UNIVERSITY OF NAIROBI

Faculty of Engineering

DEPARTMENT OF ELECTRICAL AND INFORMATION ENGINEERING

MULTI-OBJECTIVE INTEGRATED POWER SYSTEM EXPANSION PLANNING WITH RENEWABLE ENERGY CONSTRAINTS USING ADAPTIVE HYBRID META-HEURISTIC APPROACH

By

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F80/52776/2018

Research Thesis submitted in fulfillment of the requirements of Doctor of Philosophy Degree in Electrical and Electronic Engineering of the University of Nairobi

November, 2023

DECLARATION

This PhD research thesis is my original work and has not been represented for award of a degree in this or any other University.

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DEDICATION

I dedicate this thesis work to my children Musau and Museo as well as my loving wife Martha.

ACKNOWLEDGEMENT

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I do thank God for blessing me with these special people in my life: my beloved wife Martha Mbenge, my son Charles Musau and daughter Chelsea Museo. Their presence made this labour a worthy cause; my success is a family success. Thank you for understanding the commitment and dedication, which at the expense of your rights have made me what I am, not forgetting the occasional much needed distractions you provided.

To my parents, siblings, relatives and friends, thank you for being there for me when I needed you most.

God bless us all.

ABSTRACT

Multi-objective Integrated Power System Expansion Planning with Renewable Energy Constraints using Adaptive Hybrid Meta-Heuristic Approach

Federal and state government agencies as well as utilities have been using optimization models in evaluating their power system expansion plans. In the recent past, the separation of generation and transmission expansion optimization processes has caused many challenges, which have forced network planners and researchers to reconsider going back to the integrated planning approach. The available integrated Generation and Transmission Expansion Planning (GTEP) formulations are majorly based on DC power flow models, which are usually over simplified leading to less accurate or infeasible expansion results. In this research work, the GTEP problem is formulated based on the more accurate and reliable AC-power flow representation while considering optimal penetration of intermittent renewable energy sources. The complexity, increased dimensionality and non-linearity of the formulated optimization problem required a powerful solution methodology. To solve this, an adaptive hybrid meta-heuristic approach was formulated and tested using standard benchmark functions and selected constrained engineering optimization problems. Transmission Constrained Generation Expansion Planning (TC-GEP), Multi-Objective Dynamic GTEP (MODGTEP) and Multi-Area MODGTEP (MAMODGTEP) optimization problems have been formulated and solved applying standard test networks frequently used by previous researchers in this area (IEEE 6-bus and Garver's test systems). The problems were simulated in MATLAB R2015b. Compared to other existing methods, the proposed methodology reduced total TC-GEP and MODGTEP costs by 4-5% and 7% respectively. Inclusion of N-1 contingency criterion in the optimization increased the TC-GEP and MODGTEP costs by 16% and 9% respectively. The optimal vRES shares in TC-MOGEP problem were 6.5% and 4.5% for installed capacity and generated energy mix respectively while for MODGTEP the shares increased to 20.2% and 12.8% respectively. Optimal vRES penetration in TC-MODGEP problem reduced the overall costs by approximately 19%. Up to 28% and 17% annual vRES penetration levels in installed capacity and energy mix were achieved for MAMODGTEP. Averagely, the optimized vRES penetration level resulted to a 55% reduction in CO_2 emissions.

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NOMENCLATURE

Acronym	Description
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ADP	Approximate Dynamic Programming
AHP	Analytic Hierarchy Process
AIS	Artificial Immune Systems
ANN	Artificial Neural Network
BA	BAT Algorithm
BBA	Branch and Bound Algorithm
BBO	Biogeography-Based Optimization
BCO	Bee Colony Optimization
BD	Benders Decomposition
BeFS	Best First Search
BeS	Beam Search
BFOA	Bacterial Foraging Optimization Algorithm
BrFS	Breadth First Search
C&CG	Column-and-Constraint Generation Method
CBGA	Chu-Beasley Genetic Algorithm
DBLS	Discrepancy Bounded Local Search
DE	Differential Evolution
DeFS	Depth First Search
DEP	Distribution Expansion Planning
DEPSO	Discrete Evolution Particle Swarm Optimization
DG	Distributed Generation
DGEP	Dynamic Generation Expansion Planning
DP	Dynamic Programming
DSM	Demand-Side Management
DTEP	Dynamic Transmission Expansion Planning
ECOST	Expected Customer Interruption
ED	Economic Dispatch
EENS	Expected Energy Not Supplied
EM	Enumeration Method
ENS	Energy Not Served
EP	Evolutionary Programming
ERR	Emission Reduction Rate
ES	Evolution Strategies
EUE	Expected Unserved Energy
FGA	Fuzzy-Genetic Algorithm
FMP	Flowgate Marginal Prices
FOR	Forced Outage rate
FS	Fuzzy Sets
FST	Fuzzy Set Theory

Acronym	Description
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
GATE-PRO	Generation and Transmission Expansion Program
GENCOs	Generation Companies
GEP	Generation Expansion Planning
GRASP	Greedy Randomized Adaptive Search Procedure
GTEP	Generation and Transmission Expansion Planning
HBD	Hierarchical Benders Decomposition
HC	Hill Climbing
HD	Hierarchical Decomposition
HLRU	Hourly Net Load Ramping Uncertainty
IA	Immune Algorithm
IAEA	International Atomic Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
IP	Interior Point
IP/CP	Interior Point with Cutting Plane
IPM	Interior Point Method
ISDF	Injection Shift Distribution Factor
LDC	Load Duration Curve
LDCU	Load Duration Curve Uncertainty
LEAP	Long-range Energy Alternative Planning software
LMP	Locational Marginal Prices
LOEE	Loss of Energy Expectation
LOEP	Loss of Energy Probability
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LP	Linear Programming
MAMODGTEP	Multi-area Multi-Objective Dynamic Generation & Transmission Expansion Planning
MATLAB	Matrix Laboratory
MILP	Mixed Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MIP	Mix Integer Programming
MODGEP	Multi-objective Dynamic Generation Expansion Planning
MODGTEP	Multi-objective Dynamic Generation and Transmission Expansion Planning
MODTEP	Multi-objective Dynamic Transmission Expansion Planning
MOGA	Multi-Objective Genetic Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MOSGTEP	Multi-objective Static Generation and Transmission Expansion Planning
MOSTEP	Multi-objective Static Transmission Expansion Planning
NLP	Non-Linear Programming
O&M	Operation and Maintenance
OO	Ordinal Optimization

Acronym	**Description**
PCA	Principal Component Analysis
PHA	Progressive Hedging Algorithm
PNS	Power Not Supplied
PSO	Particle Swarm Optimization
PSP	Power System Planning
PV	Photo Voltaic
QP	Quadratic Programming
R/DCGA	Real/Decimal Coded Genetic Algorithm
RED	Relax-and-Enforce Decomposition
REI	Radial Equivalent Independent
RES	Renewable Energy Sources
RIA	Refined Immune Algorithm
SA	Simulated Annealing
SGEP	Static Generation Expansion Planning
SMIP	Stochastic Mixed-Integer Programming
STEP	Static Transmission Expansion Planning
SWF	Social Welfare Function
TC-DGEP	Transmission Constrained Dynamic Generation Expansion Planning
TEP	Transmission Expansion Planning
TLA	Teacher Learning Algorithm
TLBO	Teaching Learning Based Optimization
TRANSCOs	Transmission Companies
TS	Tabu Search
UC	Unit Commitment
UnCS	Uniform Cost Search
VOLL	Value of Lost Load
vRES	Variable Renewable Energy Sources
WASP	Wein Automatic System Planning package
WTLR	Weighted Transmission Loading Relief factor

1 CHAPTER 1: INTRODUCTION

1.1 Background

1.1.1 Power System Expansion Planning

There are many broad definitions of power system planning as given in various textbooks and other literature materials on this subject. Power system planning can be defined as a process in which the aim is to decide on new as well as upgrading existing system elements, to adequately satisfy the loads for a foreseen future [1]. It is about using the available resources of a system in the best way possible by considering the technical prerequisites of the system as well as economic factors [4]. Power system planners desire to achieve the best possible performance with the least possible price, which in many occasions calls for a trade-off between technology and cost.

From a broad perspective, the objective of power system expansion optimization is to ensure that demand is covered adequately, securely and in the most feasible cost-effective manner. To achieve adequacy, the system should be able to meet current demand needs and those for the future while security is assured when the said demand can be met at all times despite of any unanticipated events. In the recent years, powerful and attractive multiple criteria decision-making and optimization tools have been developed and applied to power system planning. In some of the developed approaches, the expansion plans are generated through the models/processes themselves while in other approaches the expansion plans are known (or developed using other approaches) before and only their comparison and optimization/final selection process is done [5].

Generally, all planning tools share the three-step procedure shown in Figure 1-1 their difference in degree of modeling complexity notwithstanding [6].

