

Université Mohamed Khider Biskra
Faculté des Sciences et de la Technologie
Département : Génie Electrique
Ref :.....



جامعة محمد خيضر بسكرة
كلية العلوم و التكنولوجيا
قسم: الهندسة الكهربائية
المرجع:.....

جامعة محمد خيضر بسكرة

Thèse présentée en vue de l'obtention
du diplôme de
Doctorat LMD en Génie Electrique

Filière : Électrotechnique

Option : Réseaux électriques

**Contribution à l'optimisation de l'écoulement de
puissance par les méthodes d'intelligence artificielle
améliorées**

Réalisé par:

SALHI Souheil

Encadré par :

Dr. SALHI Ahmed

Devant le jury composé de :

BETKA Achour
SALHI Ahmed
ARIF Salem
CHARROUF Omar
NAIMI Djemai

Professeur
M. C. A
Professeur
M. C. A
Professeur

President
Rapporteur
Examineur
Examineur
invited

Biskra University
Biskra University
Laghouat university
Biskra University
Biskra University

2022/2023

University Mohamed Khider Biskra
Faculty of Science and Technology
Department: Electrical Engineering
Ref :.....



جامعة محمد خيضر بسكرة
كلية العلوم و التكنولوجيا
قسم: الهندسة الكهربائية
المرجع:.....

جامعة محمد خيضر بسكرة

Thesis presented in view of obtaining the diploma of
Doctorat LMD en Génie Electrique

Field: Electrical engineering

Option: Electrical networks

Contribution to power flow optimization by enhanced artificial intelligence methods

Realized by:

SALHI Souheil

Supervised by:

Dr. SALHI Ahmed

Before the jury composed of :

BETKA Achour
SALHI Ahmed
ARIF Salem
CHARROUF Omar
NAIMI Djemai

Professor
M. C. A
Professor
M. C. A
Professor

President
Reporter
examiner
examiner
invited

Biskra University
Biskra University
Laghouat university
Biskra University
Biskra University

2022/2023

ملخص

يعد التوزيع الأمثل للاستطاعة الارتكاسية (ORPD) مسألة مهمة لتحقيق حالة تشغيل أكثر اقتصاداً وأماناً واستقراراً لنظام الشبكات الكهربائية. يتم صياغتها كمسألة معقدة لتحديد متغيرات التحكم المثلى لمختلف معدات النظام و ذلك بتقليل الداله الهدف مع الأخذ بعين الاعتبار قيود التشغيل. تم اقتراح العديد من التقنيات للتغلب على التعقيدات المختلفة في حل مسألة ORPD، والتي تتميز باليتين للبحث و هما الاستكشاف والاستغلال. يمثل التوازن بين هاتين الخاصيتين مشكلة صعبة للتوصل لحل أفضل جودة لحل المسألة. أثبتت خوارزمية مستعمرة النحل الاصطناعية (ABC) باعتبارها خوارزمية معروفة و مشهورة بأنها جيدة في الاستكشاف و ضعيفة عند الاستغلال حيث يصبح تحسين إصدار ABC الأساسي ضرورياً. خوارزمية (SSA) هي خوارزمية جديدة قائمة على سرب تم تطويرها حديثاً، والتي تتمتع بأفضل قدرة بحث محلية باستخدام أفضل الحلول في كل تكرار لاكتشاف الحلول الواعدة. في هذا البحث ، تم تطوير وتطبيق منهج هجين جديد يعتمد على خوارزميات ABC و SSA لحل مشكلة ORPD. يحاول النهج المقترح تعزيز قدرة استغلال خوارزمية ABC باستخدام SSA. يتم التحقق من كفاءة ABC-SSA باستخدام أربعة شبكات اختبار قياسية IEEE 30bus, IEEE 57bus, IEEE 118 bus و على النطاق الواسع IEEE 300 bus وذلك من خلال الأخذ بعين الاعتبار دوال الهدف الشهيرة الخاصة بمسألة ORPD بما في ذلك إجمالي ضياعات الاستطاعة الفعالة (Ploss)، والانحراف الكلي للجهد (TVD) من مقدار الجهد المقنن ومؤشر استقرار الجهد (VSI) قضيب التحميل. أثبتت نتائج المحاكاة التي تم التوصل إليها أن طريقة ABC-SSA المقترحة هي الأكثر كفاءة من ABC و SSA والتقنيات الأمثلة الأخرى التي تم تطويرها مؤخراً في الأدبيات محور البحث.

الكلمات المفتاحية: التوزيع الأمثل للاستطاعة الارتكاسية (ORPD)، إجمالي ضياعات الاستطاعة الفعالة (Ploss)، الانحراف الكلي للجهد (TVD)، مؤشر استقرار الجهد (VSI)، مستعمرة النحل الاصطناعية الهجينة و خوارزمية سرب سالب (ABC-SSA).

Abstract

Optimal Reactive Power Dispatch (ORPD) is an important task for achieving more economical, secure and stable state of the electrical power system. It is expressed as a complex optimization problem that is stated to identify the optimal control variables of various regulating equipments for minimizing an objective function under constraints. Many meta-heuristic techniques have been proposed to overcome various complexities in solving ORPD problem, which are characterized by exploration and exploitation of the search mechanism. The balance between these two characteristics is a challenging problem to attain the best solution quality. The Artificial Bee Colony (ABC) algorithm as a reputed meta-heuristic has proved its goodness at exploration and weakness at exploitation where the enhancement of the basic ABC version becomes necessary. Salp Swarm Algorithm (SSA) is a

newly developed swarm-based meta-heuristic, which has the best local search capability by using the best global solution in each iteration to discover promising solutions. In this research, a novel hybrid approach based on ABC and SSA algorithms (ABC-SSA) is developed and applied for solving ORPD problem. The proposed approach tries to enhance the exploitation capability of the ABC algorithm using SSA. The efficiency of ABC-SSA is investigated using four standard test systems IEEE 30bus, IEEE 57bus, IEEE 118bus and large-scale IEEE 300bus and that by considering the famous objective functions in ORPD problem including total transmission active power losses (P_{loss}), Total Voltage Deviation (TVD) from the rated voltage magnitude and the Voltage Stability Index (VSI) of load buses. The reached simulation results have proved that the proposed ABC-SSA is more efficient overcoming ABC, SSA and other recently developed meta-heuristic optimization techniques in the literature.

Key words: Optimal reactive power dispatch (ORPD), Total transmission active losses (P_{loss}), Total voltage deviation (TVD), Voltage stability index (VSI), Hybrid artificial bee colony and salp swarm algorithm (ABC-SSA).

Résumé

La répartition optimale de la puissance réactive (ORPD) est une tâche importante pour atteindre un meilleur état d'économie, de sécurité et de stabilité du système de l'énergie électrique. Il s'agit d'un problème d'optimisation complexe qui vise à identifier les variables de contrôle optimales des différents équipements de régulation du réseau afin de minimiser une fonction objective sous contraintes. De nombreuses techniques méta-heuristiques ont été proposées pour surmonter les diverses complexités dans la résolution du problème ORPD, qui sont caractérisées par l'exploration et l'exploitation du mécanisme de recherche. L'équilibre entre ces deux caractéristiques est un défi à surmonter pour aboutir à une meilleure qualité de solution. L'algorithme de la colonie Artificiel des Abeilles (Artificial Bee Colony - ABC) est une méthode méta-heuristique réputée, s'est avéré efficace en matière d'exploration et faible en matière d'exploitation, ce qui rend nécessaire l'amélioration de la version de base de l'algorithme ABC. L'algorithme Salp Swarm (SSA) est une méta-heuristique nouvellement développée, basée sur un essaim, qui possède la meilleure capacité de recherche locale en utilisant la meilleure solution globale à chaque itération pour découvrir des solutions

prometteuses. Dans ce sujet de recherche, une nouvelle approche hybride basée sur les algorithmes ABC et SSA (ABC-SSA) est développée et appliquée pour résoudre le problème ORPD. L'approche proposée tente d'améliorer la capacité d'exploitation de l'algorithme ABC en utilisant SSA. L'efficacité de l'ABC-SSA est examinée en utilisant quatre réseaux électriques d'essai standard : IEEE 30 bus, IEEE 57 bus, IEEE 118 bus et IEEE 300 bus à grande échelle, en tenant compte des célèbres fonctions objectives du problème ORPD, notamment les pertes totales de puissance active de transmission (Ploss), l'écart total de tension (TVD) par rapport à l'amplitude de tension nominale et l'indice de stabilité de la tension (VSI) des jeux de barres de charge. Les résultats de simulation obtenus ont prouvé que l'ABC-SSA proposé est plus efficace que l'ABC, le SSA et d'autres techniques d'optimisation méta-heuristiques récemment développées dans la littérature du domaine d'application.

Mots clés : Répartition optimale de la puissance réactive (ORPD), pertes actives totales de transmission (Ploss), déviation totale de la tension (TVD), indice de stabilité de la tension (VSI), algorithme hybride de colonie d'abeilles artificielles et d'essaim salpêtre (ABC-SSA).

Dedication

I owe all to my wife without her unconditional support I would not have reached this height and dream.

I owe a debt of gratitude to my parents Comfort for their support, understanding and constant encouragement and prayers

I am eternally grateful to my brothers and my sisters for their love

Souheil

Acknowledgement

First of all, I would like to express my thanks to my thesis director

I would like to thank my *PhD Supervisor* Dr. SALHI Ahmed for his constant motivation and support during the course of my dissertation. I am thankful for his valued tutelage and support all through the period of my study. I am highly indebted to him for being patient with me. I was honored to have him as my supervisor.

I would like to warmly thank Pr. NAIMI Djemai, Professor at Mohamed KHIDER Biskra University, for his encouragement that he lavished on me during the period of the thesis.

I would like to sincerely thank the members of the jury:

1. I also thank Pr. BETKA Achour, Professor at university Mohamed Khider Biskra, (president of the jury).
2. Pr. ARIF Salem, Professor at university Amar Telidji Laghouat, for the interest shown in our work and his participation in the jury as an examiner.
3. Dr. CHARROUF Omar, Doctor at Mohamed KHIDER Biskra University, finds here the expression of my most sincere thanks for his participation in the jury as an examiner.

Publications & Communications associated with the thesis

The contributions presented in this thesis manuscript have been published in the following articles.

- **International Publications**

S Souheil, N Djemai, S Ahmed, A Saleh, N Abdelouahab, "A novel hybrid approach based artificial bee colony and salp swarm algorithms for solving ORPD problem," *Indonesian Journal of Electrical Engineering and Computer Science* 23, 1825_1837.

A. Necira, D. Naimi, A. Salhi, **S. Salhi**, and S. Menani, "Dynamic crow search algorithm based on adaptive parameters for large-scale global optimization," *Evolutionary Intelligence*, pp. 1-17, 2021.

- **International communications**

S Souheil, S Ahmed, N Djemai, N Abdelouahab, " a novel optimization algorithm for optimal reactive power dispatch: salp swarm algorithm ," at the second international conference on electrical engineering ICEEB '18 ," december 2018, Biskra, Algeria.

List of Figures

Chapter 2

Figure 2.1	Schematic diagram of the principle of electricity generation, transmission and distribution	7
Figure 2.2	Electrical line feeding a load	9
Figure 2.3	System load line	10
Figure 2.4	π -model of a power line	13
Figure 2.5	Equivalent diagram of transformer with on-load tap-changer	14
Figure 2.6	Equivalent diagram of phase-shifting transformer	14
Figure 2.7	Equivalent diagram of a transformer: π -model	14
Figure 2.8	The load model	16
Figure 2.9	Illustration of an isolated bus	18
Figure 2.10	Admittance schema of a 3-bus system	18
Figure 2.11	Flowchart of Newton-Raphson method	26
Figure 2.12	Optimum global vs optimum local	33

Chapter 3

Figure 3.1	Flowchart of ABC algorithm	51
Figure 3.2	(a) Individual Salp, (b) Swarm of Salps (Salps chain)	52
Figure 3.3	Flowchart of SSA	54
Figure 3.4	Structure of the ABC-SSA method	56
Figure 3.5	Flowchart of the ABC-SSA algorithm	57

Chapter 4

Figure 4.1	Single line diagram of IEEE 30 bus bus power system	60
Figure 4.2	Convergence curves for Ploss minimization, IEEE 30 bus	61
Figure 4.3	Convergence curves for TVD minimization of IEEE 30 bus power system	63
Figure 4.4	Convergence curves for VSI minimization of IEEE 30 bus power system	64
Figure 4.5	Single line diagram of IEEE 57 bus test system	65
Figure 4.6	Bus voltage profile for IEEE 57 bus power system	67
Figure 4.7	Convergence curves for Ploss minimization, IEEE 57 bus	68
Figure 4.8	Convergence curves for TVD minimization of IEEE 57 bus power system	69
Figure 4.9	Convergence curves for VSI minimization of IEEE 57 bus power system	70
Figure 4.10	Single line diagram of IEEE 118 bus test system	71
Figure 4.11	Convergence curves for Ploss minimization, IEEE 118 bus	72
Figure 4.12	Bus voltage profile for IEEE 118 bus power system for three methods (ABC-SSA)	75
Figure 4.13	Reactive of production units in relation to their min / max	75

	permissible limits for test system IEEE 118 bus	
Figure 4.14	Convergence curves for TVD minimization of IEEE 118 bus power system	76
Figure 4.15	Convergence curve for VSI minimization, IEEE 118 bus	77
Figure 4.16	Bus voltage profile for IEEE 300 bus power system	78
Figure 4.17	Convergence curves for Ploss minimization IEEE 300 bus	79

List of Tables

Chapter 4

Table 4.1	Description of test power systems	59
Table 4.2	Control parameter settings of ABC, SSA, and ABC-SSA algorithms for test power systems	60
Table 4.3	Simulation results using ABC-SSA and other optimization techniques for P_{loss} minimization-IEEE 30 bus.	62
Table 4.4	Comparison of minimum real power losses for different methods for IEEE 30 bus system.	62
Table 4.5	Comparison of simulation results for IEEE 30 bus test power system with TVD minimization objective.	63
Table 4.6	Comparison of simulation results for IEEE 30 bus test power system with improvement of VSI	64
Table 4.7	Comparison of simulation results for Ploss minimization in case of IEEE 57 bus system.	66
Table 4.8	Reactive power from units in relation to their min / max permissible limits for test system IEEE 57 bus.	67
Table 4.9	Comparison of simulation results for Ploss minimization in case of IEEE 57 bus system.	68
Table 4.10	Comparison of simulation results for IEEE 57 bus test power system with TVD minimization objective (a) and improvement of VSI (b).	69
Table 4.11	Comparison of simulation results for IEEE 118 bus test system with PLoss minimization objective	73
Table 4.12	Comparison of simulation results for IEEE 118 bus test power system with TVD minimization objective.	76
Table 4.13	Comparison of simulation results for IEEE 118bus test power system with improvement of VSI.	77
Table 4.14	Comparison of simulation results for IEEE 300 bus with Ploss minimization	78
Table 4.15	Comparison of simulation results for IEEE 300 bus system with TVD minimization.	79

Acronyms and Abbreviations

P_G / Q_G	: Active power generation / reactive power generator
P_l / Q_l	: Active power load demand / reactive power load demand
S_l	: Apparent power flow of l -th branch
G_k	: Conductance of k -th branch of the network
δ_{ij}	: Difference of voltage angle between buses i and j
Q_c	: Injected VAR power from compensator
I_{PV} / I_{PQ}	: Injected current vector of generator and load buses, respectively
$F(x, u)$: Objective function.
Y_{ij} / α_{ij}	: Magnitude/angle of admittance matrix element between buses i and j
NLB / NG	: Number of load buses / number of generator buses
NTL / NT	: Number of transmission lines / number of tap setting transformers
NC / NB	: Number of shunt capacitor banks/ number of total buses
T_k	: Ratio of k -th tap changing transformers
$g(x, u) / h(x, u)$: Set of equality constraints/set of inequality constraints
x	: Vector of dependent variables (state variables)
u	: Vector of independent variables (Control Variables)
V_i / V_j	: Voltage magnitude of i -th and j -th bus, respectively
V_{PV} / V_{PQ}	: Voltage vector of generator and load buses, respectively
V_G / V_L	: Voltage at the generator and load buses, respectively

Table of contents

	<i>page</i>
Abstract	I
Dedication	IV
Acknowledgement	V
Publications & Communications associated with the thesis	VI
List of Figures	VII
List of Tables	IX
Acronyms and Abbreviations	X
Table of Contents	XI
<i>Chapter 1: Introduction</i>	
1.1 Motivation	3
1.2 Objectives	4
1.3 Organization of the thesis	5
<i>Chapter 2 : Optimal Reactive Power Dispatch</i>	
Introduction	6
2.1 Electrical network	6
2.2 Electrical systems	6
2.2.1 The production	7
2.2.2 The transport	7
2.2.3 The distribution	8
2.3 Power Transmitted by a Power Line	8
2.4 Voltage drop	10
2.5 The power elements modeling of an electrical network	12
2.5.1 Generator of power	12
2.5.2 Transmission lines	12
2.5.3 Transformer of power	13
2.5.4 Electrical loads	15
2.5.5 Shunt elements	16
2.6 Power Flow	16
2.6.1 General concept of power flow	17
2.6.2 Objectives of the power flow study	17
2.7 Nodal admittance matrix	17
2.8 Power flow calculation methods	20
2.8.1 Newton-Raphson method	20
2.8.1.1 Advantages of the Newton-Raphson method	25
2.8.1.2 The inconvenience of the Newton-Raphson method	25
2.8.1.3 Flowchart of Newton-Raphson method	26
2.8.2 Gauss-Seidel method	27
2.8.3 Fast decoupled method of power flow	27

2.9 Optimal Power Flow	31
2.9.1 Definition of the optimization	31
2.9.2 Optimization problems	32
2.9.3 Global optimum, local optimum	32
2.9.4 The ORPD problem formulation	33
2.9.4.1 Objective functions	33
2.9.4.1.1 Total active transmission losses	34
2.9.4.1.2 Voltage deviation	34
2.9.4.1.3 Voltage stability index	34
2.9.4.2 Operational Constraints	35
2.9.4.2.1 Power flow equality constraints	35
2.9.4.2.2 Operating inequality constraints	35
2.10 Optimal reactive power dispatch	36
2.11 Conclusion	37
<i>Chapter 3: Metaheuristics</i>	
Introduction	38
3.1 Conventional Optimization Techniques	39
3.2 Evolutionary Optimization Techniques	42
3.2.1 Evolutionary computation techniques (EC)	42
3.2.2 Physical heuristic methods	43
3.2.3 Swarm intelligence	43
3.3 Choice of an optimization method	44
3.4 Exploration and exploitation of optimization algorithms	46
3.5 The most used meta-heuristics	46
3.6 Artificial bee colony	47
3.6.1 Flowchart of Artificial bee colony (ABC)	51
3.7 Salp swarm algorithm	51
3.7.1 Flowchart of Salp swarm algorithm (SSA)	54
3.8 Hybrid ABC-SSA Approach	55
3.8 Steps of Hybrid ABC-SSA Approach	54
3.8.1 Contribution structure of the ABC-SSA method	56
3.8.2 Flowchart of Hybrid ABC-SSA Approach	56
3.9 Conclusion	58
<i>Chapter 4: Simulation results and analysis</i>	
4.1 Simulation results and discussions	59
4.2.1 IEEE 30 bus System	60

4.2.1 Active power losses minimization for IEEE 30 bus system	61
4.2.2 TVD minimization for IEEE 30 bus system	62
4.2.3 VSI improvement for IEEE 30 bus system	63
4.3 IEEE 57 bus system	64
4.3.1 Active power losses Ploss minimization for IEEE 57 bus system	65
4.3.2 TVD minimization for IEEE 57 bus system	68
4.3.3 VSI improvement for IEEE 57 bus system	70
4.4 IEEE 118 bus system	70
4.4.1 Active power losses minimization for IEEE 118 bus system	72
4.4.2 TVD minimization for IEEE 118 bus system	75
4.4.3 VSI improvement for IEEE 118 bus system	76
4.5 IEEE 300 bus system	77
Conclusion	80
References	82
Appendices	87

CHAPTER 1

INTRODUCTION

The Optimal Reactive Power Dispatch (ORPD) is an optimization problem recognized as an important tool in the electrical power engineering area, to manage reactive power in electrical networks. The main objective of ORPD is to assess the optimal operating state of the electrical power grid based on the criteria of economy, service quality and security. Economy and service quality require appropriate voltage control at all buses of the system with tolerable limits to ensure proper reactive power flows and minimal active transmission losses. On the other hand, the security of the power system requires sufficient voltage levels and reactive reserves to prevent voltage stability failures and to maintain the integrity of the power grid in a safe state when critical unforeseen events occur. Power grid security control can be performed by improving the voltage stability margin reflected by the Voltage Stability Index (VSI) or minimizing the Total Voltage Deviation (TVD) from the rated voltage magnitude. The aforementioned goals of ORPD problem can be achieved through the optimal adjustments of all kinds of control variables in the power system given by the voltage magnitude at all buses of generation (continuous control variables), tap setting transformers and reactive power from volt-ampere reactive (VAR) compensators (discrete control variables). By combining these two types of control variables, the ORPD becomes a Mixed Integer Nonlinear Programming (MINLP) optimization problem. The mono-objective resolution of ORPD is stated for minimizing the transmission power active losses (P_{loss}), reduce the TVD or improve the VSI related to load buses, while accomplishing the satisfaction of predefined operational constraints related to the physical system. Generally, the classifications of the optimization problems are done according to the mathematical features of the fitness function, constraints and control variables. The problem formulation of any optimization problem can be thought of as a sequence of steps [1]. These steps are:

- Formulating objective functions
- Choosing the design variables (control and state variables)
- Formulating constraints
- Setting up variable limits
- Choosing an optimization technique to solve the problem

- Solving the problem in order to obtain the optimal solution.

In literature, many classical optimization methods have been applied to solve the ORPD problem. Linear Programming (LP), Nonlinear Programming (NLP) [1] and Newton method [2] were among the presented techniques in literature. Unfortunately, these conventional methods present some drawbacks in dealing with non-convex and MINLP optimization problems considering non-differentiable objective functions and constraints. These methods have also proved premature convergence trapping in local optima by solving complex optimization problems. Recently, computational intelligence methods have been imposed as an alternative to the classical optimization techniques called meta-heuristics, which are based on mimicking physical or biological phenomena and their main advantage concerns the ability in dealing with combinatorial and non-convex optimization problems. Another interesting feature is that, no requirements are imposed for these methods to get differentiable mathematical constraints and objective functions. Many meta-heuristic optimization techniques have been developed in recent years, and each of them is inspired according to a natural phenomenon. Some of them have been widely employed in solving the ORPD problem, such as Genetic Algorithms (GA) [3], Particle Swarm Optimization (PSO) [4], Artificial Bee Colony (ABC) [5], Firefly Algorithm (FA) [6], Gravitational Search Algorithm (GSA) [7], and Whale Optimization Algorithm (WOA) [8].

There is no guarantee for a particular meta-heuristic algorithm to reach a perfectly optimal solution, and none of them can solve all optimization problems effectively referring to the No Free Lunch (NFL) theorem [9]. Therefore, wide research works have been elaborated to enhance the search capability of some meta-heuristics in solving ORPD problem. Generally, meta-heuristics are judged by their two search mechanisms: search space exploration called diversification and best solutions exploitation named intensification, where the balance between these two mechanisms is a challenging goal to get a better near optimal solution. To reach this goal, a hybrid model is adopted by combining two meta-heuristic methods to profit from the advantages of both methods and accordingly attain better solution quality than using each one separately [10-12]. In this regard, extensive competitive research works have been carried out in the last decade for enhancing the solution quality of ORPD problem. The research presented in [13] proposes a Hybrid Firefly Algorithm (HFA), which begins the exploration by the conventional FA method and ends by exploitation the Nelder Mead simplex method. This paradigm allows the HFA to escape from premature convergence

of the original FA. In [14], a combination of GSA and Sequential Quadratic Programming (SQP) and presented as (GSA-SQP) has been implemented as an efficient hybrid algorithm to solve ORPD problem in the case of IEEE 30 bus test system. This approach tends to avoid a premature convergence of GSA without trapping in local optima. In [15], a Modified Imperialist Competitive Algorithm (MICA) was hybridized with the Invasive Weed Optimization (IWO) method to improve the optimal solution of the ORPD problem compared to that of the original ICA or IWO method. In the aim to surmount the early convergence problem of the PSO algorithm, the authors in [16] suggest a more effective alternative method by hybridizing the basic PSO and Ant Lion Optimizer (ALO) algorithm named PSO-ALO with no significantly undermining the fast convergence of (PSO) technique. This hybrid approach has proved its success in improving ORPD solution since it finds a better objective functions than most competitive optimization techniques.

To this end, this research contributes to the ongoing research by developing a hybrid approach based ABC algorithm and SSA (ABC-SSA) for the optimal solution of the ORPD problem. The main advantage of the developed approach is to profit from both superiorities of the ABC and the SSA algorithms, mainly exploration and exploitation, respectively. To the best of our knowledge, this is the first time that this hybrid approach ABC-SSA is developed and applied to the solution of the ORPD problem. Various test systems are implemented such as IEEE 30 bus, IEEE 57 bus, IEEE 118 bus and large system IEEE 300 bus to confirm the validity of the proposed hybrid ABC-SSA in finding a better solution than using one method at a time and over the proposed hybrid techniques in literature. The simulation results obtained using ABC-SSA are compared to those of other recently published techniques in literature for the same problem. The presented comparison proves the robustness of this hybrid technique under different case studies on various scales of power systems. The presented technique promotes its extension to other complex optimization fields.

1.1 Motivation

In the last few decades, (ORPD) has received great attention and it has become a tool for improving the economy and security of power system operation. The ORPD, which is a non-linear, non-convex and non-differentiable optimization problem, aims at minimizing the objective functions such as voltage stability and real power losses and power system via the adjustments of control parameters like generators voltages, switchable (VAR) sources,

transformer tap settings etc. in a power system while satisfying equality and inequality constraints [7].

Reactive power requirement changes continuously with load and system configuration. The change in reactive power causes voltage variations in the system. Any change in the system formation or power demands may result in a change in voltage levels in the system. Injecting reactive power into the power system raises voltages while absorbing the reactive power from the system lowers voltages. The main task of a power system is to sustain the load bus voltages within the nominal range for consumer satisfaction especially in a deregulated or restructured power industry. Despite the importance of deregulation which includes but is not limited to removal or reduction of government control over the power industry and electricity price reduction etc., it leads to expansion and reconfiguration of the power system. This situation, if not properly handled, can lead to huge active power transmission line losses. These power transmission losses lead to power shortage, voltage collapse, and electrical blackouts which affect the economic growth of the country. For a reliable operation of any power system, the active power transmission losses are to be minimized. This situation can be improved by the system operator through the reallocation of reactive power generation in the system by modeling it as an ORPD optimization problem, with the active power transmission loss as the objective function [17].

1.2 Objectives

The following are the objectives of the research:

- Resolve the optimal reactive power allocation problems by meta-heuristic optimization algorithm namely Artificial Bee Colony based Salp Swarm Algorithm (ABC-SSA).
- To explore the advantages and disadvantages of ABC and SSA optimization techniques.
- To explore the applications of the ABC and SSA optimization techniques in solving the ORPD problems.
- To design a hybrid method of ABC with SSA optimization techniques to extend the ABC capabilities and improve its accuracy in solving ORPD problems.
- To demonstrate the application and implementation of the hybridized ABC-SSA algorithm in solving ORPD problems for active power transmission loss minimization minimized Voltage Deviation and improvement of the voltage stability.

- To compare the results from the above and draw conclusion

1.3 Organization of the thesis

With this in mind, this thesis comprises four chapters:

- **Chapter 1:** The first chapter provides the general overview of the study by discussing the research background, problem statement, research objectives, scope, and significance of the research.
- **Chapter 2:** Presents generalities on the electrical network, the modeling of the power elements of an electrical network, the formulation of the power flow problem and the different types of objective functions.
- **Chapter 3:** presents in detail the most used meta-heuristics and we focus on those that we have studied in the context of this thesis, it also describes ABC and SSA pseudo-code and their basic principles. Also presented in this chapter are the details of the contribution (the hybridization between the two methods ABC and SSA).
- **Chapter 4:** Hybrid ABC-SSA Model describes the hybridization of the ABC with the SSA algorithm including its motivations. The approach was carefully designed to achieve a better and quality optimized result. Standard IEEE 30 bus, IEEE 57 bus, IEEE 118 bus and large system IEEE 300 bus were used to validate the robustness, accuracy and efficiency of the proposed approach. The simulation results and analysis of the test function optimization and ORPD problem were presented and compared with other results in the literature. Finally, the thesis ends with a general conclusion that summarizes the outcomes of the research and outlines the contributions of this research to the development of power systems.

CHAPTER 2

Optimal Reactive Power Dispatch

Introduction

For the formulation of the ORPD problem, we give in this chapter a general overview of the Modeling of the electrical network by exposing the power flow methods to describe:

- The physical limits: tap transformers, reactive power regulators and automatic voltage regulators (related to the inequality constraints).
- the power balance (active and reactive) highlighting the constraints of equality
- Technical data of lines, transformers, loads and generators for power flow analysis.

2.1 Electrical Network

The main role of the electrical network or transmission network is to link the large consumption centers and the production means. This role is particularly important because electrical energy cannot be stored on a large scale at present.

A transmission system must be operated in a particular way, it must be operated within the authorized operating limits. These limits or constraints on the network are expressed by maximum or minimum values on certain network variables (frequency, power flow on lines or voltage level transformers, etc.). If these limits are exceeded, the system may become unstable.

The transmission capacity constraints are mainly related to the maximum power flows that can flow on each of the network elements. These capacity constraints are of particular importance in power systems because power flows are difficult to control and follow paths governed by Kirchhoff laws.

2.2 Electrical Systems

There are many things to know about the power system to improve it, such as: power plants or energy sources, transmission network, power consumption, power consumption fluctuations, power system balance, thermal limits of power lines in normal operation, voltage performance, these elements give a very clear picture of the power system status [18]. Figure

2.1 presents a schematic diagram of the principle of electricity generation, transmission and distribution.

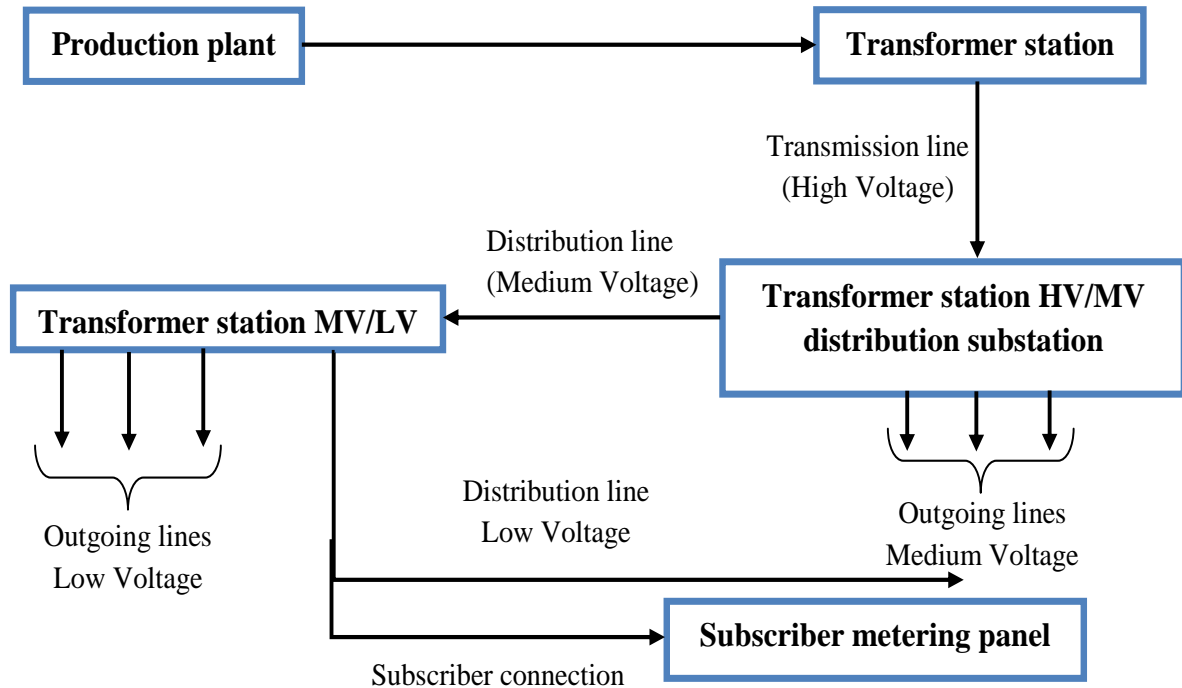


Figure 2.1 Schematic diagram of the principle of electricity generation, transmission and distribution

2.2.1 The production

Electric energy is produced in the power plant with the help of generators at a voltage level of ≤ 20000 volts. For technical and environmental reasons (emissions), the power plants are usually located far away from urban areas.

The passage of electric current in the lines of the electrical network generates energy losses due to the resistance of these lines.

2.2.2 The transport

Once generated, the electricity must be transported to the various locations where it is used via transmission lines. The high voltage transmission lines are supported by large steel towers.

