	0.177	0.8
BS	**801.8202**	**0.1259**	**112.36**
BSA	803.3270	0.1263	126.98
ABC [93]	801.6650	0.1379	-
MSA [162]	801.2248	0.1371	-
MPSO[162]	801.6966	0.1374	-
MDE [162]	802.0991	0.1374	-
MFO[162]	801.668	0.1375	-
FPA [162]	801.1487	0.1375	-

Table 4.4: Optimum value of control variable for case 1 – case 3

S. No.	Control variables	Initial Case	Case 1(FCM)		Case 2(TVDM)		Case 3(VSE)	
			BS	BSA	BS	BSA	BS	BSA
Generator active power output								
1	Pg_2	0.80	0.4879	0.48910	0.4877	0.4853	0.5484	0.4973
2	Pg_5	0.50	0.2146	0.21410	0.2213	0.2128	0.3140	0.2185
3	Pg_8	0.20	0.2110	0.21440	0.1867	0.2077	0.2372	0.2103
4	Pg_{11}	0.20	0.1198	0.12300	0.1328	0.1511	0.2029	0.1162
5	Pg_{13}	0.20	0.1110	0.11410	0.1203	0.1220	0.2640	0.1267
Generator voltage								
6	Vg_1	1.05	1.0838	1.07910	1.0450	1.0417	1.0516	1.0996
7	Vg_2	1.04	1.0643	1.05880	1.0282	1.0302	1.0467	1.0956
8	Vg_5	1.01	1.0323	1.03140	1.0069	1.0144	1.0426	1.0638
9	Vg_8	1.01	1.0374	1.03780	1.0065	1.0078	1.0533	1.0722
10	Vg_{11}	1.05	1.0473	1.05130	1.0858	1.0752	1.0509	0.9828
11	Vg_{13}	1.05	1.0506	1.04080	0.9804	0.9672	1.0449	1.0089
Tap settings								
12	T_{6-9}	1.078	1.0019	1.12500	1.0988	1.0987	1.0255	0.9001
13	T_{6-10}	1.069	0.9900	0.90470	0.9004	0.9000	1.0318	1.1000
14	T_{4-12}	1.032	0.9862	0.98520	0.9264	0.9047	1.0330	0.9000
15	T_{28-27}	1.068	0.9823	0.97340	0.9739	0.9702	0.9882	0.9768
Shunt VAR source								
16	Qc_{10}	0.0	0.0279	0.07570	0.0228	0.0495	0.0500	0.0500
17	Qc_{12}	0.0	0.0275	0.05500	0.0009	0	0.0498	0.0500
18	Qc_{15}	0.0	0.0251	0.02220	0.0496	0.0500	0.0440	0.0498
19	Qc_{17}	0.0	0.0353	0.04090	0	0.0002	0.0499	0.0500
20	Qc_{20}	0.0	0.0248	0.02290	0.0492	0.0485	0.0500	0.0487
21	Qc_{21}	0.0	0.0474	0.06330	0.0477	0.0463	0.0500	0.0498
22	Qc_{23}	0.0	0.0111	0.01230	0.0494	0.0471	0.0372	0.0500

23	Qc_{24}	0.0	0.0414	0.03100	0.0486	0.0492	0.0500	0.0471
24	Qc_{29}	0.0	0.0154	0.01430	0.0378	0.0329	0.0162	0.0500
Fuel cost ($\h)		902.0046	**800.5000**	800.8374	803.7503	**804.5222**	**801.8202**	803.3270
TVDM (pu)		1.1601	0.7314	1.0672	0.1052	**0.1000**	1.1419	1.0663
Emission (ton/h)		0.2359	0.3412	0.3306	0.3369	0.3308	0.3227	0.3332
RPLM (MW)		5.8423	9.1709	8.8245	9.9840	9.9416	8.7599	9.7639
L-Index (LI)		0.1772	0.1454	0.1330	0.1407	0.1405	**0.1259**	0.1263

4.4.4 Voltage stability enhancement during contingency

In practical power system operation, there might be various types of contingencies occurring such as transmission line outage and generator unit outage. It is necessary to have enough stability margins in normal as well as under contingency conditions of a power system. So, the objective function of the present case is the minimization of the fuel cost and enhancement of voltage stability of the power system simultaneously under (N-1) contingency, which is simulated as an outage of the line connected between bus no. 2 and bus no. 6. The comparison of the results obtained using the proposed BS, BSA and reported results using other algorithms are given in Table 4.5. From Table 4.5, it is clear that the bat search optimization algorithm has provided better results as compared to other reported algorithms.

Table 4.5: Comparison of OPF results of case 4

Method	**Fuel cost ($/h)**	**L-index (pu)**	**Computation Time (sec)**
Base Case	902.004	0.1805	0.08
BS	**804.5271**	**0.1393**	**124.38**
BSA	804.5307	0.1395	128.73
ABC [93]	809.0112	0.1474	
MPSO[162]	807.6519	0.1405	

MDE[162]	806.6668	0.1398	
MFO[162]	804.556	0.1393	
FPA [162]	805.5446	0.1414	

4.4.5 Real power loss minimization

The proposed algorithms have been applied for minimization of the real power loss. The minimum value of power loss obtained by the BSA was 3.1281 MW which is the least among the other algorithms mentioned in Table 4.6. The comparison of the results obtained by BSA with the BS optimization algorithm and other reported methods is given in Table 4.6. From Table 4.6, it is clear that the least power loss was found by BSA compared to other reported methods. Fig. 4.5 displays the convergence characteristic of both the algorithms for the minimization of active power losses.

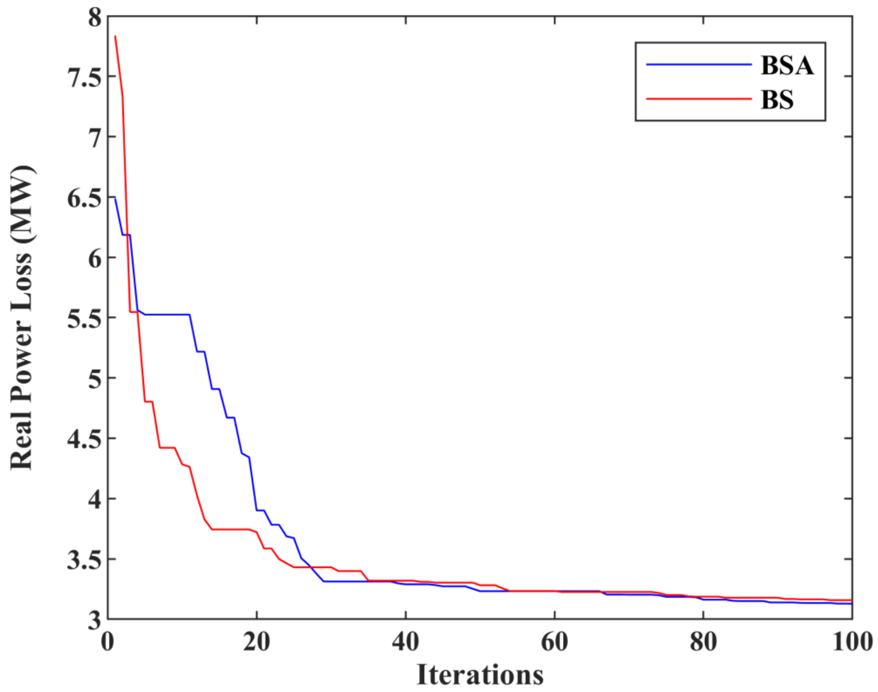


Fig 4.5: Convergence characteristics for IEEE 30-bus system, Case 5

Table 4.6: Comparison of OPF results of Case 5

Method	RPLM (MW)	Computation Time (sec)
Base Case	5.8423	0.08
BSA	**3.1281**	**102.45**
BS	3.1578	106.28
GWO [123]	3.4100	-
DE [123]	3.3800	-
MSA[162]	4.5404	-
MPSO[162]	4.5409	-
MDE[162]	4.3891	-
MFO[162]	4.5772	-
FPA[162]	4.7981	-

4.4.6 Emission minimization

In this case, minimization of emission gasses has been selected as an objective function and it is defined in Eq. (3.20). The minimum value of emission obtains by the proposed BSA method was 0.2037 ton/h, which is the least among the other algorithms mentioned in Table 4.7. The comparison of minimum emissions obtained by proposed algorithms and other reported methods are given in Table 4.7. It is found that the performance of BSA technique is superior as compared to the BS algorithm and other algorithms reported in the recent literature. In the present case, the total emissions are reduced to 0.2037 ton/h (40.29%) in comparison to 0.3412 ton/h in case 1. The control variable setting obtained by the proposed algorithms is given in Table 4.8. Fig. 4.6 displays the convergence characteristic of the proposed algorithms for this case.

Table 4.7: Comparison of OPF results of Case 6

Method	Emission (ton/h)	Computation Time (sec)
Base Case	0.2359	0.08

BSA	**0.2037**	**98.36**
BS	0.2038	100.25
ABC[93]	0.2048	-
MSA[162]	0.2048	-
MPSO[162]	0.2324	-
MDE[162]	0.2092	-
MFO[162]	0.2048	-
FPA[162]	0.2052	-
ARCBBO[177]	0.2048	-
MSFLA [249]	0.2247	-
SFLA [249]	0.2249	-

Table 4.8: Optimum value of control variable for case 4 - case 6

S. No.	**Control Variables**	**Case 4 (VSE during Contingency)**		**Case 5 (RPLM)**		**Case 6 (EM)**	
		BS	**BSA**	**BSA**	**BSA**	**BS**	**BSA**
	Generator active power output						
1	Pg_2	0.57500	0.4821	0.7989	0.8000	0.6643	0.66810
2	Pg_5	0.32490	0.2109	0.5000	0.5000	0.5000	0.50000
3	Pg_8	0.24840	0.2352	0.3500	0.3499	0.3499	0.35000
4	Pg_{11}	0.20060	0.1285	0.3000	0.2987	0.3000	0.30000
5	Pg_{13}	0.27160	0.1200	0.3990	0.4000	0.4000	0.40000
	Generator voltage						
6	Vg_1	1.05340	1.0915	1.0679	1.0693	1.0367	1.05410
7	Vg_2	1.04600	1.0775	1.0628	1.0660	1.0301	1.05610
8	Vg_5	1.03070	1.0500	1.0366	1.0414	1.0108	1.03880
9	Vg_8	1.04420	1.0527	1.0485	1.0540	1.0138	1.04570
10	Vg_{11}	1.06510	1.0959	1.0829	1.0921	1.0917	1.06760
11	Vg_{13}	1.04370	1.0030	1.0768	1.0597	1.0999	1.00620
	Tap settings						
12	T_{6-9}	1.01610	0.9043	0.9750	0.9892	0.9001	1.06590
13	T_{6-10}	1.03510	0.9912	1.0898	1.0725	0.9000	1.02670
14	T_{4-12}	1.00680	1.0919	1.0035	1.0039	0.9288	1.01590
15	T_{28-27}	1.00400	0.9932	0.9840	0.9903	0.9000	1.05050
	Shunt VAR source						
16	Qc_{10}	0.04980	0.0500	0.0500	0.0497	0.0046	0.04120
17	Qc_{12}	0.04310	0	0.0500	0.0130	0.0500	0.03300

18	Qc_{15}	0.04560	0.0498	0	0.0124	0.0424	0.04410
19	Qc_{17}	0.04860	0.0495	0.0500	0.0413	0.0500	0.04150
20	Qc_{20}	0.05000	0.0496	0.0343	0.0499	0.0500	0.04990
21	Qc_{21}	0.05000	0.0500	0.0500	0.0462	0.0495	0.05000
22	Qc_{23}	0.04920	0.0499	0.0500	0.0425	0.0491	0.04260
23	Qc_{24}	0.05000	0.0500	0.0469	0.0498	0.0500	0.05000
24	Qc_{29}	0.03110	0.0500	0.0500	0.0305	0.0259	0.04850
Fuel cost ($\h)		804.5271	804.5307	967.2963	967.4409	942.9017	943.7488
TVDM (pu)		0.9455	0.9467	0.9581	0.8657	1.6781	0.4145
Emission (ton/h)		0.3321	0.3319	0.2066	0.2066	0.2038	**0.2037**
RPLM (MW)		10.0044	10.0081	3.1578	**3.1281**	3.3805	3.4737
L-Index (LI)		**0.1393**	0.1395	0.1290	0.1317	0.1215	0.1427

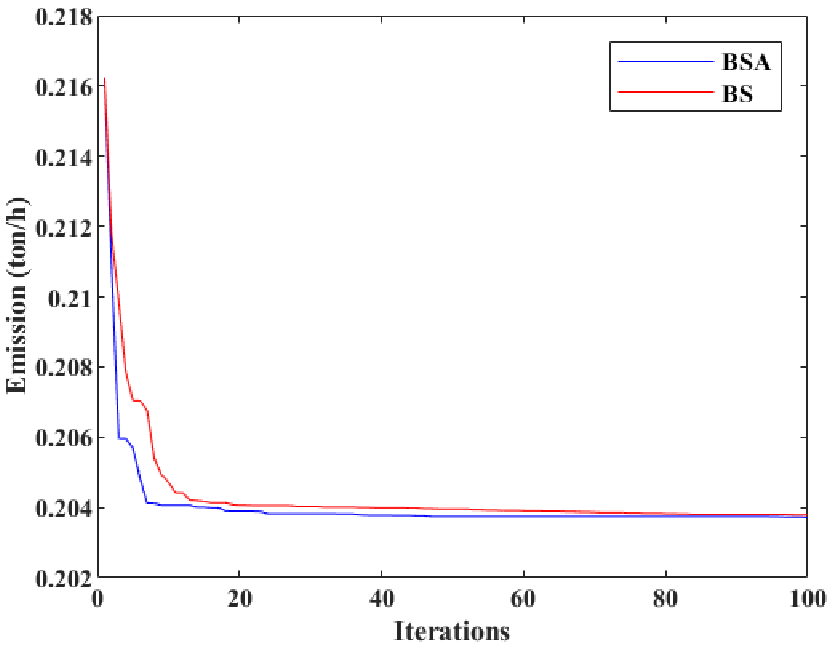


Fig 4.6: Convergence characteristics for IEEE 30-bus system, Case 6

4.5 SUMMARY

This chapter presents detailed studies of two meta-heuristic algorithms namely, bat search optimization and bird swarm algorithms to solve the optimal power flow problem. These algorithms have been employed in IEEE 30-bus test system for fuel cost minimization, total voltage deviation minimization, emission minimization, real power losses minimization and enhancement of voltage stability under normal as well as during contingency conditions. The comparative analysis of the bat search algorithm with the bird swarm algorithm on the OPF problem is carried out.

Based on of numerical results, it seems that both the algorithms are competitively better or competitive in nature in comparison with other reported meta-heuristic methods. For fuel cost minimization, enhancement of voltage stability under normal as well as during contingency conditions, BS optimization algorithm has given the least value of objective functions. However, in case of total voltage deviation minimization, emission minimization, real power losses minimization; BSA performed better and provided least values of objective functions compared to other reported results mentioned in recent literature.

CHAPTER 5

PARAMETER LESS OPTIMIZATION ALGORITHMS FOR OPTIMAL POWER FLOW

CHAPTER 5

PARAMETER LESS OPTIMIZATION ALGORITHMS FOR OPTIMAL POWER FLOW

5.1 INTRODUCTION

The OPF problem formulation yields a highly non-linear, multi-modal, non-convex, non-differential objective function having discrete and continuous control variables. In recent years, various EC-based techniques have been implemented to solve different types of optimization problems as well as OPF problems. These population-based random search optimization techniques are heuristic in nature. The performance of EC-based techniques does not depend upon the problems and nature of objective functions. Therefore, these algorithms can be applied to any type of optimization problem and have the potential to offer near-global optimal solutions within acceptable computation time.

EC-based algorithms, notwithstanding their benefits, have several drawbacks. They need parameters tuning to find the near-global best solution. It has been observed that parameter tuning of meta-heuristic optimization algorithms plays a very important role and it is a very crucial and time taking task to tune its parameters for solving a given optimization problem. Hence, in this chapter, application of a parameter-less, Rao algorithms has been presented to solve the OPF problem.

This chapter offers three easy to use metaphor-less optimization algorithms proposed by Rao to solve the optimal power flow problem. Rao algorithms are parameter-less optimization algorithms. As a result, algorithm-specific parameter tuning is not required at all. This quality makes these algorithms simple to use and able to solve various kinds of complex constrained numerical and engineering optimization problems.

5.2 RAO ALGORITHMS

The Rao algorithms employ the worst and best solutions, which can be obtained during the phases of optimization and random interaction among candidate solutions. The key benefit of the proposed algorithms is their algorithm-specific parameter-less property, and hence, these algorithms can be easily implemented for solving different types of optimization problems [290].

Assume that there is *'m'* population size (i.e. candidate solutions, k=1, 2…, m) and *'n'* design variables (i.e. j=1, 2, 3…, n) for any iteration *i*. The best candidate will provide the best value of an objective function in all the candidate solutions, while the worst candidate will give the worst value of the objective function. During the i^{th} iteration, if $R_{i,j,k}$ is the j^{th} variable value for the k^{th} candidate, then its value is updated according to the following Eqs. (5.1) - (5.3).

$$\mathrm{R_{j,k,i}}' = \mathrm{R_{j,k,i}} + \alpha_{\mathrm{1,j,i}}\left(\mathrm{R_{j,best,i}} - \mathrm{R_{j,worst,i}}\right) \tag{5.1}$$

$$\mathrm{R_{j,k,i}}' = \mathrm{R_{j,k,i}} + \alpha_{\mathrm{1,j,i}}\left(\mathrm{R_{j,best,i}} - \mathrm{R_{j,worst,i}}\right) + \alpha_{\mathrm{2,j,i}}\left(\left|\mathrm{R_{j,k,i}}\,\mathrm{or}\,\mathrm{R_{j,l,i}}\right| - \left|\mathrm{R_{j,l,i}}\,\mathrm{or}\,\mathrm{R_{j,k,i}}\right|\right) \tag{5.2}$$

$$\mathrm{R_{j,k,i}}' = \mathrm{R_{j,k,i}} + \alpha_{\mathrm{1,j,i}}\left(\mathrm{R_{j,best,i}} - \left|\mathrm{R_{j,worst,i}}\right|\right) + \alpha_{\mathrm{2,j,i}}\left(\left|\mathrm{R_{j,k,i}}\,\mathrm{or}\,\mathrm{R_{j,l,i}}\right| - \left(\mathrm{R_{j,l,i}}\,\mathrm{or}\,\mathrm{R_{j,k,i}}\right)\right) \tag{5.3}$$

In Eqs. (5.1) - (5.3), the value of the j^{th} variable for the best candidate is $R_{j,best,i}$, and the value of the j^{th} variable for the worst candidate is $R_{j,worst,i}$. The modified value of $R_{j,k,i}$ is $R_{j,k,i}'$. For the j^{th} variable, $\alpha_{1,j,i}$ and $\alpha_{2,j,i}$ are the two random numbers in the range [0, 1] during the i^{th} iteration.

The term, "$R_{j,k,i}$ or $R_{j,l,i}$" in Eqs. (5.2) - (5.3) shows that the solution for the candidate *k* is compared with any randomly picked candidate solution *l* and the information is shared based on objective function values. If the k^{th} solution's objective function value is better than the l^{th} solution's objective function value, then the term "$R_{j,k,i}$ or $R_{j,l,i}$ " becomes $R_{j,k,i}$. Similarly, the term "$R_{j,k,i}$ or $R_{j,l,i}$" becomes $R_{j,l,i}$ when the objective function value of l^{th} solution is better than the fitness value of k^{th} solution.

The flowchart of the Rao algorithm is shown in Fig. 5.1. The flowcharts for the Rao-2 and Rao-3 algorithms will be the same, except that Eq. (5.1) in the flowchart will be replaced by Eq. (5.2) and Eq. (5.3), respectively.

Computational steps of Rao algorithms for OPF problem

The following are the computational steps for applying Rao algorithms:

1. Randomly generate the initial population having control variables and set the stopping criteria i.e. $iter_{max}$.

2. Set iteration count $Iter = 0$.

3. Identify the worst and best solutions in the population by observing the value of the augmented objective function (3.14).

4. Update the solutions based on the worst and best solutions (5.1 to 5.3).

5. Proceed to step 6 if the updated solution is better than the previous solution; otherwise, proceed to step 7.

6. Replace the old solution with the new one. Go to step 8.

7. Keep the old solution.

8. If $Iter < iter_{max}$, increase the count of iteration (i.e. $Iter = Iter+1$) by 1 and go to step 3.

Else go to step 9.

9. Stop and display the best results.

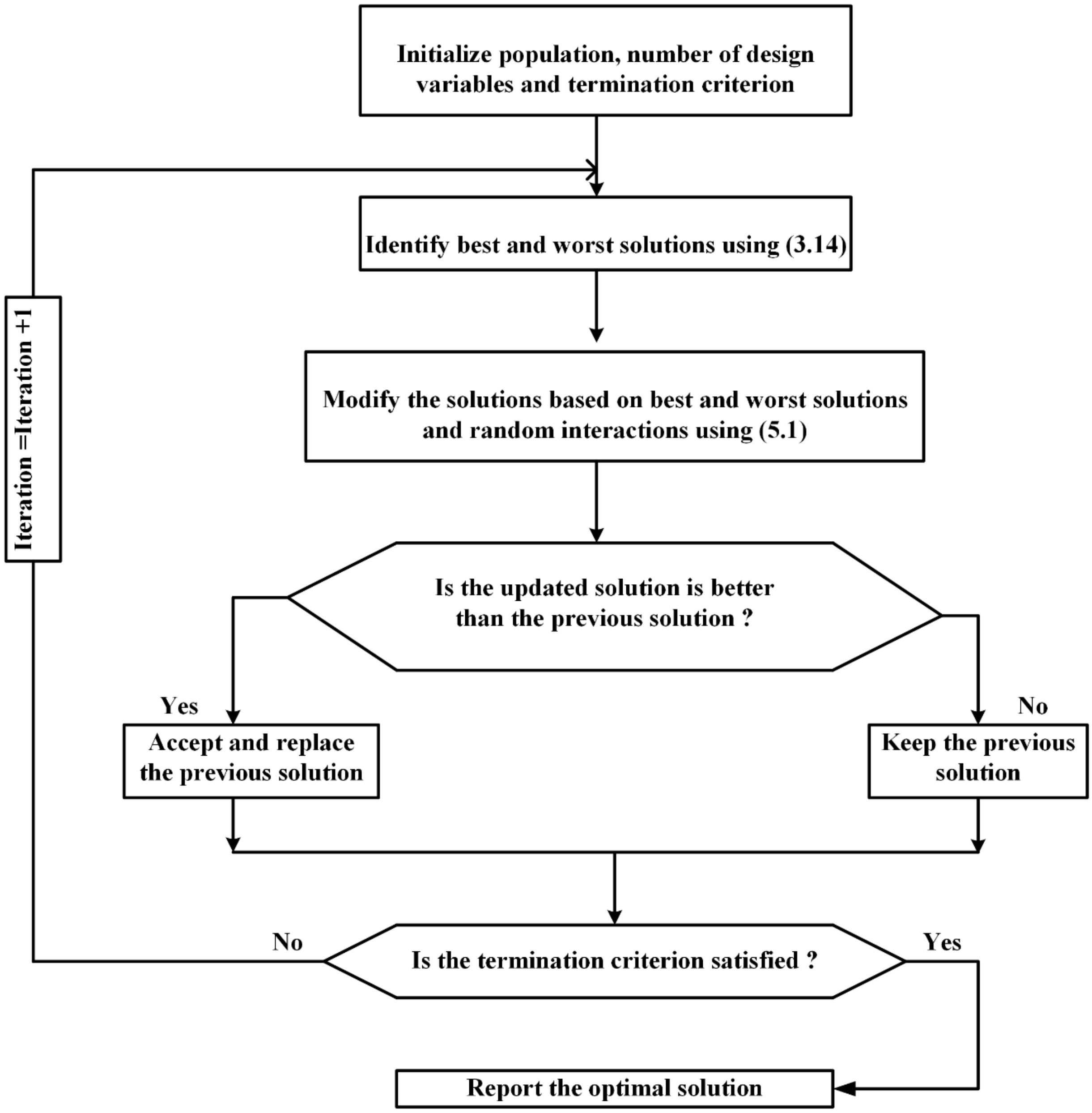


Fig. 5.1: Flowchart of Rao-1 algorithm

5.3 RESULTS AND DISCUSSION:

Three standard test systems, IEEE (30-bus, 57-bus, and 118-bus), are used to check the efficacy of the Rao algorithms, considering various objective functions. Several trials have been carried out, but the best results obtained and presented in this chapter are with the population size (*pop.*) = 40 and the maximum number of iterations ($iter_{max}$) = 100 for the IEEE 30-bus system and *pop*. = 50 and $iter_{max}$ =150 for IEEE 57-bus and IEEE 118-bus.

To demonstrate the effectiveness of the proposed algorithm, 11 cases are considered as given below:

Table 5.1: Various case studies of OPF problem for three systems

IEEE-30 bus system		
S. no.	**Case name**	**Objective Function**
1	Case 1	FCM
2	Case 2	FCM + W_{TVDM} × TVDM
3	Case 3	FCM + W_{VSE} × VSE
4	Case 4	FCM + W_{VSE} × VSE during contingency
5	Case 5	RPLM
6	Case 6	EM
IEEE-57 bus system		
7	Case 7	FCM
8	Case 8	FCM + W_{TVDM} × TVDM
9	Case 9	FCM + W_{VSE} × VSE
10	Case 10	RPLM
IEEE-118 bus system		
11	Case 11	FCM

*FCM=Fuel Cost Minimization; TVDM=Total voltage deviation Minimization; VSE = Voltage Stability Enhancement; RPLM=Real power loss minimization

5.3.1 Test System 1 # (IEEE 30-bus System)

The system data along with control variables operating limits are given in *Appendix A*. Also, the emission and fuel cost coefficients of the IEEE 30-bus system are given in *Appendix A*. For this system, 30 runs were performed using Rao algorithms to solve the different objective functions of the OPF problem and the best results out of 30 independent trials are given below.

5.3.1.1 Case 1# (Fuel Cost Minimization):

Here, the first objective of the OPF problem is to reduce the total cost of generation or the fuel cost. This function can be described as Eq. (3.15). The minimum cost attained by the Rao-3 algorithm is 799.9683 \$/h, while Rao-2 and Rao-1 algorithms provided the minimum fuel cost of 799.9918 \$/h and 800.4391 \$/h, respectively. Table 5.2 compares the simulation results of case 1 obtained by the proposed algorithms and by the other reported algorithms listed in recent literature. The OPF results of the proposed Rao-3 algorithm and optimal control variable settings are presented in Table 5.3. Based on the outcomes, it is clear that the Rao-3 algorithm provided the least value of the fuel cost as compared to the other methods. This demonstrates the effectiveness of the proposed Rao-3 algorithm as compared to Rao-2, Rao-1 algorithms, and other competitors for this case. The fuel cost convergence characteristics of case 1 are presented in Fig. 5.2.

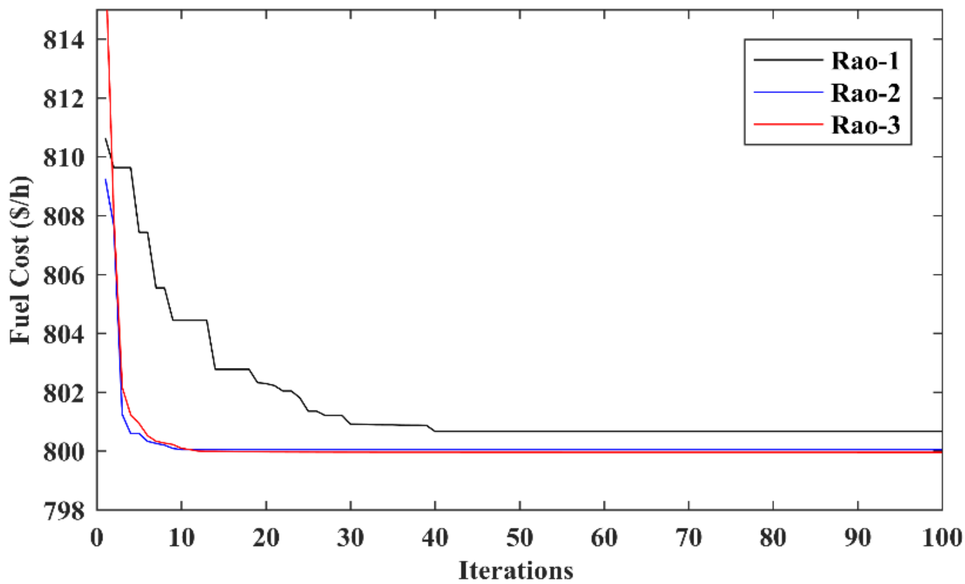


Fig 5.2: Convergence characteristics for IEEE 30-bus system, Case 1

Table 5.2: Comparison of OPF Results in IEEE 30-Bus System, Case 1

Algorithm	**Fuel Cost ($/h)**	**Computation Time (Second)**
Base Case	902.0046	0.08
Rao-3	**799.9683**	**89.56**
Rao-2	799.9918	89.74
Rao-1	800.4391	91.62
BS	800.5000	98.34
BSA	800.8374	102.83
ABC [93]	800.66	-
GWO [123]	801.41	-
DE [123]	801.23	-
DSA [149]	800.3887	-
Jaya [155]	800.479	-
MSO [161]	801.571	-
MSA [162]	800.5099	-
MPSO [162]	800.5164	-
MDE [162]	800.8399	-
MFO [162]	800.6863	-
FPA [162]	802.7983	-
ARCBBO [177]	800.5159	-
RCBBO [177]	800.8703	-
ECHT-DE [200]	800.4148	-
SF-DE [200]	800.4131	133.1
SP-DE [200]	800.4293	-
IMFO [225]	800.3848	-
MFO [225]	800.6206	-
GA [225]	800.4346	-
PSO [225]	800.4075	-
TLBO [225]	800.4104	-
MGOA [226]	800.4744	-
GOA [226]	800.7806	-
QOJA [229]	800.352	-
MGBICA [291]	801.1409	-
GBICA [291]	801.1513	-
SKH [292]	800.5141	-

Table 5.3: Optimum values of control variables for Case 1 to Case 3, IEEE 30-bus system

S. No.	Control variable	Case 1(FCM)			Case 2(TVDM)			Case 3(VSE)		
		Rao-1	**Rao-2**	**Rao-3**	**Rao-1**	**Rao-2**	**Rao-3**	**Rao-1**	**Rao-2**	**Rao-3**
Generator active power output										
1	Pg_2	0.4869	0.4923	0.4879	0.4957	0.4855	0.4827	0.4884	0.4906	0.4873
2	Pg_5	0.2131	0.2134	0.2144	0.2137	0.2166	0.2176	0.2127	0.2158	0.2119
3	Pg_8	0.2078	0.2059	0.2093	0.2228	0.2188	0.2253	0.2044	0.2087	0.2149
4	Pg_{11}	0.1186	0.1195	0.1192	0.1253	0.1243	0.1227	0.1221	0.1143	0.1159
5	Pg_{13}	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.1201	0.1201
Generator voltage										
6	Vg_1	1.1	1.0933	1.0944	1.0444	1.0504	1.0492	1.0909	1.0941	1.0948
7	Vg_2	1.0707	1.0751	1.0752	1.0253	1.032	1.0319	1.0748	1.0745	1.0758
8	Vg_5	1.0299	1.0441	1.0444	1.0078	1.0122	1.0118	1.0475	1.0435	1.043
9	Vg_8	1.0405	1.0491	1.0486	1.0044	1.0059	1.0072	1.052	1.0489	1.0493
10	Vg_{11}	1.1	1.1	1.0994	1.0751	1.073	1.0724	1.0999	1.0981	1.1
11	Vg_{13}	1.0592	1.0498	1.0574	0.9904	0.9696	0.9771	1.0551	1.0558	1.048
Tap settings										
12	T_{6-9}	1.1	1.0992	1.0659	1.1	1.1	1.1	1.0806	1.0382	1.1
13	T_{6-10}	0.9	0.9	0.9267	0.9	0.9	0.9002	0.9004	0.9451	0.9014
14	T_{4-12}	0.9763	0.9711	0.969	0.9451	0.9218	0.9229	0.9708	0.9745	0.9635
15	T_{28-27}	0.9813	0.9735	0.9759	0.9708	0.9699	0.9713	0.9815	0.9738	0.9821
Shunt VAR source										
16	Qc_{10}	0.0369	0.05	0.0442	0.05	0.0499	0.0496	0.0457	0.0214	0.0484
17	Qc_{12}	0.0003	0.05	0.0026	0	0.05	0.003	0.0053	0.05	0.05
18	Qc_{15}	0.0453	0.05	0.05	0.0495	0.05	0.05	0.0481	0.0335	0.0479
19	Qc_{17}	0.05	0.0492	0.0495	0	0.0001	0.0003	0.0499	0.0493	0.0368
20	Qc_{20}	0.0419	0.05	0.0414	0.0496	0.05	0.05	0.0264	0.046	0.049
21	Qc_{21}	0.05	0.0499	0.05	0.0499	0.05	0.0498	0.0499	0.0466	0.0498
22	Qc_{23}	0.0332	0.037	0.0352	0.0496	0.05	0.0497	0.0432	0.0404	0.0418
23	Qc_{24}	0.05	0.0493	0.0497	0.05	0.05	0.0491	0.05	0.0489	0.0476
24	Qc_{29}	0.0278	0.0178	0.029	0.033	0.0265	0.0285	0.0333	0.0309	0.05
Fuel cost ($/h)		800.4391	799.9918	**799.9683**	803.4877	**803.5375**	803.5304	800.0492	800.001	**800.025**
TVDM (pu)		0.9714	1.1168	1.1356	0.1031	**0.0993**	0.1001	1.1481	1.1409	1.1449
Emission (ton/h)		0.3362	0.3351	0.3351	0.3315	0.3338	0.3331	0.3357	0.3355	0.3354
RPLM (MW)		9.0613	8.91	8.8872	9.7465	9.8209	9.7724	8.941	8.9086	8.9098
L-Index		0.1307	0.1285	0.1281	0.1404	0.1404	0.1408	0.128	0.1278	**0.1264**

5.3.1.2 Case 2 # (Total Voltage Deviation):

The main motive of the second case is to minimize the voltage variation in all the load buses from 1.0 pu along with fuel cost. The multi-objective function is transformed into a single objective function by using the weighted sum method, using Eq. (3.17). In the combined objective function, the value of the weighting factor (W_{TVDM}) assigned to voltage deviation was taken as 160.

The optimal control variable settings are presented in Table 5.3, while the Load (PQ) bus voltage profile obtained by the Rao-2 algorithm in case 2 is shown in Fig. 5.3. The OPF results attained using Rao algorithms are compared with other reported results in Table 5.4. As can be observed from Table 5.4, the Rao-2 algorithm provided a minimum total voltage deviation of 0.0993 pu, which is the least among the Rao algorithm variants. Based on the OPF results, it is clear that the Rao-2 algorithm provided the least value of the total voltage deviation as compared to the other variants of the Rao methods. This demonstrates the effectiveness of the Rao-2 algorithm in comparison to the Rao-1, and Rao-3 algorithms for this case.