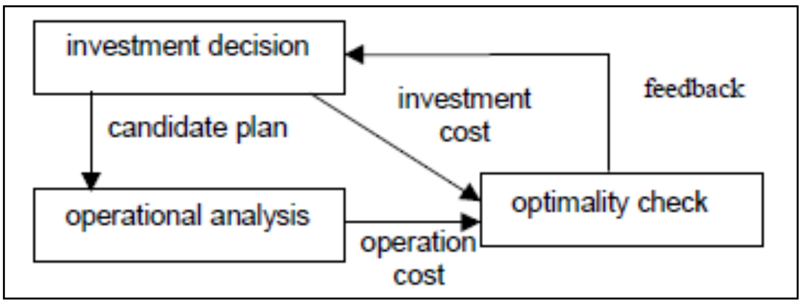


Figure 1-1: General Procedure for Planning Tools [6]

The three steps are briefly described as follows:

(i) Investment Decision – Here the planner selects a candidate plan. The input data to this stage include set of all candidate plants and interconnections as well as various investment constraints e.g. resource availability/capacity limits, maximum number of lines per corridor etc. The output from this stage is a set of initial operation times/dates for all selected projects.

(ii) Operation Analysis – This step computes operation cost associated with the candidate plan. The input data here is the candidate expansion plan and the existing system information (generation, interconnection, hydrology, loads characteristics etc.). The output is the present value of the system operation cost.

(iii) Optimality Check – This final stage compares the candidate plan with that of the current best available plan and updates the results accordingly. If the convergence or termination criterion is not met, all information is updated and the process returns to investment decision step.

1.1.2 Co-optimization of Generation and Transmission Planning

Traditionally, Generation Expansion Planning (GEP) methodologies employed single-bus approaches where all existing and candidate generators are assumed connected to the same bus as well as the load demand. These approaches have several limitations, as they do not allow for distribution of generators and loads in the system. As a result, the investment and O&M costs of new generators, which are site dependent, may not be accurately represented in the optimization as they are presumed to be uniform. In such an approach, it is also difficult to account for some non-technical factors such as investment costs associated with interconnections to the grid and the cost of land. In addition, the transmission network constraints are ignored in such formulations, which may lead to the adoption of technically infeasible or highly costly expansion plans [7].

To solve the above problems associated with single-bus models, researchers are now adopting multi-bus models in formulating the power system expansion planning problem. This is of much importance when renewable energy is included in the planning. This has led to an optimization problem commonly known as Transmission Constrained GEP (TC-GEP). The TC-GEP problem is limited in meeting the ever-increasing power demand adequately and securely; thus the transmission network has to be expanded in concurrency with the generation system. This concurrency in power system expansion has been realized through co-optimization of Generation and Transmission Expansion Planning (GTEP). This is a new developing area of research, which has much potential of bringing positive impact to the power system sector.

The increasing awareness of environmental issues in the past few years has made both researchers and utility planners to devise ways of considering environmental impact in the power system expansion planning optimization problem [22]. This has greatly enhanced the competitiveness of Renewable Energy Sources (RES) in the selection of candidate expansion plants. As a result, the exploitation and penetration of RES in the power system network has been increasing tremendously day by day. Their inclusion in the generation mix should be done optimally to ensure system security and reliability.

1.2 Problem Statement

The unbundling and deregulation of power systems in the recent years led to the separation of Generation, Transmission and Distribution Expansion planning. This separation has given rise to several challenges in power system planning. One such challenge is that the results from these separate expansion problems have to be combined during implementation and may result to sub-optimal or technically infeasible scenarios. For example, improper commitment of generators may lead to unnecessary expansive transmission lines, increased transmission losses or avoidable ancillary requirements e.g. reactive power compensation. In addition, such sub-optimal expansion plans may take extremely long durations to be realized. Due to these challenges, the need for integration of GEP and TEP has risen again with research in this area growing day by day. From the literature review, there is need to develop better techniques for handling this complex, high dimensional and non-linear optimization problem more accurately so as to obtain reliable results. This research as one of its objectives formulates and tests an adaptive hybrid meta-heuristic approach that is able to handle a multi-objective problem in a multi-area dynamic environment with reduced space and accurate search. The developed algorithm was first formulated and tested using standard test functions/problems as well as the classical Transmission-Constrained GEP problem.

The increasing interest in RES integration to the grid makes co-optimization of GEP and TEP even more necessary. This is because a tradeoff is often necessary between transmission investment and operation cost and benefits of these renewable energy resources which are often located in remote area where transmission network is weak or unavailable. Most research works in this area have employed DC power flow models in their formulations. The DC power flow based results cannot be relied upon especially with the inclusion of intermittent/variable Renewable Energy Sources (vRES) in the expansion problem. This is because such formulations are usually over simplified and do not account for reactive power characteristics of the network. Therefore, nodal voltages, power flows and power losses cannot be accurately represented in such formulations. Thus power system expansion planning optimization results based on DC power flow analysis are less accurate and cannot be relied upon in a practical environment. Only few research works which have used AC power flow models; these formulations need to be revised and improved to come up with a better representation of the integrated GTEP problem considering optimal variable RES (solar PV and wind) penetration. Based on the accessed and reviewed literature on power system planning there is no research work that has tackled this issue yet. Due to the rising environmental concerns that have resulted to rigid regulations on emissions, the optimal integration of vRES into the grid has been of much interest and cannot be taken lightly in the formulation and solution of the power system expansion planning problem. This research work filled this gap by employing detailed AC power flow and intermittent RES constraints in the formulation of the GTEP problem.

Another major challenge associated with the integration of renewable energy to the grid is the intermittency nature of some readily available renewable sources. As a result, the power systems and their codes of operation are continuously being modified to take into account the specific characteristics of the variable renewable energy operation with wind and solar PV (Photo Voltaic) leading in the penetration. In this research work, the penetration of intermittent RES to the grid is subject to the reserve requirement constraints in the system. To achieve optimal vRES penetration, both vRES underutilization and overutilization penalties were formulated and used to further constrain the optimization problem.

From the accessed and reviewed works in open literature, the modern Multi-Area Multi-Objective Dynamic Generation and Transmission Expansion Planning (MAMODGTEP) problem has not been formulated and solved employing AC power flow analysis and considering optimal intermittent RES penetration.

1.3 Research Objectives

1.3.1 Main Objective

To formulate and solve the modern Multi-Area Multi-Objective Dynamic Generation and Transmission Expansion Planning (MAMODGTEP) optimization problem in presence of intermittent RES.

1.3.2 Specific Objective

To achieve the overall objective, the following specific objectives are addressed:

(i) To develop and test an adaptive Hybrid Meta-heuristic optimization approach for optimizing multi-objective expansion planning problem based on a hybrid of Differential Evolution and Bacterial Foraging Optimization Algorithms adapted using Genetic Improved Particle Swarm Optimization (DE-ABFOA-GIPSO).

(ii) To formulate and solve the multi-objective Transmission Constrained GEP (TC-GEP) optimization problem considering intermittent RES and applying formulated sensitivity factors.

(iii) To formulate and solve a multi-objective integrated GTEP (MOGTEP) optimization problem using AC power flow models in intermittent RE environment.

(iv) To formulate and solve the modern multi-area, multi-objective dynamic GTEP (MAMODGTEP) optimization problem in intermittent RE environment.

(v) To validate the expansion planning results obtained from the proposed problem formulations and the developed adaptive Hybrid Meta-heuristic optimization approach.

As stated in specific objective (i), the research first aimed at developing an adaptive Hybrid Meta-heuristic algorithm for solving the expansion planning problem. The hybrid approach was developed by combining the attributes of Genetic, Particle Swarm, Bacterial Foraging and Differential Evolution Optimization Algorithms in its formulation. The developed algorithm was tested using the Standard Benchmark Functions as well as selected Constrained Engineering Test Problems and the obtained results compared with those obtained by other researchers [92, 96 - 118]. After the developed algorithm was tested and confirmed to be producing reliable results, it was adopted to solve other optimization sub-problems as formulated in the research work. In objective (ii) a TC-GEP optimization problem was formulated with intermittent RE considerations. This was important to cater for cases where generation and transmission sub-sectors of the power sector are segmented and their planning are not always performed concurrently. In this case the developed algorithm in objective (i) was adapted and used to solve the formulated TC-GEP problem considering intermittent RES penetration.

Currently, the results of a TC-GEP are not exhaustive since the GEP and TEP are streamlined in most cases. Thus, the third objective aimed at formulating and solving a MODGTEP problem using AC power flow models and ensuring optimal intermittent RES penetration. Where applicable, obtained results were compared to those from other researchers [2, 84]. The comparison was not only based on the cost of expansion plans but also on adherence to set constraints e.g. generator loading limits, thermal limits of transmission lines, bus voltages etc. Objective (iv) aimed at formulating and solving the modern MAMODGTEP in an intermittent RES environment by adapting the formulations in objective (iii) to a multi-area environment. In the last objective, results achieved using the proposed expansion planning formulations and the developed optimization algorithm were validated by comparing them with those obtained by other researchers in the area in addition to performing scenario analysis where applicable.