The electrical energy then arrives at a substation (transformer and distribution station), which converts the high voltage to medium voltage, before being distributed to the distribution network.

However, some operating centers do not have transmission lines. The electrical energy is sent directly to the distribution network, after undergoing a transformation to MV. This depends on the location of the plant and the power to be transmitted.

2.2.3 The distribution

Medium-voltage (MV) line outlets run from the substation (which is part of the transmission system) to surrounding towns.

The current trend is to standardize MV voltages to 30,000 volts. The power lines of the distribution network can be overhead (suspended by electric poles: concrete, wood or metal), or underground (buried in the ground).

The medium voltage (MV) is then transformed into low voltage (LV) by MV/LV transformer stations installed in different locations.

Subscriber connections are connected from the low voltage lines coming from these transformers. Voltages are currently standardized at 230 volts for single-phase connections, and 230/400 volts for three-phase connections (230 volts between one phase and neutral, 400 volts between two different phases).

Each subscriber connection is equipped with an electrical meter to measure energy consumption.

2.3 Power transmitted by a power line [19]

Electrical energy is carried by power lines of limited capacity because of the thermal limits of the cables, the voltages applied to the terminals, and the angle of loading (δ). The powers transmitted by a radial electric are given by the following formulas:

Looking at figure 2.2 which shows an electric line feeding a load ($P + jQ$), admitting that the resistance of the line is very low compared to the reactance, the impedance: $Z_s = jX_s$

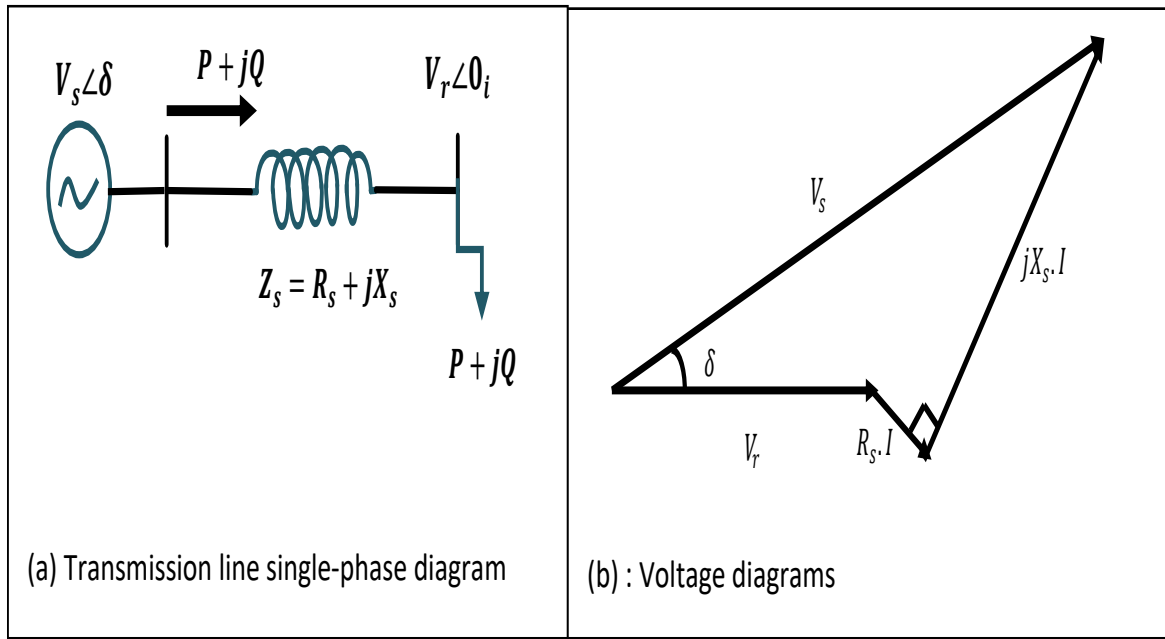


Figure 2.2 electrical line feeding a load

Taking the voltage at the load terminal as the phase reference figure 2.2.b and not considering the resistance R_s , the current will be in phase with V_r , and the power required by the load will be given by the following equations:

$$S_r = P + jQ = V_r I_r^* , \text{ with } I_r = \frac{V_s - V_r}{Z_s}$$

$$P = \frac{V_s \cdot V_r}{X_s} \sin \delta \tag{2.1}$$

$$Q = \frac{V_s \cdot V_r}{X_s} \cos \delta - \frac{V_r^2}{X_s} \tag{2.2}$$

The relationship between the voltage at the load bus and the load current I is described by the straight line in figure 2.3 called the system load line which is defined by the equation of a straight line passing through V_s and having slope $-Z_s$:

$$V_s - V_r = Z_s * I \quad \rightarrow \quad V_r = -Z_s * I + V_s$$

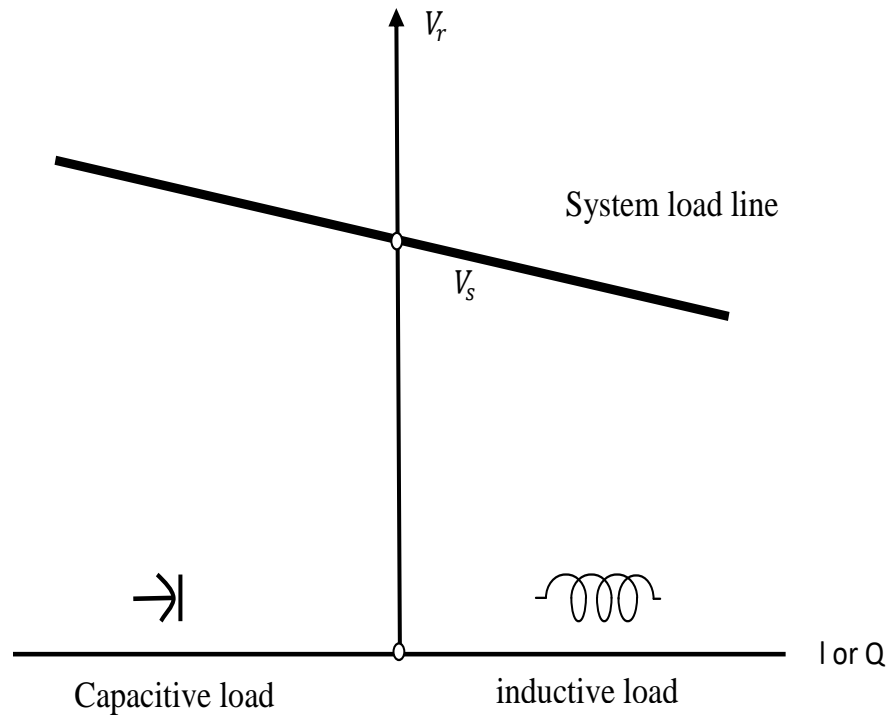


Figure 2.3 System load line

The need to maintain the voltage across the load to allow maximum power to be transmitted is easily demonstrated: If the load varies and no precautions are taken to keep the voltage V_r equal to V_s then from the phase diagram in figure 2.2.b :

$$V_r = V_s \cos \delta$$

Replacing in equation (2.1) will give:

$$P = \frac{V_s^2}{X_s} \sin \delta \cdot \cos \delta = \frac{V_s^2}{2X_s} \sin 2\delta$$

In this case it can only carry a maximum power for an angle $\delta = 45^\circ$.

$$\text{Equal to: } P_{max} = \frac{V_s^2}{2X_s}$$

In the case where the voltage V_r is kept equal to V_s we can have, from the equation (2.1), a maximum power: $P_{max} = \frac{V_s^2}{X_s}$.

2.4 Voltage Drop

Voltage drop is the decrease of electrical potential along the path of a current flowing in an electrical circuit. Current flow in the line causes a voltage drop. The voltage is then lower at the end of the line than its origin, and the more the line is loaded in transit of power, the greater the voltage drop will be.

Voltage drop is calculated by the following formulation:

$$\Delta V = V_1 - V_2 = Z * I \quad (2.3)$$

The vector relation is then written:

$$\bar{V}_1 = \bar{V}_2 + R\bar{I} + jL\omega\bar{I} = \bar{V}_2 + R\bar{I} + jX\bar{I} \quad (2.4)$$

By projection along the horizontal and vertical axes, we obtain two real equations:

$$V_1 \cos \delta = V_2 + RI \cos \varphi + XI \sin \varphi \quad (2.5)$$

$$V_1 \sin \delta = -RI \sin \varphi + XI \cos \varphi \quad (2.6)$$

Squaring and then summing these two expressions, we get:

$$V_1^2 = V_2^2 + R^2I^2 + X^2I^2 + 2(RV_2I \cos \varphi + XV_2I \sin \varphi) \quad (2.7)$$

It is then possible to replace the different terms of this expression by using the powers:

With $P = V_2I \cos \varphi$ the single-phase active power consumed by the load, $Q = V_2I \sin \varphi$ the single-phase reactive power called by the load, $P_J = RI^2$ the losses by Joule effect in the line and $Q_L = XI^2$ the reactive power consumed by the line reactance, it becomes:

$$V_1^2 - V_2^2 = RP_J + XQ_L + 2(RP + XQ) \quad (2.8)$$

$$(V_1 - V_2)(V_1 + V_2) = RP_J + XQ_L + 2(RP + XQ) \quad (2.9)$$

Noting:

$V = (V_1 + V_2)/2$ and $\Delta V = (V_1 - V_2)$ the voltage drop, we obtain :

$$\frac{\Delta V}{V} = \frac{\frac{1}{2}RP_J + \frac{1}{2}XQ_L + RP + XQ}{V^2} \quad (2.10)$$

In a well-dimensioned transmission network, the Joule effect losses in the lines usually represent a few percent of the total transmitted power. If we consider a case where the reactive power consumption of the line compared to the transmitted power is low, we obtain the following simplified relation:

$$\frac{\Delta V}{V} = \frac{RP + XQ}{V^2} \quad (2.11)$$

2.5 Modeling the power elements of an electrical network

To calculate the optimization of power flow, some components in the electrical network affect this calculation, it is important to know its model such as power generators, electrical loads, transmission lines, power transformers, and static compensators.

2.5.1 Power generator

A generator is a device that converts motive power (mechanical energy) into electrical power. Sources of mechanical energy include steam turbines, water turbines, gas turbines, wind turbines and the power of the sea waves. Generators provide almost all of the power for the electrical grids.

The generator's current injectors and terminal voltage and their control is mainly related to the injection of reactive power to the generation buses.

The active power output of the generator is controlled through the turbine control which must be kept within the capacity of the turbine-generator system.

2.5.2 Transmission lines

The transmission of electrical power is the process of moving electrical power in bulk from a generating base, to the consumer. The inter-connected lines that make this movement possible are called a transmission network. These cables differ from each other in terms of voltage resistance.

The transmission lines are designed with a π model, this model contains series and shunt elements, are defined for a line connected between buses i and j - the π -model is shown in figure 2.4

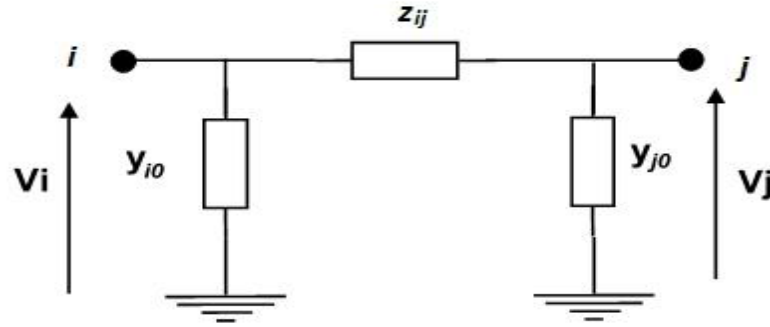


Figure 2.4 π -model of a power line.

The following equation gives the complex expression of the series impedance:

$$z_{ij} = r_{ij} + jx_{ij} \quad (2.12)$$

with:

$$y_{ij} = \frac{1}{z_{ij}} = \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2} - j \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2} = g_{ij} + jb_{ij} \quad (2.13)$$

$$y_{ij0} = \frac{g_{ij0} + jb_{ij0}}{2} \quad (2.14)$$

where:

r_{ij} The equivalent series resistance of the line.

x_{ij} The equivalent inductive reactance of the line.

g_{ij0} Equivalent transverse conductance of the line at node i .

b_{ij0} Capacitive susceptance of the line at node i

In most cases, the conductance value is so small that it can be neglected.

2.5.3 Power transformer

Transformers play an important role in controlling the active and reactive power in the transmission line. The basic principle of operation is to vary the modulus or phase shift of the voltage, which allows control of the active and reactive power in the transmission line. Therefore, there are two types of transformers: the voltage regulator transformer with a load tap changer (figure 2.5) and the phase-shifting transformer (figure 2.6). Following figure 2.7 gives the schematic of this model [18] [20] :

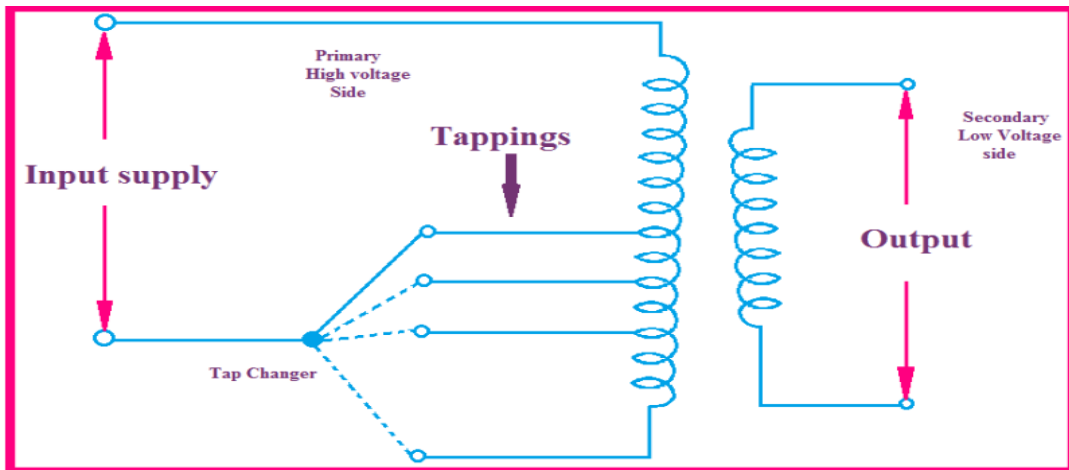


Figure 2.5 Equivalent diagram of transformer with on-load tap-changer

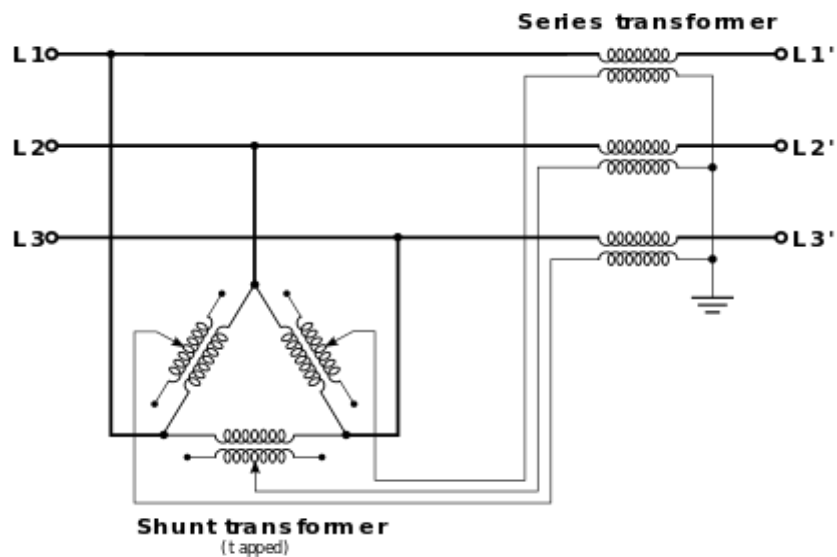


Figure 2.6 Equivalent diagram of phase-shifting transformer

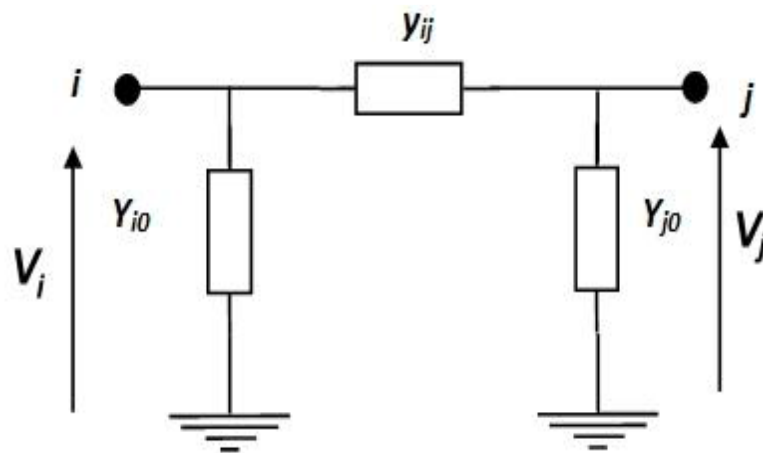


Figure 2.7 Equivalent diagram of a transformer: π -model

with:

$$y_{ij} = y_t N_{ij} \quad (2.15)$$

$$Y_{i_0} = y_t (1 - N_{ij}) + \frac{y_{ij_0}}{2} \quad (2.16)$$

$$Y_{j_0} = y_t N_{ij} (N_{ij} - 1) + N_{ij}^2 \frac{y_{ij_0}}{2} \quad (2.17)$$

where

$$z_t = r_t + jx_t \quad (\text{with } |z_t| = \frac{v_{cc} v_{ni}^2}{100 S_n}), \quad Y_t = \frac{1}{z_t}, \quad r_t = \Delta P_c \frac{v_{ni}^2}{S_n^2} 10^{-3} \quad \text{and} \quad x_t = \sqrt{z_t^2 - r_t^2}$$

z_t the equivalent series impedance

y_t series admittance

r_t equivalent resistance of the transformer

x_t equivalent inductive reactance of the transformer

v_{cc} short-circuit voltage in (pu)

S_n nominal apparent power of the transformer

V_{ni} nominal simple voltage of the transformer

ΔP_c active power losses in the transformer windings

y_{ij_0} the admittance in derivation given by $y_{ij_0} = g_{ij_0} + jb_{ij_0}$ with $b_{ij_0} = -\frac{i_0 S_n}{100 V_{ni}^2}$ and

$$g_{ij_0} = \Delta P_f \frac{10^{-3}}{V_{ni}^2}$$

i_0 no-load magnetizing current of the transformer in (pu)

ΔP_f active no-load losses of the transformer

$N_{ij} = \frac{V_i}{V_j}$ the nominal transformation ratio

2.5.4 Electrical loads

The loads are often substations that supply the distribution networks, they are statically modeled as negative power injectors in the bus bars. The connection of the load to the network is made through a load tap transformer that keeps the voltage level constant, this means that the active and reactive powers of the load can be represented by constant values [18].

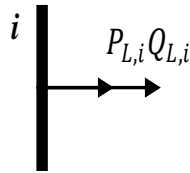


Figure 2.8 The load model.

$$S_{Li} = P_{Li} + jQ_{Li} \quad (2.18)$$

Where

S_{Li} The complex power of the load

P_{Li} The active power

Q_{Li} The reactive power (can be positive or negative depending on whether the load is inductive or capacitive).

2.5.5 Shunt elements

Shunt elements are distributed elements in the electrical network that play the role of compensating reactive energy in order to control the tension. Capacitors and inductors are placed at several points in the electrical network, and they are studied, of course, in order to supply or absorb reactive energy. In the case where Q_c is positive at a point of the electrical network, the shunt compensator is capacitive and supplies reactive power at this point. If Q_c is a negative, the conversion compensator is inductive and absorbs the excess reactive energy.

This step of modeling the line and its elements is essential for the calculation of the main equations of the network, especially the nodal admittance matrix

2.6 Power flow

In power systems, many problems affect the main goal of keeping the power system functional in its normal state. Among these problems is the power flow problem.

The study of the load flow allows having the solution of the quantities of an electrical network in regular and irregular operation to ensure an efficient operation, i.e. in conformity with the technical standards. These quantities are the voltages at the nodes, the powers injected at the nodes, and those that transit in the lines. The losses and currents are deduced from them. The power flow studies allow to plan the construction and the extension of the electrical networks as well as the management and the control of these networks.

2.6.1 General concept of power flow

The power flow problem is solved for the steady state determination of the complex voltages at the network busses, from which the active and reactive power flows in each line and transformer are calculated.

The set of equations represents the electrical network and is non-linear in nature. In the practical methods of power flow calculation, the configuration of the network and the properties of its equipment are used to determine the complex voltage at each node. On the other hand, the symmetry between the three phases of the three-phase system of the electrical network is perfect.

2.6.2 Objectives of the power flow study

The objective of power flow is to ensure the balance between the production and demand of electric energy (the improvement of electricity expenditure, energy production according to need), not to exceed the limit values (the theoretical stability, according to the good duration of use), it is necessary to keep the bus-bar voltages between the theoretical limits, using the power control and network planning (from load calculation). Increase the security of operation of networks by a good strategy of power flow before the disturbances.

2.7 Nodal admittance matrix

The large, interconnected AC power system (network) consists of numerous power stations, transmission lines, and transformers. Shunt reactors and capacitors and distribution networks through which loads are supplied. All this leads to a high voltage, largely interconnected AC power transmission system, and the assessment of the steady state behavior of all the components of the network acting together as a system requires computer-based large-scale system analysis of the network model. In a computer-based power system analysis, the network model takes on the form of Bus Admittance Matrix $[Y_{BUS}]$. $[Y_{BUS}]$ is often used in solving load flow (or complex power flow) problems. Its widespread application in power system computations is due to its simplicity in data preparation and the ease with which it can be formed and modified for any network change (e.g. addition or tripping of line etc.). $[Y_{BUS}]$ Matrix is highly sparse and facilitates minimum computer storage as well as reduces computer operation time.

In the nodal analysis of an electrical network, it is common to use branch admittances (y_{ij}) rather than branch impedances. For an isolated line as shown in Figure 2.9 [21, 22].

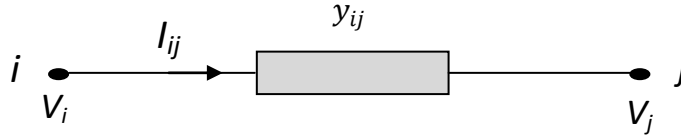


Figure 2.9 Illustration of an isolated bus.

where :

V_i and V_j are the voltages at the buses i and j , respectively,

I_{ij} is the current circulating from node i to node j . In a complex network, the nodes being numbered $0, 1, 2, \dots, N$, (N = the number of nodes in the network)

$$I_{ij} = y_{ij}(V_i - V_j) \tag{2.19}$$

The node 0 is the reference node, the injected current I_i being equal to the sum of all the currents leaving the node i (by Kirchoff's current law (KCL)), we can write:

$$I_i = \sum_{j=0}^n I_{ij} = \sum_{j=0}^n y_{ij} (V_i - V_j) \tag{2.20}$$

The following is a simple 3-bus system as shown in Figure 2.10.

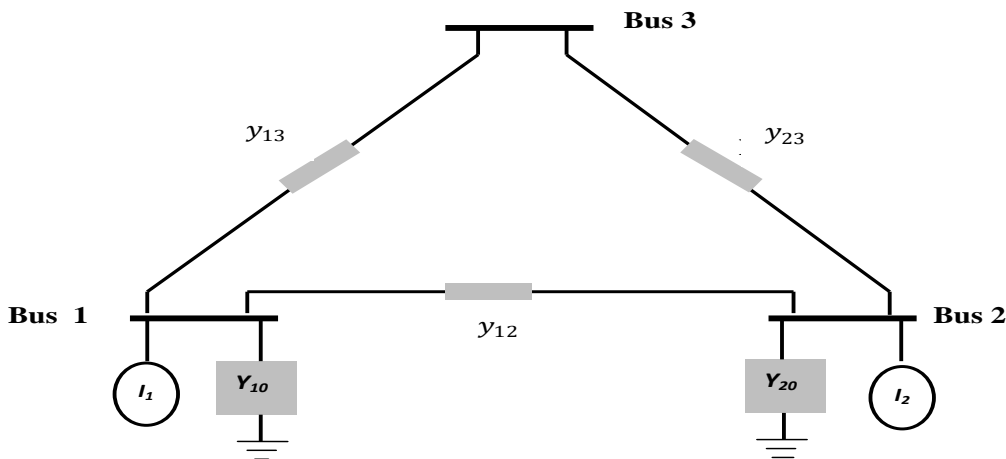


Figure 2.10 Admittance Schema of a 3-bus system.

$$I_1 = y_{10}V_1 + y_{12}(V_1 - V_2) + y_{13}(V_1 - V_3)$$

$$I_2 = y_{20}V_2 + y_{12}(V_2 - V_1) + y_{23}(V_2 - V_3)$$

$$0 = y_{13}(V_3 - V_1) + y_{23}(V_3 - V_2)$$

Node 0, which is usually considered as ground, is considered a reference node.

Can be simplified the above node equations in the following manner:

$$I_1 = Y_{11}V_1 + Y_{12}V_2 + Y_{13}V_3$$

$$I_2 = Y_{21}V_1 + Y_{22}V_2 + Y_{23}V_3$$

$$I_3 = Y_{31}V_1 + Y_{32}V_2 + Y_{33}V_3$$

with:

$$Y_{11} = y_{10} + y_{12} + y_{13}$$

$$Y_{22} = y_{20} + y_{21} + y_{23}$$

$$Y_{33} = y_{13} + y_{23}$$

$$Y_{12} = Y_{21} = -y_{12}$$

$$Y_{13} = Y_{31} = -y_{13}$$

$$Y_{23} = Y_{32} = -y_{23}$$

$$\text{And } I_3 = 0$$

For an n-bus electrical network, these equations in matrix form can be expressed as follows:

$$\begin{bmatrix} I_1 \\ I_2 \\ \cdot \\ \cdot \\ \cdot \\ I_N \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} & \cdot & Y_{1N} \\ Y_{21} & Y_{22} & \cdot & Y_{2N} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ Y_{N1} & Y_{N2} & \cdot & Y_{NN} \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ \cdot \\ \cdot \\ \cdot \\ V_N \end{bmatrix} \quad (2.21)$$

Or :

$$[I] = [Y_{BUS}][V] \quad (2.22)$$

Finally this matrix $[Y_{BUS}]$ is called bus admittance matrix, $[Y_{BUS}]$ is a square matrix of order $n \times n$, and symmetrical, since $y_{ij} = y_{ji}$. The elements of $[Y_{BUS}]$ are important and therefore defined as follows:

Y_{ii} : The diagonal element, it is the sum of all admittances connected to it. And it can be expressed as:

$$Y_{ii} = \sum_{\substack{j=0 \\ j \neq i}}^n y_{ij} \quad (2.23)$$

Y_{ij} : The off-diagonal element, it is equal to the negative of admittance between nodes i and j , and it can be expressed as:

$$Y_{ij} = -y_{ij} \quad (2.24)$$

2.8 Power flow calculation methods

There are several methods of calculating power flow, but we will mention only the three most important ones:

2.8.1 Newton-Raphson Method

Because of its quadratic convergence, Newton's method is mathematically superior to the many methods in the literature and is less prone to divergence with ill-conditioned problems. For large power systems, the Newton-Raphson method is found to be more efficient and practical. The number of iterations required to obtain a solution is independent. The governing equation in any multi-bus network, using nodal admittance matrix form, is given by **[21, 23]**:

$$I_i = \sum_{j=1}^{NB} Y_{ij} V_j \quad (2.25)$$

Where:

I_i the current entering into bus i .
 NB The total number of buses.

In the equation above, j includes the bus i , and the power flow formulations are usually expressed in polar form because the real power and voltage magnitude are specified for the PV buses. The equations in polar coordinates are usually expressed in the following form:

$$V_i = |V_i| \angle \delta_i = |V_i|(\cos \delta_i + j \sin \delta_i) = |V_i|e^{j\delta_i} \quad (2.26)$$

$$Y_{ij} = |Y_{ij}|(\cos \alpha_{ij} + j \sin \alpha_{ij}) = |Y_{ij}|e^{j\alpha_{ij}} \quad (2.27)$$

Where

Y_{ij}/α_{ij} = Magnitude/angle of admittance matrix element between buses i and j

δ_i/δ_j = Voltage angle of *bus-i* and *bus-j*, respectively.

When expressing eq. (2.25) in polar form, we have:

$$I_i = \sum_{j=1}^{NB} |Y_{ij}| |V_j| \angle \alpha_{ij} + \delta_j \quad (2.28)$$

The bus power at bus- i is given by:

$$P_i - jQ_i = V_i^* I_i = V_i^* \sum_{j=1}^{NB} Y_{ij} V_j \quad (2.29)$$

Substitution of the polar forms of V_i and Y_{ij} in Eq. (2.29):

$$P_i - jQ_i = \sum_{j=1}^{NB} |V_i| |V_j| |Y_{ij}| e^{j(\alpha_{ij} - \delta_i + \delta_j)} \quad (2.30)$$

Since from trigonometry:

$$e^{j(\alpha_{ij} - \delta_i + \delta_j)} = \cos(\alpha_{ij} - \delta_i + \delta_j) + j \sin(\alpha_{ij} - \delta_i + \delta_j) \quad (2.31)$$

Hence substitution of Eq. (2.30) in Eq. (2.31) yields, after separating the real and imaginary components, these equations (2.32) and (2.33) represent a set of nonlinear simultaneous equations in polar form for each bus in the power system network.

$$P_i = \sum_{j=1}^{NB} |V_i| |V_j| |Y_{ij}| \cos(\alpha_{ij} - \delta_i + \delta_j) \quad (2.32)$$

$$Q_i = - \sum_{j=1}^{NB} |V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \quad (2.33)$$

The study of the load flow of an electrical network involves solving these equations for voltage amplitudes $|V|$ and voltage phase angles δ . The voltage amplitude and the phase angle of the loose or oscillating bus voltage are specified and fixed for a network with NB -bus, so a number of $2(NB-1)$ nonlinear equations must be solved for this system [21]. For small variations of δ and $|V|$, a linear relationship is obtained by forming the partial differential equations as follows:

$$\Delta P_i = \sum_{j=1}^{NB} \frac{\partial P_i}{\partial \delta_j} \Delta \delta_j + \sum_{j=1}^{NB} \frac{\partial P_i}{\partial |V_j|} \Delta |V_j| \quad (2.34)$$

Equation (2.34) is applicable to all bus types except the slack bus.
Also:

$$\Delta Q_i = \sum_{j=1}^{NB} \frac{\partial Q_i}{\partial \delta_j} \Delta \delta_j + \sum_{j=1}^{NB} \frac{\partial Q_i}{\partial |V_j|} \Delta |V_j| \quad (2.35)$$

For all non voltage-controlled buses, equation (2.35) is valid. Thus, for an NB -bus system (with no voltage-controlled buses), we can write these equations as follows:

$$\begin{bmatrix} \Delta P_2^{(k)} \\ \vdots \\ \Delta P_{NB}^{(k)} \\ \Delta Q_2^{(k)} \\ \vdots \\ \Delta Q_{NB}^{(k)} \end{bmatrix} = \begin{bmatrix} \frac{\partial P_2^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial P_2^{(k)}}{\partial \delta_{NB}} & \frac{\partial P_2^{(k)}}{\partial |V_2|} & \cdots & \frac{\partial P_2^{(k)}}{\partial |V_{NB}|} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial P_{NB}^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial P_{NB}^{(k)}}{\partial \delta_{NB}} & \frac{\partial P_{NB}^{(k)}}{\partial |V_2|} & \cdots & \frac{\partial P_{NB}^{(k)}}{\partial |V_{NB}|} \\ \frac{\partial Q_2^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial Q_2^{(k)}}{\partial \delta_{NB}} & \frac{\partial Q_2^{(k)}}{\partial |V_2|} & \cdots & \frac{\partial Q_2^{(k)}}{\partial |V_{NB}|} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial Q_{NB}^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial Q_{NB}^{(k)}}{\partial \delta_{NB}} & \frac{\partial Q_{NB}^{(k)}}{\partial |V_2|} & \cdots & \frac{\partial Q_{NB}^{(k)}}{\partial |V_{NB}|} \end{bmatrix} \begin{bmatrix} \Delta \delta_2^{(k)} \\ \vdots \\ \Delta \delta_{NB}^{(k)} \\ \Delta |V_2^{(k)}| \\ \vdots \\ \Delta |V_{NB}^{(k)}| \end{bmatrix}$$

Also equations (2.34) and (2.35) can be expressed:

$$\Delta P_i = \sum_{j=1}^{NB} J_{1(i,j)} \Delta \delta_j + \sum_{j=1}^{NB} J_{2(i,j)} \Delta |V_j| \quad (2.36)$$

$$\Delta Q_i = \sum_{j=1}^{NB} J_{3(i,j)} \Delta \delta_j + \sum_{j=1}^{NB} J_{4(i,j)} \Delta |V|_j \quad (2.37)$$

In its matrix form, it can be represented as follows:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta |V| \end{bmatrix} \quad (2.38)$$

Or, in abbreviated form:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = [J] \begin{bmatrix} \Delta \delta \\ \Delta |V| \end{bmatrix}$$

The Jacobian matrix $[J]$ elements are obtained by the partial derivatives of (2.32) and (2.33), concerning $\Delta \delta_i$ and $\Delta |V_i|$ as shown below:

For quadrant [J1]:

J_1 is of the order of $[NB-1] \times [NB-1]$

Diagonal elements:

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{j=1, j \neq i}^{NB} |V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \quad (2.39)$$

Off – diagonal elements:

$$\frac{\partial P_i}{\partial \delta_j} = -|V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \quad (2.40)$$

For quadrant [J2]:

J_2 is of the order of $[NB-1] \times [NB-1-m]$, if m buses of the system are voltage-controlled

Diagonal elements:

$$\frac{\partial P_i}{\partial |V_i|} = 2|V_i| |Y_{ii}| \cos \alpha_{ii} + \sum_{j=1, j \neq i}^{NB} |V_j| |Y_{ij}| \cos(\alpha_{ij} - \delta_i + \delta_j) \quad (2.41)$$

Off – diagonal elements:

$$\frac{\partial P_i}{\partial |V_j|} = |V_i| |Y_{ij}| \cos(\alpha_{ij} - \delta_i + \delta_j) \quad (2.42)$$

For quadrant [J3]:

J_3 is of the order of $[NB-1-m] \times [NB-1]$

Diagonal elements:

$$\frac{\partial Q_i}{\partial \delta_i} = \sum_{j=1, j \neq i}^{NB} |V_i| |V_j| |Y_{ij}| \cos(\alpha_{ij} - \delta_i + \delta_j) \quad (2.43)$$

Off – diagonal elements:

$$\frac{\partial Q_i}{\partial \delta_j} = -|V_i||V_j||Y_{ij}| \cos(\alpha_{ij} - \delta_i + \delta_j) \quad i \neq j \quad (2.44)$$

For quadrant [J4]:

J_4 is of the order of $[NB-1-m] \times [NB-1-m]$

Diagonal elements:

$$\frac{\partial Q_i}{\partial |V_i|} = -2|V_i||Y_{ii}| \sin \alpha_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^{NB} |V_j||Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \quad (2.45)$$

Off – diagonal elements:

$$\frac{\partial Q_i}{\partial |V_j|} = -|V_i||Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \quad i \neq j \quad (2.46)$$

The Jacobian matrix $[J]$ is of order $[2(NB - 1) - m] \times [2(NB - 1) - m]$. When the Jacobian elements have been formulated, the steps for calculation of the Newton power flow solution are as follows:

-
- | | |
|--------|--|
| Step 1 | Start the process by scanning all the data input |
| Step 2 | Create the Y-bus matrix and initialize for all load buses, $ V_i^{(0)} = 1.0$ (pu) and $\delta_i^{(0)} = 0$ (rd) and for voltage-regulated buses, $\delta_i^{(0)} = 0$ (rd). |
| Step 3 | Calculate the real and reactive powers from (2.32) and (2.33), for the load buses and $\Delta P_i(k)$ and $\Delta Q_i(k)$ which are the differences between the calculated and predicted values, given by: |
| | $\Delta P_i^{(k)} = P_{i_{sch}} - P_{i_{cal}}^{(k)} \quad (2.47)$ |
| | $\Delta Q_i^{(k)} = Q_{i_{sch}} - Q_{i_{cal}}^{(k)} \quad (2.48)$ |
| Step 4 | Calculate $P_i(k)$ and $\Delta P_i(k)$ from (2.32) and (2.47), respectively, and it is for voltage-controlled buses. |
| Step 5 | Verify $\Delta P_i(k) \leq \varepsilon$ and $\Delta Q_i(k) \leq \varepsilon$ for all buses if they are less than the specified accuracy or not : |
-

$$\left| \Delta P_i^{(k)} \right| \leq \varepsilon$$

$$\left| \Delta Q_i^{(k)} \right| \leq \varepsilon$$

If these measurements are less than the specified accuracy, go to step 10, if not, go to step 6.

