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COMPARATIVE ANALYSIS OF THE PARTICLE SWARM OPTIMIZATION AND MIXED INTEGER LINEAR PROGRAMMING METHODS FOR TRANSMISSION CONGESTION MANAGEMENT IN DEREGULATED POWER SYSTEMS

by

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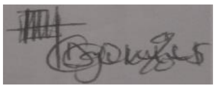
DECLARATION

I, Emmanuel Idowu Ogunwole, declare that the contents of this thesis represent my own unaided work and that the thesis has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my opinions, not necessarily those of the Cape Peninsula University of Technology.



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ABSTRACT

Restructuring has taken over all aspects of human activity, including the electric power industry, due to the massive rise in population and industrialization over the last few years. Due to highly competitive market needs among participants, the electric power industry's restructuring has resulted in significant changes, including overloading critical portions of the transmission networks, leading to the inevitable congestion of the transmission lines. Congestion can be defined as a violation of transmission line capacity constraints that endanger the system's dependability and security. Furthermore, an open-access transmission network configuration in the contemporary deregulated electricity market has exacerbated congestion difficulties. As a result, congestion management (CM) in deregulated power networks is essential to the efficient and productive operation of the modern electricity power market.

Significantly, generator rescheduling has been widely viewed as an approach towards alleviating the network congestion difficulty resulting from the ever-increasing volume of power/energy transactions in the power industry. Thus, this research aims to develop an efficient approach for managing transmission network congestion in a deregulated environment. Significantly, the goal of the study is to describe and define the appropriate mathematical optimization approach that lowers the cost of active and reactive power of the generators, thereby reducing the deviation of rescheduled active and reactive power from scheduled values using particle swarm optimization (PSO) and mixed integer linear programming (MILP), comparatively. Including reactive power rescheduling and voltage stability consideration in this research is innovative compared to other existing methodologies that solely examine active power rescheduling.

This research yielded the subsequent contributions: developed a reliable multi-objective function for managing congestion in an electric transmission network; derived suitable generator sensitivity factors to detect overloaded lines and determine the generators that will be participating in congestion management; solving the formulated congestion management problems with a comparative optimal analysis using PSO and MILP algorithms. The developed CM problem solutions were validated using three IEEE standard test system networks (14, 30, and 118). The simulation results prove that the developed approaches in this study achieved better performance in the system’s generator rescheduling, resulting in the inexpensive cost of both active and reactive powers compared to other approaches, with MILP showing better strength when the problem is linearized. The active power losses for each of the considered IEEE 14, 30, and 118 cases with PSO are 4.7%, 11.03%, and 10.87%, respectively, and the reactive power losses are 3.67%, 15.39%, and 12.31%, respectively. Meanwhile, MILP has 5%, 15.5%, and 12.5% for active power losses and 5%, 24%, and 13% for reactive power losses, respectively. Furthermore, the developed approaches significantly enhanced voltage stability and voltage profile while reducing the transmission system operation cost.

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DEDICATION

The entirety of this work is dedicated to the Almighty God, who is the ultimate source and bestower of wisdom, knowledge, and insight. The fulfillment of this aspiration was achieved through HIS divine intervention; may HIS name be exalted eternally.

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GLOSSARY

Terms/Abbreviations/Acronyms	Definitions/Explanation
ATC	Available transfer capability
ABC	Artificial bee colony
ACO	Ant colony optimization
BFA	Bacterial foraging algorithm
BIM	Bus impedance matrix
CM	Congestion management
CO	Combinatorial optimization
CSA	Cuckoo search algorithm
DISCOs	Distribution of electric power
DSO	Distribution system operator
DCOPF	Direct current optimal power flow
DR	Demand response
DGs	Distributed generations
DRs	Distributed resources
DE	Differential evolution
DP	Dynamic programming
ETC	Existing transfer commitments
EPS	Electrical power systems
ESDs	Energy storage devices
EP	Evolution programming
ERCOT	Electricity Reliability Council of Texas
FACTS	Flexible Alternating Current Transmission Systems
FA	Firefly algorithm
FPA	Flower pollination algorithm
GENCOs	Generation of electric power
GSF	Generator sensitivity factor
GR	Generator rescheduling
GM	Gradient method
GSA	Gravitational search algorithm
GA	Genetic algorithm
GTEP	Generation and transmission expansion planning
HNN	Hopfield neural network
ISOs	Independent system operators
IP	Interior Point

IEEE	Institute of Electrical and Electronics Engineers
LODF	Line outage distribution factor
LMP	Local marginal price
LS	Load shedding
LP	Linear programming
LA	Lion algorithm
LRA	Lagrangian relaxation algorithm
MATLAB	MATrix LABoratory
NPS	Nodal pricing schemes
NM	Newton methods
N-R	Newton-Raphson
NLP	Non-linear programming
OASIS	Open Access Same-time Information System
OPF	Optimal power flow
PACM	Price area congestion management
PST	Phase shifter transformer
PSP	Pool sales price
PPP	Pool leverage price
PSO	Particle swarm optimization
PC	Parallel computing
PS	Pattern search
PI	Performance index
PMU	Phasor measurement unit
PTDF	Power transfer distribution factor
POD	Power oscillation damper
PSSs	Power systems stabilizers
PSCAD	Power Systems Computer Aided Design
QP	Quadratic programming
RM	Reserved margin
RPTCF	Real power transmission congestion factor
RTS	Reliability test system
STATCOM	Static synchronous compensator
SOPF	Stochastic optimum power flow
SSSC	Shunt-series synchronous compensator
SA	Simulated annealing
SG	Smart grid
TRANSCOs	Transmission of generated electric power
TTC	Total transfer capability

TRM	Total required margin
TCSC	Thyristor control series capacitor
TS	Tabu search
TLR	Transmission loading relief
UPFC	Unified power flow controller
VSM	Voltage stability margin

MATHEMATICAL NOTATIONS

C_{Pg}	Cost of rescheduling active power of the generator
C_{Qg}	Cost of rescheduling reactive power of the generator
ΔP_g	Generator's active power adjustments
ΔQ_g	Generator's reactive power adjustments
L_{max}	Maximum voltage stability indicator
PF	Penalty factor
S_{Gmax}	Generator's maximum nominal apparent power
C_g^P	Cost of generating reactive power by the generator
φ	Profit rate of reactive power generation
NB	Number of buses
P_{Gi}	Active power produced at bus i
Q_{Gi}	Reactive power produced at bus i
P_{Di}	Active power demand at bus i
Q_{Di}	Reactive power demand at bus i
$\lvert V_i \rvert < \delta_i$	Bus i complex voltage
$\lvert V_j \rvert < \delta_j$	Bus j complex voltage
$\lvert Y_{ij} \rvert < \delta_{ij}$	Bus i and j mutual admittance
θ_{ij}	Bus i and j impedance angle
P_g^{min}	Minimum active power generation
P_g^{max}	Maximum active power generation
Q_g^{min}	Minimum reactive power generation
Q_g^{max}	Maximum reactive power generation
ΔP_g^{min}	Change in minimum active power generation
ΔP_g^{max}	Change in maximum active power generation
ΔQ_g^{min}	Change in minimum reactive power generation
ΔQ_g^{max}	Change in maximum reactive power generation
V_i^{min}	Bus i minimum voltage
V_i^{max}	Bus i maximum voltage
ΔV_i^{min}	Change in minimum voltage at bus i
ΔV_i^{max}	Change in maximum voltage at bus i
S_k	Transmission line k power flow
S_k^{max}	Maximum power flow on transmission line k
P_{ij}	Active power flow at bus i and j
Q_{ij}	Reactive power flow at bus i and j
N_g	Overall number of generator buses
N_d	Overall number of load buses

N_l	Overall number of transmission lines
N_b	Overall number of buses
x^{min}	Minimum variable limit
x^{max}	Maximum variable limit
k_n	Penalty function constant
PG_{gn}	Generator's active power
QG_{gn}	Generator's reactive power
V_i	Voltage at bus i
V_j	Voltage at bus j
θ_i	Phase angle at bus i
G_{ij}	Line k conductance
B_{ij}	Line k susceptance
δ_{ij}	phase angle at buses ij
V_{k+1}^i	New velocity
P_k^i	Particle location
P_k^g	Best particles location among the neighbors
X_k^i	Particle position
w	Inertia weight
$c1$ and $c2$	Learning factors
$rand()$	Random numbers
$X_i^{(1,k+1)}$	Newly generated offspring
γ_i	Crossover that generate random solution range
$X_i^{(1,k)}, X_i^{(2,k)}$	Parent solutions
$C(i)$	Running length vector
$\Delta(i)$	Random swim direction vector
$j, k,$ and l	Are chemotactic, reproduction, and elimination corresponding error values
P_i	Food source probability value
fit_i	Fitness value of the solution
SN	Number of food search
$\emptyset_{ij}$	Random number between [-1, 1]
X_i^t	Pollen solution vector
γ	Scaling factor
g_*	Current best solution
$L(\lambda)$	Corresponding parameter to the pollination strength
P_{Li}	Active power of the line
Q_{Li}	Reactive power of the line

$\boldsymbol{P_{DGi}}$	Active power of the DG
$\boldsymbol{Q_{DGi}}$	Reactive power of the DG
$\boldsymbol{k_1, k_2}$	Constants
$\boldsymbol{a_n, b_n, and\ c_n}$	Generator predetermined cost coefficients
$\boldsymbol{S_{Gmax}}$	Generator maximum norminal power
$\boldsymbol{\varphi}$	Active power generation profit rate
$\boldsymbol{P_g, Q_g}$	Active and reactive power of the generator
$\boldsymbol{GSF_{Pgn}^k}$	Active power generator sensitivity factor
$\Delta\boldsymbol{P_{ij}}$	Change in active power between buses $\boldsymbol{i\ and\ j}$
$\Delta\boldsymbol{PG_{gn}}$	Unit change in active power injection at bus $\boldsymbol{n}$
$\boldsymbol{G_{ij}, B_{ij}}$	Conductance and susceptance of the line between buses $\boldsymbol{i\ and\ j}$
$\boldsymbol{GSF_{Qgn}^k}$	Rective power generator sensitivity factor
$\Delta\boldsymbol{Q_{ij}}$	Change in reactive power between buses $i\ and\ j$
$\Delta\boldsymbol{QG_{gn}}$	Unit change in reactive power injection at bus $\boldsymbol{n}$

CHAPTER ONE
INTRODUCTION

1.1 Introduction

Historically, the electric power business has been mostly controlled by major utilities that possess complete jurisdiction over all aspects of electricity generation, transmission, and distribution within their operational boundaries (David & Fang, 1998). These utilities are commonly known as vertically integrated utilities. They functioned as the sole electricity provider in the area and were required to supply electricity to all residents in the region (Sourabh & Kaur, 2018). During the late 1980s, there was a general consensus among policymakers and academic experts that energy generation should transition from a monopolistic system to structured and competitive markets. Nevertheless, the distribution and transmission parts of the industry continued to operate as natural monopolies. This process of reorganizing the sector was commonly referred to as "liberalization" and "deregulation." (Nagi & Kaur, 2018). Electric power networks and utility corporations around the world have shifted their method of operation from vertically integrated structures to open market systems for a variety of reasons, which vary from area to region and are also distinct from one another. These causes range from political to merely economic (Wang et al., 2001). This deregulation was brought about in industrialized nations as a result of the demand to lower prices and tariffs while simultaneously enhancing market competitiveness (Kadam & Chatur, 2016). The current modifications in the power system framework have resulted in a substantial increase in the intricacy of its functioning. The deregulation led to the restructuring of the vertically integrated energy industry into a decentralized sector, where the ownership and control of generation, transmission, and distribution were no longer concentrated in a single entity, but instead distributed among multiple businesses (Bhattacharjee & Chakraborty, 2012). Open access allows individuals with the necessary license to freely use existing transmission infrastructure to inject or draw power from the system at any location.

Consequently, as a result of open access, the operation of power system networks becomes more challenging for the purpose of electric power evacuation and injection. This is due to the fact that under a deregulated power system, both the purchasers and the generators of electricity utilize the same transmission network for the purposes of conducting transactions (Chanda et al., 2018). When it comes to an open market technique, all of the participants are concerned with making a profit and have a tendency to buy energy from the source that is the least expensive. Due to this, a number of difficulties emerged as a consequence. Transmission lines were compelled to run in the region of their thermal limits as a result of an unforeseen power transaction that occurred as a result of the creation of a power network to meet the energy consumption demand. Because of this, the relevant lines are typically overloaded, which is referred to as congestion. This, in turn, contributes to the occurrence of contingency (Suganyadevi & Parameswari, 2011). This affects power system transmission network reliability.

Besides, some of the technical challenges associated with power system deregulation are transmission pricing, proliferation of distributed generators, system security assessment and determination, voltage and reactive power management, load frequency control, and power system stability control, among others (Androcec & Wangensteen, 2006).

1.2 Awareness of the problem

Between the years 1973 and 1983, Chile was the first country to implement restructuring in its government-owned electrical sector (Jeong et al., 2007). Consequently, this resulted in other nations in Latin America and the global community adopting and implementing the change. Large utilities have been in charge of the electric power business for a considerable amount of time. These utilities have the authority to oversee all activities related to the generation, transmission, and distribution of electricity within their respective domains of operation (Gitizadeh & Kalantar, 2008). Their responsibility entails supervising the all-encompassing design and functioning of the networks, with the goal of ensuring a consistent and continuous supply to the load, in accordance with established policies and standards. These utilities have exclusive control over the provision of power in their respective areas.

With deregulation's emergence, many participants partake in the electricity market, and this has changed the scope of operation and the activities of the existing operators. These new participants requesting transmission access and, in numerous instances, result in congestion and overload of infrastructure. These factors are the main contributors to issues with the reliability of system transmission (Chanda et al., 2018). The transmission capacity is currently constrained owing to multiple considerations, and it must now accommodate the additional requirements resulting from deregulation. These demands involve power flows that the transmission systems were not originally designed to handle. These demands are a result of both free access to the transmission systems and the installation of new power production sources without much consideration for the transmission needs.

The blackouts that occurred in numerous nations from 2003 to 2004 are partially ascribed to the reorganization/restructuring of the electricity sector (Zhang & Yao, 2008). However, the current operational methods are derived from reliability criteria that were established in the 1960s as a response to certain incidents (Riyaz et al., 2021). If no action is taken to alleviate congestion or enhance transmission capacity, there is a likelihood of experiencing additional power failure or other undesirable situations. Hence, this study looks into the issue of transmission capacity and congestion in a deregulated power sector. Also, the research will investigate into the solution of the following research questions:

i. What methods may be used to accurately evaluate the transmission capacity of a deregulated power network?

ii. What are the effective strategies for managing system contingency in a deregulated electricity network?

iii. What are the impacts of distributed generators in congestion mitigation in a deregulated power system?

iv. How can contemporary optimization methods and tools be adopted to solve problems arising in deregulated power networks, especially congestion management?

1.3 Research Aim and Objectives

This section provides the details breakdown on how the problems of transmission congestion management in deregulated power systems was mitigated via the use of the developed classical (Mixed integer linear programming) and heuristic (Particle swarm optimization) methods. The aim is to reduce congestion on transmission lines and minimise the operating cost of the system. The correlation between congestion and operating costs is strong, with congestion directly leading to increased operating costs due to the need for redispatch, out-of-merit dispatch, and additional ancillary services. By using advanced optimization techniques, implementing demand-side management, enhancing grid infrastructure, and deploying real-time control systems, it is possible to reduce congestion and minimize operating costs simultaneously. The aplicability of the developed methods was validated using the IEEE synthetic networks.

1.3.1 Aim

This research aims to develop the classical (MILP) and heuristic (PSO) methods for the transmission congestion management system and validate the the developed methods on the considered IEEE synthetic networks.

1.3.2 Objectives

The objectives of this research work are:

i. To conduct comparative literature studies on transmission congestion management (TCM) in deregulated power systems and various solution methodologies such as optimization (classical and heuristics) methods for optimal placement of distributed generation and Flexible Alternating Current Transmission Systems devices.

ii. Formulate mathematical modeling to determine the transmission capacity and manage the line congestions along the network in deregulated power systems using the PSO and MILP algorithms.

iii. Develop an improved dedicated PSO algorithm in the MATLAB environment for efficient transmission network congestion management using IEEE 14, 30, and 118 standards as the case studies.

iv. Develop a MILP method for congestion management (CM) in a deregulated power system and validate the simulation results for the IEEE 14, 30, and 118 systems.

v. Asses the performance of the developed PSO algorithm by comparative analysis with the standard MILP algorithm methods as mentioned in (iii & iv) above.

1.4 Hypothesis

The hypothesis was formulated based on a thorough examination of the methodologies and algorithms employed in the relevant articles to solve the problem of congestion management in electric power networks. The reviewed investigation stated that several methods were used to solve congestion management problems in electric power systems; each technique is characterized by its advantages and disadvantages, as evident in its solution, accuracy, reliability, computational time, and other features. Many reference papers use the cost-free method to solve the congestion management problem in a deregulated power system. However, this research work deployed an improved PSO algorithm (PSO is significant in optimization due to its simplicity, efficiency, versatility, and robustness. Its wide range of applications across various fields and the ongoing research to further enhance its capabilities underline its importance as a valuable tool for solving complex optimization problems) benchmarked with MILP. Based on the characteristics of the proposed methods, standard parameters are required to tune with less computational time, consistency, and accuracy.

1.5 Delimitation of the research

This research work emphasized the characteristics of the optimization algorithms (PSO and MILP) developed to solve the CM problem in deregulated power systems.

i. Due to the random search process, PSO easily falls into the local optimum in high-dimentinal.

ii. PSO can be computationally intensive and has a poor rate of convergence during the iterative procedure.

iii. MILP algorithm cannot take nonlinear effects into consideration.

iv. With MILP algorithm, there is a chance that the problem will be highly dimensional.

1.6 Motivation of the research work

The primary goal of this work is to provide a new and efficient strategy for managing congestion in deregulated power networks. According to the literature, numerous researchers have employed several methods to mitigate the CM problem. These approaches have similar control factors, such as size of population and number of generations, which are both specific and necessary. The Genetic Algorithm (GA) employs mutation and crossover rates, while the Harmony Search (HS) use a pitch altering rate along with a memory consideration rate. If the parameters of these methods are not properly tuned, the performance of the optimisation algorithm methods may deviate. This work will employ the enhanced particle swarm optimisation (PSO) technique, which will be compared to mixed integer linear programming, to address congestion management issues while considering the crucial control of parameters. Based on the evidence, the proposed method is efficient, consistent, accurate, and requires less computational time and effort.

1.7 Assumptions

The research relied on the assumptions employed to address congestion management issues in deregulated power systems.. The following assumptions will be carefully followed:

i. The PSO method's initial guess (e.g., acceleration factors, inertial constant, and random numbers) will be considered when starting the search process.

ii. Due to the absence of the gradient mechanism in the PSO algorithm, it cannot ensure the attainment of an optimal solution.

iv. The computational cost and memory usage of MILP remain constant at every iteration of the iterative optimization technique.

v. MILP problems are assigned variables with integer values.

1.8 Deliverables of the research work

The deliverables of this research work are as follows:

- Studies of literature review on TCM in deregulated power systems.
- Mathematical formulation for the congestion management problems considering different test cases and operation conditions.
- Develop an improved PSO algorithm and MILP methods to solve the TCM system in deregulated power systems.
- Comparative analysis of the existing methods (Optimization (Classical and heuristics) and DG Penetration) for the CM solution in deregulated power systems.
- For the effectiveness of service delivery and cost savings, judicious utilization of existing grid infrastructure by active congestion management along the transmission lines has remained one of the front operational goals of the electricicity

industry especially with the advent of deregulation. This study has contributed to the electricity industry by developing models for CM and providing insights to the better approach to CM.

1.9 Thesis chapters breakdown

This research work is divided into six chapters as follows:

- Chapter One: This section provides an overview and explanation of the research effort being proposed. It includes an understanding of the research topic, a clear statement of the problem, the research goals and objectives, the hypothesis, the limitations of the research, the reasons for conducting the research, and the underlying assumptions.
- Chapter Two: This section provides an overview of the existing literature on CM in deregulated power systems. It also reviews different strategies and algorithms that have been utilized to address the issue of transmission congestion in deregulated power systems.
- Chapter Three: This section presents the research methodologies and mathematical problem formulation for the proposed congestion management method/technique.
- Chapter Four: This section provides a comprehensive analysis of the performance and outcomes of PSO in managing transmission congestion in deregulated power networks.
- Chapter Five: This section provides the performance comparison between PSO and MILP methods for transmission congestion management.
- Chapter Six: This section presents the research conclusion and recommendations.

1.10 Conclusion

This thesis identified TCM problem in deregulated power system networks as a research problem and developed two optimization methods; classical (MILP) and heuristic (PSO) algorithm to provide solutions. The two methods were validated with three case studies of IEEE synthetic networks. To fully comprehend the extent of the problem, it is crucial to examine literature that especially focuses on publications proposing methods and algorithms for addressing congestion management in deregulated electricity networks. These methods can include classical, heuristic, or meta-heuristic optimisation techniques. Therefore, chapter two provides an overview of the current literature on the techniques employed for managing congestion in deregulated power systems.

CHAPTER TWO

REVIEW INVESTIGATION ON OPTIMIZATION METHODS FOR TRANSMISSION CONGESTION MANAGEMENT SYSTEMS

2.1 Introduction

Because of the ever-increasing population size, growth in electricity demand, and recursively increasing technological improvements, the electric power utility is quickly transitioning from a regulated (bundled) to a deregulated (unbundled) power system. Several decades ago, all activities in the electric power business were managed by a single organization identified as a vertically integrated utility (David & Fang, 1998; Karthikeyan et al., 2013). In bundle industries, one organization controls all three phases (generation, transmission, and distribution) of electric power system networks (Nagi & Kaur, 2018). The transition of the electric sector from a monopolistic to a deregulated state began in the late 1980s, with an agreement reached between academic experts and policymakers that generated power should be made available in coordinated and competitive markets (Sourabh & Kaur, 2018; Wang et al., 2001). This industry restructuring was known as "liberalization" and "deregulation." The restructuring of the electric power system splits the system into three distinct categories: GENCOs (generation of electric power), TRANSCOs (responsible for the transmission of generated electric power), and DISCOs (accountable for the distribution of electric power) (Singh et al., 2023; Prajapati & Mahajan, 2021). Chile was the first country to implement reorganization in its power sector from 1973 to 1983 (Jeong et al., 2007). This prompted other Latin American and international countries to embrace and implement the reform.

GENCOs, TRANSCOs, and DISCOs emerge with the liberalization of electric power systems. It also makes it more difficult for independent system operators (ISO) to run the system in synchronism (Verma & Mukherjee, 2016; Mishra et al., 2022; Yoon et al., 2024). Many difficulties have arisen due to the power industry restructuring, such as reducing transmission congestion, improving market efficiency and market power, providing ancillary services, and ensuring system reliability. The most serious and current of the aforementioned challenges is congestion management (CM) (Pillay et al., 2015). In deregulated power networks, all consumers want access to electricity from the tawdriest generator available, regardless of the separating distance between them. Purchasing from the most inexpensive available generator creates rivalry among consumers, which leads to overloading the transmission lines that connet the generator and the consumers. Due to consumer rivalry, the thermal limits of the transmission network were violated, resulting in line overloading and congestion. Congestion is breaching or violating a transmission line's thermal capacity by overflowing the line (Riyaz et al., 2021). Congestion has been one of the most momentous difficulties that independent system operators (ISOs) have faced since the restructuring of electric power systems in terms of system dependability and security. Poor attention to congestion in system operation may result in total system failure, which may harm the country's social economy and many other factors. The CM technique is critical to keeping the system running smoothly and safely. Several CM technologies have been devised and implemented to power system networks throughout the years to relieve congestion and improve system performance.

2.1.1 Causes of Congestion

Congestion can be caused by any of the following factors (Ogunwole & Krishnamurthy, 2023; Ansaripour et al., 2022):

- Line overloading is caused by a shortage of transmission capacity caused by a lack of investment in energy networks.
- There is a lack of matched generation and transmission services.
- Cross-border electricity trade has increased significantly.
- Electrical prices have decreased because of the deregulation of the electricity business. Electric power is traded off due to unexpected large-scale transmission, pushing transmission networks beyond their physical thermal limits (Reddy et al., 2010a).
- Congestion management is problematic due to the large-scale integration of continuous and rapidly changing power flows with the current grid, such as solar power integration and wind.

To avoid system failure and maintain pure and safe distribution of power/supply to customers / end-users, the above-mentioned sources of congestion in restructured power systems demand proper and long-term solutions.

2.1.2 Purpose of Congestion Management

CM serves two primary functions in a restructured power system: security, reliability, and safe operation. This can be performed by keeping the system's power flow transactions within security constraints. Compensating the grid investment fund by collecting congestion charges from all participants and paying them to the grid owners. Congestion management is critical in the electric power system because it ensures that power is delivered to participants while also providing system safety and improving system performance. Figure 2.1 depicts the overall chapter overview, and Table 2.1 shows the year-wise publications that were reviewed in this chapter starting from 1997 to 2022, and its graphical interpretation is shown in Figure 2.2.

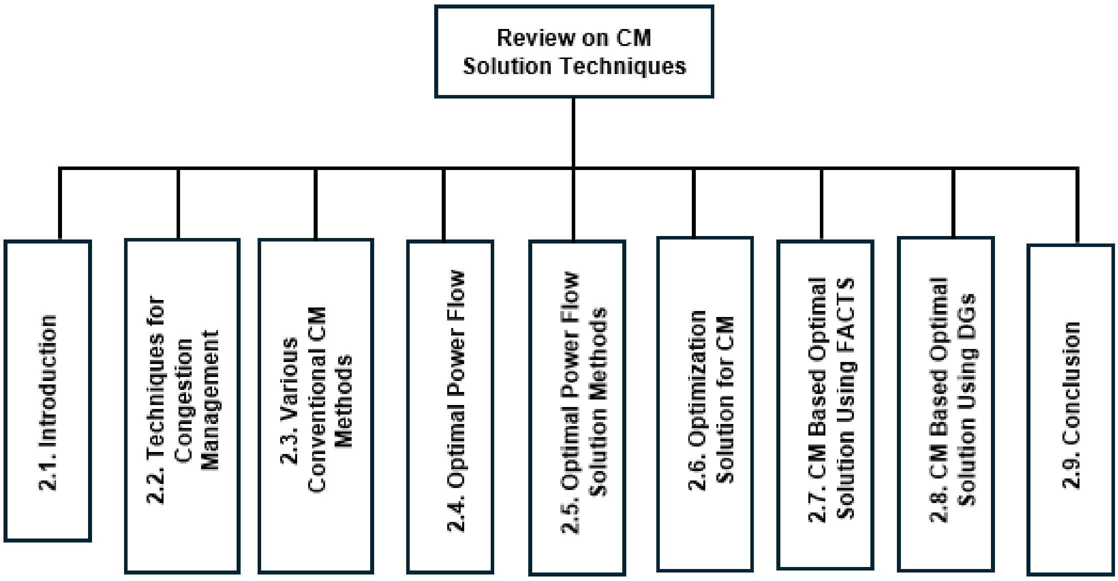


Figure 2. 1: Chapter overview

Table 2. 1: Number of publication year wise

NUMBER OF PUBLICATIONS – YEAR WISE		
References	**Year of publication**	**No. of publication**
(Dorigo & Gambardella, 1997)	1997	1
(David & Fang, 1998)	1998	1
(Wang et al., 2001)	2001	1
(Chang et al., 2002)	2002	1
(Ramírez & Giovanni, 2004)	2004	1
(Dorigo & Blum, 2005)	2005	1
(Androcec & Wangensteen, 2006), (Nabav et al., 2006), (Granelli et al., 2006)	2006	3
(Jeong et al., 2007), (Karaboga & Basturk, 2007)	2007	2
(Gitizadeh & Kalantar, 2008), (Shankaralingappa & Jangamashetti, 2008)	2008	2
(Panigrahi & Ravikumar Pandi, 2009), (Karaboga & Akay, 2009)	2009	2
(Reddy et al., 2010a), (Reddy et al., 2010b), (Reddy et al., 2010c), (Gitizadeh & Khalilnezhad, 2010), (M. Afkousi-Paqaleh et al., 2010), (Mohammad Afkousi-Paqaleh et al., 2010), (Milano, 2010), (Jiang et al., 2010), (Clerc, 2010), (Passino, 2010)	2010	10
(Suganyadevi & Parameswari, 2011), (Nguyen & Yousefi, 2011), (Balijepalli et al., 2011), (Hoseynpoor et al., 2011), (Khemani & Patel, 2011), (Khanabadi & Ghasemi, 2011), (Venkaiah & Vinod Kumar, 2011)	2011	7
(Singh & Verma, 2012), (Anwer et al., 2012), (Kumar & Kumar, 2012), (Bindeshwar Singh et al., 2012), (Frank et al., 2012), (Gupta & Sharma, 2012), (Sirjani et al., 2012), (Muneender & Vinodkumar, 2012), (Kuang & Huang, 2012), (Rajakumar, 2012), (Wang et al., 2012)	2012	11
(Karthikeyan et al., 2013), (Deb et al., 2013), (Guguloth Ramesh, 2013)	2013	3
(Nandini et al., 2014), (Bjorndal et al., 2014), (Tembhurnikar et al., 2014), (Pal & Sengupta, 2014), (Chen et al., 2014), (Rajakumar, 2014), (Siddiqui et al., 2014)	2014	7
(Pillay et al., 2015), (Al-Hajri et al., 2015), (Satyanarayana Rao & Reddy, 2015), (Saranya et al., 2015)	2015	4
(Verma & Mukherjee, 2016), (Retnamony & Raglend, 2016), (Sandhiya et al., 2016), (Gope et al., 2016), (Sarwar & Siddiqui, 2016a), (Gope et al., 2016), (Demirovic, 2016), (Sagwal & Kumar, 2016), (Bae et al., 2016),	2016	14

(Mahala, 2016), (Abdelaziz et al., 2016), (Deb & Goswami, 2016), (Sarwar et al., 2016), (Sarwar & Siddiqui, 2016b)		
(Khan & Siddiqui, 2017), (Saraswat et al., 2017), (Rejula & Balamurugan, 2017), (Varma & Paserba, 2017), (Priyankara et al., 2017), (Sidea et al., 2017), (Rani et al., 2017), (Tavakoli et al., 2017)	2017	8
(Nagi & Kaur, 2018), (Sourabh & Kaur, 2018), (Padmini et al., 2018), (Surya et al., 2018), (Paul et al., 2018), (Sharma, 2018), (Jena et al., 2018), (Straub et al., 2018), (Gaonkar et al., 2018), (Tapre et al., 2018), (Peesapati et al., 2018), (Gupta et al., 2018), (Varghese et al., 2018), (Sarwar et al., 2018)	2018	14
(Adewolu & Saha, 2019), (Gumpu et al., 2019), (Tina et al., 2019), (Li & Xia, 2019), (Sarwar et al., 2019), (Mahdavi & Rouhinia, 2019), (Meibner et al., 2019), (Choudekar et al., 2019)	2019	8
(Yadav et al., 2020), (Masood et al., 2020), (Babatunde Olusegun Adewolu & Saha, 2020), (Vatambeti & Dhal, 2020), (Sharmila et al., 2020), (Babatunde O. Adewolu & Saha, 2020), (Yasasvi et al., 2020)	2020	7
(Prajapati & Mahajan, 2021), (Riyaz et al., 2021), (Asija & Choudekar, 2021), (Malav et al., 2021), (Tarashandeh & Karimi, 2021), (Namilakonda & Guduri, 2021a), (Kim & Hur, 2021), (Verma et al., 2021), (Zarco-Soto et al., 2021), (Zhang et al., 2021), (Ghaderi et al., 2021), (Kumar et al., 2021), (Okelola et al., 2021)	2021	13
(Mishra et al., 2022), (Ansaripour et al., 2022), (Zakaryaseraji & Ghasemi-Marzbali, 2022), (Roustaei et al., 2022), (Dehnavi et al., 2022), (Kaushal et al., 2022), (Zaidan & Toos, 2022), (Manohar et al., 2022), (Gajjala & Ahmad, 2022), (Prashant et al., 2022), (de Oliveira et al., 2022), (Mhanna & Mancarella, 2022), (Welhazi et al., 2022), (Delgado et al., 2022), (Kardoš et al., 2022), (Li et al., 2022), (Srivastava & Yadav, 2022)	2022	16
(Singh et al., 2023), (Ogunwole & Krishnamurthy, 2023), (Dehnavi et al., 2023)	2023	3
(Yoon et al., 2024), (Yang et al., 2024), (Yang et al., 2024), (Al-Obaidi et al., 2024), (2024; Khan et al., 2024)	2024	5

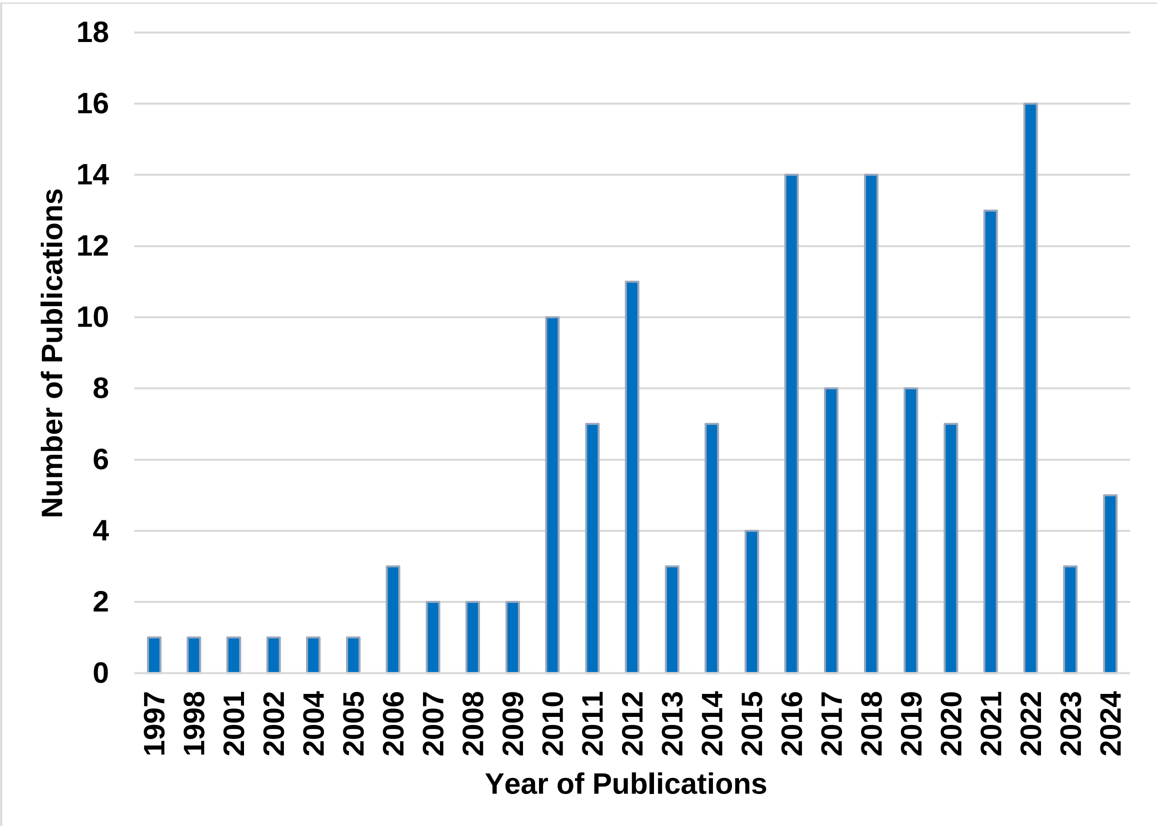


Figure 2. 2: Number of publications year wise

2.2 Techniques for Congestion management in electric power systems

Deregulation of the electric power business has not only established a channel for consumer competition, but it has also allowed for the existence of congestion in the system. Since the presence of congestion on the system, the main key problem of concern to system operators (ISO) has been congestion management. With the advent of technology, researchers have used numerous strategies in the literature to alleviate / manage system congestion (Asija & Choudekar, 2021; Yang et al., 2024).

The traditional electrical power system has historically been categorised into three components: generating (GENCOs), transmission (TRANCOs), and distribution (DISCOs) (Nagi & Kaur, 2018). At first, a single body called a vertically integrated utility oversaw and managed all three divisions of the electrical system. Nevertheless, due to the swift increase in population, hasty industrialization, and technological progress, there is an immense and exponential need for additional clean and dependable energy on the consumer side. Consequently, various countries are undergoing restructuring and deregulation in their electric power industry on a global scale (Sourabh & Kaur, 2018; Vadavathi et al., 2024).

The reformation and deregulation of the electric power business have resulted in a significant increase in the number of consumers who have access to the network. Every consumer vies for access to a cost-effective and reliable supply from the most economical generator, irrespective of the distance. In addition to the main objective of reorganising the electric power system to satisfy the increased demand for energy, there are several other drawbacks that significantly contribute to the system's unfavourable condition. These include auxiliary service, an inefficient market, and congestion. Congestion is the primary drawback linked to the deregulation of the electric power market, and it is receiving increased attention (Al-Obaidi et al., 2024; Khan et al., 2024).

Congestion arises when the temperature, voltage, and stability constraints of a transmission line are breached or surpassed as a result of excessive loading. Additional unforeseen circumstances that contributed to the congestion of the electric transmission network encompassed an abrupt power failure, malfunctioning equipment, and an unanticipated surge or decline in demand. Congestion management solutions are employed to alleviate these situations. Nevertheless, it is imperative to promptly address any signs of congestion in order to uphold a robust and efficient system and prevent a complete system failure, which could result in a complete power outage. Thus, it is imperative to establish an appropriate congestion management plan. Efficiently managing congestion is crucial for maintaining system balance, ensuring system security, and guaranteeing reliability. It also helps address any financial issues arising from congestion. As a result, numerous congestion management techniques have been examined in academic publications, and a considerable volume of research has been focused on determining the most suitable techniques for mitigating congestion in transmission networks without significantly impacting consumer electricity demand. Commonly used techniques in the field of congestion management (CM) comprise Rescheduling of Generators, Flexible Alternating Current Transmission System devices, Optimisation techniques, Re-dispatch, and CM-based Available Transfer Capability, as stated in the literature (Pillay et al., 2015; Androcec & Wangensteen, 2006; Yadav et al., 2020).

The technique proposed by (Reddy et al., 2010b) involves using a genetic algorithm (GA) for optimal positioning and sizing of FACTS devices, for the purpose of voltage stability analysis in power systems. The technique was validated effectively by analysing the impact of TCSC on the IEEE 30-bus network, and it was established that the network with TCSC abridged congestion. (Suganyadevi & Parameswari, 2011) conducted a study on the optimal positioning of FACTS devices using the Performance Index (PI) based on active power. The study addressed technical challenges associated to current modulation in power system deregulation. The methodology was verified by employing MATLAB Simulink on an IEEE 14 bus system.

(Singh & Verma, 2012) proposed a method that uses Genetic Algorithm (GA) to allocate FACTS devices in a liberalised power system network. The method reduce overloading without incurring any additional costs. The nonlinear objective function in congestion management was resolved using GA. The effectiveness of this method in an actual real-world system was proved by applying it to the IEEE 30-bus system network. (Anwer et al., 2012) demonstrated the effectiveness of a new method for mitigating power system congestion. This method involved the integration of a Power Oscillation Damper (POD) with FACTS devices, specifically the SSSC and the UPFC. The proposed method alleviates the congestion in the lines and enhances their power capacity. (Malav et al., 2021) utilised the phase shift transformer technique to alleviate congestion on very crowded transmission lines. The validity of the technique was confirmed using a modified IEEE 24-bus test system network. (Verma et al., 2021) introduced a method for mitigating congestion by employing a thyristor-controlled phase shifting transformer technology and utilising the GAMS solver. The feasibility of the technique was assessed using the IEEE 24-bus network.

(Retnamony & Raglend, 2016) devised a cost-effective technique for CM by examining the possibilities of TCSC. The results gotten from the FACTS analysis were evaluated and confirmed using the IEEE 14-bus system network. The authors (Sandhiya et al., 2016) introduced a congestion management strategy that utilises the simulated annealing (SA) technique to find the ideal location of UPFC. The alleged technique was employed to solve the multi-objective function problem of UPFC placement. The proposed method was validated using MATLAB software. The authors (Khan & Siddiqui, 2017) introduced a novel method for the efficient distribution of FACTS controllers using a combination of GA and the Strength Pareto Evolutionary Algorithm (SPEA). Both methodologies were employed simultaneously for single-objective and multi-objectives optimisation on power systems. The validity of the procedure was confirmed by employing MATLAB software on an IEEE 30 bus test configuration. (Masood et al., 2020) developed an enhanced UPFC control circuit to mitigate congestion. A sensitivity analysis technique was employed to precisely determine the position of UPFC. The model in PSCAD/EMTDC utilised a transmission network consisting of 5 buses and 7 lines for simulation. The authors (Padmini et al., 2018) explained a comprehensive description of several index strategies that can be used to determine the appropriate location of FACTS devices. The method was validated using an IEEE 30-bus test system network.

(Sourabh & Kaur, 2018) conducted a survey on various methodology and approaches aimed at mitigating congestion on electricity transmission lines. They also examined numerous significant congestion management tactics employed by researchers. The author in (Zakaryaseraji & Ghasemi-Marzbali, 2022) employs an innovative demand response programme to mitigate congestion. The most favourable timing for implementing Distributed Renewable Power (DRP) systems utilising wind power was determined, and the effectiveness of the proposed model was confirmed by testing on the IEEE 39-bus system network. (Gope et al., 2016) proposed a technique for rescheduling generators in order to prevent congestion. The authors utilise the firefly optimisation technique to rearrange the output power of the participating generator in order to mitigate congestion. The model's performance was evaluated using the IEEE 39-bus system network. (Surya et al., 2018) developed an innovative approach for condition monitoring (CM) in transmission networks. They designed a control algorithm that effectively regulates the active power flow in the network. To validate their method, they conducted experiments on an IEEE 5-bus test system network. (Sarwar & Siddiqui, 2016a) introduced a probabilistic method to assess the likelihood of occurrence in congestion management (CM). This method focused on analysing the most crucial lines and evaluated its effectiveness using the IEEE 14-bus system network. The technique alleviate transmission network congestion by rescheduling the active output power of participating generators specifically for congested lines.