1.4 Research Questions

To help achieve the objectives in Section 1.3.2, the following research questions were addressed:

(i) What challenges are there in the existing formulations of the power system expansion planning problem?

(ii) How can the TC-GEP problem be formulated taking in to account AC power flow and intermittent RE constraints?

(iii) What are the strengths and weaknesses of the available power system expansion planning optimization methods that have been used so far?

(iv) How can the integrated GTEP problem be formulated to suit the modern power system multi objectives of reducing cost, emissions while utilizing renewable energy in a secure manner?

(v) How can an adaptive hybrid meta-heuristic method for solving the MODGTEP and its sub-problems be formulated and coded?

(vi) How can the MAMODGTEP problem in modern power systems be formulated and solved considering RE constraints and employing AC power flow?

1.5 Justification

Traditionally, Generation Expansion Planning (GEP) and Transmission Expansion Planning (TEP) used to be co-optimized. The unbundling and liberalization of the energy sector in the recent past led to a shift to separate GEP and TEP expansions. This separation has caused many challenges that have forced network planners and researchers to reconsider going back to the integrated planning scenario. Some of these challenges include; sub-optimal results during implementation, infeasible expansion plans, additional unnecessary network requirements as well as extremely long implementation time requirements. As a result, there is need to come up with improved algorithms which can be applied to solve both unbundled power systems where GEP and TEP are done separately and the modern environment where there is interactive coordination of transmission and generation expansion planning. Mostly, the GTEP problem formulation has been done using DC power flow models that have several limitations as previous explained. Thus, there is need to revisit and improve these formulations by incorporating more accurate AC power flow analysis.

There has been a global effort to reduce emissions from the environment; the power industry is a major contributor of these emissions. Researchers and utility planners jointly agree that one of the most practical and effective mechanism of curbing this problem in the power sector is by replacing high carbon intensive sources of generation with less-carbon intensive ones like the vRES. This coupled with other vRES advantages has resulted to a spectacular growth in their penetration in electricity production. Just like many other energy sources, renewable energy sources are located far from the load centres and where grid is mostly weak or not available. This necessitates the need to upgrade the transmission network to be able to evacuate and accept more power from these sources. There is an economical limit on the viability of transmission capacity investment needed to evacuate energy produced by remotely located high quality variable renewables. In addition to cost implications, transmission power losses and reactive power requirements are other technical constraints that determine this limit. If this limit is violated, it may be more efficient to develop/operate the less efficient resources nearer to load centres. This calls for coordination in GEP and TEP to come up with the optimal integrated expansion plan. Thus, there is need to study the integrated GTEP problem in presence of intermittent/variable RES.

Unlike conventional generation sources, power from most vRES is less controllable, stochastic and intermittent with anti-peak shaving characteristics. This phenomenon introduces uncertainties for operation and planning of power systems. It is thus necessary for utility planners and researchers to develop ways of ensuring optimal RES penetration without violating the power system operation conditions or subjecting the network to operational risks.

1.6 Scope of the Thesis

Power System Planning (PSP) includes Generation Expansion Planning (GEP), Transmission Expansion Planning (TEP) and Distribution Expansion Planning (DEP). These three areas of power system planning are somehow inter-related; however, there is a stronger inter-relation between GEP and TEP when compared to DEP. This is because the location of generation energy resources with respect to load centres will greatly influence transmission network evolution. On the other hand, expansion or upgrade of distribution networks is majorly dependent on how specific loads are spread in a particular load centre. In terms of GEP, only the distributed generation sources have significant effect on distribution networks. In addition, distribution network planning is very dynamic and its long-term plan may not be as effective as is the case for generation and transmission expansions. This is majorly due to accuracy in electricity demand forecasting. Forecasting of total load requirement in a particular load centre can be done with significant accuracy for a fairly long period (exceeding even 20 years) which is not the case when predicting specific load distribution in that load centre whose accuracy greatly reduces with increased forecast horizon (more than 5 years). As a result, the scope of this research work was limited to the integration of GEP and TEP processes. This also helps in reducing the complexity and dimensionality of the optimization problem.

The research work formulated and solved the integrated GEP and TEP optimization problem considering optimal intermittent RES penetration in a multi-objective, multi-area and multi-period (dynamic) environment. First, a hybrid algorithm that is able to handle a multi-objective problem in a multi-area dynamic environment with reduced space and accurate search was formulated. The algorithm was tested using selected Standard Benchmark Functions and Constrained Engineering Test Problems after which it was applied in solving the conventional TC-GEP problem. Then, a Transmission-Constrained GEP problem considering intermittent RES penetration was formulated and solved. The TC-GEP problem paved way for formulation of Multi-Objective Dynamic GTEP (MODGTEP) problem using simplified AC power flow analysis. The formulated MOGTEP problems was then used to formulate and solve the Multi-Area, Multi-Objective Dynamic GTEP (MAMODGTEP) problem as applicable in modern power system planning. In all the formulations and testing the sub-problems' objectives were subjected to relevant operational constraints. All problems were simulated using MATLAB R2015b. For comparison of obtained results, the choice of network systems for testing the formulated problem and the developed optimization technique was majorly based on test bus systems adopted by previous researchers in this area. These mainly included IEEE 6-bus [2] & the Garver's 6-bus test systems [84]. The success of the proposed formulation and solution methodology was measured by comparing the cost of the obtained expansion plans as well as their technical feasibility (voltage profile, line loading, generator loading etc.) to those obtained by other researchers. Though the research work did not cover any specific case study its findings can be applied to the Kenyan Case.

1.7 Publications Derived From This PhD Research Work

1.7.1 Publications in International Journals

1. Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Metaheuristic-based Adaptive Hybrid Algorithm for solving Constrained Optimization Problems", *European Journal of Advances in Engineering and Technology, 2020, 7(6):57-65, Volume 7, Issue 6,* 2020.
2. Julius Kilonzi Charles, Dr. Musau Moses, Prof. Mbuthia, "Integrated Generation & Transmission Expansion Planning Optimization in Power Systems: A Review", *International Journal of Emerging Technology and Advanced Engineerin*g, *Volume 9, Issue 7*, July 2019.
3. Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "AC Power Flow-Based Integrated GTEP with optimal penetration of Intermittent RES", *IEEE Journal of Power and Energy, 2023* (submitted).

1.7.2 Conference Papers

1. Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "AC Power Flow-based Transmission Constrained Generation Expansion Planning with Intermittent RES", *2023 IEEE AFRICON,* September 2023.
2. Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Co-optimized Generation & Transmission Expansion Planning in Kenya: A Drive Towards Realization of Affordable Quality Electricity Supply" *Ketraco 3rd Annual Conference*, July 2022.

3. Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Security Constrained MODGTEP using Adaptive Hybrid Meta-Heuristic Approach", *IEEE PES & IAS, Power Africa Conference,* August 2020.
4. Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "An Adaptive Hybrid Meta-Heuristic Approach for Transmission Constrained MOGEP", *IEEE PES & IAS, Power Africa Conference,* August 2020.

1.8 Thesis Organization

The rest of the thesis is organized in five chapters as follows:

Chapter 2: In this chapter, literature review on various categories of power system expansion planning problems as well as different optimization methodologies/techniques applied in solving these optimization problems is given. The chapter also gives a detailed survey of earlier works on integrated Generation and Transmission Expansion planning optimization problem. The optimization techniques review gives examples of works solved as well as the advantages and the drawbacks of the applied techniques. From this literature review, a number of research gaps were identified with the chapter ending by giving a summary of the research gaps addressed in this research work.

Chapter 3: This chapter is dedicated to the formulation, verification and validation of the proposed optimization algorithm. In this chapter, a brief introduction to optimization approaches is given. The chapter also gives a detailed step-by-step procedure used in formulating the proposed Adaptive Hybrid Meta-Heuristic Algorithm (DE-ABFOA-GIPSO). A detailed justification for selection of the optimization techniques as well as the hybridization and adaptation process is also included. The chapter ends by presenting the algorithm verification and validation results.

Chapter 4: Formulation and solution of the TC-MOGEP optimization problem using AC power flow analysis and considering intermittent RES is presented in this chapter. The chapter begins with an introduction of the TC-GEP optimization problem. The developed adaptive meta-heuristic algorithm in Chapter 3 is then applied in solving the classical TC-MOGEP problem. The formulation of a TC-MOGEP optimization problem is then done based on AC power flow analysis and considering presence of intermittent RES. IEEE 6-bus test system was used and the obtained results as well as their discussions are highlighted in this chapter.