Table 5.4: Comparison of OPF Results in IEEE 30-Bus System, Case 2

Algorithm	Fuel Cost ($/h)	TVDM (pu)	Time (Second)
Base case	902.0046	1.1601	0.08
Rao-3	803.5304	0.1001	88.14
Rao-2	**803.5375**	**0.0993**	**87.36**
Rao-1	803.4877	0.1031	89.91
BS	803.7503	0.1052	108.23
BSA	804.5222	0.1000	123.83
MSA [162]	803.3125	0.1084	-
MPSO [162]	803.9787	0.1202	-
MDE [162]	803.2122	0.1265	-

MFO [162]	803.7911	0.1056	-
FPA [162]	803.6638	0.1366	-
MFO [225]	803.5173	0.1007	-
GA [225]	803.2347	0.1018	-
MGOA [226]	803.4176	0.1107	-
GOA [226]	803.4488	0.1709	-

* TVDM= Total Voltage Deviation Minimization

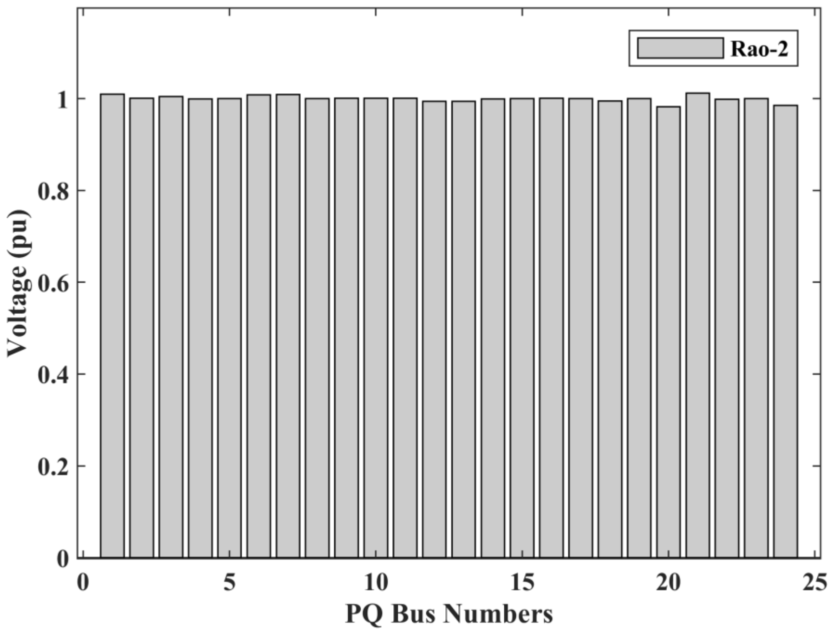


Fig. 5.3: Load bus voltage profile for IEEE 30-bus system, Case 2

5.3.1.3 Case 3 # (Voltage stability enhancement):

The system voltage stability can be increased by reducing the L-index. In this case, fuel cost minimization and voltage stability enhancement were considered using two-fold objective function as Eq. (3.19). The OPF results of Rao algorithms and the results provided by other methods published in recent literature have been compared in Table 5.5. The OPF results in Table 5.5 prove that the Rao-3 algorithm is the best among the three variants of Rao algorithms for case 3. As can be observed from Table 5.5, the Rao-3 algorithm provided a minimum L-Index value of 0.1264, which is the least among the Rao variants. In this case, the minimum L-Index values obtained by the proposed Rao algorithms are slightly higher than some reported results, but the fuel cost is less. Such types of situations will be there only because the different research papers might have selected different weighting factors. The control variables' settings of this case obtained using the three variants of Rao algorithms are given in Table 5.6.

Table 5.5: Comparison of OPF Results in IEEE 30-Bus System, Case 3

Algorithm	**Fuel Cost ($/h)**	**L-Index**	**Time(Second)**
Base Case	902.0046	0.1772	0.08
Rao-3	**800.0250**	**0.1264**	**87.94**
Rao-2	800.0010	0.1278	88.50
Rao-1	800.0492	0.1280	88.11
BS	801.8202	0.1259	-
BSA	803.3270	0.1263	-
MSA [162]	801.2248	0.1371	-
MPSO [162]	801.6966	0.1375	-
MDE [162]	802.0991	0.1374	-
MFO [162]	801.668	0.1376	-
FPA [162]	801.1487	0.1376	-
ECHT-DE [200]	800.4321	0.13739	130.4
SF-DE [200]	800.4203	0.13745	-
SP-DE [200]	800.4365	0.13748	-
IMFO [225]	800.4762	0.1255	-
MFO [225]	800.9415	0.1266	-
GA [225]	800.4385	0.1254	-
PSO [225]	800.5815	0.128	-
TLBO [225]	800.4738	0.1247	-

* L-Index = voltage collapse proximity indicator.

5.3.1.4 *Case 4 # (Voltage stability enhancement during contingency):*

In case 4, voltage stability has been improved considering single line outage (*n*-1) contingency. The prime objective in this case is to improve voltage stability and reduce fuel cost under a single line (connected between bus no. 2 to bus no. 6) outage condition. The control variables settings obtained in this case using the three Rao algorithms are given in Table 5.6. Table 5.7 compares the OPF results of Case 4 obtained by the proposed Rao algorithms with other efficient optimization algorithms reported in the recent literature. The results shown in Table 5.7 demonstrate the Rao-3 algorithm's dominance over other recently developed optimization methods.

Table 5.6: Optimum values of control variables of Case 4 to Case 6 of IEEE 30-bus system

S. No.	Control variable	Case 4 (VSE) during contingency			Case 5 (RPLM)			Case 6 (ECM)		
		Rao-1	Rao-2	Rao-3	Rao-1	Rao-2	Rao-3	Rao-1	Rao-2	Rao-3
Generator active power output										
1	Pg_2	0.4034	0.4515	0.4811	0.8	0.8	0.8	0.6633	0.6631	0.7421
2	Pg_5	0.2951	0.2132	0.214	0.5	0.5	0.5	0.5	0.5	0.4638
3	Pg_8	0.2935	0.2808	0.2416	0.35	0.35	0.35	0.35	0.35	0.3154
4	Pg_{11}	0.168	0.12	0.1279	0.3	0.3	0.3	0.3	0.3	0.2867
5	Pg_{13}	0.2854	0.12	0.12	0.4	0.4	0.4	0.4	0.4	0.3127
Generator voltage										
6	Vg_1	1.0414	1.1	1.02	1.066	1.0616	1.0718	1.0737	0.9963	1.0473
7	Vg_2	1.0035	1.469	1.02	1.0509	1.0577	1.0679	1.0677	0.95	1.0441
8	Vg_5	1.0416	1.095	1.092	1.025	1.0381	1.0484	1.0477	0.956	1.0317
9	Vg_8	1.0799	1.095	1.08	1.0409	1.0495	1.0552	1.0539	1.0932	1.0488
10	Vg_{11}	1.0602	1.06	1.1	1.02	1.1	1.1	1.1	0.9539	1.0924
11	Vg_{13}	1.0237	1.0714	1.1	1.0452	1.07	1.063	1.0613	1.1	1.0719
Tap settings										
12	T_{6-9}	0.9602	1.0496	0.914	1.1	1.0858	1.0822	1.0445	0.9063	1.0493
13	T_{6-10}	1.0208	1.0657	0.9747	0.9108	0.9001	0.9	0.9518	0.9054	1.0764

14	T_{4-12}	1.0379	1.0012	0.9549	1.0307	0.9977	0.9966	0.9928	0.9762	1.0378
15	T_{28-27}	0.9724	0.9327	0.9256	1.0072	0.9772	0.9774	0.9761	0.9156	1.0724
Shunt VAR source										
16	Qc_{10}	0.021	0.05	0.05	0.05	0	0	0.0293	0.0317	0.0217
17	Qc_{12}	0.0324	0.05	0.05	0.045	0.0479	0.0478	0.05	0.0414	0.0429
18	Qc_{15}	0.032	0.05	0.05	0.0495	0.039	0.0471	0.0448	0	0.0342
19	Qc_{17}	0.0151	0.05	0.05	0.05	0.0499	0.0498	0.05	0.0349	0.0343
20	Qc_{20}	0.0283	0.05	0.05	0.05	0.0413	0.0412	0.0413	0.0018	0.0122
21	Qc_{21}	0.0344	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0433
22	Qc_{23}	0.0147	0.05	0.05	0.0427	0.0371	0.0341	0.0332	0.05	0.0358
23	Qc_{24}	0.0282	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0458
24	Qc_{29}	0.0232	0.05	0.05	0.0205	0.0257	0.0252	0.0236	0.05	0.0383
Fuel cost		827.3375	810.3012	**818.5353**	968.1496	967.683	967.5828	942.3443	944.1722	915.2185
TVDM		0.5925	0.5754	0.7439	0.4125	1.0361	1.1277	1.1261	0.821	0.5493
Emission		0.2792	0.3324	0.3375	0.2066	0.2066	0.2066	**0.2037**	0.204	0.2126
RPLM		9.2645	11.3868	14.145	3.3041	3.1086	**3.0675**	3.2162	3.9623	4.2325
L-Index		0.1485	0.1439	**0.1363**	0.1391	0.1302	0.1289	0.1286	0.1328	0.1467

Table 5.7: Comparison of OPF Results in IEEE 30-Bus System, Case 4

Algorithm	Fuel Cost ($/h)	L-Index	Time (Second)
Base Case	904.9201	0.1805	0.08
Rao-3	**818.5353**	**0.1363**	**90.65**
Rao-2	810.3012	0.1439	92.32
Rao-1	827.3375	0.1485	91.87
BS	804.5271	0.1393	-
BSA	804.5307	0.1395	-
MSA [162]	804.4838	0.1392	-
MPSO [162]	807.6519	0.1405	-
MDE [162]	806.6668	0.1398	-
MFO [162]	804.556	0.1394	-
FPA [162]	805.5446	0.1415	-

5.3.1.5 Case 5 # (Real power loss minimization):

In Case 5, RPLM was selected as the main objective function. Mathematically, RPLM can be represented by Eq. (3.21). The minimum power loss attained by the Rao-3 algorithm is 3.0675 MW, while Rao-2 and Rao-1 algorithms provided minimum power loss of 3.1086 MW and 3.3041 MW, respectively. The results of Rao algorithms and optimal control variable settings are presented in Table 5.6. Table 5.8 compares the simulation results of case 5 obtained by the proposed algorithms and other methods proposed in recent literature. Based on the OPF outcomes, it can be concluded that the Rao-3 algorithm provided the least value of real power loss as compared to the other methods. The power loss convergence characteristic of case 5 is presented in Fig 5.4.

Table 5.8: Comparison of OPF Results in IEEE 30-Bus System, Case 5

Algorithm	**Power Loss (MW)**	**Time (Second)**
Base Case	5.8423	0.08
Rao-3	**3.0675**	**85.72**
Rao-2	3.1086	90.89
Rao-1	3.3041	89.07
BS	3.1578	-
BSA	3.1281	-
MSA [162]	3.1005	-
MPSO [162]	3.1031	-
MDE [162]	3.1619	-
MFO [162]	3.1111	-
FPA [162]	3.5661	-
MSO [161]	3.4052	-
ECHT-DE [200]	3.0850	-
SF-DE [200]	3.0845	-
SP-DE [200]	3.0844	136.4
IMFO [225]	3.0905	-
MFO [225]	3.139	-
GA [225]	3.118	-

PSO [225]	3.103	-
TLBO [225]	3.088	-
SKH [292]	3.0987	-

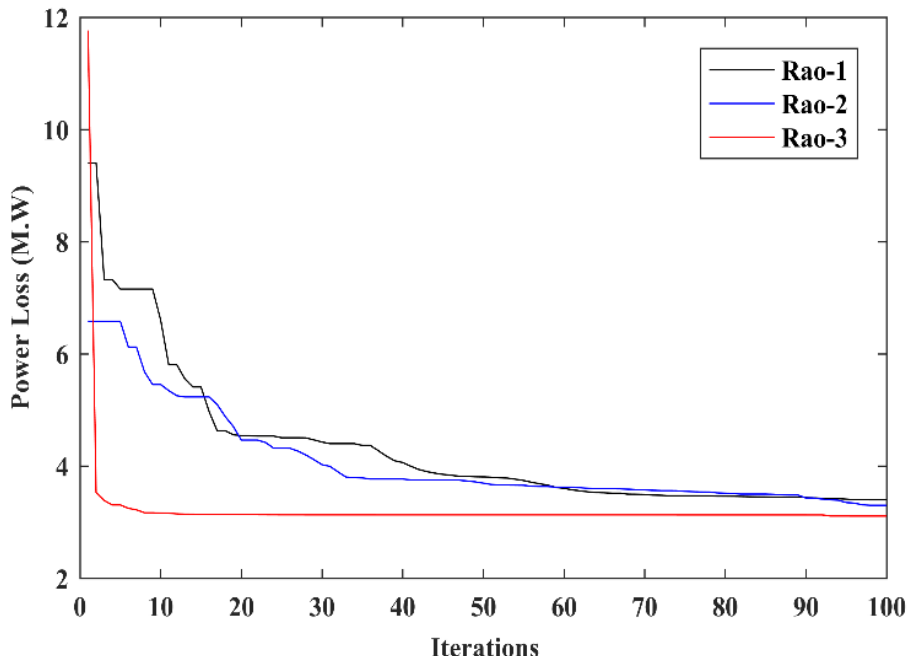


Fig. 5.4: Convergence characteristics for IEEE 30-bus system, Case 5

5.3.1.6 Case 6 # (Emission minimization):

For a given electrical network, the total emission cost can be calculated using Eq. (3.20). Table 5.9 compares the results obtained by the proposed Rao algorithms for case 6 with other efficient algorithms reported in the recent literature. The results shown in Table 5.9 demonstrate the dominance of the Rao-1 algorithm over other variants of Rao techniques. The convergence characteristics offered by the three Rao algorithms are shown in Fig. 5.5. The control variables' settings for case 6 obtained using the three Rao algorithms are given in Table 5.6.

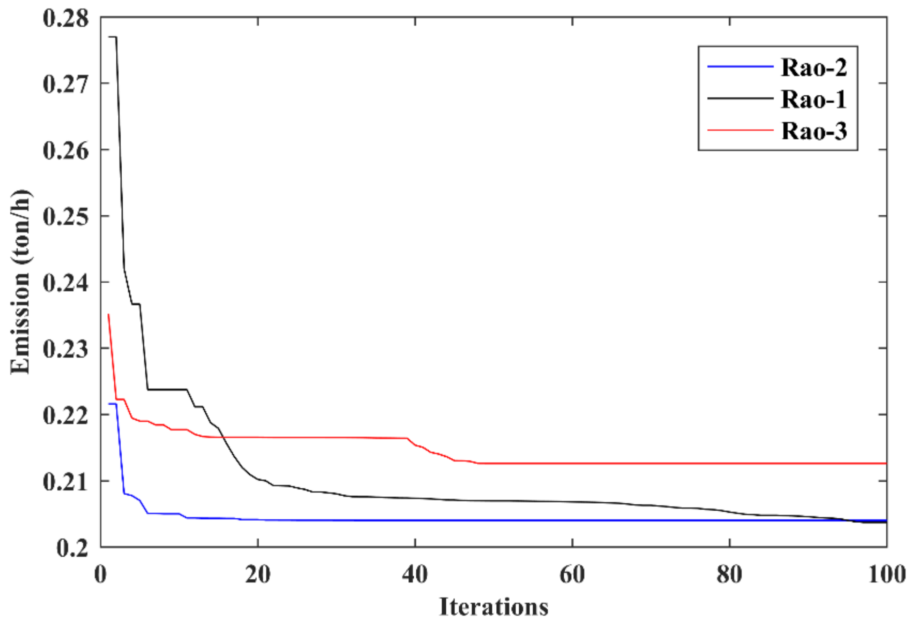


Fig. 5.5: Convergence characteristic for IEEE 30-bus system, Case 6

Table 5.9: Comparison of OPF Results in IEEE 30-Bus System, Case 6

Algorithm	Emission (ton/h)	Time (Second)
Base Case	0.2359	0.08
Rao-3	0.2126	87.87
Rao-2	0.2040	85.45
Rao-1	**0.2037**	**89.82**
BS	0.2038	-
BSA	0.2027	-
ABC [93]	0.2048	-
DSA [149]	0.2058	-
MSO [161]	0.2175	-
MSA [162]	0.2048	-
MPSO [162]	0.2325	-
MDE [162]	0.2093	-
MFO [162]	0.2049	-
FPA [162]	0.2052	-
ECHT-DE [200]	0.2048	138.2
SF-DE [200]	0.2048	-
SP-DE [200]	0.2048	-
IMFO [225]	0.2048	-

MFO [225]	0.2048	-
GA [225]	0.2048	-
PSO [225]	0.2048	-
TLBO [225]	0.2048	-
MGBICA [291]	0.2048	-
GBICA [291]	0.2049	-
SKH [292]	0.2048	-

5.3.2 Test System 2 # (IEEE 57-bus System)

To evaluate the effectiveness of the Rao algorithms, it is applied to the IEEE 57-bus system to solve OPF problems. The system data, shunt capacitor data, transformer data, and control variables limits are given in *Appendix B*. The active and reactive power demands of this system on the 100 MVA base are 12.508 pu and 3.364 pu respectively. Thirty independent runs were taken using Rao algorithms to solve the OPF problem for this system, and the best results obtained are given in this chapter.

5.3.2.1 Case 7# (Fuel Cost Minimization):

FCM is selected as the primary objective as in case 1 and defined in Eq. (3.15). Table 5.10 compares the simulation results of case 7 as obtained by the proposed Rao algorithms and by other methods reported in recent literature. The minimum cost attained by the Rao-3 algorithm is 41,659.2621 $/h, while Rao-2 and Rao-1 algorithms offered the minimum fuel cost as 41,872.0668 $/h and 41,771.1088 $/h, respectively. Based on the OPF outcomes, it is clear that the Rao-3 algorithm provided the least fuel cost as compared to other methods. This demonstrates the effectiveness of the proposed Rao-3 algorithm as compared to Rao-2, Rao-1 algorithms, and other reported algorithms. The OPF results of the proposed Rao-3 algorithm and optimal control variable settings are presented in Table 5.11. The fuel cost characteristics of case 7 are presented in Fig. 5.6.

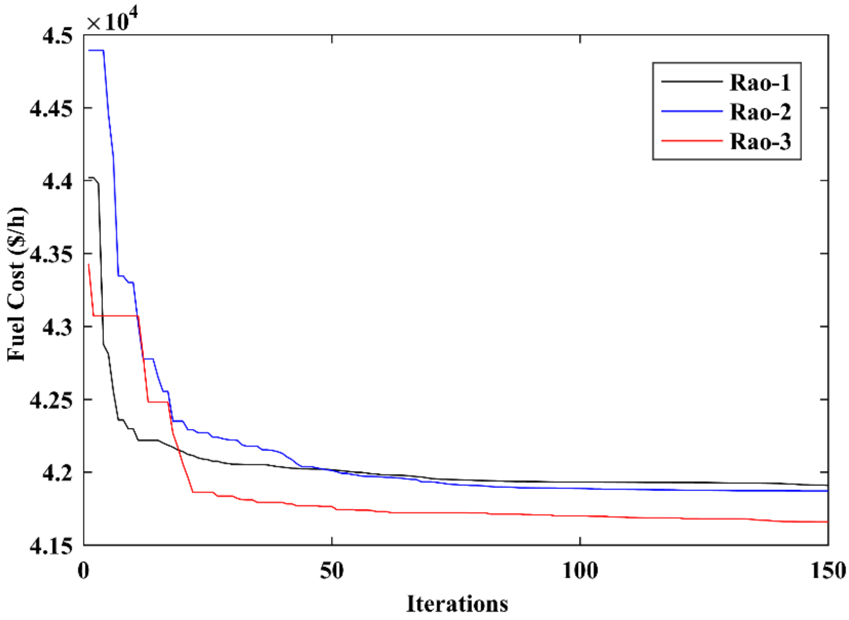


Fig. 5.6: Convergence characteristics for IEEE 57-bus system, Case 7

Table 5.10: Comparison of OPF Results in IEEE 57-Bus System, Case 7

Algorithm	**Fuel Cost ($/h)**	**Time (Second)**
Base Case	51348.2153	0.02
Rao-3	**41659. 2621**	**131.23**
Rao-2	41872. 0668	132.94
Rao-1	41771.1088	131.87
SSA [95]	41,672.30	80.61
DSA [149]	41686.82	-
MSO[161]	41,747.20	-
MSA [162]	41673.7231	-
MPSO [162]	41678.6762	-
MDE [162]	41695.8123	-
MFO [162]	41686.4119	-
FPA [162]	41701.9592	-
TSA [163]	41,685.07	75.61
ECHT – DE [200]	41670.562	-
SF-DE [200]	41667.85	-
SP-DE [200]	41667.82	219.9
IMFO [225]	41692.7178	-
MFO [225]	41719.8471	-

GA [225]	41700.4162	-
PSO [225]	41684.4009	-
TLBO [225]	41694.7778	-
MGOA [226]	41671.0980	-
GOA [226]	41679.6792	-
SKH [292]	41676.9152	-

5.3.2.2 Case 8 # (Total Voltage Deviation):

In case 8, total voltage deviation is considered as an objective function in addition to fuel cost, as defined in Eq. (3.16). The optimal control variables' settings are presented in Table 5.11. The minimum total voltage deviation attained by the Rao-3 algorithm is 0.5725 pu, while the Rao-1 and Rao-2 algorithms provided the minimum total voltage deviation of 0.9882 and 0.7645 pu, respectively. Table 5.12 compares the simulation results of case 8 obtained by the proposed Rao algorithms and other proposed methods reported in recent literature. Based on the OPF outcomes shown in Table 5.12, it can be concluded that the Rao-3 algorithm provided the least value of total voltage deviation compared to the other methods. This demonstrates the effectiveness of the proposed Rao-3 algorithm over Rao-1, Rao-2 algorithms, and other algorithms. PQ bus voltage profiles obtained in case 8 are shown in Fig. 5.7.

Table 5.11: Optimum control variables setting of Case 7 and Case 8 in IEEE 57-bus system

S. No.	Control Variable	CASE 7 (FCM)			CASE 8 (TVDM)		
		Rao-1	**Rao-2**	**Rao-3**	**Rao-1**	**Rao-2**	**Rao-3**
Generator active power output							
1	Pg_2	0.8722	0.9999	0.8857	0.8822	0.8866	0.4027
2	Pg_3	0.42	0.5217	0.4494	0.4506	0.4497	0.42
3	Pg_6	0.7856	0.3264	0.7324	0.7298	0.7183	0.3135
4	Pg_8	4.6615	4.5567	4.6028	4.6168	4.5992	4.814
5	Pg_9	0.8309	0.94	0.9588	0.963	0.9726	0.962
6	Pg_{12}	3.639	3.9341	3.5953	3.5936	3.607	4.087
Generator voltage							

7	Vg_1	1.0791	1.0629	1.0603	1.0484	1.0322	0.9965
8	Vg_2	1.0822	1.0694	1.0637	1.0526	1.0362	1.014
9	Vg_3	1.0602	1.0556	1.0529	1.043	1.0255	1.0097
10	Vg_6	1.0611	1.0493	1.0615	1.057	1.04	1.0032
11	Vg_8	1.0656	1.0626	1.0741	1.0757	1.0592	1.0135
12	Vg_9	1.0508	1.0484	1.0541	1.0502	1.0329	1.0148
13	Vg_{12}	1.0518	1.046	1.0462	1.0342	1.0175	1.044
Tap settings							
14	T_{4-18}	1.0824	1.001	1.1	0.982	1.0872	0.9031
15	T_{4-18}	1.0075	1.0173	0.9416	1.0113	0.9243	1.0393
16	T_{21-20}	1.0187	1.0649	1.0154	0.9892	0.991	0.9757
17	T_{24-25}	1.0879	1.0289	0.9447	1.017	0.9452	1.1
18	T_{24-25}	1.0887	0.9164	1.0887	1.0503	1.0952	1.0996
19	T_{24-26}	1.0277	0.9031	1.0327	1.1	1.0224	1.0152
20	T_{7-29}	1.0149	1.0082	0.9954	1.034	1.014	1.0054
21	T_{34-32}	1.0011	0.9549	0.9565	0.938	0.9356	0.9334
22	T_{11-41}	1.0006	0.9111	0.9083	0.9	0.9008	0.9002
23	T_{15-45}	1.01	1.1	0.9781	0.989	0.9691	0.9524
24	T_{14-46}	0.9841	0.9489	0.9612	0.9866	0.9651	0.9798
25	T_{10-51}	1.0997	0.9788	0.9748	1.0039	0.9848	1.0138
26	T_{13-49}	0.9037	0.9328	0.936	0.9553	0.9357	0.9001
27	T_{11-43}	1.0938	1.0018	0.9771	1.0047	0.9745	0.9781
28	T_{40-56}	0.9067	0.9	0.9975	1.0041	0.9975	0.9849
29	T_{39-57}	0.9182	0.9	0.9675	0.9415	0.9384	0.9
30	T_{9-55}	1.0134	1.1	1.0026	1.0285	1.0115	1.0146
Shunt VAR source							
31	Qc_{18}	0.1858	0.0559	0.1724	0.0127	0.0628	0.0003
32	Qc_{25}	0.2803	0.1939	0.1439	0.163	0.1747	0.3
33	Qc_{53}	0.2381	0.1577	0.1267	0.1705	0.1481	0.3
Fuel cost ($\h)		41771. 1088	41872. 0668	**41659. 2621**	41688.4417	41691.1102	**42043. 2728**
TVD (pu)		1.5465	1.6713	1.6953	0.9882	0.7645	**0.5725**
L-Index		0.231	0.2411	0.2349	0.2438	0.2415	0.2297
PLoss (MW)		17.364	16.4837	14.7262	15.4719	15.4214	18.0100

Table 5.12: Comparison of OPF Results in IEEE 57-Bus System, Case 8

Algorithm	Fuel Cost ($/h)	TVD (pu)	Time (Second)
Base Case	51348.2153	1.2236	0.02
Rao-3	**42043. 2728**	**0.5725**	**134.25**
Rao-2	41691.1102	0.7645	136.34
Rao-1	41688.4417	0.9882	131.87
DSA [149]	41699.4	0.762	-
MSA [162]	41714.9851	0.67818	-

MPSO [162]	41721.6098	0.67813	-
MDE [162]	41717.3874	0.6781	-
MFO [162]	41718.8659	0.67796	-
FPA [162]	41726.3758	0.69723	-
TSA [163]	54,045.17	0.72	75.41
ECHT-DE [200]	41694.82	0.81659	-
SF-DE [200]	41697.52	0.77572	-
SP-DE [200]	41697.50	0.77253	203.6
IMFO [225]	41692.7178	0.7182	-
MFO [225]	41719.8471	0.7551	-
GA [225]	41700.4162	0.8051	-
PSO [225]	41684.4009	0.7624	-
TLBO [225]	41694.7778	0.712	-
MGOA [226]	41697.9735	0.7381	-
GOA [226]	41715.1396	0.8260	-

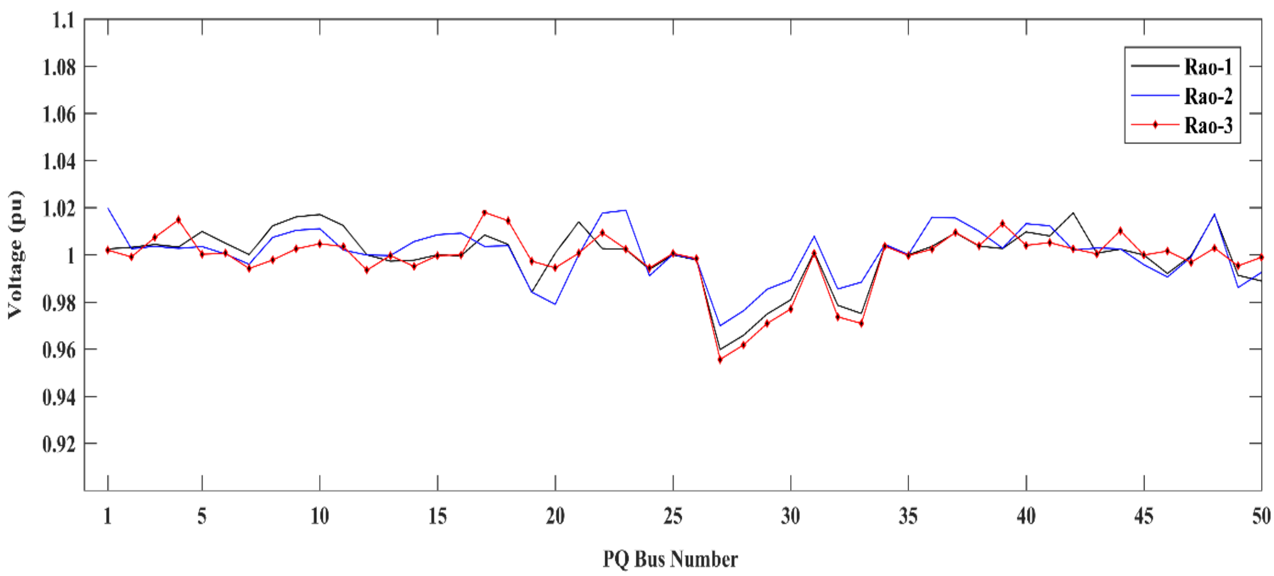


Fig. 5.7: Voltage profile at load buses in IEEE 57-bus system, Case 8

5.3.2.3 Case 9 # (Voltage stability enhancement):

In case 9, the VSE is considered as an objective function in addition to fuel cost as defined in Eq. (3.19). The control variables' values obtained using the three Rao algorithms are provided in Table 5.13. The OPF results of case 9 attained by the proposed Rao methods and the other optimization algorithms mentioned in the recent literature are compared in Table 5.14. The OPF results shown in Table 5.14 prove the dominance of the Rao-3 algorithm over other optimization algorithms for this case also.

Table 5.13: Optimum control variables setting of Case 9 and Case 10 in IEEE 57-bus system

S. No.	Control variable	Case 9 (VSE)			Case 10 (RPLM)		
		Rao-1	Rao-2	Rao-3	Rao-1	Rao-2	Rao-3
Generator active power output							
1	Pg_2	0.8747	0.9749	0.9637	0.3048	0.3	0.3
2	Pg_3	0.4513	0.4486	0.4518	1.3241	1.322	1.3549
3	Pg_6	0.7085	0.7029	0.7067	0.9937	0.9999	0.9996
4	Pg_8	4.6141	4.5994	4.5916	3.1132	3.0842	3.0604
5	Pg_9	0.9998	0.9324	0.934	0.9978	0.9999	0.99998
6	Pg_{12}	3.5892	3.572	3.5912	4.1	4.1	4.0999
Generator voltage							
7	Vg_1	1.047	1.0873	1.0873	1.0542	1.0723	1.0712
8	Vg_2	1.0502	1.1	1.1	1.0559	1.0722	1.0721
9	Vg_3	1.0425	1.0672	1.0676	1.0563	1.067	1.0666
10	Vg_6	1.0569	1.0621	1.062	1.0623	1.0633	1.0631
11	Vg_8	1.0717	1.0689	1.0697	1.0654	1.0697	1.0695
12	Vg_9	1.0465	1.0507	1.0509	1.0492	1.0576	1.0572
13	Vg_{12}	1.0328	1.0384	1.0382	1.0441	1.0572	1.0567
Tap settings							
14	T_{4-18}	1.0999	0.9016	0.9	1.1	0.9117	1.1
15	T_{4-18}	0.9081	1.1	1.0428	1.0023	1.082	0.9014
16	T_{21-20}	1.0138	1.0321	1.0025	0.998	1.042	1.0128
17	T_{24-25}	1.083	1.1	1.0999	0.9036	1.0356	1.0902
18	T_{24-25}	1.1	1.0998	1.1	1.0698	0.9704	0.9354
19	T_{24-26}	1.0252	1.0268	1.0262	1.0086	1.0109	1.0098
20	T_{7-29}	0.9991	0.9993	0.9986	0.9953	0.9963	0.9961
21	T_{34-32}	0.9423	0.9522	0.9476	0.9318	0.9528	0.9526
22	T_{11-41}	0.9112	0.9129	0.9002	0.9111	0.9174	0.9025
23	T_{15-45}	0.9707	0.9909	0.9916	0.9733	0.9892	0.9889
24	T_{14-46}	0.9539	0.9695	0.9686	0.9671	0.9751	0.9722
25	T_{10-51}	0.9676	0.9709	0.9699	0.9797	0.9821	0.9819
26	T_{13-49}	0.9076	0.9389	0.9365	0.9411	0.9449	0.9451
27	T_{11-43}	0.9643	0.9782	0.9811	0.9776	0.9817	0.9939
28	T_{40-56}	0.9945	0.9924	1.0152	0.9826	0.9938	0.993
29	T_{39-57}	0.9753	0.9655	0.9639	0.96	0.9624	0.9638
30	T_{9-55}	0.9912	0.9934	0.9978	0.9986	0.9961	0.9947
Shunt VAR source							
31	Qc_{18}	0.1139	0.0375	0.0002	0.2771	0.0002	0.0239
32	Qc_{25}	0.2412	0.2613	0.2576	0.1081	0.1448	0.1554

33	Qc_{53}	0.1405	0.1428	0.1293	0.1445	0.1339	0.129
Fuel cost ($\h)		41670.4726	41692.9720	**41692.6149**	44418.4740	44438.1623	44600.2741
TVD (pu)		1.7637	1.7835	1.8735	1.5278	1.7464	1.793
PLoss (MW)		15.0175	15.561	15.4768	10.005	9.766	**9.759**
L-Index		0.22	0.2191	**0.2186**	0.2434	0.2353	0.2330

Table 5.14: **Comparison of OPF Results in IEEE 57-Bus System, Case 9**

Algorithm	Fuel Cost ($/h)	L-Index	Time (Second)
Base Case	51348.2153	0.3098	0.02
Rao-3	**41692.6149**	**0.2186**	**131.78**
Rao-2	41692.9720	0.2191	132.54
Rao-1	41670.4726	0.2200	132.76
DSA [149]	41761.22	0.2383	-
MSA [162]	41675.9948	0.27481	-
MPSO [162]	41694.1407	0.27918	-
MDE [162]	41689.5878	0.27677	-
MFO [162]	41680.1937	0.27467	-
FPA [162]	41684.1859	0.27429	-
ECHT-DE [200]	41671.09	0.28152	-
SF-DE [200]	41667.53	0.28022	214.4
SP-DE [200]	41668.45	0.28092	-
IMFO [225]	41673.6204	0.23525	-
MFO [225]	41688.6522	0.2395	-
GA [225]	41670.0872	0.2413	-
PSO [225]	41670.1755	0.242	-
TLBO [225]	41685.353	0.24787	-
MGOA [226]	41682.4031	0.2297	-
GOA [226]	41698.1175	0.2395	-
SKH [292]	43937.1058	0.2721	-

5.3.2.4 Case 10 # (Real power loss minimization):

The function F_{Loss} is selected for the RPLM as described in Eq. (3.21). The minimum real power loss attained by the Rao-2 algorithm is 9.759 MW, while the Rao-1 and Rao-3 algorithms provided the real power loss as 10.005 MW and 9.770 MW, respectively. Results of the proposed Rao algorithms and optimal control variable settings are presented in Table

5.13. Table 5.15 compares the simulation results of this case as obtained by the Rao algorithms and other methods reported in recent literature. The OPF results shown in Table 5.15 demonstrate the superiority of the Rao-2 algorithm over Rao-1, Rao-3, and the other competitors. The power loss convergence characteristic of case 10 is presented in Fig. 5.8.

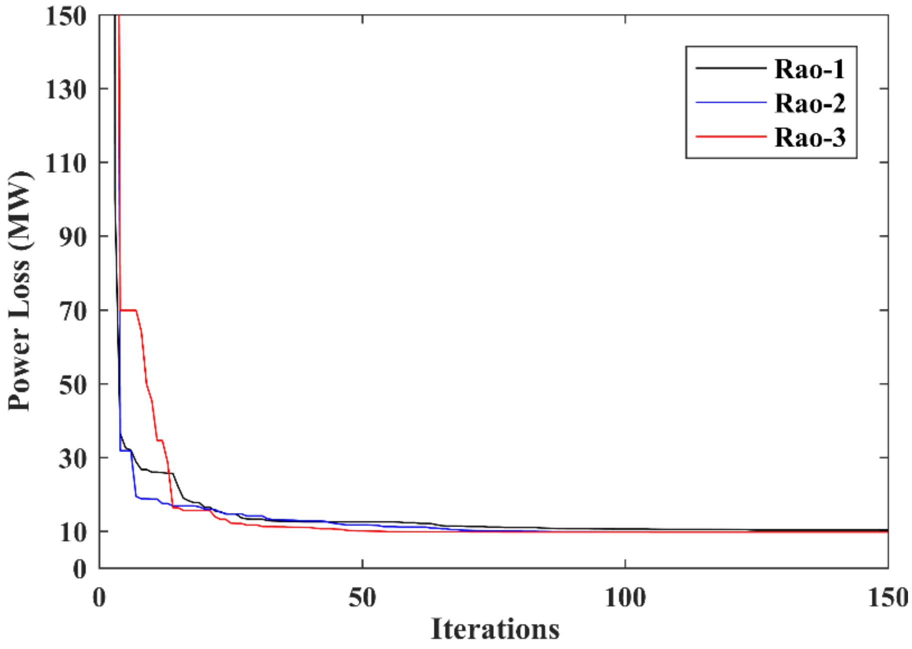


Fig. 5.8: Convergence characteristic for IEEE 57-bus system, Case 10

Table 5.15: Comparison of OPF Results in IEEE 57-Bus System, Case 10

Algorithm	**Real Power Loss (MW)**	**Time (Second)**
Base Case	27.8282	0.02
Rao-3	**9.7590**	**131.26**
Rao-2	9.7660	132.18
Rao-1	10.005	135.77
SSA [95]	11.321	81.17
MSO [161]	12.743	-
TSA [163]	12.473	76.17
SKH [292]	10.687	-

5.3.3 Test system 3 # (IEEE 118-bus system)

To demonstrate the scalability of Rao algorithms and to prove their efficacy to solve large-scale problems, all the three versions of Rao algorithms were applied to solve the OPF problem in the IEEE 118-bus test system. The IEEE 118-bus test system has 54 generation units, two reactors, and 12 capacitors, 186 branches, and nine tap-changing transformers. The system data along with control variable operating limits are given in *Appendix D***.** Thirty independent runs were taken using Rao algorithms to solve the OPF problem for the proposed test system, and the best results obtained out of 30 trials are shown in this section.