The paper by (Tarashandeh & Karimi, 2021) introduced a technique for strategically positioning energy storage systems (ESSs) to alleviate congestion in electric power transmission networks. The authors resolved these multi-objective functions by employing a combination of the generalised algebraic modelling system (GAMS) based security constraint unit commitment (SCUC). The efficacy of this approach was confirmed using the IEEE 24-bus RTS. The GAMS software is used to minimise the running cost of the system, through the use of the SCUC technique. On the other hand, the MATLAB software, using the NSGA-II algorithm, is employed to minimise the investment and storage costs. This approach provides a range of alternatives that are considered Pareto optimal. The authors (Namilakonda & Guduri, 2021a) introduced a new and innovative method called real-time hierarchical congestion management (RHCM). The suggested method alleviates congestion by rearranging the scheduling of generators in two stages, taking into account the Available Congestion Clearing Time (ACCT) of the transmission lines, while considering the existence of renewable energy sources such as solar and wind. The proposed two-stage RHCM approach offers a viable solution to ISO for alleviating congestion by minimising the expense of congestion relief.

(Kim & Hur, 2021) introduced a prospective probabilistic approach that utilises wind power outputs to address the congestion issues in power systems resulting from load fluctuations. To implement and validate the suggested approach, the authors used historical data from wind farms on Jeju Island in South Korea. They fitted the Weibull distribution and conducted Monte Carlo simulations. The authors (Asija & Choudekar, 2021) introduced a mechanism for managing congestion in a deregulated power market on an hourly basis. The authors employed transmission congestion rent (TCR) to ascertain the ideal placement of DGs, while the optimal size of the DGs was established using a hybrid technique combining differential evolution and particle swarm optimisation. The proposed technique was implemented on the IEEE 30-bus test system.

Authors (Roustaei et al., 2022) introduced an innovative method for mitigating congestion (overloading) by utilising transmission switching, which is both cost-effective and efficient. The model was designed to optimise the minimum voltage security index and alleviate congestion in transmission lines. The developed model was used for a 6-bus IEEE test system and a 93-bus real test network, specifically the Transmission network of Fars province in Iran, to demonstrate the accuracy and credibility of the research. (Dehnavi et al., 2022) proposed a novel congestion management approach utilising the power system partitioning technique. The proposed technique utilised a congestion index to identify the lines experiencing congestion. CM was then carried out by finding the candidate zones that could relieve congestion on the essential lines. The concept was applied to an IEEE 39-bus test system.

(Kaushal et al., 2022) presented a probabilistic model for managing congestion in the power grid called the security-constrained optimal power flow (SCOPF). This model is based on the non-linear alternating current (AC) formulation. The proposed method employed a second-order cone (SOC) relaxation to effectively regulate power system devices. The technique was verified using a modified IEEE-118 bus test system, and a comparison was made between the outcomes of the state of charge (soc) and the conventional altern AC power flow. CM approaches can be categorised into two types: technical and non-technical (Androcec & Wangensteen, 2006; Dehnavi et al., 2022). The literature review presents an overview of the latest advancements in managing congestion in transmission networks. It includes both technical and non-technical methods, utilising state-of-the-art devices and innovative algorithms. The findings from various authors in the literature are brief in Table 2.2. Table 2.3 details a comprehensive overview of the advantages and disadvantages of modern methods used to manage transmission congestion.

Table 2. 2: State-of-the-art review on transmission congestion management techniques

TCM techniques used	References	Device used to mitigate TC	Algorithm Used	Validated networks
Technical Methods	(Reddy et al., 2010c)	FACT Devices	Genetic algorithm	IEEE 30-bus network
	(Suganyadevi & Parameswari, 2011)	FACT Devices	Active power performance Index	IEEE 14-bus network
	(Singh & Verma, 2012)	FACT Devices	Cost free approach-based GA	IEEE 30-bus system
	(Malav et al., 2021)	Phase shift transformer	Generalized algebraic modelling system optimization	IEEE 24-bus system
	(Verma et al., 2021)	Phase shift transformer	Generalized algebraic modelling system solver	Modified IEEE 24-bus system
Non-Technical Methods using DGs	(Gope et al., 2016)	Generator rescheduling	Firefly optimization algorithm	IEEE 39-bus system
	(Zakaryaseraji & Ghasemi-Marzbali, 2022)	Demand response	Demand response programs	IEEE 39-bus system
	(Namilakonda & Guduri, 2021a)	Renewable Energy resources	Real-time hierarchical congestion management	IEEE 39-bus system
	(Asija & Choudekar, 2021)	Distributed generation	Hybrid differential Evolution	IEEE 30-bus system
	(Roustaei et al., 2022)	Transmission switching	Transmission switching based cost-effective	IEEE 6-bus and 93-bus Irania system
	(Dehnavi et al., 2022)	System generators and loads	Power system partitioning technique	IEEE 39-bus network
	(Kaushal et al., 2022)	Renewable Energy resources	Probabilistic security-constraint optimal power flow	IEEE 118-bus system

Table 2. 3: Comparison of various congestion management techniques

S/N	CM Techniques	Merits	Demerits
1.	Available Transfer Capacity	Congestion was reduced based on ATC data at the time of dispatch.	When the network load condition exceeds the normal load condition, this approach performs better.
2.	Re-dispatch	Congestion was alleviated by the rise and fall of the generator output regulation, as instructed by ISO.	Suffers from a decrease in generator efficiency levels.
3.	Generation Rescheduling	Congestion is reduced by rescheduling the generator's output power optimally.	Due to changes in the output power of the generators, there is a significant loss of economic profit.
4.	Demand Response	Customers' participation in the operation of the power market reduces congestion. This is accomplished by balancing load from peak to non-peak hours.	The power market's high growth and complex operations.
5.	Distributed Generation	Because of the optimal placement of DG units on the power network, there was a significant reduction in network congestion.	For improved system performance, complex market operation and close monitoring of network security, stability, and dependability are required.
6.	Optimization Techniques	The optimization method optimally mitigates congestion in both difficult and multi-objective systems.	Few of these strategies suffer from computational time depending on the type of optimization.
7.	FACTS devices	Congestion was managed in this case by optimizing the placement of FACTS devices on the power network and managing the power flow on the network.	The incorrect placement of FACTS devices aggravates the network's stability, security, and reliability.

2.2.1 Technical methods

Methods that are technically or cost-free ("cost-free" methods refer to approaches and strategies that do not require additional financial expenditures or investments beyond the existing resources and systems in place. They focus on optimizing, adjusting, or improving the use of current assets and practices to achieve desired outcomes without incurring extra costs). Outages in congested lines are taken into account using this strategy, and no economic impact is involved. The diagrammatic depiction of this strategy is shown in Figure 2.3. This strategy recommends the use of FACTS devices and a phase shifting transformer.

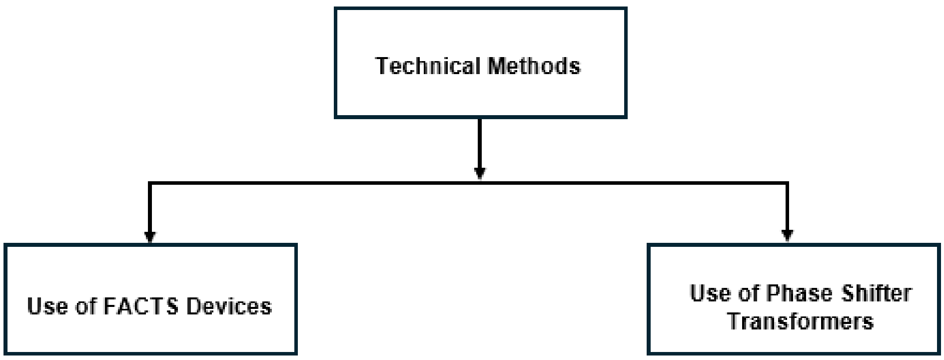


Figure 2. 3: Technical methods of CM

2.2.1.1 Use of FACTS devices

Over the years, advancements in the power electronics area have given rise to FACTS devices, which have significantly contributed to the resolution of many challenges in power systems (Gitizadeh & Kalantar, 2008). These devices contribute to the efficient use of the existing power network by ensuring system security, reliability, and affordability (Zaidan & Toos, 2022). Furthermore, the use of FACTS devices on transmission networks reduces transmission congestion. Subsection 2.3.5 and 2.7 goes into greater depth regarding how FACTS devices are utilized for CM in deregulated electricity networks.

2.2.1.2 Use of phase shifter transformers

The phase shifter transformer (PST), also known as one of the FACTS devices that regulate the physical flow on the power network (Gitizadeh & Khalilnezhad, 2010; Chang et al., 2002). Also, it's one of the FACTS devices that control the physical flow on the power network. It is the appropriate placement on the transmission network resorted to congestion control that provides the system with a free and safe operation condition for successful power delivery to customers.

2.2.2 Non-Technical methods

Methods that are non-technical or free of charge. The economy is the most crucial role to consider here. Demand Response (DR), Generator Rescheduling (GR), Nodal Pricing Schemes (NPS), Load Shedding (LS), and Distributed Generations (DG) are a few common approaches (Wang et al., 2001). The diagrammatic depiction of this strategy is shown in Figure 2.4.

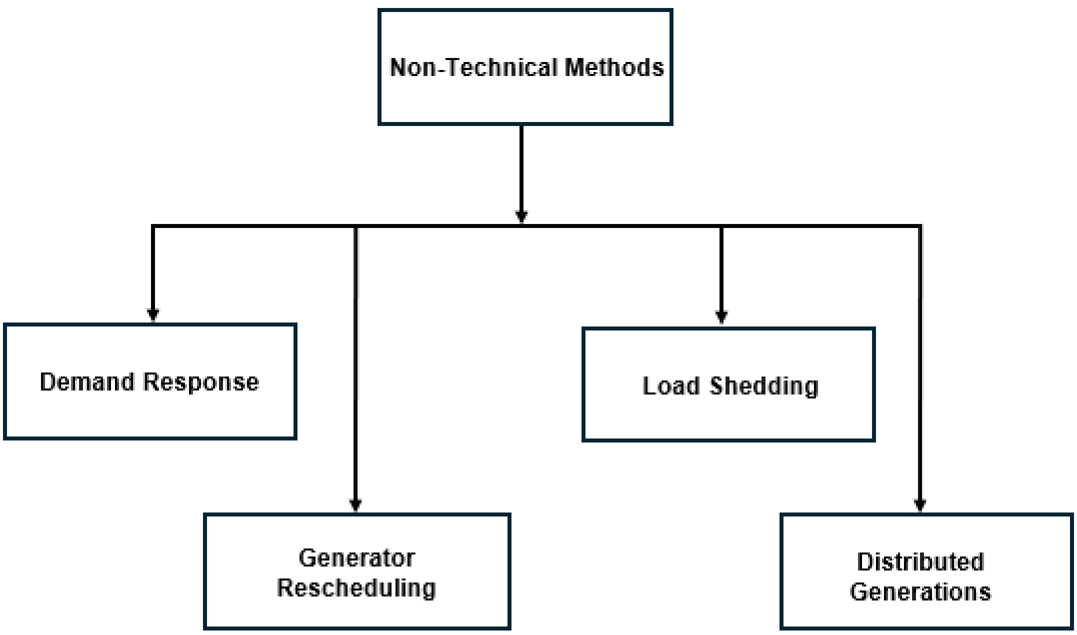


Figure 2. 4: Non-Technical methods of CM

2.2.2.1 Demand response

Demand response (DR) is one of the most successful techniques for reducing transmission congestion (TC). It is sometimes referred to as an incentive or time-based program introduced to encourage end-users to improve their electric usage (Nandini et al., 2014; Dehnavi et al., 2023). The influence of selected load buses on the network is critical to the successful execution of DR programs (Nguyen & Yousefi, 2011; Balijepalli et al., 2011).

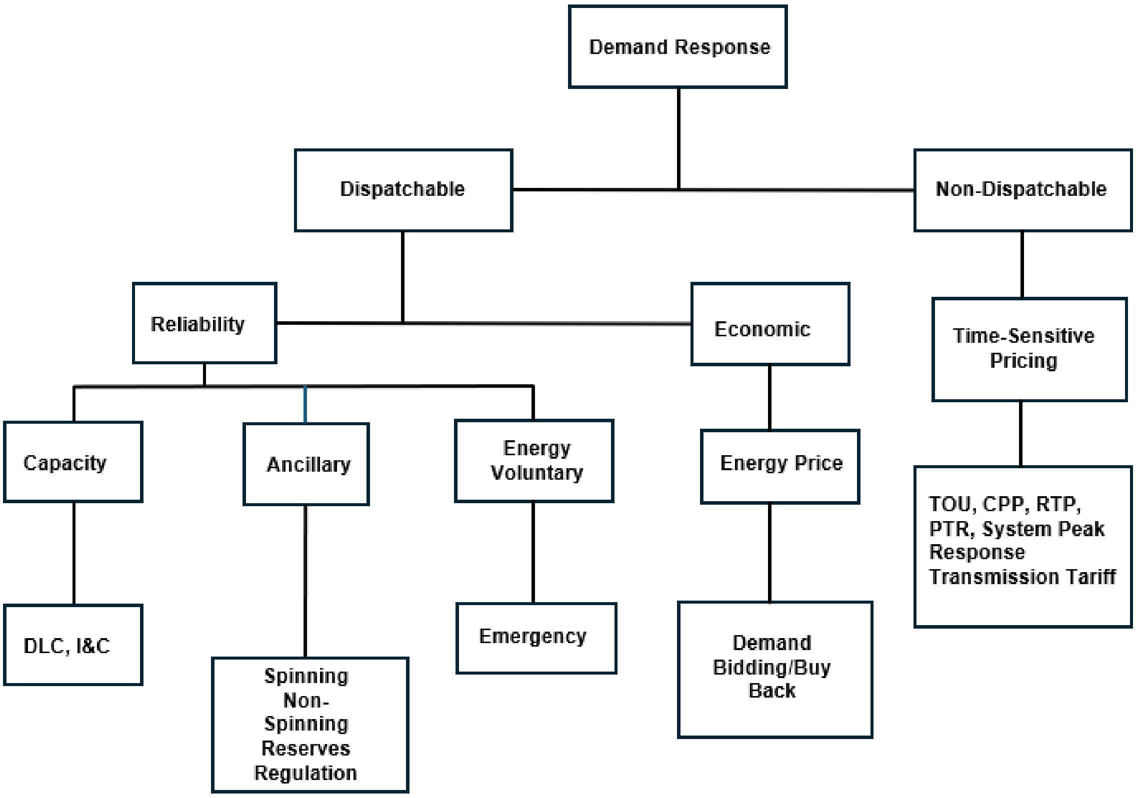


Figure 2. 5: Demand response schemes classification **(Zakaryaseraji & Ghasemi-Marzbali, 2022)**

Any of the sensitivities analysis methodologies are used to make the selection. With technological advancements bringing forth smart grid technology, which aids in the integration of DR through infrastructure of both communication and information into the existing grid. DR serves an important role in the electricity market by balancing demand and supply. Figure 2.5 above depicts the many classifications of DR systems.

2.2.2.2 Generator rescheduling

ISOs ensure that the resulting power flows do not cause line overloading when the generated power is redispatched. Furthermore, ISOs are responsible for bidding for the most efficient manner of balancing the market (Namilakonda & Guduri, 2021a). This, however, may be accomplished by any producing unit by increasing or lowering its output (real and reactive power) (Saraswat et al., 2017). Figure 2.6 depicts the rescheduling bid structure for real power generators. The max and min sides in the generator's net gain and decrement in real power output. Figure 2.7 also depicts the variation in reactive power of the generator output power.

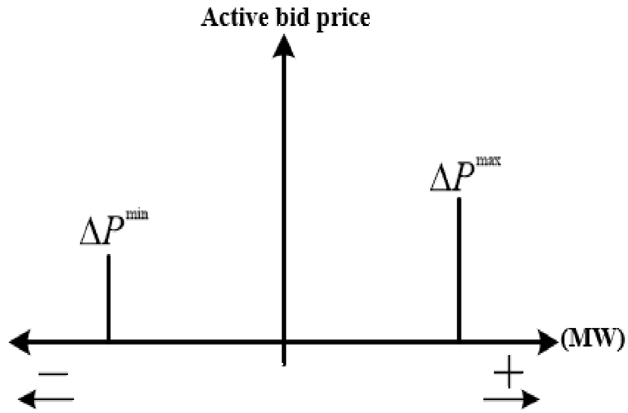


Figure 2. 6: Bid structure for real power rescheduling **(Saraswat et al., 2017)**.

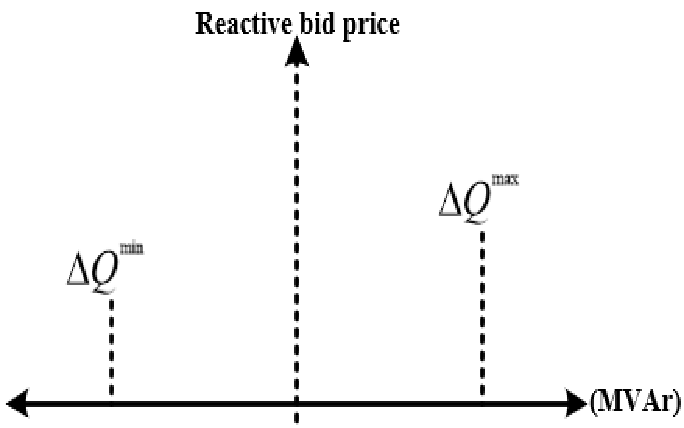


Figure 2. 7: Bid structure for reactive power rescheduling **(Saraswat et al., 2017)**.

2.2.2.3 Load scheduling

This is a mechanism designed to protect the electric power system in the event of a power outage caused by any of the two most important generating units. This type of congestion management becomes highly significant in minimizing congestion in the electric power system network to ensure effective and efficient system performance (Paul et al., 2018).

2.2.2.4 Distributed generation

Power system restructuring has opened the door to the use of Distributed Resources (DRs), such as energy storage devices (ESDs) and distributed generation (DGs), to alleviate congestion in the electric power system network. These devices play a critical role in the planning and operation of electric power system networks. Furthermore, these devices are deliberately and methodically positioned and managed to increase system performance (M. Afkousi-Paqaleh et al., 2010; Mohammad Afkousi-Paqaleh et al., 2010).

2.2.3 Discussion summary on techniques for congestion management

Both technical and non-technical methods have advantages and disadvantages, particularly in terms of how they affect the performance of electric power systems. Economically, the cost-free approach has comparative higher advantages and is thus preferred over the non-cost-free alternatives because the cost involved is modest and has no detrimental impact on the economy or the security system. Also, these approaches are mostly for economic considerations and the presence of a marginal cost of nominal in their applications. The approaches are dominated solely by TSOs, and neither generation nor distribution utilities are involved. The use of any of the free approaches relieves the system by altering the network's topology. With these approaches' incapacity to effect generation and rescheduling in order to minimize load transaction, non-technical methods, also known as non-cost-free methods, are being examined due to their advantages over cost-free methods. These approaches have an impact on creation and rescheduling, they also lower burden transaction. Nonetheless, there are other unique conventional CM approaches that will be explored later.

2.3 Various conventional congestion management methods

This section addresses numerous typical approaches for CM, and Figure 2.8 depicts a diagrammatic representation of various congestion management methods used in electrical power systems:

2.3.1 Available transfer capability-based congestion management

This method estimated the amount of extra power that could be sent over the wires. It can be written as (Adewolu & Saha, 2019; Manohar et al., 2022):

$$ATC = TTC - TRM - \left(ETC + CBM\right) \tag{2.1}$$

where ATC is for Available Transfer Capability, TTC stands for Total Transfer Capability, TRM stands for Total Required Margin, ETC stands for Existing Transfer Commitments, and RM stands for Reserved Margin for Generation Reliability.

ATC is one of the key parameters that is calculated on a transmission line, and it is one of the most basic means of relieving network congestion. Every ISO is responsible for maintaining a record of ATC information for a congested line and updating it on the Open Access Same-time Information System (OASIS) (Kumar & Kumar, 2012).

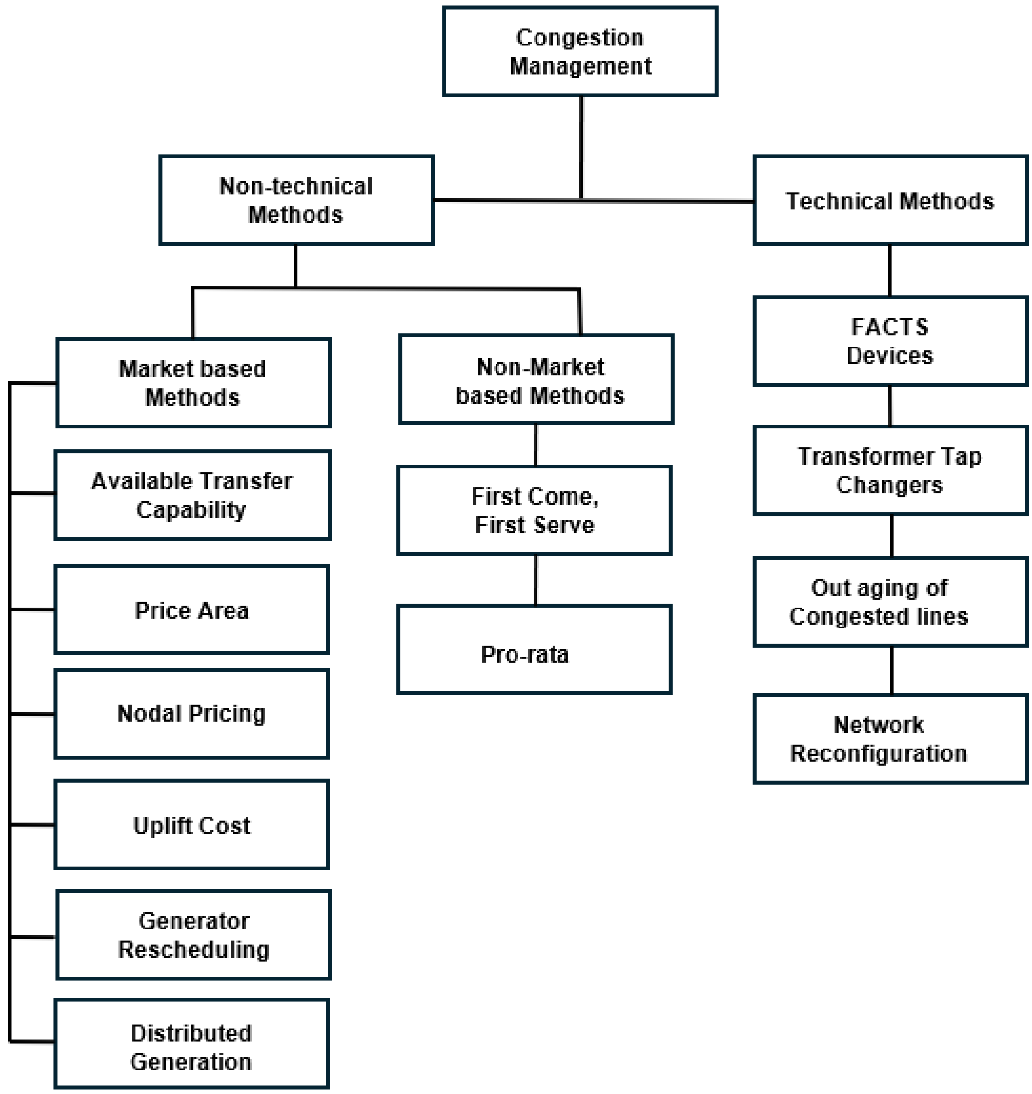


Figure 2. 8: Summary of congestion management methods **(Gumpu et al., 2019)**.

2.3.2 Price area congestion management method

PACM is widely used in nations with bilateral, decentralized, and open access markets, such as Sweden, Finland, Denmark, and Norway (Nordic countries). In addition, in 2003, India adopted this strategy. This strategy entails dividing power into different geographical zones based on load and generator numbers (Rejula & Balamurugan, 2017). This approach consists of two scenarios: congestion (different prices throughout the region) and free congestion (the same price across the region exists). As a result, regions with more than enough generation benefit from price decreases, while those with high demand suffer from price increases. Initially, the system and region prices are estimated based on bids and offers, and when there is more than adequate power among auctioning regions. The capacity cost, which is the difference between the system and area prices, can be used to calculate the additional unit installation. As a result, the power is maintained to be suitable for both high generation and high demand zones based on the line capability.

2.3.3 Nodal pricing method of congestion management

Many countries have established a nodal pricing plan as part of their congestion control strategy. All buses in the grid are classified as a zone (Bjorndal et al., 2014; Gajjala & Ahmad, 2022). This strategy tries to maximize the social welfare of the established market model, which includes several technological and economic characteristics. Nodal rates vary according to geographical location throughout the network. With price modifications, the nodal pricing method is also known as local marginal prices (LMP). This strategy generates large excesses that are used to pay for 'contract rights.' The ability to inject or remove power at any node in the transmission network is a contract right (Nabav et al., 2006).

2.3.4 Uplift cost

The early British (UK) pool has a uniform price in terms of congestion cost when the uplift cost is added. The difference between the total supply price in limited and unconstrained conditions, as well as the security cost, is referred to as the Uplift Cost. Cost increases include an increase in energy, unscheduled availability charges, transmission service enhancements, and a reactive power rise. (Sharma, 2018) contains additional information. The mathematical expression is as follows:

$$PP = SMP + CP \tag{2.2}$$

$$PSP = PPP + Uplift \tag{2.3}$$

where,

SMP means the required unit marginal to satisfy forecast demand period in a market. PPP this means pool leverage price and it's a day ahead calculated price before the main trading day. PSP means the pool sales price. CP represent the available capacity payment, whether or not there is power production by the generator or not. Uplift additional payment for transmission cost and it's the difference between the cost of trading day and the unconstrained schedule. The bid price has already been calculated as a variable cost. Assuming an unconstrained planned environment, a few specific generators were chosen, but due to system constraints that do not allow for generation, adjustment calculations are performed to offset for generators.

$$Adj_{unconstrained}OFF = (Capacity - Generation)*(PPP - Bid\ \ \mathrm{Pr}ice) \tag{2.4}$$

As a result, when the initial timetable conflicts with security limits, it must be postponed. During the rescheduling process, the generator is frequently paid a PPP fee that is less than the bid price. The calculation of the amount of adjustment required can be expressed as follows:

$$Adj_{constrained}ON = (Capacity - Generation)*(PPP - Bid\ \ \mathrm{Pr}ice) \tag{2.5}$$

The adjustment cost is then admitted to the generator revenue.

$$Generator\ income = (Capacity) * (PPP) + Adjustment \tag{2.6}$$

2.3.5 FACTS devices for congestion management

Traditionally, there are two types of CM in both unbundling and bundling power systems: cost free and non-cost free. Because they do not involve economic inequity, cost-free approaches are the most commonly and often utilized strategies for congestion management. According to (Hoseynpoor et al., 2011; Tembhurnikar et al., 2014), FACTS devices are classified into three types: series controllers, shunt controllers, and a mix of series and shunt controllers. The series controllers type FACTS devices TCSC, SSSC, and TCPAR are used to boost the transfer capabilities of the lines by ensuring power flow and easing line overloads. The STATCOM and SVC FACTS devices, which are shunt controllers, are used to correct voltages on low voltage buses by injecting or absorbing reactive power. The final category, UPFC, which is a combination of both series and shunt FACTS devices, is utilized to reduce transmission line congestion while also improving the voltage profile of the line. Figure 2.9 depicts a basic TCSC architecture for network relief on a transmission network.

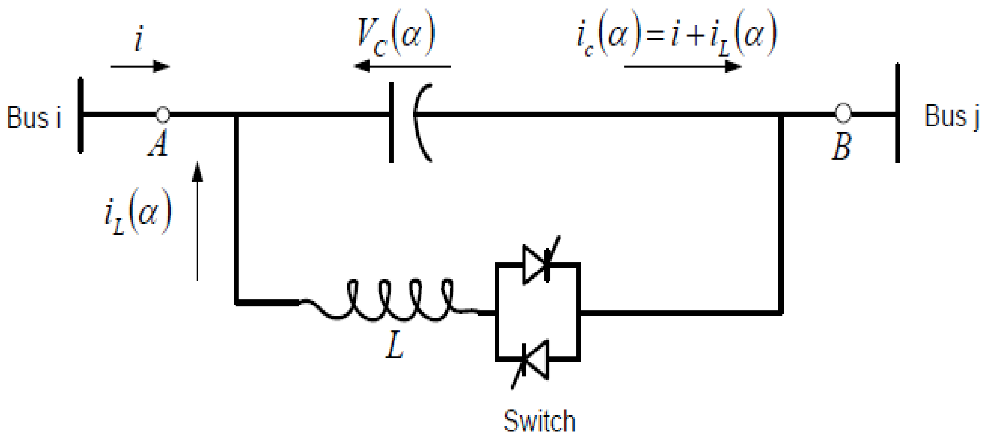


Figure 2. 9: Basic schemes for thyristor control series capacitor **(Babatunde Olusegun Adewolu & Saha, 2020)**.

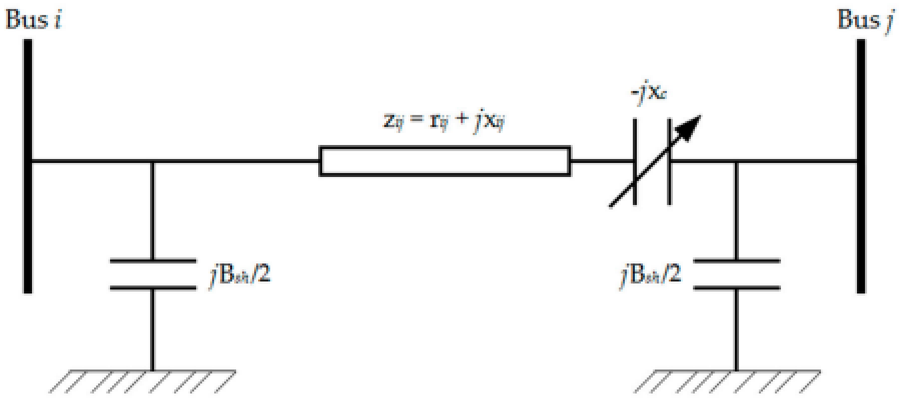


Figure 2. 10: Transmission line π equivalent post TCSC integration

From Figure 2.10, the OPF equations for both active and reactive power at bus i and j is stated as:

$$P_{ij} = V_i^2 G_{ij} - V_i V_j \left(G_{ij} cos\delta_{ij} + B_{ij} sin\delta_{ij} \right) \tag{2.7}$$

$$Q_{ij} = -V_i^2 \left(B_{ij} + B_{sh} \right) - V_i V_j \left(G_{ij} sin\delta_{ij} - B_{ij} cos\delta_{ij} \right) \tag{2.8}$$

In the presence of TCSC, both equation (2.7) and (2.8) can be further written as:

$$P_{ij}^c = V_i^2 G'_{ij} - V_i V_j \left(G'_{ij} cos\delta_{ij} + G'_{ij} sin\delta_{ij} \right) \tag{2.9}$$

$$Q_{ij}^c = -V_i^2 \left(B'_{ij} + B_{sh} \right) - V_i V_j \left(G'_{ij} sin\delta_{ij} + B'_{ij} cos\delta_{ij} \right) \tag{2.10}$$

Where,

P_{ij}, Q_{ij}	are active and reactive power flow at buses ij
V_i, V_j	are the voltage at buses ij
G_{ij}, B_{ij}	are the conductance and susceptance between the lines
δ_{ij}	is the phase angle at buses ij

2.3.6 Discussion summary on various conventional congestion management methods

This section and its sub-sections provide details information of traditional congestion management (CM) strategies such as Technical and Non-Technical methods. Market design schemes, which have a significant impact on congestion management, are separated into market-based and non-market-based strategies. More emphasis is placed on market-based solutions to promote fairness and economic efficiency. Market-based methods include the methods outlined in subsection 2.3. While non-market-based solutions do not contribute to the pricing scheme's efficiency. Table 2.3 details a well comparison amongs the various CM techniques with their merits and demerits. CM is a non-linear solution that involves several variables and whose solution can be found using an optimization technique. Based on the state-of-the-art review on transmission CM, Table 2.2 details a comprehensive review on application of optimization algorithms for both Technical and Non-Technical CM methods for the purpose of congestion management in an electrical power system networks.

2.4 Optimal power flow

Optimal power flow (OPF) is a crucial tool for network operators during both the operating and planning stages. To maximise an objective function in an Optimal Power Flow, it is necessary to determine the values of all the control variables (Kaushal et al., 2022). The problem should be delineated with clearly stated objectives from the beginning. The objective function can be defined in several ways, including considering transmission losses, allocating reactive sources, and accounting for fuel costs (Bindeshwar Singh et al., 2012; Milano, 2010; Frank et al., 2012).

The target function to be minimised is the overall production cost of scheduled generating units. It is primarily used because it accurately represents the current economic dispatch practice and places significant importance on cost-related factors, which are consistently recognised as a top priority in Power Systems' operational requirements. The primary aim of OPF is to minimize a particular objective, while simultaneously complying with the constraints imposed by the system's load flow equations and the operational limits of the equipment. The optimal solution is achieved by modifying the controls to maximise an objective function while adhering to security requirements and defined operating conditions (Demirovic, 2016; Shankaralingappa & Jangamashetti, 2008)

2.5 Power flow optimal solution methods

Several techniques have been suggested and utilised to solve OPF in power networks. There are two main categories that are recognised, namely intelligent and traditional (conventional) approaches. The drawbacks of conventional methods need the utilisation of artificially intelligent algorithms (Varma & Paserba, 2017). The comprehensive perspectives of the aforementioned techniques are thereafter outlined.

2.5.1 Conventional solution methods

The conventional or classical methodologies are also referred to as deterministic approach optimisation strategies. The examples include Linear Programming (LP), Quadratic Programming (QP), Lagrangian Relaxation Algorithm (LRA), Non-Linear Programming (NLP), and Interior Point (IP) Methods. These standard strategies are commonly used, particularly in cases when the search space is non-linear (Al-Hajri et al., 2015).

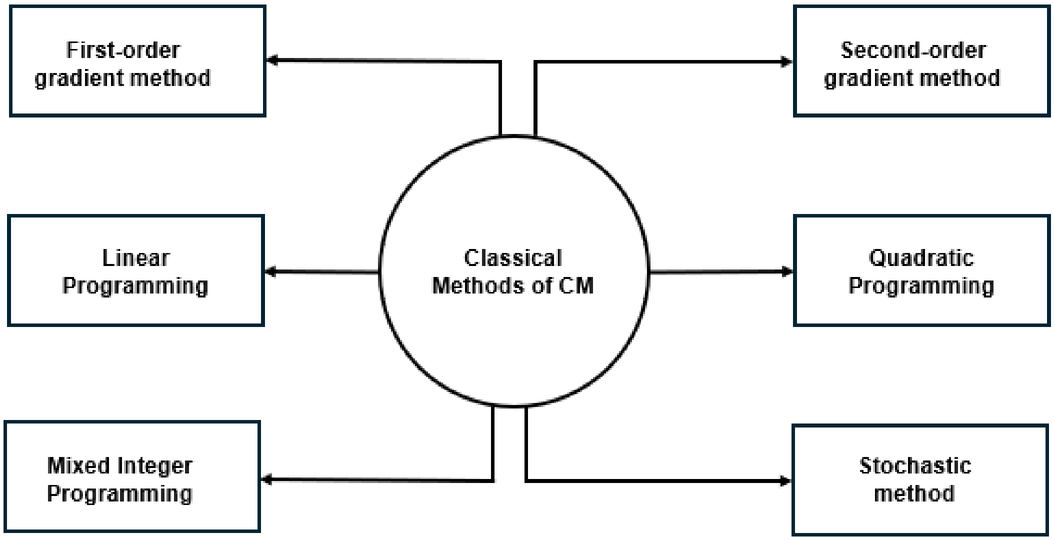


Figure 2. 11: Classical methods classification

Although there have been significant scholarly breakthroughs in classical techniques, they nevertheless have limitations when it comes to their implementation. Some of the reported restrictions include (Priyankara et al., 2017):

(i) Inadequate convergence.

(ii) The solution is quite resource-intensive in terms of computation.

(iii) Discovering a singular optimised solution and addressing the limitations of operational constraints are somehow tedious.

Most deterministic optimization methods are viewed as local search methods because they are known for producing the same set of solutions if the algorithm starts under the same initial conditions (Gupta & Sharma, 2012).

2.5.2 Intelligent solution methods

Intelligent methods, commonly referred to as metaheuristic optimisation methods, are founded on the principles of artificial intelligence. Some examples of optimisation algorithms include Cuckoo Search Algorithm (CSA), Bacterial Foraging (BF), Particle-Swarm Optimisation (PSO), Artificial Bee Colony (ABC), Evolution Programming (EP), Firefly Algorithm (FA), Differential Evolution (DE), Harmony Search (HS), and Tabu Search (TS) (Prashant et al., 2022). Researchers have shown that these algorithms are endowed with good convergence rate (Sirjani et al., 2012; Satyanarayana Rao & Reddy, 2015; Jena et al., 2018). Figure 2.12 depict the classification of various metaheuristic optimization techniques and they are more details in subsection 2.6.2.

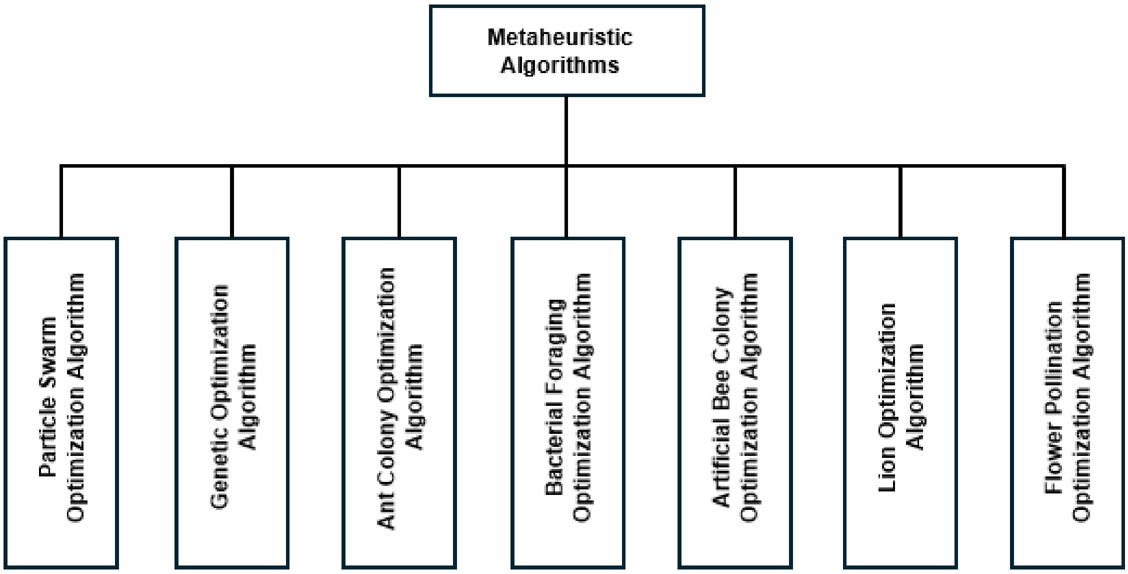


Figure 2. 12: Metaheuristic optimization algorithms classification

(i) High convergence rate.

(ii) Capacity to achieve global solutions in the most efficient timeframe.

(iii) Highly effective ability for managing intricate systems.

Table 2.4 presents a comparative analysis of different intelligent approaches for handling OPF problems, highlighting their respective advantages and disadvantages.

2.6 Solving congestion problems using optimization methods

Several research investigations have been carried out in the field of CM in deregulation and power system reorganization. In the literature, the most prevalent CM solution techniques in power system deregulation and restructuring were reported. This section examines some of the research done in this field.

2.6.1 Classical/Analytical methods for congestion management

This sub-section reviews various classical or conventional methods that are available for performing computational analysis for solving different problems that are related to power flow in deregulated power systems. Figure 2.11 depict the classification of various classical techniques.

2.6.1.1 Sensitivity analysis

In (Singh et al., 2010), a strategy based on bus impedance matrix (BIM) sensitivity was presented to reduce the issue of CM in deregulated networks. The sensitivity of line flow for congested lines was investigated using BIM. The approach's trenchancy was demonstrated on IEEE 14 and 30 bus test systems, and the findings were compared to those of a standard Jacobean matrix-based approach. To alleviate congestion, (Khemani & Patel, 2011) suggested a method based on sensitivity variables and a generation scheduling idea. And the generator's influence on congested lines is used to relieve congestion by rescheduling the generator. The method was tested on the IEEE 30 and 39 bus New England System.

(Zarco-Soto et al., 2021) presented a sensitivity CM technique for active distribution networks. To investigate the origins and propagation of mistakes, an analysis of errors linked with sensitivity was performed. This method was tested on a standard European transmission network. A technical-economic indices method was proposed in reference (Tina et al., 2019) to evaluate the transmission loading relief (TLR) sensitivity analysis. On the IEEE 24 bus system, the procedure was validated. By picking the loads bids, congestion on the line was reduced.

To address the CM issue, (M. Afkousi-Paqaleh et al., 2010) proposed a Monte-Carlo technique. The influence of load uncertainty, ideal location, and size of dispersed generations in the network were all modelled using this method. The method has been validated against the IEEE Reliability Test System (RTS). (Sidea et al., 2017) presented a strategy for optimal phase shifting transformer (PST) allocation. The approach determines which transmission lines will be crowded under normal and N-1 operating conditions based on the PST tap position range.

2.6.1.2 Mixed integer programming

In (Zhang et al., 2021), a mixed integer technique was presented to alleviate overloading (congestion) for improved system stability and safety. On the IEEE 118 bus test system, the procedure was validated. (Jiang et al., 2010) presents a novel optimal CM quoted price adjustment approach. Changes to CM were made based on the max-mini hypothesis, which states that when transmission congestion is at its most, the adjustment cost is at its lowest.

(Straub et al., 2018) offered a local method-based renewable energy integration for CM. This strategy was proven on the French transmission network (RTE), which is congested due to the substantial integration of renewable energy. In (Khanabadi & Ghasemi, 2011), the transmission switching approach was used for CM. The technique was implemented using mixed integer programming (MIP) and was initiated as a DC optimal power flow (DCOPF) using binary variables. In (Sagwal & Kumar, 2016), a CM based on Voltage Stability Margin (VSM) was presented, taking into account hybrid (wind and hydro) power plants. On a modified 24 bus RTS system, the method was validated. (Pal & Sengupta, 2014) proposed a paradigm for day-ahead computation bandwidths. The French Transmission System Operator (RTE) was used for battery operation and framework certification. The bandwidths represent safe operating zones for grid scheduling.

2.6.1.3 Stochastic optimal power flow

(Bae et al., 2016) offered a frequency regulation approach. The author considered CM in the transmission network based on the price signal. The approach was experimented on the IEEE 39 bus system. (Li & Xia, 2019) proposed an improved stochastic optimum power flow (SOPF) approach. The suggested method demonstrates that network reconfiguration can be used for CM in post-contingency situations while also resulting in a reasonable reduction in CM cost. For CM, a generation rescheduling-based responsive bid was presented in (Sarwar et al., 2019). The sensitivity of the generators was used to choose the participating generators.