Step 6 Compute the elements in the Jacobian matrix (2.39)-(2.46), using the estimated voltages and calculated powers.

Step 7 Solve directly the simultaneous linear equation (2.38) by optimized triangular factorization and Gaussian elimination.

Step 8 Update the bus voltage magnitude and phase angles as follows:

$$\delta_i^{(k+1)} = \delta_i^{(k)} + \Delta \delta_i^{(k)} \quad (2.49)$$

$$\left| V_i^{(k+1)} \right| = \left| V_i^{(k)} \right| + \Delta \left| V_i^{(k)} \right| \quad (2.50)$$

Step 9 Return to step 3.

Step 10 Obtain output results.

2.8.1.1 Advantages of the Newton-Raphson method

The advantages of the Newton method are well known:

- The execution time of the power flow calculation program is greatly reduced.
- The size of the occupied memory is also reduced.
- The convergence will be very fast.
- The procedure is repeated until $\Delta P_i^{(k)}$ and $\Delta Q_i^{(k)}$ for all bar sets are within the specified tolerances.

2.8.1.2 The Inconvenience of the Newton-Raphson method

The inconveniences of the Newton method are well known[24]:

- The algorithm is not globally convergent

- If f is not strictly convex, the algorithm does not necessarily generate directions of descent of f

Notice: In the literature, various modifications of the Newton method have been made to improve its unfavorable aspects.

2.8.1.3 Flowchart of Newton-Raphson method

The flowchart of the Newton-Raphson method is presented in Figure 2.11 as follows:

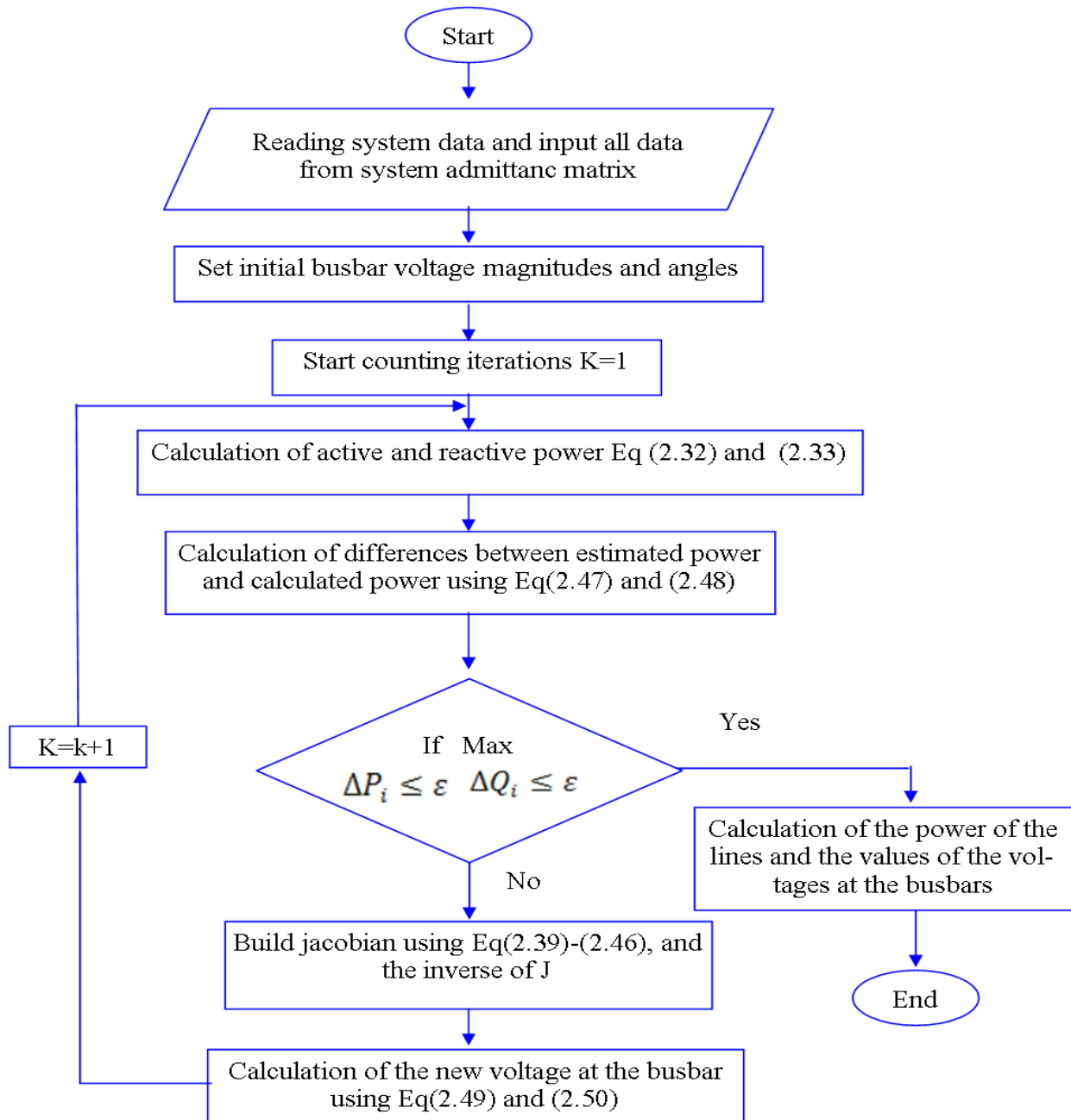


Figure 2.11 Flowchart of Newton-Raphson method.

2.8.2 Gauss-Seidel method:

This method consists in sequentially removing each node and updating its voltage according to the available values of all the voltages. In general, we compute the vector x that satisfies the nonlinear system [25]:

$$f(x) = 0 \quad (2.51)$$

We can formulate equation (2.48), as the fixed point problem, hence:

$$x = f(x) \quad (2.52)$$

The solution is obtained iteratively, from an initial value x^0 :

$$x^{k+1} = f(x^k) \quad (2.53)$$

For the concrete case of load sharing, the solution of the nodal equation (2.54) is such that:

$$V_i = \frac{1}{Y_{ii}} \left[\frac{P_i - jQ_i}{V_i^*} - \sum_{j \neq i}^n Y_{ij} \cdot V_j \right] \quad (2.54)$$

$$V_i^{k+1} = \frac{1}{Y_{ii}} \left[\frac{P_i - jQ_i}{(V_i^k)^*} - \sum_{j=i}^{i-1} Y_{ij} \cdot V_j^{k+1} + \sum_{j \neq i}^n Y_{ij} \cdot V_j \right] \quad (2.55)$$

The iterative process is obtained when the following expression is satisfied:

$$\max |V_i^{k+1} - V_i^k| \leq \varepsilon \quad (2.56)$$

The process can be accelerated, by decreasing the number of iterations, by introducing an acceleration factor α :

$$V_{i,accl}^{k+1} = V_i^k + \alpha(V_i^{k+1} - V_i^k) \quad (2.57)$$

2.8.3 Fast Decoupled Method of Power Flow

In general, for a given electrical network, the active power is less sensitive to a change in the voltage amplitude than to its phase. Then the elements of J_2 and J_3 are almost zero. The same thing, the reactive power being less sensitive to a change of the voltage phase than to its amplitude, the elements of J_3 are almost zero. Equation (2.38) thus becomes:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & 0 \\ 0 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta |V| \end{bmatrix} \quad (2.58)$$

Then:

$$\Delta P = [J_1] \Delta \delta \quad (2.59)$$

$$\Delta Q = [J_4] \Delta |V| \quad (2.60)$$

The above two systems equations are decoupled in the sense that the voltage-angle corrections ($\Delta\delta$) are obtained using the real power mismatches (ΔP) only while the voltage-magnitude correction ($\Delta|V|$) is obtained using only the reactive power mismatches (ΔQ). Because of that it requires less time to solve compared to N-R method.

For a transmission line, the following approximations can be considered as:

- The differences between voltage angles, i.e., ($\delta_j - \delta_i$) being very small

$$\cos(\delta_j - \delta_i) \approx 1; \quad \sin(\delta_j - \delta_i) \approx (\delta_j - \delta_i)$$

- For transmission lines X/R ratio is high, so the line susceptances B_{ik} become much larger than the line conductances G_{ik} and hence

$$G_{ij} \sin(\delta_j - \delta_i) \ll B_{ij} \cos(\delta_j - \delta_i)$$

- Under steady-state operation, the reactive power injected into any bus (Q_i) is much less than the reactive power that would flow if all the lines connected with that bus was short-circuited to reference. This gives:

$$Q_i \ll |V_i|^2 B_{ii}$$

The diagonal elements of J_1 reconsidered by Eq (2.39) may be written as:

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{j=1}^N |V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) - |V_i|^2 |Y_{ii}| \sin \alpha_{ii} \quad (2.61)$$

From Eq. (2.33) and (2.61), it can be written as:

$$\frac{\partial P_i}{\partial \delta_i} = -Q_i - |V_i|^2 |Y_{ii}| \sin \alpha_{ii}$$

$$= -Q_i - |V_i|^2 B_{ii} \quad (2.62)$$

Above-listed approximation, $Q_i \ll |V_i|^2 B_{ii}$ reduce the above equation as:

$$\frac{\partial P_i}{\partial \delta_i} = -|V_i|^2 B_{ii} \quad (2.63)$$

Further simplification is obtained by considering $|V_i|^2 \approx |V_i|$ which yields

$$\frac{\partial P_i}{\partial \delta_i} = -|V_i| B_{ii} \quad (2.64)$$

The off-diagonal elements of J_1 as given by (2.40) may be written as:

$$\begin{aligned} \frac{\partial P_i}{\partial \delta_i} &= -|V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \\ &= -|V_i V_j| \{B_{ij} \cos(\delta_j - \delta_i) + G_{ij} \sin(\delta_j - \delta_i)\} \end{aligned} \quad (2.65)$$

where

$$B_{ij} = |Y_{ij}| \sin \varphi_{ij} \text{ and } G_{ij} = |Y_{ij}| \cos \varphi_{ij}$$

Using the practical approximations listed above, Eq. (2.65) can be written as:

$$\frac{\partial P_i}{\partial \delta_i} = -|V_i| |V_j| B_{ij} \quad (2.66)$$

Further simplification is obtained by assuming $|V_j| \approx 1$

$$\frac{\partial P_i}{\partial \delta_i} = -|V_i| B_{ij} \quad (2.67)$$

Similarly, the diagonal elements of J_4 described by (2.45) may be written as:

$$\frac{\partial Q_i}{\partial |V_i|} = -|V_i| |Y_{ij}| \sin(\alpha_{ii}) - \sum_{j=1}^N |V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) \quad (2.68)$$

$$= -|V_i||Y_{ij}| \sin(\alpha_{ii}) + Q_i$$

Again using the approximations listed above, Eq. (2.68) is written as:

$$\frac{\partial Q_i}{\partial |V_i|} = -|V_i|B_{ii} \quad (2.69)$$

And using the approximations listed above, the off-diagonal elements of J_4 described by (2.46) may be written as:

$$\frac{\partial Q_i}{\partial |V_j|} = -|V_i|B_{ij} \quad (2.70)$$

Thus, Eqs. (2.59) and (2.60) take the following form:

$$\frac{[\Delta P]}{|V_i|} = -B'[\Delta \delta] \quad (2.71)$$

$$\frac{[\Delta Q]}{|V_i|} = -B''[\Delta |V|] \quad (2.72)$$

Where B' and B'' are the imaginary part of the Y_{Bus} matrix and both are generally symmetrical and sparse with nonzero elements. The elements are constant and they need to be triangularized and rearranged just once at the start of the cycle. The order of the matrix B' is $(N - 1)$ while for B'' it is $(N - 1 - m)$, but both are real. N being the number of total buses while m is the number of voltage-controlled buses. When there is no phase-shifting transformer, B' and B'' are symmetric. The convergence is geometric and convergence may ordinarily be obtained for normal power a system within five iterations. In the fast decoupled power flow solutions, the new estimated bus voltage magnitudes and phase angles are given by:

$$|V_i^{(k+1)}| = |V_i^{(k)}| + \Delta |V_i^{(k)}| \quad (2.73)$$

$$\delta_i^{(k+1)} = \delta_i^{(k)} + \Delta \delta_i^{(k)} \quad (2.74)$$

$$\Delta \delta = -|B'|^{-1} \frac{\Delta P}{|V|} \quad (2.75)$$

$$\Delta|V| = -|B''|^{-1} \frac{\Delta Q}{|V|} \quad (2.76)$$

The speed of iterations of the decoupled method is much faster than the N-R method. Also storage requirements are less. Hence, this method is usually called as fast decoupled load flow (FDLF) method.

2.9 Optimal Power Flow

The optimal power flow (OPF) was first introduced by Carpentier in 1962 [1]. The goal of OPF is to find the optimal settings of a given power system network that optimize the system objective functions such as total generation cost, system loss, bus voltage deviation, emission of generating units, number of control actions, and load shedding while satisfying its power flow equations, system security, and equipment operating limits. Different control variables, some of which are generators' real power outputs and voltages, transformer tap changing settings, phase shifters, switched capacitors, and reactors, are manipulated to achieve an optimal network setting based on the problem formulation [21].

In the literature, there are several techniques for solving the problem of optimal power flow. The most popular solving techniques are, analytical methods and meta-heuristic methods, from these two methods, several methods are derived. The classical or analytical method transforms the electrical network into a mathematical model in the form of a set of often very large non-linear equations. This method seems more interesting but its biggest limitation comes from the enormous computing power required which does not allow the use of too detailed models, making the solution unsuitable for use for a real power grid. Meta-heuristic methods are optimization algorithms aimed at solving difficult optimization problems. They are often inspired by natural systems [26].

2.9.1 Definition of the optimization

An optimization problem is defined as the search for the minimum or the maximum (the optimum) of a given function. We can also find optimization problems for which the variables of the function to be optimized are constrained to evolve in a certain part of the search space.

So to optimize is to minimize or maximize a function by respecting some precondition. This function called "Objective" can be a cost (minimization), profit

(maximization), and production (maximization). The objective functions are various as well as the constraints (conditions) according to the problem to be optimized.

2.9.2 Optimization problems

The formulation of the optimization problems remains very ambiguous because of the diversity of vocabularies and the possible confusion that this could generate. We have agreed to adopt the following vocabulary:

- A **mono-objective** optimization problem is defined by a set of variables, an objective function, and a set of constraints.
- A **multiobjective** optimization problem is defined by a set of variables, a set of objective functions, and a set of constraints.
- The state space, also called the search domain, is the set of domains defining the different variables of the problem.
- **The variables** of the problem also called design or decision variables can be of various natures (real, integer, boolean, etc.) and express qualitative or quantitative data, in this thesis we are interested to the real case.
- The objective function or even (**Total Active Transmission Losses, Voltage Deviation, Voltage Stability Index**) defines the goal to be achieved, we seek to minimize or maximize it. A multimodal function has several minima (local and global). While a unimodal function has only a minimum, the overall minimum.
- The set of **constraints** is usually a set of equalities or inequalities that the variables in the state space must satisfy. These constraints limit the search space. Optimization methods search for a point or a set of points in the search space that satisfy the set of constraints, and that maximize or minimize the objective function.

2.9.3 Global optimum, local optimum

Let PO be a mono-objective optimization problem and C the set of admissible solutions of the problem. Figure 2.12 presents the optimum global vs optimum local.

- If we can prove that $\forall x \in C, f(xg) < f(x)$, then we will say that xg is the global optimum (minimum) of the problem PO.

- If there is a set $V \in C$, containing x_{loc} , such as $\forall x \in V, f(x_{loc}) < f(x)$, with $x \neq x_{loc}$, then we will say that x_{loc} is a local optimum (minimum) of the PO problem [27].

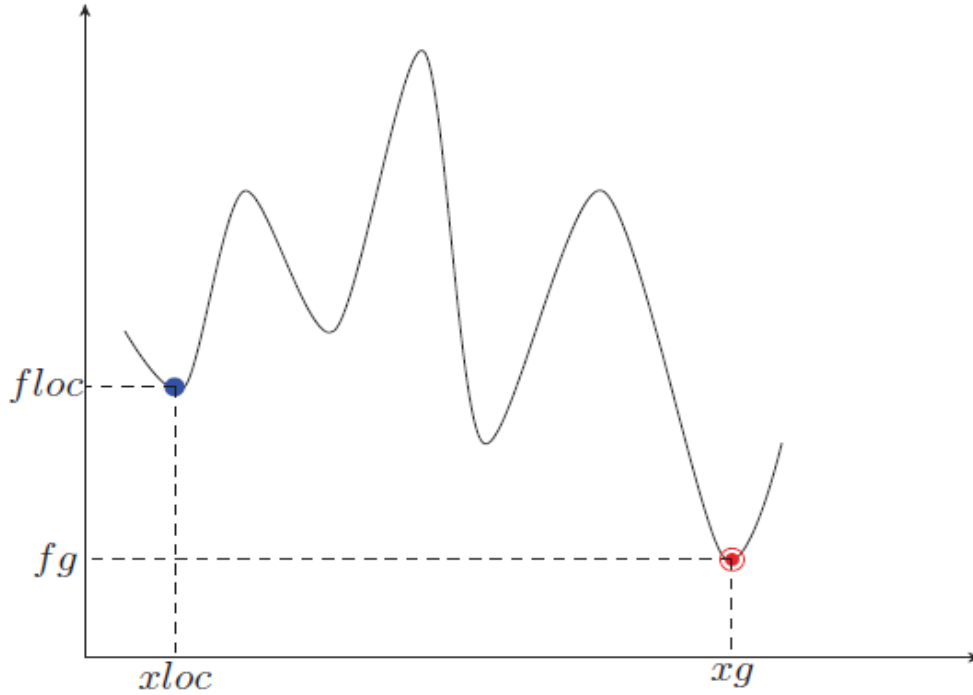


Figure 2.12 Optimum global vs optimum local.

2.9.4 The ORPD problem formulation

Generally, the ORPD problem is stated in the following manner:

Minimize $F(x, u)$

$$\text{Subject to: } \begin{cases} g(x, u) = 0 \\ u(x, u) \leq 0 \end{cases} \quad (2.77)$$

$$x = [V_{L1} \dots V_{LNLB}, Q_{G1} \dots Q_{GNG}, S_1 \dots S_{NTL}] \quad (2.78)$$

$$u = [V_{G1} \dots V_{GNG}, T_1 \dots T_{NT}, Q_{C1} \dots Q_{CNC}] \quad (2.79)$$

2.9.4.1 Objective functions

In studies of optimal power flow, different objective functions can be minimized, which are:

2.9.4.1.1 Total active transmission losses

The mathematical expression of the active transmission losses in the electrical power

network is defined as follows [28]:

$$P_{loss} = \sum_{K=1}^{NTL} G_k \times (V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij}) \quad (2.80)$$

2.9.4.1.2 Voltage deviation

The Total Voltage Deviation (TVD) forms an important objective function for electrical network analysis and operation, it represents the sum of voltage magnitude deviations for all load buses concerning their desired values ($V_L^{ref} = 1.00 \text{ pu}$). The minimization of TVD improves voltage profile and enhances the security level of power systems, it is expressed as follows [11]:

$$TVD = \sum_{i=1}^{NLB} |V_{L,i} - V_L^{ref}| \quad (2.81)$$

2.9.4.1.3 Voltage stability index

The improvement of the voltage stability is achieved through the minimization of the Voltage Stability Index (VSI) L_j given by the j -th load node of the electric power grid. In the purpose to enhance voltage stability and keeping the electric power grid so far away from the operating point which provokes the voltage collapse (by improving the stability margin), the maximum of L_j among all load buses is employed as an objective function to minimize for handling the ORPD issue. The voltage stability index L_j of j -th load bus is defined as follows[29]:

$$L_j = \left| 1 - \sum_i F_{ij} \frac{V_i}{V_j} \angle (\alpha_{ij} + (\delta_i - \delta_j)) \right| \quad i = 1, 2, \dots, NG \quad j = 1, 2, \dots, NLB \quad (2.82)$$

where: $F_{ij} = |F_{ij}| \angle \theta_{ij}$

$$F_{ij} = -[Y_1]^{-1}[Y_2] \quad (2.83)$$

δ_i/δ_j = Voltage angle of *bus-i* and *bus-j*, respectively.

Y_1 = Describes the sub-matrix linking the injection current vector and voltage vector of load nodes.

Y_2 = Describes the sub-matrix linking the injection current vector of load nodes and the voltage vector of generation nodes.

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \quad (2.84)$$

when the L_j value is closer to zero, the electric power grid is further stable. Represents an equation that maximizes a parameter:

$$L_{max} = \max(L_j) \quad \text{where: } j=1, 2 \dots NLB \quad (2.85)$$

L_{max} the maximum value of L_j among all load buses.

2.9.4.2 Operational Constraints

2.9.4.2.1 Power Flow Equality Constraints

The power flow for each node of an electrical power grid is characterized by the equality constraints expressed as follows:

$$P_{G,i} - P_{L,i} - \sum_{j=1}^{NB} |V_i| |V_j| |Y_{ij}| \cos(\alpha_{ij} - \delta_i + \delta_j) = 0 \quad (2.86)$$

$$Q_{G,i} - Q_{L,i} - \sum_{j=1}^{NB} |V_i| |V_j| |Y_{ij}| \sin(\alpha_{ij} - \delta_i + \delta_j) = 0 \quad (2.87)$$

2.9.4.2.2 Operating inequality constraints

The mathematical form of inequality operating constraints is stated in the following manner:

1. Constraints description of generator: The output voltage of each generator is characterized by its magnitude, which is limited by upper and lower limits $V_{G,i}^{min}$ and $V_{G,i}^{max}$, respectively.

The reactive power generation is also limited between lower and upper capacity limit $Q_{G,i}^{min}$ and $Q_{G,i}^{max}$, respectively.

$$\begin{cases} V_{G,i}^{min} \leq V_{G,i} \leq V_{G,i}^{max} \\ Q_{G,i}^{min} \leq Q_{G,i} \leq Q_{G,i}^{max} \end{cases} \quad i = 1, 2, 3 \dots NG \quad (2.88)$$

2. The tap setting T_k of transformers is imposed to the restrictions given by lower and upper boundary T_k^{min} and T_k^{max} , respectively. These limits are mathematically given by :

$$\{T_k^{min} \leq T_k \leq T_k^{max} \quad k = 1, 2, 3 \dots NT \quad (2.89)$$

3. The generated reactive power Q_{ci} from a capacitor bank is confined by two limits Q_{ci}^{min} and Q_{ci}^{max} of lower and upper generation bound, respectively, and expressed as follows:

$$\{Q_{c,i}^{min} \leq Q_{c,i} \leq Q_{c,i}^{max} \quad i = 1, 2, 3 \dots NC \quad (2.90)$$

4. The power flow rate for each transmission line is confined by its transit capacity limit:

$$\{S_l \leq S_l^{max} \quad l = 1, 2, 3 \dots N_{NTL} \quad (2.91)$$

For limiting the dependent variables V_{Li} , Q_G and S_l , we use the technique of penalty factors which prevents the considered dependent variable to go out of its limits (by ruling out the solutions providing the limit violations of the considered state variable) even if the objective function at these points gives a good solution. For this aim, we use an augmented objective function described by equation (2.86):

$$F_{aug} = F(x, u) + \lambda_V \sum_{i=1}^{NLB} \Delta V_{Li} + \lambda_Q \sum_{i=1}^{NG} \Delta Q_{Gi} + \lambda_S \sum_{i=1}^{NTL} \Delta S_{li} \quad (2.92)$$

where: λ_V , λ_Q and λ_S are the factors of penalty.

$$\Delta V_{Li} = \begin{cases} (V_{Li}^{min} - V_{Li})^2 & \text{if } V_{Li} < V_{Li}^{min} \\ (V_{Li} - V_{Li}^{max})^2 & \text{if } V_{Li} > V_{Li}^{max} \\ 0 & \text{if } V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max} \end{cases} \quad (2.93)$$

$$\Delta Q_{Gi} = \begin{cases} (Q_{Gi}^{min} - Q_{Gi})^2 & \text{if } Q_{Gi} < Q_{Gi}^{min} \\ (Q_{Gi} - Q_{Gi}^{max})^2 & \text{if } Q_{Gi} > Q_{Gi}^{max} \\ 0 & \text{if } Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \end{cases} \quad (2.94)$$

$$\Delta S_{li} = \begin{cases} (S_{li} - S_{li}^{max})^2 & \text{if } S_{li} > S_{li}^{max} \\ 0 & \text{if } S_{li}^{min} \leq S_{li} \leq S_{li}^{max} \end{cases} \quad (2.95)$$

2.10 Optimal reactive power dispatch

Optimal reactive power dispatch (ORPD), as one of the sub-problem of the optimal power flow (OPF) calculation, plays a significant role in power system operation. The main purpose of ORPD is to identify the optimal setting of control variables for minimization of the given objective functions while satisfying a series of system constraints over the entire dispatch period. Contain discrete variables such as tap positions of transformers and reactive

compensation capacity and continuous variables like generator voltages. Besides, system constraints are composed of two equality constraints and a set of inequality constraints. Hence, when regarded as an optimization problem, ORPD is a complex mixed integer nonlinear optimization problem and has gotten much attention over the last few decades [30].

ORPD optimization problem formulations differ greatly depending on the particular selection of variables, objective(s) and constraints. Because of the specialized nature of ORPD, formulation selection often has implications for both solution method design and solution accuracy. The two major types are Conventional and Evolutionary optimization techniques.

Traditionally, conventional methods are effectively used to solve ORPD problems. They have been applied to solving ORPD problems to suit the different objective functions and constraints. These techniques are based on mathematical formulations which have to be simplified to get an optimal solution. The conventional methods have many drawbacks such as consuming a large amount of numerical iterations, and huge computations and therefore take large time to produce results without approximations and assumptions that lead to local optimum solutions. Therefore, these methods failed to handle the nonlinear and complex problems such as ORPD problem.

To overcome the shortcomings of conventional techniques, evolutionary methods and their hybridized versions have been developed and applied to ORPD problems in the recent past. The major advantages of the evolutionary methods include: fast convergence rate, appropriate for solving non-linear optimization problems, ability to find global optimum solutions, suitable for solving multi-objective optimization problems, pertinent in finding multiple optimal solutions in a single simulation run and versatile in handling constraints [17]; [31].

2.11 Conclusion

In this chapter, we have tried to give an overview of the definitions and the problem of power flow, and modeling of the power elements of an electrical network.

Then the notion of the power flow is exposed, the different elements constituting the transport network are treated, and the formulation of the ORPD problem with its constraints is

well presented, this chapter is ended with a detailed presentation of different objective functions and their models.

CHAPTER 3

The Meta-heuristics

Introduction

This chapter presents a brief discussion of both conventional and evolutionary techniques it presents reviews the ORPD problem as part of optimization problems encountered in electric power systems and some of the optimization techniques applied in solving the ORPD problem. ABC, SSA, and hybridization of evolutionary techniques to solve the ORPD problem in the networks to reduce active power transmission line losses. This chapter also covers the hybridization tool used in this research and the proposed methodology for the hybridization. There are different methods by which these two optimization techniques can be hybridized to come up with a better method to solve the problem at hand. This chapter presents the hybridization of ABC and SSA to form ABC-SSA and the details of the proposed methodology.

3.1 Conventional optimization techniques

These methods were first introduced to solve in an exact way particular problems such as continuous and linear problems under linear constraints (Danzig's simplex algorithm), these methods have also been extended to discrete and mixed cases but only in the linear case.

The main quality of deterministic global methods is that they do not require a starting point. These methods allow handling constraints well, unlike stochastic methods and can be applied to mixed problems (real, integer, and categorical variables). They guarantee to obtain a global solution to the problem. However, it is important to know that global deterministic methods remain usable as long as the number of variables does not become too large. Beyond about twenty variables, they reach their limits [27].

The development of conventional optimization techniques and their applications to solve ORPD problems are briefed here.

In reference [32], used Dual Linear Programming (DLP) for minimizing the real power losses in the system. The constraints include the reactive power limits of the generators, limits on the load bus voltages, and the operating limits of the control variables, i.e., the transformer

tap positions, generator terminal voltages and switchable reactive power sources. Real power economic dispatch is accomplished by standard techniques.

Reference [33] used the P-Q decomposition approach to formulate OPF based upon the decoupling principle well recognized in bulk power transmission load flow. This approach decomposes the OPF formulation into a P-problem (real power model) and Q-problem (reactive power model), thereby showing ORPD as a sub-problem of OPF. The Q-Problem is defined as the minimization of real power transmission line losses by optimally setting the generator voltages, transformer tap settings, and shunt reactive power compensations. The problem of enforcing state variables (inequality constraints) is included in the problem formulation by the use of penalty functions. This approach simplifies the formulation, improves computation time, and permits certain flexibility in the types of calculations desired (i.e. P-Problem, Q-Problem, or both).

Burchett et al. [34] in their paper proposed a Quadratic Programming (QP) solution to the OPF problem. This method used the second derivatives of the objective function to find the optimal solution. This method is suitable for optimization problems with infeasible or divergent starting points.

Lee et al. [35] broadly solved the optimal real and reactive power dispatch for the economic operation of power systems. The constraints are the operating limits of the control variables, power line flows, and bus voltages. The optimization problem is solved using the gradient projection method (GPM) which is used for the first time in the power systems study. The GPM allows the use of functional constraints without the need for penalty functions or Lagrange multipliers among other advantages.