5.3.3.1 Case 11# (Fuel Cost Minimization):

In case 11, fuel cost is selected as the primary objective as in Case 1. The minimum cost attained by the Rao-3 algorithm is 1,29,220.6794 \$/h, while Rao-2 and Rao-1 algorithms offered the minimum fuel cost of 1,29,256.5242 \$/h and 1,29,241.1787 \$/h, respectively. The OPF results of the proposed Rao-3 algorithm and the optimal control variable settings are presented in Table 5.16. Table 5.17 compares the OPF results of case 11 obtained by the Rao algorithms and other methods reported in recent articles. Based on OPF outcomes, it is clear that the Rao-3 algorithm provided the least fuel cost as compared to the other methods. This demonstrates the effectiveness of the Rao-3 algorithm over Rao-1, Rao-2 algorithms, and other algorithms for fuel cost minimization in IEEE 118-bus system. The fuel cost characteristics of case 11 are presented in Fig. 5.9.

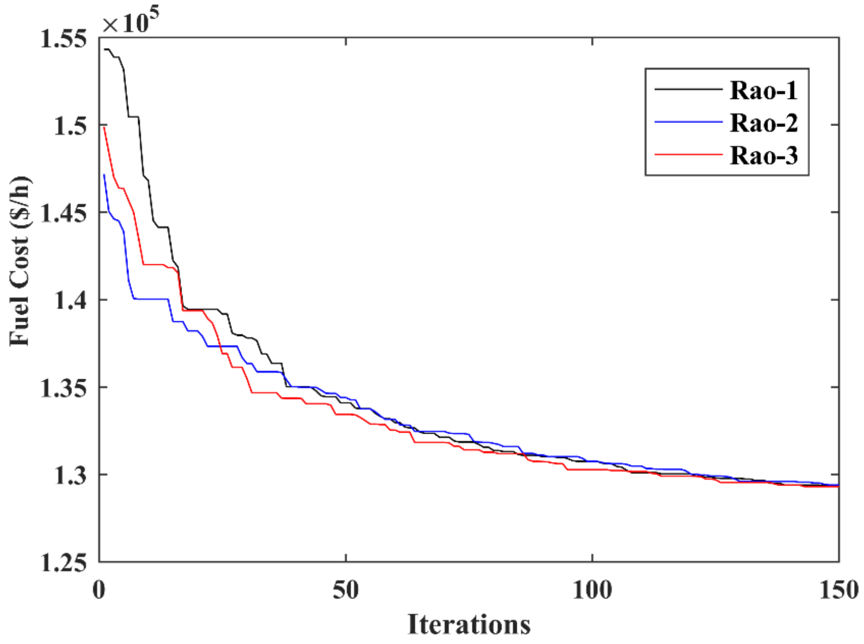


Fig. 5.9: Convergence characteristic for IEEE 118-bus system, Case 11

Table 5.16: Optimum control variables settings of Case 11 in IEEE 118-bus system

S. No	Control variables	Initial	Rao-3	S. No	Control variables	Initial	Rao-3	S. No	Control variables	Initial	Rao-3
1	P_{g1}	0	0.07872	45	P_{g103}	0.4	0.33181	89	V_{g77}	1.006	1.00706
2	P_{g4}	0	0.07685	46	P_{g104}	0	0.24175	90	V_{g80}	1.04	1.02122
3	P_{g6}	0	0.0662	47	P_{g105}	0	0.06467	91	V_{g85}	0.985	1.03344
4	P_{g8}	0	0.1337	48	P_{g107}	0	0.0083	92	V_{g87}	1.015	1.01663
5	P_{g10}	4.5	4.27188	49	P_{g110}	0	0.03809	93	V_{g89}	1.005	1.02186
6	P_{g12}	0.85	0.58259	50	P_{g111}	0.36	0.33608	94	V_{g90}	0.985	0.9779
7	P_{g15}	0	0.02101	51	P_{g112}	0	0.18375	95	V_{g91}	0.98	0.96364
8	P_{g18}	0	0.00159	52	P_{g113}	0	0.00423	96	V_{g92}	0.99	1.0142
9	P_{g19}	0	0.00782	53	P_{g116}	0	0.0008	97	V_{g99}	1.01	0.98147
10	P_{g24}	0	0.0178	54	V_{g1}	0.995	1.02416	98	V_{g100}	1.017	1.03575
11	P_{g25}	2.2	2.1492	55	V_{g4}	0.998	1.03241	99	V_{g103}	1.01	1.05908
12	P_{g26}	3.14	2.84427	56	V_{g6}	0.99	1.03808	100	V_{g104}	0.971	1.05774
13	P_{g27}	0	0.31058	57	V_{g8}	1.015	0.97062	101	V_{g105}	0.965	1.05895
14	P_{g31}	0.07	0.09645	58	V_{g10}	1.05	0.9431	102	V_{g107}	0.952	1.05859
15	P_{g32}	0	0.00434	59	V_{g12}	0.99	1.05326	103	V_{g110}	0.973	0.96628
16	P_{g34}	0	0.17751	60	V_{g15}	0.97	1.01875	104	V_{g111}	0.98	0.95313

17	P_{g36}	0	0.32141	61	V_{g18}	0.973	1.0552	105	V_{g112}	0.975	0.94652
18	P_{g40}	0	0.46268	62	V_{g19}	0.962	1.02694	106	V_{g113}	0.993	1.03236
19	P_{g42}	0	0.68702	63	V_{g24}	0.992	1.04181	107	V_{g116}	1.005	0.97069
20	P_{g46}	0.19	0.25232	64	V_{g25}	1.05	1.04186	108	T_{5-8}	0.985	0.9002
21	P_{g49}	2.04	1.87987	65	V_{g26}	1.015	0.95537	109	T_{26-25}	0.96	1.03159
22	P_{g54}	0.48	0.30277	66	V_{g27}	0.968	1.03944	110	T_{30-17}	0.96	0.9885
23	P_{g55}	0	0.74996	67	V_{g31}	0.967	1.03063	111	T_{38-37}	0.935	0.95581
24	P_{g56}	0	0.35764	68	V_{g32}	0.963	1.02981	112	T_{63-59}	0.96	1.09927
25	P_{g59}	1.55	1.53703	69	V_{g34}	0.984	1.02045	113	T_{64-61}	0.985	0.91596
26	P_{g61}	1.6	1.65333	70	V_{g36}	0.98	1.03052	114	T_{65-66}	0.935	1.08267
27	P_{g62}	0	0.09242	71	V_{g40}	0.97	0.98601	115	T_{68-69}	0.935	0.90129
28	P_{g65}	3.91	3.98068	72	V_{g42}	0.985	0.97303	116	T_{81-80}	0.935	1.0949
29	P_{g66}	3.92	3.33319	73	V_{g46}	1.005	1.03671	117	Q_{C5}	0	0.0397
30	P_{g70}	0	0.12369	74	V_{g49}	1.025	1.00562	118	Q_{C34}	0	0.13264
31	P_{g72}	0	0.04355	75	V_{g54}	0.955	0.96514	119	Q_{C37}	0	0.29284
32	P_{g73}	0	0.01357	76	V_{g55}	0.952	0.98114	120	Q_{C44}	0	0.22743
33	P_{g74}	0	0.05	77	V_{g56}	0.954	0.96645	121	Q_{C45}	0	0.16846
34	P_{g76}	0	0.05541	78	V_{g59}	0.985	1.04398	122	Q_{C46}	0	0.01255
35	P_{g77}	0	0.05941	79	V_{g61}	0.995	1.05939	123	Q_{C48}	0	0.00779
36	P_{g80}	4.77	3.5775	80	V_{g62}	0.998	1.05898	124	Q_{C74}	0	0.27942
37	P_{g85}	0	0.12274	81	V_{g65}	1.005	0.96444	125	Q_{C79}	0	0.01159
38	P_{g87}	0.04	0.01293	82	V_{g66}	1.05	1.05809	126	Q_{C82}	0	0.3
39	P_{g89}	6.07	4.56372	83	V_{g69}	1.035	1.04551	127	Q_{C83}	0	0.15625
40	P_{g90}	0	0.06063	84	V_{g70}	0.984	0.94113	128	Q_{C105}	0	0.13484
41	P_{g91}	0	0.01788	85	V_{g72}	0.98	0.94008	129	Q_{C107}	0	0.26686
42	P_{g92}	0	0.05746	86	V_{g73}	0.991	0.94036	130	Q_{C110}	0	0.01831
43	P_{g99}	0	0.00446	87	V_{g74}	0.958	1.00781				
44	P_{g100}	2.52	2.33746	88	V_{g76}	0.943	0.96203				

OPF RESULTS

Optimized Results	**Rao-1 Algorithm**	**Rao-2 Algorithm**	**Rao-3 Algorithm**
Fuel Cost ($/h)	1,29,241.1787	1,29,256.5242	**129220.67**
TVDM (p.u)	1.4070	1.4205	1.5416
RPLM (MW)	101.1756	109.2671	109.1203
P_{g69} (Slack bus power)	442.6168	492.0928	471.2005

Table 5.17: Comparison of OPF Results in IEEE 57-Bus System, Case 11

Algorithm	Fuel Cost ($/h)	Time (Second)
Base Case	1,31,220.020	0.13
Rao-3	**1,29,220.6794**	**164.19**
Rao-2	1,29,256.5242	169.24
Rao-1	1,29,241.1787	167.33
GPU-PSO [154]	1,29,627.03	-
IMFO [225]	1,31,820.00	-
PSOGSA [268]	1,29, 733.58	-

5.4 STATISTICAL COMPARISON OF RAO-1, RAO-2 AND RAO-3 ALGORITHMS

To assess the robustness of the Rao-1, Rao-2 and Rao-3 algorithms to solve the OPF problem, statistical analysis was performed. Thirty separate trials for the same population size and number of iterations were conducted. Tables 5.18 shows the results of the 30 trials, which were used to measure the best, worst, average (mean), and standard deviation (SD). The lowest values of the best, worst, average, and standard deviation offered by the Rao algorithms demonstrate that the proposed Rao algorithms provides statistically significant results in all the cases. This confirms the robustness of the Rao algorithms.

Table 5.18: Statistical analysis of the various cases using the Rao algorithms

Algorithm	Best	Worst	Mean	SD	Best	Worst	Mean	SD
Case 1					**Case 7**			
Rao-3	799.9683	801.8023	800.8813	0.0186	41659. 2621	41674. 4259	41669. 0213	1.7866
Rao-2	799.9918	801.9718	800.9032	0.0203	41872. 0668	41894. 0668	41887. 0668	2.2906
Rao-1	800.4391	802.1403	801.2391	0.0223	41771.1088	41782.4437	41776.6512	2.1860
Case 5					**Case 10**			
Rao-3	3.0675	3.1182	3.0714	0.0288	9.7590	9.8460	9.7971	0.0318
Rao-2	3.1086	3.1761	3.1271	0.0360	9.7660	9.8541	9.8065	0.0339
Rao-1	3.3041	3.4065	3.3389	0.0408	10.0050	10.9451	10.4515	0.0351

Case 6					Case 11			
Rao-3	0.2126	0.2246	0.2206	0.0166	129220.6794	129440.3458	129331.6023	4.0910
Rao-2	0.2040	0.2065	0.2048	0.0131	129256.5242	129541.2740	129402.0961	4.7350
Rao-1	0.2037	0.2049	0.2043	0.0110	129241.1787	129511.7206	129381.4028	4.5210

* SD = standard deviation

5.5 SUMMARY

It has been observed that parameter tuning of meta-heuristic optimization algorithms plays a very important role and it is a very crucial and time taking task to tune its parameters for solving a given optimization problem. Hence, in this chapter Rao algorithms have been proposed to solve the OPF problem. As the proposed Rao algorithms are parameter tuning free optimization algorithm, the exploration and exploitation search ability of the algorithm is not dependent on algorithm-specific parameters.

This chapter offers three easy to use metaphor-less optimization algorithms proposed by Rao to solve the optimal power flow problem considering technical and economical objective functions. The proposed Rao algorithms have been applied on three standard IEEE test systems e.g. 30-bus, 57 bus and 118 bus which have 24 control variables, 33 control variables, and 130 control variables, respectively to test the efficacy of the proposed algorithm for different problem dimensions. As the Rao algorithms performed well in all the 3 power networks having different dimensions of the control variables, they can also be employed to solve OPF problems in practical power systems.

Various objectives considered for solving the OPF problem in this chapter were minimization of fuel cost, minimization of total voltage deviation, enhancement of voltage stability under normal and under contingency conditions, minimization of real power loss, and minimization of emission cost. The performance of Rao-1, Rao-2 and Rao-3 is found to be competitive with one another as mentioned in [290].

Another appealing feature of the Rao algorithm is that with small variation in the update equation, three different versions can be developed and applied for solving any optimization problem. Consequently, based on the performance, the best version can be selected out of the three versions for solving the optimization problem at hand.

CHAPTER 6

SINE-COSINE MUTATION BASED MODIFIED JAYA ALGORITHM FOR OPTIMAL POWER FLOW

CHAPTER 6

SINE-COSINE MUTATION BASED MODIFIED JAYA ALGORITHM FOR OPTIMAL POWER FLOW

6.1 INTRODUCTION

A modification of the existing meta-heuristic algorithm is the latest research trend to solve practical optimization problems. In recent literature, a large number of modified meta-heuristics algorithms have been proposed to solve complex optimization problems. When applied to real-world engineering optimization problems, standard versions of some of the common meta-heuristic approaches have been found to have some limitations. For example, premature convergence or local optima trapping is a common occurrence in GA and moth search optimization (MSO) algorithms. Similarly, the simulated annealing (SA) and PSO algorithms are relatively ineffective in searching for optimal global solutions. In addition, poor communication in the TLBO algorithm during the second phase (Learning Phase) may result in insufficient knowledge sharing, therefore may get trapped in the local solution. Various modifications and hybridization of meta-heuristic algorithms have been proposed in the literature to address the shortcomings of the poorly performing standard versions of meta-heuristic algorithms.

Jaya algorithm has a strong capacity to explore search space globally, but sometimes it suffers from premature convergence and can be stuck simply in local optima. To overcome this problem and to make this algorithm more efficient, in this chapter, a sine-cosine mutation-based modified Jaya algorithm (SCM-MJ) for solving the OPF problem has been proposed. The efficacy of the SCM-MJ algorithm is primarily evaluated using thirteen (uni-modal and multi-modal) mathematical benchmark functions. Later, the

SCM-MJ algorithm is applied to the Algerian 59-bus system and IEEE 118-bus test system to handle the OPF problems. The proposed SCM-MJ algorithm has successfully offered a minimum value of objective function over several runs than other modern meta-heuristic optimization approaches in all the thirteen mathematical benchmark functions as well as in OPF case studies. The SCM-MJ algorithm has provided high-quality solutions for mathematical benchmark functions and OPF problems quickly and efficiently.

6.2 JAYA ALGORITHM

Jaya algorithm is a comparatively new meta-heuristic optimization algorithm developed by Rao [293]. The working principle of the Jaya algorithm is that the numerical solution that has been obtained should go towards the best solution and should avoid the inferior solutions for a particular optimization problem. The key benefit of the Jaya algorithm is that algorithm-specific parameter tuning is not required at all in it and thus it is easy to implement this algorithm for solving various kinds of optimization problems.

Initial population '*p*' is randomly generated within the upper and lower limits of the control variables and is updated as per Eq. (6.1). The best and worst solutions are determined based on the fitness values of the objective function.

Let, the number of design variables is '*m*' (i.e. $j = 1, 2, 3\ldots, m$) and '*n*' is the population size ($k = 1, 2\ldots, n$). Let $J_{i,j,k}$ represents the value of the j^{th} variable for k^{th} candidate during the i^{th} iteration, and then this value is modified as (6.1)

$$J_{i+1,j,k} = J_{i,j,k} + \gamma_{i,j,1}(J_{i,j,B} - \mathrm{abs}(J_{i,j,k})) - \gamma_{i,j,2}(J_{i,j,W} - \mathrm{abs}(J_{i,j,k})) \tag{6.1}$$

Where, $J_{i,j,k}$ represents the value of the j^{th} variable for the k^{th} candidate during the i^{th} iteration. $J_{i,j,W}$ and $J_{i,j,B}$ are the worst candidate and best candidate value of the j^{th} variable respectively. $\gamma_{\ i,j,1}$ and $\gamma_{\ i,j,2}$ are the two random numbers for the j^{th} variable during the i^{th} iteration in the range [0, 1].

6.3 MODIFIED JAYA ALGORITHM

The modified Jaya algorithm has been derived by changing the solution update equation of the Jaya algorithm using (6.1).

$$\mathrm{J}_{\mathrm{i+1,j,k}} = \mathrm{J}_{\mathrm{i,j,k}} + \gamma_{\ \mathrm{i,j,1}} \times \left(\mathrm{J}_{\mathrm{i,j,B}} - \mathrm{J}_{\mathrm{i,j,k}}\right) - \gamma_{\ \mathrm{i,j,2}} \ \times \mathrm{S} \times \ \left(\mathrm{J}_{\mathrm{i,j,W}} - \mathrm{J}_{\mathrm{i,j,k}}\right) \tag{6.2}$$

where *S* is updated in each iteration as follows;

$$\mathrm{S} = \begin{cases} 1 & \text{If rand2} > 0.5 \\ -1 & \text{else} \end{cases} \tag{6.3}$$

Where, *rand2* is the random number in the range [0, 1].

6.4 SINE-COSINE MUTATION OPERATOR

Zhou et.al [294] suggested a sine-cosine mutation operator that enhances the global search ability of the meta-heuristic techniques. The key benefit of the sine-cosine mutation operator is that it avoids the loss of diversity of populations during the search process. The sine-cosine mutation operator typically constructs new offspring (solutions) similar to the parent candidate solutions. When the sine-cosine mutation operator is used during the search process, smaller steps are taken, allowing the candidate solutions to explore every corner of the solution space. The sine-cosine mutation operator is capable of diversifying the population and making global searches more effective, so that the objective function does not converge prematurely with local optima. The sine-cosine mutation operator function is calculated as follows:

$$J_{new(i+1,j,k)} = \begin{cases} J_{i,j,k_{c1}} + A \times \sin(B) \times \left|C.\, J_{i,j,k_{c2}} - J_{i,j,k_{c3}}\right| & C < 1.0 \\ J_{i,j,k_{c1}} + A \times \cos(B) \times \left|C.\, J_{i,j,k_{c2}} - J_{i,j,k_{c3}}\right| & \text{otherwise} \end{cases} \quad (6.4)$$

Eq. (6.4) is used to achieve the k^{th} candidate's new position value $J_{new(i+1,j,k)}$ during $(i+1)^{th}$ iteration. In Eq. (6.4), $J_{i,j,k_{c1}}$, $J_{i,j,k_{c2}}$ and $J_{i,j,k_{c3}}$ are three random solutions in the i^{th} iteration, which are different from one another. The parameter '*A*' is changed iteratively as determined by Eq. (6.4), whereas '*B*' and '*C*' are random numbers in the range [0, 2π] and [0, 2] respectively.

$$A = 2 \times \left(1 - \frac{iter}{iter_{max}}\right)^2 \quad (6.5)$$

To maintain a constant population size in next generations, sine-cosine mutation uses a greedy selection procedure. The new position value of $J_{new(i+1,j,k)}$ replaces the old value $J_{(i,j,k)}$ if and only if $f(J_{new(i+1,j,k)}) < f(J_{(i,j,k)})$.

6.5 THE PROPOSED METHODOLOGY

Jaya algorithm is an efficient optimization algorithm. This algorithm is good in the exploration of the search space but is slow in the exploitation part. Therefore, hybridizing Jaya with an algorithm having strong exploitation capability might balance the exploitation and exploration of the Jaya algorithm. Hence, to boost the operational efficacy of the Jaya algorithm, a sine-cosine mutation operator has been incorporated into it. The motivation to incorporate the sine-cosine mutation operator with the Jaya algorithm is to combine the benefits of both of them.

The SCM-MJ algorithm can maintain the population's diversity throughout the search space to avoid sub-optimal solutions, enhance the convergence speed, and find near-global solution as well. The hybridization of the modified Jaya algorithm and sine-cosine mutation operator would lead to better results for real-world complex, constrained and high dimensional optimization problems. The flow chart of the proposed hybrid method is given in Fig. 6.1.

The main computational step for solving OPF using the SCM-MJ algorithm can be summarized as follows:

Step 1: Initialize population '*P*' having control variables, with the dimension of problem '*D*' and set the stopping criteria.

Step 2: For each individual, run NRLF (Newton Raphson load flow) program and evaluate the value of the augmented objective function (3.14).

Step 3: Set iteration *Iter* =0.

Step 4: Identify the worst and best solution in the population based on the value of the augmented objective function (3.14).

Step 5: Modify the solution based on the worst and the best solutions using (6.2).

Step 6: For each individual, is the new fitness value better than the previous one? If yes, then replace the previous solution with a new solution. Otherwise, keep the previous solution.

Step 7: Apply the sine-cosine mutation operator to update the position of all the members of the population and calculate the augmented objective function value.

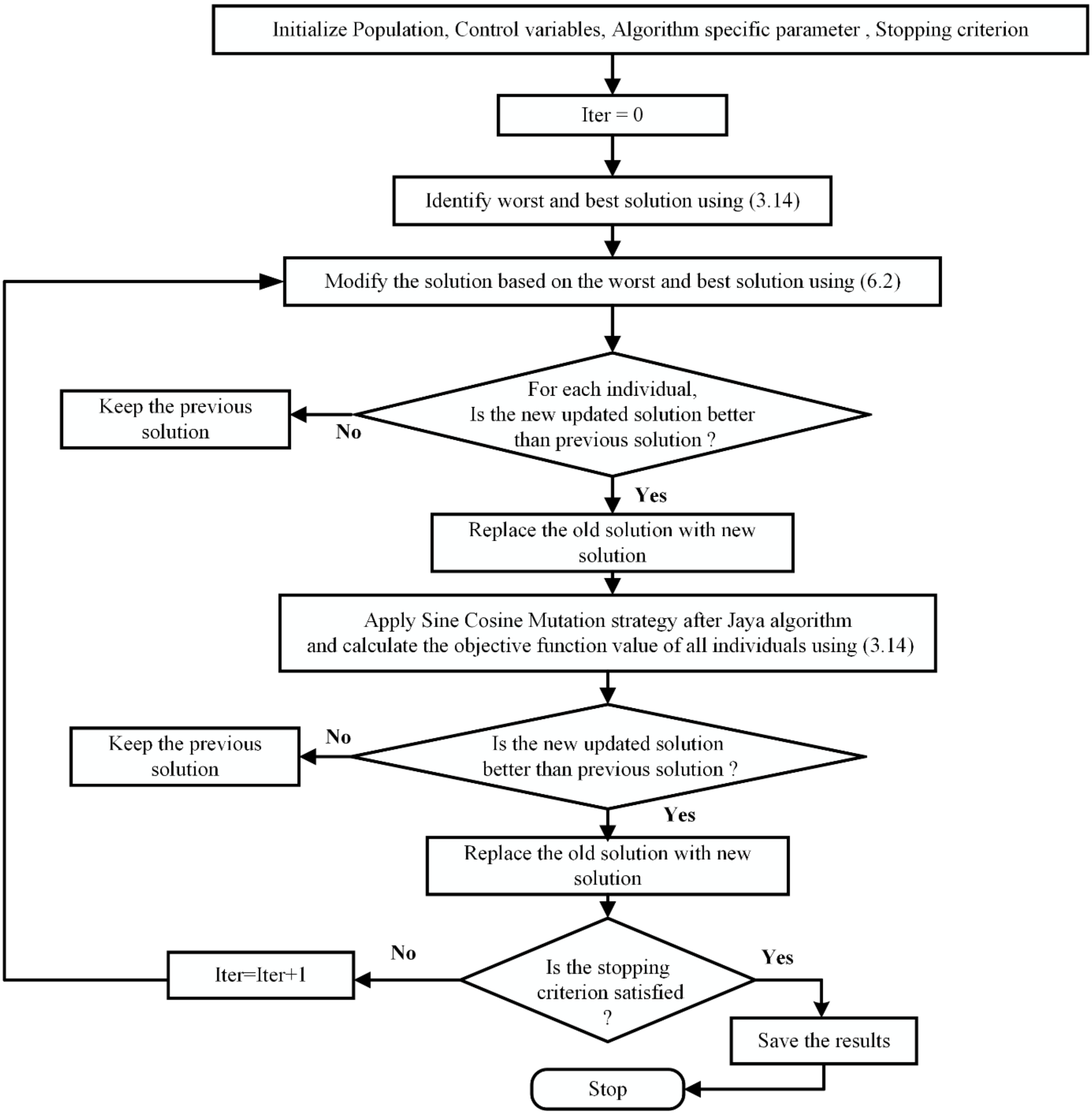


Fig. 6.1: Flowchart of the proposed SCM-MJ algorithm

Step 8: If a new solution achieved after the mutation operator is better than the previous solution, accept the new solution otherwise keep the previous solution.

Step 9: If the stopping criteria is satisfied then go to step 10, otherwise go to step 4 and increase the iteration count by 1, i.e. *Iter* = *Iter* + 1.

Step 10: Stop and display optimal solutions.

6.6 RESULTS AND DISCUSSION

To check the efficacy of the proposed SCM-MJ algorithm, it has been applied to thirteen standard mathematical benchmark functions. Table 6.1 presents the input parameters of the SCM-MJ algorithm. Details of these benchmark functions and simulation outcomes can be seen in Table 6.2 and Table 6.3 respectively.

To compare the performance of the proposed SCM-MJ algorithm with the M-Jaya algorithm, ant lion optimizer (ALO), bat algorithm (BA), cuckoo search (CS) algorithm, flower pollination algorithm (FPA), firefly algorithm (FA), GA, PSO, and states of matter search (SMS) algorithms [295], these algorithms were applied and run with the population size of 100 for the 5000 iterations on all the thirteen benchmark functions. The number of functions evolution (NFE) for ALO, BA, CS, FPA, FA, GA, PSO, and SMS algorithms, proposed SCM-MJ algorithm and M-Jaya algorithm are also the same which is equal to 5,00,000. Details of the implementation of hybrid SCM-MJ and M-Jaya algorithms are given in Table 6.1.

Table 6.1: Algorithm specific parameters setting of SCM-MJ algorithm

S. No.	Parameter	Value
1	Population size	100 (for benchmark function), 30 (for OPF problem)
2	Maximum Iteration	2500 (for benchmark function), 150 (for OPF problem)
3	Number of function Evolution	(2,50,000×M-Jaya+2,50,000×SCM) = 5,00,000 (for benchmark function) (45,00×M-Jaya +45,00×SCM) = 9,000 (for OPF problem)

SCM = Sine-cosine mutation operator; M-Jaya = Modified Jaya algorithm

Table 6.2: Mathematical benchmark functions

S. No.	Formulation	Dimension	Search range	fmin
Uni-modal benchmark functions				
1	$F_1(x) = \sum_{i=1}^{n} x_i^2$	200	[-100, 100]	0
2	$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	200	[-10, 10]	0
3	$F_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	200	[-100, 100]	0
4	$F_4(x) = \max_i \{\lvert x_i \rvert, \quad 1 \le i \le n\}$	200	[-100, 100]	0
5	$F_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	200	[-30, 30]	0
6	$F_6(x) = \sum_{i=1}^{n} ([(x_i + 0.5])^2$	200	[-100, 100]	0
7	$F_7(x) = \sum_{i=1}^{n} i x_i^4 + \mathrm{random}[0,1)$	200	[-1.28, 1.28]	0
Multi-modal benchmark functions				
8	$F_8(x) = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	200	[-500, 500]	$-418.982 \times \mathrm{Dim}$
9	$F_9(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	200	[-5.12, 5.12]	0
10	$F_{10}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	200	[-32, 32]	0
11	$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	200	[-600, 600]	0
12	$F_{12}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2 [1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u = (x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < a \end{cases}$	200	[-50, 50]	0

13	$F_{13}(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2\,[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5,100,4)$	200	[-50, 50]	0

Table 6.3: Comparison of SCM-MJ algorithm with M-Jaya and reported algorithms

Fun.	SCM-MJ		M-Jaya		ALO [295]		PSO [295]		SMS [295]	
	ave	Std	ave	std	ave	std	ave	std	ave	std
F1	0.0000	0.0000	0.0088	0.0094	7.8e-07	1.1e-07	23.799	11.721	1039.2	0.4243
F2	0.0000	0.0000	7.6897	1.2159	530.82	222.67	237.87	22.432	1832.4	0.0122
F3	0.0000	0.0000	1.6e+05	1.4e+05	2331.4	507.18	4693.3	503.57	2034.8	0.3780
F4	0.0000	0.0000	30.013	1.5509	30.58	1.1446	40.111	0.5879	300.26	0.0023
F5	188.71	0.2105	627.31	12.737	167.04	49.746	911.23	95.245	3863.5	0.5329
F6	2.5 e-07	1.3 e-07	0.0455	0.0601	7.6e-07	7.3e-08	43.421	14.206	2494.4	0.0003
F7	1.8 e-05	1.0 e-05	0.3724	0.0689	0.0505	0.0144	17.321	4.0133	28.359	1.9e-05
F8	-50837	2395.9	-22549	14867	-44,426	1442.5	-18,136	4962.4	-35,969	0.8765
F9	0.0000	0.0000	1445.3	424.37	613.89	66.795	748.58	24.301	480.01	0.2365
F10	8.8e-16	0.0024	2.3669	1.2515	2.3058	0.2554	15.183	0.5762	17.293	0.0974
F11	0.0000	0.0000	0.0200	0.0391	0.0074	0.0065	3241.2	137.49	4801.5	0.8532
F12	0.7421	2.1e-02	6.4463	1.6378	5.3982	0.5959	4.0e+05	4.7e+05	1.0e+08	1.9e-05
F13	19.772	2.3e-04	154.35	21.675	0.1391	0.2219	1.2e+06	5.8e+05	1.0e+08	1.9e-05
	BA [295]		**FPA** [295]		**CS** [295]		**FA** [295]		**GA** [295]	
	ave	Std	ave	std	ave	std	ave	std	ave	std
F1	1117.3	20731	55. 989	32. 678	3.8e-05	1.8e-05	76.128	1.5744	227.75	186.56
F2	3842.8	468.28	280.6	6.9384	400.10	0.8656	611.19	71.219	6322.6	1092.7
F3	1090.7	475.06	24219	8540	12,957	633.75	14852	6418.4	11,206	3986.1
F4	65.667	2.8293	37.689	2.4572	30.936	1.6877	2.736	0.5472	101.54	2.5321
F5	1410.8	591.07	3150.7	1490.6	332.67	159.88	1321.7	114.76	964.49	748.76
F6	51.205	12.005	166.99	41.109	8.1e-05	4.5e-05	78.42	2.3405	482.56	278.61

F7	2.4344	0.1275	4.8391	1.5354	0.4013	0.0087	0.0273	0.0041	116.56	60.161
F8	-25632	869.47	-45771	3097.8	-52600	156.04	-39,753	649.69	-28,660	1011.0
F9	723.38	100.96	702.95	69.653	541.58	41.889	475.45	28.058	1645.8	37.155
F10	18.159	0.0677	17.544	0.1668	17.654	2.9820	2.4297	0.0385	20.361	0.1425
F11	4937.0	268.42	180.74	36.084	0.0011	0.0011	1.7048	0.0143	3306.8	113.30
F12	1.6e+09	4.2e+08	4.3e+07	3.2e+07	1.0e+10	0.0045	23.426	0.5598	8.1e+09	9.5e+08
F13	2.2e+09	8.8e+08	9.8e+07	3.8e+07	1.0e+10	0.0568	2.8614	0.0568	1.3e+10	1.4e+09

*****ave = average value, std. = standard deviation

The SCM-MJ algorithm is applied subsequently on the two systems (Algerian 59-bus and IEEE 118-bus) to solve the OPF problem. Several trials were taken, but the best results obtained and given in this work are with population size 30 and the maximum number of iterations 150 for both the power systems. The simulation outcomes obtained by the SCM-MJ algorithm are compared with other meta-heuristic algorithms and it is observed that the SCM-MJ algorithm produces better results than its competitors for mathematical benchmark functions as well as for OPF problems. The computational work was carried out on a personal computer having a 1.7 GHz Intel Processor, 4GB RAM, Core i3, and 64-bit operating system using MATLAB-13a computing environment. Several case studies were carried out using SCM-MJ algorithm and are given in Table 6.4.

Table 6.4: Various case studies of Optimal Power Flow problem

Algerian 59-bus system	Case 1 : (FCM)
	Case 2 : (FCM+ W_{TVDM} × TVDM)
	Case 3 : (FCM + W_{RPLM} × RPLM)
IEEE 118- bus system	Case 4 : (FCM)
	Case 5 : (TVDM)
	Case 6 : (RPLM)
	Case 7 : (FCM+ W_{TVDM} × TVD + W_{RPLM} × RPLM)

6.6.1 Algerian 59-bus system

To evaluate the effectiveness of the proposed SCM-MJ algorithm, it is tested for solving the OPF problem in a practical power system, namely, the Algerian 59-bus system. The system data, maximum and minimum limits of the control variables are the same as provided in *Appendix C*. It is worth mentioning that generator at bus No. 13 is not in service. For this system, 30 runs were taken using SCM-MJ and M-Jaya algorithms to solve the different objective functions of the OPF problem and the best results are given here.

6.6.1.1 Case 1# (FCM): Algerian 59-bus system

The proposed SCM-MJ algorithm has been applied to solve the OPF problem in the Algerian 59-bus system to test its performance in solving practical power system problems. Table 6.5 shows the numerical results attained by the SCM-MJ algorithm and other methods mentioned in recent papers, while Table 6.6 shows the OPF results as well as the optimal control variable settings of the SCM-MJ algorithm. The numerical outcomes reveal that the proposed SCM-MJ algorithm produces better results as compared to other meta-heuristic algorithms for solving OPF problems. The convergence characteristic of case 1 is shown in Fig. 6.2.

6.6.1.2 Case 2# (FCM+W_{TVDM} ×TVDM): Algerian 59-bus system

The proposed SCM-MJ algorithm has been applied to solve the OPF problem, which involves the minimization of fuel cost and improvement of voltage profile by minimization of total voltage deviation. In this case, the total voltage deviation and fuel cost obtained by the SCM-MJ algorithm are 1.8815pu and 1718.4893 $/h, respectively. The numerical outcomes of case 2 attained by the proposed method and recent optimization algorithms mentioned in the recent literature are compared in Table 6.5. The OPF results along with optimum control variables settings are given in Table 6.6. The voltage profiles of the base case, achieved by the SCM-MJ and M-Jaya algorithm are presented in Fig. 6.3. This can be observed from Fig. 6.3, that voltages at various load buses are within the specified limits.