Chapter 5: This chapter is dedicated to formulation and solution of an Integrated Generation and Transmission Expansion Planning (IGTEP) optimization problem. The formulation is based on AC-Power Flow and is extended to include optimal penetration of Intermittent RES. The formulations are then extended to explore the modern Multi-Area, Multi-Objective Dynamic Generation and Transmission Expansion Planning (MAMODGTEP) optimization problem. The problems are formulated and solved taking into account transmission and vRES related constraints.

Chapter 6: This final chapter briefly describes how the thesis research objectives were met by answering the set research questions. In addition, it contains a summary of the thesis contributions, overall conclusions and recommendations of possible areas of further work and adoption of results.

The thesis ends by listing all referred literature during its preparation as well as extracts from the utilized MATLAB codes.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Power System Planning

There is no doubt that an electric power system network is one of the largest man-made machine. This comes with its own challenges both in operation and planning since the current system needs to be run efficiently and effectively while at the same time proper insights should be given to the future [1]. As a result, power system planning has become one of the most important aspects in the energy sector. Recently different optimization approaches have been used (and others proposed) to solve the power system expansion planning problem.

The system expansion problem can be of a static or dynamic type based on the stages under consideration for the planning horizon. A static expansion problem is solved for a specific stage (typically a year) at a time while a dynamic type is solved for several stages in the specified period (1-20 years or even more) concurrently [1, 7]. The optimization problem is a complex, mixed-integer optimization problem involving many continuous and discrete decision variables and constraints. The complexity is further increased by the considerations of multiple time horizons, multiple generation technologies, multiple fuel sources, uncertainty in input data, multiple conflicting constraints and criteria among others [8].

Power system planning is broadly classified into Generation, Transmission and Distribution Expansion Planning (GEP, TEP & DEP) [14]. As explained in Section 1.6, the scope of this PhD research work was limited to the highly inter-dependent GEP and TEP processes. Some of the reviewed research works in GEP and TEP are presented in Sections 2.2 and 2.3.

2.2 Generation Expansion Planning (GEP)

The preparation of a long-term power system expansion plan starts with a proper forecasting of the load demand for a specified future period. After demand forecasting, Generation Expansion Planning (GEP) is the next crucial step in the expansion process. Here we need to determine when the new generators are required and existing ones are retiring, what type of new generators to install and where the power plants are to be located so that the existing and forecasted loads are adequately supplied for a foreseen future and in an optimized way. Several approaches have been proposed and applied to solve the GEP problem. Table 2-1 gives a summary of some of the reviewed GEP research works. Other than these reviewed works, additional woks on GEP are given in references [1, 9, 15, 26, 28, 32, 34-35, 43-48].

Table 2-1: Review of GEP

Research Work	Research Objectives	Constraints Considered	Type/ Nature	Methodology used
Amir Ghorbani *2015 [16]*	C	LOLP, E, RM, LOEE (EENS), DC, F	DGEP	Real/Decimal Coded Genetic Algorithm (R/DCGA)
Moon et al. *2015 [8]*	C	CL, T, PB, DC	DGEP	Interior Point with Cutting Plane (IP/CP)
Lee et al. *2015 [83]*	C	RM, PB, T, RA, E	DGEP	Generation and Transmission Expansion program (GATE-PRO)
Esteban et al. *2014 [24]*	C, LOEE, H	EB, DC, RA, H	MODGEP	Stochastic Mixed-Integer Programming (SMIP), Scenario Reduction
Ahmad et al. *2013 [17]*	C	RM, LOLP, H, F, E, RT, CL	DGEP	Wein Automatic System Planning package (WASP IV)
Zhang et al. *2013 [18]*	C, E, EENS	PB, LOLP, E	MODGEP	Two-stage Multi-Objective Particle Swarm Optimization (MOPSO)
Habib et al. *2013 [81]*	C, E	RA, E, CL, RM, PB	MODGEP	Long-range Energy Alternative Planning software (LEAP)
Kamphol & Bundit *2013 [82]*	C, E, EC	RM, PB, RA, PR	MODGEP	Mixed Integer Linear Programming (MILP), Multi-Objective Genetic Algorithm (MOGA), Analytic Hierarchy Process (AHP)
Arash Shabani et al. *2012 [10]*	C	PB, CL, F, RM, E	SGEP	Genetic Algorithm (GA)
Khakbazan et al. *2010 [20]*	C, EENS	RM, CL, LOLP	MODGEP	Wein Automatic System Planning package (WASP IV)
Diego et al. *2010 [22]*	C, E	PB, PR, RA, RM, E	MODGEP	Lagrangean Method
Vishnu et al. *2009 [36]*	C	DC, PB	DGEP	Caurnot Model, Game Theory
Chen et al. *2006 [11]*	C, E	E, PB, CL, LOLP, EENS	MODGEP	Immune Algorithm (IA), Tabu Search (TS), Refined IA (RIA)
Angela et al *2001 [21]*	P	RM, RA, EB	DGEP	Caurnot Model, Game Theory

Key: *P=Profit, C= Cost (Investment and Production), E=Emissions, EC=External Cost, D=Dynamic, RM=Reserve Margin, PB=Power Balance, DC=Direct Current load flow constraints, F=Fuel, CL=Construction Limit, RT=Repair Time, H=Hydro Plants, EB=Energy Balance, RA=Resource Availability, T=Thermal Plants, PR=Plant Retirement, other abbreviations are in the Nomenclature.*

The GEP review in Table 2-1 covered the research objectives and associated constraints in each research work, the nature of the problem formulation in terms of study period (static or dynamic) and objectives considered (single or multi-objective) as well as the solution methodology employed. Majority of the reviewed works considered minimization of the investment and operation cost as the optimization objective [16, 8, 83, 17, 10 & 36] with cost associated with unmet demand included in some of the formulations [18 & 20]. In [21] the main objective was to maximize the profit margin of each player in an electricity market. Nearly all the reviewed GEP works have considered some aspects of reserve margin, resource availability and power balance constraints in their formulation. Though [16, 8, 24 & 36] extended their formulation to consider network constraints in the formulations (multi-bus approach) were based on DC power flow analysis. It also worth noting that, most of the recent research works in this area have included emission components in their formulations. This is mostly as an objective (cost) or as a constraint as shown in the Table 2-1[10, 11, 18, 22, 17, 81, 82 & 83]. From the review, GEP problem has been attracting considerable interest over time. This may be attributed to the fact that generation sub-sector has been liberalized in many countries thus attracting private investors. This necessitates proper planning to ensure fair allocation and competition. Another reason may be due to the environmental concern and the need to incorporate less pollution generating plants in the energy mix. In this research work, the GEP problem was formulated taking into account optimal intermittent RES penetration. This was done by incorporating intermittent RES constraints in the formulation. The formulated GEP problem was solved in a transmission-constrained environment in which a multi-bus approach is adopted rather than a single-bus approach though without transmission network enhancements.

2.3 Transmission Expansion Planning (TEP)

The characteristics and performance of the future electric power system network is greatly determined by the decisions made during Transmission Expansion Planning (TEP). In addition, TEP directly influences the operation of the power system, which makes it an important component of power system planning [49]. The aim of a TEP model is to determine when new transmission facilities or upgrades to the existing network are needed, the types and the location of these facilities/upgrades in order to ensure an adequate transmission capacity taking into account future generation options and load requirements [20].

The expansion problem is a highly dimensional and non-linear. New sector developments have led to new challenges in the electricity market such as more uncertainties and competitive environments. So as to meet the demands arising from these challenges new methods have been presented directed towards minimizing the planning risks brought by the uncertainties and while satisfying the market–based criteria [50]. Table 2-2 gives a summarized analysis of some of the reviewed TEP research works.