Mota-Palomino and Quintana [36] presented a Linear Programming based solution for the reactive power dispatch problem. The reactive power model of the fast decoupled load flow algorithm was used to derive linear sensitivities. A suitable criterion was suggested to form a sparse reactive power sensitivity matrix. The sparse sensitivity matrix was modelled as a bipartite graph to define an efficient constraint relaxation strategy to solve linearized reactive power dispatch problems.

In reference [37], Nanda et al. developed Fletcher's Quadratic Programming to solve the OPF problem. The algorithm decoupled the OPF problem into sub-problems with two different objective functions: minimization of generation cost and minimization of active

power transmission line losses. These sub-problems were solved to optimally set the control variables while restricting the system constraints without violations. This algorithm showed some potential for online solving of OPF problems.

In [38], a penalty-based discretization algorithm. The algorithm handles the discreteness of shunt capacitors/reactors during the solution process of a Newton OPF without a combinatorial search. It can be easily incorporated with existing OPF programs in a straightforward manner. Tests on two actual systems show that the algorithm provides near-optimal discrete solutions.

Granville [39] presented an Interior Point Method (IPM) technique based on the primal-dual method to solve the ORPD problem in large-scale power systems. In the problem formulation, the inequality constraints were eliminated by incorporating them as a logarithmic barrier function. The main feature of the IPM is:

- 1) Insusceptibility of the size of the power system to the number of iterations

- 2) Numerical robustness

- 3) Effectiveness in solving ORPD problems in large-scale power systems

Granville [39] presented an Interior Point Method (IPM) technique based on the primal-dual method to solve the ORPD problem in large-scale power systems. In the problem formulation, the inequality constraints were eliminated by incorporating them as a logarithmic barrier function.

Reference [40] proposed a new Newton method approach to solve the OPF problem which incorporates an augmented Lagrangian function that has the function of combining all the equality and inequality constraints. The mathematical formulation and computation of the method are exploited using the sparsity of the Hessian matrix of the augmented Lagrangian. Optimal solutions were achieved by this method and can be utilized for an infeasible starting point as its set of constraints does not have to be identified.

Momoh and Zhu [41] proposed an improved Quadratic Interior Point Method (QIPM) to solve the OPF problem. The proposed method has the features of fast convergence and a general starting point, rather than a selected good point as in the general IPM.

3.2 Evolutionary Optimization Techniques

These non-deterministic methods use random number draws. They allow exploring the search space more efficiently. In the following, the focus will be on the meta-heuristic:

The word meta-heuristic is derived from the composition of two Greek words:

- Heuristics comes from the verb heuriskein (euriskein) and which means to find.
- Meta which is a suffix meaning beyond, in a higher level.

The first meta-heuristics date from the 1980s. They are generally used when classical methods fail. The term meta-heuristic is used in contrast to heuristics. Indeed, meta-heuristics can be used for several types of problems, while a heuristic is adapted to a given problem. Meta-heuristics have as common characteristics that they are stochastic, i.e. that part of the search is conducted randomly, and that they are inspired by analogies with reality: physics (simulated annealing,...), biology (evolutionary algorithms, tabu search,...) or ethology (ant colonies,...). In addition to this stochastic basis, meta-heuristics are generally iterative, i.e. the same search scheme is applied several times during the optimization, and direct, i.e. they do not use the gradient information of the objective function. They are particularly interesting because of their ability to avoid local optima, either by accepting a degradation of the objective function during their progress, or by using a population of points as a search method. Because of the abundance of research in this field, a large number of such methods exist. In the following, notably biological inspiration, can help in the design of new meta-heuristics [27].

Of late, several artificial intelligence algorithms appear to solve ORPD problems efficiently without any requirements on the attributes of objective functions and variables, which aim to search for the global optimal solution of problems, even though they cannot always guarantee the global optimal solution, a suboptimal solution that is near the global optimal solution may also be found. There are three categories of artificial intelligence algorithms listed as follows [42]:

3.2.1 Evolutionary Computation Techniques (EC):

Reference [43] presented the application of the differential evolution (DE) algorithm for optimal settings of ORPD control variables. This algorithm is examined and tested on the

standard IEEE 30 bus test system with different objectives that reflect power losses minimization, voltage profile improvement, and voltage stability enhancement.

Devaraj [44] presented an improved GA approach for solving the multi-objective reactive power dispatch problem. Loss minimization and maximization of the voltage stability margin were taken as the objectives. In the proposed GA, voltage magnitudes are represented as floating point numbers and transformer tap-settings, and the reactive power generation of a capacitor bank was represented as integers. This alleviates the problems associated with conventional binary-coded GAs to deal with real variables and integer variables. Crossover and mutation operators which can deal with mixed variables were proposed.

3.2.2 Physical Heuristic Methods

Song Woo Geem and Joong Hoon kim give a new heuristic algorithm HSA Harmony Search Algorithm [45] derived from an artificial phenomenon found in musical performance (for example, a jazz trio), namely the process of searching for better harmony (Music is one of the most satisfying processes generated by human endeavors). This method has been implemented the ORPD problem for the determination of the global or near global optimum solution in [46].

In [47], an efficient and reliable optimization procedure based on the behaviors of a swarm in nature, for solving multi-objective optimal reactive power dispatch problems, which minimizes transmission loss while maintaining the quality of voltages. The gravitational search algorithm is based on Newton's law of gravity and the interaction of masses. In the algorithm, the searcher agents which are a collection of masses interact with each other using Newton's laws of gravity and motion.

3.2.3 Swarm Intelligence (SI)

Abido [4], presents an efficient and reliable algorithm to solve the optimal power flow (OPF) problem. This method employs the particle swarm optimization (PSO) algorithm for optimal settings of OPF problem control variables. The incorporation of PSO as a derivative-free optimization technique in solving OPF problems significantly relieves the assumptions imposed on the optimized objective functions. This application has been examined and tested on the standard IEEE 30 bus test system with different objectives.

Abbasy and Hosseini [48], applied Ant Colony Optimization (ACO) technique to solve the ORPD problem. The approach consisted of mapping the solution space on a search graph, where artificial ants walk. They proposed four variants of the ant systems: 1) basic ant system, 2) elitist ant system, 3) rank-based ant system and 4) max-min ant system. They also portrayed that applying the elitist and ranking strategies to the basic ant system improves the algorithm's performance in every respect.

In [49], a Gray Wolf Optimizer (GWO) algorithm (which was inspired by gray wolves' leadership and hunting behavior) is presented to solve the ORPD problem. GWO is utilized to find the best combination of control variables such as generator voltages, tap changing transformers' ratios as well as the number of reactive compensation devices so that the loss and voltage deviation minimizations can be achieved.

The Whale Optimization Algorithm (WOA) [8], the meta-heuristic technique inspired by the bubble-net hunting technique of humpback whales, has been applied to solve the ORPD problem. The WOA method has been examined and confirmed on the IEEE 14 bus, and IEEE 30 bus, in addition to a practical and large-scale Algerian electric 114 bus test system.

3.3 Choice of an optimization method

One may ask what is the purpose of classification of problem types and methods. This classification can be justified as when a user is confronted with a global optimization problem, the first thing to do is to properly define the problem, namely:

- Assumptions on f (differentiability, convexity...).
- Assumptions on the search domain,
- Existence or not of constraints, what kind of constraints,
- Cost of evaluating the function (CPU time, number of subprograms needed),
- Ease of evaluation (access, explicit formula of f),
- Precision available on the calculations,
- Type of hardware used,
- Time available to solve the problem.

So, it can be seen that knowing a classification of problems and methods can facilitate the task of the user and guide him in his choice, which allows him to set his objectives

accordingly. Because it is better to have an approximate solution (with an insufficient precision) within a reasonable time than an exact solution (with the desired precision) outside the time limit in certain contractual cases.

Unfortunately, no optimization method can efficiently handle all cases. Indeed, [50], has shown that if one considers all possible optimization problems, then no algorithm is better than another ("no free lunch theorems for optimization"). The choice of an algorithm cannot, therefore, be made by comparison on general test cases, but must also study problems representative of the applications envisaged. The comparison of local or global optimization algorithms can only take place once the problem being addressed, i.e. the objective function, has been specified. According to [51], optimization is not only a mathematical theory but also a kind of algorithmic kitchen where it is mainly the experience that guides the user in the choice of the algorithm to be implemented. To choose the most suitable method for a specific problem, the main characteristics taken into account are:

- **The ability to avoid local minima:** It is according to the complexity of the problem that one can choose one or the other of the methods presented above. For example, if the objective function is convex, it is undoubtedly recommended to work with a local method that allows reaching the optimum quickly compared to the global optimization methods. However, if the objective function is multimodal it is probably not worth applying a local method and the use of global methods becomes necessary. Although here again several methods exist, in this section, the focus will be on the hybrid approaches to highlight their effectiveness and efficiency.

- **Robustness of an optimum:** The robustness of an optimum is also a determining notion for designers, and must not be neglected when choosing the optimization algorithm. The shape to be optimized is modeled in a deterministic way; this shape is thus optimized by neglecting the uncertainties related for example to the manufacturing processes or the simplifications of the problem. To reduce the probability that the performance of the optimized shape is not verified in reality, a robust optimum must be sought. A robust optimum is a solution that is not very sensitive to uncertainties.

- **The ability to deal with single or multi-objective problems:** Multi-objective optimization is a very active research field because the economic and industrial stakes are enormous. Multi-objective optimization methods provide the designer with a set of solutions

corresponding to as many trade-offs between the various antagonistic objectives of the problem, hence their importance.

- **The speed of convergence:** That is to say, how many variables must be evaluated in order to converge towards a global optimum? The answer to this question lies in the compromise that must be found between exploration and exploitation.

3.4 Exploration and exploitation of optimization algorithms

For an optimization algorithm, exploration is its ability to explore the domain of variables to find the best valley, i.e. the one that contains the global optimum. Conversely, exploitation is its capacity to converge quickly to the minimum of a given valley from a starting point.

The success and efficiency of a resolution technique depends most of the time on a trade-off between exploration and exploitation. However, some methods use only one of these operators to reach the optimum. Thus, deterministic methods, exploiting the derivatives of the objective function and the constraints to reach quickly and precisely the local minimum closest to the starting point, favor exploitation at the expense of exploration.

Any optimization algorithm must use these two strategies to find the global optimum: exploration to search for unexplored regions of the search space and exploitation to exploit the knowledge acquired at the points already visited and thus find better points.

3.5 The Most used meta-heuristics

Recognized for many years for their efficiency, meta-heuristics are a family of stochastic methods that consist in solving optimization problems. They generally exploit random processes in the exploration of the search space to cope with the combinatorial explosion generated by the use of exact methods.

Their particularity lies in the fact that they are adaptable to a large number of problems without major changes in their algorithms, hence the term "meta". One of the advantages of these methods is their ability to optimize a problem with a minimal amount of information, but they do not guarantee the optimality of the best solution found. Only an approximation of the global optimum is given. Meta-heuristics are methods that have an iterative behavior, i.e. the same scheme is reproduced a certain number of times during the optimization, and they are direct, in the sense that they do not call upon the calculation of the gradient of the function. The user is certainly looking for fast and efficient methods, but he is also looking for

easy to-use methods. A major issue of meta-heuristics is therefore to facilitate the choice of methods and to simplify their settings, in order to adapt them to the problems at hand. Meta-heuristics are in permanent evolution. Many methods are proposed each year to improve the solution of the most complex problems. Because of this permanent activity, a large number of classes of meta-heuristics currently exist. The most common methods are simulated annealing, particle swarm optimization, ant colony algorithms, artificial bee colony, or the Salp swarm algorithm. The following section is dedicated to the presentation of these methods.

3.6 Artificial bee colony algorithm

Recently, the ABC algorithm inspired by the foraging behavior of honeybees to find and exploit the nectar of flowers has been extensively applied as an efficient population-based algorithm. Since its development by Karaboga in 2005 [52], it has gained great popularity to solve complex optimization problems in various fields of engineering, especially in electrical power system considering Economic Dispatch (ED) [53], Optimal Power Flow (OPF) [54] and ORPD [55] due to its simple implementation. Referring to a huge number of works regarding ABC algorithm applications, practical studies have brought into focus that this algorithm is weak in the exploitation of promising solutions and powerful in the exploration of search space [10, 11, 56]. Hence, improved versions of the ABC algorithm have been developed based literature review in with the aim to reinforce exploitation capacity. The presented research in [56] proposes an improved version of the ABC the named g_{best} -guided ABC (GABC) algorithm by incorporating the best overall solution (g_{best}) information into the solution-finding equation to enhance exploitation. A hybrid approach of the ABC algorithm and Grenade Explosion Method (GEM) has been suggested in 2015 by Zhang et al. [13] to make the ABC algorithm more effective in exploiting the promising solutions discovered by GEM. The ABC-GEM performance has been justified by relying on simulation results of the wide variety of benchmark functions. This hybrid technique was first applied in [14] to solve the OPF problem for multi-objective functions including total fuel cost, voltage deviation and voltage stability index, considering IEEE 30 bus and IEEE 57 bus test systems.

The artificial bee colony algorithm as an interesting meta-heuristic optimization technique has proven its efficiency for solving various numerical optimization problems in the engineering area [54]. It has been inspired by the honey bees activities to collect the nectar of the food sources and share roles during the foraging process. The ABC algorithm considers

the food source position as a proposed solution in the search space, while the nectar quantity of food source corresponds to the fitness value of the potential solution. The hive population is divided in two groups of bees: employed and unemployed bees, where each group contains the half population of the hive. The employed bees are sent to search for food sources, while the unemployed bees, called onlooker bees, are waiting in the hive to receive information about food sources discovered by employed bees. Once onlooker bees have received information about food sources, they try to select the best ones among them (with a high quantity of nectar) to further explore the vicinity of the best food source positions (exploiting the best solutions). When a food source is exhausted, its employed bee changes its role to become a scout bee, which tries to find a new food source in another location. Three phases are performed to accomplish one cycle after the initialization phase of the population. A predefined number of cycles can be selected as the stopping criteria of the ABC algorithm [10, 52, 54].

- **Initializing a population of solutions**

Initially, random positions of SN food sources are generated in the hive environment using the following equation:

$$x_{ij} = x_{j,min} + R_n \cdot (x_{j,max} - x_{j,min}) \quad (3.1)$$

where $x_{j,max}$, $x_{j,min}$ are, the upper and lower limits of j -th decision variable in the D -dimensional search space respectively with $i \in [1, 2, \dots, SN]$, $j \in [1, 2, \dots, D]$, and R_n is a randomly generated number in the interval $[0, 1]$.

- **Exploiting Food Sources by Employed Bees**

After the initialization of food source locations, all employed bees are sent to discover the food sources in the neighborhood of the previously memorized food source positions. Each employed bee tries to find a food source around an old one in its memory. This behavior is modeled mathematically using the following equation:

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{Kj}) \quad (3.2)$$

where v_{ij} and x_{ij} indicate the new and the old j -th variable related to the i -th position of the food source, respectively, with $i \in \{1, 2, \dots, SN\}$ and $j \in \{1, 2, \dots, D\}$. x_{Kj} is the j -th variable of the k -th position of the food source chosen randomly. Φ_{ij} is a randomly generated real

number between -1 and 1. If v_{ij} in equation (3.2) violates its predefined limits, it is fixed to its violated limit. A greedy selection process is carried out to select between x_i and v_i .

- **Exploiting food sources by onlooker bees**

Once the employed bees have accomplished their investigation phase, they will communicate with onlooker bees about all information on food sources, particularly, the positions and nectar quantities. Each onlooker bee must choose one food source based on the probability evaluation p_i corresponding to this food source. Using the probability of the roulette wheel, p_i can be evaluated by the following expression:

$$P_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \quad (3.3)$$

fitness_i: Fitness value of solution i

The vector from the population of solutions $x_i = [x_{i1}, x_{i2}, \dots, x_{iD}]$ is evaluated by calculating its corresponding objective function $f(x_i) = f_i$ and the fitness function $fitness_i$ is given by:

$$fitness_i = \begin{cases} \frac{1}{1 + f(x_i)} & \text{if } f(x_i) \geq 0 \\ 1 + abs(f(x_i)) & \text{if } f(x_i) < 0 \end{cases} \quad (3.4)$$

The onlooker bee searches the neighborhood of selected food source position x_i in order to produce a new candidate solution by changing one parameter in the vector x_i using equation (3.2). The newly generated solution v_i is evaluated by referring to equation (3.4). Then the greedy selection takes part again in this case, to retain the best solution and reject that of poor quality.

- **Exchanging role of the employed bee to a scout bee**

After the full exploitation of a food source, its corresponding employed bee becomes a scout bee and it will change the location to look for a new food source in the search space. This stage is reached when a proposed solution x_i has not improved after a predetermined number of trials named "limit" and based on a Trial Counter (TC) corresponds to each potential solution. TC_i of i -th solution is incremented by 1 if no improvement of this solution, else TC_i is reset to zero. Thus, the new food source is generated randomly using equation

(3.1). The control parameter "limit" can be used as a key factor to avoid the ABC algorithm to be trapped in local minima during the search process. The ABC algorithm steps are illustrated below:

- Step 1: Set the ABC algorithm parameters SN , $limit$, D and $maxCycle$.
- Step 2: Creating an initial random population (food sources) using equation (3.1).
- Step 3: Evaluating each food source by determining the fitness value using equation (3.4) and reset TC to zero for each one.
- Step 4: Start $Cycle = 1$.
- Step 5: Start the phase of employed bees.
for $i = 1$ *to* SN
 Discover a new food source position v_i depending on the old one x_i by applying equation (3.2) where ($k \neq i$),
 Evaluate each new food source using equation (3.4), apply the greedy selection to choose between x_i and v_i ,
 Increment TC_i by 1 if no improvement of the i -th food source, else reset TC_i to zero.
end for
- Step 6: Calculating the probability p_i for each bee using equation (3.3).
- Step 7: Start the phase of onlooker bees.
for $i = 1$ *to* SN
 Generate a random value Rn
 if $Rn < p_i$
 Discover a new food source position v_i depending on the old one x_i by applying equation (3.2) where ($k \neq i$),
 Evaluate each new food source using equation (3.4), apply the greedy selection to choose between x_i and v_i ,
 Increment TC_i by 1 if no improvement of the i -th food source, else reset TC_i to zero.
 end if
end for
- Step 8 : Start the scout bee phase
for $i = 1$ *to* SN
 if $TC_i > limit$
 Create a new food source emplacement x_i using equation (3.2)
 end if
end for
- Step 9 : Store the global best food source obtained until now.
- Step 10: Verifying if $Cycle > maxCycle$, if yes exit by stopping the algorithm execution, otherwise do $Cycle = Cycle + 1$ and go to step 5.

3.6.1 Flowchart of artificial bee colony (ABC)

Figure 3.1 delineates the flowchart of the algorithm ABC as thus:

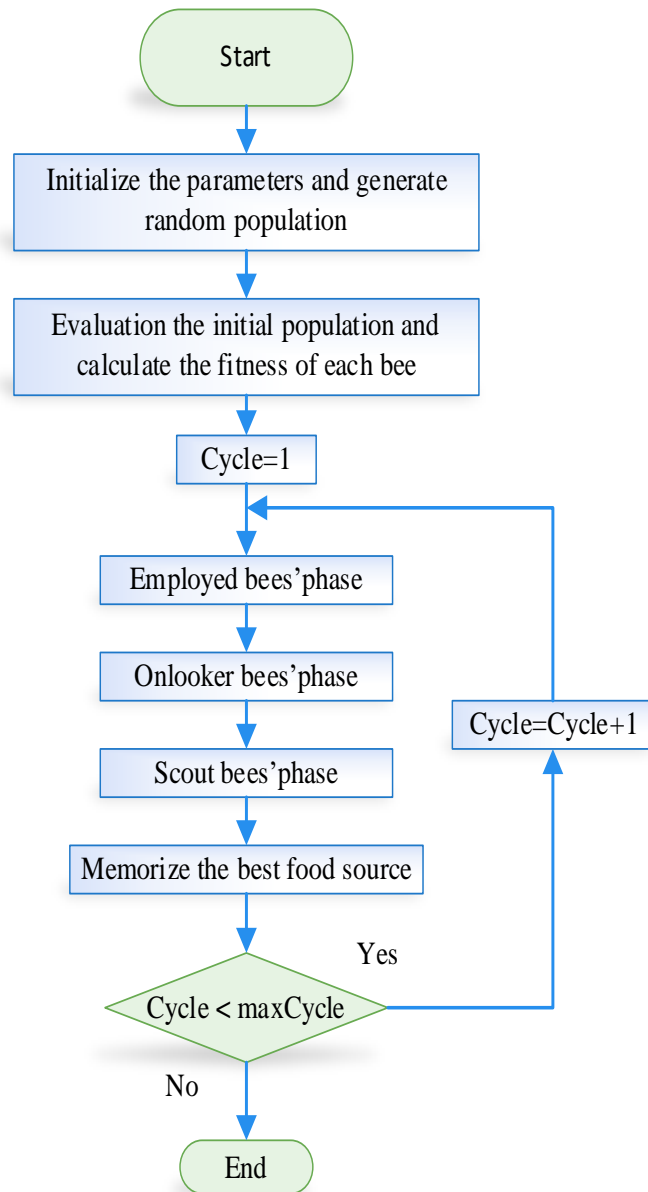


Figure 3.1 Flowchart of ABC algorithm.

3.7 Salp swarm algorithm

In the year 2017, a new meta-heuristic optimization technique named Salp Swarm Algorithm (SSA) has been developed and investigated for solving a set of standard real optimization problems [57]. In the previous study, SSA pointed out better performances considering quantitative and qualitative simulation outcomes on several benchmark functions. It has been inspired by navigating and foraging behaviors of salp swarms living in oceans.

Based on the SSA applications in the OPF problem [58] and feature section (FS) [59], the common assessment report of these applications highlights that the SSA is weak in exploration search mechanism and powerful in exploitation capability [59, 60].

The imitation of the SSA is from the attitude of salps belonging to salpidae species, living in oceans and possessing a transparent body in the form of a barrel like a jelly-fish. The salps move with pumped water through their body to propel themselves forward Figure 3.2 (a). It is believed that the salps move so that they organize a salp chain in oceans and seas searching for the best sources of food as shown in Figure 3.2 (b).

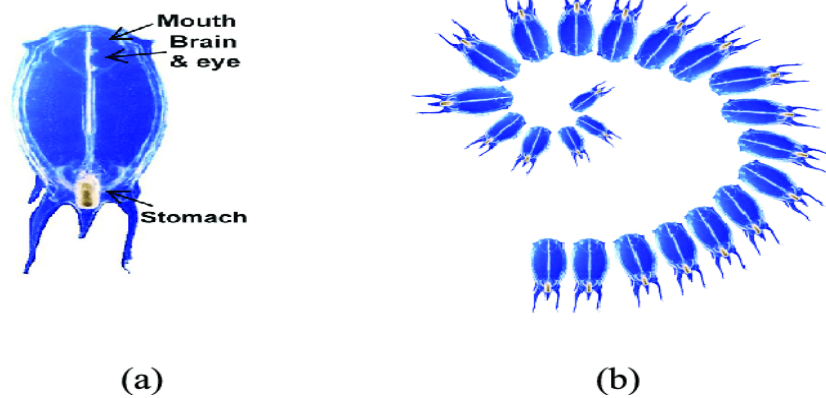


Figure 3.2 (a) Individual salp, (b) swarm of salps (salps chain).

To model the salp chain behavior in the mathematical aspect, the salp swarm is partitioned into two sub-populations of leader and followers. By leading the salp chain, the leader tries to govern the displacement of the followers. Each follower of the salp chain tracks the path mapped by one leader. In a similar manner as other categories of optimization techniques founded on the swarm attitude, the salp position is expressed in the search space with D -dimensions, where D reflects the number of control variables relating to the optimization problem. Consequently, Np positions of salps are memorized in a matrix X with two-dimensions. By assuming that the target of the swarm is a food source designated by F_j , the salp chain attempt to reach it during the search process [57, 61]. To deal with the update of the leader position, equation (3.5) can be suggested.

$$X_j^1 = \begin{cases} F_j + c_1 \left((ub_j - lb_j)c_2 + lb_j \right) & c_3 \geq 0.5 \\ F_j - c_1 \left((ub_j - lb_j)c_2 + lb_j \right) & c_3 \leq 0.5 \end{cases} \quad (3.5)$$

where

- X_j^1 = Leader position in j -th dimension relating to the first salp.
- F_j = The position occupied by the best food source in the dimension j at each iteration.
- ub_j and lb_j = Are the upper and lower limits in the dimension j of D -dimensional space, respectively.
- c_2, c_3 : = Two randomly generated numbers in the interval between 0 and 1.

Equation (3.5) exposes the update of the leader position by referring to the food source position. The factor c_1 represents the key factor in the harmonization between two important mechanisms of meta-heuristics exploration and exploitation during the research for good solutions specified in the following equation:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad (3.6)$$

By considering:

l : Current iteration, L : Maximum number of iterations.

For updating the follower salp position, this task is accomplished according to the suggested equation (3.7).

$$X_j^i = \frac{1}{2}(X_j^i + X_j^{i-1}) \quad (3.7)$$

where the index i must be greater or equal to 2 and X_j^i depicts the i -th follower salp position in j -th dimension. By employing equation (3.5) and (3.7), the simulation process of salps in regrouped chains can be mimicked. Referring to mathematical inspiration, the principal steps of the SSA algorithm are shown below:

- Step 1: Set SSA parameters like as D , N_p , ub , lb , L and initialize $l=1$.
- Step 2: Create a random population of solutions by initializing the positions of salps.
- Step 3: Evaluate the population for the objective function and find the best global solution F (food source).
- Step 4: Dividing the salp population in two sub-populations of leaders and flowers.
- Step 5: Updating iteration number $l=l+1$.
- Step 6: Calculate the constant c_1 based equation (3.6), while c_2 and c_3 are generated randomly.

- Step 7: Update leader and follower positions using equation (3.5) and equation (3.7), respectively.
- Step 8: Amending salp positions referring to lower and upper limits of variables.
- Step 9: Update the food source F .
- Step 10: Verifying if $l < L$ go to step 5, else extract the best global solution F and exit from the algorithm execution.

3.7.1 Flowchart of Salp Swarm Algorithm (SSA)

Figure 3.3 shows the flowchart of the SSA algorithm as follows:

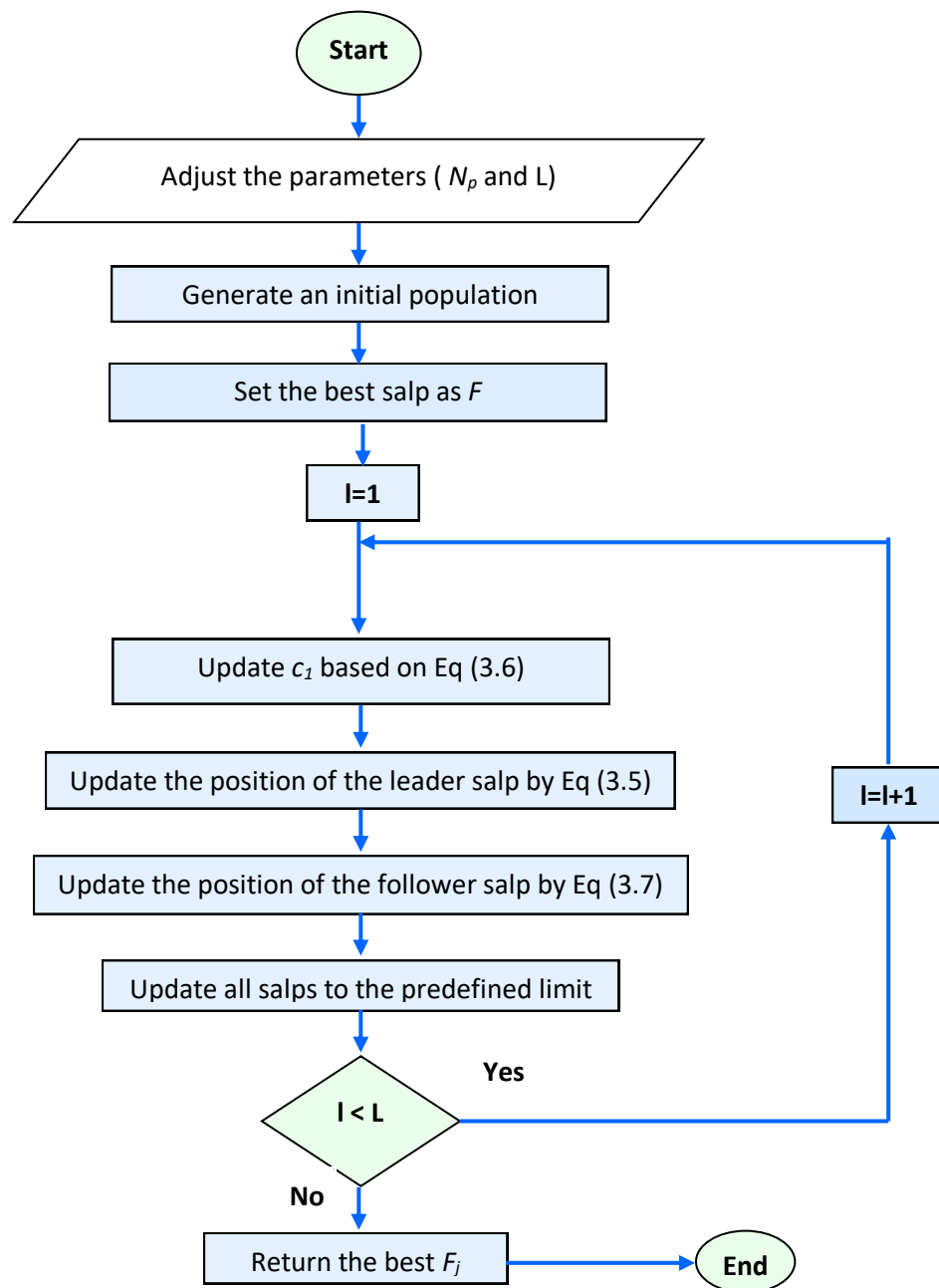


Figure 3.3 Flowchart of SSA.

3.8 Hybrid ABC-SSA approach

All meta-heuristic optimization techniques try to balance between their two important mechanisms: exploration and exploitation. The exploration is related to the search capacity of the algorithm in finding encouraging new solutions, while exploitation is associated with the capability of the algorithm to discover an optimum near the best solution. Referring to equation (3.2), which describes the search mechanism of the ABC algorithm, the newly generated position v_i (new solution) moves away from (or near) the old position (solution x_i) depending on the selection probability p_i in equation (3.4). This behavior tends to improve the exploration capability. The main disadvantage affecting the ABC algorithm is the update of the position x_i based on only one search equation (3.2) by changing one parameter (one variable related to this solution). In addition, when the greedy selection is applied between x_i and v_i , the bad solution is ignored without giving it more chance of exploitation. Therefore, the ABC method is good at exploration but poor at exploitation. The SSA uses equation (3.5) in order to update the position of the leader referring to the best solution F_j (food source), which enhances the exploitation capability to find promising solutions in the vicinity of the optimal solution found so far F_j . The hybrid ABC-SSA approach tries to improve the exploitation proficiency of the ABC algorithm by introducing the bad solutions S_{n_i} which have not been improved (extracted using greedy selection between x_i and v_i in the employed and onlooker bee phases) in SSA. In such a manner, these solutions are more exploited using the local search process by SSA in order to improve the solution quality of the optimization problem. The best global solution achieved by the ABC algorithm is stored as food source F_j in the SSA. To support all these stages, the hybrid ABC-SSA steps are described below:

- Step 1: Firstly, set the ABC algorithm parameters (N , D and $maxCycle$) and accomplish the ABC method steps (from step 2 until step 3).
- Step 2: Start Cycle =1.
- Step 3: Begin with step 4 until step 8 in the ABC steps (employed bees phase and onlooker bees phase).
- Step 4: Extracting the population of solutions S_{n_i} which has not been improved during ABC method and memorizing the best global solution achieved so far by ABC algorithm as best food source F_ABC .
- Step 5: Starting with SSA and evaluate the population of solutions S_{n_i} using equation (3.5).
- Step 6: Complete the same steps mentioned in the SSA method (from step 5 until step 9), and

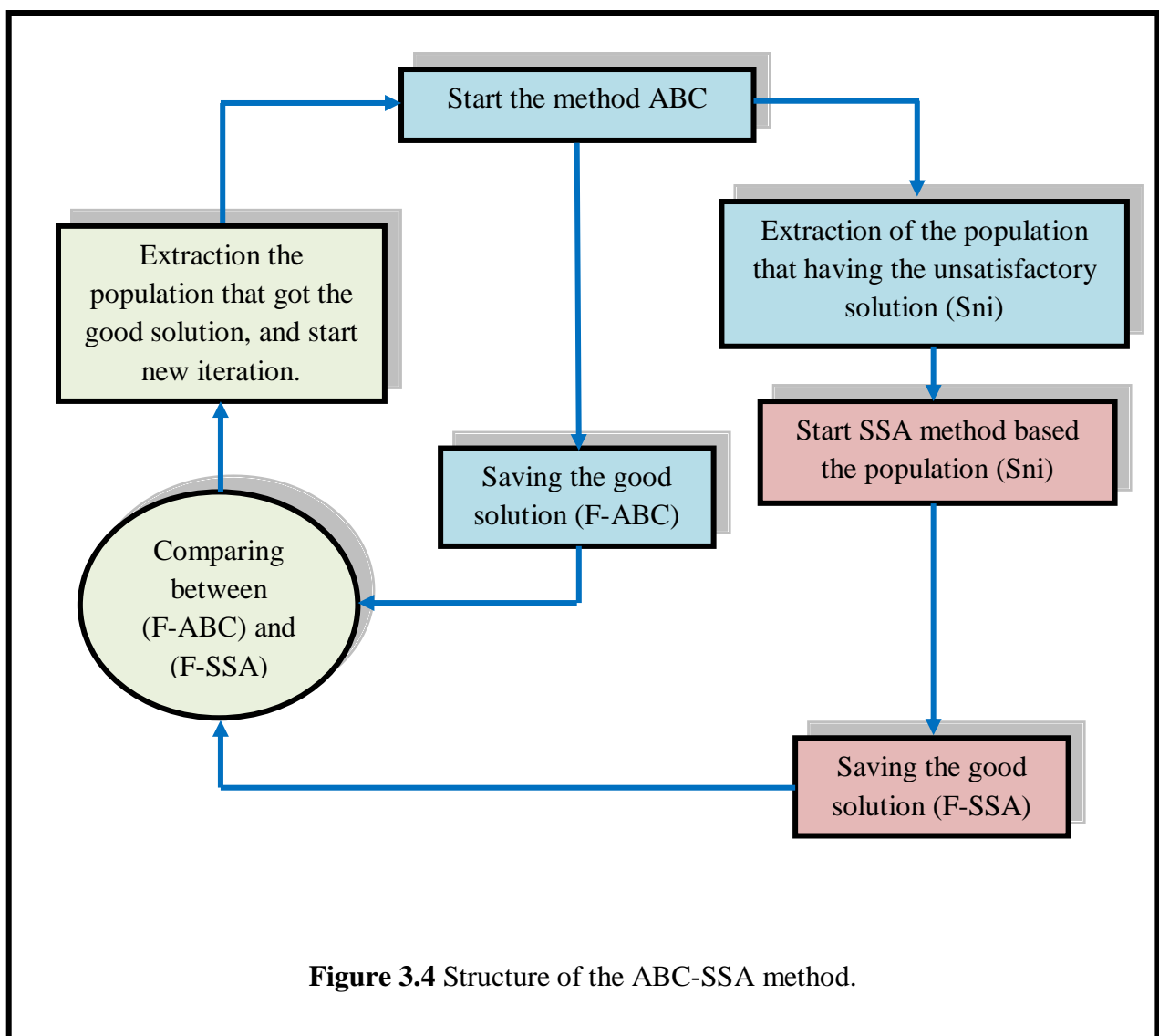
memorize the best food source as F_SSA .