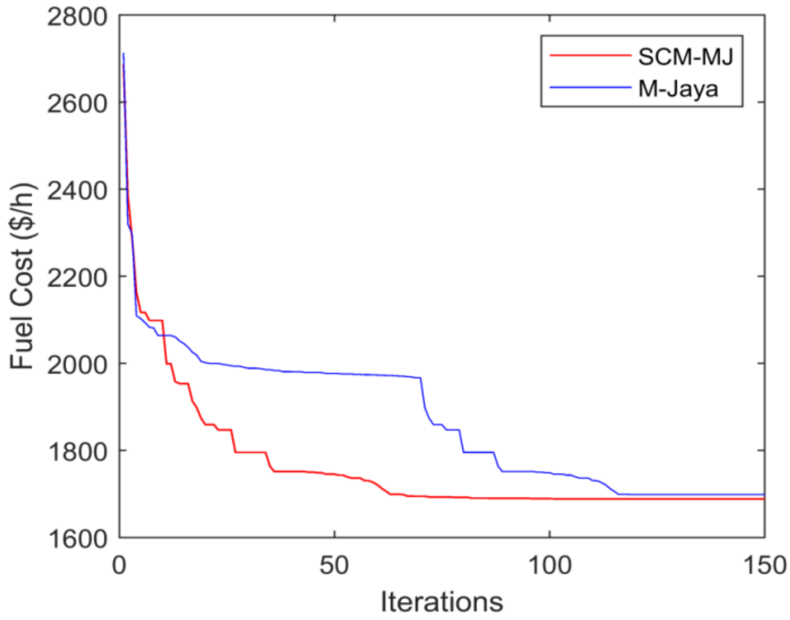


Fig. 6.2: Convergence characteristics of fuel cost for Case 1

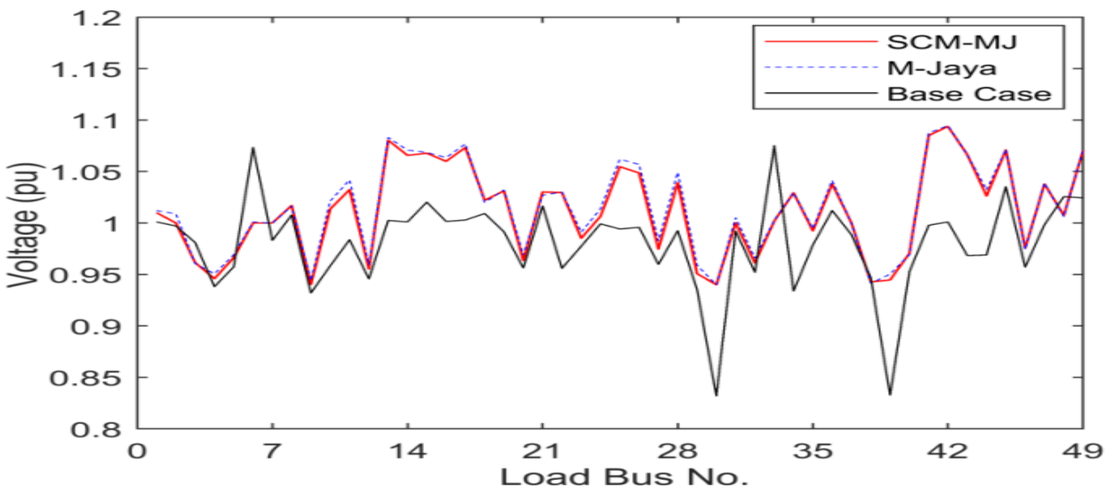


Fig. 6.3: Load bus voltage profile for Case 2

6.6.1.3 Case 3 # (FCM+ W_{RPLM} ×RPLM): Algerian 59-bus system

The main motive of case 3 is to minimize the real power loss along with the fuel cost. The multi-objective function is transformed into a single objective function by using the weighted sum method. In the combined objective function, the value of the weighting factor (W_{RPLM}) assigned to real power loss was 10. The OPF results attained using the SCM-MJ and M-Jaya algorithm are compared with other reported results in Table 6.5. As can be observed from Table 6.5, the SCM-MJ algorithm provided the total fuel cost as 1724.01823$/h and real power loss as 15.4330 MW, while the ESDE-MC algorithm provided the total fuel cost and real power loss as 1719.9456 $/h and 16.1682 MW respectively.

In this case, the real power loss obtained by the proposed algorithm is less than the reported ESDE-MC results, while the fuel cost obtained by the proposed SCM-MJ algorithm is slightly higher than the reported ESDE-MC method [198]. Such type of situations will be only because of the preference given to one objective as compared to the other objective and as discussed above, in this case, the relative weightage given to real power loss is 10 as compared to fuel cost. The OPF results along with the control variable setting for this case also are shown in Table 6.6, while Fig. 6.4 displays the real power loss convergence characteristics of the SCM-MJ and M-Jaya algorithms in this case.

Table 6.5: Comparison of SCM-MJ algorithm for case1-case3 in Algerian 59-bus system

Algorithm	Fuel Cost ($/h)	Voltage (p.u)	Real Power Loss (MW)	COF	Computation Time (Sec)
Case – 1 (FCM)					
SCM-MJ	**1688.5933**	**-**	**-**	**-**	**39.80**
M-Jaya	1689.0281	-	-	-	37.23

SKH [20]	1688.5742	-	-	-	47.32
BHBO [115]	1710.0859	-	-	-	-
ESDE-MC [198]	1688.5586	-	-	-	42.34
ESDE-EC [198]	1690.3171	-	-	-	45.93
ESDE [198]	1692.0624	-	-	-	40.02
Case- 2 (FCM + W_{TVDM} × TVDM)					
SCM-MJ	**1718.48938**	**1.8815**	**-**	**2207.6711**	**39.78**
M-Jaya	1719.8954	1.8842	-	2209.7874	36.09
LCA [147]	1755.5775	1.8404	-	-	-
Case- 3 (FCM + W_{RPLM}× RPLM)					
SCM-MJ	**1724.01823**	**-**	**15.4330**	**1878.3480**	**39.23**
M-Jaya	1719.8684	-	15.9020	1878.8884	36.73
ESDE-MC [198]	1719.9456	-	16.1682	-	127.34
ESDE-EC [198]	1723.9823	-	16.5586	-	137.43
ESDE [198]	1724.6272	-	16.7660	-	120.53

Table 6.6: Control variables settings for Case 1- Case 3 of Algerian 59-bus system

S. No.	Control variable	Minimum Value	Initial Case	Case-1	Case-2	Case-3	Maximum Value
Generator active power output							
1	Pg_2	0.1	0.7	0.23372	0.20114	0.3073	0.7
2	Pg_3	0.3	0.7	1.01775	1.0115	1.06134	5.1
3	Pg_4	0.2	1.15	1.10507	1.20036	1.38107	4.0
4	Pg_{13}	0.15	0	0	0	0	1.5
5	Pg_{27}	0.1	0.4	0.25832	0.35014	0.39958	1.0
6	Pg_{37}	0.1	0.3	0.50955	0.47721	0.43504	1.0
7	Pg_{41}	0.15	1.1	0.97038	0.71526	0.61906	1.4
8	Pg_{42}	0.18	0.7	1.40855	1.49762	1.29505	1.75
9	Pg_{53}	0.3	2	1.03189	1.19992	1.11455	4.5
Generator voltage							
10	Vg_1	0.94	1.06	1.1	1.06605	1.09999	1.1
11	Vg_2	0.94	1.04	1.08796	1.07318	1.09973	1.1
12	Vg_3	0.94	1.05	1.1	1.09944	1.09998	1.1
13	Vg_4	0.94	1.0283	1.09998	1.03878	1.08747	1.1
14	Vg_{13}	0.94	1	1.09878	0.99749	1.1	1.1
15	Vg_{27}	0.94	1.0266	1.09932	1.03703	1.08661	1.1
16	Vg_{37}	0.94	1.0273	1.1	1.02878	1.1	1.1

17	Vg_{41}	0.94	1.0966	1.1	1.01045	1.09404	1.1
18	Vg_{42}	0.94	1.034	1.1	1.1	1.1	1.1
19	Vg_{53}	0.94	1	1.1	1.09991	1.09999	1.1
Fuel Cost ($\h)		-	1943.7010	**1688.5933**	**1718.4893**	**1724.0182**	-
Voltage (pu)		-	1.5757	2.8062	**1.8815**	2.9395	-
Real Power Loss (MW)		-	29.1409	27.6423	24.9567	**15.4330**	-
Pg1(Slack bus)		-	8.2409	58.2193	43.7417	38.2340	-
Combined Objective Function		-	-	-	2207.6711	1878.3480	-

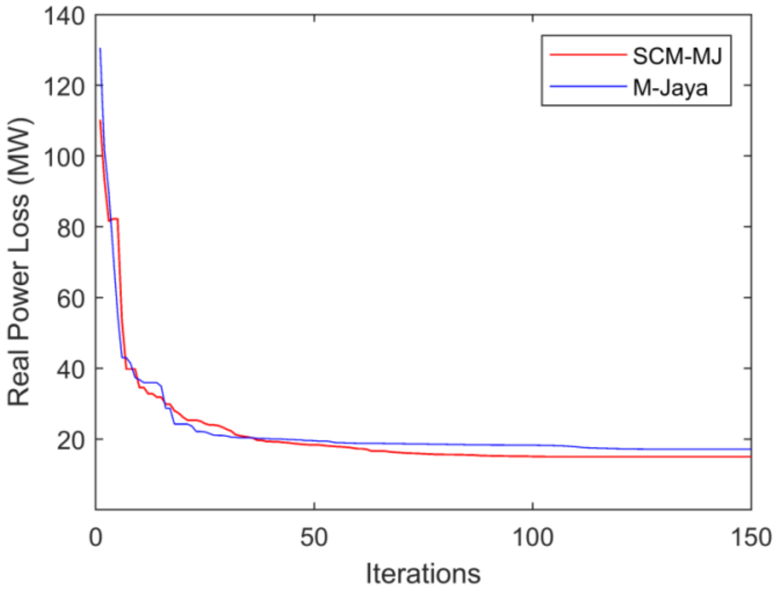


Fig. 6.4: Convergence characteristics of real power loss for Case 3

6.6.2 IEEE 118-bus system:

To evaluate the scalability of the SCM-MJ algorithm and to verify its efficacy to solve large scale problems, the SCM-MJ method was applied to solve the OPF problem in the IEEE 118-bus test system. The system data and maximum and minimum limits of the control variable are given in *Appendix D*. For this system also, 30 runs were taken using the SCM-MJ and M-Jaya algorithm to solve the different objective functions of the OPF problem and the best results are presented here.

6.6.2.1 Case 4 # (FCM): IEEE 118-bus system

As in Case 1, FCM is chosen as the main objective function for the IEEE 118-bus test system in case 4. Table 6.7 displays the OPF outcomes along with the optimal control variable settings of the SCM-MJ algorithm. The OPF results attained by the SCM-MJ technique are compared with the reported results available in recent literature in Table 6.8. The proposed SCM-MJ algorithm provides the minimum fuel cost as compared to other reported results with all the operating constraints within their pre-specified limits. This demonstrates the effectiveness of the SCM-MJ algorithm as compared to the M-Jaya algorithm and its other competitors. Fig. 6.5 represents the fuel cost convergence characteristics for M-Jaya and SCM-MJ algorithms.

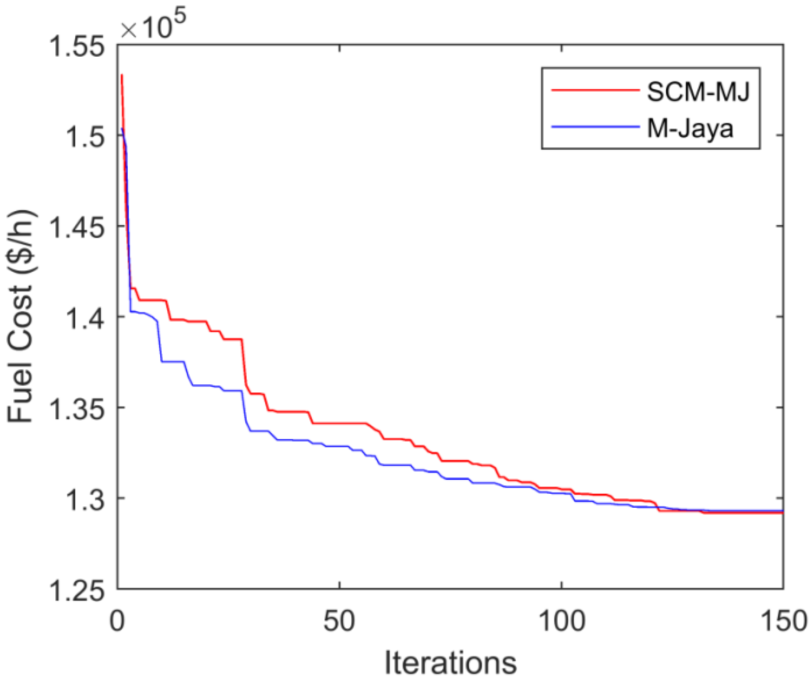


Fig. 6.5: Convergence characteristics of fuel cost minimization for Case 4

6.6.2.2 Case 5#(TVDM): IEEE 118-bus system

The proposed SCM-MJ method has been employed to solve the OPF problem for minimization of voltage deviation from 1.0pu at all the PQ (load) buses. The OPF results along with the optimum value of control variables are shown in Table 6.7. The total voltage deviation at load buses provided by the SCM-MJ algorithm is 0.4366pu. The OPF results of case 5 attained by using the SCM-MJ method, M-Jaya method and other efficient methods reported in the recent literature are compared in Table 6.8. The voltage profile of the base case and this case are displayed in Fig. 6.6. The voltage profile obtained by the proposed SCM-MJ and M-Jaya algorithm shows that all the PQ buses' voltages are within the operating limits.

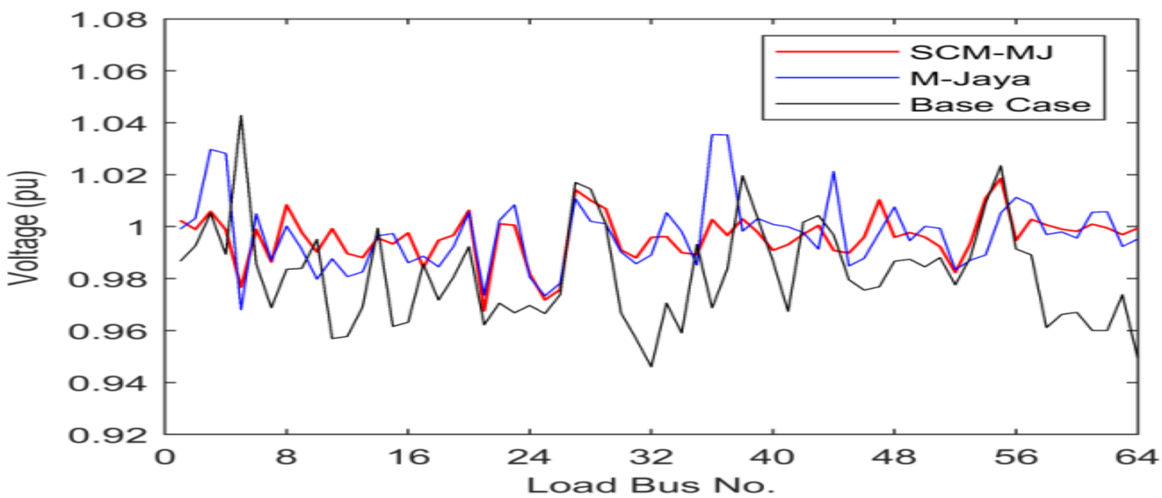


Fig. 6.6: Load bus voltage profile for Case 5

6.6.2.3. Case 6#(RPLM): IEEE 118-bus system

In this case, minimization of real power loss is selected as an objective function. The power loss is significantly improved in this case as compared to the base case. Table 6.7 shows the OPF results with the optimal control variable settings of the SCM-MJ algorithm and Table 6.8 compares the numerical outcomes offered by the SCM-MJ algorithm, M-Jaya algorithm and other reported results. The convergence characteristics of the proposed algorithm are depicted in Fig. 6.7. As can be seen from Fig. 6.7, the proposed SCM-MJ method has offered smooth convergence characteristics as compared to the M-Jaya algorithm.

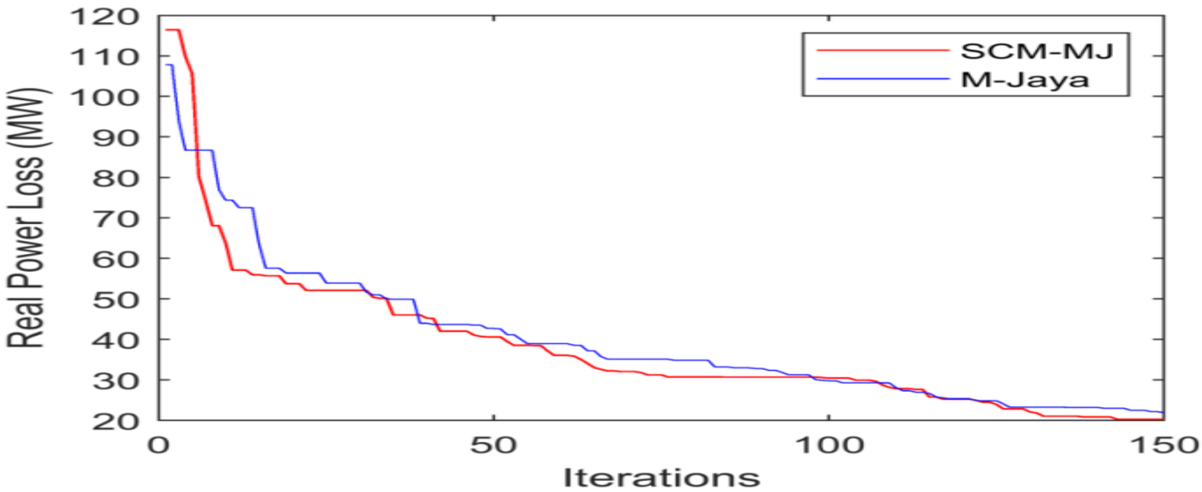


Fig. 6.7: Convergence of SCM-MJ algorithm for Case 6

Table 6.7: Optimum values of control variables of Case 4 - Case 6, IEEE 118-bus system

S. No.	CV	Case 4	Case 5	Case 6	S. No.	CV	Case 4	Case 5	Case 6
1	P_{g1}	0.0074	0.2476	0.7493	68	V_{g32}	1.0064	1.012	1.0013
2	P_{g4}	0.0352	0.0904	0.0879	69	V_{g34}	0.9818	1	1.004
3	P_{g6}	0.1114	0.1369	0.2065	70	V_{g36}	0.9569	0.9964	0.9947
4	P_{g8}	0.1151	0.4611	0.7209	71	V_{g40}	0.9917	1.0088	0.9877
5	P_{g10}	4.0965	3.0116	1.044	72	V_{g42}	1.0561	1.0033	1.0028
6	P_{g12}	0.8912	0.6187	1.7026	73	V_{g46}	0.9457	1.0037	1.0226
7	P_{g15}	0.0537	0.1774	0.887	74	V_{g49}	0.9765	1.0197	1.0049
8	P_{g18}	0.0778	0.1317	0.8205	75	V_{g54}	1.0265	1.0176	1.0166
9	P_{g19}	0.027	0.5426	0.9457	76	V_{g55}	1.0264	0.9804	1.0203
10	P_{g24}	0.2123	0.0001	0.1748	77	V_{g56}	1.0269	0.9938	1.0173
11	P_{g25}	1.8093	1.9346	0.1804	78	V_{g59}	0.9837	0.9547	1.015

12	P_{g26}	2.8809	2.1913	0.2349	79	V_{g61}	0.9705	0.9993	1.0161
13	P_{g27}	0.231	0.4348	0.9624	80	V_{g62}	0.9713	0.9699	1.0192
14	P_{g31}	0.0799	0.0224	0.9218	81	V_{g65}	0.9586	0.9486	1.0223
15	P_{g32}	0.0789	0.0647	0.3108	82	V_{g66}	0.9756	1.0436	1.0162
16	P_{g34}	0.5587	0.2384	1	83	V_{g69}	0.9869	1.0373	1.0126
17	P_{g36}	0.0755	0.5328	0.2322	84	V_{g70}	0.9542	0.9928	1.0159
18	P_{g40}	0.0019	0.7794	0.9251	85	V_{g72}	0.9439	0.9679	1.0153
19	P_{g42}	0.6441	0.1771	0.9828	86	V_{g73}	0.9895	0.9926	1.0463
20	P_{g46}	0.2165	0.2659	0.9008	87	V_{g74}	0.9713	0.9786	1.0228
21	P_{g49}	1.831	1.886	1.403	88	V_{g76}	0.9547	1.0195	1.0024
22	P_{g54}	0.4066	0.4281	1.1292	89	V_{g77}	0.9801	1.0011	1.0069
23	P_{g55}	0.3165	0.6398	0.9997	90	V_{g80}	1.0254	1.0384	1.0177
24	P_{g56}	0.0687	0.1811	0.8698	91	V_{g85}	0.9769	1.0239	0.9996
25	P_{g59}	1.4468	1.1159	2.3818	92	V_{g87}	0.9565	0.9738	1.0269
26	P_{g61}	1.4983	0.9604	0.9092	93	V_{g89}	1.0313	0.9937	0.9859
27	P_{g62}	0.01	0.1131	0.2029	94	V_{g90}	1.0071	0.9824	0.9881
28	P_{g65}	3.2906	3.3113	2.3234	95	V_{g91}	1.022	0.9535	0.9849
29	P_{g66}	3.0704	3.1084	1.8803	96	V_{g92}	1.0584	1.008	0.9934
30	P_{g70}	0.0411	0.1137	0.6109	97	V_{g99}	1.0509	1.0517	0.9888
31	P_{g72}	0.1232	0.0082	0.2463	98	V_{g100}	1.0525	1.007	1.0054
32	P_{g73}	0.1004	0.1719	0.1671	99	V_{g103}	1.0204	1.0391	1.0115
33	P_{g74}	0.568	0.6359	0.6442	100	V_{g104}	0.9664	1.0178	1.0177
34	P_{g76}	0.0944	0.9307	0.5954	101	V_{g105}	0.9723	1.0015	1.007
35	P_{g77}	0.066	0.1893	1	102	V_{g107}	0.9747	1.0339	0.9822
36	P_{g80}	4.0032	3.7289	3.3519	103	V_{g110}	1.0487	0.9994	1.041
37	P_{g85}	0.1829	0.0703	0.4759	104	V_{g111}	1.0114	1.0035	1.0599
38	P_{g87}	0.045	0.0337	0.3066	105	V_{g112}	1.0595	1.0273	1.0288
39	P_{g89}	5.0749	4.05	0.9493	106	V_{g113}	0.9989	0.9884	1.0184
40	P_{g90}	0.0029	0.3006	0.9232	107	V_{g116}	0.9881	1.0167	1.0238
41	P_{g91}	0.1777	0.0136	0.4551	108	T_{5-8}	0.9009	0.9016	0.989
42	P_{g92}	0.0083	0.1151	0.7886	109	T_{26-25}	0.9432	0.9919	0.9057
43	P_{g99}	0.094	0.6149	0.0599	110	T_{30-17}	1.0151	1.019	0.9779
44	P_{g100}	2.678	2.0898	1.697	111	T_{38-37}	1.0627	0.9422	0.9394
45	P_{g103}	0.402	0.0909	0.2765	112	T_{63-59}	1.0973	1.0673	1.0151
46	P_{g104}	0.2142	0.3885	0.121	113	T_{64-61}	1.0682	1.0303	1.0208
47	P_{g105}	0.0959	0.0661	0.8569	114	T_{65-66}	1.0956	1.0847	0.9631
48	P_{g107}	0.1201	0.3794	0.3457	115	T_{68-69}	0.9036	0.9	0.9158
49	P_{g110}	0.1723	0.0102	0.6948	116	T_{81-80}	0.9001	0.9303	1.0363
50	P_{g111}	0.4485	0.361	0.416	117	Q_{C5}	0.136	0.0155	0.2081

51	P_{g112}	0.0194	0.4748	0.2227	118	Q_{C34}	0.0683	0.152	0.0029
52	P_{g113}	0.0271	0.1551	0.3846	119	Q_{C37}	0.1855	0.0305	0.0471
53	P_{g116}	0.0144	0.0216	0.4062	120	Q_{C44}	0.0824	0.042	0.1477
54	V_{g1}	1.0203	0.9991	1.0276	121	Q_{C45}	0.2582	0.1835	0.1186
55	V_{g4}	0.9948	0.9866	0.9998	122	Q_{C46}	0.0141	0.2967	0.0114
56	V_{g6}	1.0054	0.9914	0.9978	123	Q_{C48}	0.0013	0.0142	0.2974
57	V_{g8}	0.959	0.9617	0.9783	124	Q_{C74}	0.1131	0.2324	0.1259
58	V_{g10}	1.0122	0.9651	0.9909	125	Q_{C79}	0.2902	0.2698	0.0911
59	V_{g12}	1.0041	1.0126	1.015	126	Q_{C82}	0.082	0.0363	0.0599
60	V_{g15}	0.9876	1.0004	1.01	127	Q_{C83}	0.0982	0.0217	0.2881
61	V_{g18}	0.9813	0.9885	1.0165	128	Q_{C105}	0.2955	0.024	0.0371
62	V_{g19}	0.9754	1.0178	1.0164	129	Q_{C107}	0.0011	0.0268	0.0484
63	V_{g24}	1.0311	0.9905	0.9927	130	Q_{C110}	0.2277	0.0703	0.0032
64	V_{g25}	1.0273	0.9931	0.9975	Fuel Cost		**129171.96**	130879.62	163639.21
65	V_{g26}	1.0587	0.949	0.9846	TVDM		1.2721	**0.4366**	0.6099
66	V_{g27}	1.0253	0.9971	1.0026	RPLM		114.5312	85.8153	**19.1525**
67	V_{g31}	0.9954	1.0021	1.0018	Pg69		459.6014	439.9788	52.9582

Table 6.8: Comparison of SCM-MJ algorithm for Case4 -Case6 in IEEE 118-bus system

Algorithm	Fuel Cost ($/h)	TVDM (pu)	RPLM (MW)	COF	Computation Time (Sec)
Case – 4 (FCM)					
SCM-MJ	**129171.96**	**-**	**-**	**-**	**63.85**
M-Jaya	129248.10	-	-	-	59.79
Rao-1	129220.67	-	-	-	164.19
Rao-2	129256.52				169.24
Rao-3	129241.17				167.33
NLP [27]	129700.00	-	-	-	0.80
QP [27]	129600.00	-	-	-	0.36
ALC-PSO [189]	129546.08	-	-	-	-
MSCA [193]	129620.22	-	-	-	-
SCA [193]	129622.65	-	-	-	-
IMFO [225]	131820.00	-	-	-	-
FAHSPSO-DE [267]	129519.38	-	-	-	64.93
PSOGSA[268]	129733.58	-	-	-	-
Interior point [296]	129720.70	-	-	-	0.13

Case- 5 (TVDM)					
SCM-MJ	**-**	**0.4366**	**-**	**-**	**62.98**
M-Jaya	-	0.6771	-	-	60.08
ALC-PSO [189]	-	0.4412	-	-	-
MSCA [193]	-	0.995	-	-	-
SCA [193]	-	1.32	-	-	-
Case- 6 (RPLM)					
SCM-MJ	**-**	**-**	**19.1525**	**-**	**63.19**
M-Jaya	-	-	21.6419	-	59.07
MSCA [193]	-	-	77.0873	-	-
SCA [193]	-	-	77.1113	-	-
QOTLBO [221]	-	-	35.3191	-	-
TLBO [221]	-	-	36.8482	-	-
EGA [297]	-	-	31.3519	-	-
DE-HS [297]	-	-	30.78047	-	-

6.7 STATISTICAL ANALYSIS

Thirty separate trials for the same population size and number of iterations were conducted for each case of both the power systems. Tables 6.9 shows the results of the 30 trials, which were used to measure the best, worst, average (mean), and standard deviation (SD). In all the cases, the lowest values of the best, worse, average, and standard deviation of the SCM-MJ algorithm are the clear evidence of statistically significant outcomes from the proposed SCM-MJ method. The lowest values of the best, worst, average, and standard deviation offered by the SCM-MJ algorithm demonstrate that the proposed SCM-MJ algorithm provides statistically significant results in all the cases. This proves the strength of the proposed SCM-MJ algorithm.

Table 6.9: Statistical analysis of various cases using SCM-Jaya and M-Jaya algorithms

Algorithm	Algerian 59-bus system				IEEE 118-bus system			
	Best	Worst	Mean	Std.	Best	Worst	Mean	Std.
Case 1					Case 4			
SCM-MJ	1688.5933	1689.0236	1688.7502	0.0330	129171.96	129188.14	129181.62	9.190
M-Jaya	1689.0281	1690.2490	1689.9762	0.0372	129248.10	129264.24	129255.09	9.276
Case 2					Case 5			
SCM-MJ	2207.6711	2210.9225	2208.2497	0.0290	0.4366	0.4401	0.4386	0.029
M-Jaya	2210.0867	2214.7244	2212.9852	0.0341	0.6771	0.6779	0.6775	0.034
Case 3					Case 6			
SCM-MJ	1878.3480	1880.1783	1879.9610	0.0271	19.1525	20.7123	19.6571	0.028
M-Jaya	1862.9864	1864.7612	1864.0213	0.0421	21.6419	23.0154	22.1765	0.031

*std. = standard deviation

6.8 SUMMARY

Like other population-based algorithms, the Jaya algorithm sometimes suffers from premature convergence. A versatile combination of two meta-heuristic algorithms may overcome their common weaknesses while taking advantage of the strengths of the two algorithms. In this chapter, a sine-cosine mutation-based modified Jaya algorithm for solving the OPF problem has been discussed in detail. The suggested SCM-MJ algorithm is found to be faster and immune to the local optima trapping as compared to the classical Jaya algorithm. The proposed SCM-MJ algorithm aims to maintain the diversity of the solutions throughout the search to avoid sub-optimal solutions, and find near-global optimum solution.

To test the efficacy of the suggested SCM-MJ method, it is applied to calculate the mean value and standard deviations using 13 benchmark functions. Observations of the numerical results shown in the chapter prove the dominance of the SCM-MJ algorithm over eight well-known optimization methods reported in the recent publications: ALO, BA, CS, FPA, FA, GA, M-Jaya, PSO, and SMS. Later, the proposed algorithm was implemented in the Algerian 59-bus and IEEE 118-bus systems for solving the OPF problem for minimization of fuel cost, voltage profile improvement, and real power loss minimization. A comparison of the optimization results acquired from the SCM-MJ algorithm with those of modern meta-heuristic optimization approaches published in recent literature demonstrates that the proposed SCM-MJ algorithm is highly efficient and robust over other recently developed popular algorithms.

The statistical analysis indicates that the SCM-MJ method is a reliable and robust optimization algorithm over other modern meta-heuristic optimization approaches proposed in recent literature. The lowest values of the best, worst, average, and standard deviation given by the SCM-MJ algorithm demonstrate that the proposed SCM-MJ solution provides statistically significant results in all the cases of OPF problems. This confirms the effectiveness of the SCM-MJ algorithm to solve the large-scale complex optimization problem.

CHAPTER 7

HYBRID JAYA ALGORITHM FOR OPF INCORPORATING DISTRIBUTED GENERATION

CHAPTER 7

HYBRID JAYA ALGORITHM FOR OPF INCORPORATING DISTRIBUTED GENERATION

7.1 INTRODUCTION

Recently, meta-heuristic algorithms hybridization has become more popular because of its improved ability to deal with complex optimization problems. These hybrid algorithms are highly flexible, which means that they are appropriate to solve various types of optimization problems, including linear problems, non-linear problems, and complex constrained optimization problems.

In this chapter, a hybrid Jaya-Powel's Pattern Search (Jaya-PPS) algorithm combining the Jaya algorithm with Powell's Pattern Search algorithm has been presented to solve the OPF problem with and without distributed generation (DG) in a power system. The aim to incorporate PPS with Jaya is to combine the benefits of both the algorithms. Three variants of the Jaya-PPS algorithm, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 are developed by incorporating hybridization in different manners. When any hybrid algorithm is developed for solving an optimization problem, some options to incorporate hybridization should also be tried to obtain the best one. To demonstrate the efficacy of the proposed algorithm and its potential to solve OPF problems with and without DG, it is tested on the standard IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems for minimization of fuel cost, emission cost, real power loss, and total voltage deviation simultaneously by combining these objective functions. The obtained results of the three versions of Jaya-PPS algorithm are compared to the Dragonfly Algorithm, Grey

Wolf Optimization algorithm, Jaya algorithm and already published results using other reported methods.

7.2 JAYA ALGORITHM

Jaya algorithm, recently developed by Rao [293] is an efficient meta-heuristic optimization algorithm. The Jaya algorithm is an algorithm-specific parameter-less algorithm like the TLBO algorithm. The main advantage of the Jaya algorithm over most of the other meta-heuristic algorithms is that algorithm operations do not require algorithm-specific parameter tuning other than population size and maximum iterations. Hence, it is simple to implement this algorithm for solving various kinds of optimization problems.

Initial population '*p*' is randomly generated within the upper and lower limits of the control variables and is updated as per Eq. (7.1). The best and worst solutions are determined based on the fitness values of the objective function.

Let, the number of design variables is '*m*' (i.e. j =1, 2, 3…, m) and '*n*' is the population size (k =1, 2…, n). Let $J_{i,j,k}$ represents the value of the j^{th} variable for k^{th} candidate during the i^{th} iteration, and then this value is modified as (7.1)

$$J_{i+1,j,k} = J_{i,j,k} + \gamma_{i,j,1}(J_{i,j,B} - abs(J_{i,j,k})) - \gamma_{i,j,2}(J_{i,j,W} - abs(J_{i,j,k})) \qquad (7.1)$$

Where, $J_{i,j,W}$ and $J_{i,j,B}$ are the worst candidate and best candidate value of variable j respectively. The updated value of $J_{i,j,k}$ is $J_{i+1,j,k}$, and throughout the i^{th} iteration, $\gamma_{i,j,1}$ and $\gamma_{i,j,2}$ are the two random numbers between 0 and 1, for the j^{th} variable.

7.3 POWELL'S PATTERN SEARCH

Powell's pattern search (PPS) was proposed by Powell in 1962. This method is an expansion of the basic pattern search method. It is based on the conjugate direction method and is a derivative-free optimization technique. PPS with a meta-heuristic algorithm offers a flexible, balanced operator to enhance local search capability in contrast to other meta-heuristic algorithms. The following is the summary of the PPS algorithm underlying mechanism [298], [299].

The search direction for l^{th} coordinate for g^{th} dimension of the *'n'* dimension search space can be defined as:

$$S_g^l = \begin{cases} 1 & ; g = l \\ 0 & ; g \neq l \end{cases} (g = 1,2,..n; \quad l = 1,2,..n) \tag{7.2}$$

The step length λ_g^* for g^{th} decision variable can be determined as:

$$\lambda_g^* = \lambda_g^{min} + \text{rand} \times \left(\lambda_g^{max} - \lambda_g^{min}\right)(g = 1,2,\dots n) \tag{7.3}$$

Here, $\lambda_g^{min}, \lambda_g^{max}$ is the minimum and maximum step length for g^{th} decision variable, respectively. The decision variable (X_g) is modified once along the coordinate direction (l) as:

$$X_g = X_g + \lambda_g^* \times S_g^l \qquad (g = 1,2,\dots n) \tag{7.4}$$

The vector of control variables is modified based on the minimum objective function value. For all 'n' coordinates, this process is continued. The pattern search direction is obtained for the next optimization cycle as:

$$S_g^l = X_g - Z_g (g = 1,2,..n; \quad l = n+1) \tag{7.5}$$

where Z_g is the initial value of the decision variable X_g. Additionally, one of the coordinate's directions is discarded in the direction of pattern 'm' as:

$$S_g^m = S_g^l(g = 1, 2, .. n; \quad l = n + 1) \tag{7.6}$$

The process is continued till the entire direction of the coordinate is discarded and the entire operations restart in one of the coordinate directions again. Finally, until the PPS method has reached maximum iterations, the process of updating continues.

7.4 HYBRID JAYA-PPS ALGORITHM

Jaya algorithm has a strong capability to explore the search space globally, but sometimes it suffers from the issue of premature convergence and it can be stuck simply in local optima. To overcome this problem and to make this algorithm more efficient, a hybrid Jaya algorithm that combines the Jaya algorithm and PPS algorithm is developed in this chapter. The aim to incorporate PPS with Jaya is to combine the benefits of both the algorithms. The integration of the local search procedure (Powell's Pattern Search) into the classical Jaya algorithm has been carried out in three different ways, which resulted in three variants termed Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3. To evaluate the performance of these variants, the common controlling parameters and the total number of function evaluations (NFE) used in the three variants are set to be the same as that of the classical Jaya algorithm. The NFE has been used as a reference to the check efficiency of various algorithms in this work.

In the first strategy which is in Jaya-PPS1, the Jaya algorithm and PPS algorithm have been applied sequentially in each iteration. The optimal setting of control variables as provided by the Jaya algorithm is used as the initial point setting for the PPS technique to acquire a better solution around this solution by applying the PPS algorithm for a pre-defined number of function evaluations. This better solution as provided by the PPS technique replaces the earlier one in the population of the Jaya algorithm and is used for further modification in the next iteration by the Jaya algorithm. This procedure is repeated for a pre-specified number of iterations. The flow chart of the proposed hybrid Jaya-PPS algorithm is shown in Fig. 7.1.