(Mahdavi & Rouhinia, 2019) proposed a strategy for installing distributed energy resources that takes voltage profile enhancement and CM into account. To avoid grid congestion, the OpSim co-simulation architecture was introduced in (Meibner et al., 2019). The method was tested on a real network of Brunsbuttel in Northern Germany, and the findings proved that the method functioned better and more effectively. The Table 2.4 below gives detail review on various classical methods:

Table 2. 4: Detail review on various classical methods

Classical methods	Reference	Objectives	Test system	Research Gap & Findings
Linear Programming	(de Oliveira et al., 2022)	Generator redispatch for transmission congestion management.	IEEE 118 test system network.	Only considered redispatch of active power output.
	(Mhanna & Mancarella, 2022)	Solution to optimal power flow problem for easy generation of locational marginal prices (LMP)	IEEE distribution test system with 33-nodes, 69-nodes, and 119-nodes.	The proposed method was adaptable to distribution network
Quadratic Programming	(Ghaderi et al., 2021)	Prediction of an efficient energy management and minimization of hydrogen consumption.	Muti-stack fuel cell hybrid electric vehicle.	The method can only work for a three-wheel electric vehicle (Tri-cycles)
	(Welhazi et al., 2022)	Power system design based on optimum coordination of SVC and PSSs.	Validated on a benchmark function.	The work only considered SVC type of FACTS devices

Interior Point Method	(Delgado et al., 2022)	Minimization of active power loss through optimal power flow solution.	IEEE 30, 57, 118, and 300 bus test systems	Authors did not considered Voltage profile enhancement
	(Kardoš et al., 2022)	Performance comparison of BELTISTOS and interior point method for a large-scale power system network.	A large-scale power networks up to 193,000 buses.	The proposed method lack computational efficiency
Mixed-Integer Programming	(Kumar et al., 2021)	Determination of optimal location of Phasor Measurement Unit for complete observability in deregulated power system for smart grid	IEEE 14, 30, 39, 118, and NRPG 246 bus system.	The proposed technique works only for online system
	(Li et al., 2022)	Mathematical formulation of generation and transmission expansion planning in power systems.	Electricity Reliability Council of Texas (ERCOT) nework	The authors only considered renewable generation as the case study.

2.6.1.4 Discussion summary on classical congestion management methods

Analytical approaches have been obsolete due to advances in the computational area, and novel and effective metaheuristic optimization algorithms (MOAs) have been employed to replace analytical methods due to their enormous computational size and speed of implementation. Table 2.4 above details an eye-bird review of various classical methods showing their key research findings and gaps. The novel MOAs approaches and their application to congestion problems in deregulated electricity networks are addressed more below.

2.6.2 Metaheuristic algorithms solution methods

Congestion management (CM) has always been the most important issue in a restructured power system or a deregulated market. CM is one of the solutions that involves a non-linear program, and it may be solved using a variety of numerical optimization strategies. The following sub-sections explain various sorts of optimization strategies and their details:

2.6.2.1 Particle swarm optimization method

Kennedy and Eberhart (Clerc, 2010; Mahala, 2016; Okelola et al., 2021), contributed PSO to the body of knowledge in 1995. It was inspired by the behavior of flocking and swarming birds. The velocity vector and position vector are the two vectors that are related to each particle (Vatambeti & Dhal, 2020). Individual particles change their location based on their own experience (Personal best (Pbest)) as well as the position of their neighbors (Global best (Gbest)). PSO is frequently utilized as an optimization approach to handle a variety of issues in various fields of study. PSO was used in (Muneender & Vinodkumar, 2012) to manage congestion on a crowded transmission network utilizing the Newton-Raphson (NR) approach. On an IEEE 30-bus test system, the approach was validated. The reference (Gaonkar et al., 2018) described a sensitivity-based PSO algorithm CM technique for reducing congestion on an electric power network. The objectives examined were voltage improvement and cost reduction. On an IEEE 14-bus test system, the approach was validated. Figure 2.13 depicts the PSO search mechanism in a multidimensional search space. Assuming an n dimensional search space S with N number of particles, with instant k. The particle position defined as $\boldsymbol{X_k^i}$ and velocity as $\boldsymbol{V_k^i}$ at S space. Therefore, both velocity and position of each particle for the future generation can be expressed as (Vatambeti & Dhal, 2020):

$$\boldsymbol{V_{k+1}^i = w \times V_k^i + c1 \times rand() \times \left(P_k^i - X_k^i\right) + c2 \times rand() \times \left(P_k^g - X_k^i\right)} \tag{2.11}$$

$$\boldsymbol{X_{k+1}^i = X_k^i + X_{k+1}^i}, \ \forall \boldsymbol{i = 1, 2 \ldots\ldots.. N} \tag{2.12}$$

Where,

$\boldsymbol{V_{k+1}^i}$	new velocity
$\boldsymbol{P_k^i}$	particle location
$\boldsymbol{P_k^g}$	best particles location among the neighbors
$\boldsymbol{X_k^i}$	particle position
$\boldsymbol{w}$	inertia weight
$\boldsymbol{c1 \ and \ c2}$	the learning factors
$\boldsymbol{rand}()$	the random numbers

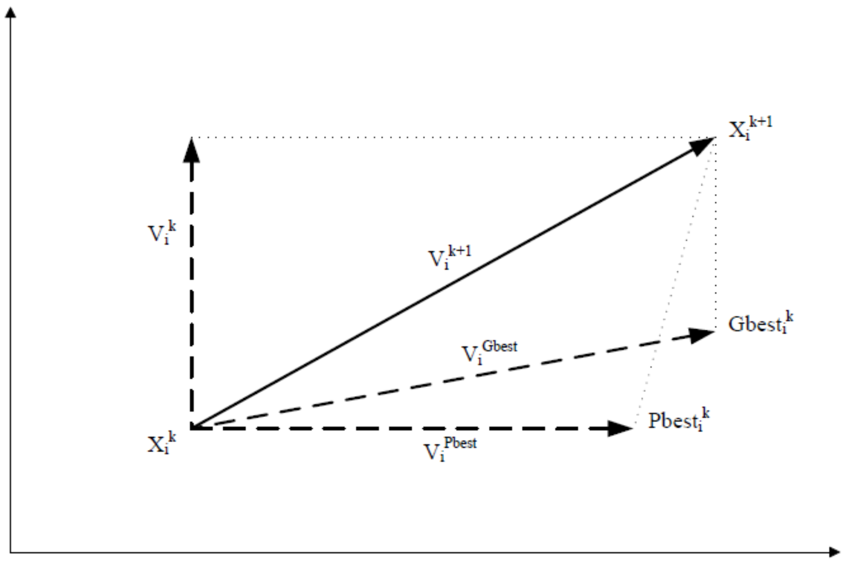


Figure 2. 13: PSO search mechanism in multidimensional search space

2.6.2.2 Genetic algorithm method

GA was inspired by Charles Darwin's theory of evolution. GA, like PSO, is used to tackle non-linear problems (Ramírez & Giovanni, 2004; Granelli et al., 2006). GA was defined by the notion of chromosomes as the process of selecting individuals for their fitness for reproduction of offspring of the next generation. Individuals are chosen at random from a group in GA to bear the following generation's children. In (Sharmila et al., 2020), GA was used in an electrical power system (EPS) to solve a congestion problem. The method was employed to address difficulties connected to the power system's poor performance and growth. This was overcome by defining the chromosomes. In GA, the operators of reproduction, crossover and mutation are applied successfully to generate the offspring. For two parent solutions of $\boldsymbol{X_i^{(1,k)}}$ and $\boldsymbol{X_i^{(2,k)}}$, the generated offspring can be expressed mathematically as (Granelli et al., 2006):

$$\boldsymbol{X_i^{(1,k+1)} = (1-\gamma_i)X_i^{(1,k)} + \gamma_i X_i^{(2,k)}} \tag{2.13}$$

Where,

$\boldsymbol{X_i^{(1,k)}, X_i^{(2,k)}}$	two parent solutions
$\boldsymbol{X_i^{(1,k+1)}}$	newly generated offspring
$\boldsymbol{\gamma_i}$	crossover that generate random solution range

2.6.2.3 Ant colony optimization method

M. Dorigo developed the ACO algorithm, which is a nature-inspired metaheuristic optimization technique for solving combinatorial optimization (CO) (Dorigo & Blum, 2005; Dorigo & Gambardella, 1997). Because of the inspired foraging behavior of ants in search of food, and then evaluating the quantity and quality of the food before taking some of it into the nest, and then dropping trail chemical component of the food on the path back to the nest as a communication medium to direct others. This ant behavior is employed in artificial ant colonies to solve optimization problems (Kuang & Huang, 2012). ACO can be defined as stochastic search procedures, in which their pheromone model uses probability search space as their central component. Figure 2.14 depict the ACO pseudocode framework.

Algorithm 1 The framework of a basic ACO algorithm

input: An instance P of a CO problem model $\mathcal{P} = (\mathcal{S}, f, \Omega)$.
InitializePheromoneValues($\mathcal{T}$)
$\mathfrak{s}_{bs} \leftarrow$ NULL
while termination conditions not met **do**
  $\mathfrak{S}_{iter} \leftarrow \emptyset$
  for $j = 1, \ldots, n_a$ **do**
    $\mathfrak{s} \leftarrow$ ConstructSolution($\mathcal{T}$)
    if $\mathfrak{s}$ is a valid solution **then**
      $\mathfrak{s} \leftarrow$ LocalSearch($\mathfrak{s}$)   {optional}
      if $(f(\mathfrak{s}) < f(\mathfrak{s}_{bs}))$ or $(\mathfrak{s}_{bs} =$ NULL$)$ **then** $\mathfrak{s}_{bs} \leftarrow \mathfrak{s}$
      $\mathfrak{S}_{iter} \leftarrow \mathfrak{S}_{iter} \cup \{\mathfrak{s}\}$
    end if
  end for
  ApplyPheromoneUpdate($\mathcal{T}, \mathfrak{S}_{iter}, \mathfrak{s}_{bs}$)
end while
output: The best-so-far solution $\mathfrak{s}_{bs}$

Figure 2. 14: Basic ACO pseudocode framework **(Dorigo & Blum, 2005)**

2.6.2.4 Bacterial foraging optimization method

(Panigrahi & Ravikumar Pandi, 2009; Passino, 2010; Chen et al., 2014) are the pioneers of the BFO algorithm in evolution theory. Based on the behavior of bacteria known as E. coli, the BFO approach can be better described. E. coli bacteria live in the human gut in four ways: chemical taxis, elimination-dispersal, crowding, and reproduction. Chemotaxis, a foraging action performed by microorganisms, inspired the algorithm. They interact with their companions by sending signals, and they always retain their energy level at its peak while foraging. With a broad range of applications (for distributed optimization and control) and widespread acceptance, BFO is similar to optimization techniques such as PSO, GA, and ACO (Venkaiah & Vinod Kumar, 2011) presented CM based on optimal power flow analysis, with the goals of reducing congestion, increasing voltage, and reducing line losses. Line available capacity is assessed and monitored for congestion in wheeling transactions. On an IEEE 30-bus test system, the approach was validated. In BFO model, there are four basic mechanisms which are; swarming, elimination dispersal, reproduction, and chemotaxis. The mathematical expression for both chemotaxis and swarming mechanisms are expressed in equations (2.14) and (2.15), respectively.

$$\boldsymbol{\theta^i(j+1,k,l)=\theta^i(j,k,l)+C(i)}\frac{\Delta(\boldsymbol{i})}{\sqrt{\Delta^{\boldsymbol{T}}(\boldsymbol{i})\Delta(\boldsymbol{i})}} \tag{2.14}$$

$$\boldsymbol{J_{cc}\left(\theta^i(j,k,l),\theta(j,k,l)\right)=\sum_{t=1}^{s}J_{cc}^{t}(\theta^i,\theta)} \tag{2.15}$$

Where,

$\boldsymbol{j,k, and\ l}$ are chemotactic, reproduction, and elimination corresponding error values.

$\Delta(\boldsymbol{i})$ is the random swim direction vector, and

$\boldsymbol{C(i)}$ is the running length vector.

2.6.2.5 Artificial Bee Colony Algorithm Method

The ABC algorithm was developed in 2005 based on the cognitive behavior of bees (Karaboga & Basturk, 2007; Karaboga & Akay, 2009). For numerical problem optimization, the approach is a population-based metaheuristic optimization. This optimization strategy incorporates both local and global exploration methods for finding optimal solutions to issues, and it is commonly used in congestion management (Saranya et al., 2015). The rescheduling of selected generators was proposed by (Deb et al., 2013) as a method of congestion control based on the ABC algorithm. To begin, the power transfer distribution factor (PTDF) was calculated for wind farm allocation. The program was able to minimize the number of participating generators and then reschedule them using the generator sensitivity factor (GSF). The technique's effectiveness was validated using the IEEE 39-bus test system. In the ABC algorithm, an onlooker be chooses a food source depending on the probability value associated with the food source, which is estimated mathematically as:

$$\boldsymbol{P_i=\frac{fit_i}{\sum_{n=1}^{SN}fit_n}} \tag{2.16}$$

The ABC algorithm utilises the mathematical expression stated in equation (2.17) to generate a new food position candidate from the existing one stored in memory.

$$\boldsymbol{V_{ij}=X_{ij}}+\emptyset_{\boldsymbol{ij}}\boldsymbol{(X_{ij}-X_{kj})} \tag{2.17}$$

Where,

$\boldsymbol{P_i}$ food source probability value

$\boldsymbol{fit_i}$ represent the fitness value of the solution

$\boldsymbol{SN}$ is the number of food search, equal employed bees number

$\boldsymbol{k\ and\ j}$ are random chosen index

$\emptyset_{ij}$ random number between [-1, 1]

2.6.2.6 Lion algorithm method

Lion Algorithm (LA) was designed as a new population-based algorithm based on the social behavior of lions (Rajakumar, 2012; Rajakumar, 2014; Wang et al., 2012). Lions have a distinct personality among the numerous species of wild cats, expressing opposition and collaboration. Lions are divided into two types (Srivastava & Yadav, 2022): inhabitants and nomads. The resident lions were discovered in groups and are also known as prides. Five females with pups of both sexes are present in each pride group. Females attending to males in the group result in the birth of children. In the case of nomads, lions can be encountered either in groups or alone. The ideal answer for LA is found based on two lion special characters. In reference (Tapre et al., 2018), the LA approach was presented to reduce the cost of rescheduling for CM. On an IEEE 30-bus test system, the approach was validated. When compared to other optimization strategies, the algorithm showed to be more effective and efficient in terms of results. Figure 2.15 displays the LA for rescheduling-based CM.

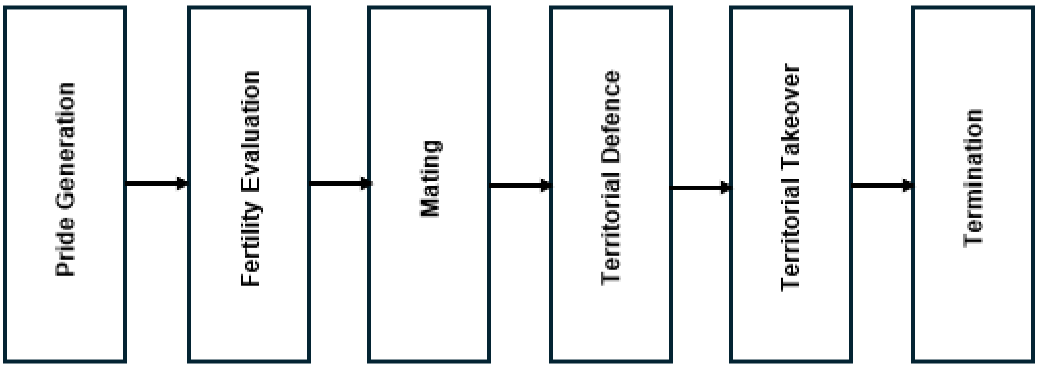


Figure 2. 15: Lion algorithm flow diagram

2.6.2.7 Flower pollination algorithm method

The concept of how plants reproduce through a process known as pollination prompted Xin-She Yang to create the Flowering Pollination Algorithm (FPA) in 2012 (Abdelaziz et al., 2016; Peesapati et al., 2018). Pollination occurs by the transmission (with the help of birds and insects) of pollen grains formed by the union of male gametes to the stigma. Plants pollinate in two ways: biotically and abiotically. It is the agents that aid in the transport of pollen grains in biotic form, and this form accounts for around 90% of pollination. Abiotic pollination, on the other hand, happens through external forces such as diffusion and wind. (Deb & Goswami, 2016) developed a new congestion control method based on FPA. To choose the specific generator involved in the congestion process, the generator sensitivity factor was calculated. To manage congestion and reduce rescheduling costs, the generator's output was rescheduled using the flower pollination algorithm (FPA). The technique was carried out and its usefulness was demonstrated using the IEEE 39-bus New England system. In FPA, the global pollination step and flower constancy procedure can be written mathematically as:

$$\boldsymbol{X_i^{t+1} = X_i^t + \gamma L(\lambda)(g_* - X_i^t)} \quad (2.18)$$

Where,

$\boldsymbol{X_i^t}$ is the pollen solution vector

$\boldsymbol{\gamma}$ is the scaling factor

$\boldsymbol{g_*}$ is the current best solution

$\boldsymbol{L(\lambda)}$ is the corresponding parameter to the pollination strength

2.6.3 Discussion summary on metaheuristic optimization algorithms methods

Artificial intelligence approaches (optimization algorithms) are strategies for tackling various problems in electric power system networks in the most efficient way possible. When it comes to resolving congestion concerns (congestion management) in electric power networks, optimization methods play a critical role. Subsection 2.6.2 provides detailed information on several types of optimization algorithm methods and how they are utilized to reduce congestion in electric power system networks. The Table 2.5 below gives a comprehensive review on various metaheuristic optimization methods with their key findings and research gaps.

Table 2. 5: Comparison of metaheuristic optimization algorithms

Meta-heuristic Optimization Algorithms	Findings	Research gap
Particle Swarm Optimization (PSO)	• The concept is easy to implement. • Parameter control is higly efficient and requireds minimal memory usage	When dealing with highly constrained situations, it becomes stuck in local optima due to its restricted ability to search locally or globally. To overcome the problem of PSO getting stuck in local optima, you can use a combination of hybrid algorithms, adaptive mechanisms, enhanced exploration techniques, multi-start strategies, constraint handling, and advanced PSO variants. By integrating these strategies, you can improve the ability of PSO to explore the solution space more effectively, avoid local optima, and find better solutions in highly constrained optimization problems.

Ant Colony Optimization	• Relevant to a wide variety of optimisation challenges. • Ants' ability to move simultaneously and independently without supervision makes them suitable for dynamic parallel applications.	Due to the challenges associated with theoretical analysis, research is conducted using experimental methods instead of relying solely on theoretical approaches.
Artificial Bee Colony	• Needed less values. • It has worldwide usage. • High flexibility	Lengthy computational duration
BAT Algorithm	• Offers a high level of adaptability and is easy to integrate. • Has a minimal number of control parameters.	Rapidly transitioning from the exploration stage to the exploitation stage could result in stagnation after the initial phase..
Grey Wolf Optimization	• The structure of the system allows for simple implementation. • Requires a minimal number of parameters.	The algorithm is currently being researched and developed.
Bacterial Foraging Optimization Algorithm	• The algorithm achieves global convergence, hence preventing premature convergence. • Utilization in a broad range of nonlinear functions and ability to manage a greater number of objective functions.	The biassed random walk of the swarming effect leads to an inferior performance for the ELD issue.
Firefly Algorithm	• The rate of convergence is rapid and significantly more straightforward.. • The hybridised version of APSO, HS, SA, and DE is being referred to FA	The algorithm may become stuck in local optima if the values are not properly configured.
Shuffled Frog Leaping Algorithm	• It is precise, sturdy, and effective. • The approach combines the profits of the local search tool of PSO and incorporates the concept of blending information from concurrent local searches to provide a global solution.	Experiences difficulty escaping local optima and achieves convergence to the desired aim at a late stage.
Genetic Algorithm	• The ability to work with parameter set coding allows for efficient handling of integer or discrete variables.	As a stochastic algorithm, it is tough to precisely specify convergence requirements because of the nature of the algorithm.

2.7 Optimal placement of FACTS devices for congestion management

The authors (Reddy et al., 2010a) presented a technique for spotting the most favourable position and dimensions of series FACTS devices using GA for contingency management. The method was confirmed successfully on an IEEE 30 bus test system by analysing the impact of TCSC. It was verified that the network with TCSC alleviated congestion. The authors (Suganyadevi & Parameswari, 2011) proposed a method for strategically placing FACTS devices in power systems to better the performance and overcome technical challenges associated with CM in the context of power system deregulation. The method was verified on an IEEE 14 bus test setup using MATLAB Simulink.

(Singh & Verma, 2012) proposed a method that uses Genetic Algorithms (GA) to allocate FACTS devices in a deregulated electricity system. This approach aims to reduce congestion and achieve the global optimal solution without incurring any additional costs. Due to the nonlinearity of the objective function in congestion management, it was resolved using a GA. The effectiveness of this method in a real-world practical system was proved utilising an IEEE 30 bus test system. (Anwer et al., 2012) demonstrated the effectiveness of integrating Power Oscillation Damper (POD) with FACTS devices (SSSC and UPFC) in mitigating power system congestion. The proposed approach successfully alleviated the congestion in the lines while simultaneously enhancing their power capacity. (Gupta et al., 2018) employed the TCSC technique to mitigate congestion on heavily overloaded transmission lines. The technique was validated using a modified IEEE 30 bus test system. The paper by (Siddiqui et al., 2014) introduced a way to determine the optimal location of TCSC by specifying the CM approach. The algorithm's feasibility was evaluated on the Delhi 33 bus network.

(Retnamony & Raglend, 2016) devised a cost-free method for congestion management by examining TCSC potentials. The findings of the FACTS devices were compared and verified using an IEEE 14 bus test system. The authors (Sandhiya et al., 2016) reported a congestion management strategy that involves using simulated annealing (SA) algorithm to determine the ideal location of UPFC. The proposed methodology was employed to address the multi-objective function problem in order to determine the optimal placement of the UPFC. The proposed method was verified using the MATLAB software. (Khan & Siddiqui, 2017) proposed an optimal allocation of FACTS controllers using a combination of GA and the SPEA. Both methodologies were employed concurrently to perform single-objective and three-objective optimisation on power systems. The method was validated on an IEEE 30 bus test setup using MATLAB software. To alleviate congestion, (Masood et al., 2020) designed a modified UPFC control circuit. The location of the UPFC was determined using a sensitivity-based technique. A five-bus, seven-line transmission network was used to simulate the model in PSCAD/EMTDC. (Padmini et al., 2018) describes many index techniques for optimal placement of FACTS devices. The method was validated using an IEEE 30 bus test system.

In (Sourabh & Kaur, 2018), a survey on methodologies, methodology, and approaches to reducing congestion on power transmission lines was proposed, along with reviews of several major strategies used by various researchers for CM. In (Choudekar et al., 2019), FACTS devices were employed for CM using the Newton-Raphson approach, which was accomplished by interfacing two software (MATLAB and GAMS). (Babatunde O. Adewolu & Saha, 2020) recommended optimal TCSC location to avoid congestion. An optimization method was used to determine the best site for the TCSC. The model's competency was evaluated on an IEEE 24 bus system. The method was validated using an IEEE 5 bus test system. (Surya et al., 2018) developed a novel technique for CM in transmission networks, building a control algorithm that manages real power flow in the network and validating it on an IEEE 5 bus test system. In (Sarwar et al., 2016), a method of probability occurrence was proposed, in which the most critical lines were analyzed, and the technique's performance was validated using an IEEE 14 bus test system.

2.7.1 Discussion summary on optimal placement of FACTS Devices for CM

Other methods of properly regulating transmission network congestion include using FACTS devices. Better position and size of FACTS devices may be known using optimization techniques to overcome specific irregularities and improve the performance of electric power system networks. The installation of these devices falls under the technological (free) approaches to congestion control. Section 5 describes how various FACTS devices are utilized to reduce congestion in electric power system networks.

2.8 Congestion management by optimal placement of distributed generation

The integration of distributed generators (DGs) is critical in today's electric power system networks. To alleviate transmission line congestion, (Guguloth Ramesh, 2013) presented a sensitivity-based optimal allocation of DG. In (Sarwar & Siddiqui, 2016b), a technique based on the weakest bus identification was developed for CM in a deregulated environment. In (Varghese et al., 2018), a novel method based on sensitivity factor and severity index was presented for efficient DG allocation to decrease transmission network congestion. In (Rani et al., 2017), a smart wire gadget was developed to alleviate congestion and protect transmission lines. This device functions by restricting the flow of current in transmission lines. For validation, the operation of the smart wire was implemented on an IEEE 5 bus test system. (Tavakoli et al., 2017) suggested a revolutionary CM technique called the Monte-Carlo technique based on the optimal placement of DGs. The load flow probabilistic technique was used to detect congested lines.

By evaluating the linear sensitivity factor, (Yasasvi et al., 2020) presented a linear sensitivity-based congestion control approach. Installing a Distributed Generator (DG) reduced congestion on the indicated bus. MATLAB was used to implement the IEEE 30 bus test system procedure. In (Sarwar et al., 2018), a strategy for suitable DG positioning was proposed by considering four different LMP techniques for congestion mitigation. The performance of the provided approach was validated using an IEEE 14 bus test system.

Distributed generators (DGs) that are incorporated into the power system can be represented as either PQ (constant power) or PV (constant voltage) nodes in a model. Small distributed generators are typically represented as PQ nodes and are commonly assumed to be negative constant power loads, as depicted in Figure 2.16.

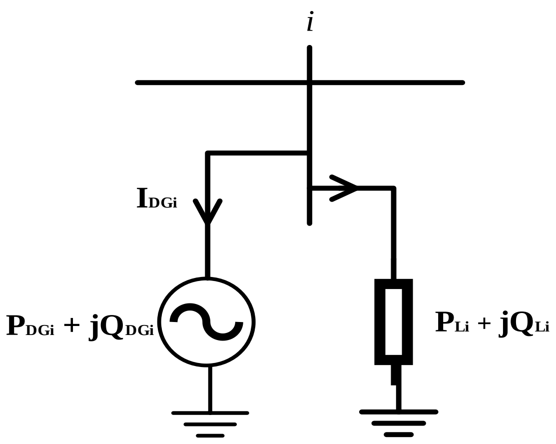


Figure 2. 16: A DG and PQ load connected to bus *i*

The load is modelled as a constant power load, and its current is given as:

$$\boldsymbol{I_{Li}} = \left(\frac{\boldsymbol{P_{Li}} + j\boldsymbol{Q_{Li}}}{\boldsymbol{V_i}}\right)^* \tag{2.19}$$

The current supplied by the DG is defined as:

$$\boldsymbol{I_{DGi}} = \left(\frac{\boldsymbol{P_{DGi}} + j\boldsymbol{Q_{DGi}}}{\boldsymbol{V_i}}\right)^* \tag{2.20}$$

Where,

$\boldsymbol{P_{Li}}$ active power of the line

$\boldsymbol{Q_{Li}}$ reactive power of the line

$\boldsymbol{P_{DGi}}$ active power of the DG

$\boldsymbol{Q_{DGi}}$ reactive power of the DG

$\boldsymbol{V_i}$ line voltage at bus $\boldsymbol{i}$

2.8.1 Discussion summary on optimal placement of DGs for CM

DGs serve critical roles in providing additional capacity to assist generating stations in meeting consumer needs. DGs have greatly aided system operators in controlling operations, improving system performance, and bringing about system reliability and security. The effect of optimal DG allocation on networks results in a reasonable reduction in system running costs.

2.9 Conclusion

The review looked at the technical, non-technical, classical, heuristic, and optimal placement of FACTS, DGs, and parallel computing optimization approaches used in transmission congestion management systems. However, each method has advantages and disadvantages. The review work identifies the need for a parallel computing-based algorithm to solve the complex transmission CM problem using the proposed novel parallel computing-based PSO algorithm to tackle the challenges of CM for a better alternative solution than existing sequential-based computation methods. Parallel computing solutions will be a huge help to the power industry in terms of reducing congestion on transmission networks. The proposed algorithm's application would be simplified for easy deployment by utility companies to improve transmission network performance.

The next chapter details the background mathematical theory formulation for the solution of transmission CM in deregulated power systems. The objectives of the research is been put into mathematical expression for better understanding of the problem to be solved.

CHAPTER THREE
MATHEMATICAL FORMULATION FOR TRANSMISSION CONGESTION MANAGEMENT IN DEREGULATED POWER SYSTEMS

3.1 Introduction

This research is grounded in the fundamental principles and theories of constrained optimisation problems. The objective is to create a highly effective model or method using the particle swarm optimisation (PSO) algorithm. Because, in terms of optimization capacity: PSO is capable of finding near-optimal solutions for complex, high-dimensional problems like transmission congestion in power systems. By adjusting generator outputs and other control variables, PSO can minimize power losses and improve voltage profiles, thereby reducing congestion. The aim is to ease congestion on transmission lines and minimise the operating cost of the system. This approach aims to address the issues related to TCM and minimise the operational expenses by efficiently determining the appropriate number of generators involved and optimising the rescheduling of active and reactive power outputs. The objective is to alleviate congestion while keeping the rescheduling costs to a minimum.

Given that different generators exhibit varying levels of sensitivity to power flow on congested lines, the resolution to the stated issues of congestion management and cost reduction in operations will be implemented through a series of distinct measures. During the initial stage (stage 1), an analysis was conducted to determine the sensitivity factors of both active and reactive power of the generators in relation to the congested line, while aiming to identify the generators that are involved in the congested lines. During the second step (Step 2), the objective is to minimise the cost associated with rescheduling the total active and reactive power of the generators involved in the congestion. Additionally, the possibility of adjusting the voltage of the generator will be taken into account in order to maintain the load bus voltages within their specified limits. This is done to prevent any voltage deviations that might potentially lead to a collapse of the entire system.

3.2 Problem formulation for congestion management

3.2.1 Objective function

The objective of this study was to allivate congestion in an electric transmission network by minimising the cost associated with adjusting the output power of the generators affected by congestion. The PSO technique is used to solve this nonlinear OPF problem. The total amount of rescheduling required by the specified generator can be expressed as (3.1) (Siddiqui et al., 2015):

$$\boldsymbol{Minimize} \sum_{g}^{N_g} C_{Pg}(\Delta P_g)\Delta P_g + \sum_{g}^{N_g} C_{Qg}(\Delta Q_g)\Delta Q_g + k_1 L_{max} + k_2 \sum_{i=1}^{N_d} |1 - V_i| + PF \quad (3.1)$$

Where,

C_{Pg} cost of rescheduling active power of the generator

ΔP_g generator's active power adjustments

C_{Qg} cost of rescheduling reactive power of the generator

ΔQ_g generator's reactive power adjustments

k_1, k_2 are constants

PF penalty function

$\sum_{i=1}^{N_d}|1 - V_i|$ voltage profile enhancement expression

L_{max} stability voltage indicator

$C_{Qg}(\Delta Q_g)$ cost of rescheduling reactive power of the generator's participating in CM. It can be deduced mathematically as (3.2):

$$C_{Qg}(\Delta Q_g) = \left\{C_g^P(S_{Gmax}) - C_g^P\left(\sqrt{S_{Gmax}^2 - \Delta Q_g^2}\right)\right\}\varphi \tag{3.2}$$

Where, C_g^P cost of generating active power by the generator and it can be quadratically expressed as (3.3):

$$C_g^P(\Delta PG_{gn}) = a_n(\Delta PG_{gn}^2) + b_n(\Delta PG_{gn}) + c_n \tag{3.3}$$

Where,

S_{Gmax} is the generator maximum norminal power

$a_n, b_n, and\ c_n$ are the generator predetermined cost coefficients

φ is the active power generation profit rate

The proposed objective function is subjected to the following constraints:

3.2.1.1 Equality constraints

These are system power balance constraints, and they can be written as (3.4) and (3.5):

$$P_{Gi} - P_{Di} = \sum_{n=1}^{NB}|V_i||V_j|\,|Y_{ij}|cos(\delta_i - \delta_j - \theta_{ij}) \tag{3.4}$$

$$Q_{Gi} - Q_{Di} = \sum_{n=1}^{NB}|V_i||V_j|\,|Y_{ij}|sin(\delta_i - \delta_j - \theta_{ij}) \tag{3.5}$$

Where,

P_{Gi}, Q_{Gi} the active and reactive power generation at bus i

P_{Di}, Q_{Di} the active and reactive power demand at bus i

$|V_i|, |V_j|$ voltage magnitude at bus $i\ and\ j$

$|Y_{ij}|$ bus admittance matrix element i, j

θ_{ij} is the Phase angle at bus $i\ and\ j$

3.2.1.2 Inequality constraints

These are control variables constraints, and they can be expresed as (3.6) to (3.10):

$$P_g - P_g^{min} = \Delta P_g^{min} \leq \Delta P_g \leq \Delta P_g^{max} = P_g^{max} - P_g, \; g\forall N_g \tag{3.6}$$

$$Q_g - Q_g^{min} = \Delta Q_g^{min} \leq \Delta Q_g \leq \Delta Q_g^{max} = Q_g^{max} - Q_g, \; g\forall N_g \tag{3.7}$$

$$|S_k| \leq S_k^{max}, \; k\forall N_i \tag{3.8}$$

$$V_i - V_i^{min} = \Delta V_i^{min} \leq \Delta V_i \leq \Delta V_i^{max} = V_i^{max} - V_i, \; i\forall N_b \tag{3.9}$$

$$\left(\sum_g^{N_g}\left(GS_{Pgn}^k \times \Delta P_g\right) + P_{ij}\right)^2 + \left(\sum_g^{N_g}\left(GS_{Qgn}^k \times \Delta Q_g\right) + Q_{ij}\right)^2 \leq \left(S_{ij}^{max}\right)^2, \; ij \in N_l \quad 3.10)$$

The penalty function PF is defined in equations (3.11) and (3.12) to regulate the boundaries of all the inequality constraint variables.

$$PF = k_3 \times f(P_i) + k_4 \times \sum_{i=1}^{N_g} f\left(Q_{gi}\right) + k_5 \times \sum_{i=1}^{N_b} f(V_i) + k_6 \times \sum_{i=1}^{N_l} f(S_k) \quad 3.11)$$

$$f(x) = \begin{Bmatrix} 0 & if\ x^{min} \leq x \leq x^{max} \\ (x - x^{maax})^2 & if\ x > x^{max} \\ (x^{max} - x)^2 & if\ x < x^{min} \end{Bmatrix} \tag{3.12}$$

Where,

P_g, Q_g	are the active and reactive power of the generator
P_g^{min}, P_g^{max}	minimum and maximum active power generation limit
Q_g^{min}, Q_g^{max}	minimum and maximum reactive power generation limit
$\Delta P_g, \Delta Q_g$	generator active and reactive power adjustment
V_i^{min}, V_i^{max}	voltage magnitude limits at bus i
$\Delta V_i^{min}, \Delta V_i^{max}$	mini. and max. change in voltage limits at bus i
$S_k^{max} = S_{ij}^{max}$	transmission line MVA flow limits at bus i and j
S_k	actual power flow in the transmission line k
N_g	sum number of the generator buses
N_l	sum number of the transmission lines
N_b	sum number of buses
x^{min}, x^{max}	minimum and maximum limits of variable x
k_3, k_4, k_5, k_6	are constant of penalty coefficients

3.3 Formation of the generator sensitivity factors

The generator sensitivity to the congested line (GSF) refers to the change in power flow on transmission line k, which connects buses i and j, due to a unit variation in active and reactive power injection by generator-g at bus-n. This change is influenced by the different sensitivities of the generators to power flow on the overloaded lines. GSF values typically range from -1 to 1. However, in practice, they can exceed these limits in highly interconnected or complex networks. A GSF of 1 indicates that a 1 MW increase in generation at a specific bus will result in a 1 MW increase in power flow on the line. Similarly, a GSF of -1 indicates a 1 MW increase in generation will result in a 1 MW decrease in power flow on the line. Extremely high or low GSF values (e.g., significantly greater than 1 or less than -1) indicate strong sensitivity, which may pose risks to system stability and reliability if not managed properly. Active power rescheduling is used primarily for managing congestion, balancing supply and demand, and regulating frequency. It focuses on adjusting generation levels to address operational constraints and economic considerations. Reactive power management is crucial for voltage control, system stability, and efficiency. It involves adjusting reactive power to maintain voltage levels and improve system performance. Sensitivity factors for both active and reactive power provide critical insights for effective power system management: GSFs help in understanding how changes in generation impact power flows and identifying strategies to manage congestion. VSFs guide the management of reactive power to control voltage levels and ensure system stability. By leveraging these sensitivity factors, operators can make informed decisions to optimize system performance, enhance reliability, and minimize operational costs. Active and reactive power rescheduling are essential for managing power flows and maintaining system stability. A multifaceted approach that includes infrastructure investment, market mechanisms, advanced control systems, and demand response is necessary to effectively manage congestion. By integrating these strategies, operators can address the complexities of deregulated markets and achieve more effective and sustainable congestion management.

3.3.1 Active power generator sensitivity factors

Mathematically, GSF for active power at line k can be stated as (3.13) (Siddiqui et al., 2015; Dutta & Singh, 2008)

$$\boldsymbol{GSF_{Pgn}^{k}} = \frac{(\Delta \boldsymbol{P_{ij}})}{(\Delta \boldsymbol{PG_{gn}})} \tag{3.13}$$

Where,

$\boldsymbol{GSF_{Pgn}^{k}}$ is the active power generator sensitivity factor

ΔP_{ij} is the change in active power between buses $i \text{ and } j$

ΔPG_{gn} is the unit change in active power injection at bus n

By disregarding the P-V coupling, (3.13) can be further uttered as (3.14):

$$GSF_{Pg}^{k} = \frac{\partial P_{ij}}{\partial \theta_i} \cdot \frac{\partial \theta_i}{\partial PG_{gn}} + \frac{\partial P_{ij}}{\partial \theta_j} \cdot \frac{\partial \theta_j}{\partial PG_{gn}} \quad (3.14)$$

The congested line power flow equation can be stated as (3.15):

$$P_{ij} = -V_i^2 B_{ij} + V_i V_j G_{ij} cos(\theta_i - \theta_j) + V_i V_j B_{ij} sin(\theta_i - \theta_j) \quad (3.15)$$

Where,

P_{ij} is the main active power flow between buses $i \text{ and } j$

$V_{i,} V_j$ are the voltage magnitude at buses $i \text{ and } j$

θ_i, θ_j are the voltage angle at buses $i \text{ and } j$

G_{ij}, B_{ij} are conductance and susceptance between buses $i \text{ and } j$

Differentiating (3.15) gives the first and the third term of (3.14) and can be written as (3.16) and (3.17).

$$\frac{\partial P_{ij}}{\partial \theta_i} = -V_i V_j G_{ij} sin(\theta_i - \theta_j) + V_i V_j B_{ij} cos(\theta_i - \theta_j) \quad (3.16)$$

$$\frac{\partial P_{ij}}{\partial \theta_j} = +V_i V_j G_{ij} sin(\theta_i - \theta_j) - V_i V_j B_{ij} cos(\theta_i - \theta_j) \quad (3.17)$$

The injected real power at bus $\mathbf{i}$ can be stated as (3.18):

$$P_i = P_{Gi} - P_{Di} \quad (3.18)$$

Where,

$P_{Gi}, \text{and } P_{Di}$ are the active power generation and demend at bus i respectively.

P_i can be conveyed as (3.19):

$$P_i = |V_i|^2 B_{ii} + |V_s| \sum_{\substack{j=1 \\ j \neq i}}^{n} \left\{ \left(G_{ij} cos(\theta_i - \theta_j) + B_{ij} sin(\theta_i - \theta_j) \right) |V_j| \right\} \quad (3.19)$$

The differentiation of equation (3.19) with respect to $\boldsymbol{\theta_i}$ ***and*** $\boldsymbol{\theta_j}$ yields equations (3.20) and (3.21) respectively. By ignoring the P-V coupling, the formula that determines the relationship between the incremental change in active power at the system buses and the phase angles of voltages can be represented in matrix form as equations (3.22) to (3.24).

$$\frac{\partial P_i}{\partial \theta_j} = |V_s||V_j|\left\{\left(G_{ij}sin(\theta_i - \theta_j) - B_{ij}cos(\theta_i - \theta_j)\right)\right\} \qquad (3.20)$$

$$\frac{\partial P_i}{\partial \theta_i} = |V_s|\sum_{\substack{j=1 \\ j\neq i}}^{n}\left\{\left(-G_{ij}sin(\theta_i - \theta_j) + B_{ij}cos(\theta_i - \theta_j)\right)|V_j|\right\} \qquad (3.21)$$

$$[\Delta P] = [H][\Delta\theta] \qquad (3.22)$$

$$[\Delta\theta] = [H]^{-1}[\Delta P] \qquad (3.23)$$

$$[M] = [H]^{-1} \qquad (3.24)$$

3.3.2 Reactive power generator sensitivity factors

Mathematically, GSF for reactive power at line $\mathbf{k}$ can be expressed as (3.25) (Namilakonda & Guduri, 2021b):

$$GSF_{Qgn}^{k} = \frac{(\Delta Q_{ij})}{(\Delta QG_{gn})} \qquad (3.25)$$

Where,

GSF_{Qgn}^{k} is the reactive power generator sensitivity factor

ΔQ_{ij} is the change in reactive power between buses $\boldsymbol{i}$ ***and*** $\boldsymbol{j}$

ΔQG_{gn} is the unit change in reactive power injection at bus $\boldsymbol{n}$

By neglecting the $\boldsymbol{Q - \delta}$ coupling, (3.25) can be further expressed as (3.26):

$$GSF_{Qg}^{k} = \frac{\partial Q_{ij}}{\partial V_i} \cdot \frac{\partial \theta_i}{\partial QG_{gn}} + \frac{\partial Q_{ij}}{\partial V_j} \cdot \frac{\partial V_j}{\partial QG_{gn}} \qquad (3.26)$$

The congested line reactive power flow equation can be penned as (3.27):

$$Q_{ij} = -V_i^2 B_{ij} + V_i V_j G_{ij} sin(\theta_i - \theta_j) + V_i V_j B_{ij} cos(\theta_i - \theta_j) \quad (3.27)$$

Where,

Q_{ij} is the main reactive power flow between buses i and j

$V_{i,} V_j$ are the voltage magnitude at buses i and j

θ_i, θ_j are the voltage angle at buses i and j

G_{ij}, B_{ij} are conductance and susceptance of the line between buses i and j

By differentiating (3.27), gives first and the third term of (3.26) and can be given as (3.28) and (3.29).

$$\frac{\partial Q_{ij}}{\partial V_i} = -2V_i B_{ij} + V_j G_{ij} sin(\theta_i - \theta_j) - V_j B_{ij} cos(\theta_i - \theta_j) \quad (3.28)$$

$$\frac{\partial Q_{ij}}{\partial V_j} = V_i G_{ij} sin(\theta_i - \theta_j) - V_i B_{ij} cos(\theta_i - \theta_j) \quad (3.29)$$

Therefore, injected reactive power at bus $\mathbf{i}$ can be written as (3.30):

$$Q_i = Q_{Gi} - Q_{Di} \quad (3.30)$$

Where,

Q_{Gi}, and Q_{Di} are the reactive power generation and demend at bus i respectively.