Step 7: Compare between F_ABC and F_SSA and extract the best food source among them.

Step 8: Check if $Cycle < maxCycle$, if Yes do $Cycle = Cycle + 1$ and then go to step 3, else extract the best food source and exit from the program.

3.8.1 Contribution structure of the ABC-SSA method

For further clarification, Figure 3.4 illustrates the structure of the proposed ABC-SSA method:



3.8.2 Flowchart of Hybrid ABC-SSA Approach

Figure 3.5 shows the flowchart of the ABC-SSA algorithm as follows:

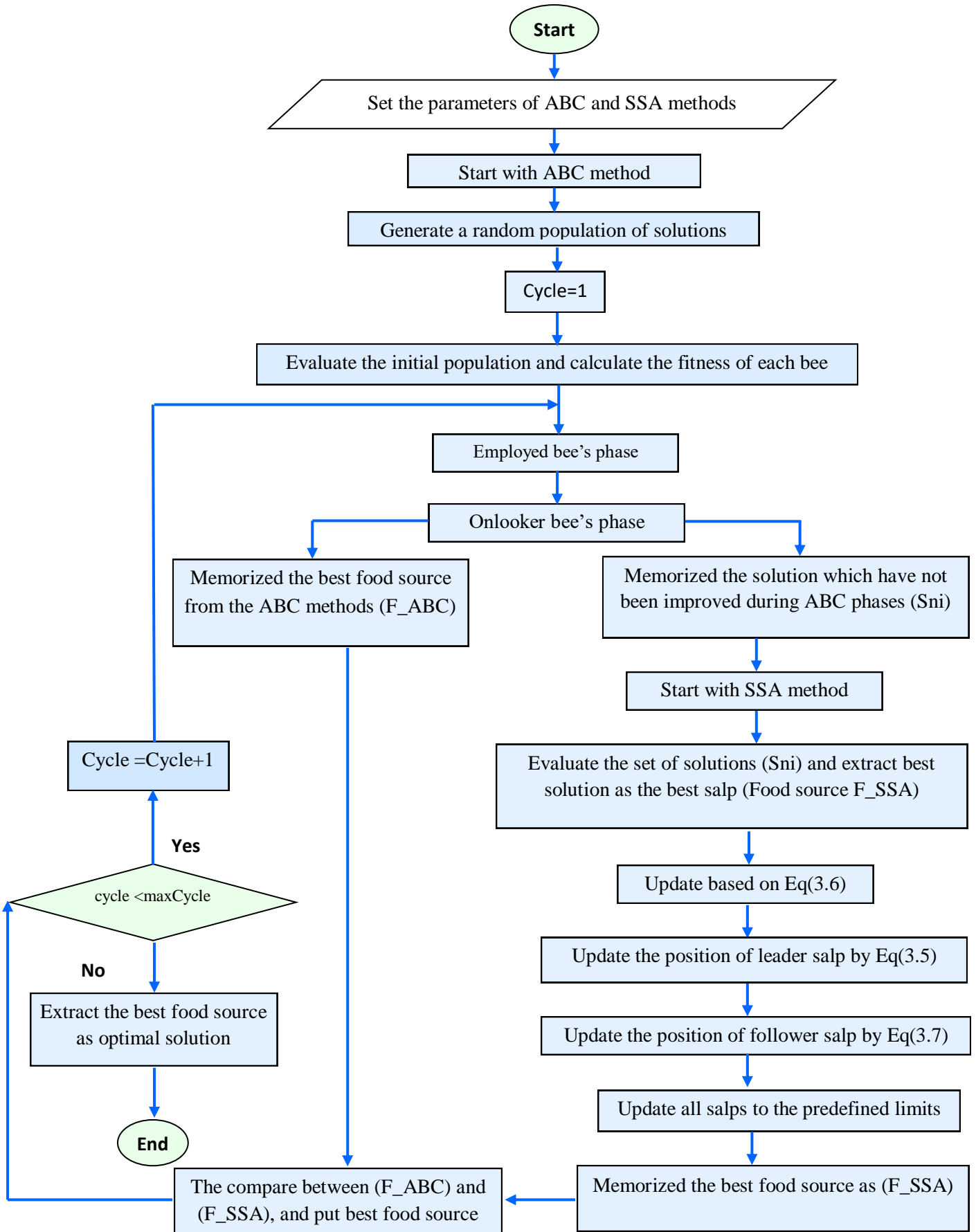


Figure 3.5 Flowchart of the ABC-SSA algorithm.

3.9 Conclusion

This chapter reviews the development and application of conventional and evolutionary optimization techniques to solve the ORPD problem by different authors in the power system area. In addition, it reviews the development and application of some hybrid methods to solve the ORPD. It also gives details of the application of ABC, as well as SSA in solving an ORPD problem. And presents the hybridization of ABC and SSA to form ABC-SSA and shows in a flowchart how they can be used to solve the ORPD problem.

CHAPTER 4

Simulation Results and Analysis

This chapter covers the hybridization tool used in this research and the proposed methodology for the hybridization. There are different methods by which these two optimization techniques can be hybridized to come up with a better method to solve the problem at hand. This chapter presents the hybridization of ABC and SSA to form ABC-SSA and the details of the proposed methodology.

4.1 Simulation results and discussions

To investigate the enhancement of the proposed ABC-SSA approach in solving the ORPD problem, four standard test systems are considered which are IEEE 30 bus, IEEE 57 bus, IEEE 118 bus, and IEEE 300 bus. The mono-objective optimization issue is stated by minimizing the total active power losses (P_{loss}), voltage stability index (L-index) or total voltage deviation (TVD). Table 4.1 presents the characteristics of the test systems. The software used is running under MATLAB R2013a computing environment and applied on a 2.40 GHz Pentium IV personal computer with 3GB RAM. The population size (N_P), the maximum number of iterations (Max_iteration), and penalty factors λ_V , λ_Q in Eq. **Error! Reference source not found.** for each test power system are given in Table 4.2. The optimal solution achieved by the developed algorithm (ABC-SSA) is selected for the best solution over thirty runs independently executed.

Table 4.1 Description of test power systems.

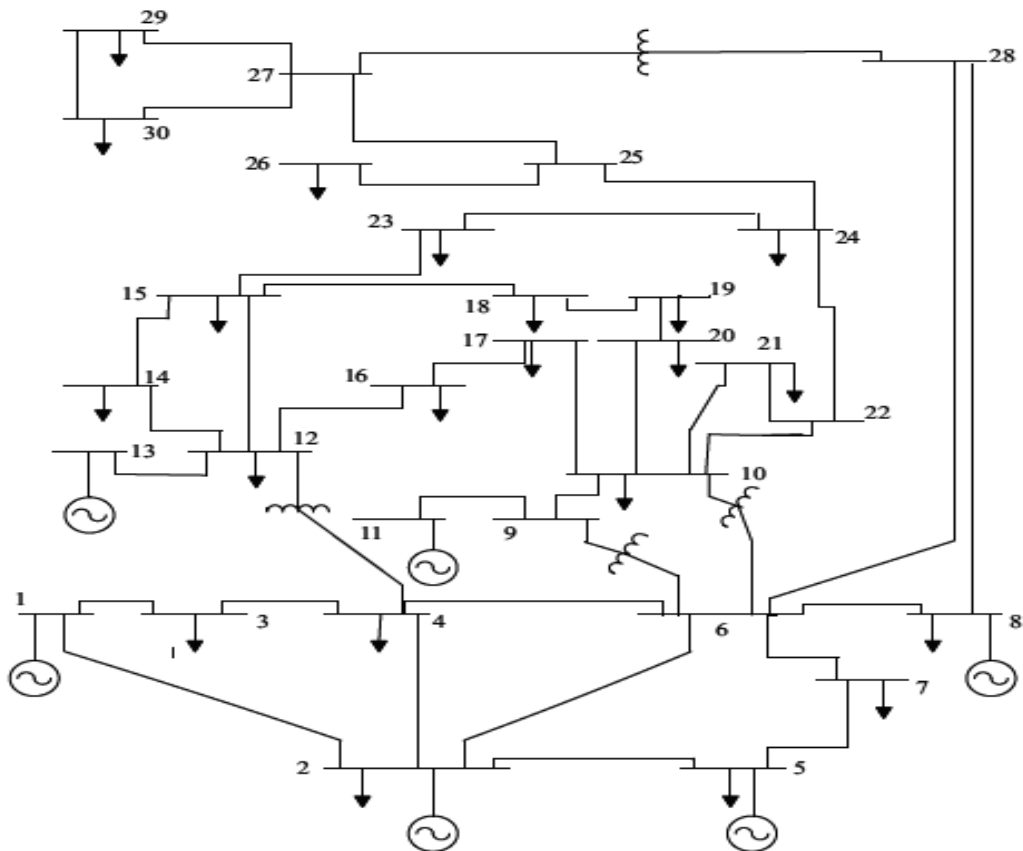
Description	IEEE 30 bus	IEEE 57 bus	IEEE 118 bus	IEEE 300 bus
Number of control variables	19	25	77	190
Number of Generators	6	7	54	69
Number of Taps	4	15	9	107
Number of Q-shunt	9	3	14	14
Equality constraints	60	114	236	530
Inequality constraints	125	245	572	706
Discrete variables	13	18	23	121
P _{loss} (MW)	5.81	28.462	132.863	408.316
TVD (pu)	0.5821	1.233	1.439	5.4286

Table 4.2 Control parameter settings of ABC, SSA, and ABC-SSA algorithms for test power systems

Algorithm	ABC, SSA, and ABC-SSA			
Parameters	λ_V	λ_Q	N	Max_iteration or maxCycle
IEEE 30 bus	0.001	0.001	80	150
IEEE 57 bus	20	20	150	300
IEEE 118 bus	10	10	300	500
IEEE 300 bus	10^2	10^{-6}	500	500

4.2.IEEE 30 bus System

The first test system implemented in the ORPD problem is that of IEEE 30 bus. It contains 19 control variables including 6 for generator voltage magnitude outputs located in buses 1; 2; 5; 8; 11 and 13, 4 for tap setting transformers connected between buses ([6–9], [6–10], [4–12] and [28–27]), and 9 for reactive power output from shunt capacitors in buses 10; 12; 15; 17; 20; 21; 23; 24 and 29. The data base for this network is mentioned in [62], and the total real power demand is 2.834 (pu) at 100 MVA base. The limit of the control variables is shown in[62].

**Figure 4.1** Single line diagram of IEEE 30 bus power system [63]

4.2.1 Active Power Losses Minimization for IEEE 30 bus System

In this case, P_{loss} is selected as an objective function to minimize and the best control variables resulting from ABC-SSA computing code running are shown in Table 4.3. The results established after the simulation phase by applying the ABC-SSA method are compared with those of other available methods in the literature as PSO[62], CLPSO[62], WOA[8], GSA-CSS, and IGSA-CS [30], as well as the implementation of the developed approaches in this paper ABC-SSA. The minimum obtained P_{loss} from the ABC-SSA algorithm is 4.5578 MW and it is less by 0.1152 MW (2.53%) than SSA, which gives 4.6730 MW. A statistical comparison is performed based on Table 4.4 proving the capability of ABC-SSA to overcome other optimization techniques reported in the same table. The convergence curves for ABC, SSA, and ABC-SSA methods are illustrated in Figure 4.2, which demonstrates that the new hybrid approach does not have any stagnations for the global best solution evolution as it does for SSA and ABC methods. This characteristic shows better performances of ABC-SSA in tackling premature convergence.

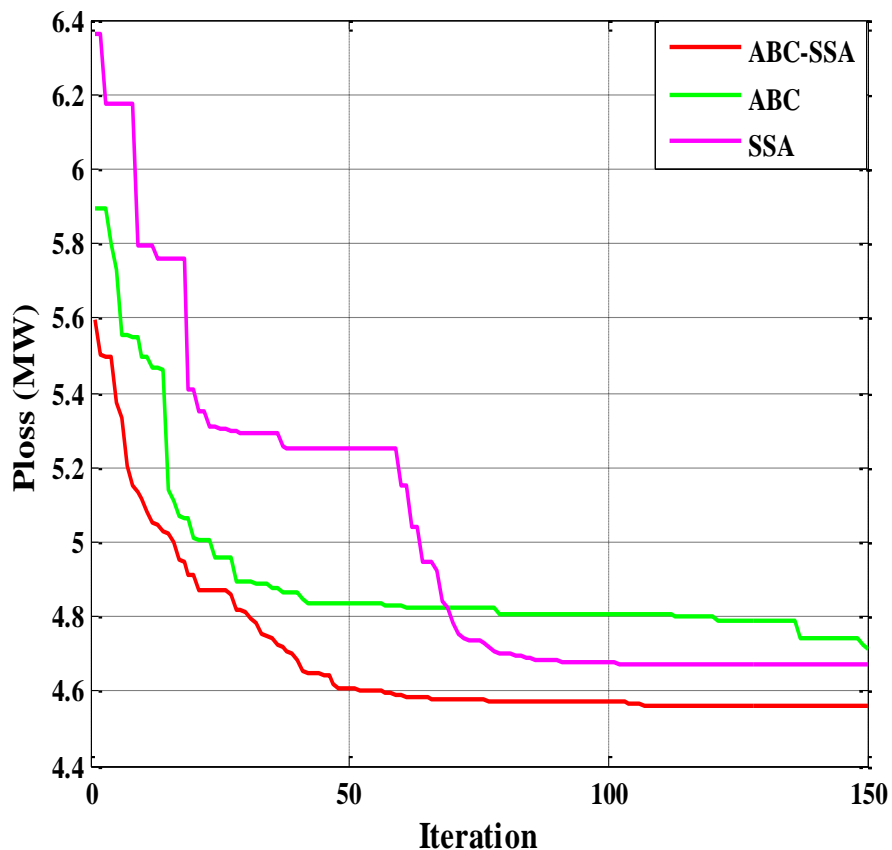


Figure 4.2 Convergence curves for Ploss minimization, IEEE 30 bus.

Table 4.3 Simulation results using ABC-SSA and other optimization techniques for P_{loss} minimization IEEE 30 bus.

Control variables	ABC-SSA	ABC	SSA	PSO[62]	CLPSO[62]	WOA[8]	GSA_CSS[30]	IGSA_CSS[30]
Generator voltage								
V_1	1.1000	1.0578	1.1000	1.1000	1.1000	1.1000	1.108098	1.081281
V_2	1.0942	1.0565	1.0945	1.1000	1.1000	1.0963	1.071832	1.072177
V_5	1.0738	1.0236	1.0749	1.0867	1.0795	1.0789	1.049583	1.050142
V_8	1.0762	1.0176	1.0768	1.1000	1.1000	1.0774	1.049744	1.050234
V_{11}	1.1000	1.0426	1.0707	1.1000	1.1000	1.0955	1.087238	1.100000
V_{13}	1.1000	1.0686	1.0814	1.1000	1.1000	1.0929	1.073330	1.068826
Transformer tap ratio								
T_{6-9}	1.0684	1.0380	1.0147	0.9587	0.9154	0.9936	1.040	1.080
T_{6-10}	0.9000	1.0289	1.0036	1.0543	0.9000	0.9867	0.964	0.902
T_{4-12}	0.9998	1.0755	1.0593	1.0024	0.9000	1.0214	1.020	0.990
T_{28-27}	0.9760	1.0396	1.0040	0.9755	0.9397	0.9867	0.972	0.976
Capacitor banks								
Q_{C-10}	5.0000	2.7614	4.3881	4.2803	4.9265	3.1695	0.0255	0.00
Q_{C-12}	5.0000	2.0468	4.3416	5.00	5.0000	2.0477	0.0335	0.00
Q_{C-15}	5.0000	0.9966	2.6818	3.0265	5.0000	4.2956	0.0315	0.0380
Q_{C-17}	5.0000	2.7687	1.6046	4.0365	5.0000	2.6782	0.0350	0.0490
Q_{C-20}	5.0000	4.5165	1.4919	2.6697	5.0000	4.8116	0.0260	0.0395
Q_{C-21}	5.0000	3.3702	2.7040	3.8894	5.0000	4.8163	0.0300	0.0500
Q_{C-23}	3.8635	3.5046	2.7881	0.0000	5.0000	3.5739	0.0350	0.0275
Q_{C-24}	5.0000	2.4227	4.3374	3.5879	5.0000	4.1953	0.0360	0.0500
Q_{C-29}	3.1172	3.8632	2.4971	2.8415	5.0000	2.0009	0.0300	0.0240
P_{loss} MW	4.5578	4.7157	4.6730	4.6282	4.5615	4.5943	4.79301	4.76601
TVD (pu)	1.8117	0.4789	1.0592	1.0883	0.4773	-	-	-
L-index (pu)	0.1169	0.1452	0.1277	0.1423	0.1230	-	-	-

Table 4.4 Comparison of minimum real power losses for different methods for IEEE 30 bus system.

Algorithms	P_{loss} MW	Algorithms	P_{loss} MW
MICA-IWO [15]	4.5984	LDI-PSO [64]	4.6124
IWO [15]	4.6287	B-DE [64]	4.6124
ICA [15]	4.6155	R-DE [64]	4.6675
C-PSO [64]	4.6801	SFLA [64]	4.6148
CI-PSO [64]	4.6124	ABC-SSA	4.5578

4.2.2 TVD Minimization for IEEE 30 bus System

In this case, TVD is the objective function to be minimized for the same IEEE 30 bus test network. Table 4.5 presents the results deduced from the simulation stage, which includes the best optimum (TVD) with the proposed ABC-SSA algorithm and the two implemented approaches ABC and SSA. A comparison is made with other optimization methods provided in the literature, like FA [13], HFA[13], PSO[62], and CLPSO[62]. Therefore, as shown in Table 4.5, there is a TVD improvement of 5.15% than the best result obtained by HFA [13] which gives 0.098 pu. Figure 4.3 illustrates the convergence characteristics of each method

confirming the fastest convergence rate of ABC-SSA in reaching the best global optimum.

Table 4.5 Comparison of simulation results for IEEE 30 bus test power system with TVD minimization objective.

Algorithm	TVD						
	ABC-SSA	ABC	SSA	FA [13]	HFA [13]	PSO[62]	CLPSO[62]
P_{loss} MW	6.0744	6.0945	5.7451	6.3400	5.75	4.7075	4.6969
TVD (pu)	0.0932	0.1097	0.1053	0.1157	0.098	0.2577	0.2450
L-index(pu)	0.1369	0.1374	0.1367	-	-	0.1273	0.1247

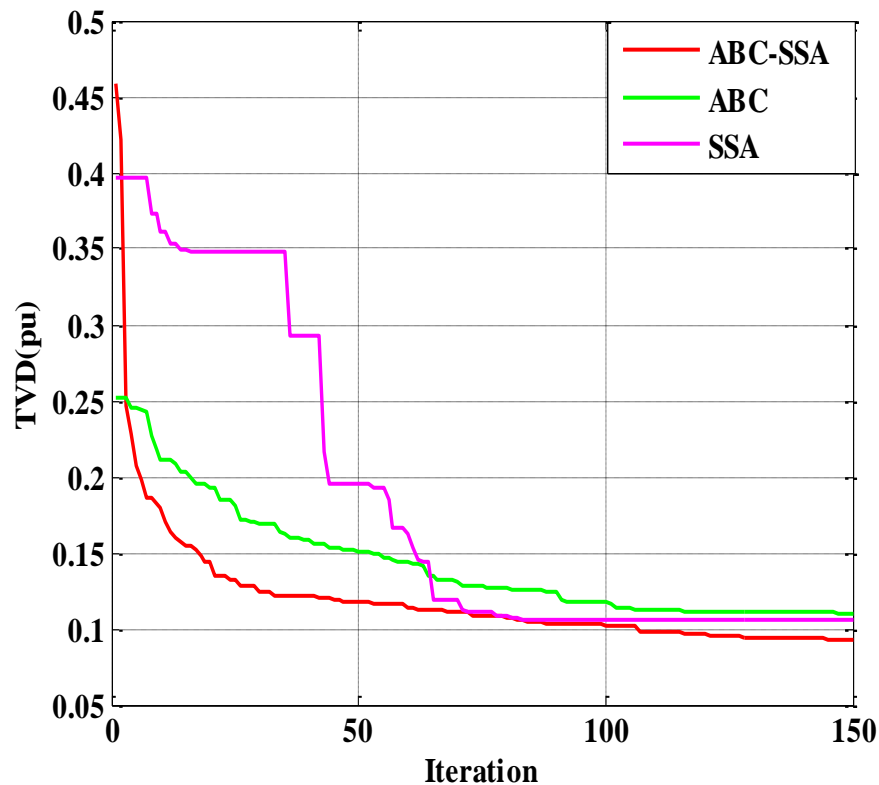


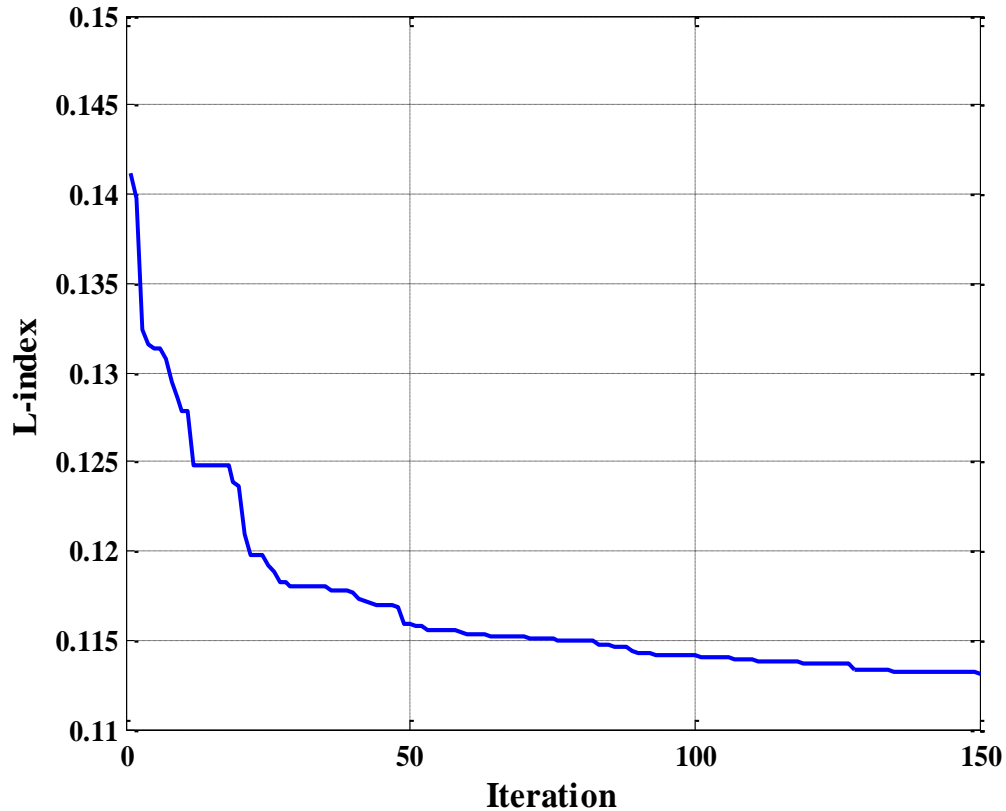
Figure 4.3 Convergence curves for TVD minimization of IEEE 30 bus power system

4.2.3 VSI Improvement for IEEE 30 bus system

In order to enhance the margin stability of IEEE 30 bus system, the VSI given by $\max(\text{L-index})$ is minimized by applying the ABC-SSA. The simulation results are listed in Table 4.6 and compared with those of ABC, SSA, GSA[7], and opposition-based gravitational search algorithm OGSA[65]. The optimal value of VSI using ABC-SSA is better than that of the OGSA method in the literature signalling a remarkable reduction (important improvement) equal to 9.82%. Figure 4.4 shows the variation of the voltage stability index. The good convergence property of ABC-SSA is noted from the figure by means of its ability to reach optimal solution.

Table 4.6 Comparison of simulation results for IEEE 30 bus test power system with improvement of VSI

Algorithms	ABC-SSA	ABC	SSA	OGSA [65]	GSA[7]
Ploss MW	4.7173	5.4268	4.6581	5.9198	4.975298
TVD (pu)	2.1341	1.8551	2.0349	1.9887	0.215793
L-index(pu)	0.1120	0.1138	0.1139	0.1230	0.136844

**Figure 4.4** Convergence curves for VSI minimization of IEEE-(30buses) power system

4.3 IEEE 57 bus system

IEEE 57 bus test system includes 80 transmission lines and seven generators on buses 1, 2, 3, 6, 8, 9, 12, and 15 branches under the transformer. Reactive shunt power sources are taken into account on buses 18, 25, and 53. The total system demand is $(12.508 + j3.364)$ pu to 100 MVA basis. Other input data from the system are given in [66], and limits of the control variables are given in [67].

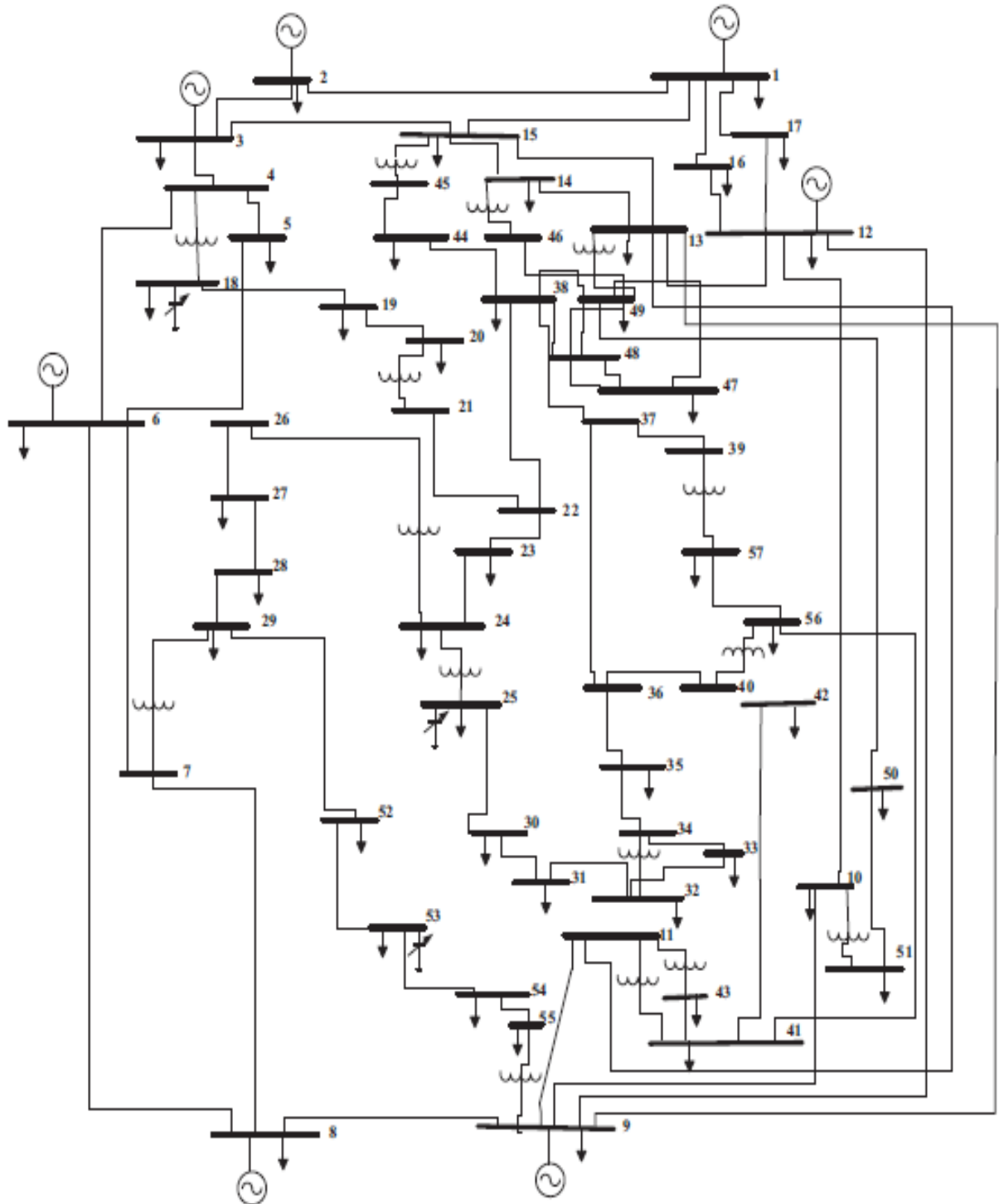


Figure 4.5 Single line diagram of IEEE 57 bus test system [63]

4.3.1 Active power losses Ploss minimization for IEEE 57 bus system

The active transmission losses are minimized in this case for IEEE 57 bus test system by adjusting all control variables using the proposed method ABC-SSA, where Table 4.7 indicates the optimal simulation results obtained for the objective function and control variables. A comparative review is assigned between the optimal solution using ABC-SSA

and that given by other optimization methods in the same literature like ABC, SSA, L-DE [23], BBO [24], and GSA [12] in Table 4.7. It can be recorded that the active power losses of 22.6134 MW achieved by ABC-SSA is better than that of the other comparison methods, confirming that this novel optimization algorithm is more robust. A reduction in active power losses of 3.19% is achieved using the ABC-SSA approach versus the best solution obtained among the comparison techniques (ABC). Table 4.9 demonstrates the results achieved in the same literature and the comparison with the ABC-SSA method. Figure 4.7 represents the convergence graphs arising from ABC-SSA, ABC and SSA, which asserts the capacity of the suggested ABC-SSA technique in detecting the most qualified solutions in the search space and in converging with a faster manner than ABC, and SSA. Figure 4.6 shows the voltage profile of the three methods ABC-SSA, ABC, and SSA, when the optimal solution is reached for the current test system, noting that the voltage amplitude on all buses is within its allowed range with no violations beyond the allowed limits. The entries of Table 4.8 in this regard illustrate the actual values of reactive power generations in MVAR of the generating units versus the allowable limits, in which all generating reactive powers are within their limits

Table 4.7 Comparison of simulation results for Ploss minimization in case of IEEE 57 bus system.