Table 2-2: Review of TEP

Research Work	Research Objectives	Constraints Considered	Type/ Nature	Methodology used
Amir & Hossein *2017 [105]*	C, PL	PB, DC, TL, PL	STEP	Teaching Learning Based Optimization (TLBO)
Jundi Jia *2014 [65]*	C, LS	DC, LS, GL, N-1, TL	DTEP	Mixed Integer Linear Programming (MILP), WARD, Radial Equivalent Independent (REI)
Francisco David *2014 [69]*	C	KL, DC, TL, PB, KL	STEP	Scenario Techniques, Mixed Integer Linear Programming (MILP), Benders Decomposition (BD)
Pearl *2014 [66]*	C, EENS	KL, DC, TL, EB, GL	MODTEP	Approximate Dynamic Programming (ADP), Branch and Bound Algorithm (BBA)
Faruk Ugranli & Engin Karatepe *2013 [88]*	TWWE, C	KL, DC, TL, EB, GL	MOSTEP	Genetic Algorithm (GA)
Rosa et al. *2011 [104]*	C	CL, DC, PB, KL, TL	STEP	Greedy Randomized Adaptive Search Procedure (GRASP)
Shivaie et al. *2011 [38]*	C, CC, SWF, EC	PB, GL, DL, DC	MODTEP	Fuzzy-Genetic Algorithm (FGA)
Manuel José *2011 [68]*	C	TL, DC, PB, PL, PNS, KL,	DTEP	Discrete Evolution Particle Swarm Optimization (DEPSO)
Zhao & Foster, *2011 [70]*	C	AC, GL, TL, EUE, CC	STEP	Particle Swarm Optimization (PSO)
Luciano et al. *2010 [25]*	C	KL, DC, PB, TL, GL, N-1	DTEP	"big-M" Approach
Sebastián et al. *2008 [132]*	SWF	TL, AC, PL, GL, DL, PB	MOSTEP	Mixed Integer Scenario-Weighted (Metric) Models,
A.M. Silva et al. *2006 [40]*	C, LOLC	PB, KL, DC, GL, TL	DTEP	Evolution Strategies (ES) and GRASP
Sevin Sozer *2006 [103]*	C, CC	CC, KL, DC, TL, PB, LC	DTEP	Mixed-Integer Non-Linear Programming (MINLP), Hierarchical Benders Decomposition (HBD)
Majid Oloomi 2004 [67]	LMP	CC, GL, PB, DC, KL, TL	STEP	Scenario Techniques, Fuzzy Techniques

Key: *CC=Congestion Cost, TL= Transmission corridor Limit, AC=Alternating Current load flow constraints, GL=Generator Limits, LOLC= Loss of Load Costs, DL=Demand Limits, KL=Kirchhoff's Laws Constraints, N-1=N-1 Redundancy constraint, PL=Power Loss, LS=Load shedding, LC=Load Curtailment, TWWE=Total Wasted Wind Energy, other abbreviations are defined in Table 2-1 and Nomenclature.*

From Table 2-2, the key objective in nearly all the research works is cost. This is similar to the GEP objective as shown in Table 2-1 save for the fact that emission consideration is more pronounced in GEP. Unlike in GEP where emission/environmental concern may play a key role in the decision making of the expansion plans, in TEP the planner is majorly interested in ensuring secure and reliable transmission network at the least cost possible. To ensure supply reliability and security, [65 & 103] included load shedding and load curtailment constraints in their formulations respectively. In addition, line capacity utilization limits including congestion cost were included in majority of the reviewed TEP works as an objective and/or constraint [38, 67, 70 & 103]. The TEP work in [88] considered optimal expansion of transmission network while considering wind generation. This was done by expanding the objective function to include minimization of total wasted wind energy in addition to transmission system expansion cost. Majority of the reviewed TEP research works have employed DC power flow in their formulations. Among the reviewed TEP works, only two have employed AC-power flow based formulations [70 & 132] with the rest utilizing DC power flow models, which are unrealistic in a practical scenario. These models do not consider reactive power flow and their results can't be relied upon. The TC-GEP and GTEP formulations in this research work were based on AC-power flow analysis. Various transmission constraints were taken into account including bus voltage, phase angle and line flow limits. When considering the MODGTEP problem these constraint violations were formulated as penalties, with their costs included in the objective function. Deterministic, heuristic and meta-heuristic approaches have been used to solve this problem. The review of previous works showed that meta-heuristic-based approaches like PSO [68 & 70] & GA [38 & 88] gave better results in highly constrained TEP problems.

Section 2.4 reviews integrated GEP & TEP research works.

2.4 Integrated/Coordinated Generation and Transmission Expansion Planning (GTEP)

The coordination of GEP and TEP problems is an emerging trend gaining interest day by day due to its numerous advantages [86, 87]. Table 2-3 gives a review of some of the GTEP research works.

Table 2-3: Review of GTEP

Research Work	Research Objectives	Constraints	Type/ Nature	Methodology used
Meisam Mahdavi et al. ***2023 [137]***	C, LOL, PL, LS	GL, TL, PB, CL, RA, LS, DC	MOSGTEP	Discrete PSO (DPSO) & Decimal Codification Genetic Algorithm (DCGA)
Xie, Y. et al. ***2022 [136]***	C	GL, TL, PB, VL, AC	SGTEP	Scenario Based MINLP
Shengfei Y. & Jianhui W. ***2022 [133]***	C, LS	GL, TL, PB, LS, DC	MODGTEP	C&CG and L-shaped Algorithms
Ansari, M.R. et al. ***2021 [135]***	C, SF	GL, TL, PB, VL, ES, RA, SF, AC	MODGTEP	Scenario-Based Stochastic Programming (SBSP).
Ping Zhou et al. ***2020 [134]***	C, ATC	GL, TL, PB, LS, DC	MOSGTEP	Genetic Algorithm
Catalina et al. ***2019 [12]***	C	PB, TL, CL, DC, KL, RA,	SGTEP	MINLP
Filipe V. et al ***2019 [3]***	C, EENS	PB, TL, DC, EENS, KL, CL	MODGTEP	C&CG
Isaac-Camilo et al. ***2019 [13]***	P, C, SWF	PB, CL, TL, ES, MC, DC	MOSGTEP	MINLP
Yusuke et al. ***2019 [19]***	C	AC, PB, KL, MC, TL, CL, RA	DGTEP	MINLP
Majid Z.M et al. ***2019 [58]***	C	DC, PB, TL, KL, DSM	DGTEP	BD, HSA
Ramachandran M. C. et al. ***2018 [23]***	PL	AC, PB, KL, FOR, POR,PL	SGTEP	PSAT
Jia Li et al. ***2018 [108]***	C	PB, TL, DC, EENS, KL, CL, C, LS	DGTEP	MILP- (C&CG, RED)
Yixian et al. ***2018 [41]***	C	EUE, ES, PB, TL, CL, DC, KL	DGTEP	PHA
Dawei et al. ***2017 [56]***	C	RA, RM, PB, EB, DC, TL, KL	DGTEP	Genetic-Tabu Hybrid Algorithm
Hyoungtae et al. ***2015 [57, 60,63]***	C	AC, PB, KL, MC, TL, CL, RA	DGTEP	Generalized Bender's Decomposition Method
J. Aghaei et al. ***2014 [2]***	C, EENS	DC, KL, PB, RA, EENS	MOSGTEP	Probabilistic MILP
Hyoungtae & Wook ***2014 [84]***	C	AC, PB, KL, TL, CL	DGTEP	MINLP-GAMS
Carlos et al. ***2014 [42]***	C	DC, LS, PB, TL, CL, DC, KL, DSM	SGTEP	IPM, CBGA
Hyoungtae et al. ***2014 [61]***	C, ES	DC, KL, PB, ES, RA	MOSGTEP	Integrated Expansion algorithm
Iman et al. ***2014 [7]***	C	LOLP, PL, FC, RM, EENS, DC, PB	DGTEP	GA, EM

Research Work	Research Objectives	Constraints	Type/ Nature	Methodology used
Guk-Hyun Moon et al. ***2013 [62]***	C	PB, TL, CL, DC, KL, RA	SGTEP	Stochastic Decomposition Method
Amin & Mohammad ***2013 [109]***	C	VOLL, EENS, PB, TL, CL, DC, KL, LS	DGTEP	Scenario-Based techniques
Maziar et al. ***2013 [110]***	SWF, P, CC	PB, TL, CL, DC, KL, RA, C, EENS, RM	MODGTEP	GAMS, MATLAB
Kritika et al. ***2013 [111]***	C	PB, TL, CL, DC, KL, LC	SGTEP	BD, GAMS
Xiufan & Ying ***2012 [30]***	C	DC, RF, TL, CL, RA, PB, KL, E	SGTEP	Heuristic Algorithm
Amin et al. ***2012 [9]***	C	E, ES, DC, PB, TL, KL, CL, E, RM, H, T, FC, LC, LOLE	MADGTEP	MIP
Russell et al. ***2011 [113]***	C, GL, TL, VL	PB, AC, KL, RA, TL, CL	MOSGTEP	DBLS
Andreas & Maximilian ***2010 [27]***	SWF	AC, DC, N-1, DSM, ES, PB, KL, TL, CL	SGTEP	GAMS
S.A. Torabi & M. Madadi, ***2010 [64]***	C, E, EENS	EENS, PB, TL, CL, DC, KL, RA	MOSGTEP	Fuzzy MIP
Jae Hyung et al. ***2009 [107]***	P	EUE, PB, TL, CL, DC, KL, LOEP, VOLL	DGTEP	GAMS
C. Genesi et al. ***2008 [112]***	SWF, CC	PB, N-1, AC, KL, ISDF, WTLR	MOSGTEP	Nodal Index Methods – (ISDF, WTLR), MATLAB
Jae Hyung et al. ***2007 [39]***	P, LMP, FMP, SS	PB, TL, CL, DC, KL, LMP, FMP	MODGTEP	BD
Campodonico et al. ***2003 [6]***	C	ES, DC, PB, TL, KL, CL, E, RM, HT	MASGTEP	BD