In the second strategy (Jaya-PPS2), the Jaya algorithm and PPS algorithm have been applied sequentially after exploiting the 80% problem-solving capability of the Jaya algorithm i.e. on the solution achieved by applying the Jaya algorithm for 80% iterations. In other words, the optimization process has been divided into two steps. In step1 (for 80 % of $Iter_{max}$), only the Jaya algorithm has been applied, while in step 2 (for the remaining 20% of iterations), Jaya and PPS algorithms both have been applied sequentially as in the case of Jaya-PPS1.

In the third strategy (Jaya-PPS3), the PPS algorithm has been applied considering its initial point as the solution offered by the Jaya algorithm after applying it for 90% iterations. In this case, also, the optimization process is a two-step process. In step1 (first 90 % of $Iter_{max}$), only the Jaya algorithm has been applied. However, in step 2 (remaining 10% of iterations), Jaya and PPS algorithms both have been applied sequentially with the optimal setting of control variables offered by the Jaya algorithm as the initial point for it.

Computational Steps for hybrid Jaya-PPS Algorithm

The computational steps of this algorithm are summarized as follows:

i. Initialize the population having control variables and set maximum iteration count $Iter_{max}$ and the number of function evaluations *PSFE* for PPS method.

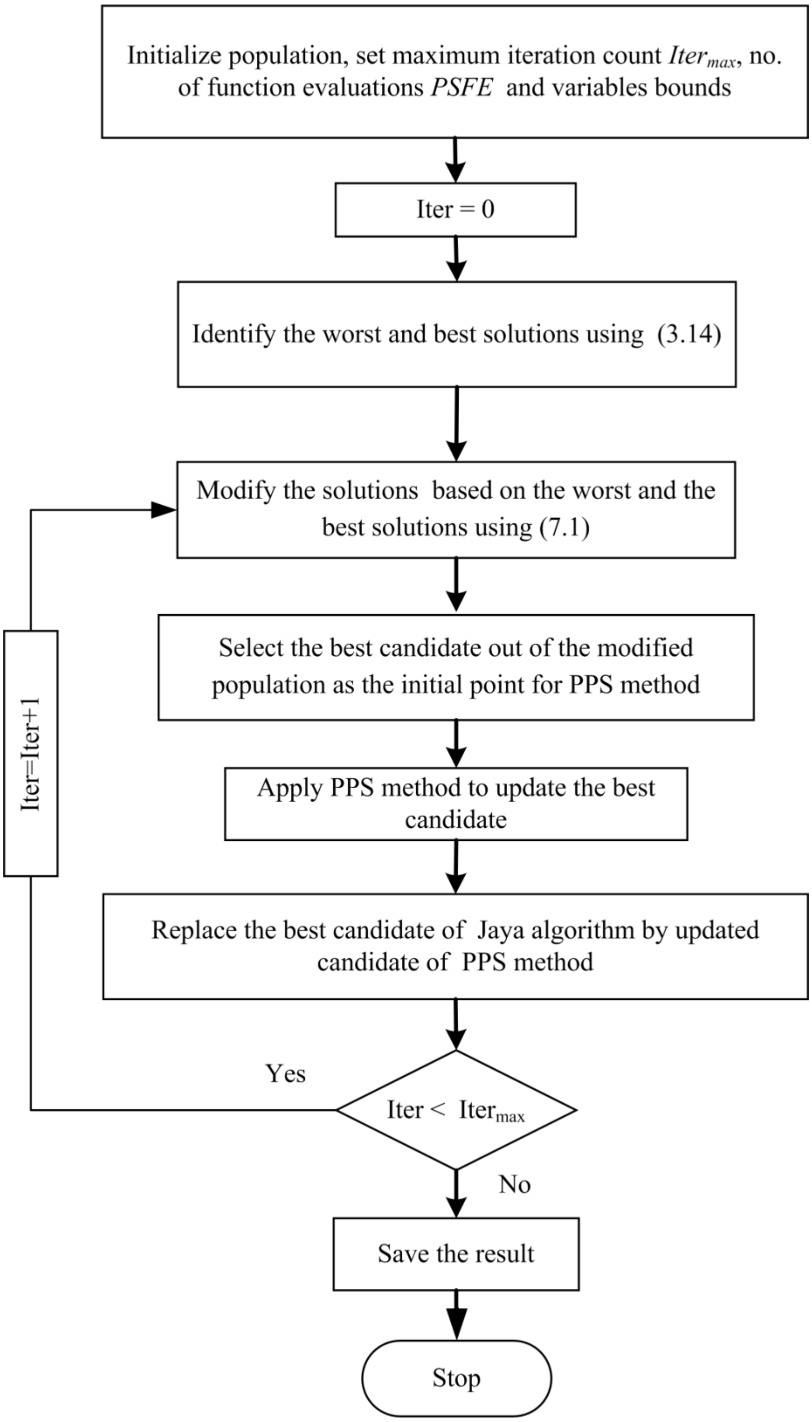


Fig. 7.1: Flowchart of the proposed hybrid Jaya-PPS algorithm

ii. Set iteration count *Iter* = 0.

iii. Identify the solutions which are worst and best in the population by observing the value of the extended objective function (3.14).

iv. Modify the solutions based on the worst and the best solutions using (7.1).

v. If the modified solution is found to be better than the previous solution, then move to step *vi*, otherwise move to step *vii*.

vi. Replace the previous solution with the modified solution. Move to step *viii*.

vii. Keep the previous solution.

viii. Select the best solution found by the Jaya algorithm so far as the initial point for the PPS method and apply the PPS method for *PSFE* to attain a better solution.

ix. Modify the population of the Jaya algorithm by replacing the best solution of the Jaya algorithm by that obtained by the PPS method.

x. Increase the iteration number by 1, i.e. $Iter = Iter + 1$.

xi. If $Iter < Iter_{max}$, then go to step *iii*, otherwise go to step *xii*.

xii. Stop. The optimal solution is achieved.

7.5 OPF RESULTS AND DISCUSSION:

Three standard test systems, IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems are used to evaluate the effectiveness of the three versions of hybrid Jaya-PPS algorithm, Jaya algorithm, Dragonfly Algorithm, and Gray wolf optimization algorithm for solving OPF problems with and without integration of DG. The emission and fuel cost coefficients, control variables' limits, line data, bus data along with their initial settings for the IEEE 30-bus system are given in *Appendix A*. The combined objective function (COF), COF is obtained by considering the weighting factors W_{EM}, W_{RPLM}, and W_{TVDM} as 19, 22, and 21 respectively [262].

The IEEE 30-bus system is modified by including DG based on renewable energy technologies. The optimal location of the DG is selected based on the sensitivity of active power loss and generation cost to each active and reactive power [19] and it is bus no. 30. At this bus, the capacity selected for the type 1 DG unit is 5MW, in this work.

The IEEE 57-bus test system has 07 generating units and 80 branches. The limits for voltage magnitude at all the buses of the system are considered to be 0.94 pu and 1.06 pu. The limits for the tap changing transformers' tap settings are taken as 0.9 pu and 1.1pu. The generator coefficients, lower and upper limits of all the 33 control variables, and system data (bus data, line data) along with their initial settings are given in *Appendix B*. The active and reactive power demands of this system are 12.508 pu and 3.364 pu respectively at 100 MVA base. In case of the IEEE 57-bus system, the combined objective function, COF is obtained by considering the weighting factors W_{EM}, W_{RPLM}, and W_{TVDM} as 300, 30, and 600 respectively in this work. This system is modified by integrating two type 1 DGs optimally at bus nos. 35 and 36 with capacities of 47.9067MW and 47.2636 MW respectively [300].

To evaluate the scalability of proposed algorithms and to prove their efficacy to solve large-scale problems, all the three variants of Jaya-PPS algorithms, GWO and DA algorithm were applied to solve the OPF problem in the IEEE 118-bus system. The system data, generator coefficients, lower and upper limits of all the 130 control variables along with their initial settings are given in *Appendix D*. The active and reactive power demands of this test system are 42.42 pu and 14.38 pu respectively at 100 MVA base.

To demonstrate the effectiveness of the proposed algorithm, five cases are considered as given below:

Case 1: OPF no DG in IEEE 30-bus system

Case 2: OPF with DG in IEEE 30-bus system

Case 3: OPF no DG in IEEE 57-bus system

Case 4: OPF with DG in IEEE 57-bus system

Case 5: OPF no DG in IEEE 118-bus system

Various trials were carried out with different population sizes and no. of maximum iterations. The best results achieved and reported in this paper are for population size (*pop*) = 30 and maximum no. of iterations ($Iter_{max}$) =200 for IEEE 30-bus system and *pop* = 40 and $Iter_{max}$ = 300 for IEEE 57-bus and IEEE 118-bus systems. All these algorithms were developed using Matlab 13a version in a 3.6 GHz Intel Processor, 8GB RAM Core i7 and 64-bit operating personal computer.

To compare the performance of various algorithms, all the algorithms were run for the same number of function evaluations (NFE) which is equal to 6000 in case of the IEEE 30-bus system and 12,000 in the case of the IEEE 57-bus and IEEE 118-bus systems. Details of the implementation of various algorithms and the inclusion of PPS in the three variants of hybrid Jaya-PPS algorithms are given in Table 7.1.

Table 7.1: Details of DA, GWO, Jaya, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 algorithms

IEEE-30 bus system			
Algorithm	**Population**	**Iterations**	**Total NFE = 6000**
Dragonfly Algorithm	30	200	30×200
GWO Algorithm	30	200	30×200
Jaya Algorithm	30	200	30×200
Jaya-PPS1	30	200	(30JFE+30PSFE)×100
Jaya-PPS2	30	200	30JFE×160+(30JFE+30PSFE)×20
Jaya-PPS3	30	200	30JFE×180+(30JFE+30PSFE)×10
IEEE-57 bus & IEEE 118 bus system			

Algorithm	Population	Iterations	Total NFE = 12000
Dragonfly Algorithm	40	300	40×300
GWO Algorithm	40	300	40×300
Jaya Algorithm	40	300	40×300
Jaya-PPS1	40	300	(40JFE+40PSFE)×150
Jaya-PPS2	40	300	40JFE×240+(40JFE+40PSFE)×30
Jaya-PPS3	40	300	40JFE×270+(40JFE+40PSFE)×15

*JFE=Jaya Function Evaluations,

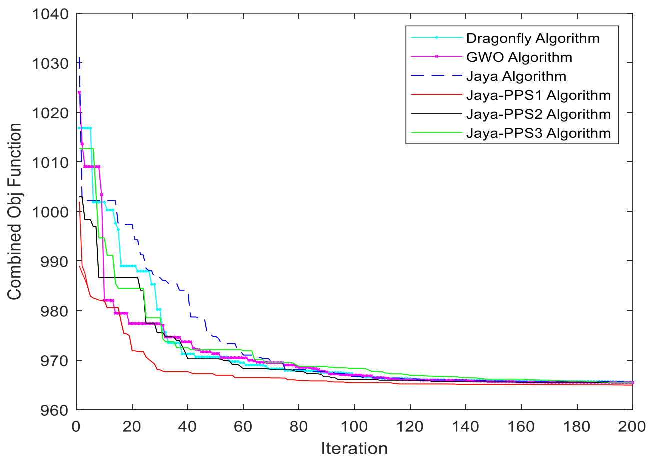
For various cases, 50 runs were taken using DA, GWO, Jaya, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 algorithms to solve the OPF problem with the above-mentioned objective functions. The best results obtained out of the 50 runs are given here.

7.5.1 Case 1: OPF no DG in IEEE 30-bus system

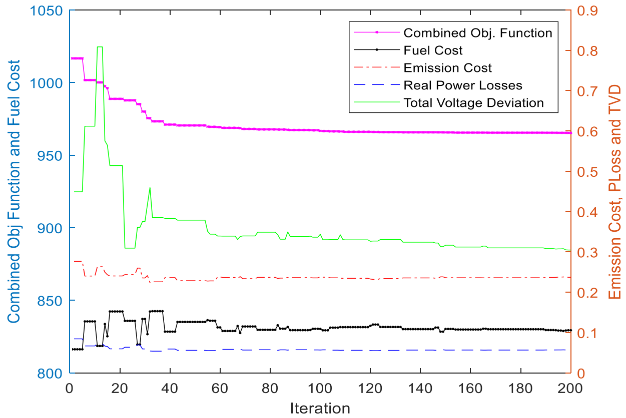
The proposed hybrid Jaya-PPS algorithms, GWO algorithm, Dragonfly algorithm, and Jaya algorithm were applied to solve the OPF problem for the combined objective function consisting of the fuel cost, emission, real power loss, and total voltage deviation. The results obtained using these methods along with optimal control variable settings are shown in Table 7.2. The simulation outcomes demonstrate that Jaya-PPS1 is superior to other techniques. Its combined objective function (964.962) is less than those achieved using other approaches without violation of the pre-specified constraints. Results of the hybrid Jaya-PPS algorithms are compared with DA, GWO, Jaya, and also with the reported results available in recent literature in Table 7.3, and it is found that the proposed Jaya-PPS1 algorithm provided the minimum value of the COF.

Convergence characteristics of DA, GWO, Jaya, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 algorithms are shown in Fig. 7.2(a). As can be observed from Fig. 7.2 (a), the Jaya-PPS1 algorithm has offered the best convergence characteristic. During the iterative process for these six algorithms, the trajectories of all the components of the COF (e.g.

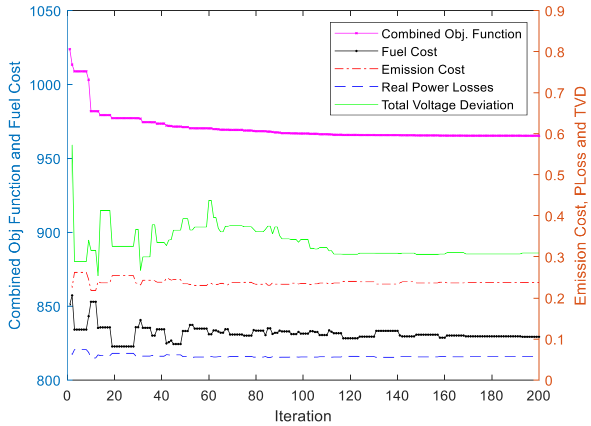
fuel cost, emission, real power loss, and total voltage deviation) are shown in Figs. 7.2(b-g). As these figures show, the Jaya-PPS1 algorithm has given smooth convergence curves with no oscillations and a fast convergence speed in comparison with other methods. Fig. 7.3 shows the voltage profile provided by the proposed Jaya-PPS1 algorithm, which indicates that all the bus voltages are within the specified upper and lower limits.



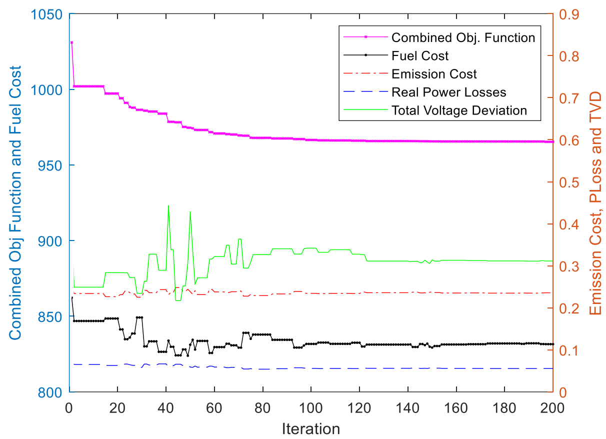
(a) Convergence Characteristics for various algorithms for Case 1



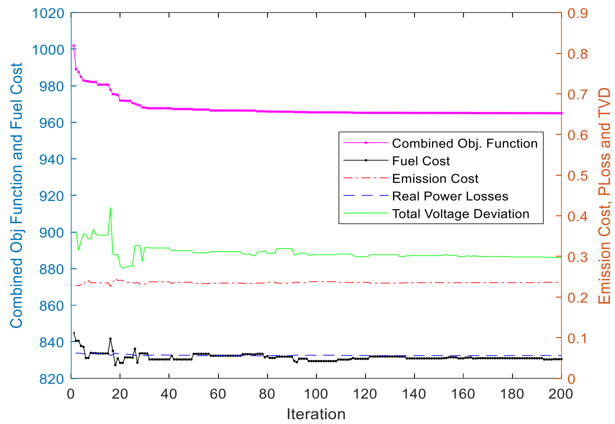
(b) Dragonfly Algorithm



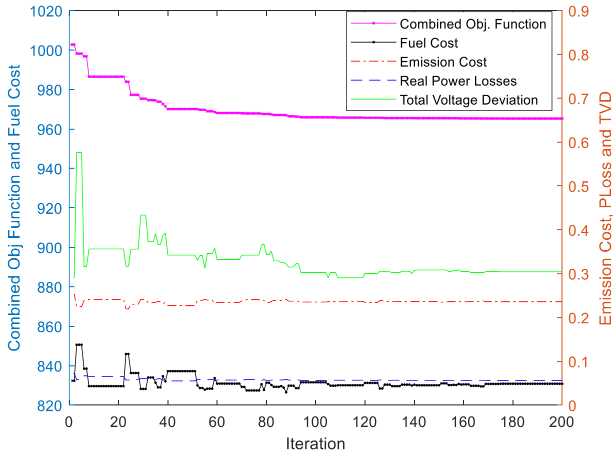
(c) GWO algorithm



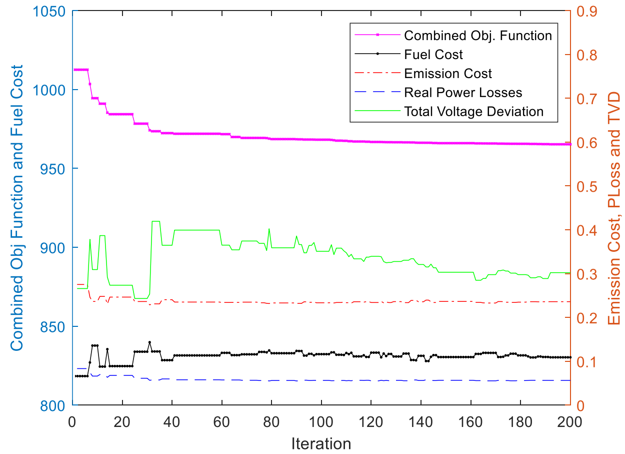
(d) Jaya Algorithm



(e) Jaya-PPS1 algorithm



(f) Jaya-PPS2 algorithm



(g) Jaya-PPS3 algorithm

Fig. 7.2: Convergence and variation of objective functions, IEEE 30-bus system, Case 1

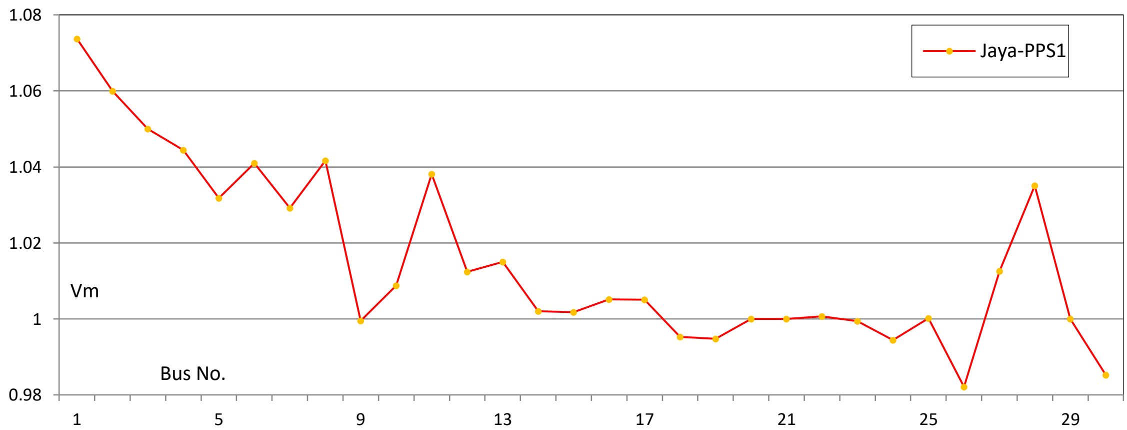


Fig. 7.3: Voltage profile obtained using Jaya-PPS1 for Case 1

Table 7.2: OPF results with control variables settings in IEEE 30-bus system (Case 1)

S. No	Control Variable	DA	GWO	Jaya	Jaya-PPS1	Jaya-PPS2	Jaya-PPS3
Generator real power output							
1	Pg_2	0.5265	0.5255	0.5167	0.5255	0.5279	0.5210
2	Pg_5	0.3114	0.3106	0.3221	0.3143	0.3146	0.3096
3	Pg_8	0.3500	0.3500	0.3497	0.3499	0.3500	0.3499
4	Pg_{11}	0.2577	0.2625	0.2726	0.2698	0.2750	0.2701
5	Pg_{13}	0.2167	0.2118	0.2071	0.2085	0.2035	0.2172
Generator voltage setting							
6	Vg_1	1.0742	1.0745	1.0728	1.0736	1.07302	1.0710
7	Vg_2	1.0597	1.0603	1.0590	1.0599	1.05934	1.0586
8	Vg_5	1.0312	1.0347	1.0337	1.0317	1.03193	1.0318
9	Vg_8	1.0414	1.0423	1.0415	1.0416	1.04188	1.0419
10	Vg_{11}	1.0545	1.0534	1.0501	1.0381	1.04865	1.0404
11	Vg_{13}	1.0160	1.0193	1.0273	1.0150	1.02283	1.0225
Transformer tap setting							
12	$T_{6\text{-}9}$	1.0677	1.0890	1.100	1.0998	1.0997	1.100
13	$T_{6\text{-}10}$	1.0140	0.9811	0.9483	0.9557	0.9459	0.9310
14	$T_{4\text{-}12}$	1.0216	1.0123	1.0258	1.0253	1.0272	1.0334
15	$T_{28\text{-}27}$	1.0018	1.0072	1.0034	1.0021	1.0046	1.0035
Shunt VAR source setting							
16	Qc_{10}	0.0496	0.0486	0.0000	0.0474	0.0038	0.0002
17	Qc_{12}	0.0002	0.0009	0.0005	0.0486	0.0445	0.0413
18	Qc_{15}	0.0363	0.0186	0.0496	0.0355	0.0003	0.0475
19	Qc_{17}	0.0487	0.0318	0.0500	0.0500	0.0499	0.0448
20	Qc_{20}	0.0499	0.0482	0.0498	0.0500	0.0464	0.0446
21	Qc_{21}	0.0500	0.0500	0.0499	0.0500	0.0492	0.0494
22	Qc_{23}	0.0489	0.0462	0.0173	0.0393	0.0498	0.0399
23	Qc_{24}	0.0497	0.0500	0.0498	0.0500	0.0470	0.0472
24	Qc_{29}	0.0253	0.0322	0.0303	0.0251	0.0290	0.0292
COF		965.351	965.302	965.286	**964.962**	965.267	965.255
Fuel Cost		829.358	829.239	831.549	**830.467**	830.850	830.290
Emission		0.237	0.237	0.235	**0.236**	0.235	0.235
Real Power Loss		5.685	5.684	5.578	**5.625**	5.616	5.642
Total Voltage Deviation		0.304	0.309	0.311	**0.297**	0.304	0.302
Pg_1 (Slack Bus Power)		122.838	123.021	122.147	**122.183**	121.891	122.250
L-Index (LI)		0.138	0.138	0.139	**0.138**	0.139	0.139

Table 7.3: Comparison of OPF Results in IEEE 30-bus system, case 1

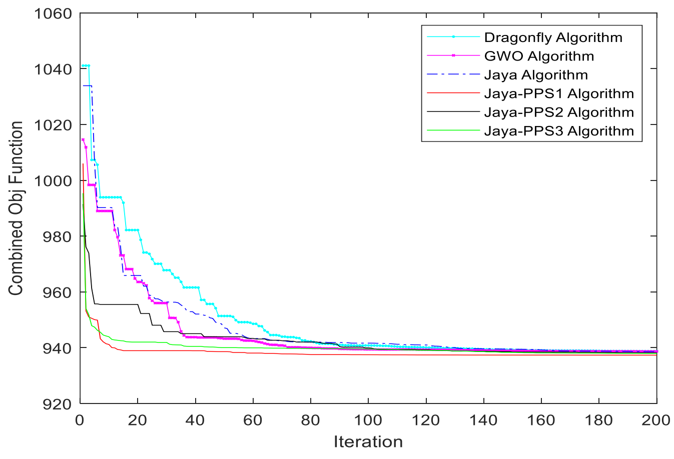
Algorithm	**COF**	**Fuel Cost**	**Emission**	**RPL**	**TVD**
Base Case	1336.645	902.004	0.222	5.842	1.160
DA	965.351	829.358	0.237	5.685	0.304
GWO	965.302	829.239	0.237	5.684	0.309
Jaya	965.286	831.549	0.235	5.578	0.311
Jaya-PPS1	**964.962**	**830.467**	**0.236**	**5.625**	**0.297**
Jaya-PPS2	965.267	830.850	0.235	5.616	0.303
Jaya-PPS3	965.255	830.290	0.235	5.642	0.302
MSA [19]	*	838.923	0.211	5.614	0.153
ABC [19]	*	835.523	0.207	5.394	0.138
CSA [19]	*	834.512	0.209	5.425	0.137
GWO [19]	*	851.049	0.205	4.892	0.201
BSOA [19]	*	830.711	0.225	5.744	0.183
MJAYA[19]	*	833.341	0.206	5.177	0.119
MOEA/D-SF [125]	-	883.322	0.218	4.452	0.132
MSA [162]	965.290	830.639	0.252	5.621	0.293
MPSO [162]	986.006	833.680	0.252	6.524	0.189
MDE [162]	973.611	829.094	0.257	6.056	0.303
MFO [162]	965.807	830.913	0.252	5.597	0.331
FPA [162]	971.907	835.369	0.247	5.515	0.496
GA [225]	-	830.580	0.252	5.577	0.308
MGOA [226]	-	829.963	0.252	5.634	0.291
GOA [226]	-	831.412	0.251	5.571	0.332
FKH [262]	-	828.327	0.254	5.382	0.492
KH [262]	-	827.705	0.252	5.497	0.493
FA [262]	-	829.577	0.252	5.510	0.566
MOMICA [301]	-	830.188	0.252	5.585	0.297
MOICA[301]	-	831.225	0.267	6.022	0.404
MNSGA-II [301]	-	834.561	0.252	5.660	0.430
BB-MOPSO [301]	-	833.034	0.247	5.650	0.394
NKEA [301]	-	834.643	0.249	5.893	0.444

*****Different weighting factors; MSA= Moth swarm algorithm, MPSO= Modified PSO; MDE = Modified DE; MFO = Moth-Flame Optimization; FPA = Flower Pollination Algorithm; ABC= Artificial bee colony; CSA= cuckoo search algorithm; BSOA= backtracking search optimization algorithm; FFA =Firefly algorithm; KH = krill herd; MOICA = Multi-Objective Imperialist Competitive Algorithm; MNSGA-II = modified NSGA-II, BB-MOPSO =bare bones multi-objective PSO; NKEA = Neighborhood knowledge-based evolutionary algorithm; GA= genetic algorithm; MGOA= modified grasshopper optimization

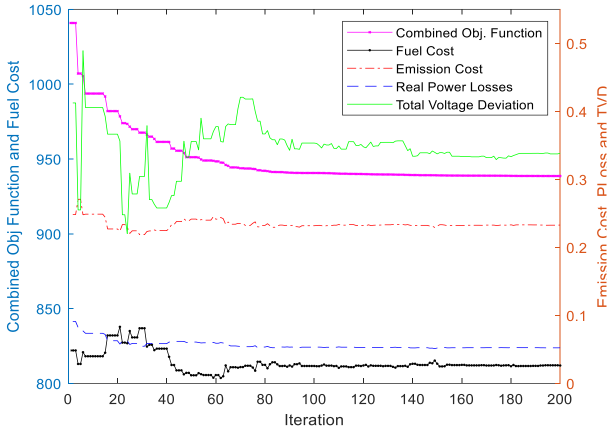
7.5.2 Case 2: OPF with DG in IEEE 30-bus system

In this case, the various algorithms were applied to solve the OPF problem incorporating one type 1 DG with the same COF. In Table 7.4, the results of this case are shown for all the six algorithms along with optimal control variable settings. Table 7.4 shows that Jaya-PPS1 algorithm is more efficient in solving the OPF problem as compared to other methods. The combined objective function value obtained using the Jaya-PPS1 algorithm is 937.340, which is a minimum than those of DA, GWO, Jaya, Jaya-PPS2, and Jaya-PPS3.

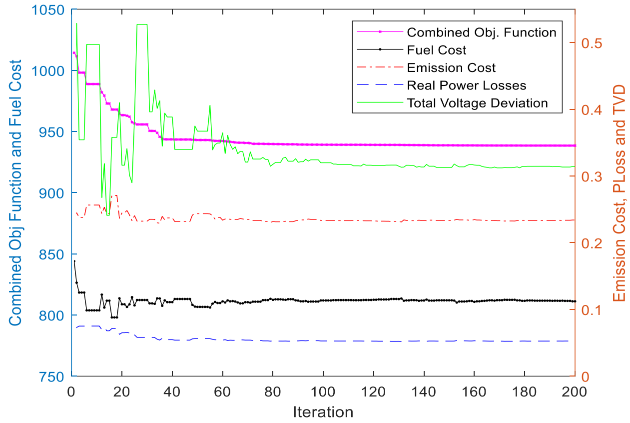
It can also be noted that after placing the DG as anticipated, the combined objective function of the proposed Jaya-PPS1 is reduced by 2.86% from 964.962 (Case1) to 937.340 (Case2). The convergence characteristics of various algorithms are depicted in Fig. 7.4(a), which shows that the proposed Jaya-PPS1 algorithm has provided a smooth convergence characteristic with no oscillations and a high convergence speed in comparison with other methods. Variations of the various objective functions during the iterative process for all the six algorithms are shown in Figs. 7.4(b-g). Fig. 7.5 displays the voltage profile provided by the proposed Jaya-PPS1 algorithm.



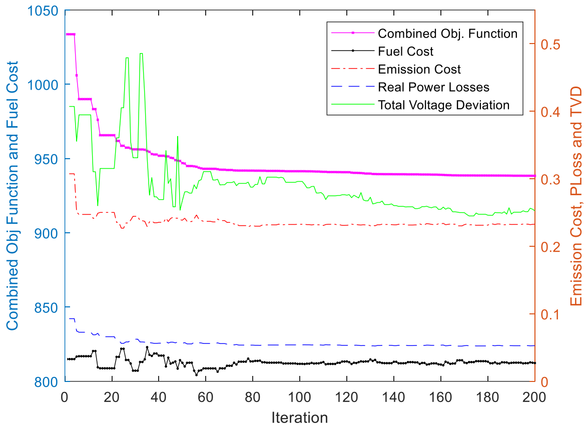
(a) Convergence Characteristics for various algorithms for Case 2



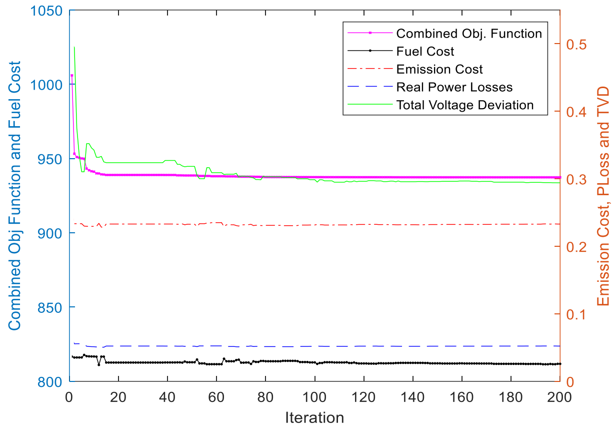
(b) Dragonfly Algorithm



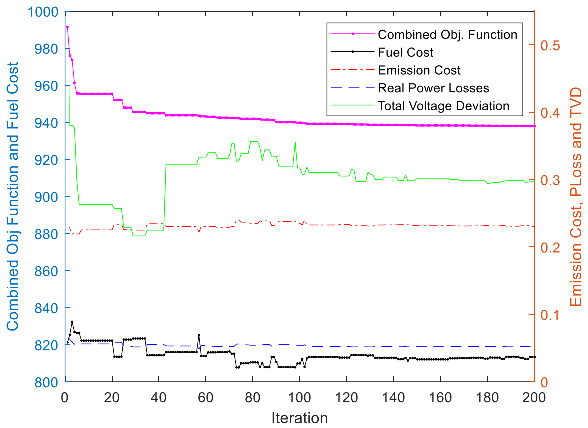
(c) GWO algorithm



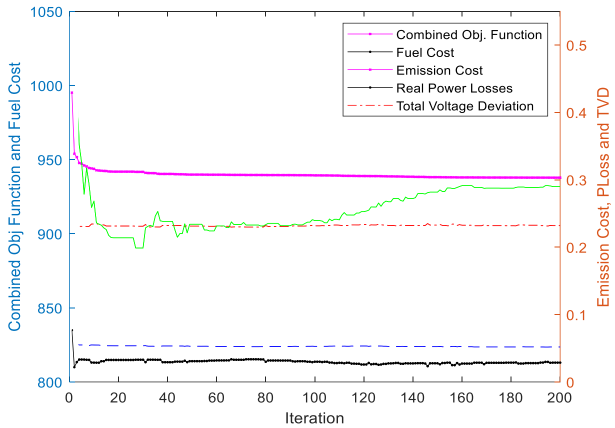
(d) Jaya algorithm



(e) Jaya-PPS1 algorithm



(f) Jaya-PPS2 algorithm



(g) Jaya-PPS3 algorithm

Fig. 7.4: Convergence and variation of objective functions, IEEE 30-bus system, Case 2

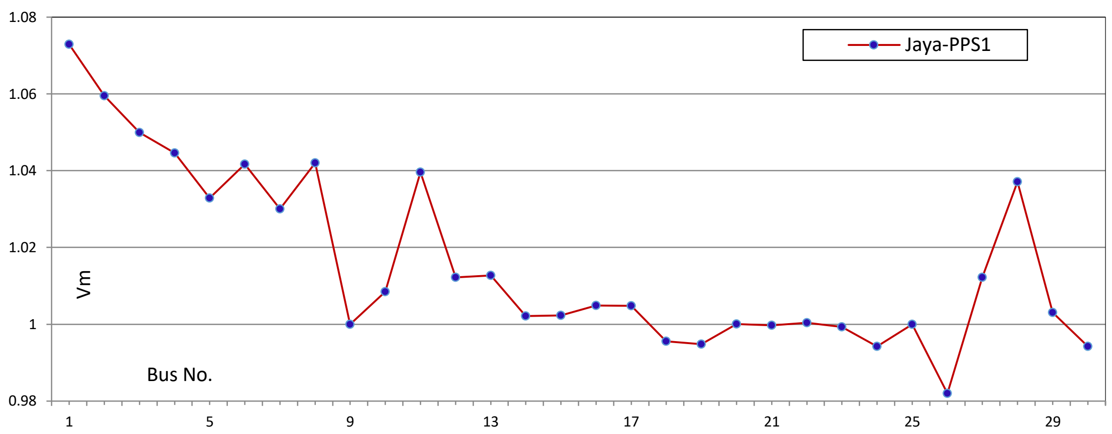


Fig. 7.5: Voltage profile of Jaya-PPS1 for Case 2

Table 7.4: OPF results with control variables settings in IEEE 30-bus system (Case 2)

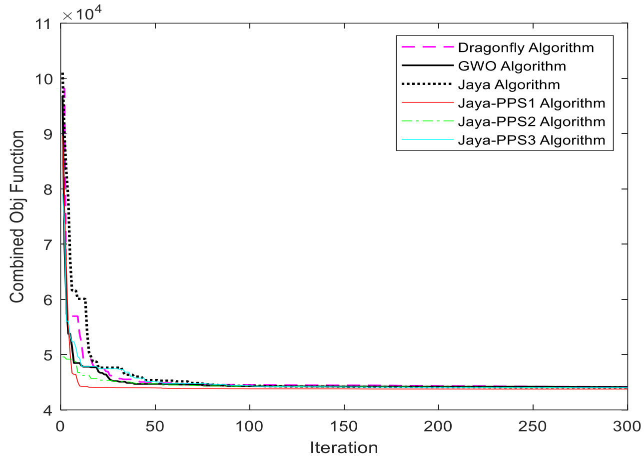
S. No.	Control Variable	DA	GWO	Jaya	Jaya-PPS1	Jaya-PPS2	Jaya-PPS3
Generator real power output							
1	Pg_2	0.5190	0.5155	0.5157	0.5192	0.5371	0.5202
2	Pg_5	0.3118	0.3116	0.3114	0.3108	0.3112	0.3171
3	Pg_8	0.3500	0.3499	0.3500	0.3500	0.3500	0.3496
4	Pg_{11}	0.2588	0.2574	0.2625	0.2605	0.2588	0.2592
5	Pg_{13}	0.2056	0.2019	0.2056	0.2037	0.2087	0.2057
Generator voltage setting							
6	Vg_1	1.0710	1.0742	1.0637	1.0729	1.0730	1.0698
7	Vg_2	1.0574	1.0601	1.0492	1.0595	1.0602	1.0568
8	Vg_5	1.0315	1.0331	1.0223	1.0328	1.0331	1.0305
9	Vg_8	1.0400	1.0420	1.0321	1.0420	1.0415	1.0394
10	Vg_{11}	1.0993	1.0415	1.0478	1.0396	1.0394	1.0347
11	Vg_{13}	1.0243	1.0159	1.0299	1.0127	1.0190	1.0306
Transformer tap setting							
12	$T_{6\text{-}9}$	1.0101	1.0990	1.0995	1.0997	1.100	1.0919
13	$T_{6\text{-}10}$	1.1000	0.9244	0.9252	0.9592	0.9334	0.9384
14	$T_{4\text{-}12}$	1.0343	1.0231	1.0334	1.0234	1.0255	1.0520
15	$T_{28\text{-}27}$	1.0054	1.0213	1.0016	1.0076	1.0202	1.0149
Shunt VAR source setting							
16	Qc_{10}	0.0000	0.0013	0.0039	0.0499	0.0162	0.0220

17	Qc_{12}	0.0141	0.0499	0.0000	0.0500	0.0163	0.0346
18	Qc_{15}	0.0498	0.0368	0.0407	0.0476	0.0465	0.0310
19	Qc_{17}	0.0393	0.0500	0.0499	0.0495	0.0306	0.0383
20	Qc_{20}	0.0212	0.0001	0.0495	0.0497	0.0491	0.0499
21	Qc_{21}	0.0491	0.0500	0.0486	0.0500	0.0496	0.0500
22	Qc_{23}	0.0364	0.0500	0.0389	0.0360	0.0377	0.0496
23	Qc_{24}	0.0500	0.0500	0.0485	0.0499	0.0479	0.0459
24	Qc_{29}	0.0149	0.0500	0.0244	0.0194	0.0500	0.034
COF		938.581	938.498	938.378	**937.340**	937.958	937.792
Fuel Cost (FC)		811.947	811.210	812.334	**811.786**	813.336	813.036
Emission		0.232	0.234	0.232	**0.232**	0.230	0.231
Real Power Loss (RPL)		5.231	5.283	5.287	**5.225**	5.182	5.193
Total Voltage Deviation (TVD)		0.338	0.314	0.252	**0.294**	0.296	0.289
Pg_1 (Slack Bus Power)		119.099	120.033	119.147	**119.178**	116.984	118.398
L-Index (LI)		0.104	0.101	0.103	**0.101**	0.101	0.102

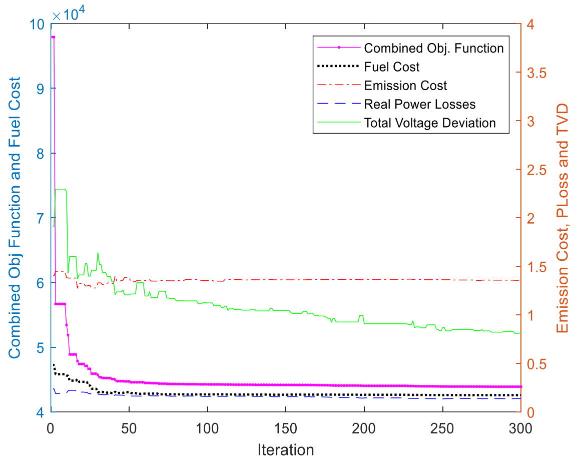
7.5.3 Case 3: OPF no DG in IEEE 57-bus system

In this case, all the six algorithms were applied to solve the OPF problem in the IEEE 57-bus system without DG for the same COF. The OPF results along with the optimal control variable settings of the Jaya-PPS1 algorithm are compared with DA, GWO, Jaya, Jaya-PPS2, and Jaya-PPS3 in Table 7.5 and with the reported results in Table 7.6.