Q_i can be expressed as (3.31):

$$Q_i = -|V_i|^2 B_{ii} + |V_i| \sum_{\substack{j=1 \\ j \neq i}}^{n} \left\{ \left(G_{ij} sin(\theta_i - \theta_j) + B_{ij} cos(\theta_i - \theta_j) \right) |V_j| \right\} \quad (3.31)$$

Differentiating equation (3.31) w.r.t θ_i and θ_j gives (3.32) and (3.33). The matrices of the partial derivatives for (3.32) and (3.33) w.r.t magnitude voltages at buses $\mathbf{i}$ **and** $\mathbf{j}$ can be stated as (3.34) and (3.35), respectively.

$$\frac{\partial Q_i}{\partial V_i} = -2B_{ii} V_i + \sum_{\substack{j=1 \\ j \neq i}}^{n} \left\{ \left(G_{ij} sin(\theta_i - \theta_j) + B_{ij} cos(\theta_i - \theta_j) \right) |V_j| \right\} \quad (3.32)$$

$$\frac{\partial Q_i}{\partial V_j} = |V_i| \sum_{\substack{j=1 \\ j \neq i}}^{n} \left\{ \left(G_{ij} sin(\theta_i - \theta_j) - B_{ij} cos(\theta_i - \theta_j) \right) \right\} \quad (3.33)$$

$$\frac{\delta V_i}{\delta QG_g} = \left[\frac{\delta Q_i}{\delta V_i}\right]^{-1} \quad (3.34)$$

$$\frac{\delta V_j}{\delta QG_g} = \left[\frac{\delta Q_i}{\delta V_j}\right]^{-1} \quad (3.35)$$

3.4 Power flow

Power flow is very important in power systems design, planning, and expansion. With power flow analysis, the voltage values of all the buses in a network under specified network conditions of operation can be computed. Other quantities, such as current values, power values, and power losses, are easily calculated when the bus voltages are known. This is needed for system planning and control. Power flow analysis is fundamental to power systems study. Several numerical solution methods are used to solve load flow equations. The Newton-Raphson, Fast Decoupled, and Gauss-Seidel methods are the most common iterative methods. The N-R increases in quadratic progression, the Gauss-Seidel method increases in arithmetic progression, while the Fast-decoupled increases in geometric progression. However, the most reliable and practical of the three power flow techniques is the Newton-Raphson due to its accurate and fast convergence (Ogunwole & Saha, 2020).

3.4.1 Newton Raphson load flow

The technique starts with the initial guess of the unknown values, followed by Taylor series expansion of the power-balanced equations ignoring the higher order terms. Newton Raphson's load flow method converges rapidly provided the initial are correctly guessed. However, longer times are required to execute each iteration. Expressing the current in terms of Y-bus gives (Ogunwole & Saha, 2020):

$$\boldsymbol{I_i = \sum_{j=1}^{n} Y_{ij} V_j} \quad (3.36)$$

In polar form, it can be expressed as:

$$\boldsymbol{I_i = \sum_{j=1}^{n} |Y_{ij}||V_J| \angle \theta_{ij} + \delta_j} \quad (3.37)$$

At bus i, the complex power can be written as:

$$\boldsymbol{P_i - jQ_i = V_i * I_i} \quad (3.38)$$

By substituting equation (37.5) into (3.38) it gives (3.39)

$$P_i - jQ_i = V_i \sum_{j=1}^{n} |Y_{ij}||V_J| \angle \theta_{ij} + \delta_j \tag{3.39}$$

By separating equation (3.39), we have equations (3.40) and (3.41), which are sets of non-linear algebraic equations.

$$P_i = \sum_{j \neq i} |V_i||V_j||Y_{ij}| cos(\theta_{ij} - \delta_i - \delta_j) \tag{3.40}$$

$$Q_i = -\sum_{j \neq i} |V_i||V_j||Y_{ij}| sin(\theta_{ij} - \delta_i - \delta_j) \tag{3.41}$$

3.4.2 The Jacobian matrix

The Jacobian matrix generalizes the scalar-valued function gradient of multiple variables, which in turn generalizes the derivative of the scalar-valued function of a single variable (Ogunwole & Saha, 2020). This implies that the Jacobian matrix for scalar-valued multivariate and single-variable functions are the gradient and derivative, respectively. The Jacobian can also be thought of as describing the amount of "stretching," "rotating," or "transforming" that a transformation imposes locally. In vector calculus, the first-order partial derivative of a vector-valued function is referred to as the Jacobian matrix. The Taylor series expansion of Equations (3.40) and (3.41) about the initiate value ignoring terms of higher order gives the linear Equation set as follows:

$$\begin{bmatrix} \Delta P_2^{(k)} \\ \vdots \\ \Delta P_n^{(k)} \\ \hline \Delta Q_2^{(k)} \\ \vdots \\ \Delta Q_n^{(k)} \end{bmatrix} = \left[\begin{array}{ccc|ccc} \frac{\partial P_2^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial P_2^{(k)}}{\partial \delta_n} & \frac{\partial P_2^{(k)}}{\partial |V_2|} & \cdots & \frac{\partial P_2^{(k)}}{\partial V_n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial P_n^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial P_n^{(k)}}{\partial \delta_n} & \frac{\partial P_n^{(k)}}{\partial V_2} & \cdots & \frac{\partial P_n^{(k)}}{\partial V_n} \\ \hline \frac{\partial Q_2^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial Q_2^{(k)}}{\partial \delta_n} & \frac{\partial Q_2^{(k)}}{\partial V_2} & \cdots & \frac{\partial Q_2^{(k)}}{\partial V_n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial Q_n^{(k)}}{\partial \delta_2} & \cdots & \frac{\partial Q_n^{(k)}}{\partial \delta_n} & \frac{\partial Q_n^{(k)}}{\partial V_2} & \cdots & \frac{\partial Q_n^{(k)}}{\partial V_n} \end{array}\right] \begin{bmatrix} \Delta \delta_2^{(k)} \\ \vdots \\ \Delta \delta_n^{(k)} \\ \hline \Delta \left|V_2^{(k)}\right| \\ \vdots \\ \Delta \left|V_n^{(k)}\right| \end{bmatrix} \tag{3.42}$$

The Jacobian matrix equation represents the linearized correlation between variations in voltage magnitude $\Delta V_i^{(k)}$ and angle $\Delta \delta_i^{(k)}$ with changes in real and reactive power $\Delta P_i^{(k)}$and $\Delta Q_i^{(k)}$. The Equations (3.40) and (3.41) calculate the partial derivatives at $\Delta \delta_i^{(k)}$and $\Delta \left|V_n^{(k)}\right|$ resulting in the elements of the Jacobian matrix. The expression can be represented concisely as Equation (3.43).

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta |V| \end{bmatrix} \tag{3.43}$$

$$J = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial |V_i|} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial |V_i|} \end{bmatrix} \tag{3.44}$$

If the transmission network contains 'm' voltage-controlled buses, the Gaussian-elimination method is used to eliminate 'm' ∆V and ∆Q equations, as well as the associated columns in the Jacobian matrix. Gaussian elimination is a mathematical procedure carried out on a matrix of coefficients. Hence, there are a total of n-1 constraints on real power and n – 1 – m limitations on reactive power. The Jacobian matrix has dimensions (2n – 2 – m) × (2n – 2 – m). The elements on the main diagonal and the elements off the main diagonal of matrix J1 are:

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{j \neq i} |V_i||V_j||Y_{ij}| \, Sin(\theta_{ij} - \delta_i - \delta_j) \tag{3.45}$$

$$\frac{\partial P_i}{\partial \delta_i} = -|V_i||V_j||Y_{ij}| Sin(\theta_{ij} - \delta_i - \delta_j) \;\; j \neq i \tag{3.46}$$

The elements of J_2 that are on the diagonal and off-diagonal are:

$$\frac{\partial P_i}{\partial |V_i|} = 2|V_i||Y_{ii}| Cos\theta_{ii} + \sum |V_i||V_j||Y_{ij}| \, (\theta_{ij} - \delta_i - \delta_j) \tag{3.47}$$

$$\frac{\partial P_i}{\partial |V_j|} = -|V_i||Y_{ij}| Cos(\theta_{ij} - \theta_i - \theta_j) \;\; j \neq i \tag{3.48}$$

The elements of J_3 that are on the diagonal and off-diagonal are:

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{j \neq i} |V_i||V_j||Y_{ij}| \, Cos(\theta_{ij} - \delta_i - \delta_j) \tag{3.49}$$

The elements of J_4 that are on the diagonal and off-diagonal are:

$$\frac{\partial P_i}{\partial |V_j|} = -|V_i||Y_{ij}| Cos(\theta_{ij} - \theta_i - \theta_j) \;\; j \neq i \tag{3.50}$$

The power mismatch is expressed as:

$$\Delta \boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})} = \boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{sch})} - \boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})} \tag{3.51}$$

$$\Delta \boldsymbol{Q}_{\boldsymbol{i}}^{(\boldsymbol{k})} = \boldsymbol{Q}_{\boldsymbol{i}}^{(\boldsymbol{sch})} - \boldsymbol{Q}_{\boldsymbol{i}}^{(\boldsymbol{k})} \tag{3.52}$$

The calculated values of voltage magnitudes and angle are:

$$\boldsymbol{\delta}_{\boldsymbol{i}}^{(\boldsymbol{k})} = \boldsymbol{\delta}_{\boldsymbol{i}}^{(\boldsymbol{k})} - \Delta \boldsymbol{\delta}_{\boldsymbol{i}}^{(\boldsymbol{k})} \tag{3.53}$$

$$\left|\boldsymbol{V}_{\boldsymbol{i}}^{(\boldsymbol{k+1})}\right| = \left|\boldsymbol{V}_{\boldsymbol{i}}^{(\boldsymbol{k})}\right| + \Delta\left|\boldsymbol{V}_{\boldsymbol{i}}^{(\boldsymbol{k})}\right| \tag{3.54}$$

3.5 Newton-Raphson power flow algorithm

The following section outlines the Newton-Raphson load flow solution process, with a visual flowchart provided in Figure 3.1.

The network Raphson power flow algorithm is providesd in Step 1 to 7 below

(i) The voltage magnitudes and angles for load buses are set to 1.0 and 0.0, respectively.

(ii) Equations (3.40) and (3.41) compute $\boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ and $\boldsymbol{Q}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ for load buses and Equations (3.51) and (3.52) compute $\Delta \boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ and $\Delta \boldsymbol{Q}_{\boldsymbol{i}}^{(\boldsymbol{k})}$.

(iii) Equations (3.40) and (3.51) compute $\boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ and $\Delta \boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ for voltage-controlled buses.

(iv) Compute the elements of Jacobian matrix (J_1, J_2, J_3, and J_4).

(v) The Equation (3.40) is solved by employing both triangular factorization and Gaussian elimination methods simultaneously.

(vi) Equations (3.53) and (3.54) calculate the updated voltage values ngles from.

(vii) The process continues until the $\Delta \boldsymbol{Q}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ and $\Delta \boldsymbol{P}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ are smaller than the tolerance.

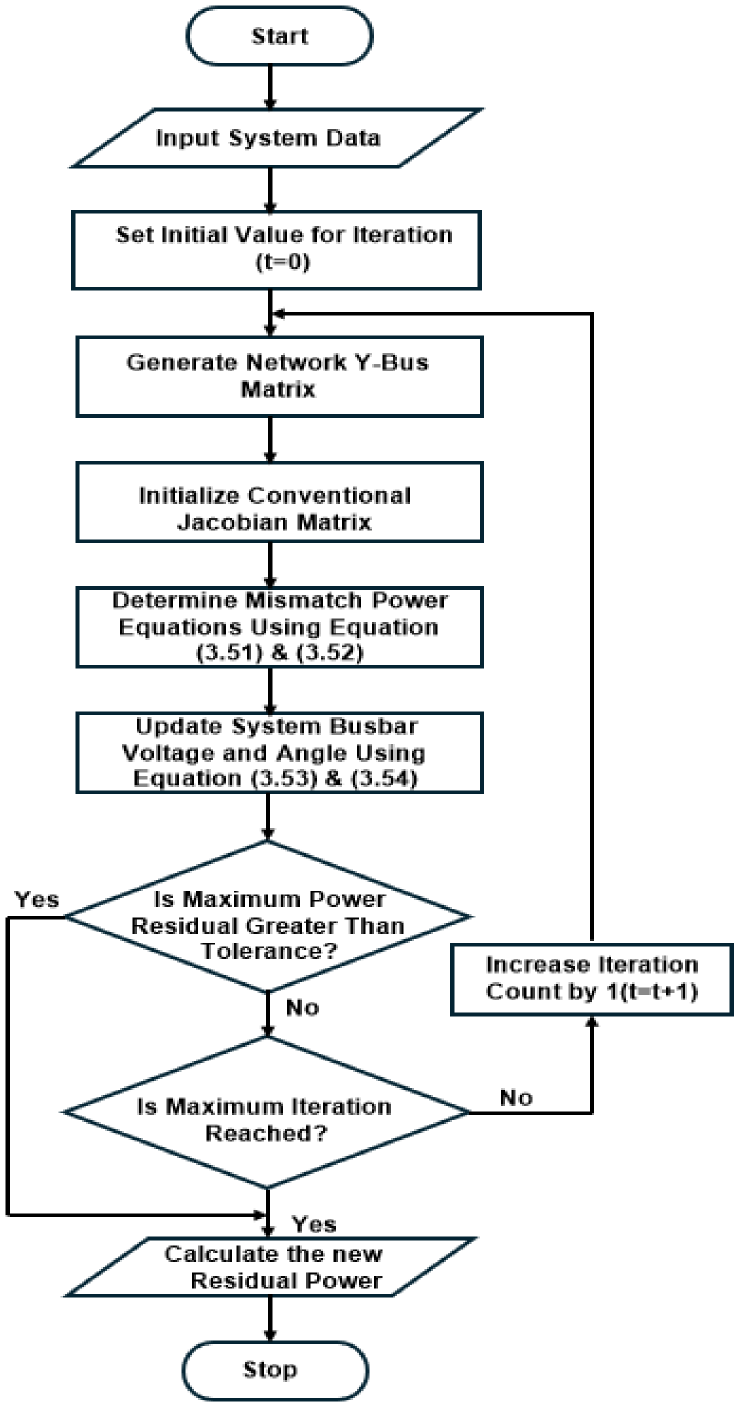


Figure 3. 1: Newton-Raphson implementation load flow flowchart **(Ogunwole & Saha, 2020)**

3.6 Conclusion

The chapter details the theoretical background and mathematical formulation for the solution of transmission congestion management in deregulated power systems. The chapter breakes into the mathematical formulation of the objectives of the research project, the formulation of the generator sensitivity factors for both active and reactive powers, and basic background of power flow equation with the flow chart that represent the sequential steps. In the next chapter, the PSO algorithm method for the solution of TCM based on generator sensitivity factors for active and reactive power rescheduling is discussed in depth. The mathematical and theoretical formulations of PSO, including its objective functions, constraints, and swarm dynamics, are versatile and can be adapted to a wide range of power system management problems. This flexibility makes PSO a powerful tool in the optimization and management of modern power systems. The approach was tested through the utilization of IEEE synthetic networks.

CHAPTER FOUR
TRANSMISSION CONGESTION MANAGEMENT USING GENERATOR SENSITIVITY FACTORS FOR ACTIVE AND REACTIVE POWER RESCHEDULING USING PARTICLE SWARM OPTIMIZATION ALGORITHM

4.1 Introduction

This chapter presents an OPF analysis-based particle swarm optimization (PSO) algorithm method to identify participating generators to congestion and optimally reschedule their output powers (active and reactive) while managing congestion at the lowest possible rescheduling cost. Furthermore, because the conventional method of OPF is premised on the exploration path, which is obtained from the function derivative, the output of the participating generators was optimally rescheduled to mitigate congestion using the PSO algorithm. From chapter three the GSF for active and reactive power rescheduling is stated in (3.13) and (3.25), respectively. Equality and Inequality constraints are given in sub-sections 3.2.1.1 and 3.2.1.2 of section 3.2, and the penalty function (3.11) and (3.12) are utilized to formulate the objective function (3.1) for the congestion management problem. By incorporating the specific CM problem, the problem mentioned above is mitigated using the PSO algorithm.

4.1.1 Multi-objective functions normalization

Normalization for multi-objective functions can be made by utilizing a weighting strategy (weighted fitness function) to convert both economic and technical parameters into a single objective function (Grodzevich & Romanko, 2006.). Any multi-objective function solutions without a weighting strategy have a higher tendency to divert toward conflicting solutions. In this study, the normalized weights were utilized to form the final fitness function for (3.1) to be optimized. The weighted multi-objective fitness function is expressed as:

$$\boldsymbol{Minimize\ J = \sum_{g}^{N_g} h_1 * C_{Pg}(\Delta P_g)\Delta P_g + \sum_{g}^{N_g} h_2 * C_{Qg}(\Delta Q_g)\Delta Q_g + h_3 L_{max} + h_4 * \sum_{i=1}^{N_d} |1 - V_i| + PF} \tag{4.1}$$

4.2 Overview of PSO and its congestion management solution

Eberhart and Kennedy introduced Particle Swarm Optimisation (PSO) as a rapid, straightforward, and efficient method for population-based optimisation (Ogunwole & Saha, 2020; Okelola et al., 2021). The movement was initiated by the behaviours of organisms, such as fish schooling. In Particle Swarm Optimisation, a 'swarm' refers to a group of particles that represent different solutions. The coordinates of each particle are associated with two vectors: location (position) vector and velocity vector. The position and velocity both have the same capacity as the issue space. The swarm particles navigate the search space in pursuit of the most optimal solutions by continuously changing their generation. Each particle is updated in every iteration with the two most optimal values. The initial value is referred to as the personal best P^{best} solution of the particle during each iteration, while the subsequent value is known as the global best G^{best} solution, which represents the best solution among all the particle solutions. The velocity and locations of each particle are updated using equations (4.2) and (4.3) correspondingly, as described by (Krishnamurthy et al., 2017):

$$\mathbf{V}[\,] = \boldsymbol{\omega}\mathbf{V}[\,] + \mathbf{c1rand1}(\,) * (\mathbf{P}^{\mathbf{best}}[\,] - \mathbf{P}_{\mathbf{present}}[\,]) + \mathbf{c2rand2}(\,) * (\mathbf{G}^{\mathbf{best}}[\,] - \mathbf{P}_{\mathbf{present}}[\,]) \tag{4.2}$$

$$\mathbf{P}_{\mathbf{present}}[\,] = \mathbf{P}_{\mathbf{present}}[\,] + \mathbf{V}[\,] \tag{4.3}$$

The inertia weight can be expressed as (4.4):

$$\boldsymbol{\omega} = \boldsymbol{\omega}^{\mathbf{max}} - \left(\frac{\boldsymbol{\omega}^{\mathbf{max}} - \boldsymbol{\omega}^{\mathbf{min}}}{\mathbf{Iter}^{\mathbf{max}}}\right)\mathbf{Iter} \tag{4.4}$$

Without a limit enacted on the particles' maximum velocity V_{max}, the particles may break away from the search space. Therefore, each particle velocity is coordinated between $-V_{max}$, to V_{max},. Also, a correct range of inertia weight in (4.4) gives good stability between global and local explorations.

4.3 Implementation of the developed NR-OPF PSO algorithm for congestion management

The problem of congestion management in the electric transmission network is theoretically stated in chapter three. The flowchart for the CM technique based on Particle Swarm Optimisation is illustrated in Figure 4.1 below. In order to align the CM issue with the PSO framework, we need to adapt the velocity and position equations described in (4.2) and (4.3). An assumption was made:

1. The number of generators equal to the number of members that were present in the various particles that made up the swarm.
2. Both the active and reactive power were used to represent the velocity variables that were utilized in order to investigate the domain of the limitation.
3. Lastly, the quantity of particles in the swarm was indicated by N_p.

Step 1: Enter data for all three IEEE networks (14, 30, and 118) in the input systems.

Step 2: Execute the Newton-Raphson method for Power Flow Analysis to identify the lines experiencing congestion.

Step 3: Determine the GSF for each generator with regard to the overloaded line using equations (3.13) and (3.25) correspondingly. This is accomplished by examining the active and reactive power GSF of all generators that correspond to the overloaded transmission lines.

Step 4: Set the PSO algorithm initial parameters, including the acceleration coefficients c1 and c2, the inertia weight $\boldsymbol{\omega^{min}}$ and $\boldsymbol{\omega^{max}}$, the random values $\boldsymbol{rand1}$ and $\boldsymbol{rand2}$, and the maximum number of iterations $\boldsymbol{Iter^{max}}$.

Step 5: The min. and max. initial velocity values were determined based on limitations related to active and reactive power limits. These values are stated using equations (3.6) and (3.7) as follows:

$$\mathbf{-0.45P_{g,i}^{min} \leq V_g \leq +0.45P_{g,i}^{max}, g = \overline{1, N_p}, i = \overline{1, n-1}} \tag{4.5}$$

$$\mathbf{-0.45Q_{g,i}^{min} \leq V_g \leq +0.45Q_{g,i}^{max}, g = \overline{1, N_p}, i = \overline{1, n-1}} \tag{4.6}$$

The velocity and position of the particle are determined by utilising (n-1) generators, with one of the generators being designated as the slack generator.

Step 6: With the exception of the slack bus generator, the initial particle velocity is determined using equation (4.7).

$$\mathbf{V_{g,i} = V_{g,i}^{min} + rand()\left(V_{g,i}^{max} - V_{g,i}^{min}\right), g = \overline{1, N_p}, i = \overline{1, n-1}} \tag{4.7}$$

Step 7: Calculate the initial position of the particle using the value (4.8).

$$\mathbf{P_{g,i} = P_{g,i}^{min} + rand()\left(P_{g,i}^{max} - P_{g,i}^{min}\right), g = \overline{1, N_p}, i = \overline{1, n-1}} \tag{4.8}$$

Typically, the electric power system buses are classified into three categories: slack bus, voltage control (PV) bus, and load (PQ) bus. The bus that is closest to the generator and has the most generating capacity is referred known as the slack bus. The purpose of a slack bus in the implementation of the PSO is to adhere to the power balance constraint specified in equations (3.4) and (3.5).

Step 8: Compute the objective function for the initial positions using (3.1).

Step 9: Compute the personal best and the global best as follows:

i. The personal best of the particles is computed using (4.9)

$$\mathbf{P_g^{best} = minP_{g,i}^{best}, i = \overline{1, n}\ ; g = \overline{1, N_g}} \tag{4.9}$$

ii. The global best is calculated using (4.10)

$$\mathbf{G^{best} = minP_g^{best}, g = \overline{1, N_g}} \tag{4.10}$$

Step 10: New velocity is computed using (4.11):

$$\mathbf{V_{g,i}^{new^l} = \omega. V_{g,i}^{l-1} + c1. rand1 \left(P_g^{best^{l-1}} - P_{g,i}^{l-1}\right) + c2. rand2 \left(G^{best^{l-1}} - P_{g,i}^{l-1}\right), g = \overline{1, N_p}, i = \overline{1, n-1}} \tag{4.11}$$

Step 11: New position in the particles is computed using (4.12):

$$\mathbf{P_{g,i}^{new^l} = P_{g,i}^{l-1} + P_{g,i}^{new^l}, g = \overline{1, N_p}, i = \overline{1, n}} \tag{4.12}$$

Step 12: Perform step 2 again to calculate the updated values for line flows, rescheduling of active and reactive power, line losses, and voltage magnitude in all buses.

Step 13: Compute the penalty function for each particle using (3.11) by finding constraint violations.

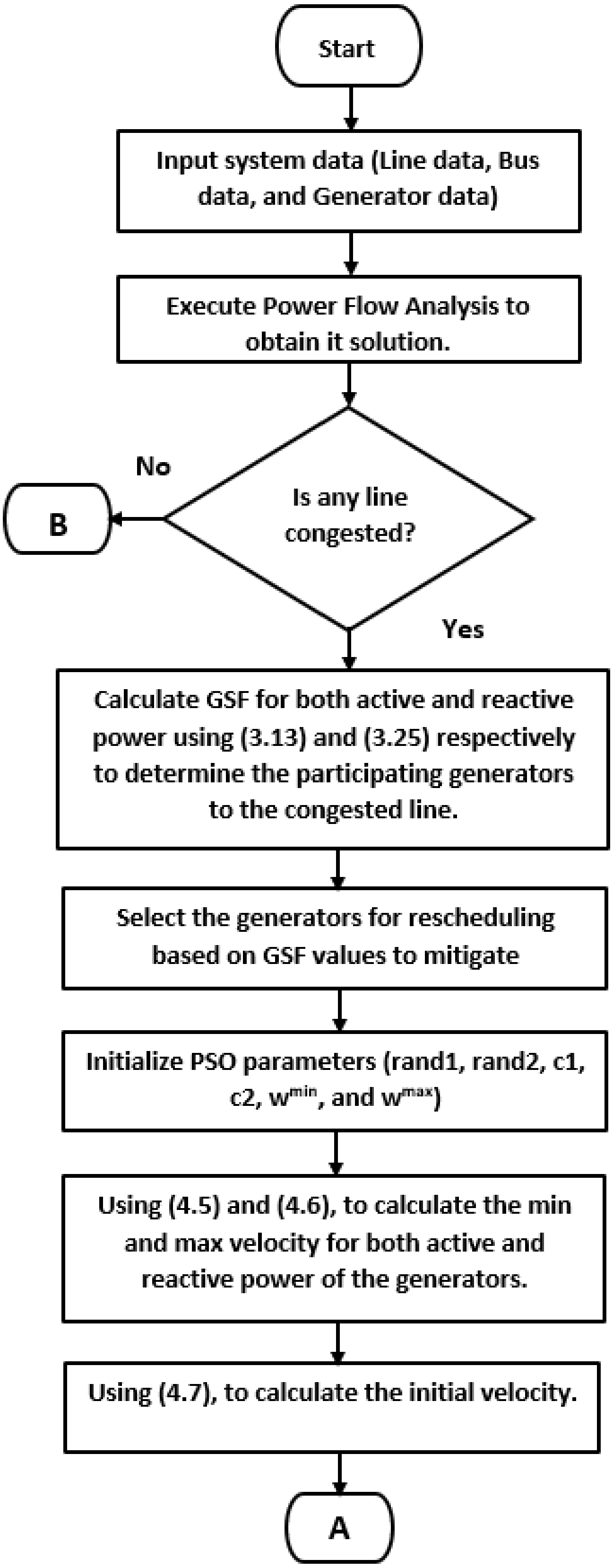
Step 14: Compute fitness function for each particle using (3.1)

Step 15: Find out the "global best" ($\boldsymbol{G^{best}}$) particle and "personal best" ($\boldsymbol{P^{best}}$) of all particles.

Step 16: Engender new population using (4.2) and (4.3).

Step 17: Continue doing steps 3, 10 to 18 repeatedly until the convergence requirement is satisfied.

Step 18: Stop simulation.



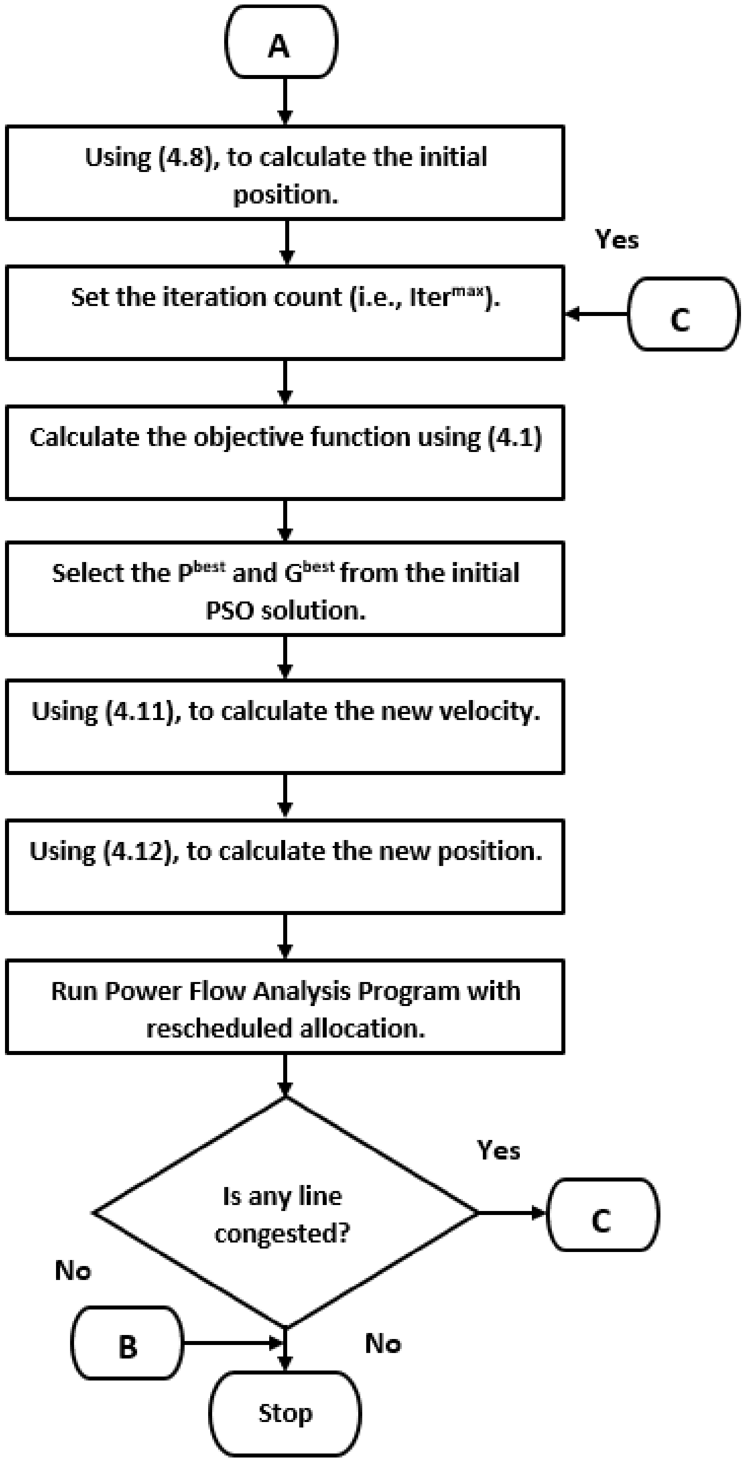


Figure 4. 1: The proposed flowchart for the congestion management based PSO

4.4 Simulation results and discussion

This section provides in-depth and thorough results regarding the efficacy of the developed method for handling transmission congestion. This study examined three case studies of IEEE 14, 30, and 118 bus transmission networks. The performance indicators taken into account were the enhancement of the voltage profile, the optimal rescheduling of active and reactive power of the generators, and the cost associated with rescheduling. The simulation was conducted using MATLAB 2022a.

4.4.1 CASE 1: IEEE 14-Bus system network

The network data were obtained from the studies conducted by (Gautam & Mithulananthan, 2007; Ogunwole & Krishnamurthy, 2022). The network consists of 14 buses, 20 interconnected lines, and 5 generators. APPENDIX A1 provided comprehensive information on both the network data and its single-line diagram. Based on the power flow analysis, line 6, which connects buses 2 and 5, was determined to be the line experiencing congestion. Table 4.1 displays the comprehensive outcome of the power flow on the congested line. Figure 4.2 displays the comprehensive outcomes of generator sensitivity factors, which were employed to determine the involvement or non-involvement of generators in congestion. A generator with a negative sensitivity factor for both active and reactive power shows that increasing its generation reduces the power flow in congested lines. Positive values of the sensitivity factor for both active and reactive power of the generator imply an increase in the power flow in the generator.

Table 4. 1: IEEE 14-Bus congested line details

	Congested line	Power Flow (MW)	Line Limit (MW)
Pre-CM	6 (2-5)	55.618	50
Post-CM	6 (2-5)	48.3635	50

Figure 4.2 illustrates that generators 1, 2, 6, and 8 are the ones that may effectively reduce congestion on the congested line. Thus, in order to reduce congestion, the output power of the generators was efficiently rescheduled using the PSO Algorithm. The results of using Particle Swarm Optimisation (PSO) to optimally adjust the output power of the participating generators in order to reduce congestion are presented in Table 4.2.

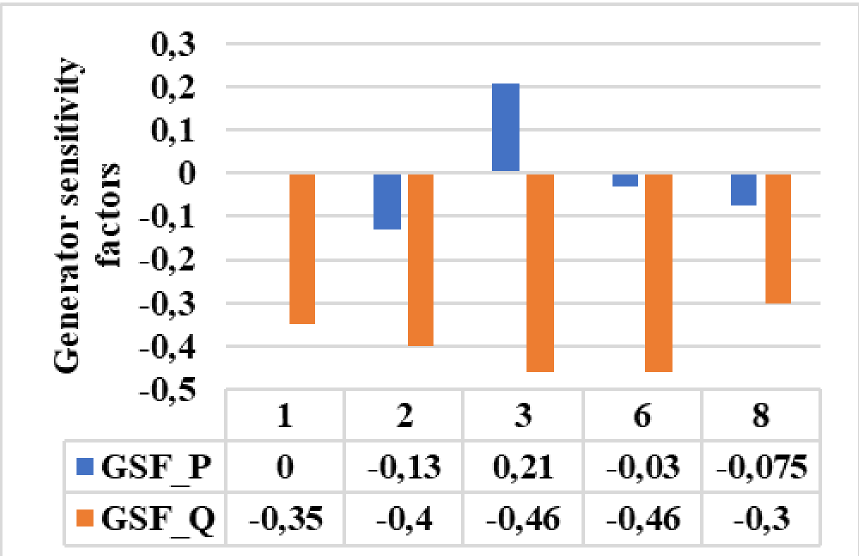


Figure 4. 2: IEEE 14-Bus system generator's sensitivity factors of the congested lines

Table 4. 2: Details of optimally obtained PSO results for the IEEE 14-Bus system

		Developed Method	Method Reported in (Srivastava & Kumar, 2002)
Active power rescheduling cost ($/day)		2.06E+04	Not reported
Reactive power rescheduling cost ($/day)		1.21E+04	Not reported
Active power rescheduling (MW)	ΔP_1	140	157.7
	ΔP_2	50	77.8
	ΔP_3	0	49.274
	ΔP_6	20	14.274
	ΔP_8	60	23.394
Amount of active power rescheduling (MW)		270	322.442
Amount of active power demand (MW)		259	Not reported
Reactive power rescheduling (MVar)	ΔQ_1	24.928	Not reported
	ΔQ_2	24.5344	
	ΔQ_3	0	
	ΔQ_6	15.5268	
	ΔQ_8	1.1483	
Amount of reactive power rescheduling (MVar)		78.3475	
Amount of reactive power demand (MVar)		77.4	Not reported

Rescheduling the generator to alleviate congestion can occasionally lead to notable or minimal deviations in bus voltage. In order to resolve the problem of voltage deviation on the load buses, adjustments were made to the generator voltages to ensure that the voltages at all load buses remain within acceptable limits. Furthermore, the rescheduling of reactive power greatly enhances the voltage profile of all load buses and safeguards the system from voltage collapse. The rescheduling of reactive power significantly improves the voltage profile by maintaining voltage levels within acceptable ranges and enhancing voltage uniformity across the network. It also plays a critical role in enhancing system stability, both in terms of voltage stability and dynamic stability, by preventing voltage collapse, improving the system's response to disturbances, and enhancing damping of oscillations. Effective reactive power management involves the coordinated control of various reactive power sources, considering both technical and practical aspects, leading to improved overall system performance. Figure 4.3 displays the improvement in voltage profile before and after the CM. Additionally, Figures 4.4 and 4.5 illustrate the convergence features of the PSO-based active and reactive power rescheduling cost for the test system network. Figures 4.4 and 4.5 demonstrate that the cost of rescheduling both active and reactive powers for the IEEE 14 bus system reduces when the convergence characteristics, specifically the iteration number, increase.

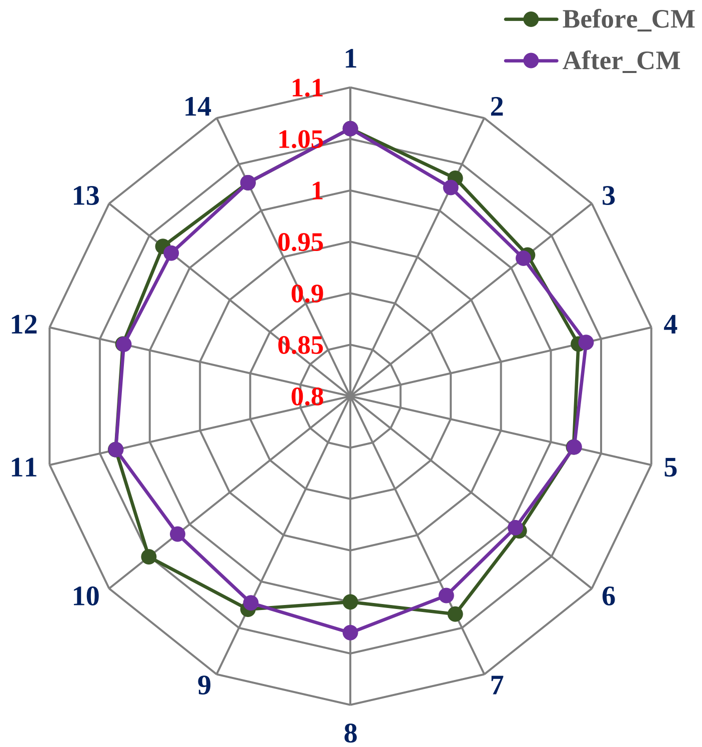


Figure 4. 3: IEEE 14-Bus voltage profile improvement before and after CM

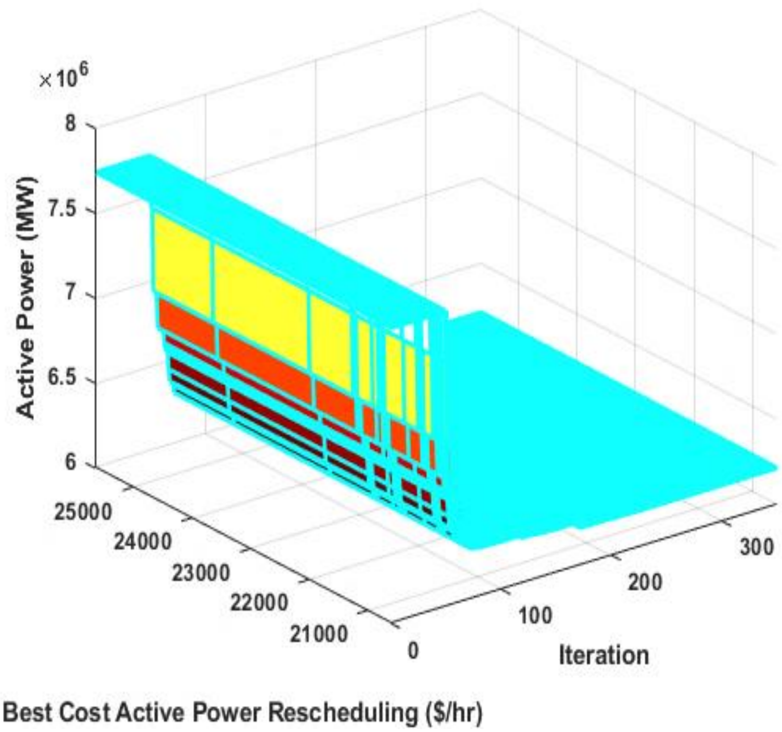


Figure 4. 4: PSO-based active power convergence characteristic for IEEE 14-Bus system

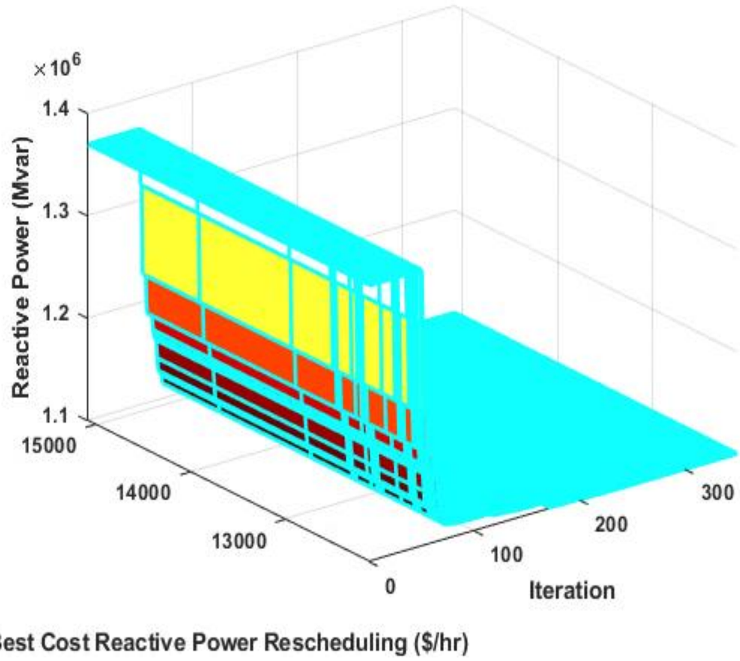


Figure 4. 5: PSO-based reactive power convergence characteristic for IEEE 14-Bus system

4.4.2 CASE 2: IEEE 30-Bus system network

The network statistics were acquired from (Adewolu, 2020; Ogunwole & Krishnamurthy, 2022). The network consists of 30 buses, 41 interconnected lines, and 6 generators. APPENDIX A2 provided comprehensive information on both the network data and its single-line diagram. Based on the power flow analysis, it has been determined that lines 1 and 5 are experiencing the highest levels of congestion. The comprehensive outcome of the power flow on the congested line is displayed in Table 4.3. Furthermore, Figures 4.6 and 4.7 present the comprehensive outcomes of GSF, which were utilised to detect any generators that are causing congestion on lines 1 and 5.