Key: *FOR=Forced Outage Rate, POR=Planned Outage Rate, VL=Voltage Limits, MC=Market constraints, HT=Hydrothermal scheduling, RF=Risk Factor, SS=System security, EC=External Cost, ES=Energy Storage, MTTR=Mean Time to Repair, VOLL=Value of Lost Load, LOL=Loss of Load, ATC=Available Transmission Capacity, other abbreviations are defined in Tables 2-1, 2-2 and Nomenclature.*

Just like in the separate GEP and TEP optimization problems, minimization of cost is the key objective in most of the reviewed GTEP works, however [13, 39 &107] have included maximization of profit margins in their objective function. Compared to GEP, consideration of emissions in GTEP formulation have been limited with only [6, 9, 30 & 64] having emission as either as an objective or constraint. As evident in Table 2-3, majority of the GTEP works have employed DC power flow formulations in their formulations. Only few research works that have included some aspects of AC power flow models in their formulation of the integrated GTEP optimization problem. There is need to build-up on these formulations and improve them to capture some key aspects of the power system. For example, in [60 & 84] AC power flow formulation were employed to consider bus voltage limits however both works ignored system power losses. Moreover, in [60], the cost due to unserved energy, which translates to load shedding was also not formulated in the objective function. Though some reactive power flow related limits were considered, for more practical and accurate results, this consideration needs to be done in the presence of intermittent RES, which generally perform poorly in terms of reactive power capabilities.

Table 2-4 gives a comparison among the reviewed GTEP research works. The comparison was based on the consideration of vRES in GTEP formulation as well as emissions and operational planning constraints. The power flow models used in the problem formulations, objective functions, nature of expansion (static/dynamic) as well as the solution methodologies applied were also compared. This comparison was used to identify and evaluate some of the research gaps that need to be filled in this area of research.

Table 2-4: Comparison of GTEP Research Works

Research Work	vRES	Emission	Operation Planning	Power Flow	Research Objectives	Type/ Nature	Methodology used
[137] ***2023***	✕	✕	✓ ED, POR, FOR	DC-PF	C, LOL, PL, LS	MOSGTEP	DPSO & DCGA
[136] ***2022***	✓ (W)	✕	✓ ED	AC-PF	C	SGTEP	Scenario Based MINLP
[133] ***2022***	✓ (S&W)	✕	✓ ED	DC-PF	C, LS	MODGTEP	C&CG and L-shaped Algorithms
[135] ***2021***	✓ (W)	✕	✓ ED	AC-PF	C, SF	MODGTEP	SBSP
[134] ***2020***	✕	✕	✕	DC-PF	C, ATC	MOSGTEP	Genetic Algorithm
[12] ***2019***	✓ (W)	✕	✓ UC	DC-PF	C	SGTEP	MINLP
[3] ***2019***	✓ (S&W)	✕	✓ ED	DC-PF	C, EENS	MODGTEP	C&CG

Research Work	vRES	Emission	Operation Planning	Power Flow	Research Objectives	Type/ Nature	Methodology used
[13] ***2019***	✓ (W)	✕	✓ ED	DC-PF	P, C, SWF	MOSGTEP	MINLP
[19] ***2019***	✓ (W)	✕	✓ UC	AC-PF	C	DGTEP	MINLP
[58] ***2019***	✕	✕	✓ ED	DC-PF	C	DGTEP	BD, HSA
[23] ***2018***	✕	✕	✓ POR, FOR	AC-PF	PL	SGTEP	PSAT
[108] ***2018***	✓ (W)	✕	✓ RR	DC-PF	C	DGTEP	MILP, C&CG, RED
[41] ***2018***	✕	✕	✓ RR	DC-PF	C	DGTEP	PHA
[56] ***2017***	✕	✕	✓ FOR	DC-PF	C	DGTEP	Genetic-Tabu Hybrid Algorithm
[57, 60,63] ***2015***	✕	✕	✕	AC-PF	C	DGTEP	Generalized BD
[2] ***2014***	✕	✕	✓ FOR	DC-PF	C, EENS	MOSGTEP	Probabilistic MILP
[84] ***2014***	✕	✕	✕	AC-PF	C	DGTEP	MINLP-GAMS
[42] ***2014***	✕	✕	✕	DC-PF	C	SGTEP	IPM, CBGA
[61] ***2014***	✕	✕	✕	DC-PF	C, ES	MOSGTEP	Integrated Expansion Algorithm
[7] ***2014***	✕	✕	✓ ED, FOR	DC-PF	C	DGTEP	GA, EM
[62] ***2013***	✕	✕	✕	DC-PF	C	SGTEP	Stochastic Decomposition Method
[109] ***2013***	✕	✕	✓ FOR	DC-PF	C	DGTEP	Scenario-Based techniques
[110] ***2013***	✕	✕	✓ FOR	DC-PF	SWF, P, CC	MODGTEP	GAMS, MATLAB
[111] ***2013***	✓ (S)	✕	✕	DC-PF	C	SGTEP	BD, GAMS

Research Work	vRES	Emission	Operation Planning	Power Flow	Research Objectives	Type/ Nature	Methodology used
[30] ***2012***	✓ (W)	✓	✕	DC-PF	C	SGTEP	Heuristic Algorithm
[9] ***2012***	✓ (W)	✓	✓ ED, POR, FOR	DC-PF	C	MADGTEP	MIP
[113] ***2011***	✕	✕	✕	AC-PF	C, GL, TL, VL	MOSGTEP	DBLS
[27] ***2010***	✕	✕	✓ RR	DC-PF	SWF	SGTEP	GAMS
[64] ***2010***	✕	✓	✕	DC-PF	C, E, EENS	MOSGTEP	Fuzzy MIP
[107] ***2009***	✕	✕	✕	DC-PF	P	DGTEP	GAMS
[112] ***2008***	✕	✕	✕	AC-PF	SWF, CC	MOSGTEP	ISDF, WTLR, MATLAB
[39] ***2007***	✕	✕	✕	DC-PF	P, LMP, FMP, SS	MODGTEP	BD
[6] ***2003***	✕	✓	✕	DC-PF	C	MASGTEP	BD
THIS RESEARCH WORK	✓ (S&W)	✓	✓ ED, UC, POR, FOR	AC-PF	C, E, PL, EENS, LP, VP, vRES optimization	MAMODGTEP	DE-ABFOA-GIPSO

Key: *OP=Operational Planning, ✓=Considered, ✕=Not-considered, S=Solar PV plants, W=Wind Power Plants, DC-PF=DC Power Flow, AC-PF=AC Power Flow, RR=Ramping requirements, FOR=Forced Outage Rate, POR=Planned Outage Rate, ED=Economic Dispatch, UC=Unit Commitment, VP=Voltage Profile, LP=Loading Profile, vRES Opt=vRES optimization, other abbreviations are defined in Tables 2-1, 2-2, 2-3 and Nomenclature.*

From the analysis in Tables 2-3 and 2-4, only three of the reviewed works [19, 135 & 136] have considered vRES penetration with AC power flow based formulations in GTEP optimization. However, the three works considered only wind power plants with none considering solar PV or environmental emissions in their optimization. In addition, there was no optimization of vRES penetration in relation to available conventional generators in the respective generation mixes. The only two reviewed research works [3 & 133] that have considered both wind and solar simultaneously have adopted the less reliable DC-power flow formulations and did not consider emissions from electric power generators. None of the reviewed research works has formulated and solved the MODGTEP optimization problem using AC power flow analysis while ensuring optimal vRES penetration, a key research gap in this area. The identified research gap was addressed in this thesis work by formulating and solving the MAMODGTEP problem employing AC power flow analysis while optimizing the penetration of vRES in the generation mix. The work also considered environmental emissions from electricity generators.

2.5 Research Gaps in GTEP

2.5.1 Power Flow Analysis

Figures 2-1 gives a summary of the findings of the reviewed GTEP works in the last 10+ years (2003 to 2023). Only 39% of the reviewed works considered multiple objectives in their formulation. Among these multi-objective GTEP works, approximately 15% were formulated in a dynamic planning environment. Adoption of AC power flow formulation in solving multi-objective dynamic GTEP is very low. Only 3% (Ansari, M.R. et al. 2021 [135]) of the reviewed works utilized AC power flow based formulation in solving the Multi-Objective Dynamic GTEP optimization problem. However, in this work the AC power flow constraints were linearized using the big-M method by adopting two assumptions similar to those adopted in DC power flow based formulations. One of the assumptions was that the difference in voltage phase angles $(\theta_i - \theta_j)$ at two connected buses is very small (small angular separation $(\theta_i - \theta_j) < 6^{\circ}$) such that $Cos(\theta_i - \theta_j) = 1$ and $Sin(\theta_i - \theta_j) = (\theta_i - \theta_j)$. The second assumption was that the nodal voltage magnitudes in all the network buses are very close to 1.0pu such that $|V_i| = |V_j| = 1.0$ and $|V_i||V_j| = 1.0$. Though these assumptions greatly reduce the complexity of the optimization problem (problem making it easily solvable by existing solvers like GAMs among others), the assumptions are only applicable for well interconnected networks but not with weakly interconnected grids (common in developing countries). In practice, angular separations of more than 30° are usually realized especially in areas interconnected by long and/or radial transmission lines. Likewise voltage profiles for most transmission grid are maintained between 0.95pu and 1.05pu with risk of under-voltages being a major problem in weakly interconnected grids. This is because among other things, locations for generators and loads are influenced by different factors and in most cases there is no even distribution in the grid. Some areas have geographical or locational advantages compared to others. This phenomenon is more heightened with vRES compared to conventional generators. Therefore these assumptions greatly decrease accuracy of obtained GTEP results especially when vRES are considered. As a result, this research work solves the non-convex mixed integer non-linear AC power flow optimization problem without linearizing the formulations by utilizing the developed adaptive meta-heuristic approach.