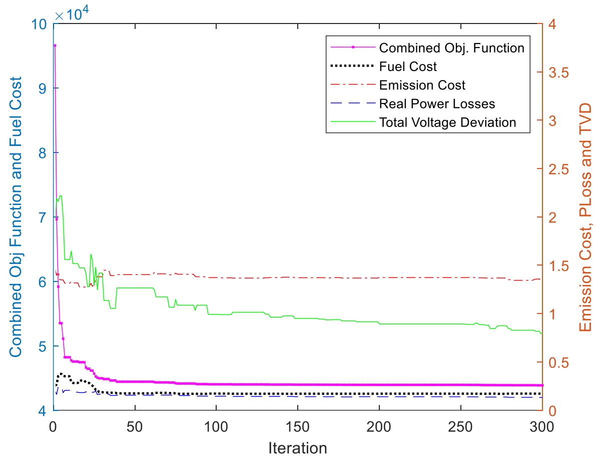
The results in Table 7.6 prove the dominance of the hybrid Jaya-PPS1 algorithm over other Evolutionary Computing based and Jaya, Jaya-PPS2, Jaya-PPS3 algorithms in solving the OPF problem. The proposed Jaya-PPS1 algorithm provided the COF value as 43763.10361, which is better than the COF offered by other reported algorithms. Also, the Jaya-PPS1 algorithm provided fast and smooth convergence characteristics in comparison with other algorithms as can be noted from Figs. 7.6 (a)-(g). The bus voltage profile obtained using the Jaya-PPS1 algorithm is within the specified limits as can be observed from Fig. 7.7.



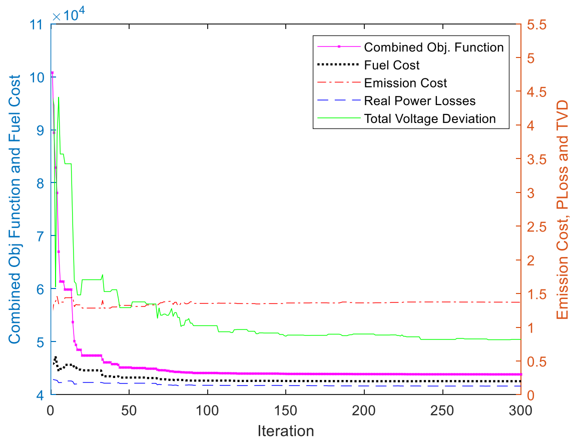
(a) Convergence Characteristics for all the six algorithms, Case 3



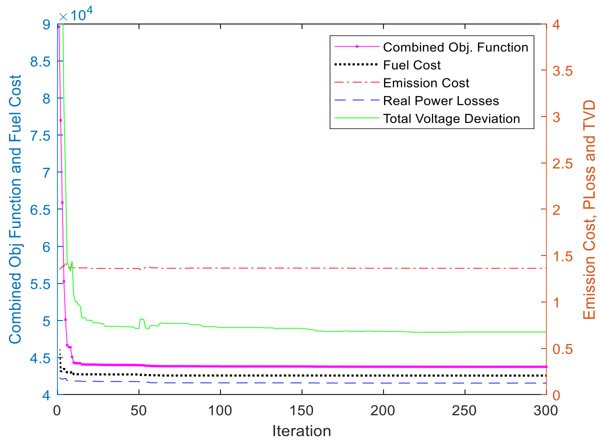
(b) Dragonfly algorithm



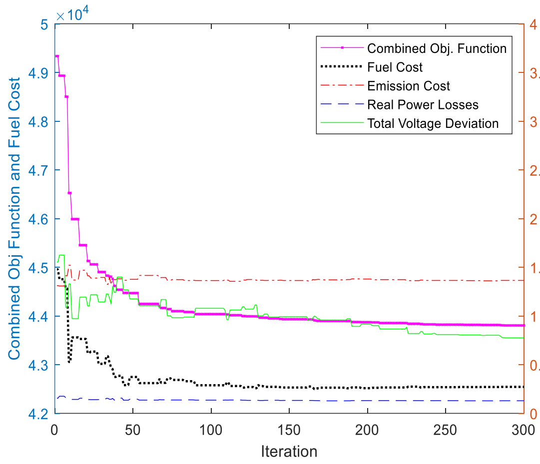
(c) GWO algorithm



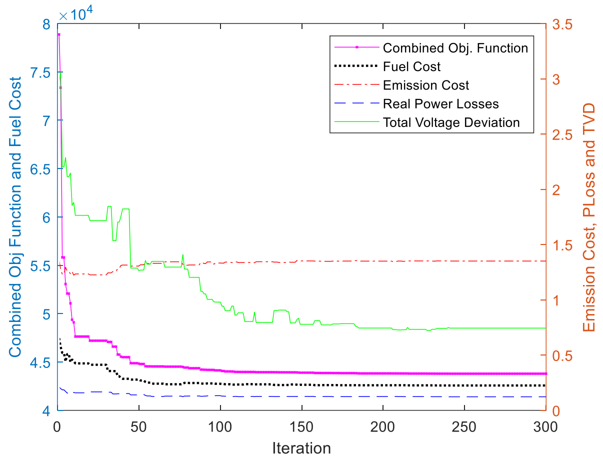
(d) Jaya algorithm



(e) Jaya-PPS1 algorithm



(f) Jaya-PPS2 algorithm



(g) Jaya-PPS3 algorithm

Fig. 7.6: Convergence and variation of objective functions, IEEE 57-bus system, Case 3

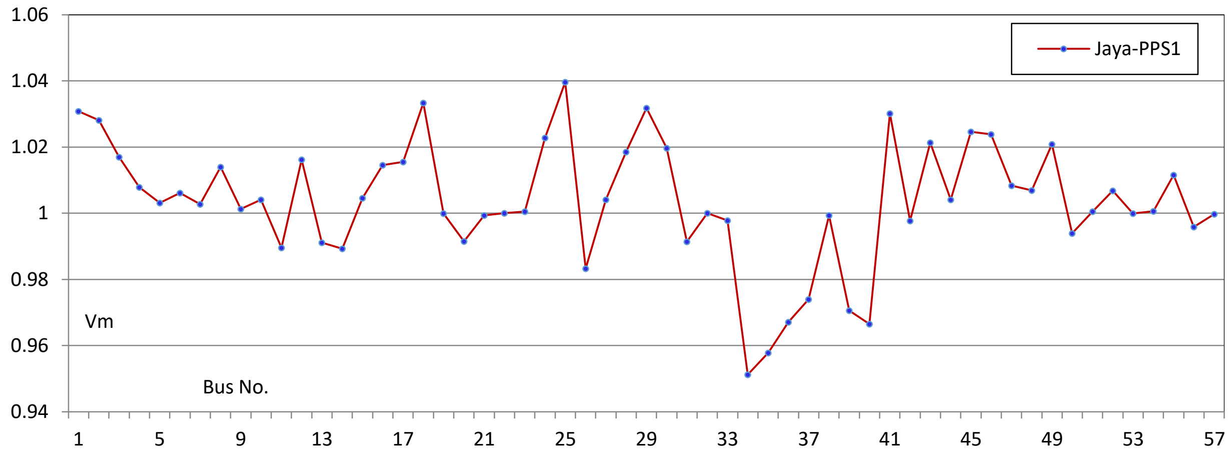


Fig. 7.7: Voltage profile of Jaya-PPS1 for Case 3

Table 7.5: OPF results with control variables settings in IEEE 57-bus system (Case 3)

S. No.	Control variable	DA	GWO	Jaya	Jaya-PPS1	Jaya-PPS2	Jaya-PPS3
Generator real power output							
1	Pg_2	0.9998	1.0000	1.0000	1.0000	0.9944	0.9999
2	Pg_3	0.5282	0.6353	0.5709	0.5891	0.5899	0.5701
3	Pg_6	0.9934	0.9236	0.8796	0.8831	0.8956	0.9564
4	Pg_8	3.1544	3.1370	3.2140	3.1814	3.2025	3.1335
5	Pg_9	0.9997	1.0000	0.9999	1.0000	1.0000	0.9977

6	Pg_{12}	4.0998	4.0985	4.0992	4.1000	4.0998	4.0995
Generator voltage setting							
7	Vg_{1}	1.0389	1.0478	1.0333	1.0308	1.0154	1.0359
8	Vg_{2}	0.9512	1.0982	1.0998	1.0478	1.0566	1.0991
9	Vg_{3}	1.0799	0.9754	1.0897	1.0170	1.0970	1.0567
10	Vg_{6}	0.9500	1.0200	0.9704	0.9505	1.0027	1.0030
11	Vg_{8}	0.9911	0.9954	1.0074	1.0139	0.9997	1.0107
12	Vg_{9}	0.9515	1.0303	0.9734	1.0683	1.0502	1.0583
13	Vg_{12}	1.0052	1.0168	1.0160	1.0162	1.0031	1.0141
Transformer tap setting							
14	T_{4-18}	1.0680	1.0991	0.9802	1.0211	1.0985	1.0990
15	T_{4-18}	0.9015	0.9000	0.9169	0.9000	0.9000	0.9482
16	T_{21-20}	1.0028	0.9716	1.0977	1.0054	0.9722	1.0132
17	T_{24-25}	0.9508	1.0332	1.0930	1.0527	1.0895	0.9002
18	T_{24-25}	1.0109	1.0663	0.9002	1.0419	1.0583	1.0501
19	T_{24-26}	1.0455	1.0357	1.0347	1.0396	1.0602	1.0314
20	T_{7-29}	0.9257	0.9528	0.9419	0.9678	0.9257	0.9654
21	T_{34-32}	0.9266	0.9371	0.9398	0.9278	0.9135	0.9403
22	T_{11-41}	0.9036	0.9000	0.9001	0.9000	0.9000	0.9025
23	T_{15-45}	0.9482	0.9631	0.9464	0.9791	0.9687	0.9667
24	T_{14-46}	0.9462	0.9643	0.9713	0.9592	0.9543	0.9644
25	T_{10-51}	0.9818	1.0261	0.9940	1.0025	0.9646	0.9790
26	T_{13-49}	0.9229	0.9000	0.9309	0.9014	0.9001	0.9070
27	T_{11-43}	0.9131	0.9141	0.9255	0.9699	0.9363	0.9729
28	T_{40-56}	1.0981	1.0306	1.0658	0.9713	0.9991	0.9843
29	T_{39-57}	0.9008	0.9542	0.9183	0.9001	0.9344	0.9054
30	T_{9-55}	0.9794	0.9463	0.9924	0.9896	0.9777	0.9810
Shunt VAR source setting							
31	Qc_{18}	0.0584	0.0326	0.0011	0.0033	0.0424	0.1997
32	Qc_{25}	0.0844	0.1924	0.1283	0.2000	0.1692	0.1240
33	Qc_{53}	0.1475	0.1004	0.1480	0.1870	0.1095	0.1815
COF		43887.417	43864.841	43833.642	**43763.103**	43804.936	43790.825
Fuel Cost (FC)		42584.455	42587.965	42547.094	**42573.898**	42542.989	42571.028
Emission		1.357	1.344	1.370	**1.363**	1.364	1.350
Real Power Loss		13.606	13.272	12.772	**12.496**	12.912	12.274
Total Voltage Deviation		0.812	0.792	0.820	**0.675**	0.775	0.743
Pg_{1} (Slack Bus Power)		186.848	184.621	187.197	**187.925**	185.465	187.339
L-Index (LI)		0.263	0.242	0.251	**0.240**	0.248	0.250

Table 7.6: Comparison of OPF results in IEEE 57-bus system without DG (Case 3)

Algorithm	**COF**	**FC ($/h)**	**Emission (ton/h)**	**RPL (MW)**	**TVD (pu)**
Base Case	53828.143	51395.570	2.761	28.365	1.255
DA	43887.437	42584.469	1.357	13.606	0.812
GWO	43864.841	42587.972	1.344	13.272	0.792
Jaya	43833.629	42547.092	1.370	12.771	0.820
Jaya-PPS1	**43763.103**	**42573.898**	**1.363**	**12.496**	**0.675**
Jaya-PPS2	43804.936	42542.989	1.364	12.912	0.775
Jaya-PPS3	43790.825	42571.028	1.350	12.274	0.743
MOEA/D-SF [125]	-	42648.69	1.343	11.886	0.671
MOMICA [301]	-	41983.058	1.496	13.696	0.797
MOICA [301]	-	41998.566	1.760	13.335	0.874
MNSGA-II [301]	-	42070.824	1.496	14.455	0.889
BB-MOPSO [301]	-	41994.019	1.533	12.609	1.074
NKEA [301]	-	42065.996	1.517	13.976	1.042

7.5.4 Case 4: OPF with DG in IEEE 57-bus system

In this case, the IEEE 57-bus test system with two DGs is considered to determine the efficacy of the Jaya-PPS1 algorithm for solving the OPF problem. The OPF results along with optimum control variable settings obtained by DA, GWO, Jaya, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 algorithms are listed in Table 7.7.

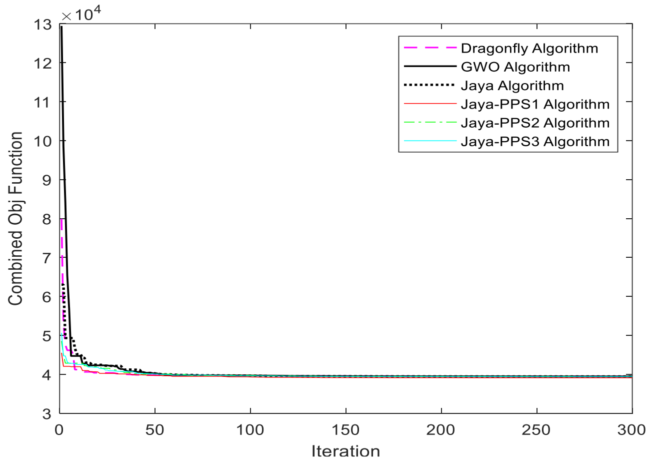
The results in Table 7.7 demonstrate the superiority of the proposed hybrid Jaya-PPS1 algorithm over other EC-based and hybrid Jaya-PPS algorithms in handling OPF problems in this case also. The proposed Jaya-PPS1 algorithm provided the COF value as 39108.172, which is less than that offered by other algorithms. Further, after implanting the two DGs, the COF of the proposed Jaya-PPS1 algorithm is decreased (by 10.64 %) from 43763.103(Case 3) to 39108.172 (Case 4).

As can be seen from Figs. 7.8 (a)-(g), the proposed Jaya-PPS1 algorithm has offered fast and smooth convergence characteristics as compared to other algorithms. The bus voltages profile obtained by the Jaya-PPS1 algorithm is also within the limits as can be observed from Fig. 7.9.

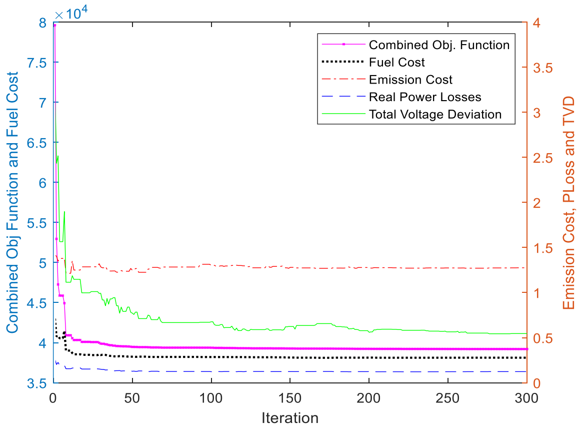
Table 7.7: OPF results with control variables settings in IEEE 57-bus system (Case 4)

S. No.	Control variable	DA	GWO	Jaya	Jaya-PPS1	Jaya-PPS2	Jaya-PPS3
Generator real power output							
1	Pg_2	0.9098	0.9991	0.8986	0.9891	0.9826	0.9750
2	Pg_3	0.4757	0.4920	0.4745	0.4775	0.4881	0.4776
3	Pg_6	0.5954	0.3695	0.4621	0.4710	0.3423	0.3086
4	Pg_8	3.3367	3.4992	3.4752	3.3728	3.4902	3.5101
5	Pg_9	0.9935	0.9999	0.9997	0.9963	1.0000	0.9985
6	Pg_{12}	3.9401	3.8602	3.9434	3.9204	3.9601	3.9447
Generator voltage setting							
7	Vg_1	1.0183	1.0183	1.0155	1.0199	1.0195	1.0146
8	Vg_2	1.1000	1.0957	1.0989	1.0817	1.0464	1.0664
9	Vg_3	1.0608	1.0541	1.0698	1.0974	1.0879	1.0996
10	Vg_6	0.9500	1.0855	1.0955	0.9821	1.0610	1.0344
11	Vg_8	1.0129	1.0101	1.0034	1.0069	0.9964	1.0084
12	Vg_9	1.0113	0.9503	0.9863	1.0445	1.0022	1.0426
13	Vg_{12}	1.0118	1.0202	1.0042	1.0017	1.0040	1.0059
Transformer tap setting							
14	$T_{4\text{-}18}$	0.9003	1.0942	0.9000	0.9472	0.9512	1.1000
15	$T_{4\text{-}18}$	1.0999	0.9000	1.0984	1.0091	0.9554	0.9449
16	$T_{21\text{-}20}$	1.0443	0.9856	0.9864	0.9794	0.9992	0.9855
17	$T_{24\text{-}25}$	0.9000	1.1000	1.034	1.0881	1.0357	0.9800
18	$T_{24\text{-}25}$	1.0793	0.9000	0.9788	1.0669	1.0255	1.0663
19	$T_{24\text{-}26}$	1.0369	1.0029	1.0099	1.0178	1.0105	1.0175
20	$T_{7\text{-}29}$	0.9720	0.9722	0.9516	0.9830	0.9670	0.9709
21	$T_{34\text{-}32}$	0.9435	1.0062	0.9959	0.9886	0.9845	0.9939
22	$T_{11\text{-}41}$	0.9784	0.9660	0.9568	0.9746	0.9309	0.9472
23	$T_{15\text{-}45}$	0.9786	0.9790	0.9809	0.9860	0.9913	0.9841
24	$T_{14\text{-}46}$	0.9785	0.9769	0.9689	0.9748	0.9764	0.9801
25	$T_{10\text{-}51}$	0.9885	0.9930	0.9800	0.9795	0.9781	0.9858

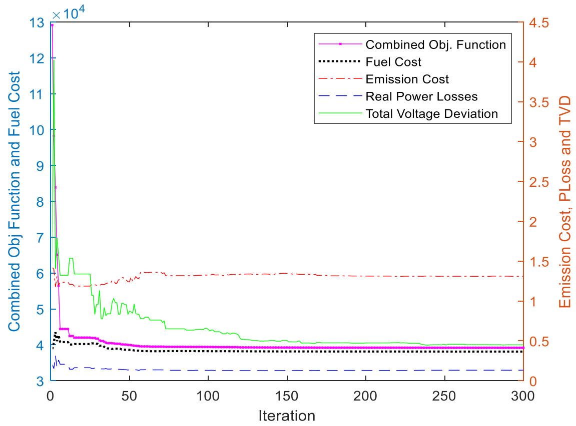
26	T_{13-49}	0.9243	0.9381	0.9309	0.9015	0.9197	0.9198
27	T_{11-43}	0.9903	1.0037	0.9842	0.9813	0.9853	0.9949
28	T_{40-56}	0.9192	0.9008	0.9364	0.9000	0.9955	0.9146
29	T_{39-57}	0.9807	0.9982	0.9877	1.0018	0.9268	0.9999
30	T_{9-55}	0.9510	0.9891	0.9815	0.9278	0.9219	0.9496
Shunt VAR source setting							
31	Qc_{18}	0.1862	0.0000	0.1289	0.0113	0.0041	0.1751
32	Qc_{25}	0.0617	0.1467	0.1143	0.1945	0.1359	0.1334
33	Qc_{53}	0.1296	0.1999	0.1662	0.1464	0.0910	0.1557
COF		39200.178	39173.097	39162.889	**39108.172**	39122.922	39119.337
Fuel Cost (FC)		38120.833	38114.735	38105.956	**38069.932**	38015.998	38056.723
Emission		1.275	1.309	1.321	**1.284**	1.333	1.341
Real Power Loss		12.318	13.170	12.570	**12.716**	12.816	12.852
Total Voltage Deviation		0.545	0.450	0.472	**0.452**	0.537	0.457
Pg_1		142.798	146.780	142.825	**145.614**	142.09	147.004
L-Index (LI)		0.139	0.124	0.129	**0.129**	0.127	0.127



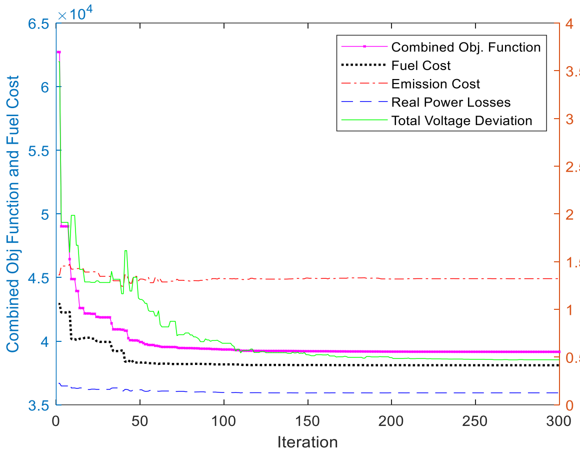
(a) Convergence Characteristics for all the algorithms for Case 4



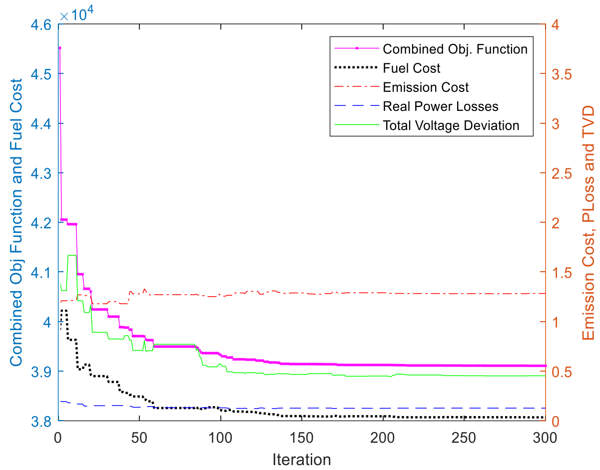
(b) Dragonfly Algorithm



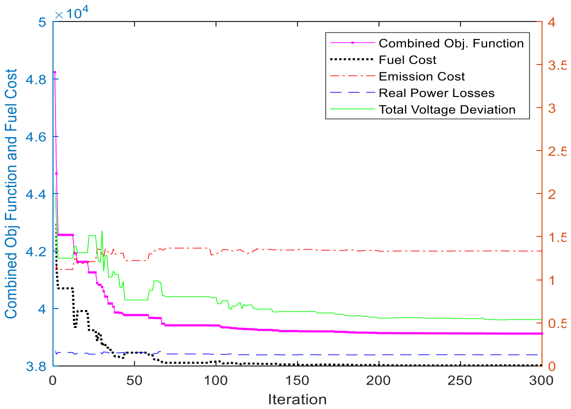
(c) GWO algorithm



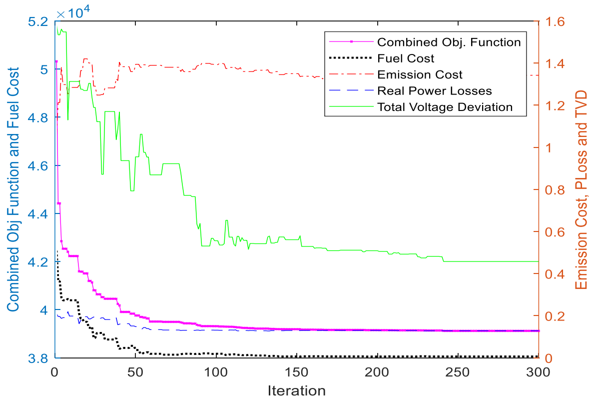
(d) Jaya algorithm



(e) Jaya-PPS1 algorithm



(f) Jaya-PPS2 algorithm



(g) Jaya-PPS3 algorithm

Fig. 7.8: Convergence and variation of objective functions, IEEE 57-bus system, Case 4

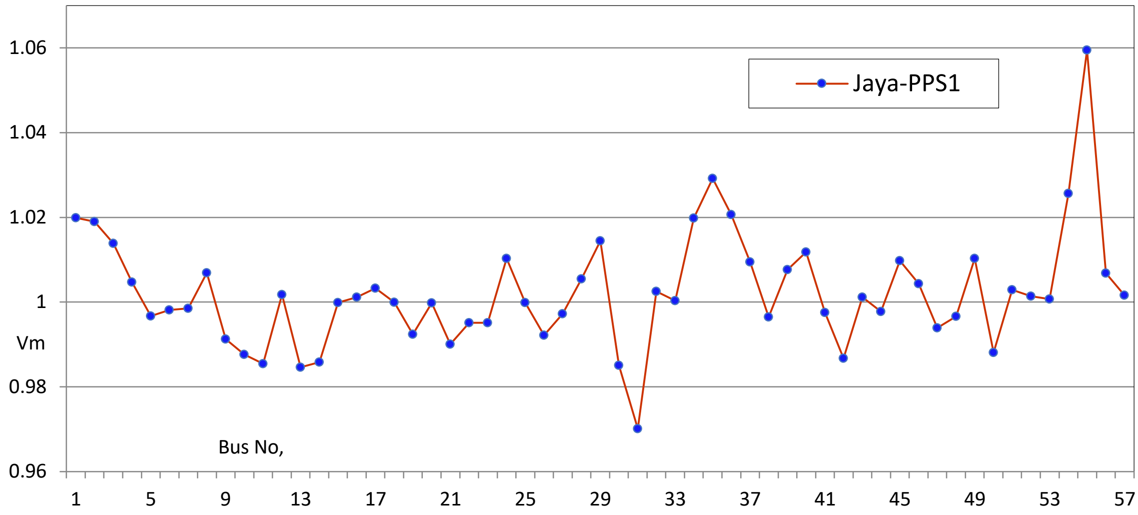


Fig. 7.9 Voltage profile obtained using Jaya-PPS1 for Case 4

7.5.5 Case 5: OPF no DG in IEEE 118-bus system

In Case 5, fuel cost is selected as the main objective function. The minimum fuel cost obtained by the Jaya-PPS1 algorithm is 129221.889 $/h, while the minimum fuel costs obtained by Jaya-PPS2 and Jaya-PPS3 algorithms are 129227.810 $/h and 129231.178 $/h respectively. The minimum fuel cost obtained using hybrid Jaya-PPS algorithms and other meta-heuristic algorithms are depicted in Table 7.8. From Table 7.8, it is clear that the fuel cost obtained from the Jaya-PPS1 algorithm is the least as compared to those of other methods. This demonstrates the effectiveness of the proposed Jaya-PPS1 algorithm as compared to Jaya-PPS2, Jaya-PPS3, DA, GWO algorithm, and other competitors in handling OPF problems in large size power systems. The fuel cost characteristics of various meta-heuristic algorithms for Case 5 are shown in Fig. 7.10. The OPF results along with optimum control variable settings obtained by Jaya-PPS1 algorithm are given in Table 7.9.

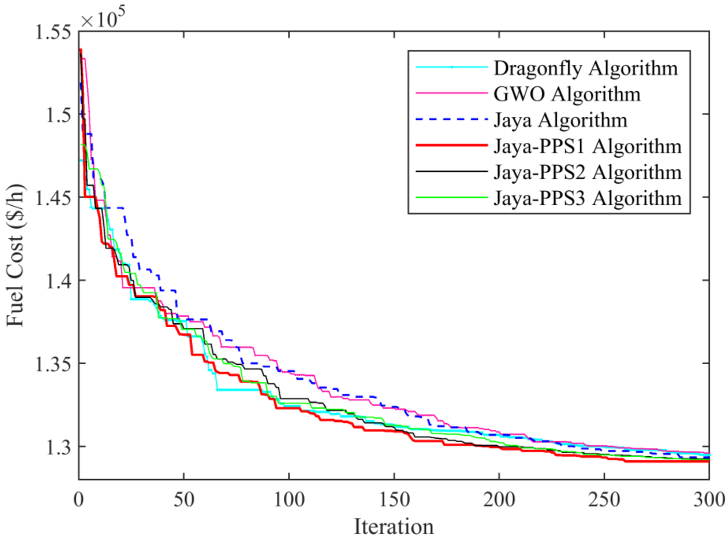


Fig. 7.10 Convergence Characteristics for various algorithms for Case 5

Table 7.8: Comparison of Fuel cost minimization results, IEEE 118-bus system (Case 5)

Algorithm	**Fuel Cost ($/h)**	**TVD (pu)**	**Slack Bus Power (P_{g69})**	**Power Loss**	
				MW	**MVAr**
Base Case	131220.020	1.438	513.810	132.810	782.607
Jaya-PPS1	129221.330	1.291	451.752	101.228	699.365
Jaya-PPS2	129227.810	1.280	468.832	102.181	647.686
Jaya-PPS3	129231.178	1.290	442.370	100.928	697.991
Jaya	129241.129	1.304	467.125	109.336	751.179
SCM-MJ	**129171.960**	**1.272**	**459.601**	**114.531**	**713.220**
Rao-3	129220.679	1.541	471.200	109.120	745.991
DA	129248.356	1.270	462.121	102.181	636.267
GWO	129257.145	1.401	441.035	100.928	695.114
NLP [27]	129700	N. A	N. A	N. A	N. A
QP [27]	129600	N. A	N. A	N. A	N. A
MIQP [27]	129600	N. A	N. A	N. A	N. A
GPU-PSO [154]	129,627.03	N. A	N. A	76.984	N. A
ALC-PSO [189]	129,546.084	N. A	N. A	N. A	N. A
IMFO [225]	131820.000	1.5944	407.192	77.652	-910.020
FAHSPSO-DE [267]	129519.38	N. A	N. A	N. A	N. A
PSOGSA [268]	129, 733.58	N. A	N. A	73.21	N. A
Interior point [296]	129,720.70	N. A	N. A	N. A	N. A

IMFO = improved moth-flame optimization; ALC-PSO = particle swarm optimization with an aging leader and challengers; PSOGSA = Hybrid Particle Swarm Optimization and Gravitational Search Algorithm; GPU-PSO = Partial swarm optimization based graphics processing units; CC-ACOPF = Chance Constrained Optimal Power Flow; QP=quadratic programming; MIQP= Mixed Integer quadratic programming

Table 7.9: Optimum values of control variables for IEEE 118-bus system (case 5)

S. No.	Control variables	SCM-MJ	Jaya-PPS1	S. No.	Control variables	SCM-MJ	Jaya-PPS1
1	P_{g1}	0.0074	0.0108	68	V_{g32}	1.0064	0.9907
2	P_{g4}	0.0352	0.01	69	V_{g34}	0.9818	1.0187
3	P_{g6}	0.1114	0.02	70	V_{g36}	0.9569	1.0153
4	P_{g8}	0.1151	0.34	71	V_{g40}	0.9917	1.0069
5	P_{g10}	4.0965	3.7962	72	V_{g42}	1.0561	0.9945
6	P_{g12}	0.8912	0.8442	73	V_{g46}	0.9457	0.9419
7	P_{g15}	0.0537	0.2103	74	V_{g49}	0.9765	0.9766
8	P_{g18}	0.0778	0.0595	75	V_{g54}	1.0265	0.9779
9	P_{g19}	0.027	0.4138	76	V_{g55}	1.0264	0.9626
10	P_{g24}	0.2123	0.9976	77	V_{g56}	1.0269	0.9702
11	P_{g25}	1.8093	1.9701	78	V_{g59}	0.9837	1.0085
12	P_{g26}	2.8809	2.988	79	V_{g61}	0.9705	1.0367
13	P_{g27}	0.231	0.1156	80	V_{g62}	0.9713	1.0455
14	P_{g31}	0.0799	0.0611	81	V_{g65}	0.9586	1.0572
15	P_{g32}	0.0789	0.1491	82	V_{g66}	0.9756	1.008
16	P_{g34}	0.5587	0.0023	83	V_{g69}	0.9869	1.0123
17	P_{g36}	0.0755	0.0457	84	V_{g70}	0.9542	0.9959
18	P_{g40}	0.0019	0.1273	85	V_{g72}	0.9439	0.942
19	P_{g42}	0.6441	0.326	86	V_{g73}	0.9895	1.0521
20	P_{g46}	0.2165	0.1809	87	V_{g74}	0.9713	0.97
21	P_{g49}	1.831	1.7882	88	V_{g76}	0.9547	0.9542
22	P_{g54}	0.4066	0.5511	89	V_{g77}	0.9801	0.9885
23	P_{g55}	0.3165	0.7758	90	V_{g80}	1.0254	0.9984
24	P_{g56}	0.0687	0.001	91	V_{g85}	0.9769	1.026
25	P_{g59}	1.4468	1.536	92	V_{g87}	0.9565	0.9506
26	P_{g61}	1.4983	1.7874	93	V_{g89}	1.0313	1.0011
27	P_{g62}	0.01	0.2111	94	V_{g90}	1.0071	0.9681
28	P_{g65}	3.2906	3.526	95	V_{g91}	1.022	0.9539
29	P_{g66}	3.0704	3.3563	96	V_{g92}	1.0584	1.0109

30	P_{g70}	0.0411	0.1242	97	V_{g99}	1.0509	0.9862
31	P_{g72}	0.1232	0.0826	98	V_{g100}	1.0525	1.0077
32	P_{g73}	0.1004	0.0083	99	V_{g103}	1.0204	1.0006
33	P_{g74}	0.568	0.0861	100	V_{g104}	0.9664	0.9753
34	P_{g76}	0.0944	0.1941	101	V_{g105}	0.9723	0.9816
35	P_{g77}	0.066	0.0004	102	V_{g107}	0.9747	0.988
36	P_{g80}	4.0032	3.8513	103	V_{g110}	1.0487	1.0137
37	P_{g85}	0.1829	0.0013	104	V_{g111}	1.0114	1.0464
38	P_{g87}	0.045	0.0295	105	V_{g112}	1.0595	0.9883
39	P_{g89}	5.0749	4.1387	106	V_{g113}	0.9989	1.0138
40	P_{g90}	0.0029	0.1424	107	V_{g116}	0.9881	0.9813
41	P_{g91}	0.1777	0.004	108	T_{5-8}	0.9009	0.9002
42	P_{g92}	0.0083	0.0034	109	T_{26-25}	0.9432	1.0506
43	P_{g99}	0.094	0.1124	110	T_{30-17}	1.0151	1.0165
44	P_{g100}	2.678	2.4494	111	T_{38-37}	1.0627	0.9351
45	P_{g103}	0.402	0.3029	112	T_{63-59}	1.0973	1.0939
46	P_{g104}	0.2142	0.0013	113	T_{64-61}	1.0682	0.9037
47	P_{g105}	0.0959	0.1605	114	T_{65-66}	1.0956	0.9151
48	P_{g107}	0.1201	0.0428	115	T_{68-69}	0.9036	0.9052
49	P_{g110}	0.1723	0.068	116	T_{81-80}	0.9001	1.0945
50	P_{g111}	0.4485	0.4298	117	Q_{C5}	0.136	0.2838
51	P_{g112}	0.0194	0.2883	118	Q_{C34}	0.0683	0.1919
52	P_{g113}	0.0271	0.0971	119	Q_{C37}	0.1855	0.1298
53	P_{g116}	0.0144	0.0598	120	Q_{C44}	0.0824	0.1978
54	V_{g1}	1.0203	1.0056	121	Q_{C45}	0.2582	0.267
55	V_{g4}	0.9948	1.0348	122	Q_{C46}	0.0141	0.0339
56	V_{g6}	1.0054	1.0307	123	Q_{C48}	0.0013	0.1915
57	V_{g8}	0.959	0.9492	124	Q_{C74}	0.1131	0.2224
58	V_{g10}	1.0122	0.9935	125	Q_{C79}	0.2902	0.2977
59	V_{g12}	1.0041	1.037	126	Q_{C82}	0.082	0.0985
60	V_{g15}	0.9876	1.0165	127	Q_{C83}	0.0982	0.0422
61	V_{g18}	0.9813	1.0095	128	Q_{C105}	0.2955	0.2935
62	V_{g19}	0.9754	1.0216	129	Q_{C107}	0.0011	0.2541
63	V_{g24}	1.0311	0.9766	130	Q_{C110}	0.2277	0.1272
64	V_{g25}	1.0273	0.9506	Fuel Cost		129171.96	129221.33

65	V_{g26}	1.0587	1.0459	Total Voltage Deviation	1.2721	1.2910
66	V_{g27}	1.0253	0.9813	Real Power Loss	114.5312	101.2288
67	V_{g31}	0.9954	0.9828	Pg_{69} (Slack Bus Power)	459.6014	451.7529

Over several runs, Jaya-PPS1 consistently provided a lower objective function value in all the case studies regardless of the complexities and size of the power system. For example, the IEEE 30-bus and IEEE 57-bus system result in savings of fuel cost of approximately 2.86% and 10.64%, respectively, in the original system, which is equivalent to the savings of 241,968.72 USD and 40,777,195.6 USD annually. In the case of the standard IEEE 118-bus system, the Jaya-PPS1 algorithm provided a fuel cost reduction of 1.52% in comparison to the base case, which is equivalent to a cost saving of 17,503,627.60 USD yearly. The policymakers should consider these findings for future planning, control, and cost-effective operation of the power system.