Table 4. 3: IEEE 30-Bus congested line details

Congested line	Power Flow (MW)		Line Limit (MW)
	Pre-CM	Post-CM	
1 (1 – 2)	179.152	125.293	130
5 (2 – 5)	83..008	59.173	65

According to the GSF principle described in sub-section 4.4.1 of case 1, generators 1, 2, 5, 8, and 13 are the generators that would help reduce congestion on the crowded line. Furthermore, the power outputs of the generator have been efficiently rescheduled utilising the Particle Swarm Optimisation (PSO) in order to decrease congestion. The comprehensive outcomes of the PSO algorithm, which effectively adjusts the output power of the participating generators to mitigate congestion, are presented in Table 4.4.

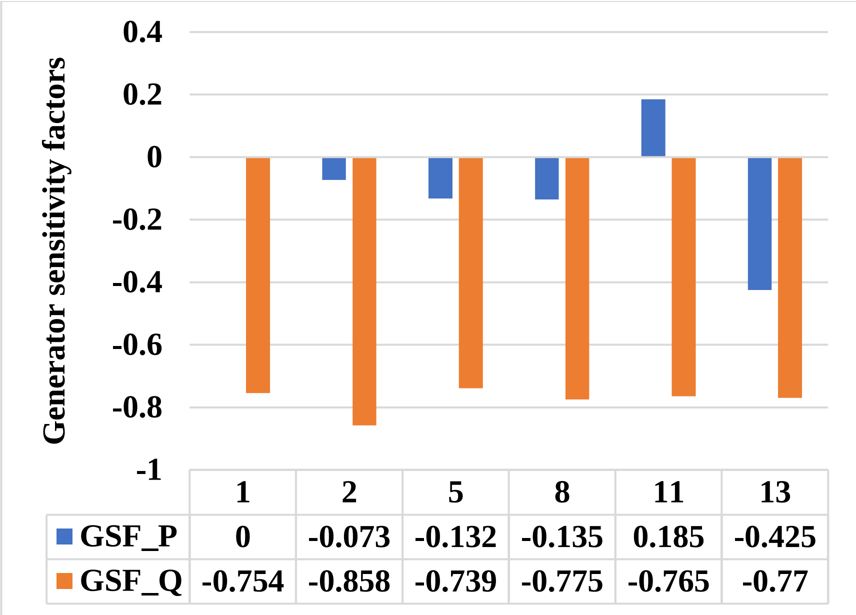


Figure 4. 6: IEEE 30-Bus system generator's sensitivity factors of the congested line 1

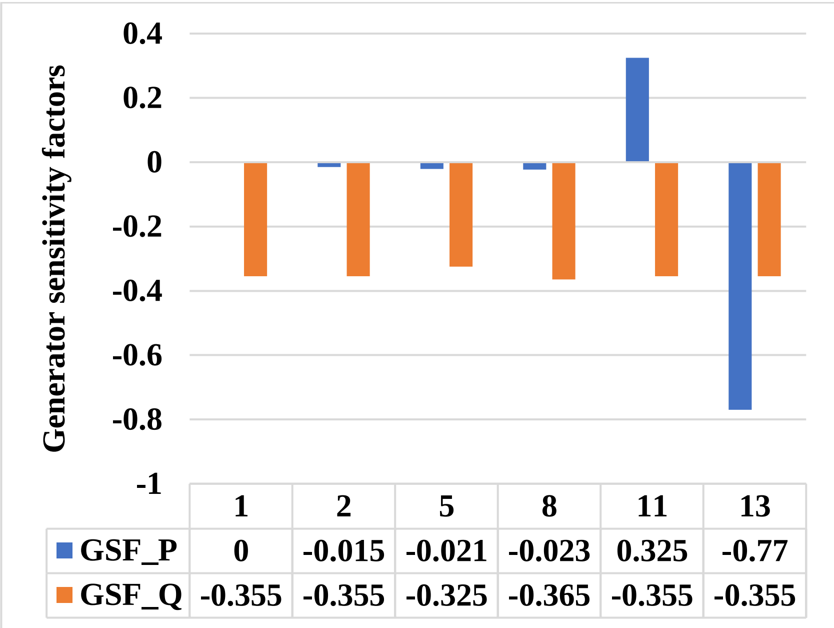


Figure 4. 7: IEEE 30-Bus system generator's sensitivity factors of the congested line 5

Table 4. 4: Details of optimally obtained PSO results for the IEEE 30-Bus system

	Proposed method	Method reported in (Kim & Salkuti, 2019)	Method reported in (Salkuti, 2018)
Active power rescheduling cost ($/day)	3.10E+04	799.56	1196.35

Reactive power rescheduling cost ($/day)		7.58E+03	Not reported	Not reported
Active power rescheduling (MW)	ΔP_1	157.772	177.285	174.46
	ΔP_2	55.58	48.93	76.37
	ΔP_5	18.563	21.29	42.08
	ΔP_8	17.744	20.49	32.72
	ΔP_{11}	0	11.93	28.79
	ΔP_{13}	41.219	12.23	31.77
Total active power rescheduling (MW)		290.878	292.155	386.19
Total active power demand (MW)		283.4	Not reported	Not reported
Reactive power rescheduling (MVar)	ΔQ_1	28.498	Not reported	Not reported
	ΔQ_2	76.275		
	ΔQ_5	24.692		
	ΔQ_8	0.965		
	ΔQ_{11}	0		
	ΔQ_{13}	9.879		
Total reactive power rescheduling (MVar)		139.344		
Total reactive power demand (MVar)		126.2	Not reported	Not reported

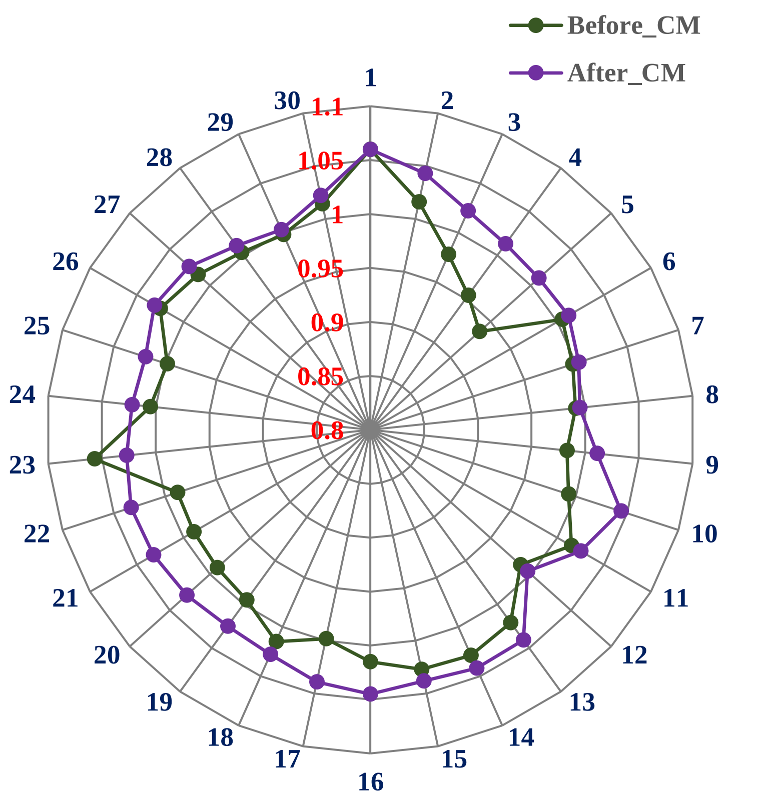


Figure 4. 8: IEEE 30-Bus voltage profile improvement before and after CM

In order to address the problem of voltage fluctuation at load buses, the generator voltages were adjusted to maintain the load bus voltages within acceptable limits. Reactive power rescheduling improves voltage stability in all load buses and prevents the system from reaching the point of voltage collapse. The voltage profile improvement is depicted in Figure 4.8, displaying the before and after states. Furthermore, Figures 4.9 and 4.10 illustrate the convergence properties of the costs associated with active and reactive power rescheduling using a PSO-based approach in the test network. Figures 4.9 and 4.10 demonstrate that the cost of rescheduling both active and reactive powers of the IEEE 30 bus system lowers when the convergence characteristics, specifically the iteration number, increase.

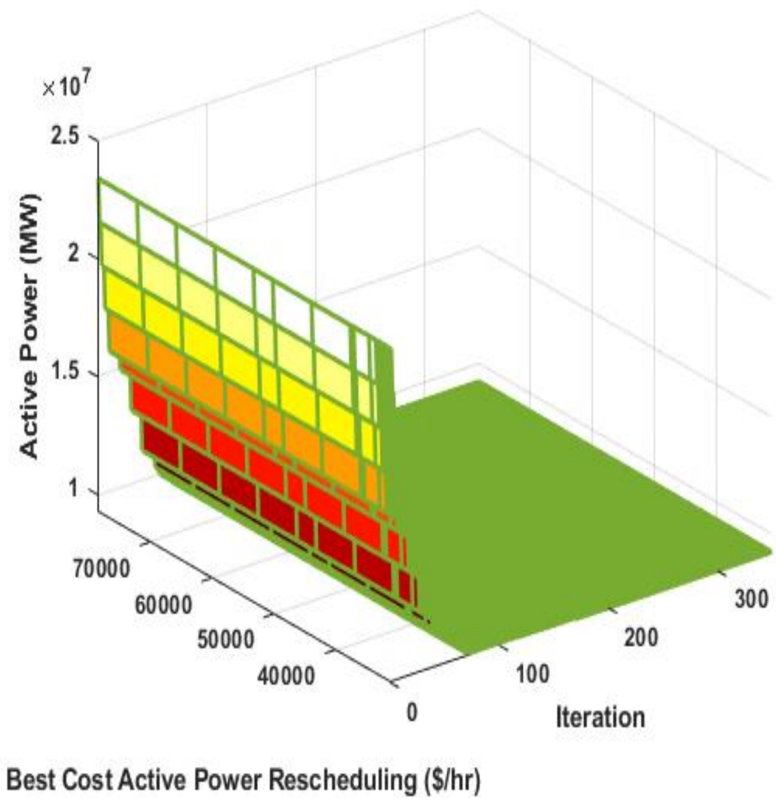


Figure 4. 9: PSO-based active power convergence characteristic for IEEE 30-Bus system

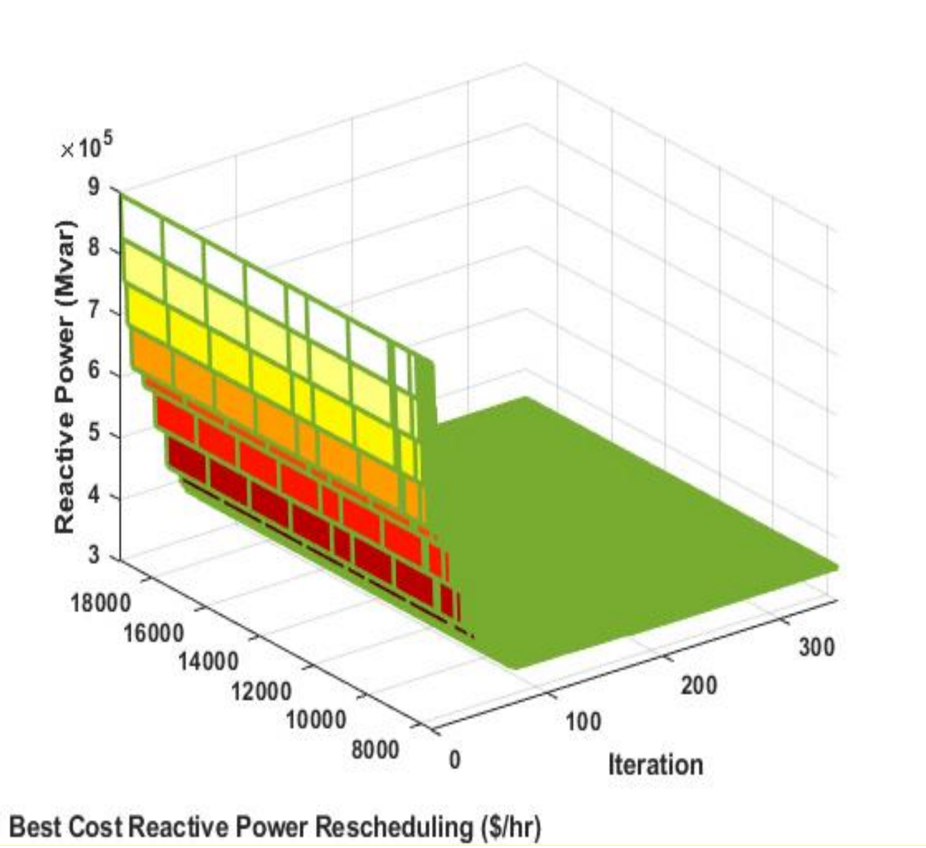


Figure 4. 10: PSO-based reactive power convergence characteristic for IEEE 30-Bus system

4.4.3 CASE 3: IEEE 118-Bus system network

The system is described in depth by (Blumsack, 2006; Ogunwole & Krishnamurthy, 2022). The system comprises a total of 118 buses, 179 interconnecting lines, and 54 generators. The network data and its single-line diagram were both provided in detail in APPENDIX A3. The comprehensive power flow analysis of the congested transmission lines is presented in Table 4.5 below. The GSF for each congested line are depicted in Figures 4.11 to 4.16, providing detailed information. Tables 4.6 and 4.7 display the specific information regarding the ideal rescheduling of the output active and reactive power of the generators involved in the PSO process, with the aim of reducing congestion. Based on the provided tables, generators 6, 24, 34, 54, 66, 85, and 105 are the only ones that are not affected by congestion.

Table 4. 5: IEEE 118-Bus congested line details

Congested line	Power Flow (MW)		Line Limit (MW)
	Pre-CM	Post-CM	
9 (4 – 11)	86.543	73.935	80
112 (37 – 40)	73.41	42.183	55
148 (49 -50)	84.65	35.557	67
205 (64 – 65)	250.466	197.583	228

264 (80 – 98)	54.094	24.487	36
331 (100 – 106)	97.245	73.245	75

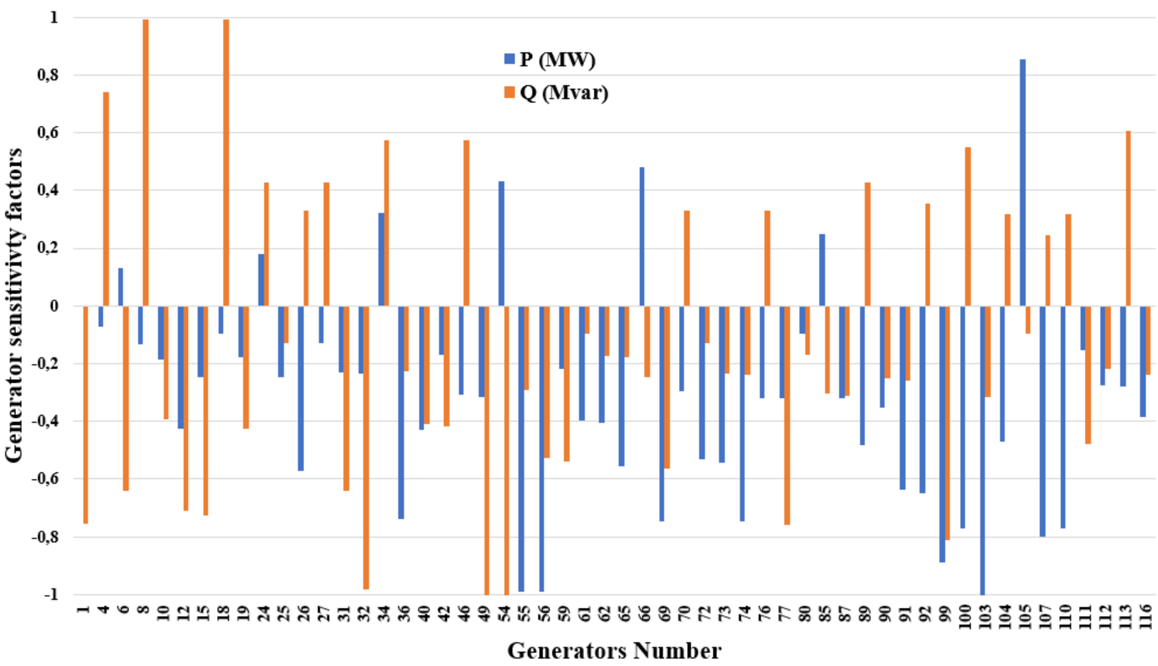


Figure 4. 11: IEEE 118-Bus system generator's sensitivity factors of the congested line 9

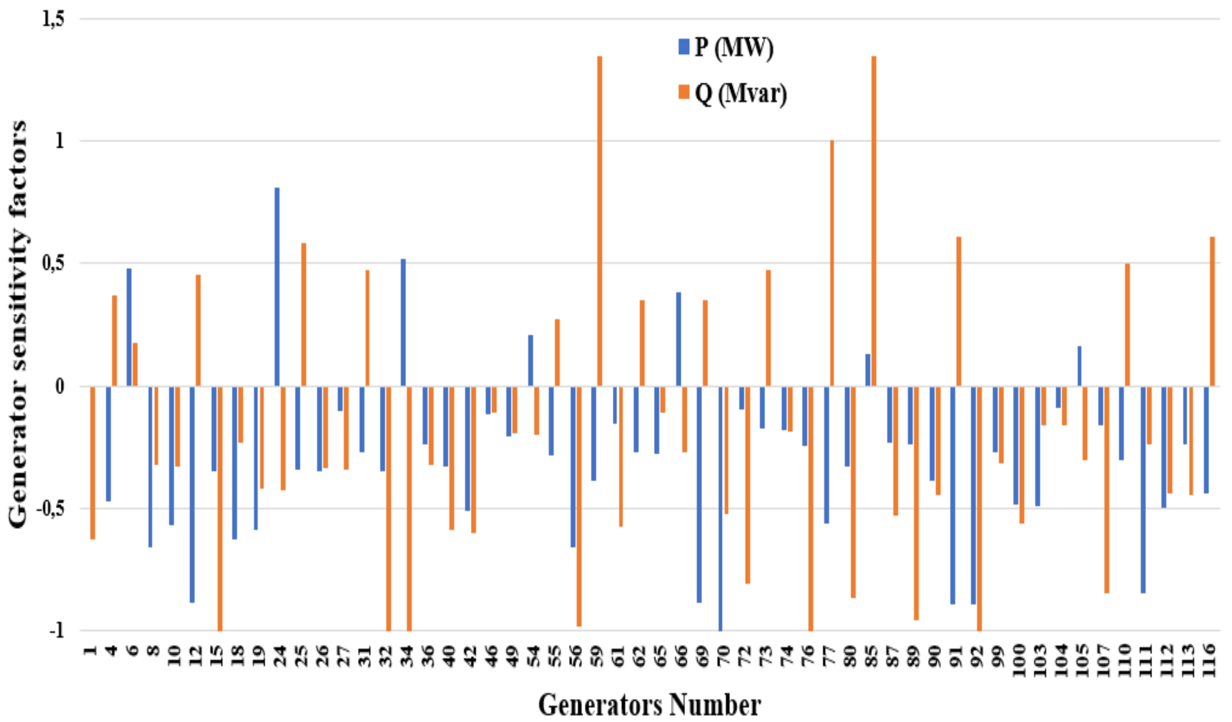


Figure 4. 12: IEEE 118-Bus system generator's sensitivity factors of the congested line 112

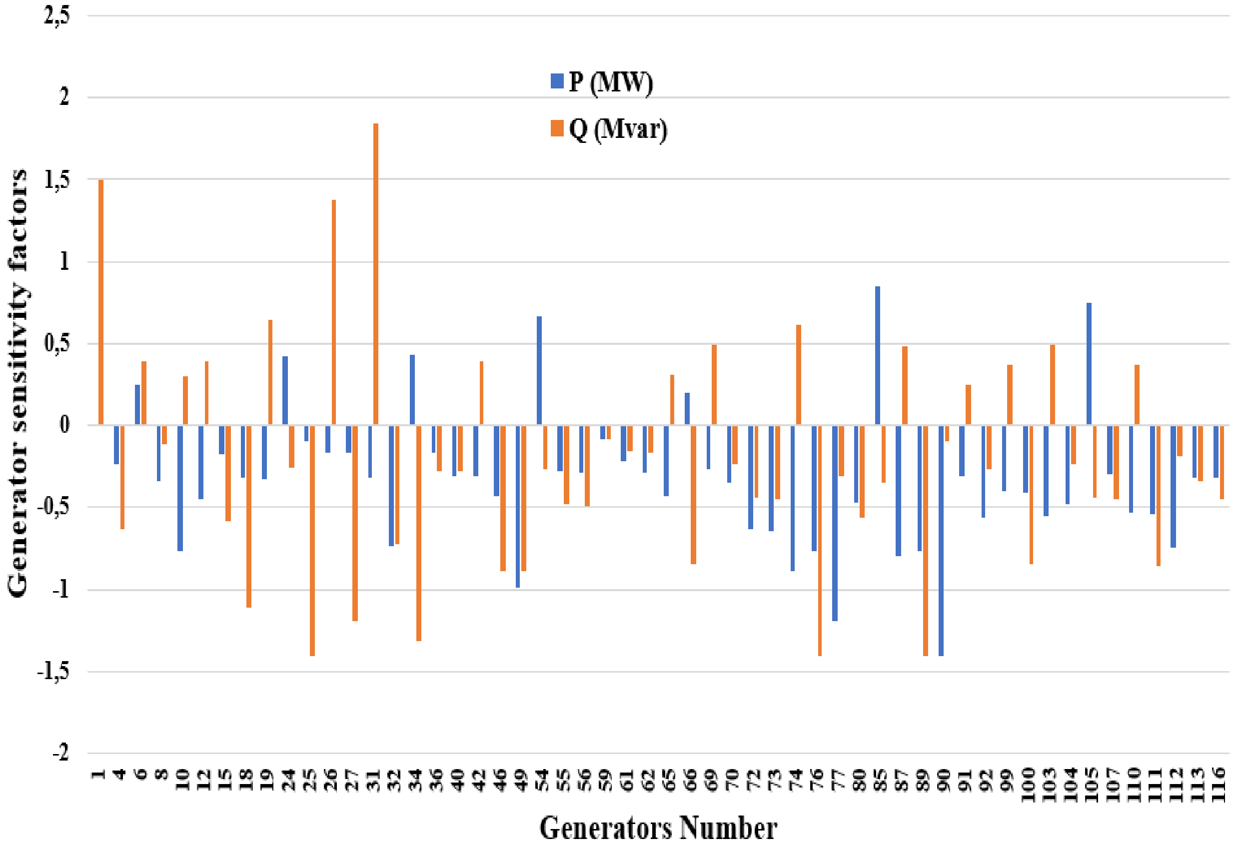


Figure 4. 13: IEEE 118-Bus system generator's sensitivity factors for the congested line 148

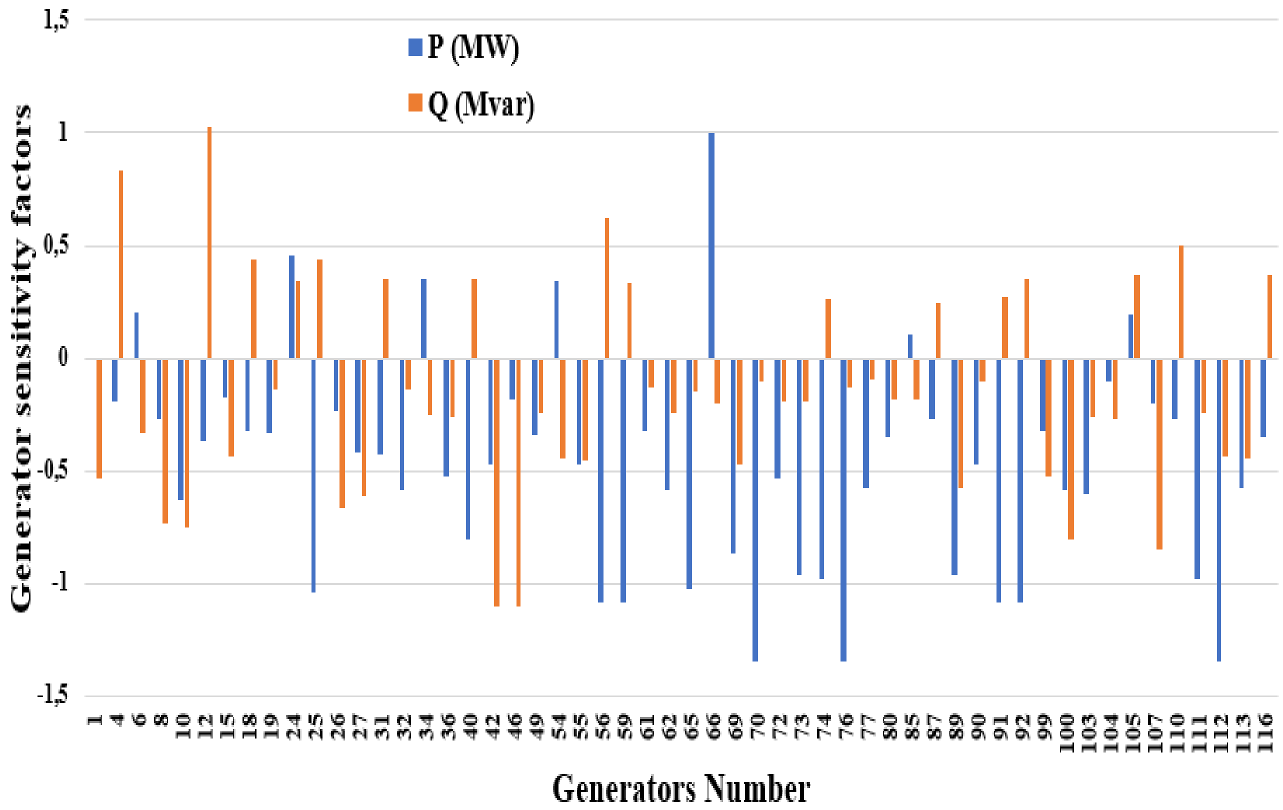


Figure 4. 14: IEEE 118-Bus system generator's sensitivity factors of the congested line 205

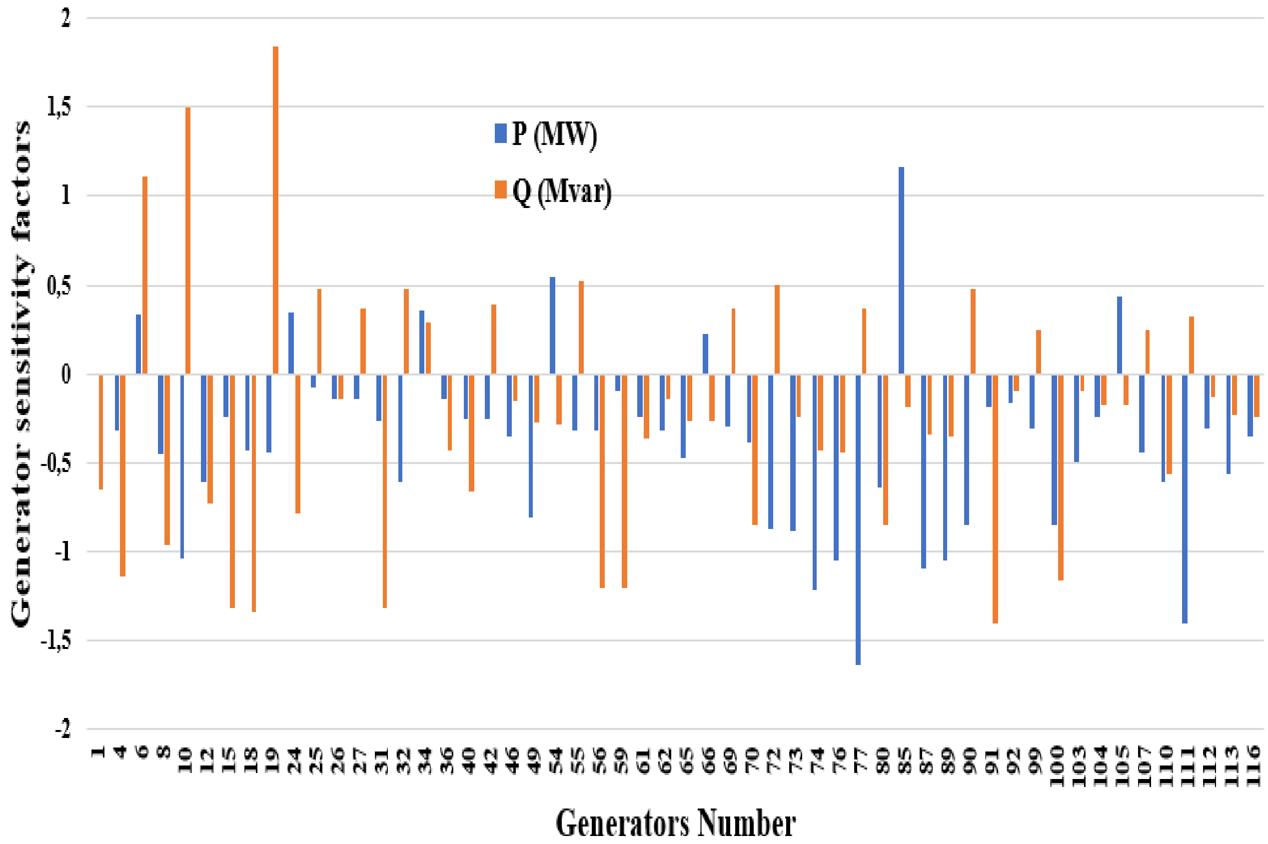


Figure 4. 15: IEEE 118-Bus system generator's sensitivity factors of the congested line 264

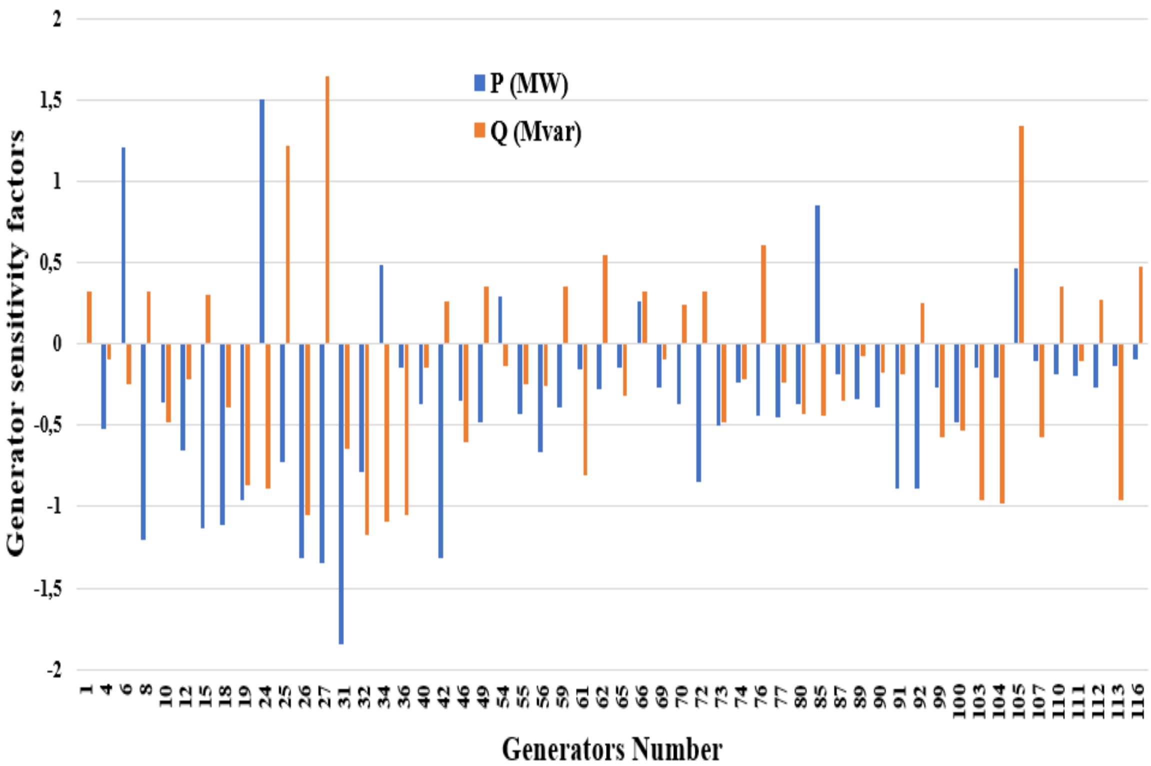


Figure 4. 16: IEEE 118-Bus system generator's sensitivity factors of the congested line 331

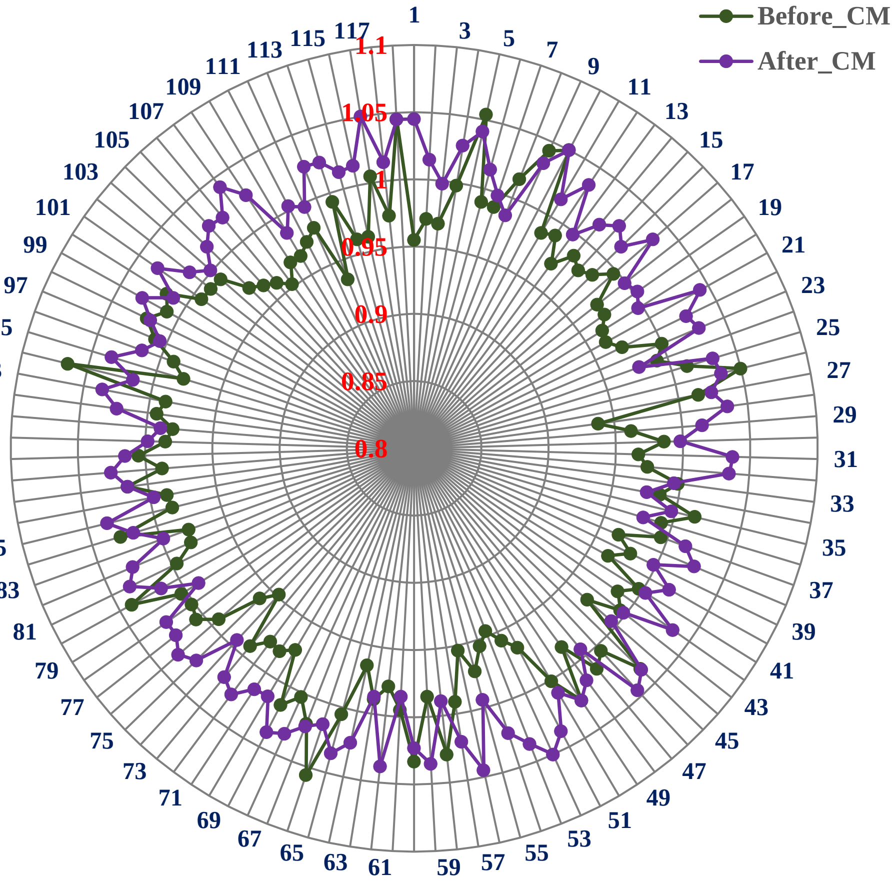


Figure 4. 17: IEEE 118-Bus voltage profile improvement before and after CM

Table 4. 6: Active power rescheduling for IEEE 118-Bus system

Active power rescheduling (MW)					
Active power rescheduling cost ($/day)				7.88E+04	
Total active power rescheduling (MW)				3711	
Total active power demand (MW)				3668	
ΔP_1	68.716	ΔP_{42}	63.314	ΔP_{80}	50.409
ΔP_4	12.427	ΔP_{46}	34.16	ΔP_{85}	0
ΔP_6	0	ΔP_{49}	38.25	ΔP_{87}	64.685
ΔP_8	30.337	ΔP_{54}	0	ΔP_{89}	59.5
ΔP_{10}	44.097	ΔP_{55}	60.361	ΔP_{90}	104.107
ΔP_{12}	72.413	ΔP_{56}	52.387	ΔP_{91}	19.75
ΔP_{15}	8.875	ΔP_{59}	58.128	ΔP_{92}	58.99
ΔP_{18}	8.839	ΔP_{61}	39.904	ΔP_{99}	92.19
ΔP_{19}	47.403	ΔP_{62}	39.432	ΔP_{100}	48.125
ΔP_{24}	0	ΔP_{65}	38.451	ΔP_{103}	13.284
ΔP_{25}	26.076	ΔP_{66}	0	ΔP_{104}	92.342
ΔP_{26}	14.776	ΔP_{69}	42.88	ΔP_{105}	0
ΔP_{27}	37.079	ΔP_{70}	36.209	ΔP_{107}	73.464
ΔP_{31}	84.863	ΔP_{72}	251.353	ΔP_{110}	43.526
ΔP_{32}	27.541	ΔP_{73}	41.127	ΔP_{111}	43.981
ΔP_{34}	0	ΔP_{74}	9.636	ΔP_{112}	15.409

ΔP_{36}	113.461	ΔP_{76}	12.27	ΔP_{113}	12.132
ΔP_{40}	75.897	ΔP_{77}	27.902	ΔP_{116}	145.859

Table 4. 7: Reactive power rescheduling for IEEE 118-Bus system

Reactive power rescheduling (MVar)					
Cost of reactive power rescheduling ($/day)				3.54E+04	
Total reactive power rescheduling (MW)				1477	
Total reactive power demand (MVar)				1438	
ΔQ_{1}	20.569	ΔQ_{42}	50.798	ΔQ_{80}	148.507
ΔQ_{4}	37.658	ΔQ_{46}	53.667	ΔQ_{85}	0
ΔQ_{6}	0	ΔQ_{49}	59.363	ΔQ_{87}	39.66
ΔQ_{8}	114.135	ΔQ_{54}	0	ΔQ_{89}	81.288
ΔQ_{10}	49.625	ΔQ_{55}	10.049	ΔQ_{90}	32.464
ΔQ_{12}	20.1	ΔQ_{56}	15.69	ΔQ_{91}	136.635
ΔQ_{15}	75.848	ΔQ_{59}	46.818	ΔQ_{92}	49.938
ΔQ_{18}	69.789	ΔQ_{61}	78.305	ΔQ_{99}	20.964
ΔQ_{19}	16.328	ΔQ_{62}	35.134	ΔQ_{100}	4.912
ΔQ_{24}	0	ΔQ_{65}	26.333	ΔQ_{103}	58.679
ΔQ_{25}	159.157	ΔQ_{66}	0	ΔQ_{104}	14.672
ΔQ_{26}	85.224	ΔQ_{69}	21.847	ΔQ_{105}	0
ΔQ_{27}	44.038	ΔQ_{70}	65.115	ΔQ_{107}	135.659
ΔQ_{31}	17.373	ΔQ_{72}	67.407	ΔQ_{110}	41.318
ΔQ_{32}	12.527	ΔQ_{73}	20.133	ΔQ_{111}	17.624
ΔQ_{34}	0	ΔQ_{74}	20.087	ΔQ_{112}	21.743
ΔQ_{36}	49.319	ΔQ_{76}	43.094	ΔQ_{113}	34.265
ΔQ_{40}	23.678	ΔQ_{77}	44.05	ΔQ_{116}	14.59

As shown in Figures 4.18 and 4.19, the cost of rescheduling both active and reactive powers of the IEEE 118 bus system decrease as the converge characteristics increases.

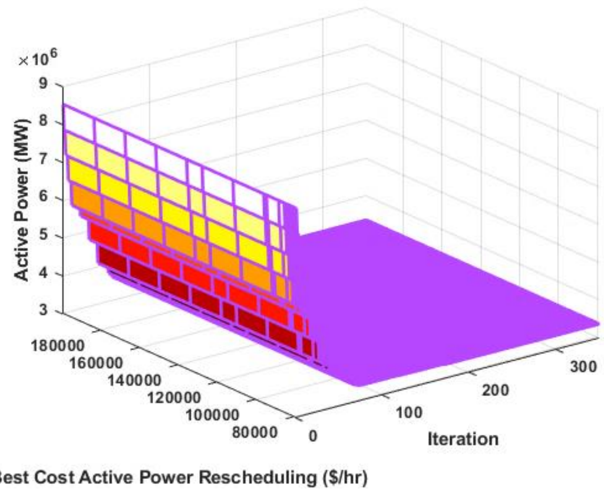


Figure 4. 18: PSO-based active power convergence characteristic for IEEE 118-Bus system

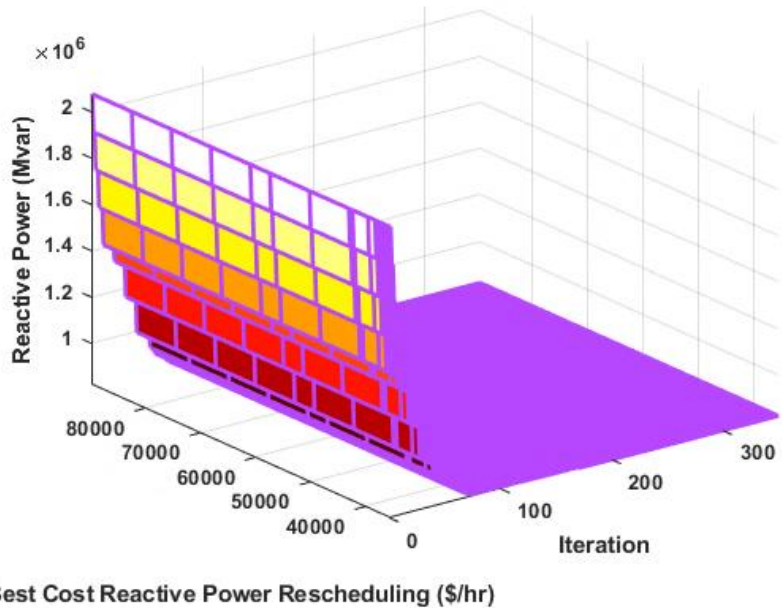


Figure 4. 19: PSO-based reactive power convergence characteristic for IEEE 118-Bus system

Table 4.8 presents a comprehensive overview of the active and reactive power loss, both before and after congestion control. Figure 4.17 displays the graphical depiction of the enhancement in voltage profile both before (Pre) and after (Post) the implementation of congestion management. Figures 4.18 and 4.19 illustrate the convergence characteristics of the costs associated with active and reactive power rescheduling using the PSO method for the test network.