Control variables	ABC-SSA	ABC	SSA	GSA[7]	BBO[68]	L_DE[69]
Generator voltage						
V_1	1.1000	1.1000	1.1000	1.060000	1.0600	1.0397
V_2	1.0901	1.0910	1.0906	1.060000	1.0504	1.0463
V_3	1.0807	1.0825	1.0825	1.060000	1.0440	1.0511
V_6	1.0774	1.0786	1.0736	1.008102	1.0376	1.0236
V_8	1.0979	1.0956	1.0996	1.054955	1.0550	1.0538
V_9	1.0650	1.0820	1.0710	1.009801	1.0229	0.94518
V_{12}	1.0702	1.0901	1.0801	1.018591	1.0323	0.99078
Transformer tap ratio						
T_{4-18}	0.9077	0.7285	0.9762	1.100000	0.96693	1.02
T_{4-18}	1.0152	0.3201	0.9832	1.082634	0.99022	0.91
T_{21-20}	1.0141	0.8644	0.9710	0.921987	1.0120	0.97
T_{24-26}	1.0129	0.6107	1.0450	1.016731	1.0087	0.91
T_{7-29}	0.9729	0.2245	1.0041	0.996262	0.97074	0.96
T_{34-32}	0.9817	0.3963	0.9638	1.100000	0.96869	0.99
T_{11-41}	0.9000	0.1285	1.0118		0.90082	0.98
T_{15-45}	0.9652	0.2605	0.9646	1.074625	0.96602	0.96
T_{14-46}	0.9491	0.1609	0.9726	0.954340	0.95079	1.05
T_{10-51}	0.9571	0.1746	1.0282	0.937722	0.96414	1.07
T_{13-49}	0.9231	0.0184	0.9621	1.016790	0.92462	0.99
				1.052572		

T_{11-43}	0.9545	0.1218	0.9464	1.100000	0.95022	1.06
T_{40-56}	0.9978	0.5815	1.0042	0.979992	0.99666	0.99
T_{39-57}	0.9652	0.4266	0.9595	1.024653	0.96289	0.97
T_{9-55}	0.9698	0.3725	1.0451	1.037316	0.96001	1.07
Capacitor banks						
Q_{C-18}	5.0000	1.0000	2.0440	0.07825	0.09782	0.00
Q_{C-25}	5.0000	1.0000	1.9894	0.005869	0.05899	0.00
Q_{C-53}	5.0000	1.0000	2.7681	0.046872	0.6289	0.00
Ploss MW	22.5866	23.3301	23.4026	23.46119	24.544	27.81264
TVD (pu)	3.2009	2.7278	2.0268	1.0883	-	-
L-index (pu)	0.2495	0.3498	0.2762	0.1423	-	-

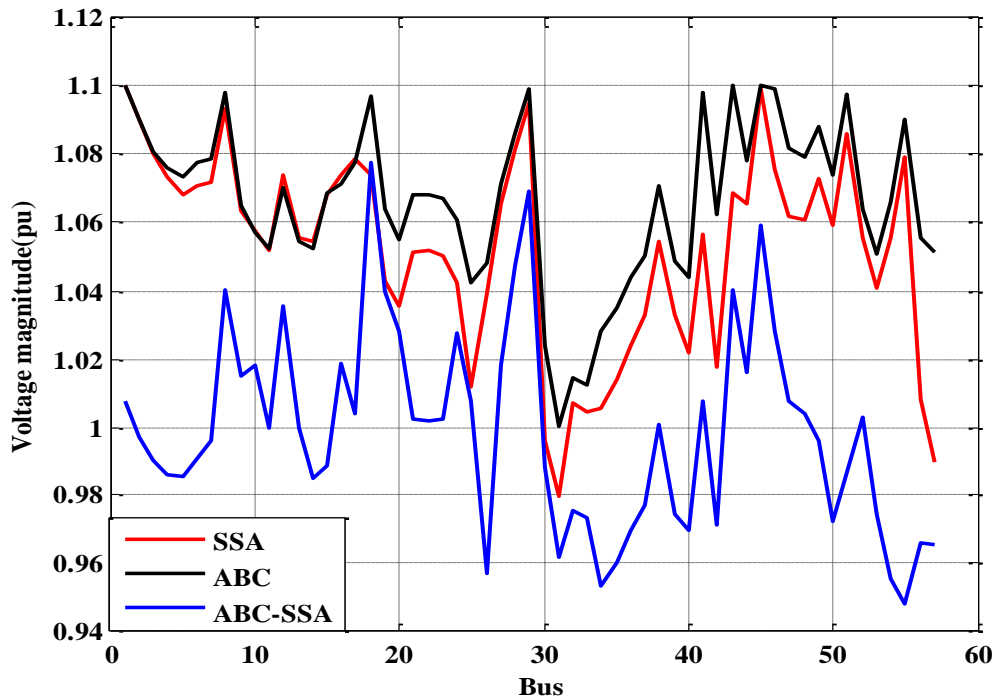


Figure 4.6 Bus voltage profile for IEEE 57 bus power system

Tableau 4.8 Reactive of production units in relation to their min / max permissible limits for test system IEEE 57 bus.

PV	$Q_{G_{MIN}}$ (MVAR)	$Q_{G_{MAX}}$ (MVAR)	QG (MVAR)
1	-200	300	34.9080
2	-17	50	49.8558
3	-10	60	46.6211
6	-8	25	6.3014
8	-140	200	79.6450
9	-3	9	7.9370
12	-150	155	63.8533

Table 4.9 Comparison of simulation results for IEEE 57 bus system with Ploss minimization.

Algorithms	Ploss MW	Algorithms	Ploss MW
L-SACP-DE [69]	27.91553	MICA_IWO [15]	24.25
PSO-w [69]	24.27052	PSO [70]	23.6266
CGA[69]	25.24411	ICA [70]	23.5471
AGA[69]	24.56484	PSO-ICA [70]	23.3535
OGSA [65]	23.43	SSA	23.0484

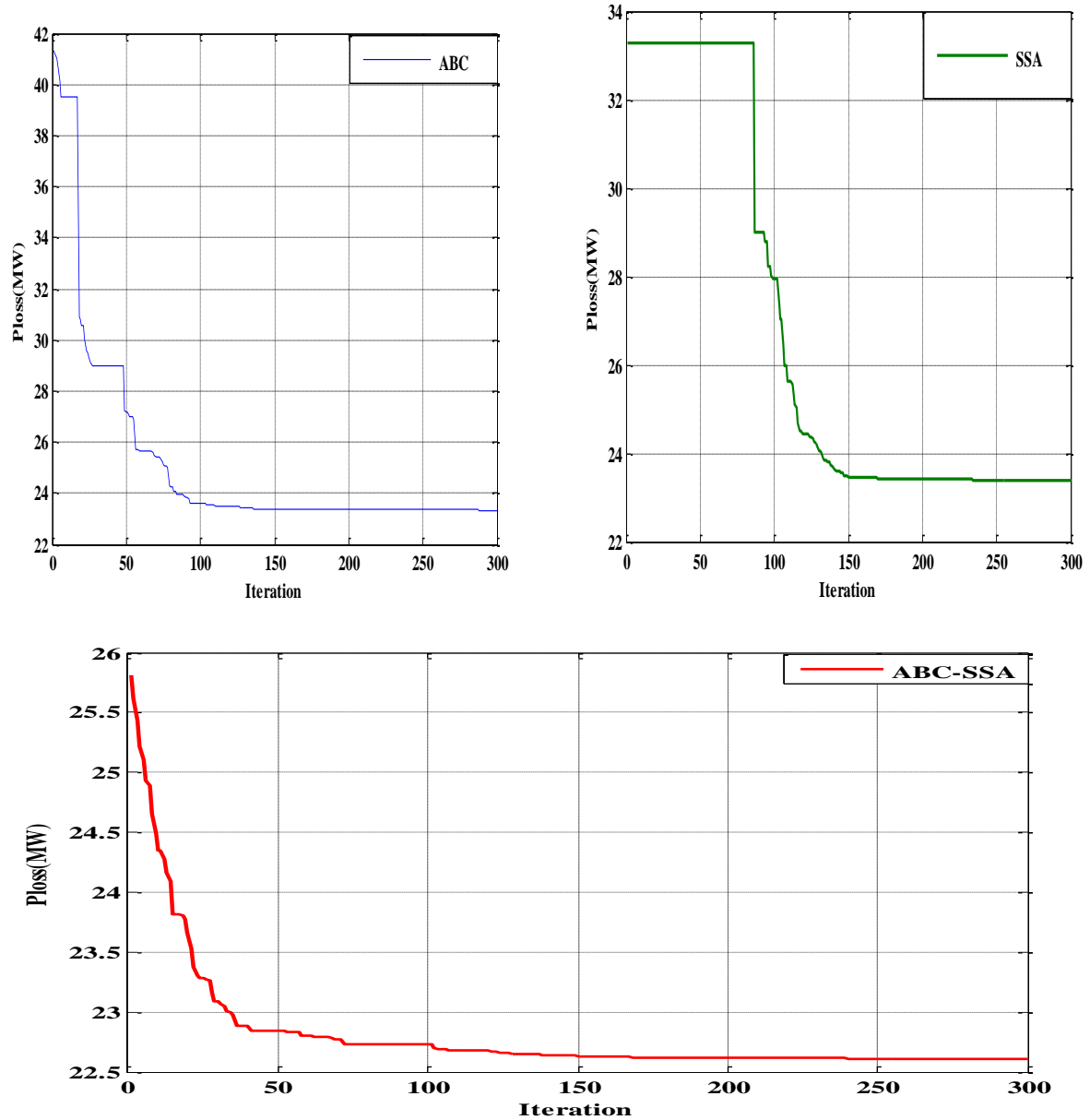


Figure 4.7 Convergence curves for Ploss minimization, IEEE-(57buses)

4.3.2 TVD Minimization for IEEE 57 bus system

In this subsection, the proposed ABC-SSA algorithm is utilized to minimize the TVD of IEEE 57 bus power system. The achieved results can be found in Table 4.10 the results

achieved by ABC-SSA and some other state of the art algorithms such as ABC, SSA, and OGSA [17], have been tabulated. The value of TVD for ABC-SSA is better than other methods. From Table 4.10, it can be observed that ABC-SSA is able to improve the TVD by 44.13 % with regard to initial TVD, compared to 1.34 % with OGSA [17]. Comparative ABC-SSA, ABC, and SSA-based convergence profiles of TVD (pu) for TVD minimization objective of this power system is presented in Figure 4.8. It may be noted from the figure that the proposed ABC-SSA based convergence profile of TVD (pu) for the TVD minimization objective of this test system is a more promising one.

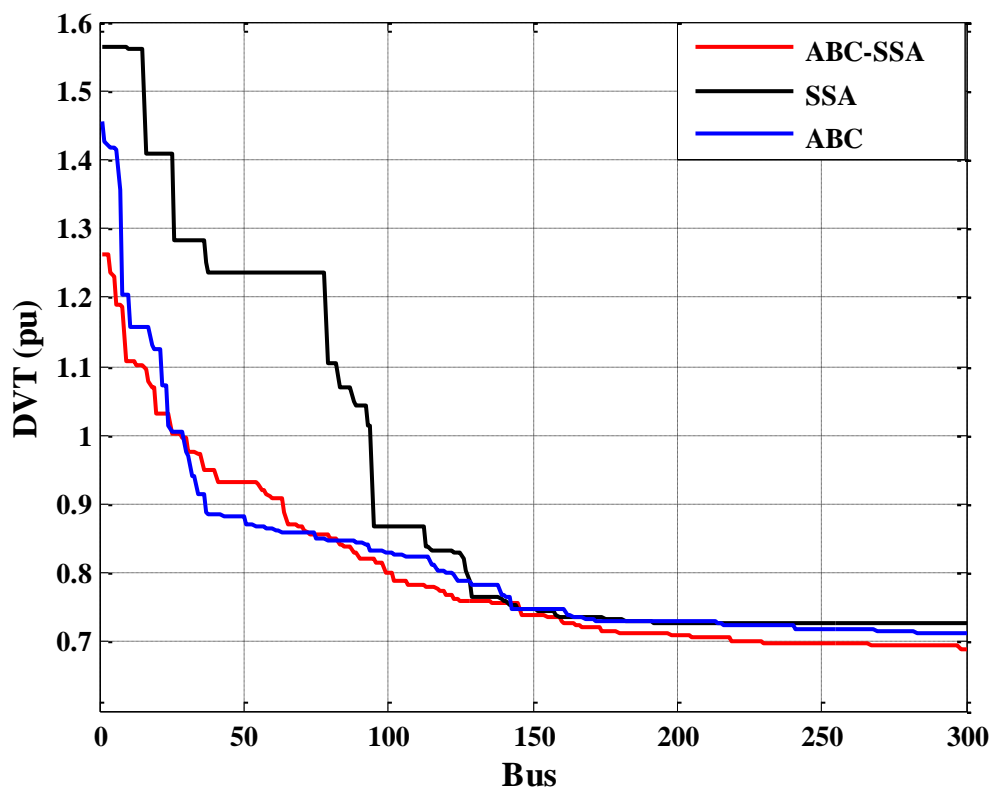


Figure 4.8 Convergence curves for TVD minimization of IEEE-(57buses) power system.

Table 4.10 Comparison of simulation results for IEEE 57 bus test power system with TVD minimization objective (a) and improvement of VSI (b).

Control variables	(A) TVD				(B) VSI		
	ABC-SSA	ABC	SSA	OGSA [65]	ABC-SSA	ABC	SSA
Ploss MW	36.7318	39.3993	31.4210	32.34	23.0640	25.8623	25.1841
TVD (pu)	0.6889	0.7125	0.7259	0.6982	7.7503	7.2551	3.4526
L-index (pu)	0.2771	0.6825	0.2783	0.5123	0.1963	0.2210	0.2360

4.3.3 VSI Improvement for IEEE 57 bus system

By running the ABC-SSA implemented for IEEE 57 bus system, VSI is minimized as an objective function. The best result of the optimal solution is assigned to the ABC-SSA by comparison with that of ABC and SSA based on Table 4.10. An improvement of the optimal VSI using ABC-SSA is equal to 11.18 % when it is compared to that of the best comparison approach ABC (0.1975). The convergence characteristic of VSI versus the number of iterations is depicted in Figure 4.9, which shows the fast and smooth convergence characteristics of ABC-SSA

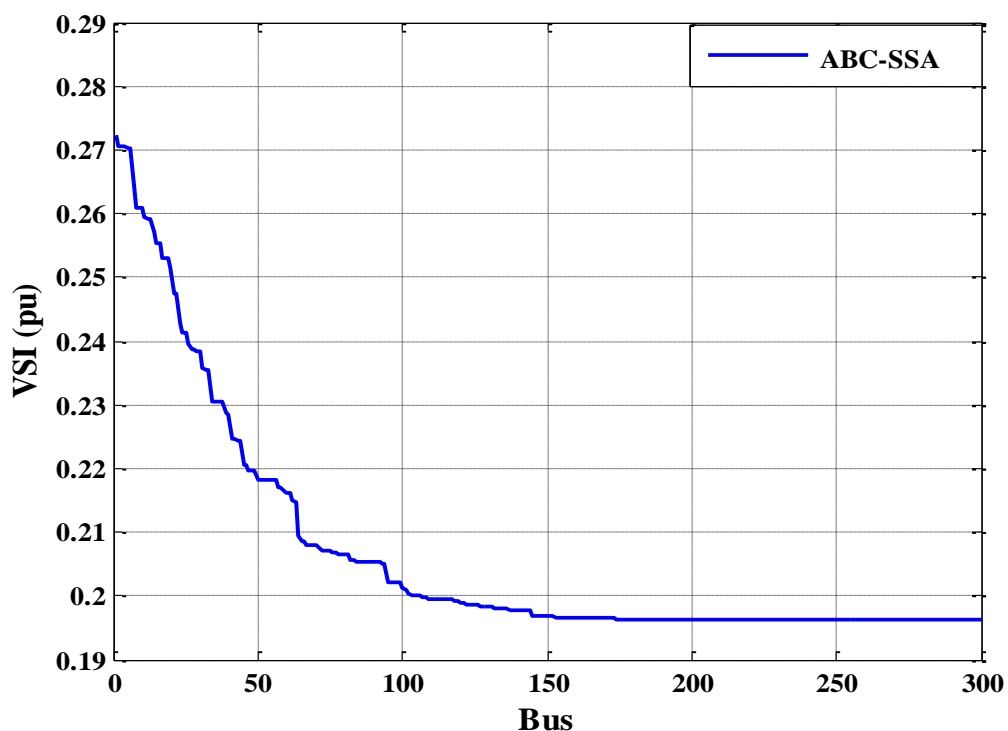


Figure 4.9 Convergence curves for VSI minimization of IEEE 57 bus power system

4.4 IEEE 118 bus system

To inspect the novel ABC-SSA algorithm and evaluate its robustness in solving the ORPD problem, a large test system IEEE 118 bus is used, where the optimization problem is dimensioned with 77 control variables including 54 for generator voltage magnitudes, nine transformer tap ratios and fourteen VAR compensation equipments. The system data base characteristics of transmission lines and buses, control variable bound limits and reactive power source limits are reported in [62]. The total load of the system related to 100 MVA-base is shown below:

$$P_{load} = 42.42 p.u. , \quad Q_{load} = 14.38 p.u.$$

The predefined total generations of active and reactive powers are:

$$\sum P_G = 43.7536 p.u. , \quad \sum Q_G = 8.8192 p.u.$$

The total active and reactive transmission losses are indicated as below:

$$P_{loss} = 1.33357 p.u. , \quad Q_{loss} = -7.5811 p.u.$$

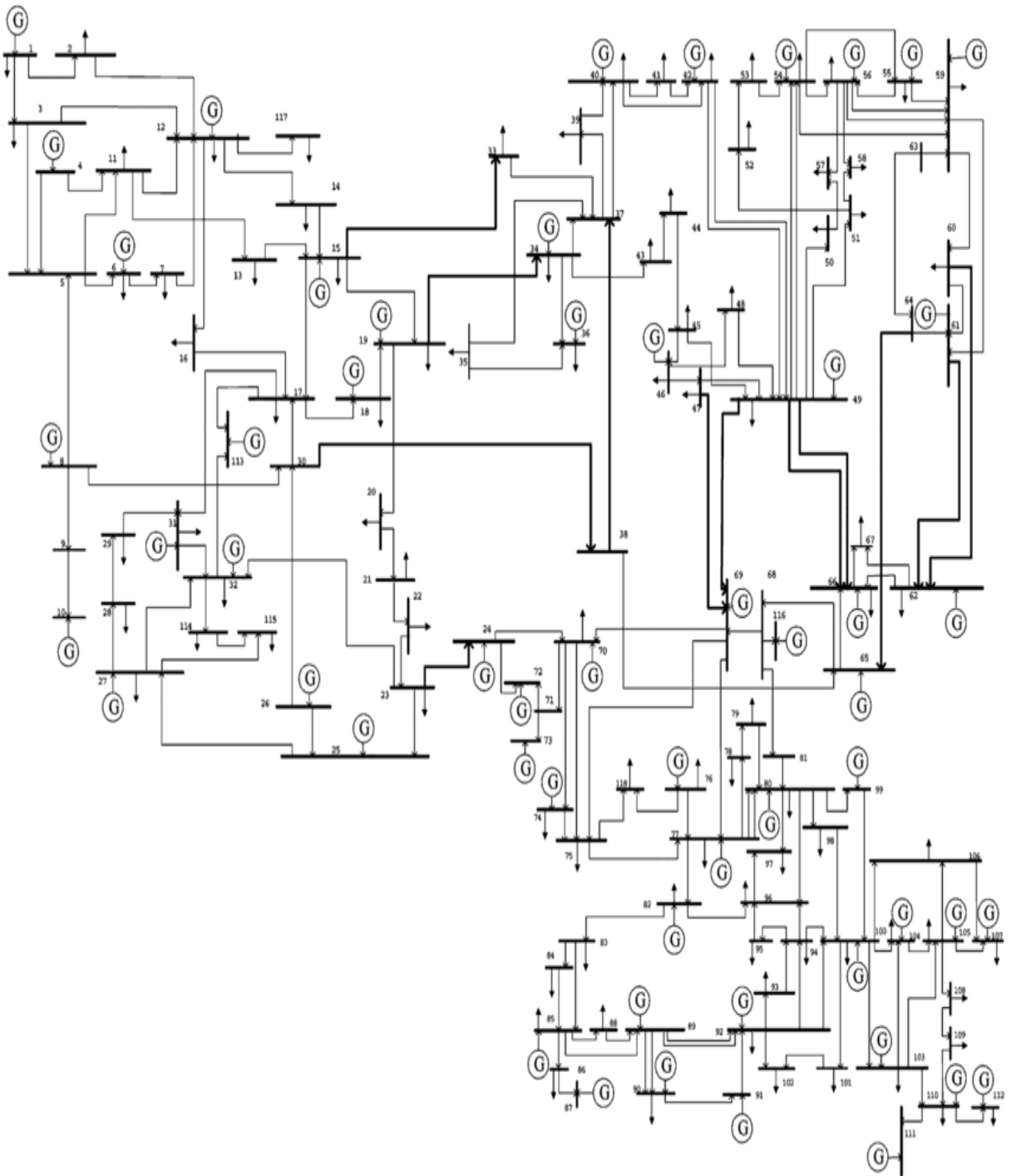


Figure 4.10 Single line diagram of IEEE 118 bus test system

4.4.1 Active power losses minimization for IEEE 118 bus system

Table 4.11 shows the optimum of decision variables and minimal P_{loss} using the ABC-SSA approach. The best results achieved are compared with those of ABC, SSA, GSA [7], OGSA [65], PSO [62], and CLPSO [62]. The comparison description shows that the ABC-SSA can reach better optimal P_{loss} than its competitive algorithms cited above. This optimal solution is estimated at 121.9015 MW, thus, we notice that there is an improvement of (4.17%) compared to the better solution achieved by OGSA. Figure 4.11 illustrates the search mechanism profile of ABC-SSA compared to the two original approaches ABC and SSA in the search space concerning the control variables limits. It is clearly remarked that the ABC-SSA approach presents a smooth convergence curve than SSA and ABC algorithm. Figure 4.12 shows the voltage magnitude at each bus for the optimal state without any limit violations. To expose the reactive power generation profile for all generation buses, Figure 4.13 shows the reactive power generated from each generating unit resulting from the simulation phase for ABC, SSA and ABC-SSA. It is clearly noticed from Figure 4.13 that there are no violations of reactive power generation limits for all generating units.

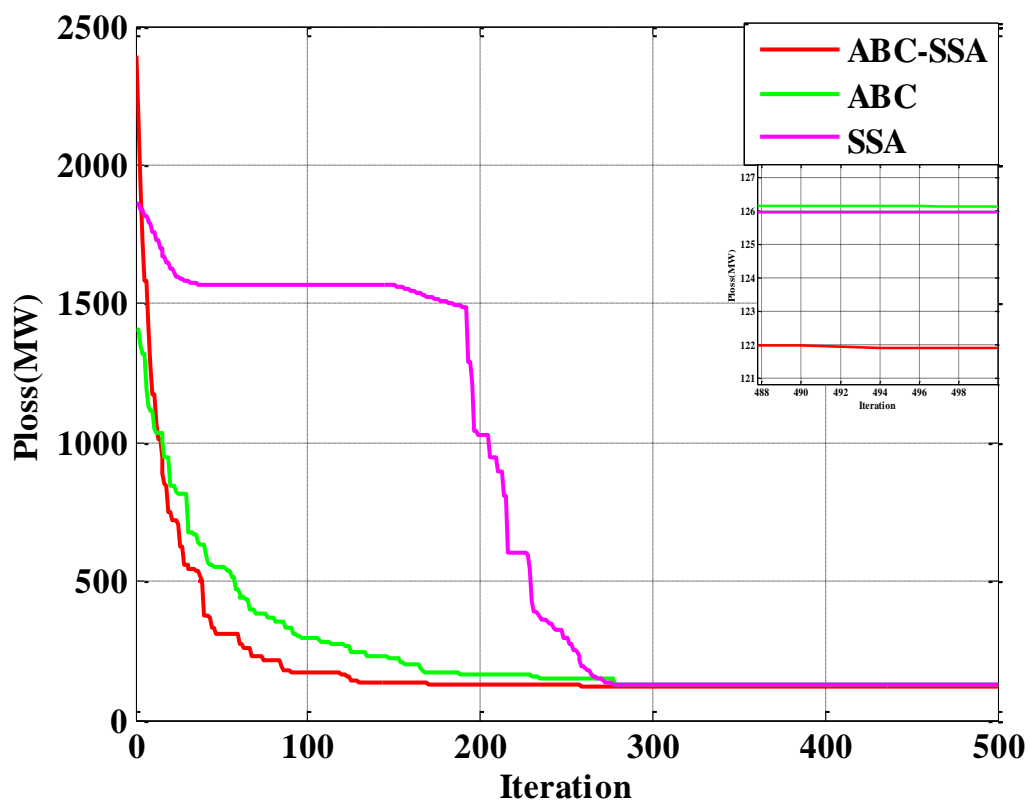


Figure 4.11 Convergence curves for P_{loss} minimization, IEEE 118 bus.

Table 4.11 Comparison of simulation results for IEEE 118 bus test system with PLoss minimization objective

variables	ABC-SSA	ABC	SSA	GSA[7]	OGSA [62]	CLPSO [62]
Generator voltage						
V _{1.p.u.}	1.0040	0.9957	1.0125	0.9600	1.0350	1.0332
V _{4.p.u.}	1.0412	1.0363	1.0482	0.9620	1.0554	1.055
V _{6.p.u.}	1.0335	1.0219	1.0363	0.9620	1.0301	0.9754
V _{8.p.u.}	1.0700	1.0114	1.0436	1.0570	1.0175	0.9669
V _{10.p.u.}	1.1000	1.0527	1.0234	1.0885	1.0250	0.9811
V _{12.p.u.}	1.0255	1.0222	1.0307	0.9630	1.0410	1.0092
V _{15.p.u.}	1.0230	1.0153	1.0229	1.0127	0.9973	0.9787
V _{18.p.u.}	1.0270	1.0159	1.0208	1.0069	1.0047	1.0799
V _{19.p.u.}	1.0205	1.0147	1.0173	1.0003	1.9899	1.0805
V _{24.p.u.}	1.0372	1.0169	1.0073	1.0105	1.0287	1.0286
V _{25.p.u.}	1.0532	1.0220	1.0330	1.0102	1.0600	1.0307
V _{26.p.u.}	1.1000	1.0050	1.0437	1.0401	1.0855	0.9877
V _{27.p.u.}	1.0313	1.0249	1.0268	0.9809	1.0081	1.0157
V _{31.p.u.}	1.0254	1.0617	1.0395	0.9500	0.9948	0.9615
V _{32.p.u.}	1.0307	1.0357	1.0245	0.9552	0.9993	0.9851
V _{34.p.u.}	1.0281	1.0233	1.0256	0.9910	0.9958	1.0157
V _{36.p.u.}	1.0215	1.0208	1.0211	1.0091	0.9835	1.0849
V _{40.p.u.}	1.0120	0.9845	1.0217	0.9505	0.9981	0.983
V _{42.p.u.}	1.0283	0.9942	1.0331	0.9500	1.0068	1.0516
V _{46.p.u.}	1.0332	1.0388	1.0443	0.9814	1.0355	0.9754
V _{49.p.u.}	1.0481	1.0349	1.0591	1.0444	1.0333	0.9838
V _{54.p.u.}	1.0272	1.0403	1.0432	1.0379	0.9911	0.9637
V _{55.p.u.}	1.0234	1.0311	1.0377	0.9907	0.9914	0.9716
V _{56.p.u.}	1.0245	1.0333	1.0389	1.0333	0.9920	1.025
V _{59.p.u.}	1.0359	1.0120	1.0298	1.0099	0.9909	1.0003
V _{61.p.u.}	1.0163	1.0351	1.0299	1.0925	1.0747	1.0771
V _{62.p.u.}	1.0107	1.0318	1.0269	1.0393	1.0753	1.048
V _{65.p.u.}	1.0358	1.0635	1.0413	0.9998	0.9814	0.9684
V _{66.p.u.}	1.0376	1.0300	1.0442	1.0355	1.0487	0.9648
V _{69.p.u.}	1.0733	1.0136	1.0585	1.1000	1.0490	0.9674
V _{70.p.u.}	1.0323	1.0189	1.0231	1.0992	1.0395	0.9765
V _{72.p.u.}	1.0305	1.0606	1.0172	1.0014	0.9900	1.0243
V _{73.p.u.}	1.0327	1.0523	1.0413	1.0111	1.0547	0.9651
V _{74.p.u.}	1.0065	0.9838	0.9942	1.0476	1.0167	1.0733
V _{76.p.u.}	0.9952	0.9712	0.9835	1.0211	0.9972	1.0302
V _{77.p.u.}	1.0358	1.0144	1.0284	1.0187	1.0071	1.0275
V _{80.p.u.}	1.0475	1.0380	1.0459	1.0462	1.0066	0.9857
V _{85.p.u.}	1.0264	1.0231	1.0219	1.0491	0.9893	0.9836
V _{87.p.u.}	1.0599	0.9906	1.0261	1.0426	0.9693	1.0882
V _{89.p.u.}	1.0282	1.0559	1.0349	1.0955	1.0527	0.9895
V _{90.p.u.}	0.9938	1.0135	1.0015	1.0417	1.0290	0.9905
V _{91.p.u.}	0.9789	1.0456	1.0186	1.0032	1.0297	1.0288
V _{92.p.u.}	1.0117	1.0369	1.0250	1.0927	1.0353	0.976
V _{99.p.u.}	1.0319	1.0042	1.0261	1.0433	1.0395	1.088

V _{100.p.u.}	1.0370	1.0125	1.0437	1.0786	1.0275	0.9617
V _{103.p.u.}	1.0282	1.0037	1.0333	1.0266	1.0158	0.9611
V _{104.p.u.}	1.0204	0.9986	1.0189	0.9808	1.0165	1.0125
V _{105.p.u.}	1.0214	1.0001	1.0152	1.0163	1.0197	1.0684
V _{107.p.u.}	1.0484	1.0184	1.0144	0.9987	1.0408	0.9769
V _{110.p.u.}	1.0224	1.0063	1.0102	1.0218	1.0288	1.0414
V _{111.p.u.}	1.0468	0.9952	1.0161	0.9852	1.0194	0.979
V _{112.p.u.}	1.0067	1.0281	1.0051	0.9500	1.0132	0.9764
V _{113.p.u.}	1.0377	1.0211	1.0471	0.9764	1.0386	0.9721
V _{116.p.u.}	1.0254	0.9837	1.0160	1.0372	0.9724	1.033
Transformer tap ratio						
T ₈₋₅	0.9774	0.9445	0.9321	1.0659	0.9568	1.0045
T ₂₆₋₂₅	1.1000	1.0045	1.0369	0.9534	1.0409	1.0609
T _{30-17.}	0.9951	1.0847	1.0096	0.9328	0.9963	1.0008
T ₃₈₋₃₇	0.9980	1.0657	1.0008	1.0884	0.9775	1.0093
T ₆₃₋₅₉	0.9801	1.0138	0.9835	1.0579	0.9560	0.9922
T ₆₄₋₆₁	1.0280	0.9836	0.9759	0.9493	0.9956	1.0074
T ₆₅₋₆₆	0.9957	1.0313	1.0266	0.9975	0.9882	1.0611
T ₆₈₋₆₉	0.9089	1.0149	1.0095	0.9887	0.9251	0.9307
T ₈₁₋₈₂	0.9694	1.0007	1.0092	0.9801	1.0661	0.9578
Capacitor banks						
Q _{C-5,P.U.}	-40.0000	-	14.6915	0.00	_ _{0.3319}	0.0
		18.8083				
Q _{C-34,P.U.}	5.2718	6.5405	3.6618	7.46	0.0480	11.713
Q _{C-37,P.U.}	-0.0000	-	15.5673	0.00	_ _{0.2490}	0
		14.4993				
Q _{C-44,P.U.}	10.0000	9.1786	6.6602	6.07	0.0328	9.8932
Q _{C-45,P.U.}	10.0000	7.2490	4.7207	3.33	0.0383	9.4169
Q _{C-46,P.U.}	5.3897	5.0803	4.6535	6.51	0.0545	2.6719
Q _{C-48P.U.}	8.9735	6.6591	5.4113	4.47	0.0181	2.8546
Q _{C-74,P.U.}	11.3409	6.5753	2.3982	9.72	0.0509	0.5471
Q _{C-79,P.U.}	20.0000	6.5801	5.1644	14.25	0.1104	14.853
Q _{C-82,P.U.}	20.0000	10.9532	4.8589	17.49	0.0965	19.427
Q _{C-83,P.U.}	10.0000	5.4023	5.5445	4.28	0.0263	6.9824
Q _{C-105,P.U.}	5.8203	12.6191	11.7043	12.04	0.0442	9.0291
Q _{C-107,P.U.}	6.0000	2.4293	3.3340	2.26	0.0085	4.9926
Q _{C-110,P.U.}	0.0000	4.2249	2.3279	2.94	0.0144	2.2086
P_{Loss} MW	121.9015	126.111	124.528	127.7603	126.99	130.96
			6			
TVD(pu)	1.5292	1.7756	1.5435	1.0883	1.1829	-
L-index (pu)	0.0589	0.0606	0.0601	0.1423	0.1400	-

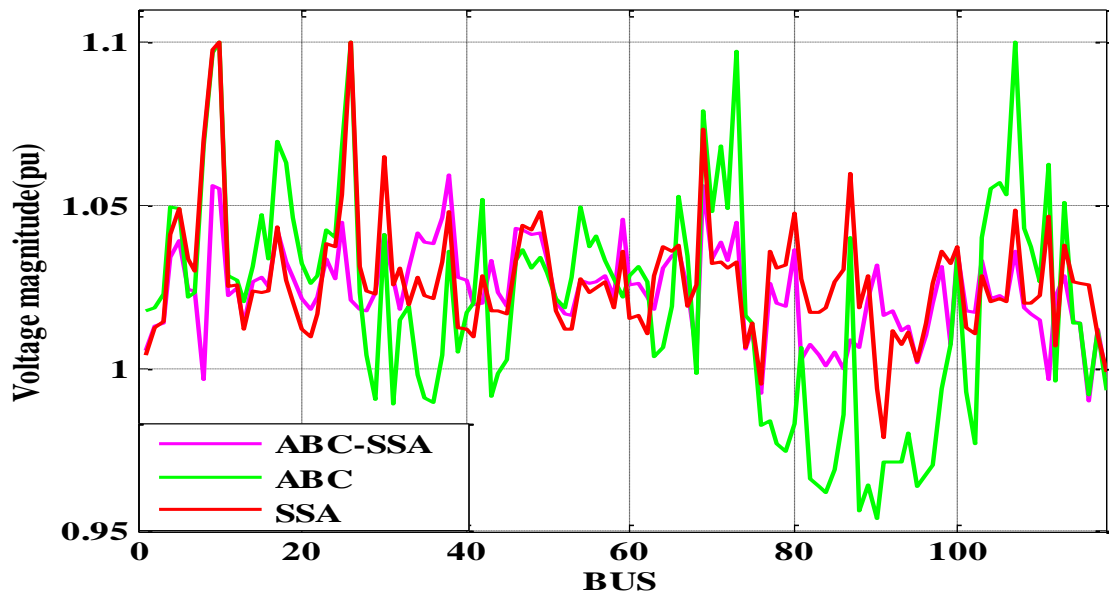


Figure 4.12 Bus voltage profile for IEEE 118 bus power system for three methods (ABC-SSA).