To provide the importance to the four objectives, minimization of cost, total voltage deviation, emission, and real power losses differently, the weighing factors are to be modified accordingly. The OPF results of all the cases obtained using various meta-heuristic algorithms were compared with the reported results.

7.6 STATISTICAL ANALYSIS

To assess the robustness of the DA, GWO, Jaya, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 algorithms to solve the OPF problem with and without DG, statistical analysis was performed. For each case of the IEEE 30-bus and IEEE 57-bus systems, 50 independent trials with the same population size and the same number of function evaluations were carried out. Results of these 50 trials used to calculate the best, the worst, the average (mean), and the standard deviation (SD) are shown in Table 7.10 and Table 7.11. Out of all the cases, the lowest values of the best, worst, average, and standard deviation provided by the proposed Jaya-PPS1 algorithm reveal that the proposed Jaya-PPS1 approach produces statistically meaningful results. This confirms the robustness of the proposed Jaya-PPS1 algorithm.

Table 7.10: Performance Measures of various algorithms for IEEE 30-Bus System

Algorithm	Without DG (Case 1)				Incorporating DG (Case 2)			
	Best	**Worst**	**Mean**	**SD**	**Best**	**Worst**	**Mean**	**SD**
DA	965.351	966.435	965.873	0.0252	938.581	939.176	938.755	0.0261
GWO	965.302	966.733	965.756	0.0215	938.498	939.246	938.867	0.0238
Jaya	965.286	966.815	965.897	0.0198	938.378	939.254	938.978	0.0195
Jaya-PPS1	**964.962**	**965.127**	**965.018**	**0.0114**	**937.340**	**938.012**	**937.832**	**0.0102**
Jaya-PPS2	965.267	966.395	965.787	0.0195	937.958	938.878	938.138	0.0161
Jaya-PPS3	965.255	966.385	965.987	0.0189	937.792	938.437	938.198	0.0158

Table 7.11: Performance Measures of various algorithms for IEEE 57-Bus System

Algorithm	Without DG (Case 3)				Incorporating DG (Case 4)			
	Best	**Worst**	**Mean**	**SD**	**Best**	**Worst**	**Mean**	**SD**
DA	43887.437	43973.873	43893.893	0.0298	39200.178	39218.879	39207.656	0.0288
GWO	43864.841	43896.887	43871.698	0.0291	39173.097	39181.365	39178.432	0.0282
Jaya	43833.629	43845.953	43839.894	0.0282	39162.889	39175.542	39168.764	0.0281
Jaya-PPS1	**43763.103**	**43774.391**	**43767.692**	**0.0133**	**39108.172**	**39112.265**	**39110.356**	**0.0132**
Jaya-PPS2	43804.936	43815.873	43811.348	0.0271	39122.922	39131.654	39126.554	0.0273
Jaya-PPS3	43790.825	43804.768	43798.562	0.0269	39119.337	39128.278	39125.456	0.0271

A comparison of the OPF results and statistical analysis proves that the Jaya-PPS1 algorithm is the best option for solving OPF problems and maybe the proposed hybrid methodology applies to solve other fields of optimization problems also.

7.7 SUMMERRY

In this chapter, a hybrid meta-heuristic Jaya-Powell's Pattern Search method is suggested to solve the optimal power flow problem. Powell's Pattern Search method for the local search with the classical Jaya algorithm has been incorporated in three different ways resulting in three variants namely; Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3. To demonstrate the efficacy of the proposed algorithm and its potential to solve the OPF problem, it is tested on the standard IEEE 30-bus system with 24 control variables, on the IEEE 57-bus system with 33 control variables, and the IEEE 118-bus system with 130 control variables.

The aim to incorporate PPS with Jaya is to combine the benefits of both algorithms. In comparison with other meta-heuristic algorithms, the proposed hybrid Jaya-PPS1 approach has the benefits of the simplicity to adopt, fast, and smooth convergence characteristics, and a guaranteed near global optimal solution. As the hybrid Jaya-PPS1 algorithm has good exploration and exploitation properties, it can be employed to solve OPF problems in practical power systems and many real-world optimization problems. When any hybrid algorithm is developed for solving an optimization problem, some options to incorporate hybridization should also be tried to obtain the best one.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

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8.1 CONCLUSIONS

The construction of the new power plants and transmission lines has been delayed for the last thirty years because of the cost of electricity, environmental issues, and restrictions on the right-of-way. As a result, the transmission system is operating near its security limits to meet the increased load demand. At the same time, the lack of reactive power sources in a power system leads to bulk power losses in transmission lines. Therefore, it is very important to consider voltage profile improvement and voltage stability improvement as the objectives of the OPF problem.

Additionally, congestion of the transmission system creates obstacles in meeting the demands. In such cases, the integration of distributed generating units is a vital option to eliminate congestion on transmission lines, to improve the voltage profile and to enhance the system stability. The optimal placement of DG has a major impact on the reliability of power supply, operational cost, voltage profile, power loss, environmental pollution, and voltage stability. Integration of DGs seems to be quite appealing, but it is important to analyse their impact on a power system network. The optimal location and size of the DG unit have a significant effect on the reliability of power supply, operational cost, voltage profile, power loss and environmental pollution and voltage stability in a power system. Therefore, it has become a crucial task for researchers and industry personnel to determine the optimal location for the DG and the size of the DG.

With the inclusion of different kinds of power electronic appliances and renewable energy sources in the modern inter-connected restructured power system, the importance of solving the OPF problem is increasing many folds. Thus, in this work, the motivation was to develop efficient and more reliable methods to determine the solution to optimal power flow problems. With this view, various solutions methods have been developed, implemented and tested on practical and standard IEEE systems.

Even though excellent advancements have been made in classical methods, they suffer from the following disadvantages: In most cases, mathematical formulations have to be simplified to get the solutions because of the extremely limited capability to solve real-world large-scale power system problems. They are weak in handling qualitative constraints. They have poor convergence, may get stuck at local optimum, can find only a single optimized solution in a single simulation run, they become too slow if the number of variables is large and they are computationally expensive for the solution of a large system. Whereas, the major advantage of the EC-based or meta-heuristic algorithms are that it is relatively versatile for handling various qualitative constraints. It can find multiple optimal solutions in a single simulation run. So they are quite suitable for solving OPF problems. In most cases, these algorithms can find the near global optimum solution.

The focus of this research work has been to solve OPF problem by EC based optimization algorithms. The EC based optimization algorithms have been found to be slower than conventional techniques. So, an attempt has been made to improve the existing EC algorithms. The research work done along with the key findings can be summarised as follows.

- Based upon the exhaustive review of literature an overview of the state of the art methods, in optimal power flow (OPF) based on analytical, meta-heuristic, modified meta-heuristic, and hybrid approaches has been carried out. Apart from presenting various methodologies of optimal power flow reported recently, the pros and cons of these optimization techniques have been identified and motivation, key contributions of the thesis are shaped.

- The mathematical modelling of optimal power flow problem has been formulated. In addition, the power flow equations and several operating constraints of these equations have been explained in detail. Also, various technical and economic objective functions associated with the OPF problem are thoroughly incorporated.
- Detailed studies of two meta-heuristic algorithms namely, bat search (BS) optimization and bird swarm algorithms (BSA) have been applied to solve the optimal power flow problem. These algorithms have been applied in IEEE 30-bus test system for fuel cost minimization, total voltage deviation minimization, emission minimization, real power losses minimization and enhancement of voltage stability under normal as well as contingency conditions. The comparative analysis of BS optimization algorithm with BSA on OPF problem is carried out. Based on numerical results, it seems that both the algorithms are competitively sound and of dominant nature.
- Three easy-to-use metaphor-less optimization algorithms, namely Rao algorithms, have been used to solve the optimal power flow problem. Meta-heuristic algorithms, notwithstanding their benefits, have some drawbacks also. They need parameter tuning to find the near-global best solution. It has been observed that parameter tuning of meta-heuristic optimization algorithms plays a very important role and is a very crucial and time-expensive task for solving a given optimization problem. Rao algorithms are parameter-less optimization algorithms. As a result, algorithm-specific parameter tuning is not required at all. To check the efficiency

and supremacy of the Rao algorithms these algorithms were applied to solve the OPF problem in three standard IEEE (30-bus, 57-bus, and 118-bus) test systems. The simulation outcomes offered by Rao algorithms were compared for the various single and multi-objective functions and with the results of other methods mentioned in recent literature. The OPF results demonstrate that the suggested Rao algorithms are efficient and robust in most of the cases over other popular methods, which are reported in recent literature.

- When used to solve complex real-life engineering optimization problems, standard versions of some of the more common meta-heuristic approaches have been found to have some limitations**.** Like other population-based algorithms, the Rao, bat and bird swarm algorithms sometimes suffers from premature convergence. Therefore, a sine-cosine mutation-based modified Jaya algorithm for solving the OPF problem has been proposed. The suggested SCM-MJ algorithm is found to be faster and immune to the local optima trapping as compared to the classical Jaya algorithm. The proposed SCM-MJ algorithm aims to maintain the diversity of the solutions throughout the search to avoid sub-optimal solutions, and find near-global optimum solutions.

To test the efficacy of the suggested SCM-MJ method, it is applied on 13 standard mathematical benchmark functions. Observations of the numerical results prove the supremacy of the SCM-MJ algorithm over eight well-known optimization methods reported in the recent publications: ALO, BA, CS, FPA, FA, GA, M-Jaya, PSO, and SMS. The proposed algorithm was implemented in the Algerian 59-bus and IEEE 118-bus systems for solving the OPF problem for minimization of fuel cost, total voltage deviation minimization, and real power loss minimization. A comparison of the optimization results acquired using the SCM-MJ algorithm with those of modern meta-heuristic optimization approaches published in recent literature demonstrate that the proposed SCM-MJ algorithm is highly efficient and robust over other recently developed popular algorithms.

- A hybrid meta-heuristic Jaya-Powell's Pattern Search (Jaya-PPS) method has been proposed to solve the optimal power flow problem integrated with distributed generating units. A versatile combination of two meta-heuristic algorithms may overcome their common weaknesses while taking advantage of the strengths of the two algorithms. The aim to incorporate PPS with Jaya is to combine the benefits of both the algorithms. When any hybrid algorithm is developed for solving an optimization problem, some options to incorporate hybridization should also be tried to obtain the best one. Therefore, three variants of the Jaya-PPS algorithm, Jaya-PPS1, Jaya-PPS2, and Jaya-PPS3 were developed by incorporating hybridization in different manner.

To demonstrate the efficacy of the proposed algorithm and its potential to solve the OPF problem, it is tested on the standard IEEE 30-bus system with 24 control variables, on the IEEE 57-bus system with 33 control variables, and the IEEE 118-bus system with 130 control variables. The OPF results of all the cases obtained using the proposed three variants of Jaya algorithms were compared with the reported meta-heuristic algorithms results. A comparison of the OPF results and statistical analysis proves that the Jaya-PPS1 algorithm is the best option for solving OPF problems.

Finally, based upon the numerical results obtained and analytic comparative study, the author is able to demonstrate the superiority of the proposed SCM-MJ algorithm over proposed BS, BSA, Rao, hybrid Jaya-PPS algorithms and other EC-based algorithms in handling OPF problems.

8.2 FUTURE SCOPE OF WORK

The process of research and development is never-ending. Each end of a study effort marks the beginning of an opportunity for new possibilities for future research. For future study, the following suggestions have been made:

- The proposed algorithm in this thesis can also be applied to solve other crucial power system optimization problems namely, economic load dispatch (ELD), automatic generation control (AGC), demand side management (DSM) and distribution systems planning (DSP) etc.
- The study can also be extended under deregulated environment.
- The stochastic wind and solar based distributed generation can be dynamically modelled and installed in an optimal location to investigate their impact on system performance.
- The inclusion of discrete control variables like transformer taps-setting and shunt compensators in OPF problem formulation is another direction for future studies.
- Machine learning or Deep learning based techniques can also be applied to solve real time OPF problems.

LIST OF RESEARCH PUBLICATIONS

List of papers (s) published in peer reviewed referred international journals:

1. Saket Gupta, Narendra Kumar & Laxmi Srivastava. "An efficient Jaya algorithm with Powell's Pattern Search for optimal power flow incorporating distributed generation". Energy Sources, Part B: Economics, Planning, and Policy, vol. 16, no. 8, pp. 759-786, 2021. https://doi.org/10.1080/15567249.2021.1942595.

2. Saket Gupta, Narendra Kumar & Laxmi Srivastava. "Solution of optimal power flow problem using sine-cosine mutation based modified Jaya algorithm: a case study". Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2021. https://doi.org/ 10.1080/15567036.2021.1957043.

3. S. Gupta, N. Kumar, L. Srivastava, H. Malik, A. Anvari-Moghaddam, F. P. García Márquez. "A Robust Optimization Approach for Optimal Power Flow Solutions Using Rao Algorithms". Energies, vol. 14, no. 17, pp. 5449, 2021. https://doi.org/10.3390/en14175449.
4. S. Gupta, N. Kumar, L. Srivastava, H. Malik, A. Pliego Marugán, F. P. García Márquez. "A Hybrid Jaya–Powell's Pattern Search Algorithm for Multi-Objective Optimal Power Flow Incorporating Distributed Generation". Energies, vol. 14, no. 10, pp. 2831, 2021. https://doi.org/10.3390/en14102831.

List of paper(s) published in international/national conferences:

1. S. Gupta, N. Kumar, L. Srivastava. "Bat Search Algorithm for Solving Multi-Objective Optimal Power Flow Problem". In: Mishra S., Sood Y., Tomar A. (eds)

Applications of Computing, Automation and Wireless Systems in Electrical Engineering. Lecture Notes in Electrical Engineering, vol. 553, 2019. Springer, Singapore. https://doi.org/10.1007/978-981-13-6772-4_30.

2. S. Gupta, N. Kumar and L. Srivastava, "Bird Swarm Algorithm for Solving Multi-Objective Optimal Power Flow Problem," *2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, pp. 280-286, 2018. https://doi.org/doi: 10.1109/ICPEICES.2018.8897433.

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APPENDIX

APPENDIX A

SYSTEM DATA FOR THE IEEE 30-BUS SYSTEM

The IEEE 30-bus system is shown in Figure A. The IEEE 30-bus system has 30 buses, 6 generators, and 41 branches. The system data along with the control variable operating limits are given in Reference[36]. The characteristics of test system, generator data, bus data, and line data are provided in the tables A.1, A.2, A.3, and A.4 respectively. The active and reactive power demands of this system on the 100 MVA base are 2.834 and 1.262 pu, respectively.

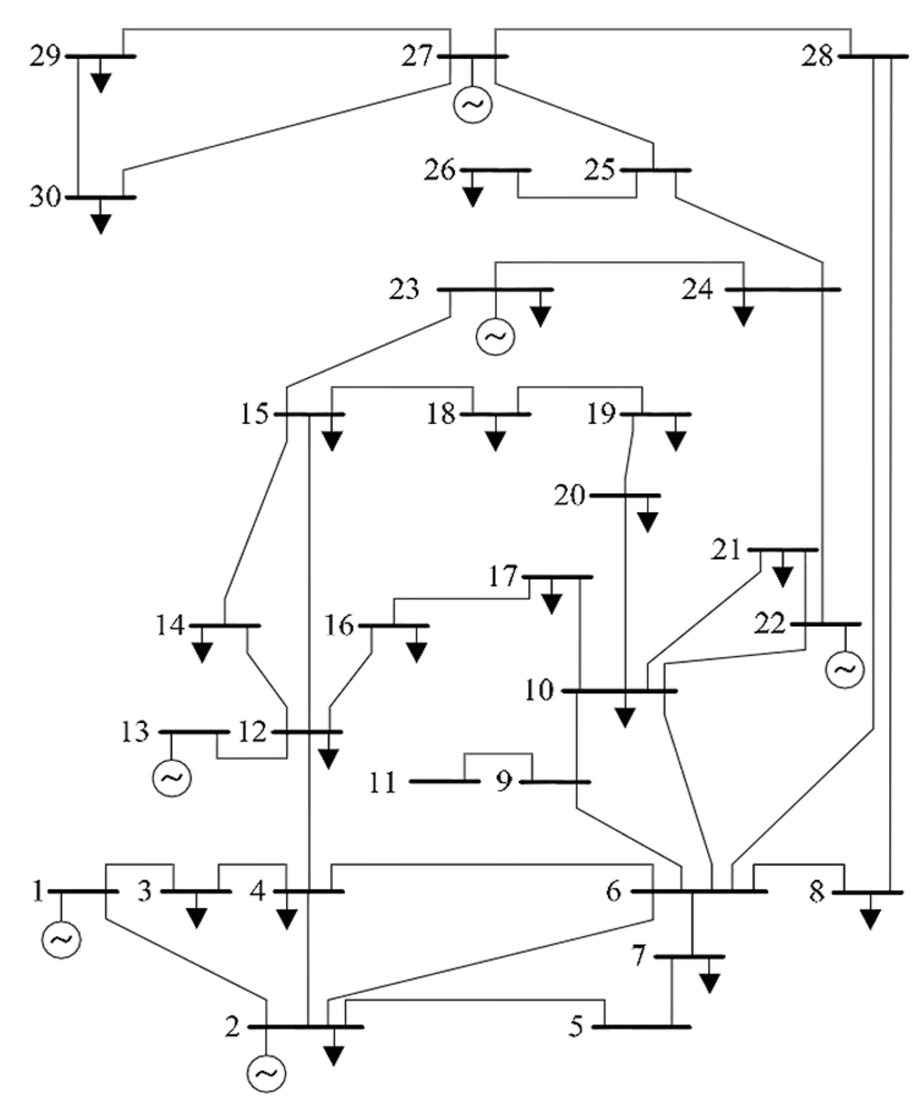

Figure A. Single line diagram of IEEE-30 Bus Test System

A1: CHARACTERISTICS OF IEEE 30-BUS TEST SYSTEM

IEEE 30-bus system			
S. No	Characteristics	Value details	Details
1	Busses	30	-
2	Branches	41	-
3	Generators	06	Busses: 1, 2, 5, 8, 11 and 13
4	Load bus voltage limits	24	[0.94:1.06]
5	Generator bus voltage limits	06	[0.95:1.1]
6	Control variables	24	(05+06+09+04)

A2: GENERATOR DATA

Bus No.	P_g^{min}	P_g^{max}	Q_g^{min}	Q_g^{max}	Cost Coefficients		
	(MW)	(MW)	(MVAR)	(MVAR)	a	b	c
1	50	200	-20	200	0.0	200	37. 5
2	20	80	-20	100	0.0	175	175
5	15	50	-15	80	0.0	100	625
8	10	35	-15	60	0.0	325	83.4
11	10	30	-10	50	0.0	300	250
13	12	40	-15	60	0.0	300	250

A3: BUS DATA

Bus No.	Bus Type	Pd (MW)	Qd (MVAR)
1	1	0	0
2	2	0.2170	0.1270
3	3	0.0240	0.0120
4	3	0.0760	0.0160
5	2	0.9420	0.1900
6	3	0	0
7	3	0.2280	0.1090
8	2	0.3000	0.3000
9	3	0	0
10	3	0.0580	0.0200
11	2	0	0
12	3	0.1120	0.0750
13	2	0	0
14	3	0.0620	0.0160
15	3	0.0820	0.0250
16	3	0.0350	0.0180
17	3	0.0900	0.0580
18	3	0.0320	0.0090
19	3	0.0950	0.0340
20	3	0.0220	0.0070
21	3	0.1750	0.1120
22	3	0	0
23	3	0.0320	0.0160
24	3	0.0870	0.0670
25	3	0	0

26	3	0.0350	0.0230
27	3	0	0
28	3	0	0
29	3	0.0240	0.0090
30	3	0.1060	0.0190

A4: LINE DATA

Line No.	From	To	R	X	B	Tap Setting
1	1	2	0.0192	0.0575	0.0132	1.0000
2	1	3	0.0452	0.1852	0.0102	1.0000
3	2	4	0.0570	0.1737	0.0092	1.0000
4	3	4	0.0132	0.0379	0.0021	1.0000
5	2	5	0.0472	0.1983	0.0104	1.0000
6	2	6	0.0581	0.1763	0.0094	1.0000
7	4	6	0.0119	0.0414	0.0022	1.0000
8	5	7	0.0460	0.1160	0.0051	1.0000
9	6	7	0.0267	0.0820	0.0043	1.0000
10	6	8	0.0120	0.0420	0.0022	1.0000
11	6	9	0	0.2080	0	1.0780
12	6	10	0	0.5560	0	1.0690
13	9	11	0	0.2080	0	1.0000
14	9	10	0	0.1100	0	1.0000
15	4	12	0	0.2560	0	1.0320
16	12	13	0	0.1400	0	1.0000
17	12	14	0.1231	0.2559	0	1.0000
18	12	15	0.0662	0.1304	0	1.0000
19	12	16	0.0945	0.1987	0	1.0000
20	14	15	0.2210	0.1997	0	1.0000
21	16	17	0.0824	0.1932	0	1.0000
22	15	18	0.1070	0.2185	0	1.0000
23	18	19	0.0639	0.1292	0	1.0000
24	19	20	0.0340	0.0680	0	1.0000
25	10	20	0.0936	0.2090	0	1.0000
26	10	17	0.0324	0.0845	0	1.0000
27	10	21	0.0348	0.0749	0	1.0000
28	10	22	0.0727	0.1499	0	1.0000
29	21	22	0.0116	0.0236	0	1.0000
30	15	23	0.1000	0.2020	0	1.0000
31	22	24	0.1150	0.1790	0	1.0000
32	23	24	0.1320	0.2700	0	1.0000
33	24	25	0.1885	0.3292	0	1.0000
34	25	26	0.2544	0.3800	0	1.0000
35	25	27	0.1093	0.2087	0	1.0000
36	28	27	0	0.3960	0	1.0680
37	27	29	0.2198	0.4153	0	1.0000
38	27	30	0.3202	0.6027	0	1.0000
39	29	30	0.2399	0.4533	0	1.0000
40	8	28	0.6360	0.2000	0.0107	1.0000
41	6	28	0.0169	0.0599	0.0032	1.0000

APPENDIX B

SYSTEM DATA FOR THE IEEE 57-BUS SYSTEM

The IEEE 57-bus system is shown in Figure B. The IEEE 57-bus system has 57 buses, 7 generator buses, and 80 branches. The system data along with the control variable operating limits are given in Reference[302]. The characteristics of test system, generator data, bus data, and line data are provided in the tables B.1, B.2, B.3, and B.4 respectively. The active and reactive power demands of this system on the 100 MVA base are 12.508 and 3.364 pu, respectively.

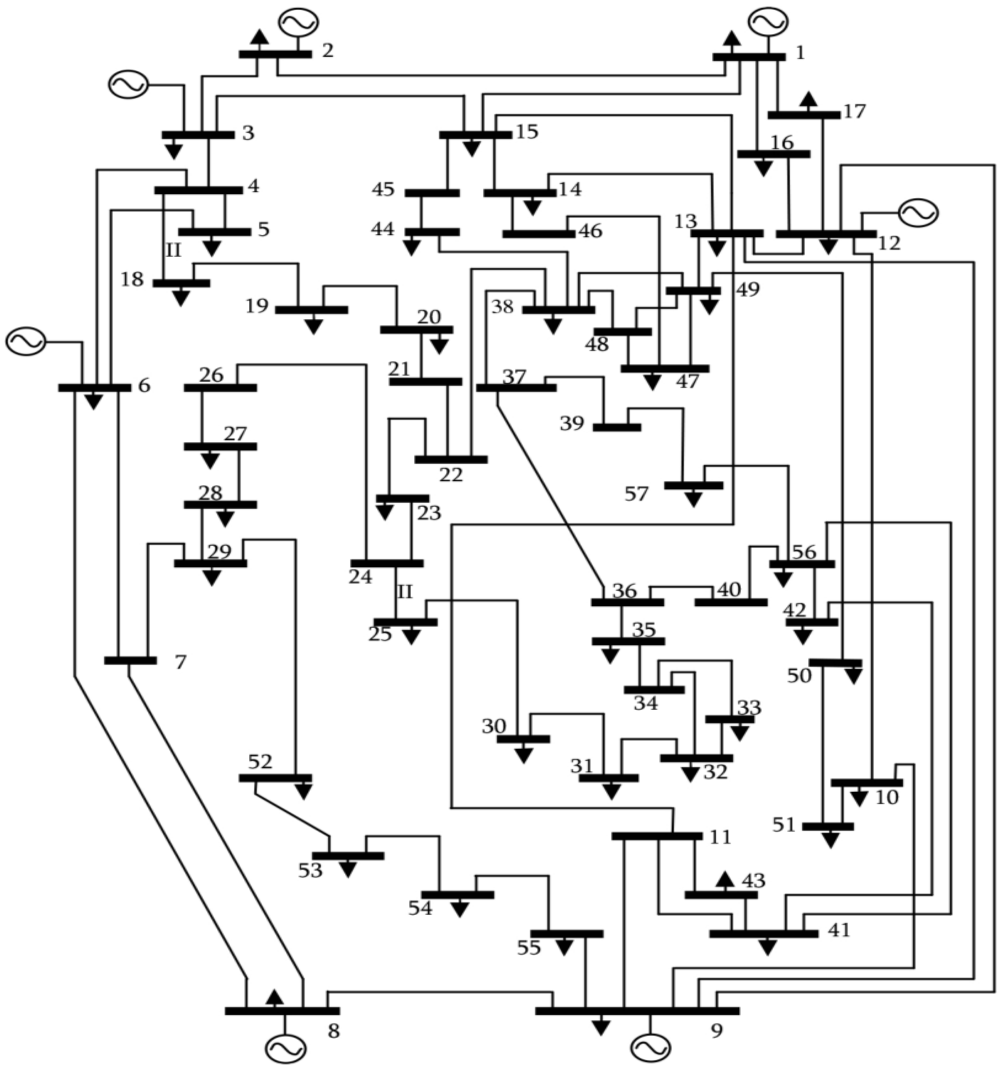

Figure B. Single line diagram of IEEE-57 Bus Test System

B1: CHARACTERISTICS OF IEEE 57-BUS TEST SYSTEM

IEEE 57-bus system			
S. No	Characteristics	Value details	Details
1	Busses	57	-
2	Branches	80	-
3	Generators	07	Busses: 1, 2, 3, 6, 8, 9 and 12
4	Load bus voltage limits	50	[0.94:1.1]
5	Generator bus voltage limits	07	[0.94 :1.1]
6	Control variables	33	06+07+03+17

B2: GENERATOR DATA

Bus No.	P_g^{min}	P_g^{max}	Q_g^{min}	Q_g^{max}	Cost Coefficients		
	(MW)	(MW)	(MVAR)	(MVAR)	a	b	c
1	0	576	-200	300	0.0	2000	7.75795
2	0	100	-17	50	0.0	4000	1
3	0	140	-10	60	0.0	2000	25
6	0	100	-8	25	0.0	4000	1
8	0	550	-140	200	0.0	2000	2.22222
9	0	100	-3	9	0.0	4000	1
12	0	410	-150	155	0.0	2000	3.22581

B3: BUS DATA

Bus No.	Type	Pd	Qd	Bus No.	Type	Pd	Qd
1	1	55	17	30	3	3.6	1.8
2	2	3	88	31	3	5.8	2.9
3	2	41	21	32	3	1.6	0.8
4	3	0	0	33	3	3.8	1.9
5	3	13	4	34	3	0	0
6	2	75	2	35	3	6	3
7	3	0	0	36	3	0	0
8	2	150	22	37	3	0	0
9	2	121	26	38	3	14	7
10	3	5	2	39	3	0	0
11	3	0	0	40	3	0	0
12	2	377	24	41	3	6.3	3
13	3	18	2.3	42	3	7.1	4.4
14	3	10.5	5.3	43	3	2	1
15	3	22	5	44	3	12	1.8
16	3	43	3	45	3	0	0
17	3	42	8	46	3	0	0
18	3	27.2	9.8	47	3	29.7	11.6
19	3	3.3	0.6	48	3	0	0
20	3	2.3	1	49	3	18	8.5
21	3	0	0	50	3	21	10.5

22	3	0	0	51	3	18	5.3
23	3	6.3	2.1	52	3	4.9	2.2
24	3	0	0	53	3	20	10
25	3	6.3	3.2	54	3	4.1	1.4
26	3	0	0	55	3	6.8	3.4
27	3	9.3	0.5	56	3	7.6	2.2
28	3	4.6	2.3	57	3	6.7	2
29	3	17	2.6				

B4: LINE DATA

Line No.	From	To	R	X	B	Tap Setting
1	1	2	0.0083	0.028	0.0645	1.0000
2	2	3	0.0298	0.085	0.0409	1.0000
3	3	4	0.0112	0.0366	0.019	1.0000
4	4	5	0.0625	0.132	0.0129	1.0000
5	4	6	0.043	0.148	0.0174	1.0000
6	6	7	0.02	0.102	0.0138	1.0000
7	6	8	0.0339	0.173	0.0235	1.0000
8	8	9	0.0099	0.0505	0.0274	1.0000
9	9	10	0.0369	0.1679	0.022	1.0000
10	9	11	0.0258	0.0848	0.0109	1.0000
11	9	12	0.0648	0.295	0.0386	1.0000
12	9	13	0.0481	0.158	0.0203	1.0000
13	13	14	0.0132	0.0434	0.0055	1.0000
14	13	15	0.0269	0.0869	0.0115	1.0000
15	1	15	0.0178	0.091	0.0494	1.0000
16	1	16	0.0454	0.206	0.0273	1.0000
17	1	17	0.0238	0.108	0.0143	1.0000
18	3	15	0.0162	0.053	0.0272	1.0000
19	4	18	0	0.555	0	0.9700
20	4	18	0	0.43	0	0.9780
21	5	6	0.0302	0.0641	0.0062	1.0000
22	7	8	0.0139	0.0712	0.0097	1.0000
23	10	12	0.0277	0.1262	0.0164	1.0000
24	11	13	0.0223	0.0732	0.0094	1.0000
25	12	13	0.0178	0.058	0.0302	1.0000
26	12	16	0.018	0.0813	0.0108	1.0000
27	12	17	0.0397	0.179	0.0238	1.0000
28	14	15	0.0171	0.0547	0.0074	1.0000
29	18	19	0.461	0.685	0	1.0000
30	19	20	0.283	0.434	0	1.0000
31	21	20	0	0.7767	0	1.0430
32	21	22	0.0736	0.117	0	1.0000
33	22	23	0.0099	0.0152	0	1.0000
34	23	24	0.166	0.256	0.0042	1.0000
35	24	25	0	1.182	0	1.0000
36	24	25	0	1.23	0	1.0000
37	24	26	0	0.0473	0	1.0430
38	26	27	0.165	0.254	0	1.0000
39	27	28	0.0618	0.0954	0	1.0000
40	28	29	0.0418	0.0587	0	1.0000
41	7	29	0	0.0648	0	0.9670

42	25	30	0.135	0.202	0	1.0000
43	30	31	0.326	0.497	0	1.0000
44	31	32	0.507	0.755	0	1.0000
45	32	33	0.0392	0.036	0	1.0000
46	34	32	0	0.953	0	0.975
47	34	35	0.052	0.078	0.0016	1.0000
48	35	36	0.043	0.0537	0.0008	1.0000
49	36	37	0.029	0.0366	0	1.0000
50	37	38	0.0651	0.1009	0.001	1.0000
51	37	39	0.0239	0.0379	0	1.0000
52	36	40	0.03	0.0466	0	1.0000
53	22	38	0.0192	0.0295	0	1.0000
54	11	41	0	0.749	0	0.9550
55	41	42	0.207	0.352	0	1.0000
56	41	43	0	0.412	0	1.0000
57	38	44	0.0289	0.0585	0.001	1.0000
58	15	45	0	0.1042	0	0.9950
59	14	46	0	0.0735	0	0.9000
60	46	47	0.023	0.068	0.0016	1.0000
61	47	48	0.0182	0.0233	0	1.0000
62	48	49	0.0834	0.129	0.0024	1.0000
63	49	50	0.0801	0.128	0	1.0000
64	50	51	0.1386	0.22	0	1.0000
65	10	51	0	0.0712	0	0.9300
66	13	49	0	0.191	0	0.8950
67	29	52	0.1442	0.187	0	1.0000
68	52	53	0.0762	0.0984	0	1.0000
69	53	54	0.1878	0.232	0	1.0000
70	54	55	0.1732	0.2265	0	1.0000
71	11	43	0	0.153	0	0.8950
72	44	45	0.0624	0.1242	0.002	1.0000
73	40	56	0	1.195	0	0.9580
74	56	41	0.553	0.549	0	1.0000
75	56	42	0.2125	0.354	0	1.0000
76	39	57	0	1.355	0	0.9800
77	57	56	0.174	0.26	0	1.0000
78	38	49	0.115	0.177	0.003	1.0000
79	38	48	0.0312	0.0482	0	1.0000
80	9	55	0	0.1205	0	0.9400

SYSTEM DATA FOR THE ALGERIAN 59-BUS SYSTEM

The Algerian 59-bus system is shown in Figure C. The Algerian 59-bus system has 59 buses, 10 generators, and 83 branches. It is worth mentioning that generator at bus No. 13 is not in service. The system data along with the control variable operating limits are given in Reference [147]. The characteristics of test system, generator data, bus data, line data are provided in the tables C.1, C.2, C.3, and C.4 respectively. The active power demands of this system on the 100 MVA base is 6.841 pu.