Table 4. 8: Summary of power loss for all the cases considered

		Proposed method		**Reported in** (Dutta & Singh, 2008)		**Reported in** (Salkuti, 2018)	
		Before	**After**	**Before**	**After**	**Before**	**After**
Case 1 [IEEE 14]	**P (MW)**	13.55	12.91	×	×	×	×
	Q (MVar)	55.56	53.52	×	×	×	×
Case 2 [IEEE 30]	**P (MW)**	17.59	15.65	21	15	×	17.76
	Q (MVar)	17.87	15.12	×	×	×	20.93
Case 3 [IEEE 118]	**P (MW)**	91.39	81.46	140	137	×	×
	Q (MVar)	87.89	77.07	×	×	×	×

4.5 Chapter Summary

This chapter introduced an innovative (the developed methods/approaches used to mitigate transmission congestion in deregulated power systems) method for rearranging the operation of generators in order to manage congestion in transmission system networks. The generators that were rescheduled were determined based on their susceptibility to the congested line, as shown by their active and reactive power attributes. Minimizing the disparity between rescheduled and planned generator outputs is effective in managing congestion costs by reducing operational costs, enhancing system stability, improving predictability, increasing system flexibility, and providing environmental benefits. Practical implementations through advanced OPF solutions, policy adjustments, and real-time control systems further enhance the effectiveness of this approach in managing congestion in power systems. Subsequently, a PSO was utilised to minimise the deviation of the rescheduled generation's active and reactive power from the scheduled generator, with the aim of reducing costs. PSO effectively finds optimal or near-optimal solutions for OPF problems, balancing generation cost, power losses, and voltage stability while minimizing congestion. The application of PSO to congestion management in power systems has provided significant insights into its effectiveness, flexibility, and practical benefits, paving the way for its continued use and development in both academic research and real-world applications.The suitability of this approach was assessed using IEEE 14, 30, and 118 standard network buses. The simulation findings demonstrate that the cost of both active and reactive powers is reduced following rescheduling. The active power losses for the IEEE 14, 30, and 118 cases are 4.7%, 11.03%, and 10.87% respectively. The reactive power losses for the same cases are 3.67%, 15.39%, and 12.31% correspondingly. The findings indicate that reducing the disparity between the active and reactive power of rescheduled generators and planned generators can effectively minimise the expenses associated with congestion management. In addition, the applied approach improved voltage stability and voltage profile while decreasing the operational cost of the gearbox system.

CHAPTER FIVE

PERFORMANCE COMPARATIVE ANALYSIS OF MIXED INTEGER LINEAR PROGRAMMING AND PARTICLE SWARM OPTIMIZATION ALGORITHM FOR TRANSMISSION CONGESTION MANAGEMENT

5.1 Introduction

In this chapter, an application of mixed integer linear programming (MILP) algorithm for the solution of transmission congestion management was proposed. The algorithm (MILP), in terms of performances and results were compared with PSO results as presented in the previous chapter four above. The mathematical expression for the objective function, generator sensitivity factor (GSF) for active and reactive power rescheduling, can be found in equations (3.13) and (3.25) in chapter three. The equality and inequality constraints are given in sub-sections 3.2.1.1 and 3.2.1.2 of section 3.2. Additionally, the penalty function (3.11) and (3.12) are used for the congestion management problem based on MILP. The MILP algorithm was used to mitigate the difficulty indicated above by addressing the unique CM problem.

5.2 Mixed Integer Linear Programming Algorithm

MILP algorithm solves discrete optimization problems using various techniques to find the optimal solution for the objective function. The MILP can be represented in a standard form as (Tahirou Halidou et al., 2023; Urbanucci, 2018):

$$\boldsymbol{min\ f^T \cdot x} \tag{5.1}$$

$$\boldsymbol{subject\ to} \begin{cases} \boldsymbol{x(intcon)\ are\ integers} \\ \boldsymbol{A_{ineq} . x \leq b_{ineq}} \\ \boldsymbol{A_{eq} . x = b_{eq}} \\ \boldsymbol{l_b \leq x \leq u_b} \end{cases} \tag{5.2}$$

Where,

$\boldsymbol{f}$ is the linear function vector

$\boldsymbol{x}$ is the solution vector

$\boldsymbol{A_{ineq}}$ is the inequality matrices

$\boldsymbol{b_{ineq}}$ is the inequality vector

$\boldsymbol{A_{eq}}$ is the equality matrices

$\boldsymbol{b_{eq}}$ is the equality vector

$\boldsymbol{l_b}$ is the lower-bound

$\boldsymbol{u_b}$ is the upper-bound

The ***intlinprog*** algorithm employs six ways to solve MILP issues and determine the solution at each stage. ***Intlinprog*** terminates if it discovers a solution at a given stage and does not continue to the subsequent step. Begin by decreasing the size of the problem with linear programme preparation. Next, solve an initial unconstrained (non-integer) issue using linear programming. Subsequently, the mixed-integer programme preprocessing is executed to enhance the linear programming relaxation of the mixed-integer issue. Subsequently, cutting-plane techniques were employed to further refine the LP relaxation of the mixed-integer problem, as depicted in Figure 5.1. Next, attempt to locate integer-feasible solutions utilising heuristics. Ultimately, a branch and bound algorithm will be employed to methodically explore and find the best possible solution.

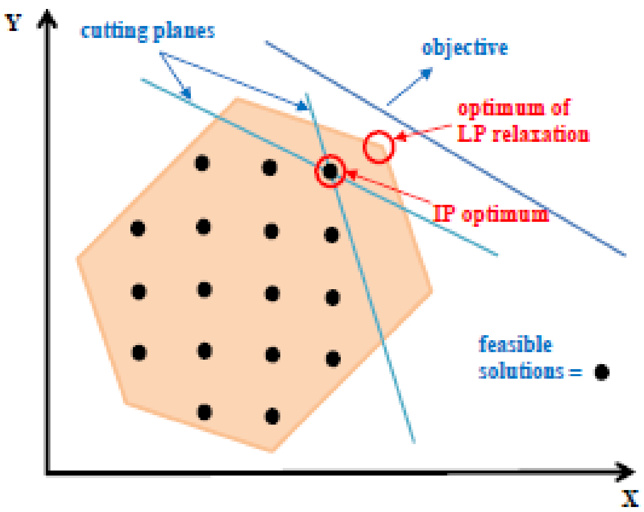


Figure 5. 1: Cutting-plane technique **(Tahirou Halidou et al., 2023)**

5.3 DC OPF-MILP Problem Formulation for Congestion Management

The goal is to reduce transmission congestion by adjusting generator schedules using generator sensitivity factors. The issue of CM can be addressed using MILP. The approach involves formulating a problem that can be solved using a MILP solver to identify the generator causing congestion and to find an appropriate solution. This approach entails converting the problem into a linear form and employing a DC network model. Furthermore, the ability to increase power injections and decrease power bids in generation is directly proportional, allowing for the submission of several power blocks at varying prices. Thus, the aforementioned issue can be formulated as the subsequent MILP optimisation algorithm:

$$\boldsymbol{Min} \sum_{i=1}^{N} \left(\boldsymbol{C_i^+} \Delta \boldsymbol{P_{gi}^+} + \boldsymbol{C_i^-} \Delta \boldsymbol{P_{gi}^-} \right) \tag{5.3}$$

Subject to;

$$\boldsymbol{P_g} + \Delta \boldsymbol{P_g^+} - \Delta \boldsymbol{P_g^-} - \boldsymbol{P_d} = \boldsymbol{A P_f} \tag{5.4}$$

$$\boldsymbol{P_f} = \boldsymbol{B_1 A^t \delta} + \boldsymbol{B_1 \varphi} \tag{5.5}$$

$$\Delta \boldsymbol{P}_g^{+min} \leq \Delta \boldsymbol{P}_g^{+} \leq \Delta \boldsymbol{P}_g^{+max} \tag{5.6}$$

$$\Delta \boldsymbol{P}_g^{-min} \leq \Delta \boldsymbol{P}_g^{-} \leq \Delta \boldsymbol{P}_g^{-max} \tag{5.7}$$

$$-\boldsymbol{u}_{\cdot}^{*} \boldsymbol{\varphi}^{max} \leq \boldsymbol{\varphi} \leq \boldsymbol{u}_{\cdot}^{*} \boldsymbol{\varphi}^{max} \tag{5.8}$$

$$\boldsymbol{1}^{T} \boldsymbol{u} \leq \boldsymbol{N}_{\varphi} \tag{5.9}$$

$$\left|\boldsymbol{P}_f\right| \leq \boldsymbol{P}_f^{max} \tag{5.10}$$

Where,

$\Delta \boldsymbol{P}_g^{+}, \Delta \boldsymbol{P}_g^{+min}, \ \Delta \boldsymbol{P}_g^{+max}$ are active power generation increment outputs and limits

$\Delta \boldsymbol{P}_g^{-}, \Delta \boldsymbol{P}_g^{-min}, \ \Delta \boldsymbol{P}_g^{-max}$ are active power generation decrement outputs and limits

$\boldsymbol{P}_d$ is the loads bus vector

$\boldsymbol{P}_g$ active power generation outputs

$\boldsymbol{P}_f, \boldsymbol{P}_f^{max}$ line power flow and limits vectors

$\boldsymbol{\varphi}, \boldsymbol{\varphi}^{max}$ are phase shifter settings and limits vectors

$\boldsymbol{A}$ node incident matrix

$\boldsymbol{u}$ binary variable vector

The cost function (5.3) in the preceding formulation seeks to minimise the expense associated with altering the provided generation output vector. In this context, a generator submits an incremental bid to indicate an increase in generation, and a decremental offer to indicate a decrease in generation. Furthermore, the increments and decrements must adhere to the prescribed range outlined in equations (5.6) and (5.7), which have a bottom bound that is not negative. In this formulation, the initial generation output level is a predetermined and specified parameter established through negotiated agreements among market participants. The variable in question is not a decision variable in this technique, but rather a defined parameter. The goal is to reduce the expenses/cost associated with adjusting these initial values in congestion management/re-dispatch.

5.4 AC OPF-MINLP Problem Formulation for Congestion Management

Equations (5.3) to (5.10) can be transformed into the AC form, denoted by equations (5.11) to (5.21). The primary distinction between these two sets of equations lies in the power flow equations (5.12) and (5.13), which incorporate non-linear components such as the generation and bidding of reactive power, as well as the magnitudes and angles of bus voltages. In the OPF problem, the variables can be classified into two groups: continuous variables, such as generator outputs and bus voltage magnitude, and discrete variables, such as phase shifter settings and binary variables indicating the presence of a phase shifter in the congested line. Furthermore, because the constraints that equate active and reactive power are nonlinear, the problem can be expressed as a Mixed Integer Nonlinear Programming (MINLP) problem.

$$\boldsymbol{Minimize} \sum_{i=1}^{N} \left(C_{pgi}^{+} \Delta P_{gi}^{+} + C_{pgi}^{-} \Delta P_{gi}^{-} + C_{qgi}^{+} \Delta Q_{gi}^{+} + C_{qgi}^{-} \Delta Q_{gi}^{-} \right) \tag{5.11}$$

Subject to;

$$P_{gi} + \Delta P_{gi}^{+} - \Delta P_{gi}^{-} - P_{di} = \sum_{j=1}^{N} |V_i| \left| V_j \right| \left[G_{ij} cos\left(\delta_i - \delta_j \pm \theta_{ij}\right) + B_{ij} sin\left(\delta_i - \delta_j \pm \theta_{ij}\right) \right] \tag{5.12}$$

$$Q_{gi} + \Delta Q_{gi}^{+} - \Delta Q_{gi}^{-} - Q_{di} = \sum_{j=1}^{N} |V_i| \left| V_j \right| \left[G_{ij} sin\left(\delta_i - \delta_j \pm \theta_{ij}\right) - B_{ij} cos\left(\delta_i - \delta_j \pm \theta_{ij}\right) \right] \tag{5.13}$$

$$0 \le \Delta P_{gi}^{+} \le \Delta P_{gi}^{+max} \tag{5.14}$$

$$0 \le \Delta P_{gi}^{-} \le \Delta P_{gi}^{-max} \tag{5.15}$$

$$0 \le \Delta Q_{gi}^{+} \le \Delta Q_{gi}^{+max} \tag{5.16}$$

$$0 \le \Delta Q_{gi}^{-} \le \Delta Q_{gi}^{-max} \tag{5.17}$$

$$\left| P_{ij} \right| \le P_{ij}^{max} \tag{5.18}$$

$$V_i^{min} \le V_i \le V_i^{max} \tag{5.19}$$

$$\delta_i^{min} \le \delta_i \le \delta_i^{max} \tag{5.20}$$

$$-u_{ij} \theta_{ij}^{max} \le \theta_{ij} \le u_{ij} \theta_{ij}^{max} \tag{5.21}$$

Where;

$\Delta P_{gi}^{+}, \Delta P_{gi}^{+max}$ are incremental change in active power generation at bus i and limits

$\Delta P_{gi}^{-}, \Delta P_{gi}^{-max}$ are decremental change in active power generation at bus i and limits

$\Delta Q_{gi}^{+}, \Delta Q_{gi}^{+max}$ are incremental change in reactive power generation at bus i and limits

$\Delta Q_{gi}^{-}, \Delta Q_{gi}^{-max}$ are decremental change in reactive power generation at bus i and limits

C_{pgi}^{+}, C_{pgi}^{-} are incremental and decremental costs of active power generation at bus i

C_{qgi}^{+}, C_{qgi}^{-} are incremental and decremental costs of reactive power generation at bus i

$\boldsymbol{P_{di}}, \boldsymbol{Q_{di}}$ are active and reactive loads at bus $\boldsymbol{i}$

$\boldsymbol{P_{gi}}, \boldsymbol{Q_{gi}}$ are active and reactive generation output at bus $\boldsymbol{i}$

$\boldsymbol{P_{ij}}, \boldsymbol{P_{ij}^{max}}$ are transmission line flow limits

$\boldsymbol{V_i}, \boldsymbol{V_i^{max}}, \boldsymbol{V_i^{min}}$ are the upper and lower limits voltage magnitude at bus $\boldsymbol{i}$

$\boldsymbol{\delta_i}, \boldsymbol{\delta_i^{max}}, \boldsymbol{\delta_i^{min}}$ are the upper and lower limits voltage angle at bus $\boldsymbol{i}$

$\boldsymbol{G_{ij}}$ is the conductance matrix between line $\boldsymbol{ij}$

$\boldsymbol{B_{ij}}$ is the susceptance matrix between line $\boldsymbol{ij}$

$\boldsymbol{N}$ is the number of buses

$\boldsymbol{L}$ is the number of lines

$\boldsymbol{\theta_{ij}}, \boldsymbol{\theta_{ij}^{max}}$ are the phase shifter setting and limit between line $\boldsymbol{ij}$

Equation (5.11) minimizes the rescheduling cost for active and reactive power in an electric power transmission network. The active power incremental bid offered by the generator for the incremental active generation change is a decremental bid submitted by the generator for its decremental active generation change. Similarly, an incremental bid submitted by the generator for the incremental reactive generation change is a decremental bid submitted by the generator for its decremental reactive generation change. The active and reactive power increments and decrements must be within specified values as defined by (5.14) to (5.17). The initial levels of active and reactive generation outputs are not decision variables because they are known and defined by prearranged agreements between market participants. The power flow equations (5.12) and (5.13) were employed as equality constraints; the active and reactive incremental and decremental generation limits in (5.14) to (5.17), active power flow limits in transmission lines (5.18), bus voltage and angle limits (5.19) and (5.20), phase shifter setting (5.21), is used as inequality constraints.

5.5 Implementation of the developed NR-OPF MILP algorithm for congestion management

Chapter three formulates the CM problem in the electric power transmission network mathematically. Figure 5.2 below depicts the proposed flowchart for the MILP-based congestion management and the procedural steps involveds as follows:

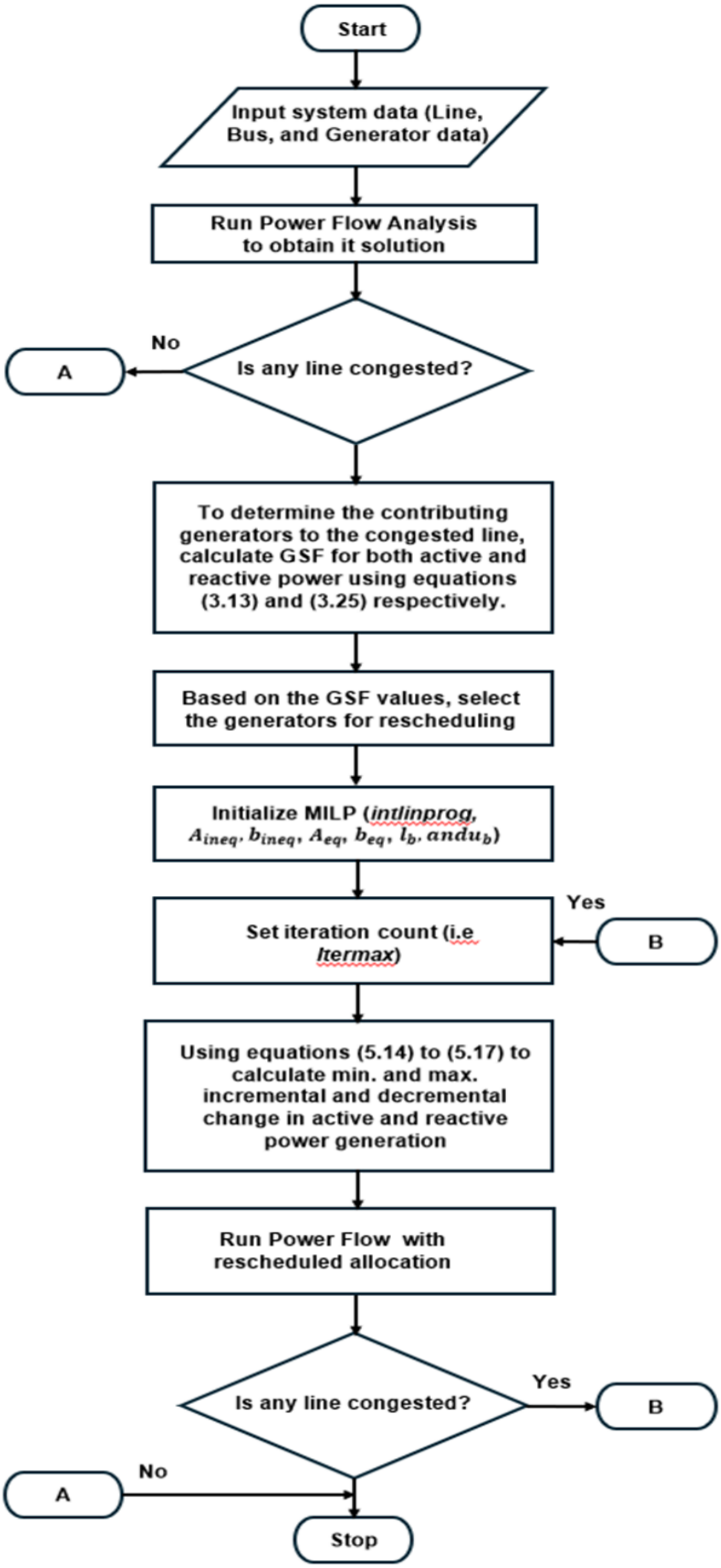


Figure 5. 2: The proposed flowchart for the congestion management based MILP

Step 1: Input systems data for all three IEEE networks (14, 30, and 118) considered.

Step 2: Execute the OPF method by Newton-Raphson to determine the congested lines.

Step 3: Calculate GSF for all generators to the overloaded line using (3.13) and (3.25), respectively. This is done by checking out for active and reactive power GSF of all generators matching the overloaded lines.

Step 4: Initialize MILP parameters; **(*intlinprog*, A_{ineq}, b_{ineq}, A_{eq}, b_{eq}, l_b, *and* u_b).**

Step 5: Using equations (5.14) to (5.17) to calculate min. and max. incremental and decremental change in active and reactive power generation.

Step 6: Compute the objective function using (5.11).

Step 7: Repeat step 2 to compute new line flows, new rescheduling active and reactive power, line losses, and new voltage magnitude in all buses.

Step 8: Again, repeat steps 3 to 9 until the convergence criterion is satisfied.

Step 9: Stop simulation.

5.6 Simulation Results and Discussion

This section provides detailed, comprehensive findings based on the effectiveness of the proposed technique for alleviating transmission congestion. Three case studies of IEEE 14, 30, and 118 bus transmission networks, were considered in this work. Voltage profile improvement, optimal rescheduling of active and reactive power of the generators, and cost of rescheduling were the performance metrics considered. The simulation results were compared with the previous PSO results in chapter four in terms of cost of rescheduling both active and reactive powers.

5.6.1 CASE 1: IEEE 14-Bus system network

The considered network consist of 14 buses, 20 interconnected lines, and 5 generators. Its single-line diagram and the network data were obtained from (Gautam & Mithulananthan, 2007) and are detailed in APPENDIX A1 and B1 respectively. According to the power flow results as detailed in the previous chapter (Chapter Four), line number 6 (between buses 2 and 5) was identified as the congested line. The same principle of identifying participating generator via generator sensitivity factor (GSF) was also applied as discussed in subsection 4.4.1. Hence, in order to mitigate congestion, the output power of the participating generators was optimally rescheduled using MILP Algorithm. Table 5.1 and 5.2 detailed the rescheduling cost comparison and simulation results of MILP compared with PSO Algorithm and proposed method from literature respectively.

Table 5. 1: Rescheduling cost comparison between PSO and MILP

	Developed MILP Method	Developed PSO Method	Method Reported in (Srivastava & Kumar, 2002)
Active power rescheduling cost ($/day)	838	2.06E+04	Not reported
Reactive power rescheduling cost ($/day)	189.6	1.21E+04	Not reported

Table 5. 2: Optimally obtained PSO and MILP results for IEEE 14-Bus system

		Developed MILP Method	Developed PSO Method	Method Reported in (Srivastava & Kumar, 2002)
Active power rescheduling (MW)	ΔP_1	130	140	157.7
	ΔP_2	45	50	77.8
	ΔP_3	20	0	49.274
	ΔP_6	30	20	14.274
	ΔP_8	43	60	23.394
Amount of active power rescheduling (MW)		268	270	322.442
Amount of active power demand (MW)		259	259	Not reported
Reactive power rescheduling (MVar)	ΔQ_1	19.5	24.928	Not reported
	ΔQ_2	15.9	24.5344	
	ΔQ_3	5.5	0	
	ΔQ_6	10.8	15.5268	
	ΔQ_8	25	1.1483	
Amount of reactive power rescheduling (MVar)		76.7	78.3475	
Amount of reactive power demand (MVar)		77.4	77.4	Not reported

Generator rescheduling for congestion alleviation might lead to considerable or modest deviations in the bus voltage profile. To address the problem of voltage profile deviation on the load buses, the generator voltages were adjusted to ensure that the voltages at all load buses remain within acceptable limits. Furthermore, the rescheduling of reactive power greatly enhances the voltage profile of every load bus and safeguards the system from voltage collapse. Figure 5.3 displays the enhancement of voltage profile before and after the CM.

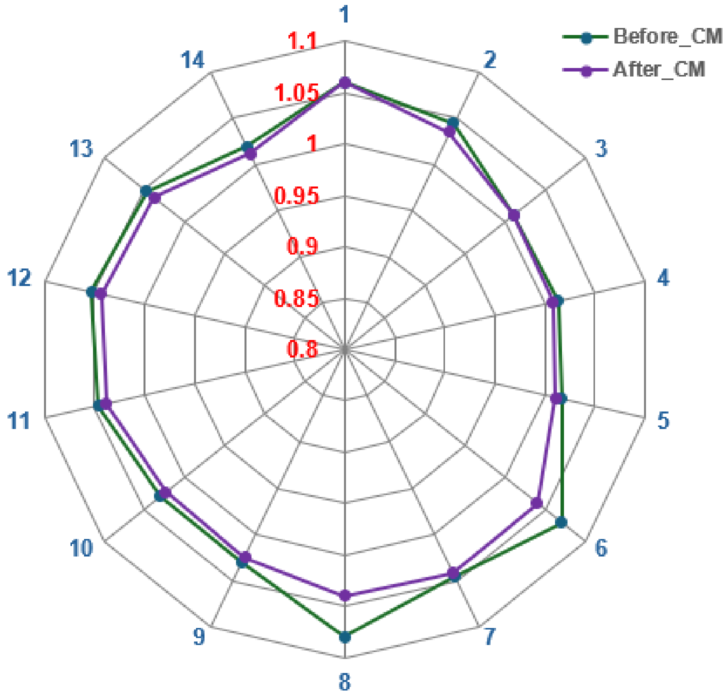


Figure 5. 3: IEEE 14-Bus voltage profile improvement before and after MILP

5.6.2 CASE 2: IEEE 30-Bus system network

The network consists of 30 buses, 41 interconnected lines, and 6 generators. The SLD and the network data were obtained from (Adewolu, 2020) and are detailed in APPENDIX A2 and B2 respectively. According to the power flow results as detailed in the previous chapter (Chapter Four), lines 1 and 5 was identified as the congested lines. The same principle of identifying participating generator via generator sensitivity factor (GSF) was also applied as discussed in subsection 4.4.2. Hence, in order to mitigate congestion, the output power of the participating generators was optimally rescheduled using MILP Algorithm. Table 5.3 and 5.4 detailed the rescheduling cost comparison and simulation results of MILP algorithm compared with PSO Algorithm and proposed method from literature respectively.

In order to address the problem of voltage fluctuations at the load buses, the generator voltages were adjusted to maintain the load bus voltages within acceptable limits. Reactive power rescheduling improves voltage stability in all load buses and prevents the system from reaching the point of voltage collapse. The voltage profile improvement is depicted in Figure 5.4, illustrating the before and after states.

Table 5. 3: Rescheduling cost comparison between PSO and MILP for IEEE 30-Bus system

	Proposed MILP Method	Proposed PSO method	Method reported in (Kim & Salkuti, 2019	Method Reported in (Salkuti, 2018)

Active power rescheduling cost ($/day)	849	3.10E+04	799.56	1196.35
Reactive power rescheduling cost ($/day)	885	7.58E+03	Not reported	Not reported

Table 5. 4: Optimally obtained PSO and MILP results for IEEE 30-Bus system

		Proposed MILP method	Proposed PSO method	Method reported in (Kim & Salkuti, 2019)	Method reported in (Salkuti, 2018)
Active power rescheduling (MW)	ΔP_1	145	157.772	177.285	174.46
	ΔP_2	44	55.58	48.93	76.37
	ΔP_5	20	18.563	21.29	42.08
	ΔP_8	15	17.744	20.49	32.72
	ΔP_{11}	7.5	0	11.93	28.79
	ΔP_{13}	55	41.219	12.23	31.77
Total active power rescheduling (MW)		286.5	290.878	292.155	386.19
Total active power demand (MW)		283.4	283.4	Not reported	Not reported
Reactive power rescheduling (MVar)	ΔQ_1	35	28.498	Not reported	Not reported
	ΔQ_2	66	76.275		
	ΔQ_5	23.4	24.692		
	ΔQ_8	5	0.965		
	ΔQ_{11}	3	0		
	ΔQ_{13}	5	9.879		
Total reactive power rescheduling (MVar)		137.4	139.344		
Total reactive power demand (MVar)		126.2	126.2	Not reported	Not reported

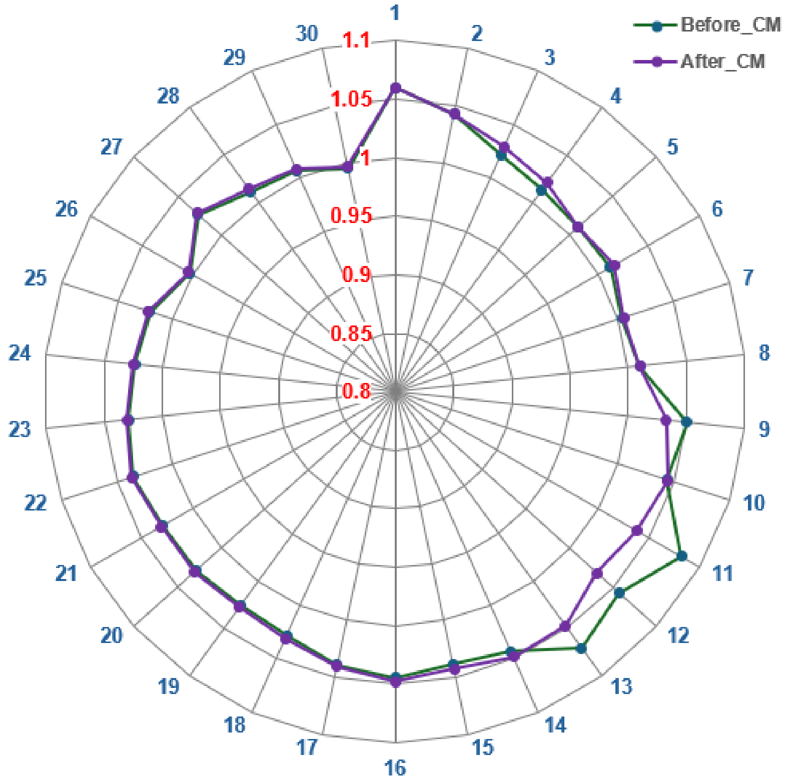


Figure 5. 4: IEEE 30-Bus voltage profile improvement before and after MILP

5.6.3 CASE 3: IEEE 118-Bus system network

The considered network details were gotten from (Blumsack, 2006) and the system consist of 118 buses, 179 interconnected lines, and 54 generators. The network SLD and its data were detailed in APPENDIX A3 and B3 respectively. Tables 5.5 to 5.8 present a detailed comparison of the results obtained from the MILP approach and the PSO approach in terms of optimally rescheduling the output active and reactive power of the participating generators to alleviate congestion. Based on Tables 5.7 and 5.8, generators 6, 24, 34, 54, 66, 85, and 105 are the only ones that are not affected by congestion. Table 5.9 presents a comprehensive overview of the active and reactive power loss, both before and after congestion control using PSO and MILP. Figure 5.5 displays the graphical depiction of the enhancement in voltage profile both before (Pre) and after (Post) implementing congestion management.

Table 5. 5: Active power rescheduling cost comparison between PSO and MILP for IEEE 118-Bus system

Active power rescheduling (MW)		
	PSO	**MILP**
Active power rescheduling cost ($/day)	7.88E+04	1.28E+04
Total active power rescheduling (MW)	3711	3684
Total active power demand (MW)	3668	3668

Table 5. 6: Reactive power rescheduling cost comparison between PSO and MILP for IEEE 118-Bus system

Reactive power rescheduling (MVar)		
	PSO	**MILP**
Reactive power rescheduling cost ($/day)	3.54E+04	1.73E+05
Total reactive power rescheduling (MW)	1477	1467
Total reactive power demand (MVar)	1438	1438

Table 5. 7: Active power rescheduling for IEEE 118-Bus system using PSO and MILP

Active power rescheduling (MW)								
	PSO	**MILP**		**PSO**	**MILP**		**PSO**	**MILP**
ΔP_1	68.716	186.3	ΔP_{42}	63.314	93.8	ΔP_{80}	50.409	84.5
ΔP_4	12.427	28.2	ΔP_{46}	34.16	50.7	ΔP_{85}	0	0
ΔP_6	0	0	ΔP_{49}	38.25	55.6	ΔP_{87}	64.685	85.3
ΔP_8	30.337	60.7	ΔP_{54}	0	0	ΔP_{89}	59.5	70.8
ΔP_{10}	44.097	50.3	ΔP_{55}	60.361	76.8	ΔP_{90}	104.107	208.6
ΔP_{12}	72.413	80.8	ΔP_{56}	52.387	80.3	ΔP_{91}	19.75	22.1
ΔP_{15}	8.875	12.4	ΔP_{59}	58.128	71.7	ΔP_{92}	58.99	55.7
ΔP_{18}	8.839	7.2	ΔP_{61}	39.904	37.5	ΔP_{99}	92.19	108.9
ΔP_{19}	47.403	80.8	ΔP_{62}	39.432	57.4	ΔP_{100}	48.125	76.3
ΔP_{24}	0	0	ΔP_{65}	38.451	50.8	ΔP_{103}	13.284	17.4
ΔP_{25}	26.076	39.9	ΔP_{66}	0	0	ΔP_{104}	92.342	180.3
ΔP_{26}	14.776	11.9	ΔP_{69}	42.88	84.8	ΔP_{105}	0	0
ΔP_{27}	37.079	77.2	ΔP_{70}	36.209	60.5	ΔP_{107}	73.464	75.3
ΔP_{31}	84.863	200.5	ΔP_{72}	251.353	278.9	ΔP_{110}	43.526	0.8
ΔP_{32}	27.541	55.7	ΔP_{73}	41.127	160.8	ΔP_{111}	43.981	58.4
ΔP_{34}	0	0	ΔP_{74}	9.636	11.7	ΔP_{112}	15.409	10.5
ΔP_{36}	113.461	147.5	ΔP_{76}	12.27	17.6	ΔP_{113}	12.132	11.5
ΔP_{40}	75.897	97.8	ΔP_{77}	27.902	40.7	ΔP_{116}	145.859	250.8

Table 5. 8: Reactive power rescheduling for IEEE 118-Bus system using PSO and MILP

Reactive power rescheduling (MVar)								
	PSO	**MILP**		**PSO**	**MILP**		**PSO**	**MILP**
ΔQ_1	20.569	11.4	ΔQ_{42}	50.798	30.8	ΔQ_{80}	148.507	70.4
ΔQ_4	37.658	20.5	ΔQ_{46}	53.667	34.2	ΔQ_{85}	0	0
ΔQ_6	0	0	ΔQ_{49}	59.363	34.6	ΔQ_{87}	39.66	28.4
ΔQ_8	114.135	78.5	ΔQ_{54}	0	0	ΔQ_{89}	81.288	45.3
ΔQ_{10}	49.625	30.2	ΔQ_{55}	10.049	7.5	ΔQ_{90}	32.464	13.2
ΔQ_{12}	20.1	15.2	ΔQ_{56}	15.69	10.4	ΔQ_{91}	136.635	66.9
ΔQ_{15}	75.848	36.4	ΔQ_{59}	46.818	32.5	ΔQ_{92}	49.938	30.7
ΔQ_{18}	69.789	37.1	ΔQ_{61}	78.305	43.9	ΔQ_{99}	20.964	17.8
ΔQ_{19}	16.328	9.6	ΔQ_{62}	35.134	41.3	ΔQ_{100}	4.912	3.9
ΔQ_{24}	0	0	ΔQ_{65}	26.333	30.2	ΔQ_{103}	58.679	30.8
ΔQ_{25}	159.157	80.5	ΔQ_{66}	0	0	ΔQ_{104}	14.672	11.8
ΔQ_{26}	85.224	53.9	ΔQ_{69}	21.847	18.6	ΔQ_{105}	0	0

ΔQ_{27}	44.038	34.9	ΔQ_{70}	65.115	46.3	ΔQ_{107}	135.659	102.6
ΔQ_{31}	17.373	11.7	ΔQ_{72}	67.407	33.9	ΔQ_{110}	41.318	45.1
ΔQ_{32}	12.527	9.4	ΔQ_{73}	20.133	24.1	ΔQ_{111}	17.624	13.2
ΔQ_{34}	0	0	ΔQ_{74}	20.087	19.0	ΔQ_{112}	21.743	20.1
ΔQ_{36}	49.319	20.8	ΔQ_{76}	43.094	29.2	ΔQ_{113}	34.265	20.2
ΔQ_{40}	23.678	15.9	ΔQ_{77}	44.05	33.7	ΔQ_{116}	14.59	10.7

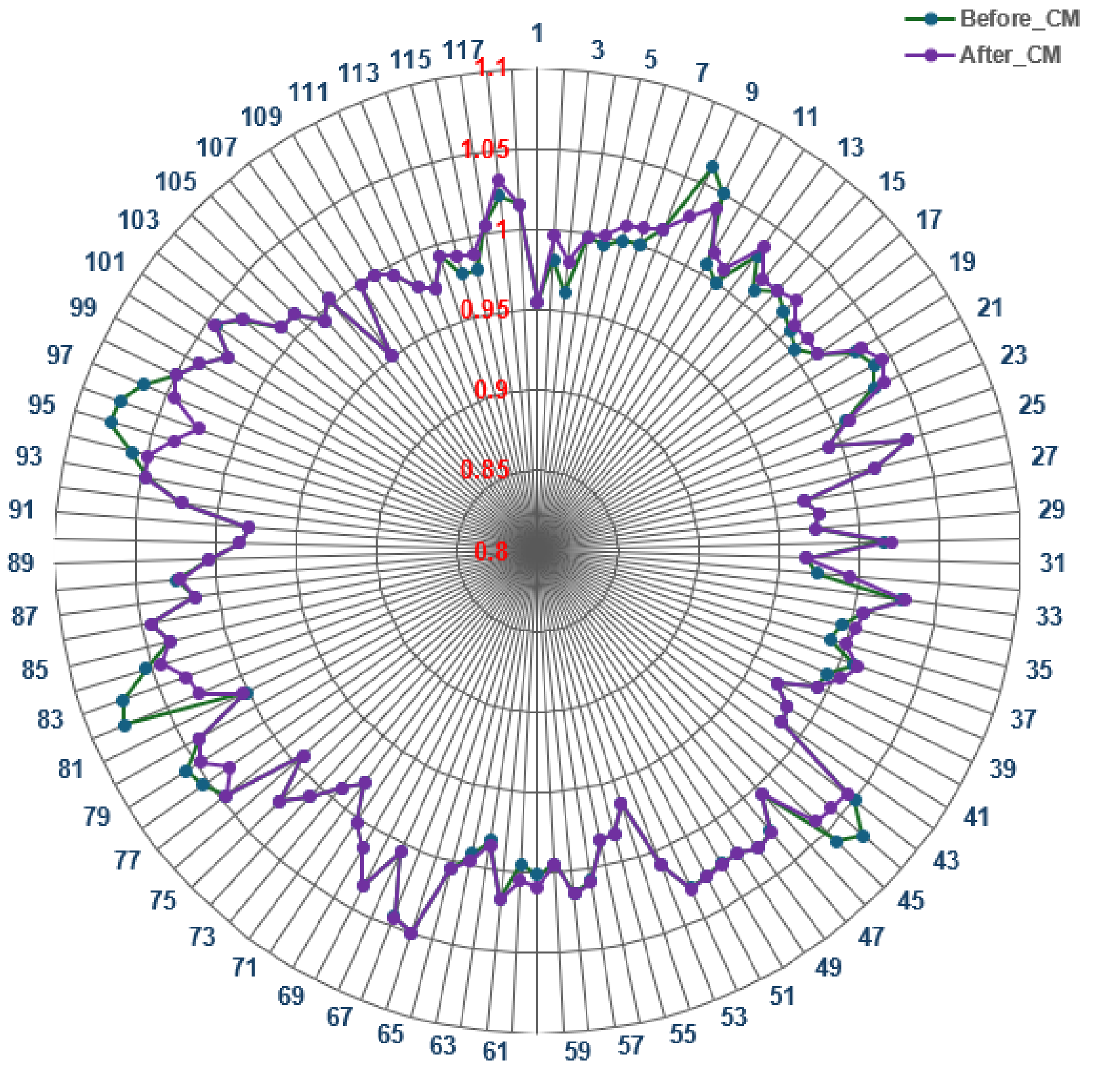


Figure 5. 5: IEEE 118-Bus voltage profile improvement before and after MILP

Table 5. 9: Power loss summary comparison results between PSO and MILP

		Base Case	With PSO	With MILP	PSO % reduction	MILP % reduction
Case 1 [IEEE 14]	P (MW)	13.55	12.91	12.88	4.7	5
	Q (MVar)	55.56	53.52	52.79	3.67	5
Case 2 [IEEE 30]	P (MW)	17.59	15.65	14.87	11.03	15.5
	Q (MVar)	17.87	15.12	13.56	15.39	24

Case 3 [IEEE 118]	P (MW)	91.39	81.46	80.00	10.87	12.5
	Q (MVar)	87.89	77.07	76.54	12.31	13

5.7 Chapter Summary

This chapter discussed the results achieved by efficiently adjusting the output active and reactive power of the generators to manage transmission congestion in a deregulated power system. The methods used for this purpose were Particle Swarm Optimisation (PSO) and Mixed Integer Linear Programming (MILP). The two proposed methods reduced the expense/cost of adjusting the power output of generators compared to the ways suggested in existing literature. Additionally, both techniques significantly reduce power loss and improve voltage profile. MILP is a powerful optimization tool that can handle both continuous and discrete decision variables, making it well-suited for complex problems like congestion management. Future research and practical applications derived from the use of MILP for congestion management in deregulated power systems can significantly enhance the efficiency, reliability, and sustainability of power systems. By addressing key challenges and leveraging advanced computational techniques, MILP can play a crucial role in optimizing various aspects of power system operation and planning. Put simply, MILP has greatly reduced the cost of adjusting active and reactive power output for congestion management and bus voltage profile optimisation. This has resulted in improved system stability and security, surpassing the capabilities of PSO. In addition, MILP has significantly reduced network active and reactive power loss compared to PSO. Thus, when comparing the performance of the given approaches, MILP outperforms PSO in terms of power loss reduction. Hence, the application of MILP for congestion management in deregulated power systems can lead to the development of more accurate, efficient, and robust methods for managing congestion. By leveraging the detailed modelling capabilities, computational techniques, and economic insights provided by MILP, new approaches can be developed that enhance the reliability, efficiency, and sustainability of power systems.

CHAPTER SIX
CONCLUSION AND RECOMMENDATION

6.1 Introduction

Undoubtedly, the ongoing electricity industry reform in several developing countries has led to a surge in electricity market participants, and this has been identified as a significant factor contributing to the overloading of the existing grid infrastructure and the consequent transmission line congestion. This, combined with the dynamic nature of contemporary power systems load and the increasing influx of power from IPPs, particularly from intermittent renewables, presents a clear danger of more congestion along the transmission networks. Thus, power systems worldwide could experience more blackouts and unfavorable technical and economic operation scenarios without adequate measures to alleviate congestion or enhance transmission capacity. Hence, this research considers the necessary exploration of viable techniques and mathematical models for managing congestion along the transmission network, considering the influences of market deregulation and distributed generators.

6.2 Aim and objectives of the research

6.2.1 Aim

This research aims to develop and validate new approaches based on the classical (MILP) and heuristic (PSO) methods for the transmission congestion management system. The simulation results were consequently analysed for different standard networks considered to verify the effectiveness of the developed methods.

6.2.2 Objectives

This The objectives of this research work are:

i. To conduct comparative literature studies on TCM in deregulated power systems and various solution methodologies such as optimization (classical and heuristics) methods for optimal placement of DG and FACTS devices.
ii. Formulate mathematical modeling to determine the transmission capacity and manage the line congestions along the network in deregulated power systems using the PSO and MILP algorithms.
iii. Develop an improved dedicated PSO algorithm in the MATLAB environment for efficient transmission network congestion management using IEEE 14, 30, and 118 standards as the case studies.
iv. Develop a MILP method for congestion management in a deregulated power system and validate the simulation results for the IEEE 14, 30, and 118 systems.
v. Asses the performance of the developed PSO algorithm by comparative analysis with the standard MILP algorithm methods as mentioned in (iii & iv) above.