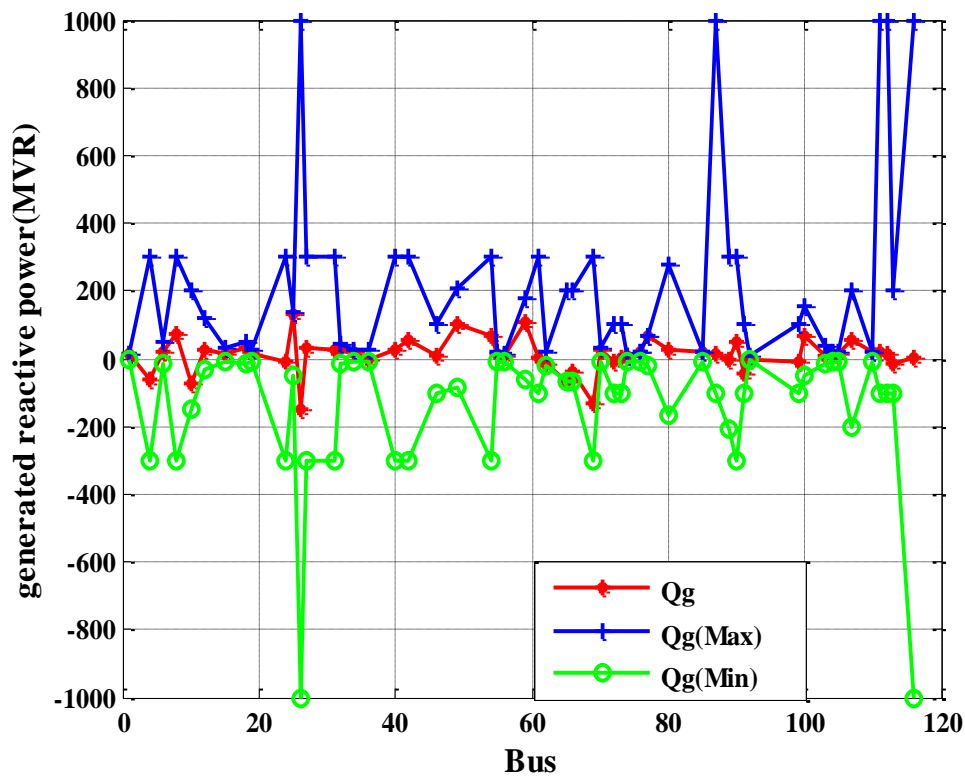


Figure 4.13 Reactive of production units in relation to their min / max permissible limits for test system IEEE 118 bus.

4.4.2 TVD minimization for IEEE 118 bus system

Table 4.12 shows the ORPD solution using the ABC-SSA method in a large test system

IEEE 118 bus where the objective functions is to minimize the total voltage deviation. The optimal obtained TVD of 0.1718 p.u is compared with the optimal TVD of various methods ABC, SSA, OGSA [65], PSO[62], and CLPSO[62]. Based on this comparison, it is noticed that the ABC-SSA gives a better reduction rate of TVD than that of the best comparison approach OGSA (0.3666 pu). Figure 4.14 illustrates the variation of the total voltage deviation. The well converged property of ABC-SSA is graphed from the figure by means of its ability to reach an optimal solution.

Table 4.12 Comparison of simulation results for IEEE 118 bus test power system with TVD minimization objective.

Algorithms	TVD					
	ABC-SSA	ABC	SSA	OGSA[65]	PSO[62]	CLPSO[62]
P_{loss} MW	183.8585	142.0647	133.6188	157.72	132.16	132.06
TVD (pu)	0.1718	0.8443	0.9678	0.3666	2.2359	1.6177
L-index(pu)	0.0610	0.0611	0.0648	0.1562	0.1854	0.1210

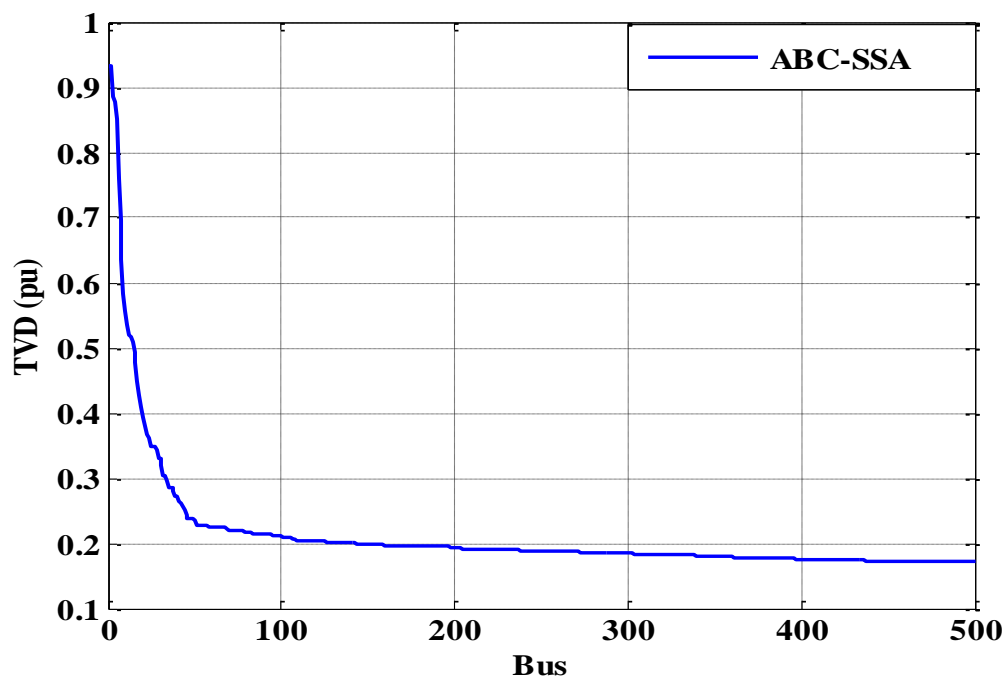


Figure 4.14 Convergence curves for TVD minimization of IEEE 118 bus power system

4.4.3 VSI Improvement for IEEE 118 bus System

In this subsection, the suggested algorithm ABC-SSA is used to minimize the VSI for a large test system of IEEE 118 bus. A comparative study of simulation results using ABC-SSA for this test system with those of ABC, SSA, OGSA, PSO, and CLPSO is executed and presented in Table 4.13. The optimal value of VSI using ABC-SSA is better than that of the

OGSA method signaling a remarkable reduction (important improvement) equal to 16.05%, this best result was supported by a smooth convergence curve in Figure 4.15.

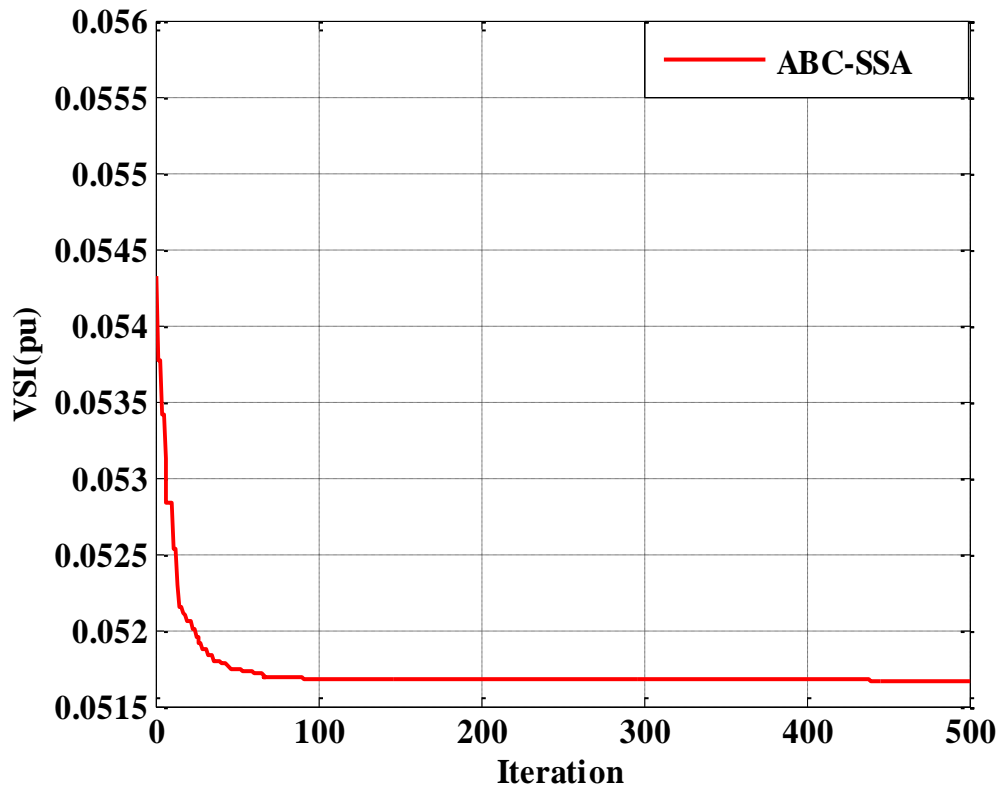


Figure 4.15 Convergence curve for VSI minimization, IEEE 118 bus.

Table 4.13 Comparison of simulation results for IEEE 118 bus test power system with the improvement of VSI.

Algorithms	VSI					
	ABC-SSA	ABC	SSA	OGSA[65]	PSO[62]	CLPSO[62]
P_{loss} MW	419.4706	163.3758	34.4736	295.112	133.08	132.08
TVD (pu)	3.0706	2.3898	1.4727	1.4804	2.3262	2.8863
L-index(pu)	0.0517	0.0534	0.0593	0.0600	0.1388	0.0965

4.5 IEEE 300 bus System

To test and prove the applicability of the ABC-SSA algorithm in more practical, complicated and large test systems, IEEE 300 bus is proposed which consists of large-scale dimensions of control variables containing 190 control variables where their types are demonstrated in Table 1. The total load data are 235.258pu and 77.8797 pu for active and reactive power, respectively[71, 72]. The control variables restrictions are indicated in [67].

For the first case of this test system application, the total active losses (P_{loss}) are

minimized using the ABC-SSA algorithm. Table 4.14 reports the best results found by the ABC-SSA method and other optimization approaches such as ABC, SSA, SGA, and ALO methods. The optimal solution of the objective function (P_{loss}) was obtained with an improvement equal to 3.05 % when it is compared to that of the SGA method. The search mechanism for the optimal solution was clarified by a convergence curve in Figure 4.17 related to the ABC-SSA, ABC, SSA. It is clearly remarked that the convergence profile using ABC-SSA is the promising one. Figure 4.16 exhibits the voltage profile when the optimal solution is achieved for the present test system, noting that the voltage magnitude at all buses is in its permissible range without any violations beyond the permissible limits. For the second case of this test system application, the total voltage deviation is selected as an objective function to minimize noting that there is an improvement of 39.44% compared to the ABC method, Table 4.15 explains this remarkable improvement.

Table 4.14 Comparison of simulation results for IEEE 300 bus with p_{loss} minimization

Results	ABC-SSA	ABC	SSA	SGA[67]	ALO[73]
P_{loss} MW	343.4272	364.347	353.886	357.10	384.922
TVD (pu)	20.3408	1.5292	18.2697	15.744	-
L-index (pu)	0.9003	0.8879	0.8340	-	0.3663

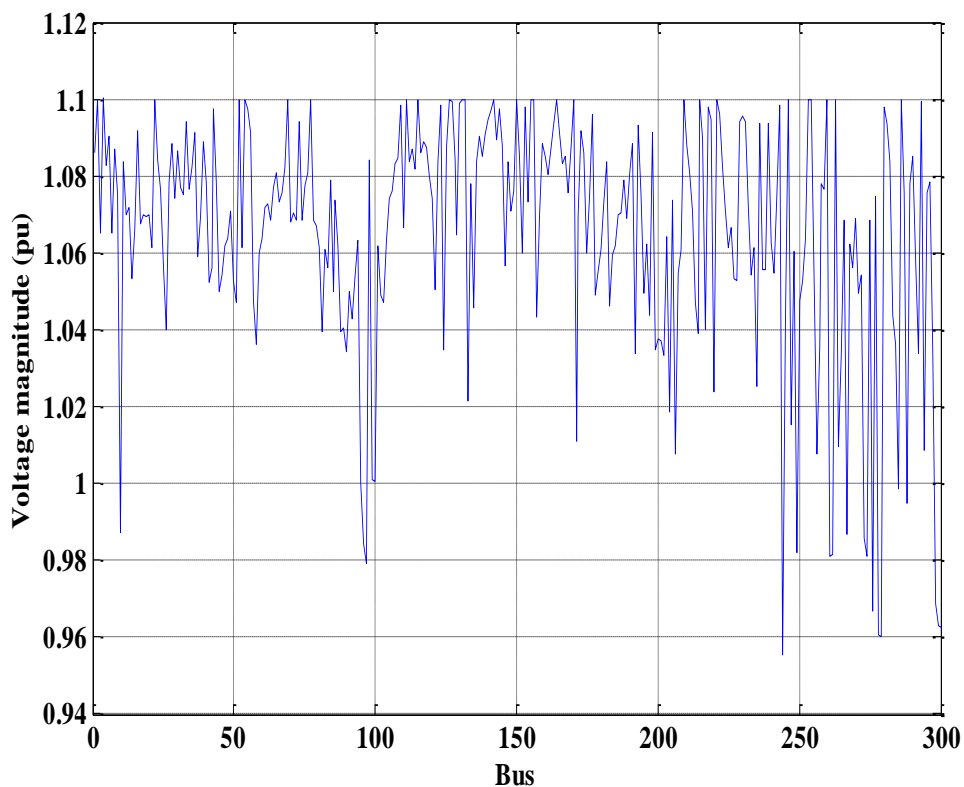


Figure 4.16 Bus voltage profile for IEEE-(300buses) power system

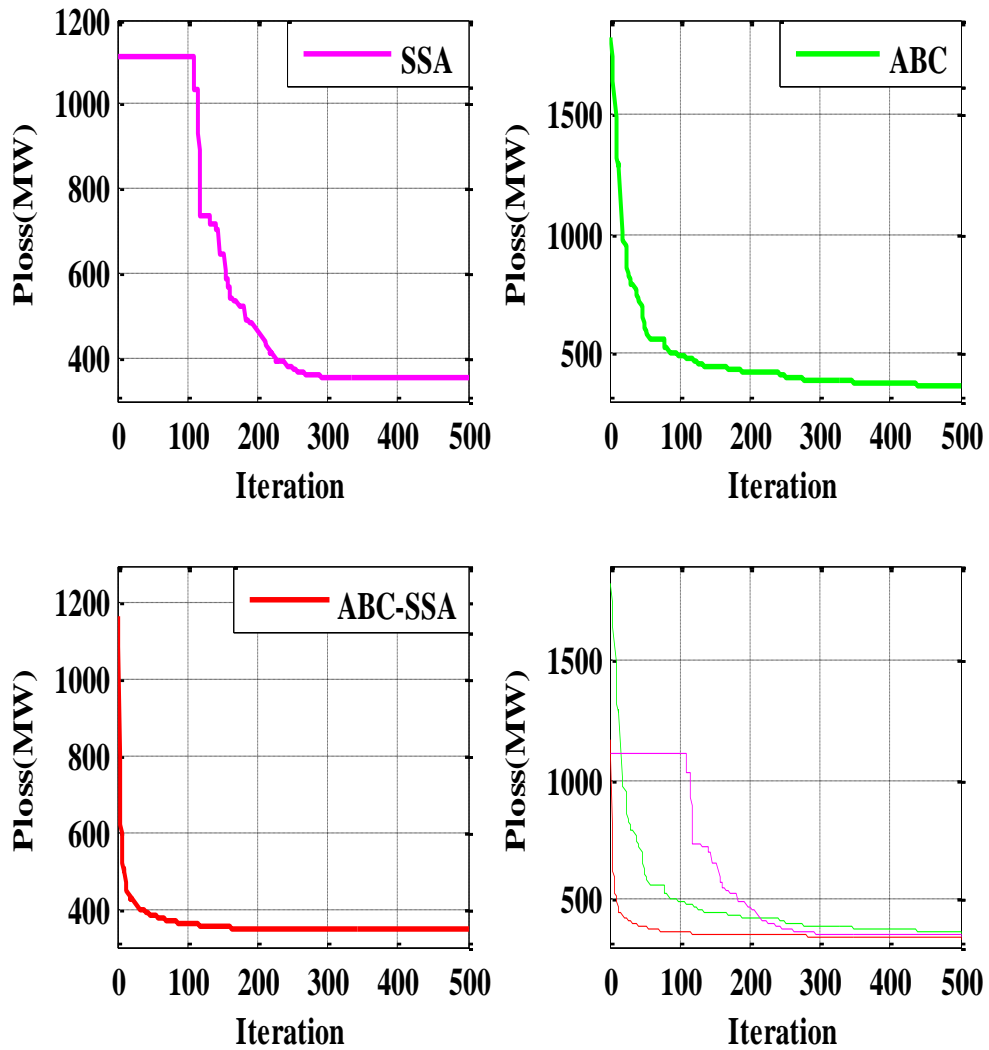


Figure 4.17 Convergence curves for P_{loss} minimization IEEE-(300buses)

Table 4.15 Comparison of simulation results for IEEE 300 bus system with TVD minimization.

	TVD		
Algorithms	ABC-SSA	ABC	SSA
P_{loss} MW	411.0579	437.2808	430.7991
TVD (pu)	4.1932	5.8468	7.5593
L-index(pu)	0.9577	0.9765	18.6393

CONCLUSION

a new hybrid optimization approach combining Artificial Bee Colony (ABC) and Salp Swarm (SSA) algorithms named (ABC-SSA) was developed and successfully employed for solving different problems of optimal reactive power dispatch (ORPD) with several types of complexities. The presented approach was examined and evaluated regarding different objective functions. The effectiveness and robustness of the novel ABC-SSA are investigated using four standard test systems IEEE. A comparison report of ABC-SSA with the original ABC and SSA algorithms is made based on convergence curves. A smooth convergence curve is devoted to the ABC-SSA approach when it is compared to that of basic ABC and SSA algorithms, which proves the capacity of the proposed approach to escape from the stagnation in local minima and to converge in a faster manner towards the global optimal solution. Another comparison survey of the ABC-SSA with different optimization techniques in the same literature is provided. The results of the simulation report prove that the ABC-SSA offers better performances than other comparison methods, indicating the robustness and the superiority of the ABC-SSA, which shows a remarkable exploitation capability by using the best solution (food source of SSA) at each iteration to achieve promising solutions. Thus, the ABC-SSA algorithm can be recommended as a promising optimization algorithm in solving other more complex optimization problems for engineering areas, particularly in electrical power systems.

The main contributions in developing the presented hybrid ABC-SSA technique are as follows:

- By using the ABC-SSA approach, a distinct solution quality improvement of ORPD problem when this solution is compared to that of the recently developed meta-heuristic techniques in literature for the same test systems, where the ORPD is considered as a sub-problem of Optimal Power Flow (OPF) issue in electrical engineering.
- A smooth convergence curve is devoted to the ABC-SSA approach when it is compared to that of basic ABC and SSA algorithms, which proves the capacity of the proposed approach to escape from the stagnation in local minima and to converge in a faster manner towards the global optimal solution.

- The ability of the proposed hybrid ABC-SSA approach to balance between the two searches mechanisms of meta-heuristics (exploitation and exploration) in order to reach better solution of ORPD problem.

We suggest for further research on this field some of the areas of research such as:

- ✓ This research considered only one function objective, further research needs to be done on adding Multi-objective optimization for solving an ORPD problem.
- ✓ Application of the proposed (ABC-SSA) on real-world ORPD problems should also be investigated.

References

- [1] A. Chebbo and M. Irving, "Combined active and reactive despatch. i. problem formulation and solution algorithm," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 142, pp. 393-400, 1995.
- [2] M. Bjelogrić, M. S. Calović, P. Ristanović, and B. S. Babić, "Application of Newton's optimal power flow in voltage/reactive power control," *IEEE Transactions on Power Systems*, vol. 5, pp. 1447-1454, 1990.
- [3] P. A. Jeyanthi and D. Devaraj, "Optimal Reactive Power Dispatch for Voltage Stability Enhancement Using Real Coded Genetic Algorithm," *International Journal of Computer and Electrical Engineering*, vol. 2, p. 734, 2010.
- [4] M. Abido, "Optimal power flow using particle swarm optimization," *International Journal of Electrical Power & Energy Systems*, vol. 24, pp. 563-571, 2002.
- [5] K. Ayan and U. Kılıç, "Artificial bee colony algorithm solution for optimal reactive power flow," *Applied soft computing*, vol. 12, pp. 1477-1482, 2012.
- [6] G. Kannan, D. P. Subramanian, and R. U. Shankar, "Reactive power optimization using firefly algorithm," in *Power Electronics and Renewable Energy Systems*, ed: Springer, 2015, pp. 83-90.
- [7] S. Duman, Y. Sonmez, U. Guvenc, and N. Yorukeren, "Optimal reactive power dispatch using a gravitational search algorithm," *IET generation, transmission & distribution*, vol. 6, pp. 563-576, 2012.
- [8] K. ben oualid Medani, S. Sayah, and A. Bekrar, "Whale optimization algorithm based optimal reactive power dispatch: A case study of the Algerian power system," *Electric Power Systems Research*, vol. 163, pp. 696-705, 2018.
- [9] T. T. Nguyen and D. N. Vo, "Improved social spider optimization algorithm for optimal reactive power dispatch problem with different objectives," *Neural Computing and Applications*, pp. 1-32, 2019.
- [10] C. Zhang, J. Zheng, and Y. Zhou, "Two modified artificial bee colony algorithms inspired by grenade explosion method," *Neurocomputing*, vol. 151, pp. 1198-1207, 2015.
- [11] A. Salhi, D. Naimi, and T. Bouktir, "Optimal power flow resolution using artificial bee colony algorithm based grenade explosion method," *Journal of Electrical Systems*, vol. 12, pp. 734-756, 2016.
- [12] M. Khamees, A. Albakry, and K. Shaker, "Multi-objective feature selection: hybrid of salp swarm and simulated annealing approach," in *International Conference on New Trends in Information and Communications Technology Applications*, 2018, pp. 129-142.
- [13] A. Rajan and T. Malakar, "Optimal reactive power dispatch using hybrid Nelder–Mead simplex based firefly algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 66, pp. 9-24, 2015.
- [14] J. Radosavljević and M. Jevtić, "Solution of optimal reactive power dispatch by a hybrid GSA-SQP algorithm," *Elektronika ir Elektrotehnika*, vol. 22, pp. 3-6, 2016.
- [15] A. Ghasemi, K. Valipour, and A. Tohidi, "Multi objective optimal reactive power dispatch using a new multi objective strategy," *International Journal of Electrical Power & Energy Systems*, vol. 57, pp. 318-334, 2014.
- [16] R. P. Singh, V. Mukherjee, and S. Ghoshal, "Optimal reactive power dispatch by particle swarm optimization with an aging leader and challengers," *Applied soft computing*, vol. 29, pp. 298-309, 2015.

- [17] E. E. Agbugba, "Hybridization of particle swarm optimization with bat algorithm for optimal reactive power dispatch," 2017.
- [18] B. Hadji, "Contribution à l'Amélioration de l'Efficacité des Réseaux Electriques par l'Intégration et le Contrôle Flexible de l'Energie Eolienne et des Systèmes FACTS," Université Mohamed Khider-Biskra, 2017.
- [19] A. Alibi, "Contrôle des Réseaux Electriques par les Systèmes FACTS:(Flexible AC Transmission Systems)," Université de Batna 2, 2009.
- [20] A. Thabet, "Estimation de l'état pour la surveillance des systèmes de grandes dimensions. Application aux réseaux électriques," Ecole Nationale d'Ingénieurs de Gabès, 2012.
- [21] K. Chakraborty and A. Chakrabarti, *Soft computing techniques in voltage security analysis*: Springer, 2015.
- [22] A. Chakrabarti and S. Halder, *Power System Analysis: Operation And Control 3Rd Ed*: PHI Learning Pvt. Ltd., 2010.
- [23] J. Zhu, *Optimization of power system operation*: John Wiley & Sons, 2015.
- [24] L. Slimani, "Contribution à l'application de l'optimisation par des méthodes métaheuristiques à l'écoulement de puissance optimal dans un environnement de l'électricité dérégulé," Université de Batna 2, 2009.
- [25] M. YAHIAOUI, "Contrôle optimal des puissances réactives et des tensions dans un réseau d'énergie électrique par dispositifs FACTS," Thèse de Doctorat en Électrotechnique Option: Réseaux Electriques, 2014.
- [26] S. Mirjalili, "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm," *Knowledge-based systems*, vol. 89, pp. 228-249, 2015.
- [27] H. Hachimi, "Hybridations d'algorithmes métaheuristiques en optimisation globale et leurs applications," INSA de Rouen; École Mohammadia d'ingénieurs (Rabat, Maroc), 2013.
- [28] P. L. Reddy and G. Yesuratnam, "A modified bacterial foraging algorithm based optimal reactive power dispatch," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 13, p. 361367, 2019.
- [29] M. Basu, "Quasi-oppositional differential evolution for optimal reactive power dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 29-40, 2016.
- [30] G. Chen, L. Liu, Z. Zhang, and S. Huang, "Optimal reactive power dispatch by improved GSA-based algorithm with the novel strategies to handle constraints," *Applied soft computing*, vol. 50, pp. 58-70, 2017.
- [31] P. Singh, P. Purey, L. Titare, and S. Choube, "Optimal reactive power dispatch for enhancement of static voltage stability using jaya algorithm," in *Information, Communication, Instrumentation and Control (ICICIC), 2017 International Conference on*, 2017, pp. 1-5.
- [32] K. Mamandur and R. Chenoweth, "Optimal control of reactive power flow for improvements in voltage profiles and for real power loss minimization," *IEEE Transactions on Power Apparatus and Systems*, pp. 3185-3194, 1981.
- [33] R. R. Shoults and D. Sun, "Optimal power flow based upon PQ decomposition," *IEEE Transactions on Power Apparatus and Systems*, pp. 397-405, 1982.
- [34] R. Burchett, H. Happ, and D. Vierath, "Quadratically convergent optimal power flow," *IEEE Transactions on Power Apparatus and Systems*, pp. 3267-3275, 1984.
- [35] K. Lee, Y. Park, and J. Ortiz, "A united approach to optimal real and reactive power dispatch," *IEEE Transactions on Power Apparatus and Systems*, pp. 1147-1153, 1985.

- [36] R. Mota-Palomino and V. Quintana, "Sparse reactive power scheduling by a penalty function-linear programming technique," *IEEE Transactions on Power Systems*, vol. 1, pp. 31-39, 1986.
- [37] J. Nanda, D. P. Kothari, and S. C. Srivastava, "New optimal power-dispatch algorithm using Fletcher's quadratic programming method," in *IEE Proceedings C-Generation, Transmission and Distribution*, 1989, pp. 153-161.
- [38] W.-H. Liu, A. D. Papalexopoulos, and W. F. Tinney, "Discrete shunt controls in a Newton optimal power flow," *IEEE Transactions on Power Systems*, vol. 7, pp. 1509-1518, 1992.
- [39] S. Granville, "Optimal reactive dispatch through interior point methods," *IEEE Transactions on Power Systems*, vol. 9, pp. 136-146, 1994.
- [40] A. J. Santos and G. Da Costa, "Optimal-power-flow solution by Newton's method applied to an augmented Lagrangian function," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 142, pp. 33-36, 1995.
- [41] J. A. Momoh and J. Zhu, "Improved interior point method for OPF problems," *IEEE Transactions on Power Systems*, vol. 14, pp. 1114-1120, 1999.
- [42] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software*, vol. 69, pp. 46-61, 2014.
- [43] A. Abou El Ela, M. Abido, and S. Spea, "Differential evolution algorithm for optimal reactive power dispatch," *Electric Power Systems Research*, vol. 81, pp. 458-464, 2011.
- [44] S. Durairaj, D. Devaraj, and P. Kannan, "Genetic algorithm applications to optimal reactive power dispatch with voltage stability enhancement," *Journal-Institution of Engineers India Part El Electrical Engineering Division*, vol. 87, p. 42, 2006.
- [45] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A new heuristic optimization algorithm: harmony search," *simulation*, vol. 76, pp. 60-68, 2001.
- [46] A. Khazali and M. Kalantar, "Optimal reactive power dispatch based on harmony search algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 33, pp. 684-692, 2011.
- [47] P. Roy, B. Mandal, and K. Bhattacharya, "Gravitational search algorithm based optimal reactive power dispatch for voltage stability enhancement," *Electric Power Components and Systems*, vol. 40, pp. 956-976, 2012.
- [48] A. Abbasy and S. H. Hosseini, "Ant colony optimization-based approach to optimal reactive power dispatch: A comparison of various ant systems," in *2007 IEEE Power Engineering Society Conference and Exposition in Africa-PowerAfrica*, 2007, pp. 1-8.
- [49] M. H. Sulaiman, Z. Mustaffa, M. R. Mohamed, and O. Aliman, "Using the gray wolf optimizer for solving optimal reactive power dispatch problem," *Applied Soft Computing*, vol. 32, pp. 286-292, 2015.
- [50] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," *IEEE transactions on evolutionary computation*, vol. 1, pp. 67-82, 1997.
- [51] G. Cohen, "Convexité et optimisation," 2000.
- [52] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Technical report-tr06, Erciyes university, engineering faculty, computer ...2005.
- [53] M. Basu, "Artificial bee colony optimization for multi-area economic dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 49, pp. 181-187, 2013.
- [54] M. R. Adaryani and A. Karami, "Artificial bee colony algorithm for solving multi-objective optimal power flow problem," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 219-230, 2013.