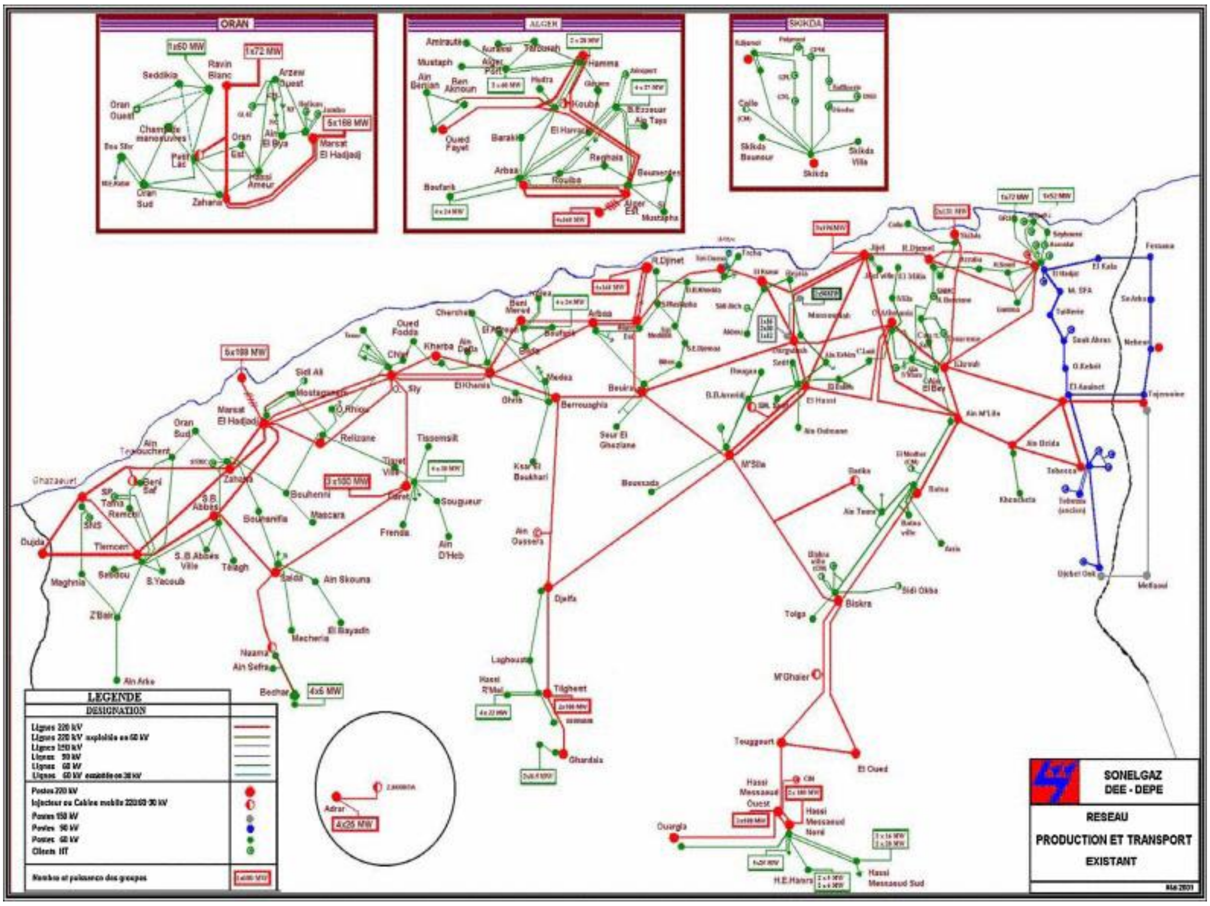

Figure C: Single line diagram of Algerian 59-bus system

C1: CHARACTERISTICS OF ALGERIAN 59-BUS SYSTEM

Algerian 59-bus system			
S. No.	Characteristics	Value details	Details
1	Busses	59	-
2	Branches	83	-
3	Generators	10	Busses: 1, 2, 3, 4, 13, 27, 37, 41, 42 and 53
4	Load bus voltage limits	49	[0.94:1.1]
5	Generator bus voltage limits	10	[0.94 :1.1]
6	Control variables	19	09+10

C2: GENERATOR DATA

Bus No.	P_g^{min}	P_g^{max}	Q_g^{min}	Q_g^{max}	Cost Coefficients		
	(MW)	(MW)	(MVAR)	(MVAR)	a	b	c
1	8	72	-10	15	0.0	1.5	0.0085
2	10	70	-35	45	0.0	2.5	0.017
3	30	510	-35	55	0.0	1.5	0.0085
4	20	400	-60	90	0.0	1.5	0.0085
13	15	150	-35	48	0.0	2.5	0.017
27	10	100	-20	35	0.0	2.5	0.017
37	10	100	-20	35	0.0	2.0	0.003
41	15	140	-35	45	0.0	2.0	0.003
42	18	175	-35	55	0.0	2.0	0.003
53	30	750	-100	160	0.0	1.5	0.0085

C3: BUS DATA

Bus No.	Type	P_d	Q_d
1	1	0	0
2	2	0.2420	0.1100
3	2	0	0
4	2	0.6850	0.3120
5	3	0.2220	0.1020
6	3	0	0
7	3	0.0600	0.0270
8	3	0.0390	0.0180
9	3	0.2840	0.1290
10	3	0.1800	0.0820
11	3	0.2500	0.1140
12	3	0	0
13	2	0	0
14	3	0.2250	0.1030
15	3	0.1940	0.0880
16	3	0	0
17	3	0.0640	0.0290

18	3	0	0
19	3	0	0
20	3	0.5290	0.2410
21	3	0	0
22	3	0	0
23	3	0.5670	0.2580
24	3	0.2140	0.0980
25	3	0	0
26	3	0.1960	0.0890
27	2	0.2350	0.1080
28	3	0.0780	0.0350
29	3	0.0590	0.0270
30	3	0	0
31	3	0	0
32	3	0	0
33	3	0.2470	0.1130
34	3	0	0
35	3	0.1390	0.0630
36	3	0.1390	0.0630
37	2	0	0
38	3	0.1560	0.0710
39	3	0.0150	0.0070
40	3	0.2160	0.0980
41	2	0.0300	0.0130
42	2	0	0
43	3	0.0730	0.0330
44	3	0.1680	0.0770
45	3	0	0
46	3	0.2220	0.1010
47	3	0.1630	0.0740
48	3	0.1920	0.0880
49	3	0.1430	0.0650
50	3	0	0
51	3	0	0
52	3	0.1600	0.0730
53	2	0	0
54	3	0.0730	0.0330
55	3	0.0870	0.0400
56	3	0.0720	0.0330
57	3	0	0
58	3	0.2230	0.1010
59	3	0	0

C4: LINE DATA

Line No.	From	To	R	X	B	Tap Setting
1	1	38	0.1520	0.4830	0.00115	1
2	1	40	0.1100	0.3520	0.00085	1
3	2	20	0.0190	0.1200	0.00035	1
4	2	55	0.0040	0.0230	0.00005	1
5	3	20	0.0180	0.1190	0.00035	1
6	4	27	0.0020	0.0060	0.00100	1
7	4	27	0.0030	0.0070	0.00100	1

8	5	9	0.0870	0.2210	0.00050	1
9	5	9	0.0880	0.2210	0.00050	1
10	5	23	0.0380	0.1380	0.00030	1
11	5	23	0.0380	0.1400	0.00030	1
12	5	27	0.0450	0.1670	0.00035	1
13	5	27	0.0450	0.1680	0.00040	1
14	5	46	0.0710	0.2310	0.00055	1
15	6	5	0.0020	0.0540	0.00000	1
16	6	13	0.0540	0.1900	0.06850	1
17	6	13	0.0570	0.2010	0.07200	1
18	6	30	0.0180	0.0850	0.03200	1
19	6	30	0.0250	0.0860	0.03100	1
20	7	40	0.5270	0.8870	0.00180	1
21	7	56	0.3640	0.6270	0.00130	1
22	8	14	0.2140	0.4910	0.00125	1
23	8	25	0.1570	0.3950	0.00095	1
24	9	14	0.2100	0.3660	0.00070	1
25	9	14	0.1290	0.3240	0.00075	1
26	10	40	0.0140	0.0180	0.00070	1
27	10	40	0.0110	0.0150	0.00150	1
28	11	48	0.2220	0.6050	0.00130	1
29	12	11	0.0200	0.0540	0.00000	1
30	12	37	0.0130	0.0450	0.00350	1
31	13	3	0.0140	0.3260	0.00000	1
32	13	34	0.0400	0.1420	0.05050	1
33	13	34	0.0400	0.1410	0.05050	1
34	14	29	0.3570	0.6220	0.00115	1
35	15	54	0.1150	0.2770	0.00300	1
36	16	15	0.0140	0.2850	0.00000	1
37	16	34	0.0300	0.1040	0.03950	1
38	17	39	0.1200	0.3080	0.00070	1
39	17	44	0.3700	0.9490	0.00215	1
40	18	22	0.0055	0.0200	0.00715	1
41	18	51	0.0110	0.0400	0.01425	1
42	19	22	0.0080	0.0285	0.01025	1
43	19	32	0.0160	0.0570	0.02050	1
44	20	28	0.2810	0.5060	0.00115	1
45	20	55	0.0160	0.1010	0.00030	1
46	21	20	0.0110	0.4390	0.00000	1
47	21	54	0.1300	0.3490	0.00400	1
48	22	20	0.0060	0.1620	0.00000	1
49	22	21	0.0140	0.3400	0.00000	1
50	23	26	0.0150	0.0200	0.00200	1
51	23	27	0.0260	0.0340	0.00350	1
52	23	46	0.0560	0.1710	0.00040	1
53	24	57	0.0138	0.0489	0.01750	1
54	25	29	0.2170	0.3690	0.00075	1
55	26	27	0.0130	0.0170	0.00200	1
56	28	43	0.2700	0.4770	0.00105	1
57	29	39	0.3120	0.7890	0.00185	1
58	30	29	0.0060	0.2160	0.00000	1
59	30	45	0.0320	0.1500	0.05650	1
60	31	34	0.0048	0.0168	0.00600	1
61	31	50	0.0095	0.0335	0.01200	1
62	32	34	0.0080	0.0285	0.01025	1
63	33	35	0.0920	0.1550	0.00030	1
64	33	48	0.8380	0.4130	0.00285	1

65	34	33	0.0060	0.2150	0.00000	1
66	36	43	0.3340	0.5780	0.00120	1
67	38	44	0.3270	0.5610	0.00115	1
68	40	41	0.0140	0.0190	0.00200	1
69	40	58	0.1060	0.3010	0.00060	1
70	40	58	0.1070	0.3070	0.00060	1
71	42	59	0.0079	0.0281	0.01000	1
72	43	52	0.0940	0.1600	0.00035	1
73	45	44	0.0140	0.3270	0.00000	1
74	45	59	0.0190	0.0890	0.03400	1
75	47	49	0.3390	0.8570	0.00195	1
76	47	58	0.2190	0.5470	0.00130	1
77	49	56	0.0160	0.0280	0.00005	1
78	50	53	0.0048	0.0168	0.00600	1
79	51	53	0.0055	0.0200	0.07150	1
80	53	52	0.0060	0.1630	0.00000	1
81	57	56	0.0100	0.3510	0.00000	1
82	57	59	0.0288	0.1020	0.03650	1
83	59	58	0.0060	0.2150	0.00000	1

APPENDIX D

SYSTEM DATA FOR THE IEEE 118-BUS SYSTEM

The IEEE-118 test bus system is shown in Figure D. The IEEE 118-bus test system has 54 generation units, two reactors, and 12 capacitors, 186 branches, and nine tap-changing transformers. The system data along with the control variable operating limits are given in Reference [303]. The characteristics of test system, generator data, bus data, line data are provided in the tables D.1, D.2, D.3, and D.4 respectively. The active and reactive power demands of this system on the 100 MVA base are 42.42 and 14.38 pu, respectively.

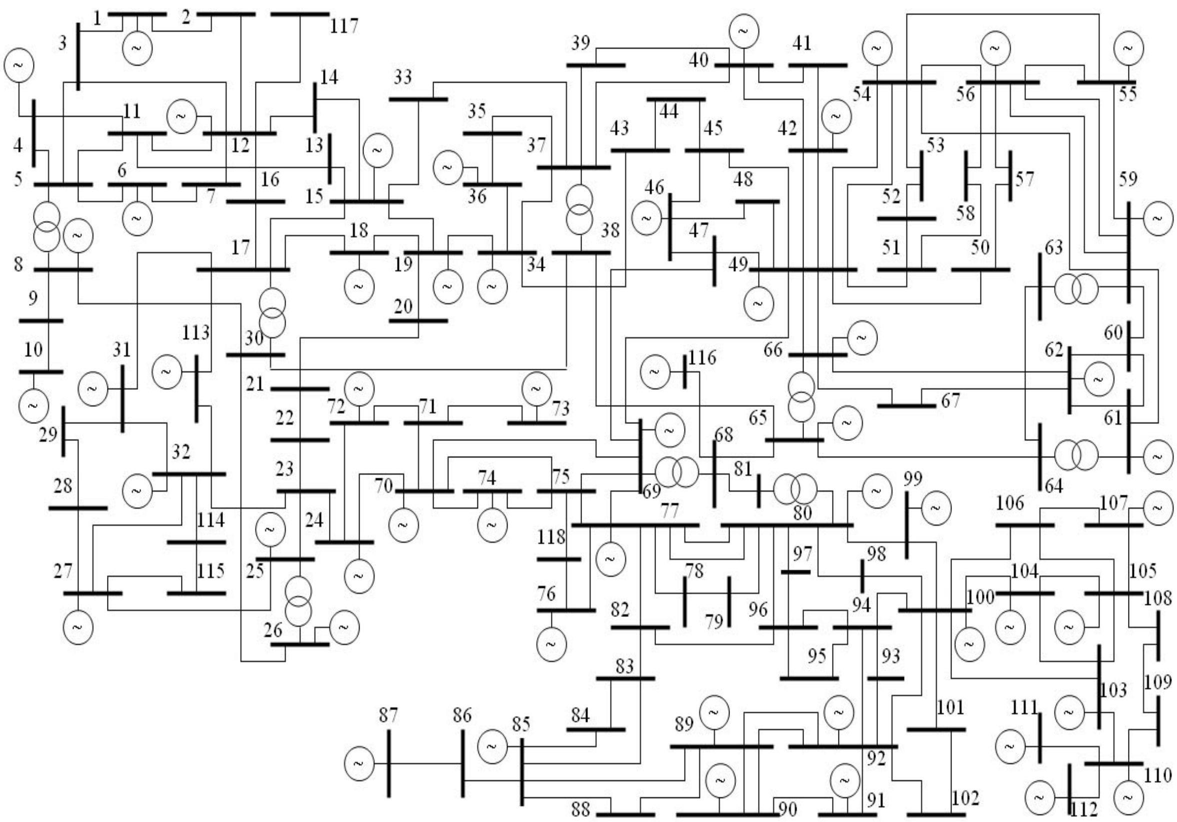

Figure D. Single line diagram of IEEE-118 Bus Test System

D1: CHARACTERISTICS OF IEEE 118-BUS TEST SYSTEM

IEEE 118-bus test system			
S. No	Characteristics	Value	Details
1	Busses	118	-
2	Branches	186	-
3	Generators	54	Busses: 1, 4, 6, 8, 10, 12, 15, 18, 19, 24, 25, 26, 27, 31, 32, 34, 36, 40, 42, 46, 49, 54, 55, 56, 59, 61, 62, 65, 66, 69, 70, 72, 73, 74, 76, 77, 80, 85, 87, 89, 90, 91, 92, 99, 100, 103, 104, 105, 107, 110, 111, 112, 113, and 116
4	Voltage limits of all busses	118	[0.94 - 1.06]
5	Transformers	09	Branches: 8, 32, 36, 51, 93, 95, 102, 107 and 127
6	Shunt VAR compensation	14	Busses: 5, 34, 37, 44, 45, 46, 48, 74, 79, 82, 83, 105, 107 and 110
7	Control variables	130	53+54+09+14

D2: GENERATOR DATA

Bus No.	P_g^{min}	P_g^{max}	Q_g^{min}	Q_g^{max}	Cost Coefficients		
	(MW)	(MW)	(MVAR)	(MVAR)	a	b	c
1	0	100.0000	-5	1.5	0.01	40	0.0
4	0	100.0000	-300	300	0.01	40	0.0
6	0	100.0000	-13	50	0.01	40	0.0
8	0	100.0000	-300	300	0.01	40	0.0
10	0	550.0000	-147	200	0.022222	20	0.0
12	0	185.0000	-35	120	0.117647	20	0.0
15	0	100.0000	-10	30	0.01	40	0.0
18	0	100.0000	-16	50	0.01	40	0.0
19	0	100.0000	-8	24	0.01	40	0.0
24	0	100.0000	-300	300	0.01	40	0.0
25	0	320.0000	-47	140	0.045455	20	0.0
26	0	414.0000	-1000	1000	0.031847	20	0.0
27	0	100.0000	-300	300	0.01	40	0.0
31	0	107.0000	-300	300	1.428571	20	0.0
32	0	100.0000	-14	42	0.01	40	0.0
34	0	100.0000	-8	24	0.01	40	0.0
36	0	100.0000	-8	24	0.01	40	0.0
40	0	100.0000	-300	300	0.01	40	0.0
42	0	100.0000	-300	300	0.01	40	0.0
46	0	119.0000	-100	100	0.526316	20	0.0
49	0	304.0000	0	210	0.04902	20	0.0
54	0	148.0000	-300	300	0.208333	20	0.0
55	0	100.0000	-8	23	0.01	40	0.0
56	0	100.0000	-8	15	0.01	40	0.0
59	0	255.0000	-60	180	0.064516	20	0.0
61	0	260.0000	-100	300	0.0625	20	0.0
62	0	100.0000	-20	20	0.01	40	0.0
65	0	491.0000	-67	200	0.025575	20	0.0
66	0	492.0000	-67	200	0.02551	20	0.0
69	0	100.0000	-300	300	0.019365	20	0.0
70	0	100.0000	-10	32	0.01	40	0.0
72	0	100.0000	-100	100	0.01	40	0.0

73	0	100.0000	-100	100	0.01	40	0.0
74	0	100.0000	-6	9	0.01	40	0.0
76	0	100.0000	-8	23	0.01	40	0.0
77	0	577.0000	-20	70	0.01	40	0.0
80	0	100.0000	-165	280	0.020964	20	0.0
85	0	104.0000	-8	23	0.01	40	0.0
87	0	707.0000	-100	1000	2.5	20	0.0
89	0	100.0000	-210	300	0.016474	20	0.0
90	0	100.0000	-300	300	0.01	40	0.0
91	0	100.0000	-100	100	0.01	40	0.0
92	0	100.0000	-3	9	0.01	40	0.0
99	0	352.0000	-100	100	0.01	40	0.0
100	0	140.0000	-50	155	0.039683	20	0.0
103	0	100.0000	-40	15	0.25	20	0.0
104	0	100.0000	-8	23	0.01	40	0.0
105	0	100.0000	-8	23	0.01	40	0.0
107	0	100.0000	-200	200	0.01	40	0.0
110	0	136.0000	-8	23	0.01	40	0.0
111	0	100.0000	-100	1000	0.277778	20	0.0
112	0	100.0000	-100	1000	0.01	40	0.0
113	0	100.0000	-100	200	0.01	40	0.0
116	0	100.0000	-1000	10000	0.01	40	0.0

D3: BUS DATA

Bus No.	Type	P_d (MW)	Q_d(MVAR)
1	2	0.5100	0.2700
2	3	0.2000	0.0900
3	3	0.3900	0.1000
4	2	0.3900	0.1200
5	3	0	0
6	2	0.5200	0.2200
7	3	0.1900	0.0200
8	2	0.2800	0
9	3	0	0
10	2	0	0
11	3	0.7000	0.2300
12	2	0.4700	0.1000
13	3	0.3400	0.1600
14	3	0.1400	0.0100
15	2	0.9000	0.3000
16	3	0.2500	0.1000
17	3	0.1100	0.0300
18	2	0.6000	0.3400
19	2	0.4500	0.2500
20	3	0.1800	0.0300
21	3	0.1400	0.0800
22	3	0.1000	0.0500
23	3	0.0700	0.0300
24	2	0.1300	0
25	2	0	0
26	2	0	0
27	2	0.7100	0.1300
28	3	0.1700	0.0700
29	3	0.2400	0.0400

30	3	0	0
31	2	0.4300	0.2700
32	2	0.5900	0.2300
33	3	0.2300	0.0900
34	2	0.5900	0.2600
35	3	0.3300	0.0900
36	2	0.3100	0.1700
37	3	0	0
38	3	0	0
39	3	0.2700	0.1100
40	2	0.6600	0.2300
41	3	0.3700	0.1000
42	2	0.9600	0.2300
43	3	0.1800	0.0700
44	3	0.1600	0.0800
45	3	0.5300	0.2200
46	2	0.2800	0.1000
47	3	0.3400	0
48	3	0.2000	0.1100
49	2	0.8700	0.3000
50	3	0.1700	0.0400
51	3	0.1700	0.0800
52	3	0.1800	0.0500
53	3	0.2300	0.1100
54	2	1.1300	0.3200
55	2	0.6300	0.2200
56	2	0.8400	0.1800
57	3	0.1200	0.0300
58	3	0.1200	0.0300
59	2	2.7700	1.1300
60	3	0.7800	0.0300
61	2	0	0
62	2	0.7700	0.1400
63	3	0	0
64	3	0	0
65	2	0	0
66	2	0.3900	0.1800
67	3	0.2800	0.0700
68	3	0	0
69	1	0	0
70	2	0.6600	0.2000
71	3	0	0
72	2	0.1200	0
73	2	0.0600	0
74	2	0.6800	0.2700
75	3	0.4700	0.1100
76	2	0.6800	0.3600
77	2	0.6100	0.2800
78	3	0.7100	0.2600
79	3	0.3900	0.3200
80	2	1.3000	0.2600
81	3	0	0
82	3	0.5400	0.2700
83	3	0.2000	0.1000
84	3	0.1100	0.0700
85	2	0.2400	0.1500
86	3	0.2100	0.1000

87	2	0	0
88	3	0.4800	0.1000
89	2	0	0
90	2	1.6300	0.4200
91	2	0.1000	0
92	2	0.6500	0.1000
93	3	0.1200	0.0700
94	3	0.3000	0.1600
95	3	0.4200	0.3100
96	3	0.3800	0.1500
97	3	0.1500	0.0900
98	3	0.3400	0.0800
99	2	0.4200	0
100	2	0.3700	0.1800
101	3	0.2200	0.1500
102	3	0.0500	0.0300
103	2	0.2300	0.1600
104	2	0.3800	0.2500
105	2	0.3100	0.2600
106	3	0.4300	0.1600
107	2	0.5000	0.1200
108	3	0.0200	0.0100
109	3	0.0800	0.0300
110	2	0.3900	0.3000
111	2	0	0
112	2	0.6800	0.1300
113	2	0.0600	0
114	3	0.0800	0.0300
115	3	0.2200	0.0700
116	2	1.8400	0
117	3	0.2000	0.0800
118	3	0.3300	0.1500

D4: LINE DATA

Line No.	From	To	R	X	B	Tap Setting
1	1	2	0.0303	0.0999	0.0254	1.0000
2	1	3	0.0129	0.0424	0.0108	1.0000
3	4	5	0.0018	0.0080	0.0021	1.0000
4	3	5	0.0241	0.1080	0.0284	1.0000
5	5	6	0.0119	0.0540	0.0143	1.0000
6	6	7	0.0046	0.0208	0.0055	1.0000
7	8	9	0.0024	0.0305	1.1620	1.0000
8	8	5	0	0.0267	0	0.9850
9	9	10	0.0026	0.0322	1.2300	1.0000
10	4	11	0.0209	0.0688	0.0175	1.0000
11	5	11	0.0203	0.0682	0.0174	1.0000
12	11	12	0.0060	0.0196	0.0050	1.0000
13	2	12	0.0187	0.0616	0.0157	1.0000
14	3	12	0.0484	0.1600	0.0406	1.0000
15	7	12	0.0086	0.0340	0.0087	1.0000
16	11	13	0.0222	0.0731	0.0188	1.0000
17	12	14	0.0215	0.0707	0.0182	1.0000
18	13	15	0.0744	0.2444	0.0627	1.0000

19	14	15	0.0595	0.1950	0.0502	1.0000
20	12	16	0.0212	0.0834	0.0214	1.0000
21	15	17	0.0132	0.0437	0.0444	1.0000
22	16	17	0.0454	0.1801	0.0466	1.0000
23	17	18	0.0123	0.0505	0.0130	1.0000
24	18	19	0.0112	0.0493	0.0114	1.0000
25	19	20	0.0252	0.1170	0.0298	1.0000
26	15	19	0.0120	0.0394	0.0101	1.0000
27	20	21	0.0183	0.0849	0.0216	1.0000
28	21	22	0.0209	0.0970	0.0246	1.0000
29	22	23	0.0342	0.1590	0.0404	1.0000
30	23	24	0.0135	0.0492	0.0498	1.0000
31	23	25	0.0156	0.0800	0.0864	1.0000
32	26	25	0	0.0382	0	0.9600
33	25	27	0.0318	0.1630	0.1764	1.0000
34	27	28	0.0191	0.0855	0.0216	1.0000
35	28	29	0.0237	0.0943	0.0238	1.0000
36	30	17	0	0.0388	0	0.9600
37	8	30	0.0043	0.0504	0.5140	1.0000
38	26	30	0.0080	0.0860	0.9080	1.0000
39	17	31	0.0474	0.1563	0.0399	1.0000
40	29	31	0.0108	0.0331	0.0083	1.0000
41	23	32	0.0317	0.1153	0.1173	1.0000
42	31	32	0.0298	0.0985	0.0251	1.0000
43	27	32	0.0229	0.0755	0.0193	1.0000
44	15	33	0.0380	0.1244	0.0319	1.0000
45	19	34	0.0752	0.2470	0.0632	1.0000
46	35	36	0.0022	0.0102	0.0027	1.0000
47	35	37	0.0110	0.0497	0.0132	1.0000
48	33	37	0.0415	0.1420	0.0366	1.0000
49	34	36	0.0087	0.0268	0.0057	1.0000
50	34	37	0.0026	0.0094	0.0098	1.0000
51	38	37	0	0.0375	0	0.9350
52	37	39	0.0321	0.1060	0.0270	1.0000
53	37	40	0.0593	0.1680	0.0420	1.0000
54	30	38	0.0046	0.0540	0.4220	1.0000
55	39	40	0.0184	0.0605	0.0155	1.0000
56	40	41	0.0145	0.0487	0.0122	1.0000
57	40	42	0.0555	0.1830	0.0466	1.0000
58	41	42	0.0410	0.1350	0.0344	1.0000
59	43	44	0.0608	0.2454	0.0607	1.0000
60	34	43	0.0413	0.1681	0.0423	1.0000
61	44	45	0.0224	0.0901	0.0224	1.0000
62	45	46	0.0400	0.1356	0.0332	1.0000
63	46	47	0.0380	0.1270	0.0316	1.0000
64	46	48	0.0601	0.1890	0.0472	1.0000
65	47	49	0.0191	0.0625	0.0160	1.0000
66	42	49	0.0715	0.3230	0.0860	1.0000
67	42	49	0.0715	0.3230	0.0860	1.0000
68	45	49	0.0684	0.1860	0.0444	1.0000
69	48	49	0.0179	0.0505	0.0126	1.0000
70	49	50	0.0267	0.0752	0.0187	1.0000
71	49	51	0.0486	0.1370	0.0342	1.0000
72	51	52	0.0203	0.0588	0.0140	1.0000
73	52	53	0.0405	0.1635	0.0406	1.0000
74	53	54	0.0263	0.1220	0.0310	1.0000
75	49	54	0.0730	0.2890	0.0738	1.0000

76	49	54	0.0869	0.2910	0.0730	1.0000
77	54	55	0.0169	0.0707	0.0202	1.0000
78	54	56	0.0027	0.0095	0.0073	1.0000
79	55	56	0.0049	0.0151	0.0037	1.0000
80	56	57	0.0343	0.0966	0.0242	1.0000
81	50	57	0.0474	0.1340	0.0332	1.0000
82	56	58	0.0343	0.0966	0.0242	1.0000
83	51	58	0.0255	0.0719	0.0179	1.0000
84	54	59	0.0503	0.2293	0.0598	1.0000
85	56	59	0.0825	0.2510	0.0569	1.0000
86	56	59	0.0803	0.2390	0.0536	1.0000
87	55	59	0.0474	0.2158	0.0565	1.0000
88	59	60	0.0317	0.1450	0.0376	1.0000
89	59	61	0.0328	0.1500	0.0388	1.0000
90	60	61	0.0026	0.0135	0.0146	1.0000
91	60	62	0.0123	0.0561	0.0147	1.0000
92	61	62	0.0082	0.0376	0.0098	1.0000
93	63	59	0	0.0386	0	0.9600
94	63	64	0.0017	0.0200	0.2160	1.0000
95	64	61	0	0.0268	0	0.9850
96	38	65	0.0090	0.0986	1.0460	1.0000
97	64	65	0.0027	0.0302	0.3800	1.0000
98	49	66	0.0180	0.0919	0.0248	1.0000
99	49	66	0.0180	0.0919	0.0248	1.0000
100	62	66	0.0482	0.2180	0.0578	1.0000
101	62	67	0.0258	0.1170	0.0310	1.0000
102	65	66	0	0.0370	0	0.9350
103	66	67	0.0224	0.1015	0.0268	1.0000
104	65	68	0.0014	0.0160	0.6380	1.0000
105	47	69	0.0844	0.2778	0.0709	1.0000
106	49	69	0.0985	0.3240	0.0828	1.0000
107	68	69	0	0.0370	0	0.9350
108	69	70	0.0300	0.1270	0.1220	1.0000
109	24	70	0.0022	0.4115	0.1020	1.0000
110	70	71	0.0088	0.0355	0.0088	1.0000
111	24	72	0.0488	0.1960	0.0488	1.0000
112	71	72	0.0446	0.1800	0.0444	1.0000
113	71	73	0.0087	0.0454	0.0118	1.0000
114	70	74	0.0401	0.1323	0.0337	1.0000
115	70	75	0.0428	0.1410	0.0360	1.0000
116	69	75	0.0405	0.1220	0.1240	1.0000
117	74	75	0.0123	0.0406	0.0103	1.0000
118	76	77	0.0444	0.1480	0.0368	1.0000
119	69	77	0.0309	0.1010	0.1038	1.0000
120	75	77	0.0601	0.1999	0.0498	1.0000
121	77	78	0.0038	0.0124	0.0126	1.0000
122	78	79	0.0055	0.0244	0.0065	1.0000
123	77	80	0.0170	0.0485	0.0472	1.0000
124	77	80	0.0294	0.1050	0.0228	1.0000
125	79	80	0.0156	0.0704	0.0187	1.0000
126	68	81	0.0018	0.0202	0.8080	1.0000
127	81	80	0	0.0370	0	0.9350
128	77	82	0.0298	0.0853	0.0817	1.0000
129	82	83	0.0112	0.0367	0.0380	1.0000
130	83	84	0.0625	0.1320	0.0258	1.0000
131	83	85	0.0430	0.1480	0.0348	1.0000
132	84	85	0.0302	0.0641	0.0123	1.0000

133	85	86	0.0350	0.1230	0.0276	1.0000
134	86	87	0.0283	0.2074	0.0445	1.0000
135	85	88	0.0200	0.1020	0.0276	1.0000
136	85	89	0.0239	0.1730	0.0470	1.0000
137	88	89	0.0139	0.0712	0.0193	1.0000
138	89	90	0.0518	0.1880	0.0528	1.0000
139	89	90	0.0238	0.0997	0.1060	1.0000
140	90	91	0.0254	0.0836	0.0214	1.0000
141	89	92	0.0099	0.0505	0.0548	1.0000
142	89	92	0.0393	0.1581	0.0414	1.0000
143	91	92	0.0387	0.1272	0.0327	1.0000
144	92	93	0.0258	0.0848	0.0218	1.0000
145	92	94	0.0481	0.1580	0.0406	1.0000
146	93	94	0.0223	0.0732	0.0188	1.0000
147	94	95	0.0132	0.0434	0.0111	1.0000
148	80	96	0.0356	0.1820	0.0494	1.0000
149	82	96	0.0162	0.0530	0.0544	1.0000
150	94	96	0.0269	0.0869	0.0230	1.0000
151	80	97	0.0183	0.0934	0.0254	1.0000
152	80	98	0.0238	0.1080	0.0286	1.0000
153	80	99	0.0454	0.2060	0.0546	1.0000
154	92	100	0.0648	0.2950	0.0472	1.0000
155	94	100	0.0178	0.0580	0.0604	1.0000
156	95	96	0.0171	0.0547	0.0147	1.0000
157	96	97	0.0173	0.0885	0.0240	1.0000
158	98	100	0.0397	0.1790	0.0476	1.0000
159	99	100	0.0180	0.0813	0.0216	1.0000
160	100	101	0.0277	0.1262	0.0328	1.0000
161	92	102	0.0123	0.0559	0.0146	1.0000
162	101	102	0.0246	0.1120	0.0294	1.0000
163	100	103	0.0160	0.0525	0.0536	1.0000
164	100	104	0.0451	0.2040	0.0541	1.0000
165	103	104	0.0466	0.1584	0.0407	1.0000
166	103	105	0.0535	0.1625	0.0408	1.0000
167	100	106	0.0605	0.2290	0.0620	1.0000
168	104	105	0.0099	0.0378	0.0099	1.0000
169	105	106	0.0140	0.0547	0.0143	1.0000
170	105	107	0.0530	0.1830	0.0472	1.0000
171	105	108	0.0261	0.0703	0.0184	1.0000
172	106	107	0.0530	0.1830	0.0472	1.0000
173	108	109	0.0105	0.0288	0.0076	1.0000
174	103	110	0.0391	0.1813	0.0461	1.0000
175	109	110	0.0278	0.0762	0.0202	1.0000
176	110	111	0.0220	0.0755	0.0200	1.0000
177	110	112	0.0247	0.0640	0.0620	1.0000
178	17	113	0.0091	0.0301	0.0077	1.0000
179	32	113	0.0615	0.2030	0.0518	1.0000
180	32	114	0.0135	0.0612	0.0163	1.0000
181	27	115	0.0164	0.0741	0.0197	1.0000
182	114	115	0.0023	0.0104	0.0028	1.0000
183	68	116	0.0003	0.0040	0.1640	1.0000
184	12	117	0.0329	0.1400	0.0358	1.0000
185	75	118	0.0145	0.0481	0.0120	1.0000
186	76	118	0.0164	0.0544	0.0136	1.0000