6.3 Thesis deliverables

6.3.1 Review investigation on optimization methods for transmission congestion management systems

This chapter provides a comprehensive literature analysis on congestion management in deregulated power networks. A comprehensive documentation was made on the traditional approaches, both technical and non-technical, as well as numerous techniques and algorithms employed to address the issue of transmission congestion in deregulated electricity networks. Furthermore, a comprehensive examination and thorough analysis of all the CM techniques and their practical implementations in electric power system networks were conducted and documented in (Ogunwole & Krishnamurthy, 2023).

6.3.2 Mathematical formulation for transmission congestion management in deregulated power systems

This chapter provides a comprehensive explanation of the research techniques and mathematical issue formulation used for the suggested congestion management method/technique. Equation (3.1) was used to mathematically design the objective function aimed at decreasing the rescheduling cost of the output power of generators involved in congestion, with the goal of alleviating electric transmission network congestion. Mathematical formulations were used to analyse the sensitivity factors of both active and reactive power of the generators to the congested line. These formulations helped identify the generators that are involved in the congested lines.

6.3.3 Transmission congestion management using generator sensitivity factors for active and reactive power rescheduling using particle swar optimization algorithm

This chapter introduces a method that uses an optimal power flow (OPF) analysis-based particle swarm optimisation (PSO) algorithm to identify which generators are causing congestion and to efficiently adjust their output powers (both active and reactive) in order to manage congestion at the lowest possible cost. Moreover, the traditional approach of Optimal Power Flow (OPF) relies on the exploration path derived from the function derivative. In this method, the output of the participating generators is optimally rescheduled using the Particle Swarm Optimisation (PSO) algorithm to alleviate congestion. The utilisation of the Particle Swarm Optimisation (PSO) algorithm to alleviate congestion in electric transmission power networks was thoroughly described and published in a research paper by (Ogunwole & Krishnamurthy, 2022). The MATLAB code for validating the proposed method can be located in APPENDIX C2 – C3.

6.3.4 Performance comparative analysis of mixed integer linear programming and particle swarm optimization algorithm for transmission congestion management

A mixed integer linear programming (MILP) technique was developed to address transmission congestion control. This approach entails converting the problem into a linear form and utilising a direct current (DC) network model. Equation (5.11) expresses the problem of TCM as an AC OPF-Mixed Integer Nonlinear Programming (MINLP) problem, taking into account the nonlinearity of the active and reactive power equality constraints. The performance and results of the MILP algorithm were compared to those of the Particle Swarm Optimisation (PSO) approach. The MATLAB code for validating the proposed method is located in APPENDIX C4 – C6.

Table 6. 1: MATLAB Programs for validating the proposed CM methods

Description	Algorithms	Network type	Appendix/Matlab script file name
Identification of congested lines	Base case: Optimal Power Flow based Newton-Raphson	IEEE 14 bus system IEEE 30 bus system IEEE 118 bus system	**Appendix C1:** OPF_NR_determine_congested_line.m
Transmission Congestion Management based PSO	Particle Swarm Optimization (PSO) Algorithm	IEEE 14 bus system IEEE 30 bus system IEEE 118 bus system	**Appendix C2:** PSO_CM_considered_case.m **Appendix C3:** Screenshot_ PSO_CM_considered_case.m
Transmission Congestion Management based MILP	Mixed Integer Linear Programming (MILP)	IEEE 14 bus system IEEE 30 bus system IEEE 118 bus system	**Appendix C4:** MILP_CM_IEEE 14 bus_system.m **Appendix C5:** MILP_CM_IEEE 30 bus_system.m **Appendix C6:** MILP_CM_IEEE 118 bus_system.m

6.4 Overview of the research findings and contribution

One of the most critical operational aims of the electricity industry, mainly since deregulation, has been to make prudent use of the grid infrastructure already in place through active congestion management along the transmission lines. This is done to maximize the efficiency of service delivery and minimize costs. The development of models for CM and the provision of insights on the most effective approach to CM are two contributions this study has made to the power industry, as reported in this thesis.

Chapter One introduced the proposed study effort, presenting a comprehensive overview of the issue description, research aim and objectives, hypothesis, delimitation, motivation, and assumptions. Chapter Two provides an overview of the existing research on CM in deregulated electricity systems. It discusses different approaches and algorithms employed to tackle transmission congestion. Chapter Three presents the research techniques and the mathematical issue formulation for the suggested congestion management technique. Chapter Four analyzes the performance and outcomes of PSO (Particle Swarm Optimization) in the context of mitigating transmission congestion. Chapter Five presents a comparison between the performance of PSO (Particle Swarm Optimization) and MILP (Mixed-Integer Linear Programming) strategies in managing transmission congestion. Chapter Six serves as the final section of the investigation, presenting the conclusive findings and offering recommendations based on the study.

This research has revealed the effectiveness of PSO and MILP in alleviating congestion in deregulated power system transmission networks. The results have shown the superiority of the proposed methods for congestion management based on voltage profile enhancement, power loss reduction, and minimization in the cost of rescheduling both active and reactive power output of the generation for transmission congestion management. Hence, both developed PSO and MILP algorithms reported in this study can be utilized by power system engineers to optimize power systems for reliability and efficient improvement of the existing transmission network.

6.5 Publications

Below are the publications that resulted from this study. These contributions to the body of knowledge are included in the research report presented in this thesis.

i. Emmanuel Idowu Ogunwole and Senthil Krishnamurthy. A Review of Optimization Methods for Transmission Congestion Management Systems, International Review of Electrical Engineering (IREE), 2023, Volume 18, Issue 3, Pages 227 – 242, Praise Worthy Prize.
ii. Emmanuel Idowu Ogunwole and Senthil Krishnamurthy, "Transmission Congestion Management Using Generator Sensitivity Factors for Active and Reactive Power Rescheduling Using Particle Swarm Optimization Algorithm," in IEEE Access, vol. 10, pp. 122882-122900, 2022, doi: 10.1109/ACCESS.2022.3224060.
iii. Emmanuel Idowu Ogunwole and Senthil Krishnamurthy, "An Economic Feasibility Study for Off-Grid Hybrid Renewable Energy Resources," 2023 31st

Southern African Universities Power Engineering Conference (SAUPEC), Johannesburg, South Africa, 2023, pp. 1-7, doi: 10.1109/SAUPEC57889.2023.10057767.

iv. Senthil Krishnamurthy, Emmanuel Idowu Ogunwole, Chapter Thirteen - Microgrid system design, modeling, and simulation, Editor(s): Ramesh C. Bansal, Jackson J. Justo, Francis A. Mwasilu, Modeling and Control Dynamics in Microgrid Systems with Renewable Energy Resources, Academic Press, 2024, Pages 345-376, ISBN 9780323909891, https://doi.org/10.1016/B978-0-323-90989-1.00009-9.

6.6 Recommendation for future research

Future research will focus on developing classical intelligence-based methods that simplify the rigorous mathematical process of the current congestion management techniques to gain more time and achieve fewer computational burdens. Moreover, the parallel computing approach is a veritable tool for fast computation and solution of transmission congestion control, and it would be an integral inclusion in future analyses.

6.7 Conclusion

Because of the ever-increasing population size, growth in electricity demand, and recursively increasing technological improvements, the electric power utility is quickly transitioning from a regulated (bundled) to a deregulated (unbundled) power system. Thus, this research considered an essential area of interest for the adequate technical and economic operation of the contemporary energy system. Transmission network overloading due to open access and the increased number of participants in the electricity market has remained at the forefront of power system operation research vis-à-vis congestion management (CM). In this research, appropriate approaches using PSO and MILP for solving the CM problem were developed, and their performance was comparatively evaluated to provide insight and direction for efficient operation and reasonable utilization of the available transmission capacity.

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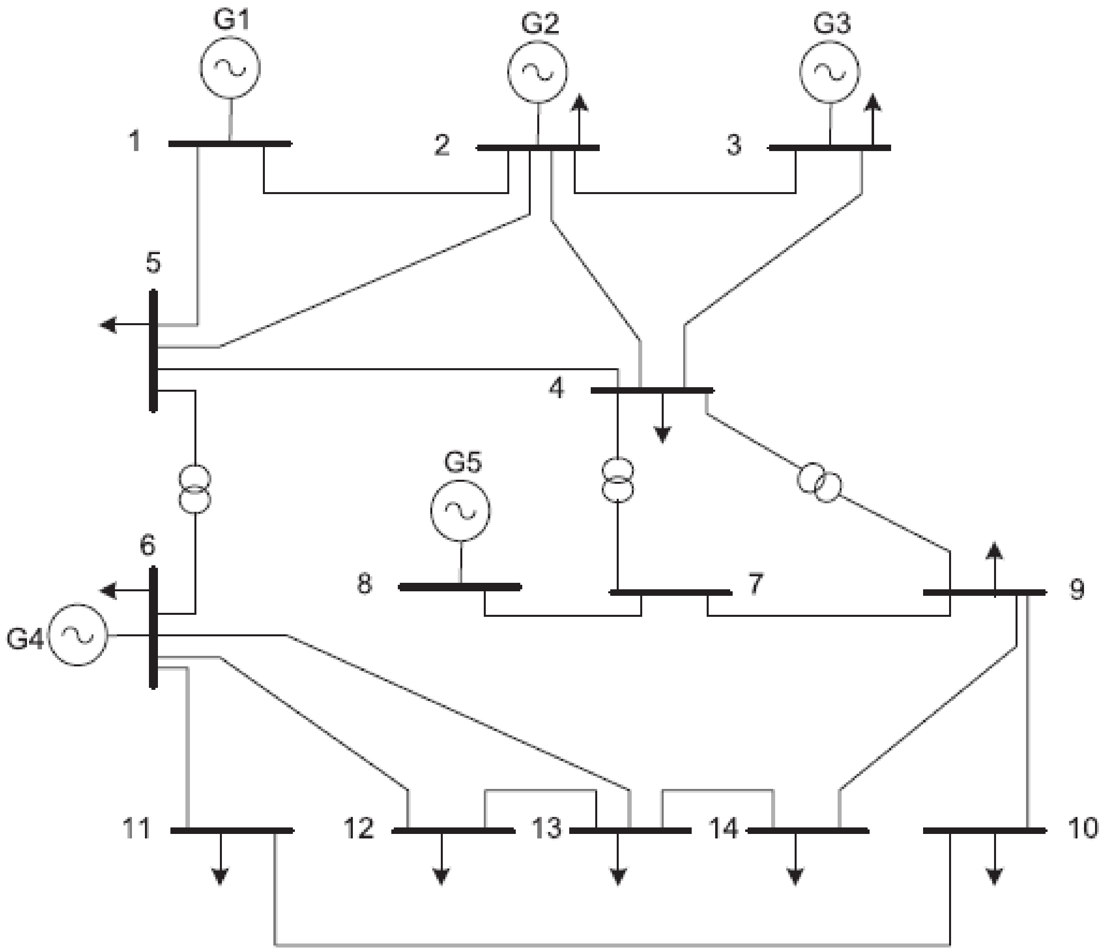
APPENDICES

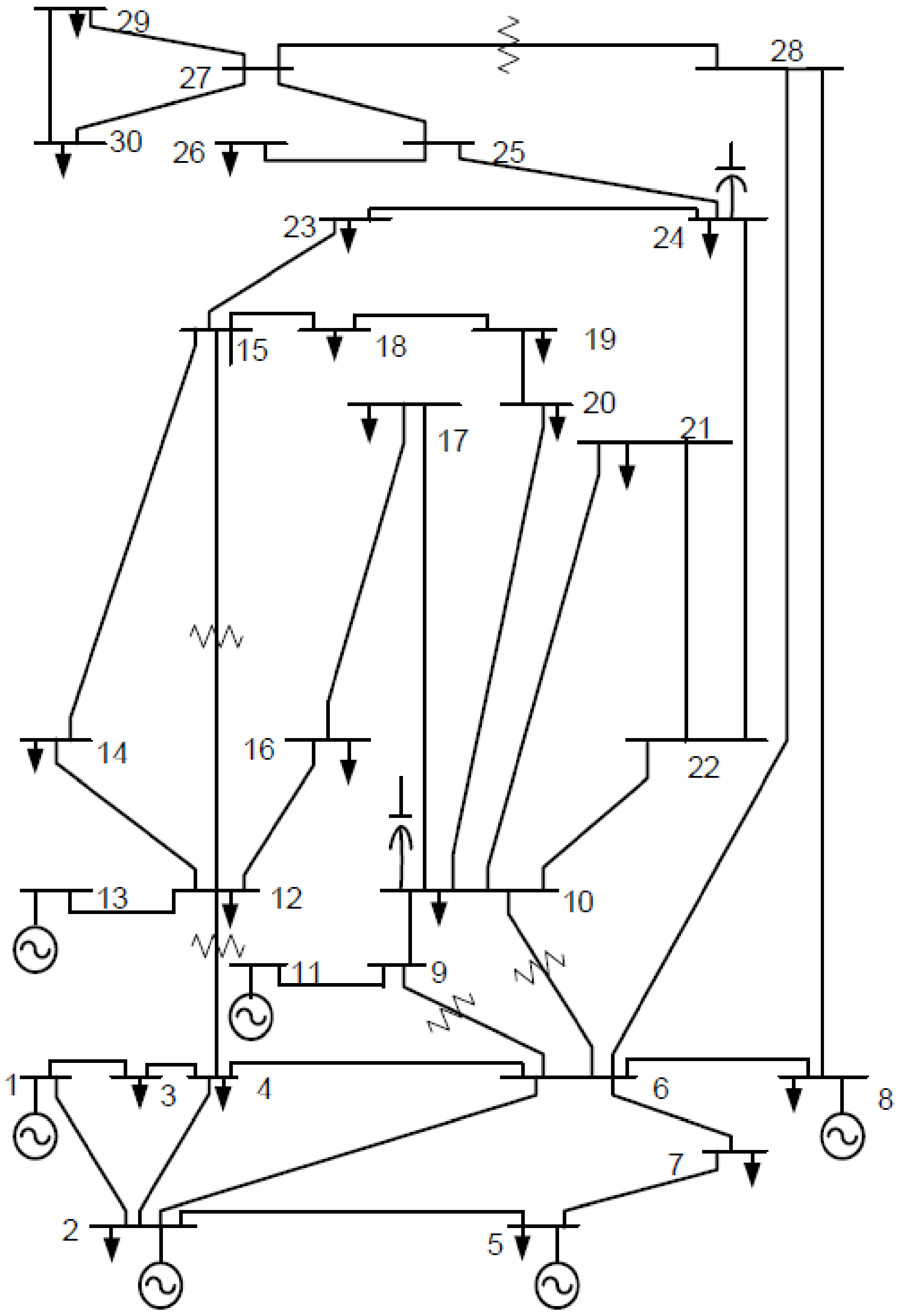
APPENDICES

APPENDIX A: Single Line Diagram (SLD) for the considered synthetic networks

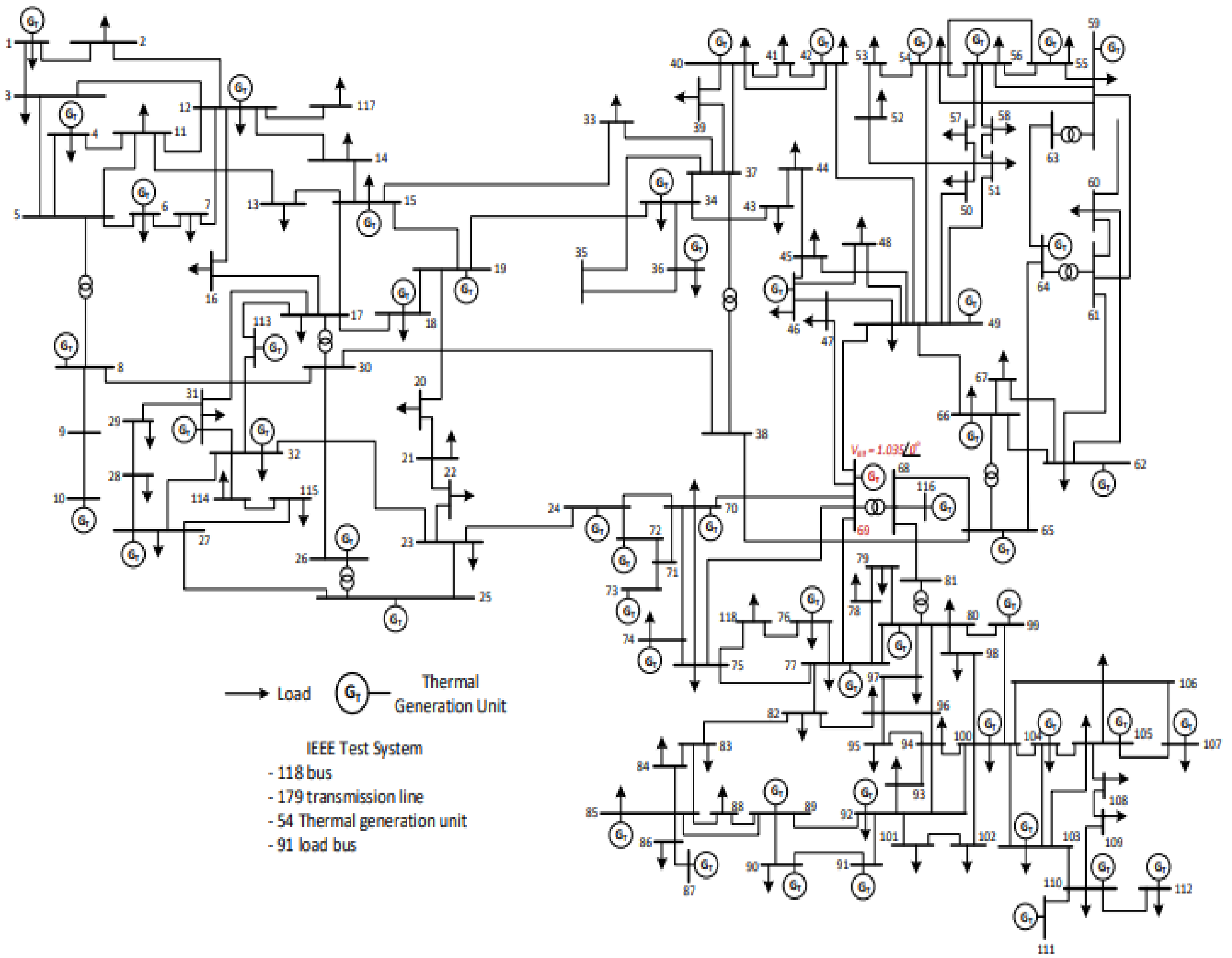
APPENDIX A1: IEEE 14 – Bus single line diagram (SLD)



APPENDIX A2: IEEE 30 – Bus single line diagram (SLD)



APPENDIX A3: IEEE 118 – Bus single line diagram (SLD)



APPENDIX B: Network datas for the considered synthetic networks

APPENDIX B1: IEEE 14 – Bus line datas

Line No.	From Bus	To Bus	Resistance (R) p.u	Reactance (X) p.u	Susceptance (B/2) p.u	X' mer Tap	MVA Rating
1	1	2	0.01938	0.05917	0.02640	1	120
2	1	5	0.05403	0.22304	0.02190	1	65
3	2	3	0.04699	0.19797	0.01870	1	36
4	2	4	0.05811	0.17632	0.02460	1	65
5	2	5	0.05695	0.17388	0.01700	1	50
6	3	4	0.06701	0.17103	0.01730	1	65
7	4	5	0.01335	0.04211	0.00640	1	45
8	4	7	0	0.20912	0	0.978	55
9	4	9	0	0.55618	0	0.969	32
10	5	6	0	0.25202	0	0.932	45
11	6	11	0.09498	0.1989	0	1	18
12	6	12	0,12291	0.25581	0	1	32
13	6	13	0.06615	0.13027	0	1	32
14	7	8	0	0.17625	0	1	32
15	7	9	0	0.11001	0	1	32
16	9	10	0.03181	0.0845	0	1	32
17	9	14	0.12711	0.27038	0	1	32
18	10	11	0.08205	0.19207	0	1	12
19	12	13	0.22092	0.19988	0	1	12
20	13	14	0.17093	0.34802	0	1	12

APPENDIX B2: IEEE 14 – Bus bus datas

Bus No.	Voltage Mag.	Phase Ang.	P (MW)	Q (MVar)	P (MW)	Q (Mvar)	Q min	Q max
1	1.060	0	114.17	-16.9	0	0	0	10
2	1.045	0	40.00	0	21.7	12.7	-42.0	50.0
3	1.010	0	0	0	94.2	19.1	23.4	40.0
4	1	0	0	0	47.8	-3.9	-	-
5	1	0	0	0	7.6	1.6	-	-
6	1	0	0	0	11.2	7.5	-	-
7	1	0	0	0	0	0	-	-
8	1	0	0	0	0	0	-	-
9	1	0	0	0	29.5	16.6	-	-
10	1	0	0	0	9.0	5.8	-	-
11	1	0	0	0	3.5	1.8	-	-
12	1	0	0	0	6.1	1.6	-	-
13	1	0	0	0	13.8	5.8	-	-
14	1	0	0	0	14.9	5.0	-	-

APPENDIX B3: IEEE 30 – Bus line datas

Line No.	From Bus	To Bus	Resistance (R) p.u	Reactance (X) p.u	Susceptance (B/2) p.u	X' mer Tap	MVA Rating
1	1	2	0.0192	0.0575	0.0264	1	130
2	1	3	0.0452	0.1652	0.0204	1	130
3	2	4	0.057	0.1737	0.0184	1	65
4	3	4	0.0132	0.0379	0.0042	1	130
5	2	5	0.0472	0.1983	0.0209	1	65
6	2	6	0.0581	0.1763	0.0187	1	130
7	4	6	0.0119	0.0414	0.0045	1	90
8	5	7	0.046	0.116	0.0102	1	65
9	6	7	0.0267	0.082	0.0085	1	70
10	6	8	0.012	0.042	0.0045	1	130
11	6	9	0	0.208	0	0.978	32
12	6	10	0	0.556	0	0.969	65
13	9	11	0	0.208	0	1	32
14	9	10	0	0.11	0	1	32
15	4	12	0	0.256	0	0.932	32
16	12	13	0	0.14	0	1	65
17	12	14	0.1231	0.2559	0	1	65
18	12	15	0.0662	0.1304	0	1	32
19	12	16	0.0945	0.1987	0	1	32
20	14	15	0.221	0.1997	0	1	32
21	16	17	0.0824	0.1923	0	1	32
22	15	18	0.1073	0.2185	0	1	65
23	18	19	0.0639	0.1292	0	1	32
24	19	20	0.034	0.068	0	1	32
25	10	20	0.0936	0.209	0	1	32
26	10	17	0.0324	0.0845	0	1	16
27	10	21	0.0348	0.0749	0	1	16
28	10	22	0.0727	0.1499	0	1	16
29	21	23	0.0116	0.0236	0	1	16
30	15	23	0.1	0.202	0	1	16
31	22	24	0.115	0.179	0	1	32
32	23	24	0.132	0.27	0	1	32
33	24	25	0.1885	0.3292	0	1	16
34	25	26	0.2544	0.38	0	1	16
35	25	27	0.1093	0.2087	0	1	16
36	28	27	0	0.396	0	0.968	16
37	27	29	0.2198	0.4153	0	1	16
38	27	30	0.3202	0.6027	0	1	16
39	29	30	0.2399	0.4533	0	1	16
40	8	28	0.0636	0.2	0.0214	1	65
41	6	28	0.0169	0.0599	0.065	1	16

APPENDIX B4: IEEE 30 – Bus bus datas

Bus No.	Voltage Mag.	Phase Ang.	P (MW)	Q (MVar)	P (MW)	Q (Mvar)	Q min	Q max
1	1.06	0	0	0	0	0	0	
2	1.043	0	40	50	21.7	12.7	-40	50
3	1	0	0	0	2.4	1.2	0	0
4	1.06	0	0	0	7.6	1.6	0	0
5	1.01	0	0	37	94.2	19	-40	40
6	1	0	0	0	0	0	0	0
7	1	0	0	0	22.8	10.9	0	0
8	1.01	0	0	37.3	30	30	-10	40
9	1	0	0	0	0	0	0	0
10	1	0	0	19	5.8	2	0	0
11	1.082	0	0	16.2	0	0	-6	24
12	1	0	0	0	11.2	7.5	0	0
13	1.071	0	0	10.6	0	0	-6	24
14	1	0	0	0	6.2	1.6	0	0
15	1	0	0	0	8.2	2.5	0	0
16	1	0	0	0	3.5	1.8	0	0
17	1	0	0	0	9	5.8	0	0
18	1	0	0	0	3.2	0.9	0	0
19	1	0	0	0	9.5	3.4	0	0
20	1	0	0	0	2.2	0.7	0	0
21	1	0	0	0	17.5	11.2	0	0
22	1	0	0	0	0	0	0	0
23	1	0	0	0	3.2	1.6	0	0
24	1	0	0	4.3	8.7	6.7	0	0
25	1	0	0	0	0	0	0	0
26	1	0	0	0	3.5	2.3	0	0
27	1	0	0	0	0	0	0	0
28	1	0	0	0	0	0	0	0
29	1	0	0	0	2.4	0.9	0	0
30	1	0	0	0	10.6	1.9	0	0

APPENDIX B5: IEEE 118 – Bus line datas

Line No.	From Bus	To Bus	Resistance (R) p.u	Reactance (X) p.u	Susceptance (B/2) p.u	X' mer Tap	Line Flow Limit (MW)
1	1	2	0.0303	0.0999	0.0254	1	15
2	1	3	0.0129	0.0424	0.0021	1	48
3	4	5	0.00176	0.00798	0.0021	1	129
4	3	5	0.0241	0.108	0.0284	1	85
5	5	6	0.0119	0.054	0.01426	1	111
6	6	7	0.00459	0.0208	0.0055	1	44
7	8	9	0.00244	0.0305	1.162	1	551
8	8	5	0	0.0267	0	0.985	423
9	9	10	0.00258	0.0322	1.23	1	557
10	4	11	0.0209	0.0688	0.01748	1	80
11	5	11	0.0203	0.0682	0.01738	1	97
12	11	12	0.00595	0.0196	0.00502	1	43
13	2	12	0.0187	0.0616	0.01572	1	41
14	3	12	0.0484	0.16	0.0406	1	12
15	7	12	0.00862	0.034	0.00874	1	21
16	11	13	0.02225	0.0731	0.01876	1	44
17	12	14	0.0215	0.0707	0.01816	1	23
18	13	15	0.0744	0.2444	0.06268	1	1
19	14	15	0.0595	0.195	0.0502	1	5
20	12	16	0.0212	0.0834	0.0214	1	9
21	15	17	0.0132	0.0437	0.0444	1	130
22	16	17	0.0454	0.1801	0.0466	1	22
23	17	18	0.0123	0.0505	0.01298	1	100
24	18	19	0.01119	0.0493	0.01142	1	24
25	19	20	0.0252	0.117	0.0298	1	13
26	15	19	0.012	0.0394	0.0101	1	14
27	20	21	0.0183	0.0849	0.0216	1	36
28	21	22	0.0209	0.097	0.0246	1	54
29	22	23	0.0342	0.159	0.0404	1	67
30	23	24	0.0135	0.0492	0.0498	1	10
31	23	25	0.0156	0.08	0.0864	1	203
32	26	25	0	0.0382	0	0.96	113
33	25	27	0.0318	0.163	0.1764	1	179
34	27	28	0.01913	0.0855	0.0216	1	41
35	28	29	0.0237	0.0943	0.0238	1	20
36	30	17	0	0.0388	0	0.96	289
37	8	30	0.00431	0.0504	0.514	1	93
38	26	30	0.00799	0.086	0.908	1	280
39	17	31	0.0474	0.1563	0.0399	1	18
40	29	31	0.0108	0.0331	0.0083	1	11
41	23	32	0.0317	0.1153	0.1173	1	116
42	31	32	0.0298	0.0985	0.0251	1	37
43	27	32	0.0229	0.0755	0.01926	1	16

44	15	33	0.038	0.1244	0.03194	1	9
45	19	34	0.0752	0.247	0.0632	1	4
46	35	36	0.00224	0.0102	0.00268	1	1
47	35	37	0.011	0.0497	0.01318	1	42
48	33	37	0.0415	0.142	0.0366	1	20
49	34	36	0.00871	0.0268	0.00568	1	38
50	34	37	0.00256	0.0094	0.00984	1	118
51	38	37	0	0.0375	0	0.935	304
52	37	39	0.0321	0.106	0.027	1	69
53	37	40	0.0593	0.168	0.042	1	55
54	30	38	0.00464	0.054	0.422	1	78
55	39	40	0.0184	0.0605	0.01552	1	34
56	40	41	0.0145	0.0487	0.01222	1	19
57	40	42	0.0555	0.183	0.0466	1	15
58	41	42	0.041	0.135	0.0344	1	27
59	43	44	0.0608	0.2454	0.06068	1	21
60	34	43	0.0413	0.1681	0.04226	1	2
61	44	45	0.0224	0.0901	0.0224	1	41
62	45	46	0.04	0.1356	0.0332	1	45
63	46	47	0.038	0.127	0.0316	1	39
64	46	48	0.0601	0.189	0.0472	1	18
65	47	49	0.0191	0.0625	0.01604	1	12
66	42	49	0.0715	0.323	0.086	1	81
67	42	49	0.0715	0.323	0.086	1	81
68	45	49	0.0684	0.186	0.0444	1	62
69	48	49	0.0179	0.0505	0.01258	1	44
70	49	50	0.0267	0.0752	0.01874	1	67
71	49	51	0.0486	0.137	0.0342	1	83
72	51	52	0.0203	0.0588	0.01396	1	36
73	52	53	0.0405	0.1635	0.04058	1	13
74	53	54	0.0263	0.122	0.031	1	16
75	49	54	0.073	0.289	0.0738	1	47
76	49	54	0.0869	0.291	0.073	1	47
77	54	55	0.0169	0.0707	0.0202	1	9
78	54	56	0.00275	0.00955	0.00732	1	23
79	55	56	0.00488	0.0151	0.00374	1	27
80	56	57	0.0343	0.0966	0.0242	1	29
81	50	57	0.0474	0.134	0.0332	1	45
82	56	58	0.0343	0.0966	0.0242	1	8
83	51	58	0.0255	0.0719	0.01788	1	23
84	54	59	0.0503	0.2293	0.0598	1	38
85	56	59	0.0825	0.251	0.0569	1	35
86	56	59	0.0803	0.239	0.0536	1	37
87	55	59	0.04739	0.2158	0.05646	1	43
88	59	60	0.0317	0.145	0.0376	1	54
89	59	61	0.0328	0.15	0.0388	1	65
90	60	61	0.00264	0.0135	0.01456	1	140

91	60	62	0.0123	0.0561	0.01468	1	12
92	61	62	0.00824	0.0376	0.0098	1	32
93	63	59	0	0.0386	0	0.96	190
94	63	64	0.00172	0.02	0.216	1	190
95	64	61	0	0.0268	0	0.985	38
96	38	65	0.00901	0.0986	1.046	1	227
97	64	65	0.00269	0.0302	0.38	1	228
98	49	66	0.018	0.0919	0.0248	1	165
99	49	66	0.018	0.0919	0.0248	1	165
100	62	66	0.0482	0.218	0.0578	1	46
101	62	67	0.0258	0.117	0.031	1	30
102	65	66	0	0.037	0	0.935	11
103	66	67	0.0224	0.1015	0.02682	1	66
104	65	68	0.00138	0.016	0.638	1	18
105	47	69	0.0844	0.2778	0.07092	1	70
106	49	69	0.0985	0.324	0.0828	1	58
107	68	69	0	0.037	0	0.935	157
108	69	70	0.03	0.127	0.122	1	135
109	24	70	0.00221	0.4115	0.10198	1	8
110	70	71	0.00882	0.0355	0.00878	1	21
111	24	72	0.0488	0.196	0.0488	1	2
112	71	72	0.0446	0.18	0.04444	1	13
113	71	73	0.00866	0.0454	0.01178	1	8
114	70	74	0.0401	0.1323	0.03368	1	20
115	70	75	0.0428	0.141	0.036	1	1
116	69	75	0.0405	0.122	0.124	1	138
117	74	75	0.0123	0.0406	0.01034	1	65
118	76	77	0.0444	0.148	0.0368	1	76
119	69	77	0.0309	0.101	0.1038	1	78
120	75	77	0.0601	0.1999	0.04978	1	43
121	77	78	0.00376	0.0124	0.01264	1	57
122	78	79	0.00546	0.0244	0.00648	1	32
123	77	80	0.017	0.0485	0.0472	1	121
124	77	80	0.0294	0.105	0.0228	1	55
125	79	80	0.0156	0.0704	0.0187	1	81
126	68	81	0.00175	0.0202	0.808	1	55
127	81	80	0	0.037	0	0.935	55
128	77	82	0.0298	0.0853	0.08174	1	4
129	82	83	0.0112	0.03665	0.03796	1	59
130	83	84	0.0625	0.132	0.0258	1	31
131	83	85	0.043	0.148	0.0348	1	53
132	84	85	0.0302	0.0641	0.01234	1	45
133	85	86	0.035	0.123	0.0276	1	21
134	86	87	0.02828	0.2074	0.0445	1	5
135	85	88	0.02	0.102	0.276	1	63
136	85	89	0.0239	0.173	0.047	1	89
137	88	89	0.0139	0.0712	0.01934	1	124

138	89	90	0.0518	0.188	0.0528	1	73
139	89	90	0.0238	0.0997	0.106	1	139
140	90	91	0.0254	0.0836	0.0214	1	2
141	89	92	0.0099	0.0505	0.0548	1	252
142	89	92	0.0393	0.1581	0.0414	1	79
143	91	92	0.0387	0.1272	0.03268	1	11
144	92	93	0.0258	0.0848	0.0218	1	72
145	92	94	0.0481	0.158	0.0406	1	65
146	93	94	0.0223	0.0732	0.01876	1	56
147	94	95	0.0132	0.0434	0.0111	1	51
148	80	96	0.0356	0.182	0.0494	1	24
149	82	96	0.0162	0.053	0.0544	1	12
150	94	96	0.0269	0.869	0.023	1	25
151	80	97	0.0183	0.0934	0.0254	1	33
152	80	98	0.0238	0.108	0.0286	1	36
153	80	99	0.0454	0.206	0.0546	1	24
154	92	100	0.0648	0.295	0.0472	1	39
155	94	100	0.0178	0.058	0.0604	1	5
156	95	96	0.0171	0.0547	0.01474	1	2
157	96	97	0.0173	0.0885	0.024	1	14
158	98	100	0.0397	0.179	0.0476	1	7
159	99	100	0.018	0.0813	0.0216	1	28
160	100	101	0.0277	0.1262	0.0328	1	21
161	92	102	0.0123	0.0559	0.01464	1	56
162	101	102	0.0246	0.112	0.0294	1	49
163	100	103	0.016	0.0525	0.0536	1	152
164	100	104	0.0451	0.204	0.0541	1	70
165	103	104	0.0466	0.1584	0.0407	1	41
166	103	105	0.0535	0.1625	0.0408	1	54
167	100	106	0.0605	0.229	0.062	1	75
168	104	105	0.00994	0.0378	0.00986	1	61
169	105	106	0.014	0.0547	0.01434	1	11
170	105	107	0.053	0.183	0.0472	1	33
171	105	108	0.0261	0.0703	0.01844	1	30
172	106	107	0.053	0.183	0.0472	1	30
173	108	109	0.0105	0.0288	0.0076	1	27
174	103	110	0.03906	0.1813	0.0461	1	76
175	109	110	0.0278	0.0762	0.0202	1	17
176	110	111	0.022	0.0755	0.02	1	45
177	110	112	0.0247	0.064	0.062	1	87
178	17	113	0.00913	0.0301	0.00768	1	3
179	32	113	0.0615	0.203	0.0518	1	5
180	32	114	0.0135	0.0612	0.01628	1	12
181	27	115	0.0164	0.0741	0.01972	1	26
182	114	115	0.0023	0.0104	0.00276	1	2
183	68	116	0.00034	0.00405	0.164	1	230
184	12	117	0.0329	0.14	0.0358	1	25

185	75	118	0.0145	0.0481	0.01198	1	50
186	76	118	0.0164	0.0544	0.01356	1	9

APPENDIX B6: IEEE 118 – Bus bus datas

Bus No.	Voltage Mag.	Phase Ang.	P (MW)	Q (MVar)	P (MW)	Q (Mvar)	Q min	Q max
1	0.955	10.67	51	27	0	0	-5	15
2	1	11.22	20	9	0	0	0	0
3	1	11.56	39	10	0	0	0	0
4	0.998	15.28	30	12	-9	0	-300	300
5	1	15.73	0	0	0	-0.4	0	0
6	0.99	13	52	22	0	0	-13	50
7	1	12.56	19	2	0	0	0	0
8	1.015	20.77	0	0	-28	0	-300	300
9	1	28.02	0	0	0	0	0	0
10	1.05	35.61	0	0	450	0	-147	200
11	1	12.72	70	23	0	0	0	0
12	0.99	12.2	47	10	85	0	-35	120
13	1	11.35	34	16	0	0	0	0
14	1	11.5	14	1	0	0	0	0
15	0.97	11.23	90	30	0	0	-10	30
16	1	11.91	25	10	0	0	0	0
17	1	13.74	11	3	0	0	0	0
18	0.973	11.53	60	34	0	0	-16	50
19	0.963	11.05	45	25	0	0	-8	24
20	1	11.93	18	3	0	0	0	0
21	1	13.52	14	8	0	0	0	0
22	1	16.08	10	5	0	0	0	0
23	1	21	7	3	0	0	0	0
24	0.992	20.89	0	0	-13	0	-300	300
25	1.05	27.93	0	0	220	0	-47	140
26	1.015	29.71	0	0	314	0	-1000	1000
27	0.968	15.35	62	13	-9	0	-300	300
28	1	13.62	17	7	0	0	0	0
29	1	12.63	24	4	0	0	0	0
30	1	18.79	0	0	0	0	0	0
31	0.967	12.75	43	27	7	0	-300	300
32	0.964	14.8	59	23	0	0	-14	-42
33	1	10.63	23	9	0	0	0	0
34	0.986	11.3	59	26	0	-0.14	-8	24
35	1	10.87	33	9	0	0	0	0
36	0.98	10.87	31	17	0	0	-8	24
37	1	11.77	0	0	0	0.25	0	0
38	1	16.91	0	0	0	0	0	0
39	1	8.41	27	11	0	0	0	0

40	0.97	7.35	20	23	-46	0	-300	300
41	1	6.92	37	10	0	0	0	0
42	0.985	8.53	37	23	-59	0	-300	300
43	1	11.28	18	7	0	0	0	0
44	1	13.82	16	8	0	-0.1	0	0
45	1	15.67	53	22	0	-0.1	0	0
46	1.005	18.49	28	10	19	-0.1	-100	100
47	1	20.73	34	0	0	0	0	0
48	1	19.93	20	11	0	-0.15	0	0
49	1.025	20.94	87	30	204	0	-85	210
50	1	18.9	17	4	0	0	0	0
51	1	16.28	17	8	0	0	0	0
52	1	15.32	18	5	0	0	0	0
53	1	14.35	23	11	0	0	0	0
54	0.955	15.26	113	32	48	0	-300	300
55	0.952	14.97	63	22	0	0	-8	23
56	0.954	15.16	84	18	0	0	-8	15
57	1	16.36	12	3	0	0	0	0
58	1	15.51	12	3	0	0	0	0
59	0.985	19.37	277	113	155	0	-60	180
60	1	23.15	78	3	0	0	0	0
61	0.995	24.04	0	0	160	0	-100	300
62	0.998	23.43	77	14	0	0	-20	20
63	1	22.75	0	0	0	0	0	0
64	1	24.52	0	0	0	0	0	0
65	1.005	27.65	0	0	391	0	-67	200
66	1.05	27.48	39	18	392	0	-67	200
67	1	24.84	28	7	0	0	0	0
68	1	27.55	0	0	0	0	0	0
69	1.035	30	0	0	516.4	0	-300	300
70	0.984	22.58	66	20	0	0	-10	32
71	1	22.15	0	0	0	0	0	0
72	0.98	20.98	0	0	-12	0	-100	100
73	0.991	21.94	0	0	-6	0	-100	100
74	0.958	21.64	68	27	0	-0.12	-6	9
75	1	22.91	47	11	0	0	0	0
76	0.943	21.77	68	36	0	0	-8	23
77	1.006	26.72	61	28	0	0	-20	70
78	1	26.42	71	26	0	0	0	0
79	1	26.72	39	32	0	-0.2	0	0
80	1.04	28.96	130	26	477	0	-165	280
81	1	28.1	0	0	0	0	0	0
82	1	27.24	54	27	0	-0.2	0	0
83	1	28.42	20	10	0	-0.1	0	0
84	1	30.95	11	7	0	0	0	0
85	0.985	32.51	24	15	0	0	-8	23
86	1	31.14	21	10	0	0	0	0

87	1.015	31.4	0	0	4	0	-100	1000
88	1	35.64	48	10	0	0	0	0
89	1.005	39.69	0	0	607	0	-210	300
90	0.985	33.29	78	42	-85	0	-300	300
91	0.98	33.31	0	0	-10	0	-100	100
92	0.993	33.8	65	10	0	0	-3	9
93	1	30.79	12	7	0	0	0	0
94	1	28.64	30	16	0	0	0	0
95	1	27.67	42	31	0	0	0	0
96	1	27.51	38	15	0	0	0	0
97	1	27.88	15	9	0	0	0	0
98	1	27.4	34	8	0	0	0	0
99	1	27.04	0	0	-42	0	-100	100
100	1.017	28.03	37	18	252	0	-50	155
101	1	29.61	22	15	0	0	0	0
102	1	32.3	5	3	0	0	0	0
103	1.001	24.44	23	16	40	0	-15	40
104	0.971	21.69	38	25	0	0	-8	23
105	0.965	20.57	31	26	0	-0.2	-8	23
106	1	20.32	43	16	0	0	0	0
107	0.952	17.53	28	12	-22	-0.06	-200	200
108	1	19.38	2	1	0	0	0	0
109	1	18.93	8	3	0	0	0	0
110	0.973	18.09	39	30	0	-0.06	-8	23
111	0.98	19.74	0	0	36	0	-100	1000
112	0.975	14.99	25	13	-43	0	-100	1000
113	0.993	13.74	0	0	-6	0	-100	200
114	1	14.46	8	3	0	0	0	0
115	1	14.46	22	7	0	0	0	0
116	1.005	27.12	0	0	-184	0	-1000	1000
117	1	10.67	20	8	0	0	0	0
118	1	21.92	33	15	0	0	0	0