- [55] S. Mouassa and T. Bouktir, "Artificial bee colony algorithm for discrete optimal reactive power dispatch," in *2015 International Conference on Industrial Engineering and Systems Management (IESM)*, 2015, pp. 654-662.
- [56] G. Zhu and S. Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," *Applied mathematics and computation*, vol. 217, pp. 3166-3173, 2010.
- [57] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems," *Advances in Engineering Software*, vol. 114, pp. 163-191, 2017.
- [58] A. A. El-Fergany and H. M. Hasanien, "Salp swarm optimizer to solve optimal power flow comprising voltage stability analysis," *Neural Computing and Applications*, pp. 1-17, 2019.
- [59] R. A. Ibrahim, A. A. Ewees, D. Oliva, M. A. Elaziz, and S. Lu, "Improved salp swarm algorithm based on particle swarm optimization for feature selection," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, pp. 3155-3169, 2019.
- [60] N. Singh, F. Chiclana, and J.-P. Magnot, "A new fusion of salp swarm with sine cosine for optimization of non-linear functions," *Engineering with Computers*, vol. 36, pp. 185-212, 2020.
- [61] H. Faris, M. M. Mafarja, A. A. Heidari, I. Aljarah, A.-Z. Ala'M, S. Mirjalili, and H. Fujita, "An efficient binary Salp Swarm Algorithm with crossover scheme for feature selection problems," *Knowledge-Based Systems*, vol. 154, pp. 43-67, 2018.
- [62] K. Mahadevan and P. Kannan, "Comprehensive learning particle swarm optimization for reactive power dispatch," *Applied Soft Computing*, vol. 10, pp. 641-652, 2010.
- [63] A. A. Heidari, R. A. Abbaspour, and A. R. Jordehi, "Gaussian bare-bones water cycle algorithm for optimal reactive power dispatch in electrical power systems," *Applied Soft Computing*, vol. 57, pp. 657-671, 2017.
- [64] A. Khorsandi, A. Alimardani, B. Vahidi, and S. Hosseinian, "Hybrid shuffled frog leaping algorithm and Nelder-Mead simplex search for optimal reactive power dispatch," *IET generation, transmission & distribution*, vol. 5, pp. 249-256, 2011.
- [65] B. Shaw, V. Mukherjee, and S. Ghoshal, "Solution of reactive power dispatch of power systems by an opposition-based gravitational search algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 29-40, 2014.
- [66] T. I.-B. T. System, p. <http://www.ee.washington.edu/research/pstca/pf57/pgtca57bus.htm>, 1993.
- [67] W. Villa-Acevedo, J. López-Lezama, and J. Valencia-Velásquez, "A Novel Constraint Handling Approach for the Optimal Reactive Power Dispatch Problem," *Energies*, vol. 11, p. 2352, 2018.
- [68] A. Bhattacharya and P. K. Chattopadhyay, "Solution of optimal reactive power flow using biogeography-based optimization," *International Journal of Electrical and Electronics Engineering*, vol. 4, pp. 568-576, 2010.
- [69] C. Dai, W. Chen, Y. Zhu, and X. Zhang, "Seeker optimization algorithm for optimal reactive power dispatch," *IEEE Transactions on power systems*, vol. 24, pp. 1218-1231, 2009.
- [70] M. Mehdinejad, B. Mohammadi-Ivatloo, R. Dadashzadeh-Bonab, and K. Zare, "Solution of optimal reactive power dispatch of power systems using hybrid particle swarm optimization and imperialist competitive algorithms," *International Journal of Electrical Power & Energy Systems*, vol. 83, pp. 104-116, 2016.
- [71] A. P. Mazzini, E. N. Asada, and G. G. Lage, "Solving control-constrained reactive power dispatch with discrete variables," in *2015 18th International Conference on Intelligent System Application to Power Systems (ISAP)*, 2015, pp. 1-6.

References

- [72] R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education," *IEEE Transactions on power systems*, vol. 26, pp. 12-19, 2010.
- [73] S. Mouassa, T. Bouktir, and A. Salhi, "Ant lion optimizer for solving optimal reactive power dispatch problem in power systems," *Engineering science and technology, an international journal*, vol. 20, pp. 885-895, 2017.

Appendices

APPENDIX 1: Standard IEEE-(30buses) test system data

baseMVA = 100.

% Type....

% 1 - Slack Bus.

% 2 - PV Bus.

% 3 - PQ Bus.

% bus data

bus_i	Type	Vsp	Theta	PGi	QGi	PLi	QLi	Qmin	Qmax
1	1	1.0600	0	0	0	0	0	-20	200
2	2	1.0450	0	80	0	21.7000	12.7000	-20	100
3	3	1.0000	0	0	0	2.4000	1.2000	0	0
4	3	1.0000	0	0	0	7.6000	1.6000	0	0
5	2	1.0100	0	50	0	94.2000	19.0000	-15	80
6	3	1.0000	0	0	0	0	0	0	0
7	3	1.0000	0	0	0	22.8000	10.9000	0	0
8	2	1.0100	0	20	0	30.0000	30.0000	-15	60
9	3	1.0000	0	0	0	0	0	0	0
10	3	1.0000	0	0	0	5.8000	2.0000	0	0
11	2	1.0820	0	20	0	0	0	-10	50
12	3	1.0000	0	0	0	11.2000	7.5000	0	0
13	2	1.0710	0	20	0	0	0	-15	60
14	3	1.0000	0	0	0	6.2000	1.6000	0	0
15	3	1.0000	0	0	0	8.2000	2.5000	0	0
16	3	1.0000	0	0	0	3.5000	1.8000	0	0
17	3	1.0000	0	0	0	9.0000	5.8000	0	0
18	3	1.0000	0	0	0	3.2000	0.9000	0	0
19	3	1.0000	0	0	0	9.5000	3.4000	0	0
20	3	1.0000	0	0	0	2.2000	0.7000	0	0
21	3	1.0000	0	0	0	17.5000	11.2000	0	0
22	3	1.0000	0	0	0	0	0	0	0
23	3	1.0000	0	0	0	3.2000	1.6000	0	0
24	3	1.0000	0	0	0	8.7000	6.7000	0	0
25	3	1.0000	0	0	0	0	0	0	0
26	3	1.0000	0	0	0	3.5000	2.3000	0	0
27	3	1.0000	0	0	0	0	0	0	0
28	3	1.0000	0	0	0	0	0	0	0
29	3	1.0000	0	0	0	2.4000	0.9000	0	0
30	3	1.0000	0	0	0	10.6000	1.9000	0	0

%Line data

From Bus	To Bus	R pu	X pu	B/2 pu	X'mer TAP (a)
1	2	0.0192	0.0575	0	1.0000
1	3	0.0452	0.1652	0	1.0000
2	4	0.0570	0.1737	0	1.0000
3	4	0.0132	0.0379	0	1.0000
2	5	0.0472	0.1983	0	1.0000

APPENDICES

2	6	0.0581	0.1763	0	1.0000
4	6	0.0119	0.0414	0	1.0000
5	7	0.0460	0.1160	0	1.0000
6	7	0.0267	0.0820	0	1.0000
6	8	0.0120	0.0420	0	1.0000
6	9	0	0.2080	0	1.0780
6	10	0	0.5560	0	1.0690
9	11	0	0.2080	0	1.0000
9	10	0	0.1100	0	1.0000
4	12	0	0.2560	0	1.0320
12	13	0	0.1400	0	1.0000
12	14	0.1231	0.2559	0	1.0000
12	15	0.0662	0.1304	0	1.0000
12	16	0.0945	0.1987	0	1.0000
14	15	0.2210	0.1997	0	1.0000
16	17	0.0824	0.1923	0	1.0000
15	18	0.1073	0.2185	0	1.0000
18	19	0.0639	0.1292	0	1.0000
19	20	0.0340	0.0680	0	1.0000
10	20	0.0936	0.2090	0	1.0000
10	17	0.0324	0.0845	0	1.0000
10	21	0.0348	0.0749	0	1.0000
10	22	0.0727	0.1499	0	1.0000
21	22	0.0116	0.0236	0	1.0000
15	23	0.1000	0.2020	0	1.0000
22	24	0.1150	0.1790	0	1.0000
23	24	0.1320	0.2700	0	1.0000
24	25	0.1885	0.3292	0	1.0000
25	26	0.2544	0.3800	0	1.0000
25	27	0.1093	0.2087	0	1.0000
28	27	0	0.3960	0	1.0680
27	29	0.2198	0.4153	0	1.0000
27	30	0.3202	0.6027	0	1.0000
29	30	0.2399	0.4533	0	1.0000
8	28	0.0636	0.2000	0	1.0000
6	28	0.0169	0.0599	0	1.0000

APPENDIX 2: Standard IEEE-(57buses) test system data

% bus data

bus_i	Type	Vsp	Theta	PGi	QGi	PLi	QLi	Qmin	Qmax
1	1	1.0400	0	128.9000	-16.1000	55.0000	17.0000	-200	300
2	2	1.0100	0	0	-0.8000	3.0000	88.0000	-17	50
3	2	0.9850	0	40.0000	-1.0000	41.0000	21.0000	-10	60
4	3	0.9810	0	0	0	0	0	0	0
5	3	0.9760	0	0	0	13.0000	4.0000	0	0
6	2	0.9800	0	0	0.8000	75.0000	2.0000	-8	25
7	3	0.9840	0	0	0	0	0	0	0
8	2	1.0050	0	450.0000	62.1000	150.0000	22.0000	-140	200
9	2	0.9800	0	0	2.2000	121.0000	26.0000	-3	9
10	3	0.9860	0	0	0	5.0000	2.0000	0	0

APPENDICES

11	3	0.9740	0	0	0	0	0	0	0
12	2	1.0150	0	310.0000	128.5000	377.0000	4.0000	-150	155
13	3	0.9790	0	0	0	18.0000	2.3000	0	0
14	3	0.9700	0	0	0	10.5000	5.3000	0	0
15	3	0.9880	0	0	0	22.0000	5.0000	0	0
16	3	1.0130	0	0	0	43.0000	3.0000	0	0
17	3	1.0170	0	0	0	42.0000	8.0000	0	0
18	3	1.0010	0	0	0	27.2000	9.8000	0	0
19	3	0.9700	0	0	0	3.3000	0.6000	0	0
20	3	0.9640	0	0	0	2.3000	1.0000	0	0
21	3	1.0080	0	0	0	0	0	0	0
22	3	1.0100	0	0	0	0	0	0	0
23	3	1.0080	0	0	0	6.3000	2.1000	0	0
24	3	0.9990	0	0	0	0	0	0	0
25	3	0.9820	0	0	0	6.3000	3.2000	0	0
26	3	0.9590	0	0	0	0	0	0	0
27	3	0.9820	0	0	0	9.3000	0.5000	0	0
28	3	0.9970	0	0	0	4.6000	2.3000	0	0
29	3	1.0100	0	0	0	17.0000	2.6000	0	0
30	3	0.9620	0	0	0	3.6000	1.8000	0	0
31	3	0.9360	0	0	0	5.8000	2.9000	0	0
32	3	0.9490	0	0	0	1.6000	0.8000	0	0
33	3	0.9470	0	0	0	3.8000	1.9000	0	0
34	3	0.9590	0	0	0	0	0	0	0
35	3	0.9660	0	0	0	6.0000	3.0000	0	0
36	3	0.9760	0	0	0	0	0	0	0
37	3	0.9850	0	0	0	0	0	0	0
38	3	1.0130	0	0	0	14.0000	7.0000	0	0
39	3	0.9830	0	0	0	0	0	0	0
40	3	0.9730	0	0	0	0	0	0	0
41	3	0.9960	0	0	0	6.3000	3.0000	0	0
42	3	0.9660	0	0	0	7.1000	4.4000	0	0
43	3	1.0100	0	0	0	2.0000	1.0000	0	0
44	3	1.0170	0	0	0	12.0000	1.8000	0	0
45	3	1.0360	0	0	0	0	0	0	0
46	3	1.0500	0	0	0	0	0	0	0
47	3	1.0330	0	0	0	29.7000	11.6000	0	0
48	3	1.0270	0	0	0	0	0	0	0
49	3	1.0360	0	0	0	18.0000	8.5000	0	0
50	3	1.0230	0	0	0	21.0000	10.5000	0	0
51	3	1.0520	0	0	0	18.0000	5.3000	0	0
52	3	0.9800	0	0	0	4.9000	2.2000	0	0
53	3	0.9710	0	0	0	20.0000	10.0000	0	0
54	3	0.9960	0	0	0	4.1000	1.4000	0	0
55	3	1.0310	0	0	0	6.8000	3.4000	0	0
56	3	0.9680	0	0	0	7.6000	2.2000	0	0
57	3	0.9650	0	0	0	6.7000	2.0000	0	0

%Line data

APPENDICES

From Bus	To Bus	R pu	X pu	B/2 pu	X'mer TAP (a)
1	2	0.0083	0.0280	0.0645	1.0000
2	3	0.0298	0.0850	0.0409	1.0000
3	4	0.0112	0.0366	0.0190	1.0000
4	5	0.0625	0.1320	0.0129	1.0000
4	6	0.0430	0.1480	0.0174	1.0000
6	7	0.0200	0.1020	0.0138	1.0000
6	8	0.0339	0.1730	0.0235	1.0000
8	9	0.0099	0.0505	0.0274	1.0000
9	10	0.0369	0.1679	0.0220	1.0000
9	11	0.0258	0.0848	0.0109	1.0000
9	12	0.0648	0.2950	0.0386	1.0000
9	13	0.0481	0.1580	0.0203	1.0000
13	14	0.0132	0.0434	0.0055	1.0000
13	15	0.0269	0.0869	0.0115	1.0000
1	15	0.0178	0.0910	0.0494	1.0000
1	16	0.0454	0.2060	0.0273	1.0000
1	17	0.0238	0.1080	0.0143	1.0000
3	15	0.0162	0.0530	0.0272	1.0000
4	18	0	0.5550	0	0.9700
4	18	0	0.4300	0	0.9780
5	6	0.0302	0.0641	0.0062	1.0000
7	8	0.0139	0.0712	0.0097	1.0000
10	12	0.0277	0.1262	0.0164	1.0000
11	13	0.0223	0.0732	0.0094	1.0000
12	13	0.0178	0.0580	0.0302	1.0000
12	16	0.0180	0.0813	0.0108	1.0000
12	17	0.0397	0.1790	0.0238	1.0000
14	15	0.0171	0.0547	0.0074	1.0000
18	19	0.4610	0.6850	0	1.0000
19	20	0.2830	0.4340	0	1.0000
21	20	0	0.7767	0	1.0430
21	22	0.0736	0.1170	0	1.0000
22	23	0.0099	0.0152	0	1.0000
23	24	0.1660	0.2560	0.0042	1.0000
24	25	0	1.1820	0	1.0000
24	25	0	1.2300	0	1.0000
24	26	0	0.0473	0	1.0430
26	27	0.1650	0.2540	0	1.0000
27	28	0.0618	0.0954	0	1.0000
28	29	0.0418	0.0587	0	1.0000
7	29	0	0.0648	0	0.9670
25	30	0.1350	0.2020	0	1.0000
30	31	0.3260	0.4970	0	1.0000
31	32	0.5070	0.7550	0	1.0000
32	33	0.0392	0.0360	0	1.0000
34	32	0	0.9530	0	0.9750
34	35	0.0520	0.0780	0.0016	1.0000
35	36	0.0430	0.0537	0.0008	1.0000

APPENDICES

36	37	0.0290	0.0366	0	1.0000
37	38	0.0651	0.1009	0.0010	1.0000
37	39	0.0239	0.0379	0	1.0000
36	40	0.0300	0.0466	0	1.0000
22	38	0.0192	0.0295	0	1.0000
11	41	0	0.7490	0	0.9550
41	42	0.2070	0.3520	0	1.0000
41	43	0	0.4120	0	1.0000
38	44	0.0289	0.0585	0.0010	1.0000
15	45	0	0.1042	0	0.9550
14	46	0	0.0735	0	0.9000
46	47	0.0230	0.0680	0.0016	1.0000
47	48	0.0182	0.0233	0	1.0000
48	49	0.0834	0.1290	0.0024	1.0000
49	50	0.0801	0.1280	0	1.0000
50	51	0.1386	0.2200	0	1.0000
10	51	0	0.0712	0	0.9300
13	49	0	0.1910	0	0.8950
29	52	0.1442	0.1870	0	1.0000
52	53	0.0762	0.0984	0	1.0000
53	54	0.1878	0.2320	0	1.0000
54	55	0.1732	0.2265	0	1.0000
11	43	0	0.1530	0	0.9580
44	45	0.0624	0.1242	0.0020	1.0000
40	56	0	1.1950	0	0.9580
56	41	0.5530	0.5490	0	1.0000
56	42	0.2125	0.3540	0	1.0000
39	57	0	1.3550	0	0.9800
57	56	0.1740	0.2600	0	1.0000
38	49	0.1150	0.1770	0.0030	1.0000
38	48	0.0312	0.0482	0	1.0000
9	55	0	0.1205	0	0.9400

APPENDIX 1: Standard IEEE-(118buses) test system data

% bus data

bus_i	Type	Vsp	Theta	PGi	QGi	PLi	QLi	Qmin	Qmax
1	1	0.9550	0	0	0	51	27	-5	15
2	3	0.9710	0	0	0	20	9	0	0
3	3	0.9680	0	0	0	39	10	0	0
4	2	0.9980	0	0	0	39	12	-300	300
5	3	1.0020	0	0	0	0	0	0	0
6	2	0.9900	0	0	0	52	22	-13	50
7	3	0.9890	0	0	0	19	2	0	0
8	2	1.0150	0	0	0	28	0	-300	300
9	3	1.0430	0	0	0	0	0	0	0
10	2	1.0500	0	450.0000	0	0	0	-147	200
11	3	0.9850	0	0	0	70	23	0	0
12	2	0.9900	0	85.0000	0	47	10	-35	120
13	3	0.9680	0	0	0	34	16	0	0

APPENDICES

14	3	0.9840	0	0	0	14	1	0	0
15	2	0.9700	0	0	0	90	30	-10	30
16	3	0.9840	0	0	0	25	10	0	0
17	3	0.9950	0	0	0	11	3	0	0
18	2	0.9730	0	0	0	60	34	-16	50
19	2	0.9620	0	0	0	45	25	-8	24
20	3	0.9580	0	0	0	18	3	0	0
21	3	0.9590	0	0	0	14	8	0	0
22	3	0.9700	0	0	0	10	5	0	0
23	3	1.0000	0	0	0	7	3	0	0
24	2	0.9920	0	0	0	13	0	-300	300
25	2	1.0500	0	220.0000	0	0	0	-47	140
26	2	1.0150	0	314.0000	0	0	0	-1000	1000
27	2	0.9680	0	0	0	71	13	-300	300
28	3	0.9620	0	0	0	17	7	0	0
29	3	0.9630	0	0	0	24	4	0	0
30	3	0.9680	0	0	0	0	0	0	0
31	2	0.9670	0	7.0000	0	43	27	-300	300
32	2	0.9630	0	0	0	59	23	-14	42
33	3	0.9720	0	0	0	23	9	0	0
34	2	0.9840	0	0	0	59	26	-8	24
35	3	0.9810	0	0	0	33	9	0	0
36	2	0.9800	0	0	0	31	17	-8	24
37	3	0.9920	0	0	0	0	0	0	0
38	3	0.9620	0	0	0	0	0	0	0
39	3	0.9700	0	0	0	27	11	0	0
40	2	0.9700	0	0	0	66	23	-300	300
41	3	0.9670	0	0	0	37	10	0	0
42	2	0.9850	0	0	0	96	23	-300	300
43	3	0.9780	0	0	0	18	7	0	0
44	3	0.9850	0	0	0	16	8	0	0
45	3	0.9870	0	0	0	53	22	0	0
46	2	1.0050	0	19.0000	0	28	10	-100	100
47	3	1.0170	0	0	0	34	0	0	0
48	3	1.0210	0	0	0	20	11	0	0
49	2	1.0250	0	204.0000	0	87	30	-85	210
50	3	1.0010	0	0	0	17	4	0	0
51	3	0.9670	0	0	0	17	8	0	0
52	3	0.9570	0	0	0	18	5	0	0
53	3	0.9460	0	0	0	23	11	0	0
54	2	0.9550	0	48.0000	0	113	32	-300	300
55	2	0.9520	0	0	0	63	22	-8	23
56	2	0.9540	0	0	0	84	18	-8	15
57	3	0.9710	0	0	0	12	3	0	0
58	3	0.9590	0	0	0	12	3	0	0
59	2	0.9850	0	155.0000	0	277	113	-60	180
60	3	0.9930	0	0	0	78	3	0	0
61	2	0.9950	0	160.0000	0	0	0	-100	300
62	2	0.9980	0	0	0	77	14	-20	20
63	3	0.9690	0	0	0	0	0	0	0

APPENDICES

64	3	0.9840	0	0	0	0	0	0	0
65	2	1.0050	0	391.0000	0	0	0	-67	200
66	2	1.0500	0	392.0000	0	39	18	-67	200
67	3	1.0200	0	0	0	28	7	0	0
68	3	1.0030	0	0	0	0	0	0	0
69	2	1.0350	0	516.4000	0	0	0	-300	300
70	2	0.9840	0	0	0	66	20	-10	32
71	3	0.9870	0	0	0	0	0	0	0
72	2	0.9800	0	0	0	12	0	-100	100
73	2	0.9910	0	0	0	6	0	-100	100
74	2	0.9580	0	0	0	68	27	-6	9
75	3	0.9670	0	0	0	47	11	0	0
76	2	0.9430	0	0	0	68	36	-8	23
77	2	1.0060	0	0	0	61	28	-20	70
78	3	1.0030	0	0	0	71	26	0	0
79	3	1.0090	0	0	0	39	32	0	0
80	2	1.0400	0	477.0000	0	130	26	-167	280
81	3	0.9970	0	0	0	0	0	0	0
82	3	0.9890	0	0	0	54	27	0	0
83	3	0.9850	0	0	0	20	10	0	0
84	3	0.9800	0	0	0	11	7	0	0
85	2	0.9850	0	0	0	24	15	-8	23
86	3	0.9870	0	0	0	21	10	0	0
87	2	1.0150	0	4.0000	0	0	0	-100	1000
88	3	0.9870	0	0	0	48	10	0	0
89	2	1.0050	0	607.0000	0	0	0	-210	300
90	2	0.9850	0	0	0	163	42	-300	300
91	2	0.9800	0	0	0	10	0	-100	100
92	2	0.9900	0	0	0	65	10	-3	9
93	3	0.9870	0	0	0	12	7	0	0
94	3	0.9910	0	0	0	30	16	0	0
95	3	0.9810	0	0	0	42	31	0	0
96	3	0.9930	0	0	0	38	15	0	0
97	3	1.0110	0	0	0	15	9	0	0
98	3	1.0240	0	0	0	34	8	0	0
99	2	1.0100	0	0	0	42	0	-100	100
100	2	1.0170	0	252.0000	0	37	18	-50	155
101	3	0.9930	0	0	0	22	15	0	0
102	3	0.9910	0	0	0	5	3	0	0
103	2	1.0010	0	40.0000	0	23	16	-15	40
104	2	0.9710	0	0	0	38	25	-8	23
105	2	0.9650	0	0	0	31	26	-8	23
106	3	0.9620	0	0	0	43	16	0	0
107	2	0.9520	0	0	0	50	12	-200	200
108	3	0.9670	0	0	0	2	1	0	0
109	3	0.9670	0	0	0	8	3	0	0
110	2	0.9730	0	0	0	39	30	-8	23
111	2	0.9800	0	36.0000	0	0	0	-100	1000
112	2	0.9750	0	0	0	68	13	-100	1000
113	2	0.9930	0	0	0	6	0	-100	200

APPENDICES

114	3	0.9600	0	0	0	8	3	0	0
115	3	0.9600	0	0	0	22	7	0	0
116	2	1.0050	0	0	0	184	0	-1000	1000
117	3	0.9740	0	0	0	20	8	0	0
118	3	0.9490	0	0	0	33	15	0	0

%Line data

From Bus	To Bus	R pu	X pu	B/2 pu	X'mer TAP (a)
1	2	0.0303	0.0999	0.0127	1.0000
1	3	0.0129	0.0424	0.0054	1.0000
4	5	0.0018	0.0080	0.0010	1.0000
3	5	0.0241	0.1080	0.0142	1.0000
5	6	0.0119	0.0540	0.0071	1.0000
6	7	0.0046	0.0208	0.0027	1.0000
8	9	0.0024	0.0305	0.5810	1.0000
8	5	0	0.0267	0	0.9850
9	10	0.0026	0.0322	0.6150	1.0000
4	11	0.0209	0.0688	0.0087	1.0000
5	11	0.0203	0.0682	0.0087	1.0000
11	12	0.0060	0.0196	0.0025	1.0000
2	12	0.0187	0.0616	0.0079	1.0000
3	12	0.0484	0.1600	0.0203	1.0000
7	12	0.0086	0.0340	0.0044	1.0000
11	13	0.0222	0.0731	0.0094	1.0000
12	14	0.0215	0.0707	0.0091	1.0000
13	15	0.0744	0.2444	0.0313	1.0000
14	15	0.0595	0.1950	0.0251	1.0000
12	16	0.0212	0.0834	0.0107	1.0000
15	17	0.0132	0.0437	0.0222	1.0000
16	17	0.0454	0.1801	0.0233	1.0000
17	18	0.0123	0.0505	0.0065	1.0000
18	19	0.0112	0.0493	0.0057	1.0000
19	20	0.0252	0.1170	0.0149	1.0000
15	19	0.0120	0.0394	0.0050	1.0000
20	21	0.0183	0.0849	0.0108	1.0000
21	22	0.0209	0.0970	0.0123	1.0000
22	23	0.0342	0.1590	0.0202	1.0000
23	24	0.0135	0.0492	0.0249	1.0000
23	25	0.0156	0.0800	0.0432	1.0000
26	25	0	0.0382	0	0.9600
25	27	0.0318	0.1630	0.0882	1.0000
27	28	0.0191	0.0855	0.0108	1.0000
28	29	0.0237	0.0943	0.0119	1.0000
30	17	0	0.0388	0	0.9600
8	30	0.0043	0.0504	0.2570	1.0000
26	30	0.0080	0.0860	0.4540	1.0000
17	31	0.0474	0.1563	0.0199	1.0000
29	31	0.0108	0.0331	0.0042	1.0000

APPENDICES

23	32	0.0317	0.1153	0.0587	1.0000
31	32	0.0298	0.0985	0.0126	1.0000
27	32	0.0229	0.0755	0.0096	1.0000
15	33	0.0380	0.1244	0.0160	1.0000
19	34	0.0752	0.2470	0.0316	1.0000
35	36	0.0022	0.0102	0.0013	1.0000
35	37	0.0110	0.0497	0.0066	1.0000
33	37	0.0415	0.1420	0.0183	1.0000
34	36	0.0087	0.0268	0.0028	1.0000
34	37	0.0026	0.0094	0.0049	1.0000
38	37	0	0.0375	0	0.9350
37	39	0.0321	0.1060	0.0135	1.0000
37	40	0.0593	0.1680	0.0210	1.0000
30	38	0.0046	0.0540	0.2110	1.0000
39	40	0.0184	0.0605	0.0078	1.0000
40	41	0.0145	0.0487	0.0061	1.0000
40	42	0.0555	0.1830	0.0233	1.0000
41	42	0.0410	0.1350	0.0172	1.0000
43	44	0.0608	0.2454	0.0303	1.0000
34	43	0.0413	0.1681	0.0211	1.0000
44	45	0.0224	0.0901	0.0112	1.0000
45	46	0.0400	0.1356	0.0166	1.0000
46	47	0.0380	0.1270	0.0158	1.0000
46	48	0.0601	0.1890	0.0236	1.0000
47	49	0.0191	0.0625	0.0080	1.0000
42	49	0.0715	0.3230	0.0430	1.0000
42	49	0.0715	0.3230	0.0430	1.0000
45	49	0.0684	0.1860	0.0222	1.0000
48	49	0.0179	0.0505	0.0063	1.0000
49	50	0.0267	0.0752	0.0094	1.0000
49	51	0.0486	0.1370	0.0171	1.0000
51	52	0.0203	0.0588	0.0070	1.0000
52	53	0.0405	0.1635	0.0203	1.0000
53	54	0.0263	0.1220	0.0155	1.0000
49	54	0.0730	0.2890	0.0369	1.0000
49	54	0.0869	0.2910	0.0365	1.0000
54	55	0.0169	0.0707	0.0101	1.0000
54	56	0.0027	0.0095	0.0037	1.0000
55	56	0.0049	0.0151	0.0019	1.0000
56	57	0.0343	0.0966	0.0121	1.0000
50	57	0.0474	0.1340	0.0166	1.0000
56	58	0.0343	0.0966	0.0121	1.0000
51	58	0.0255	0.0719	0.0089	1.0000
54	59	0.0503	0.2293	0.0299	1.0000
56	59	0.0825	0.2510	0.0285	1.0000
56	59	0.0803	0.2390	0.0268	1.0000
55	59	0.0474	0.2158	0.0282	1.0000
59	60	0.0317	0.1450	0.0188	1.0000
59	61	0.0328	0.1500	0.0194	1.0000
60	61	0.0026	0.0135	0.0073	1.0000

APPENDICES

60	62	0.0123	0.0561	0.0073	1.0000
61	62	0.0082	0.0376	0.0049	1.0000
63	59	0	0.0386	0	0.9600
63	64	0.0017	0.0200	0.1080	1.0000
64	61	0	0.0268	0	0.9850
38	65	0.0090	0.0986	0.5230	1.0000
64	65	0.0027	0.0302	0.1900	1.0000
49	66	0.0180	0.0919	0.0124	1.0000
49	66	0.0180	0.0919	0.0124	1.0000
62	66	0.0482	0.2180	0.0289	1.0000
62	67	0.0258	0.1170	0.0155	1.0000
65	66	0	0.0370	0	0.9350
66	67	0.0224	0.1015	0.0134	1.0000
65	68	0.0014	0.0160	0.3190	1.0000
47	69	0.0844	0.2778	0.0355	1.0000
49	69	0.0985	0.3240	0.0414	1.0000
68	69	0	0.0370	0	0.9350
69	70	0.0300	0.1270	0.0610	1.0000
24	70	0.0022	0.4115	0.0510	1.0000
70	71	0.0088	0.0355	0.0044	1.0000
24	72	0.0488	0.1960	0.0244	1.0000
71	72	0.0446	0.1800	0.0222	1.0000
71	73	0.0087	0.0454	0.0059	1.0000
70	74	0.0401	0.1323	0.0168	1.0000
70	75	0.0428	0.1410	0.0180	1.0000
69	75	0.0405	0.1220	0.0620	1.0000
74	75	0.0123	0.0406	0.0052	1.0000
76	77	0.0444	0.1480	0.0184	1.0000
69	77	0.0309	0.1010	0.0519	1.0000
75	77	0.0601	0.1999	0.0249	1.0000
77	78	0.0038	0.0124	0.0063	1.0000
78	79	0.0055	0.0244	0.0032	1.0000
77	80	0.0170	0.0485	0.0236	1.0000
77	80	0.0294	0.1050	0.0114	1.0000
79	80	0.0156	0.0704	0.0094	1.0000
68	81	0.0018	0.0202	0.4040	1.0000
81	80	0	0.0370	0	0.9350
77	82	0.0298	0.0853	0.0409	1.0000
82	83	0.0112	0.0367	0.0190	1.0000
83	84	0.0625	0.1320	0.0129	1.0000
83	85	0.0430	0.1480	0.0174	1.0000
84	85	0.0302	0.0641	0.0062	1.0000
85	86	0.0350	0.1230	0.0138	1.0000
86	87	0.0283	0.2074	0.0222	1.0000
85	88	0.0200	0.1020	0.0138	1.0000
85	89	0.0239	0.1730	0.0235	1.0000
88	89	0.0139	0.0712	0.0097	1.0000
89	90	0.0518	0.1880	0.0264	1.0000
89	90	0.0238	0.0997	0.0530	1.0000
90	91	0.0254	0.0836	0.0107	1.0000

APPENDICES

89	92	0.0099	0.0505	0.0274	1.0000
89	92	0.0393	0.1581	0.0207	1.0000
91	92	0.0387	0.1272	0.0163	1.0000
92	93	0.0258	0.0848	0.0109	1.0000
92	94	0.0481	0.1580	0.0203	1.0000
93	94	0.0223	0.0732	0.0094	1.0000
94	95	0.0132	0.0434	0.0056	1.0000
80	96	0.0356	0.1820	0.0247	1.0000
82	96	0.0162	0.0530	0.0272	1.0000
94	96	0.0269	0.0869	0.0115	1.0000
80	97	0.0183	0.0934	0.0127	1.0000
80	98	0.0238	0.1080	0.0143	1.0000
80	99	0.0454	0.2060	0.0273	1.0000
92	100	0.0648	0.2950	0.0236	1.0000
94	100	0.0178	0.0580	0.0302	1.0000
95	96	0.0171	0.0547	0.0074	1.0000
96	97	0.0173	0.0885	0.0120	1.0000
98	100	0.0397	0.1790	0.0238	1.0000
99	100	0.0180	0.0813	0.0108	1.0000
100	101	0.0277	0.1262	0.0164	1.0000
92	102	0.0123	0.0559	0.0073	1.0000
101	102	0.0246	0.1120	0.0147	1.0000
100	103	0.0160	0.0525	0.0268	1.0000
100	104	0.0451	0.2040	0.0271	1.0000
103	104	0.0466	0.1584	0.0204	1.0000
103	105	0.0535	0.1625	0.0204	1.0000
100	106	0.0605	0.2290	0.0310	1.0000
104	105	0.0099	0.0378	0.0049	1.0000
105	106	0.0140	0.0547	0.0072	1.0000
105	107	0.0530	0.1830	0.0236	1.0000
105	108	0.0261	0.0703	0.0092	1.0000
106	107	0.0530	0.1830	0.0236	1.0000
108	109	0.0105	0.0288	0.0038	1.0000
103	110	0.0391	0.1813	0.0231	1.0000
109	110	0.0278	0.0762	0.0101	1.0000
110	111	0.0220	0.0755	0.0100	1.0000
110	112	0.0247	0.0640	0.0310	1.0000
17	113	0.0091	0.0301	0.0038	1.0000
32	113	0.0615	0.2030	0.0259	1.0000
32	114	0.0135	0.0612	0.0081	1.0000
27	115	0.0164	0.0741	0.0099	1.0000
114	115	0.0023	0.0104	0.0014	1.0000
68	116	0.0003	0.0040	0.0820	1.0000
12	117	0.0329	0.1400	0.0179	1.0000
75	118	0.0145	0.0481	0.0060	1.0000
76	118	0.0164	0.0544	0.0068	1.0000