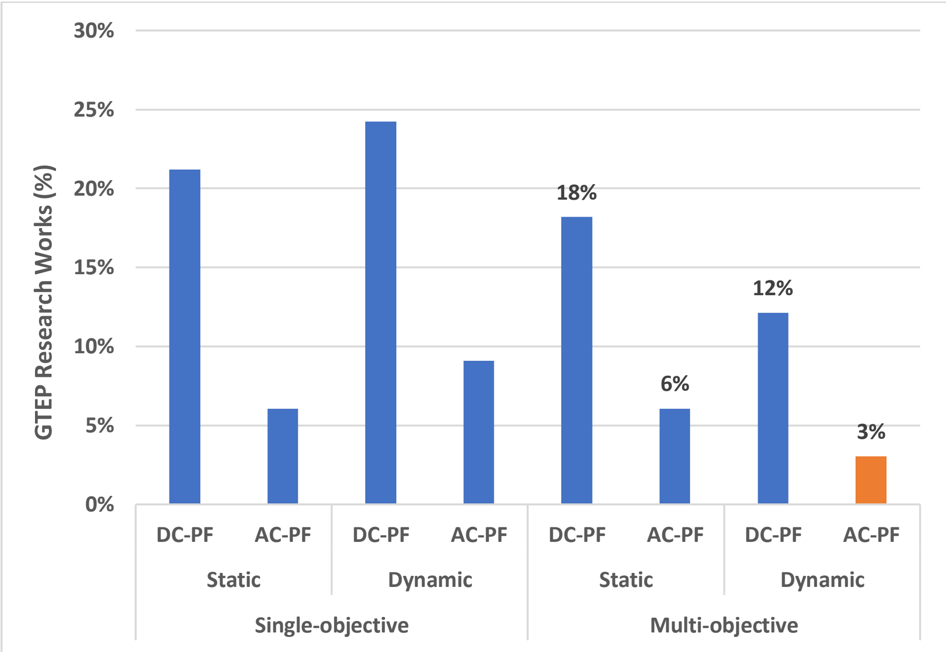


Figure 2-1: Recent GTEP Research Classification by Power Flow Formulation

2.5.2 RES Inclusion

Figure 2-2 gives a summary of vRES inclusion in all the reviewed GTEP works while Figure 2-3 compares this inclusion in terms of objective formulation (single or multiple objectives), study horizon (static or dynamic) and problem formulation (DC or AC power flow based). Generally, the optimization of vRES in the GTEP problem has not been exhaustively studied as shown in Figures 2-2. Based on the reviewed GTEP research works, vRES consideration stands at 33% with only 6% of these works including both solar PV and wind in their optimization. Among these two common vRES, wind penetration in GTEP has attracted more interest. This could be because most of the European countries where much of this research is happening have abundant onshore and offshore wind resources but limited solar potential due to their geographical locations.

From Figure 2-3, all of the reviewed GTEP research works that have considered both wind and solar in their optimization have been formulated based on the unreliable and over simplified DC power flow [3, 133]. Only 9% of the reviewed research works [3, 133 & 135] considered vRES in a multi-objective dynamic environment. Among these works, only [135] that utilized AC power flow formulations however the authors linearized these formulations using DC power flow related assumptions as explained in section 2.5.1. This linearization in formulating the GTEP problem may lead to impractical results especially when dealing with weakly interconnected grid and vRES consideration. In addition, this research work does not consider solar PV. To curb on vRES (wind) variability issues battery energy storage was included in the network to improve grid flexibility. However, there was no optimization of vRES penetration in relation to flexibility capabilities (e.g. reserve provision possibilities) of other conventional energy sources in the grid. Wind penetration was only restricted to the battery storage flexibility abilities. None of the reviewed research works in open literature has explored optimal vRES inclusion in MODGTEP problem using the most practical and reliable AC power flow analysis. This thesis research work introduces vRES overutilization and underutilization penalties to optimize vRES (solar & wind) penetration in an AC power flow formulated MAMODGTEP optimization problem.

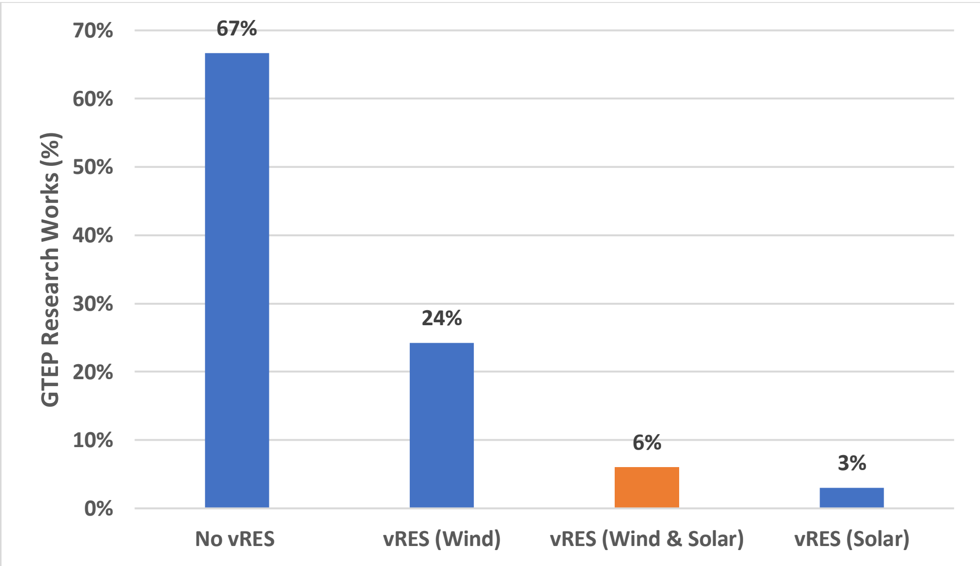


Figure 2-2: Intermittent RES Consideration in Recent GTEP Research Works

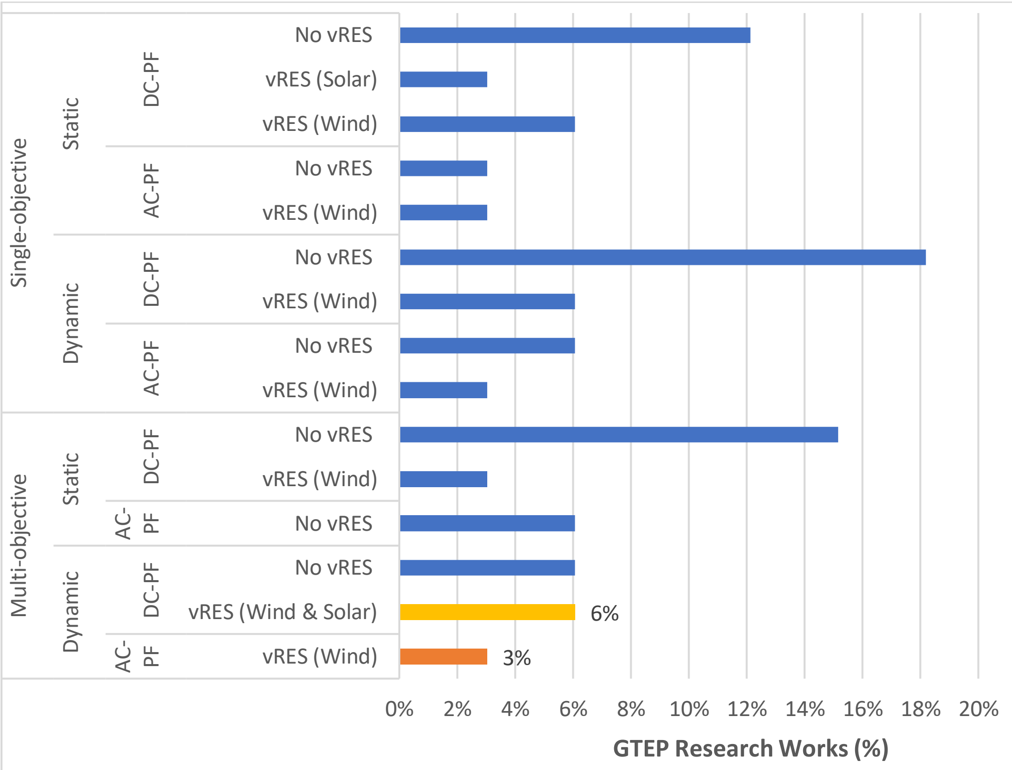


Figure 2-3: Intermittent RES, AC-PF Consideration in Recent GTEP Research Works

2.5.3 Optimization Methods

Most of the methods used in solving the reviewed GTEP problem are deterministic though interest in heuristic and meta-heuristic techniques is growing. Deterministic methods have high computational requirements especially when solving complex non-linear optimization problems and are prone to being trapped in local optima [137]. Meta-heuristic-based approaches are best suited in overcoming these limitations and thus improving on accuracy of obtained expansion results [134].