APPENDIX C: MATLAB code for the solution of congestion management

APPENDIX C1: MATLAB script file – OPF_NR_to-detemine_congested_lines

```
clc,clear
message = 'Select the data to run!!! \n\nReply with any number below and press enter! \n1  for
IEEE 14Bus; \n2  for IEEE 30Bus; \n3  for IEEE 118Bus;\n\nData Number = ';
dataToRun = input(message);
disp('Newton Raphson Simulation In Progress...')
[busdata,linedata,genData] = loadData(dataToRun); saveLineData =
[(1:length(linedata))',linedata];
saving = 'Data'; saveFun;
basemva = 100;  accuracy = 0.1; maxiter =
20;
yline=0;
lenBusData = length(busdata); volRange = [1.0 1.05];
```

Admittance bus matrix formation

```
j = sqrt(-1); i = sqrt(-1);
nl = linedata(:,1); nr = linedata(:,2); R = linedata(:,3);
X = linedata(:,4); Bc = j*linedata(:,5); a = linedata(:, 6);
nbr=length(linedata(:,1)); nbus = max(max(nl), max(nr));
Z = R + j*X; y= ones(nbr,1)./Z;
for n = 1:nbr
    if a(n) <= 0
        a(n) = 1;
    else
    end
        Ybus=zeros(nbus,nbus);
```

Formation of the off diagonal elements

```
    for k=1:nbr
        genLoc = length(k); Ybus(nl(k),nr(k))=Ybus(nl(k),nr(k))-y(k)/a(k);
        Ybus(nr(k),nl(k))=Ybus(nl(k),nr(k));
    end
end
```

Formation of the diagonal elements

```
for  n = 1:nbus
     for k = 1:nbr
         if nl(k)==n
            Ybus(n,n) = Ybus(n,n)+y(k)/(a(k)^2) + Bc(k);
         elseif nr(k)==n
            Ybus(n,n) = Ybus(n,n)+y(k) +Bc(k);
         else
         end
     end
end
clear Pgg
```

Load flow solution by Newton-Raphson method

```
ns = 0; ng = 0; vi = 0; delta = 0; yload = 0; deltad = 0;
nbus = length(busdata(:,1)); yline = 0;
for k = 1:nbus
    n = busdata(k,1);
    kb(n) = busdata(k,2); vi(n) = busdata(k,3); delta(n) = busdata(k, 4);
    Pd(n) = busdata(k,5); Qd(n) = busdata(k,6); Pg(n)=busdata(k,7); Qg(n) = busdata(k,8);
    Qmin(n) = busdata(k, 9); Qmax(n) = busdata(k, 10); Qsh(n) = busdata(k, 11);
    if vi(n) <= 0
        vi(n) = 1.0; V(n) = 1 + j*0;
    else
        delta(n) = pi/180*delta(n);  V(n) = vi(n)*(cos(delta(n)) + j*sin(delta(n)));
        P(n) = (Pg(n)-Pd(n))/basemva; Q(n) = (Qg(n)-Qd(n)+ Qsh(n))/basemva;
        S(n) = P(n) + j*Q(n);
    end
end

for k = 1:nbus
    if kb(k) == 1
        ns = ns+1;
    else
    end
    if kb(k) == 2
        ng = ng+1;
    else
    end
    ngs(k) = ng; nss(k) = ns;
end
Ym = abs(Ybus); t = angle(Ybus); m = 2*nbus-ng-2*ns; maxerror = 1; converge=1; iter = 0;
```

Start of iterations

```
clear A DC J DX
while maxerror >= accuracy & iter <= maxiter
    for i = 1:m
        for k = 1:m
           A(i,k)=0;
        end
    end
    iter = iter+1;
    for n = 1:nbus
        nn = n-nss(n); lm = nbus+n-ngs(n)-nss(n)-ns;
        J11=0; J22=0; J33=0; J44=0;
        for i=1:nbr
            if nl(i) == n | nr(i) == n
                if nl(i) == n
                    l = nr(i);
                end
                if nr(i) == n
                    l = nl(i);
                end
                J11 = J11+ vi(n)*vi(l)*Ym(n,l)*sin(t(n,l)- delta(n) + delta(l));
                J33 = J33+ vi(n)*vi(l)*Ym(n,l)*cos(t(n,l)- delta(n) + delta(l));
                if kb(n)~=1
                    J22 = J22+ vi(l)*Ym(n,l)*cos(t(n,l)- delta(n) + delta(l));
                    J44 = J44+ vi(l)*Ym(n,l)*sin(t(n,l)- delta(n) + delta(l));
                else
                end
                if kb(n) ~= 1  & kb(l) ~=1
```

```
                    lk = nbus+l-ngs(l)-nss(l)-ns;
                    ll = l -nss(l);
```

Coalating result for saving

```
for n=1:nbus
    newReVol(n,1) = n; newReVol(n,2) = vi(n);
    newReVol(n,3) = deltad(n); newReVol(n,4) = Pd(n);
    newReVol(n,5) = Qd(n); newReVol(n,6) = Pg(n);
    newReVol(n,7) = Qg(n); newReVol(n,8) = Qsh(n);
end
```

Computating line flow and line losses

```
SLT = 0;
counter = 1;
for n = 1:nbus
    busprt = 0;
    for L = 1:nbr
        if busprt == 0
            busprt = 1; newRe{counter,1} = n;
        else
            newRe{counter,1} = n;
        end
        if nl(L)==n
            k = nr(L); lenBusData = [n,k];
            In = (V(n) - a(L)*V(k))*y(L)/a(L)^2 + Bc(L)/a(L)^2*V(n);
            Ik = (V(k) - V(n)/a(L))*y(L) + Bc(L)*V(k);
            Snk = V(n)*conj(In)*basemva;
            Skn = V(k)*conj(Ik)*basemva;
            SL  = Snk + Skn;
            SLT = SLT + SL;
        elseif nr(L)==n
            k = nl(L); lenBusData = [n,k];
            In = (V(n) - V(k)/a(L))*y(L) + Bc(L)*V(n);
            Ik = (V(k) - a(L)*V(n))*y(L)/a(L)^2 + Bc(L)/a(L)^2*V(k);
            Snk = V(n)*conj(In)*basemva;
            Skn = V(k)*conj(Ik)*basemva;
            SL  = Snk + Skn;
            SLT = SLT + SL;
        else
        end
        if nl(L)==n | nr(L)==n
            newRe{counter,2} = k;qi; newRe{counter,3} = real(Snk);
            newRe{counter,4} = imag(Snk); newRe{counter,5} = abs(Snk);
            newRe{counter,6} = real(SL);
            if nl(L) ==n & a(L) ~= 1
                newRe{counter,7} = imag(SL); newRe{counter,8} = a(L);
            else
                newRe{counter,7} = imag(SL);
            end
            counter = counter+1;
        else
        end
    end
end
SLT = SLT/2;
newRe{nbr+1,6} = real(SLT); newRe{nbr+1,7} = imag(SLT);
```

```
clear Ik In SL SLT Skn Snk
count = 1;
```

Looking for the congested line(s)

```
for i_lineData = 1:length(linedata)
    for i_Check=1:2
        if i_Check==1
            searching = cell2mat(newRe(:,1:2));
            loc = find(searching(:,1) == linedata(i_lineData,1));
            for i_len = 1:length(loc)
                if searching(loc(i_len),2)==linedata(i_lineData,2)
                    if newRe{loc(i_len),4}>linedata(i_lineData,7)
                        violatedLine(count) = loc(i_len); violatedDataLine(count) =
i_lineData;
                        count = count+1;
                    end
                end
            end
        elseif i_Check==2
            searching = cell2mat(newRe(:,1:2));
            loc = find(searching(:,2) == linedata(i_lineData,1));
            for i_len = 1:length(loc)
                if searching(loc(i_len),1)== linedata(i_lineData,2)
                    if newRe{loc(i_len),4}>linedata(i_lineData,7)
                        violatedLine(count) = loc(i_len); violatedDataLine(count) =
i_lineData;
                        count = count+1;
                    end
                end
            end
        end
    end
end
violationResult = [violatedLine;[newRe{violatedLine,4}];(linedata(violatedDataLine,7))'];
```

Obtaining the Sensitivity Factor of each generator on the congested line

```
genLoc = find(busdata(:,2) == 2 | busdata(:,2) == 1);
for i_lenGenLoc = 1:length(genLoc)
    lineLoc = genLoc(i_lenGenLoc);
    rxLine = nr(lineLoc);i_lineLoc = length(lineLoc);

    iBus = linedata(violatedLine,1); jBus = linedata(violatedLine,2);
    QijVi = -2*vi(iBus)*linedata(lineLoc(i_lineLoc),5) +
vi(jBus)*(1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-deltad(jBus)) -
vi(jBus)*linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus));
    ViQG = -2*linedata(lineLoc(i_lineLoc),5)*vi(iBus) +
sum((1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-deltad(jBus)) -
linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus)))*abs(vi(jBus));
    QijVj = vi(iBus)*(1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-deltad(jBus)) -
vi(jBus)*linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus));
    VjQG = abs(vi(iBus)) * sum((1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-
deltad(jBus)) - linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-
deltad(jBus)));
qi
    gs(i_lenGenLoc,1:2) = QijVi.*(ViQG).^-1 + QijVj.*(VjQG).^-1;  end
[low] = find(gs>0); genData(low,:) = []; oldNewReVol = newReVol;
saving = 'NewtonRaphson'; saveFun; pso_NewtonRaphson
```

APPENDIX C2: MATLAB script file – PSO_CM_IEEE 14, 30, 118_bus_systems

```
disp('PSO Newton Raphson Simulation In Progress...')
cpgMin = genData(:,2); cpgMax = genData(:,3);
pgMin = 1.0; pgMax = 1.05; lmax =
volRange(2);
pf = 0; yline =0; it=0;
cpg = cpgMin + (cpgMax-cpgMin)*rand(1,1); pg = pgMin + (pgMax-pgMin)*rand(1,1);
cqg = cpgMin + (cpgMax-cpgMin)*rand(1,1); qg = pgMin + (pgMax-pgMin)*rand(1,1);
```

Problem Definition

```
objFunction = @(cpg,pg,cqg,qg,lmax,vi,pf) objFunc(cpg,pg,cqg,qg,lmax,vi,pf);
nVar = 10;
VarSize = [1 nVar];
VarMin = -100;
VarMax = 100;
```

PSO Parameters

```
MaxIt = 350;
nPop = 50;
inertiaWeight = [0 1];
wdamp = 0.99;
c1 = 2.0;
c2 = 2.0;
```

Velocity Limits

```
VelMax = 0.45; VelMin = -0.45;
```

Initialization

```
empty_particle.Position = []; empty_particle.Cost = []; empty_particle.Velocity = [];
empty_particle.Best.Position = []; empty_particle.Best.Cost=[];
particle = repmat(empty_particle,nPop,1); GlobalBest.Cost=inf;
for i_nPop=1:nPop
    particle(i_nPop).Position = unifrnd(VarMin,VarMax,VarSize);
    particle(i_nPop).Velocity = zeros(VarSize);yline = VelMin + (VelMax+VelMin)*rand(1,2);
    particle(i_nPop).Cost = objFunction(cpg,pg,cqg,qg,lmax,vi,pf);qi;
    particle(i_nPop).Best.Position = particle(i_nPop).Position;
    particle(i_nPop).Best.Cost = particle(i_nPop).Cost;
    if particle(i_nPop).Best.Cost<GlobalBest.Cost
        GlobalBest = particle(i_nPop).Best;
    end
end
```

PSO Main Loop

```
for it=1:MaxIt
    wMax = inertiaWeight(2);
    for i_nPop=1:nPop
```

Update Velocity

```
        particle(i_nPop).Velocity = wMax*particle(i_nPop).Velocity ...
            +c1*rand(VarSize).*(particle(i_nPop).Best.Position-particle(i_nPop).Position) ...
            +c2*rand(VarSize).*(GlobalBest.Position-particle(i_nPop).Position);
```

Apply Velocity Limits

```
        particle(i_nPop).Velocity = max(particle(i_nPop).Velocity,VelMin);
        particle(i_nPop).Velocity = min(particle(i_nPop).Velocity,VelMax);
```

Update Position

```
        particle(i_nPop).Position = particle(i_nPop).Position + particle(i_nPop).Velocity;
        [busdata,linedata,genData] = allDataStorage();
        basemva = 100;  accuracy = 0.1; maxiter = 20;
        lenBusData = length(busdata); volRange = [1.0 1.05];
```

Admittance bus matrix formation

```
        j = sqrt(-1); i = sqrt(-1);
        nl = linedata(:,1); nr = linedata(:,2); R = linedata(:,3);
        X = linedata(:,4); Bc = j*linedata(:,5); a = linedata(:, 6);
        nbr=length(linedata(:,1)); nbus = max(max(nl), max(nr));
        Z = R + j*X; y= ones(nbr,1)./Z;
        for n = 1:nbr
```

```
            if a(n) <= 0
                a(n) = 1;
            else
            end
                Ybus=zeros(nbus,nbus);
```

Formation of the off diagonal elements

```
            for k=1:nbr
                genLoc = length(k);
                Ybus(nl(k),nr(k))=Ybus(nl(k),nr(k))-y(k)/a(k);
                Ybus(nr(k),nl(k))=Ybus(nl(k),nr(k));
            end
```

```
        end
```

Formation of the diagonal elements

```
        for  n = 1:nbus
             for k = 1:nbr
                 if nl(k)==n
                    Ybus(n,n) = Ybus(n,n)+y(k)/(a(k)^2) + Bc(k);
                 elseif nr(k)==n
                    Ybus(n,n) = Ybus(n,n)+y(k) +Bc(k);
                 else
                 end
             end
        end
        clear Pgg
```

Load flow solution by Newton-Raphson method

```
        ns = 0; ng = 0; vi = 0; delta = 0; yload = 0; deltad = 0;
        nbus = length(busdata(:,1));
        for k = 1:nbus
            n = busdata(k,1);
            kb(n) = busdata(k,2); vi(n) = busdata(k,3); delta(n) = busdata(k, 4);
            Pd(n) = busdata(k,5); Qd(n) = busdata(k,6); Pg(n)=busdata(k,7); Qg(n) =
busdata(k,8);
            Qmin(n) = busdata(k, 9); Qmax(n) = busdata(k, 10);
            Qsh(n) = busdata(k, 11);
            if vi(n) <= 0
                vi(n) = 1.0; V(n) = 1 + j*0;
            else
                delta(n) = pi/180*delta(n);
                V(n) = vi(n)*(cos(delta(n)) + j*sin(delta(n))); P(n) = (Pg(n)-Pd(n))/basemva;
                Q(n) = (Qg(n)-Qd(n)+ Qsh(n))/basemva; S(n) = P(n) + j*Q(n);
            end
        end

        for k = 1:nbus
            if kb(k) == 1
                ns = ns+1;
            else
            end
            if kb(k) == 2
                ng = ng+1;
            else
            end
            ngs(k) = ng; nss(k) = ns;
        end
        Ym = abs(Ybus); t = angle(Ybus); m = 2*nbus-ng-2*ns;
        maxerror = 1; converge=1; iter = 0;
```

Start of iterations

```
        clear A DC J DX
        while maxerror >= accuracy & iter <= maxiter
            for i = 1:m
                for k = 1:m
                   A(i,k)=0;
                end
            end
            iter = iter+1;
            for n = 1:nbus
                nn = n-nss(n); lm = nbus+n-ngs(n)-nss(n)-ns;
                J11=0; J22=0; J33=0; J44=0;
                for i=1:nbr
                    if nl(i) == n | nr(i) == n
                        if nl(i) == n
                            l = nr(i);
                        end
                        if nr(i) == n
                            l = nl(i);
                        end
                        J11 = J11+ vi(n)*vi(l)*Ym(n,l)*sin(t(n,l)- delta(n) + delta(l));
                        J33 = J33+ vi(n)*vi(l)*Ym(n,l)*cos(t(n,l)- delta(n) + delta(l));
                        if kb(n)~=1
                            J22 = J22+ vi(l)*Ym(n,l)*cos(t(n,l)- delta(n) + delta(l));
                            J44 = J44+ vi(l)*Ym(n,l)*sin(t(n,l)- delta(n) + delta(l));
                        else
```

```
                end
                if kb(n) ~= 1  & kb(l) ~=1
```

```
                    lk = nbus+l-ngs(l)-nss(l)-ns;
                    ll = l -nss(l);
```

Computating line flow and line losses

```
SLT = 0; counter = 1;
for n = 1:nbus
    busprt = 0;
    for L = 1:nbr
        if busprt == 0
            busprt = 1; newRe{counter,1} = n;
        else
            newRe{counter,1} = n;
        end
        if nl(L)==n
            k = nr(L); lenBusData = [n,k];
            In = (V(n) - a(L)*V(k))*y(L)/a(L)^2 + Bc(L)/a(L)^2*V(n);
            Ik = (V(k) - V(n)/a(L))*y(L) + Bc(L)*V(k);
            Snk = V(n)*conj(In)*basemva;
            Skn = V(k)*conj(Ik)*basemva;
            SL  = Snk + Skn;
            SLT = SLT + SL;
        elseif nr(L)==n
            k = nl(L); lenBusData = [n,k];
            In = (V(n) - V(k)/a(L))*y(L) + Bc(L)*V(n);
            Ik = (V(k) - a(L)*V(n))*y(L)/a(L)^2 + Bc(L)/a(L)^2*V(k);
            Snk = V(n)*conj(In)*basemva;
            Skn = V(k)*conj(Ik)*basemva;
            SL  = Snk + Skn;
            SLT = SLT + SL;
        else
        end
        if nl(L)==n | nr(L)==n
            newRe{counter,2} = k;qi;newRe{counter,3} = real(Snk);
            newRe{counter,4} = imag(Snk);
            if nl(L) ==n & a(L) ~= 1
                newRe{counter,7} = imag(SL); newRe{counter,8} = a(L);
            else
                newRe{counter,7} = imag(SL);
            end
            counter = counter+1;
        else
        end
    end
end
SLT = SLT/2;
newRe{nbr+1,6} = real(SLT); newRe{nbr+1,7} = imag(SLT);
clear Ik In SL SLT Skn Snk
count = 1;
```

Looking for the congested line(s)

```
for i_lineData = 1:length(linedata)
    for i_Check=1:2
        if i_Check==1
            searching = cell2mat(newRe(:,1:2));
            loc = find(searching(:,1) == linedata(i_lineData,1));
```

```
                    for i_len = 1:length(loc)
                        if searching(loc(i_len),2)==linedata(i_lineData,2)
                            if newRe{loc(i_len),4}>linedata(i_lineData,7)
                                violatedLine(count) = loc(i_len);
                                count = count+1;
                            end
                        end
                    end
                elseif i_Check==2
                    searching = cell2mat(newRe(:,1:2));
                    loc = find(searching(:,2) == linedata(i_lineData,1));
                    for i_len = 1:length(loc)
                        if searching(loc(i_len),1)== linedata(i_lineData,2)
                            if newRe{loc(i_len),4}>linedata(i_lineData,7)
                                violatedLine(count) = loc(i_len);
                                count = count+1;
                            end
                        end
                    end
                end
            end
        end
```

Obtaining the Sensitivity Factor of each generator on the congested line

```
        genLoc = find(busdata(:,2) == 2 | busdata(:,2) == 1);
        for i_lenGenLoc = 1:length(genLoc)
            lineLoc = genLoc(i_lenGenLoc);
rxLine = nr(lineLoc);i_lineLoc = length(lineLoc);                               iBus =
linedata(violatedLine,1); jBus = linedata(violatedLine,2);
            QijVi = -2*vi(iBus)*linedata(lineLoc(i_lineLoc),5) +
vi(jBus)*(1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-deltad(jBus)) -
vi(jBus)*linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus));
            ViQG = -2*linedata(lineLoc(i_lineLoc),5)*vi(iBus) +
sum((1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-deltad(jBus)) -
linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus)))*abs(vi(jBus));
            QijVj = vi(iBus)*(1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-deltad(jBus))
- vi(jBus)*linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus));
            VjQG = abs(vi(iBus)) * sum((1/linedata(lineLoc(i_lineLoc),3))*sin(deltad(iBus)-
deltad(jBus)) - linedata(lineLoc(i_lineLoc),5)*cos(deltad(iBus)-deltad(jBus)));qi
            gs(i_lenGenLoc,1:2) = QijVi.*(ViQG).^-1 + QijVj.*(VjQG).^-1;
        end
        [low] = find(gs>0); genData(:,low) = [];
        cpgMin = genData(:,2); cpgMax = genData(:,3);
        cpg = cpgMin + (cpgMax-cpgMin)*rand(1,1); pg = pgMin + (pgMax-pgMin)*rand(1,1);
        cqg = cpgMin + (cpgMax-cpgMin)*rand(1,1); qg = pgMin + (pgMax-pgMin)*rand(1,1);
        lmax = volRange(2); pf = 0;
```

Velocity Mirror Effect

```
        IsOutside=(particle(i_nPop).Position<VarMin | particle(i_nPop).Position>VarMax);
particle(i_nPop).Velocity(IsOutside)=-particle(i_nPop).Velocity(IsOutside);
```

Apply Position Limits

```
        particle(i_nPop).Position = max(particle(i_nPop).Position,VarMin);
particle(i_nPop).Position = min(particle(i_nPop).Position,VarMax); yline = VelMin +
(VelMax+VelMin)*rand(1,1);
```

Evaluation

```
        particle(i_nPop).Cost = objFunction(cpg,pg,cqg,qg,lmax,vi,pf);qi;
```

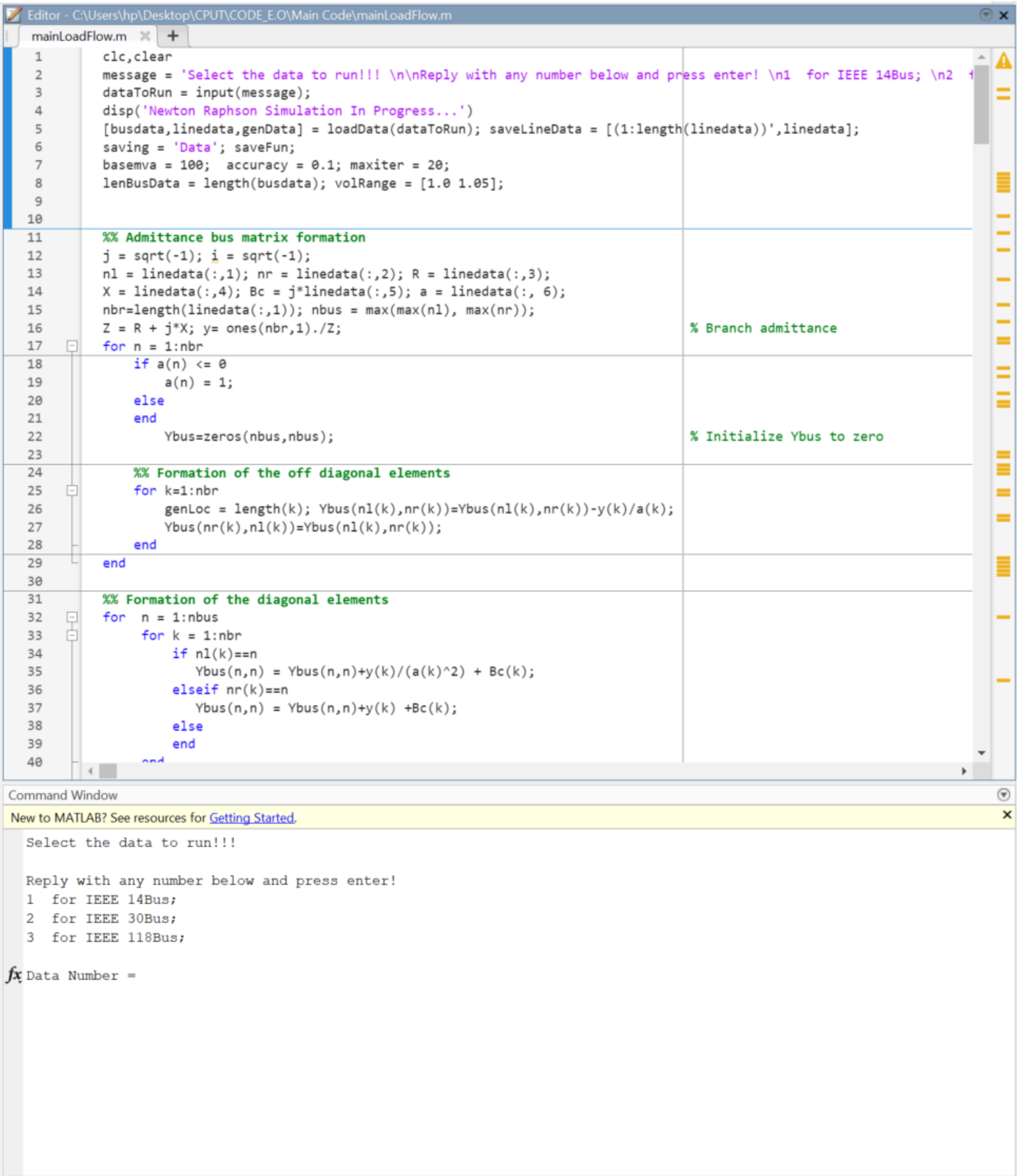
Update Personal Best

```
        if particle(i_nPop).Cost<particle(i_nPop).Best.Cost
            particle(i_nPop).Best.Position = particle(i_nPop).Position;
particle(i_nPop).Best.Cost=particle(i_nPop).Cost;
```

Update Global Best

```
            if particle(i_nPop).Best.Cost<GlobalBest.Cost
                GlobalBest = particle(i_nPop).Best;
            end
        end
    end
    BestCost(:,it) = GlobalBest.Cost; wMax = wMax*wdamp;
end
saving = 'PSO_NewtonRaphson'; saveFun; plotGraph;
```

APPENDIX C3: MATLAB script_screenshot_PSO_CM_IEEE 14, 30, 118_bus_systems



The OPF_NR code at APPENDIX C1 was written to prompt the user to select which of the considered case studies to run as seen in APPENDIX C3 (Screenshot of the prompt interface).

APPENDIX C4: MATLAB script file – MILP_CM_IEEE 14 bus_system

```
clear all
clc
%To formulate the problem,
partn_gen=[1 2 3 6 8];    %5 Participationg generator
nbus = 14;                  % IEEE-14
disp('Running, Please wait!')
Gen_resh_prob = optimproblem;
%Specifying the limits for PGsize and QGsize
PGsize = optimvar('PGsize',7,'Type','continuous','LowerBound',0,'UpperBound',1);
QGsize = optimvar('QGsize',7,'Type','continuous','LowerBound',0,'UpperBound',1);
%Create expressions for the costs associated with the variables, that is
%setting the constrainsts

[PtLosskW,Ptload,QtLosskVAr,Qtload,VmagPU]=fcn2optimexpr(@powerflowGRmlip,PGsize,QGsize,partn_
gen,nbus,'OutputSize',[1,5]);

[bPtLosskW,bPtload,bQtLosskVAr,bQtload,bVmagPU]=fcn2optimexpr(@powerflowmlip,nbus,'OutputSize'
,[1,5]);  %to extimate for the base ploss
 ploss=PtLosskW;   %total real power losses
 pload=Ptload;
 qloss=QtLosskVAr;   %total reactive power losses
 qload=Qtload;
 percent_plos_red=((bPtLosskW-ploss)./bPtLosskW)*100;
 percent_qlos_red=((bQtLosskVAr-qloss)./bQtLosskVAr)*100;
 absPGsize=fcn2optimexpr(@abs,PGsize,'OutputSize',[1,1]);
 absQGsize=fcn2optimexpr(@abs,QGsize,'OutputSize',[1,1]);
 [pgen, qgen]= fcn2optimexpr(@busdata_pq,PGsize,QGsize,partn_gen,nbus,'OutputSize',[1,1]);
 const_1= (pgen-pload-ploss); %i.e pg-pl-pd=0
 const_2= (qgen-qload-qloss); %i.e qg-ql-qd=0
 roundconst_1=fcn2optimexpr(@round,const_1,'OutputSize',[1,1]);
 roundconst_2=fcn2optimexpr(@round,const_2,'OutputSize',[1,1]);
 Gen_resh_prob.Constraints.consPloss=percent_plos_red >=1;
 Gen_resh_prob.Constraints.consQloss=percent_qlos_red >=1;
 Gen_resh_prob.Constraints.consPGsize=roundconst_1==0;
 Gen_resh_prob.Constraints.consQGsize=roundconst_2==0;
%Now that you have all the inputs, call the solver.
expr=fcn2optimexpr(@MILPSphere,PGsize,QGsize,partn_gen,nbus,'OutputSize',[1,1]);
Gen_resh_prob.Objective=expr;
x0.PGsize = [0.0 0.0 0.0 0.0 0.0];
x0.QGsize = [0.0 0.0 0.0 0.0 0.0];
options = optimoptions('intlinprog');
[sol,fval] = solve(Gen_resh_prob,x0,'Options', options);
%[sol,fval] = solve(Gen_resh_prob,x0);
% Results
Best_PGsize=sol.PGsize;
Best_QGsize=sol.QGsize;
clc;
powerflow_baesecase=powerflow(nbus);
 plossbase=powerflow_baesecase.PtLosskW;   %total real power losses
 qlossbase=powerflow_baesecase.QtLosskVAr;   %total reactive power losses
  VmagPUbase=powerflow_baesecase.VmagPU;   %voltage magnitude for the base case
 Vanglebase=powerflow_baesecase.Vangle;   %voltage magnitude for the base case
[sum_cost_pg,sum_cost_qg,ploss,qloss,sum_vmagdiff,vmagpu,vangle]=MILPresults(Best_PGsize,Best_
QGsize,partn_gen,nbus);
percent_ploss_red=((plossbase-ploss)/plossbase)*100;
percent_qloss_red=((qlossbase-qloss)/qlossbase)*100;
disp(['Active Power Resheduling Cost ($/MWhr): ',num2str(sum_cost_pg)]);
```

```
disp(['Reactive Power Resheduling Cost ($/MVARhr): ',num2str(sum_cost_qg)]);
disp(['Total Active Power Loss MW: ',num2str(ploss)]);
disp(['Percentage Active Power Loss Reduction: ',num2str(percent_ploss_red)]);
disp(['Total Reactive Power Loss MVAR: ',num2str(qloss)]);
disp(['Percentage Reactive Power Loss Reduction: ',num2str(percent_qloss_red)]);
disp(['Total Voltage Deviation: ',num2str(sum_vmagdiff)]);
fprintf('Generator Resheduling:\n')
busd = busdatas(nbus);      % Calling busdatas..
PGsize= sol.PGsize;
QGsize= sol.QGsize;
for ngen=1:length(partn_gen)
    changePG=PGsize(ngen)-busd(partn_gen(ngen),5);
    changeQG=QGsize(ngen)-busd(partn_gen(ngen),6);
    fprintf('New_PG %3d = %6.2f, New_QG %3d =
%6.2f\n',partn_gen(ngen),changePG,partn_gen(ngen),changeQG)
end

%Plots
%Voltage profile
figure;
plot(VmagPUbase,'LineWidth',2);
hold on
plot(vmagpu,'LineWidth',2);
xlabel('Bus');
ylabel('Voltage Magnitude (p.u.)');
grid on;
legend('Voltage Profile Before','Voltage Profile After')
title('Voltage profile')
hold off

%Voltage angle
figure;
plot(Vanglebase,'LineWidth',2);
hold on
plot(vangle,'LineWidth',2);
xlabel('Bus');
ylabel('Voltage Angle');
grid on;
legend('Voltage Angle Before','Voltage Angle After')
title('Voltage Angle')
hold off
disp('The Simulation is executed Successfully!')
```

APPENDIX C5: MATLAB script file – MILP_CM_IEEE 30 bus_system

```
clear all
clc
%To formulate the problem,
partn_gen=[1 2 5 8 13];    %5 Participationg generator
nbus = 30;                  % IEEE-30
disp('Running, Please wait!')
Gen_resh_prob = optimproblem;
%Specifying the limits for PGsize and QGsize
PGsize = optimvar('PGsize',7,'Type','continuous','LowerBound',0,'UpperBound',1);
QGsize = optimvar('QGsize',7,'Type','continuous','LowerBound',0,'UpperBound',1;
%Create expressions for the costs associated with the variables, that is
%setting the constrainsts

[PtLosskW,Ptload,QtLosskVAr,Qtload,VmagPU]=fcn2optimexpr(@powerflowGRmlip,PGsize,QGsize,partn_
gen,nbus,'OutputSize',[1,5]);

[bPtLosskW,bPtload,bQtLosskVAr,bQtload,bVmagPU]=fcn2optimexpr(@powerflowmlip,nbus,'OutputSize'
,[1,5]);  %to extimate for the base ploss
 ploss=PtLosskW;   %total real power losses
 pload=Ptload;
 qloss=QtLosskVAr;   %total reactive power losses
 qload=Qtload;
 percent_plos_red=((bPtLosskW-ploss)./bPtLosskW)*100;
 percent_qlos_red=((bQtLosskVAr-qloss)./bQtLosskVAr)*100;
 absPGsize=fcn2optimexpr(@abs,PGsize,'OutputSize',[1,1]);
 absQGsize=fcn2optimexpr(@abs,QGsize,'OutputSize',[1,1]);
 [pgen, qgen]= fcn2optimexpr(@busdata_pq,PGsize,QGsize,partn_gen,nbus,'OutputSize',[1,1]);
 const_1= (pgen-pload-ploss); %i.e pg-pl-pd=0
 const_2= (qgen-qload-qloss); %i.e qg-ql-qd=0
 roundconst_1=fcn2optimexpr(@round,const_1,'OutputSize',[1,1]);
 roundconst_2=fcn2optimexpr(@round,const_2,'OutputSize',[1,1]);
 Gen_resh_prob.Constraints.consPloss=percent_plos_red >=1;
 Gen_resh_prob.Constraints.consQloss=percent_qlos_red >=1;
 Gen_resh_prob.Constraints.consPGsize=roundconst_1==0;
 Gen_resh_prob.Constraints.consQGsize=roundconst_2==0;
%Now that you have all the inputs, call the solver.
expr=fcn2optimexpr(@MILPSphere,PGsize,QGsize,partn_gen,nbus,'OutputSize',[1,1]);
Gen_resh_prob.Objective=expr;
x0.PGsize = [0.0 0.0 0.0 0.0 0.0];
x0.QGsize = [0.0 0.0 0.0 0.0 0.0];
options = optimoptions('intlinprog');
[sol,fval] = solve(Gen_resh_prob,x0,'Options', options);
%[sol,fval] = solve(Gen_resh_prob,x0);
% Results
Best_PGsize=sol.PGsize;
Best_QGsize=sol.QGsize;
clc;
powerflow_baesecase=powerflow(nbus);
 plossbase=powerflow_baesecase.PtLosskW;   %total real power losses
 qlossbase=powerflow_baesecase.QtLosskVAr;   %total reactive power losses
  VmagPUbase=powerflow_baesecase.VmagPU;   %voltage magnitude for the base case
 Vanglebase=powerflow_baesecase.Vangle;   %voltage magnitude for the base case
[sum_cost_pg,sum_cost_qg,ploss,qloss,sum_vmagdiff,vmagpu,vangle]=MILPresults(Best_PGsize,Best_
QGsize,partn_gen,nbus);
percent_ploss_red=((plossbase-ploss)/plossbase)*100;
percent_qloss_red=((qlossbase-qloss)/qlossbase)*100;
disp(['Active Power Resheduling Cost ($/MWhr): ',num2str(sum_cost_pg)]);
```

```
disp(['Reactive Power Resheduling Cost ($/MVARhr): ',num2str(sum_cost_qg)]);
disp(['Total Active Power Loss MW: ',num2str(ploss)]);
disp(['Percentage Active Power Loss Reduction: ',num2str(percent_ploss_red)]);
disp(['Total Reactive Power Loss MVAR: ',num2str(qloss)]);
disp(['Percentage Reactive Power Loss Reduction: ',num2str(percent_qloss_red)]);
disp(['Total Voltage Deviation: ',num2str(sum_vmagdiff)]);
fprintf('Generator Resheduling:\n')
busd = busdatas(nbus);      % Calling busdatas..
PGsize= sol.PGsize;
QGsize= sol.QGsize;
for ngen=1:length(partn_gen)
    changePG=PGsize(ngen)-busd(partn_gen(ngen),5);
    changeQG=QGsize(ngen)-busd(partn_gen(ngen),6);
    fprintf('New_PG %3d = %6.2f, New_QG %3d =
%6.2f\n',partn_gen(ngen),changePG,partn_gen(ngen),changeQG)
end

%Plots
%Voltage profile
figure;
plot(VmagPUbase,'LineWidth',2);
hold on
plot(vmagpu,'LineWidth',2);
xlabel('Bus');
ylabel('Voltage Magnitude (p.u.)');
grid on;
legend('Voltage Profile Before','Voltage Profile After')
title('Voltage profile')
hold off

%Voltage angle
figure;
plot(Vanglebase,'LineWidth',2);
hold on
plot(vangle,'LineWidth',2);
xlabel('Bus');
ylabel('Voltage Angle');
grid on;
legend('Voltage Angle Before','Voltage Angle After')
title('Voltage Angle')
hold off
disp('The Simulation is executed Successfully!')
```

APPENDIX C6: MATLAB script file – MILP_CM_IEEE 118 bus_system

```
clear all
clc
%To formulate the problem,
partn_gen=[6 24 34 54 66 85 105];    %7 Participationg generator
nbus = 118;                  % IEEE-118
disp('Running, Please wait!')
Gen_resh_prob = optimproblem;
%Specifying the limits for PGsize and QGsize
PGsize = optimvar('PGsize',7,'Type','continuous','LowerBound',0,'UpperBound',1);
QGsize = optimvar('QGsize',7,'Type','continuous','LowerBound',0,'UpperBound',1);
%Create expressions for the costs associated with the variables, that is
%setting the constrainsts

[PtLosskW,Ptload,QtLosskVAr,Qtload,VmagPU]=fcn2optimexpr(@powerflowGRmlip,PGsize,QGsize,partn_
gen,nbus,'OutputSize',[1,7]);

[bPtLosskW,bPtload,bQtLosskVAr,bQtload,bVmagPU]=fcn2optimexpr(@powerflowmlip,nbus,'OutputSize'
,[1,5]);  %to extimate for the base ploss
 ploss=PtLosskW;   %total real power losses
 pload=Ptload;
 qloss=QtLosskVAr;   %total reactive power losses
 qload=Qtload;
 percent_plos_red=((bPtLosskW-ploss)./bPtLosskW)*100;
 percent_qlos_red=((bQtLosskVAr-qloss)./bQtLosskVAr)*100;
 absPGsize=fcn2optimexpr(@abs,PGsize,'OutputSize',[1,1]);
 absQGsize=fcn2optimexpr(@abs,QGsize,'OutputSize',[1,1]);
 [pgen, qgen]= fcn2optimexpr(@busdata_pq,PGsize,QGsize,partn_gen,nbus,'OutputSize',[1,1]);
 const_1= (pgen-pload-ploss); %i.e pg-pl-pd=0
 const_2= (qgen-qload-qloss); %i.e qg-ql-qd=0
 roundconst_1=fcn2optimexpr(@round,const_1,'OutputSize',[1,1]);
 roundconst_2=fcn2optimexpr(@round,const_2,'OutputSize',[1,1]);
 Gen_resh_prob.Constraints.consPloss=percent_plos_red >=1;
 Gen_resh_prob.Constraints.consQloss=percent_qlos_red >=1;
 Gen_resh_prob.Constraints.consPGsize=roundconst_1==0;
 Gen_resh_prob.Constraints.consQGsize=roundconst_2==0;
%Now that you have all the inputs, call the solver.
expr=fcn2optimexpr(@MILPSphere,PGsize,QGsize,partn_gen,nbus,'OutputSize',[1,1]);
Gen_resh_prob.Objective=expr;
x0.PGsize = [0.0 0.0 0.0 0.0 0.0 0.0 0.0];
x0.QGsize = [0.0 0.0 0.0 0.0 0.0 0.0 0.0];
options = optimoptions('intlinprog');
[sol,fval] = solve(Gen_resh_prob,x0,'Options', options);
%[sol,fval] = solve(Gen_resh_prob,x0);
% Results
Best_PGsize=sol.PGsize;
Best_QGsize=sol.QGsize;
clc;
powerflow_baesecase=powerflow(nbus);
 plossbase=powerflow_baesecase.PtLosskW;   %total real power losses
 qlossbase=powerflow_baesecase.QtLosskVAr;   %total reactive power losses
  VmagPUbase=powerflow_baesecase.VmagPU;   %voltage magnitude for the base case
 Vanglebase=powerflow_baesecase.Vangle;   %voltage magnitude for the base case
[sum_cost_pg,sum_cost_qg,ploss,qloss,sum_vmagdiff,vmagpu,vangle]=MILPresults(Best_PGsize,Best_
QGsize,partn_gen,nbus);
percent_ploss_red=((plossbase-ploss)/plossbase)*100;
percent_qloss_red=((qlossbase-qloss)/qlossbase)*100;
disp(['Active Power Resheduling Cost ($/MWhr): ',num2str(sum_cost_pg)]);
```

```
disp(['Reactive Power Resheduling Cost ($/MVARhr): ',num2str(sum_cost_qg)]);
disp(['Total Active Power Loss MW: ',num2str(ploss)]);
disp(['Percentage Active Power Loss Reduction: ',num2str(percent_ploss_red)]);
disp(['Total Reactive Power Loss MVAR: ',num2str(qloss)]);
disp(['Percentage Reactive Power Loss Reduction: ',num2str(percent_qloss_red)]);
disp(['Total Voltage Deviation: ',num2str(sum_vmagdiff)]);
fprintf('Generator Resheduling:\n')
busd = busdatas(nbus);      % Calling busdatas..
PGsize= sol.PGsize;
QGsize= sol.QGsize;
for ngen=1:length(partn_gen)
    changePG=PGsize(ngen)-busd(partn_gen(ngen),5);
    changeQG=QGsize(ngen)-busd(partn_gen(ngen),6);
    fprintf('New_PG %3d = %6.2f, New_QG %3d =
%6.2f\n',partn_gen(ngen),changePG,partn_gen(ngen),changeQG)
end

%Plots
%Voltage profile
figure;
plot(VmagPUbase,'LineWidth',2);
hold on
plot(vmagpu,'LineWidth',2);
xlabel('Bus');
ylabel('Voltage Magnitude (p.u.)');
grid on;
legend('Voltage Profile Before','Voltage Profile After')
title('Voltage profile')
hold off

%Voltage angle
figure;
plot(Vanglebase,'LineWidth',2);
hold on
plot(vangle,'LineWidth',2);
xlabel('Bus');
ylabel('Voltage Angle');
grid on;
legend('Voltage Angle Before','Voltage Angle After')
title('Voltage Angle')
hold off
disp('The Simulation is executed Successfully!')
```