2.5.4 Summary of Research Gaps

The above limitations in the existing GTEP research works confirm that the area is still developing compared to separate GEP and TEP. As a result, there are many research opportunities/gaps in this area. Based on open literature on power system expansion planning, the identified research gaps are summarized as follows:

(i) Development of better methodologies and algorithms for solving the integrated Generation and Transmission Expansion problem.

(ii) Optimization of the penetration of intermittent RES in the system to maximize on their benefits without jeopardizing network robustness.

(iii) Formulation and solution of modern multi-area, multi-objective dynamic expansion problems considering optimal intermittent RES penetration.

(iv) Formulation of the integrated GTEP problem employing AC power flow models to be able to account for power loss, thermal limits, voltage and reactive power requirements more accurately.

(v) Simplification of the AC power flow models for GTEP formulation to reduce its complexity, memory and computation requirements without leaving out important aspects of the power system.

(vi) Incorporation of more industry related objectives and constraints (e.g. consideration of must-runs, obligatory plants, generator interdependency etc.) in the formulation and solution of the expansion problem.

(vii) Need to accommodate various environmental policies such as carbon emission allowance and constraints in addition to carbon cost in the problem formulation.

(viii) Taking into account latest developments in other related areas that influence accuracy of GTEP results; these include Unit Commitment, Economic Dispatch, Feed-in-Tariffs, Distributed generation, Energy auctions, Energy storage, Demand Side Management etc.

2.6 Optimization Methods in Power System Planning

Different methods and techniques have been formulated to solve various optimization problems. These methods can broadly be classified into four main groups namely: deterministic (mathematic/exact) methods, heuristic (approximate) methods, meta-heuristic methods and hybrid methods.

2.6.1 Deterministic/Mathematical/Exact Optimization Methods

Deterministic methods include the unconstrained methods that convert constrained problems into unconstrained form. As stated by Lee, et al., 2006 [129], these methods include all mathematical models which are focused on exact optimization processes with objective function minimization/maximization subject to sets of constraints. As per the approaches and techniques used by different researchers, the deterministic methods can be classified into:

(i) Programming Techniques: The techniques in this category include Linear Programming (LP) [120], Dynamic Programming (DP) [121], Quadratic Programming (QP) [122], Non-Linear Programming (NLP) [123] and Mix Integer Programming (MIP) [124].

(ii) **Decomposition Techniques:** These techniques include Benders Decomposition (BD) [125], Hierarchical Decomposition (HD) [126] and Branch & Bound Algorithm (BBA) [129].

(iii) **Non-Quantity Approaches:** In this category, we have Fuzzy Set Theory (FST) [67], Analytical Hierarchical Process (AHP) [8] etc.

(iv) **Others:** Interior Point (IP) [131], Ordinal Optimization (OO) [59] etc.

When solving complex optimization problems, which are often nonlinear and non-convex, the computational effort in these deterministic methods is usually huge. In such scenarios, many of these methods require the relaxation of the binary to continuous variables to lower computation burden, however this may lead to solutions far from the optimum [68]. In addition, due to intrinsic limitations of the searching process there is a possibility that the obtained optimal solution corresponds to a local optimum.

2.6.2 Heuristic Optimization Methods

Heuristic methods are inventive techniques based on users' experience. As quoted by [68] these approaches can be interactive or non-interactive. Interactive heuristic methods interact with the planner in their step-by-step generation, evaluation, and selection of expansion options, while non-interactive do not. Since these methods are inventive techniques based on engineers' experience, their computational performance is usually better than that of the mathematical methods [129].

The key objective of approximate algorithms or heuristics is to produce good approximate solutions as quick as possible, without the necessity of providing any guarantee of solution optimality [68]. Therefore, though the heuristic methods can give good feasible solutions with reasonable computation efforts, the quality of these results cannot be guaranteed, as one cannot prove the optimality. This has led to the evolution of meta-heuristic methods. Some of the heuristic models employed in power system expansion planning optimization include the following approaches: Overload networks [120], Decomposition between the investment and the operation sub-problems [68] and Sensitivity analysis [123].

2.6.3 Meta-heuristic Optimization Methods

Meta-heuristic methods combine the attributes of both deterministic and approximate methods. Unlike heuristic methods, they are not problem-dependent however, some intrinsic parameter fine-tuning is necessary in their adaptation to specific problems. In these approaches, the constraints and objective functions in the problem formulation are not differentiated since the approaches needs no prior knowledge of the problem. The fact that these methods are not gradient-based (derivative-free) helps them avoid premature convergence as a result of being trapped in local optima. Their independence from the starting point (initial solution) eliminates the necessity for convexity in solving optimization problems. As a result, meta-heuristic methods can identify quasi-optimal solutions with acceptable computational effort even when applied to large problems [68] and have been extensively applied in power system planning [31, 73]. The meta-heuristic methods employed in power system expansion planning optimization can be classified as:

(i) **Evolutionary Algorithm (EA) Approaches:** – These approaches are based on the powerful principle of evolution—survival of the fittest. They are population-based optimization processes. They are a subset of the evolutionary computation that explores biological evolution mechanisms such as selection, recombination (crossover), mutation, and reproduction. They involve: Evolutionary Programming (EP), Genetic Algorithm (GA) [33], Evolution Strategies (ES) [40], Differential Evolution (DE), Artificial Immune Systems (AIS) etc.

(ii) **Swarm Intelligence (SI) Approaches:** - These approaches exhibit the swarm intelligence phenomenon in which the behavior of agents collectively interacting locally within their environment in a system result to the emergence of coherent functional global patterns. Using this property of SI, problem solving can be explored without centralized control or the provision of a global model. These approaches include Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Bat Algorithm (BA), Bacterial Foraging (BF), Bee Colony Optimization (BCO) etc. [68].

(iii) **Trajectory Meta-Heuristic Approaches: -** Most of these approaches are extensions of simple iterative improvement procedures in which different techniques are incorporated to enable the algorithm escape from premature convergence to local optima. The outcome from these approaches is a single optimized solution since they use a single solution during the search process [68]. They include Hill Climbing (HC); Simulated Annealing (SA), Greedy Randomized Adaptive Search Procedures (GRASP), Tabu Search (TS), Teacher Learning Algorithm (TLA), Biogeography-Based Optimization (BBO) etc.

2.6.4 Hybrid Optimization Methods

In the recent past, researchers are hybridizing various techniques to come up with powerful but less complex methods that can be used to solve different optimization problems. These hybrids techniques are formed by combining two or more of the above reviewed techniques. Hybrids can be between/among methods in the same category of in different categories [68]. In most cases, these researchers combine a deterministic approach with a heuristic or meta-heuristic approach. Recently, there is increasing hybridization of heuristic and meta-heuristic methods. The reason for this increased use of hybrids is that they exalt the strengths and improve the weaknesses of the methods concerned. Some of the hybrid approaches in power system expansion planning include:

(i) Deterministic & Deterministic Hybrids: Fuzzy Sets (FS) & "Branch and Bound" [42] and FS & risk analysis [51];
(ii) Meta-heuristic and Deterministic: GA, TS & mathematical programming, ES & mathematical methods and GA & Monte Carlo simulation [52];
(iii) Meta-Heuristic and Meta-Heuristic Hybrids: GA, SA and TS [53];
(iv) Meta-Heuristic, heuristic and deterministic hybrids: GA, Probabilistic Choice and Risk Analysis [54].

2.7 Chapter Conclusion

The PhD research work aimed at solving some of the research gaps identified in this chapter. The main gaps solved by this research work are as summarised below:

(i) Need for improved optimization methods for solving the integrated planning problem: - The research work develops, formulates and tests an adaptive hybrid meta-heuristic optimization algorithm based on a hybrid of Differential Evolution and Bacterial Foraging Optimization Algorithms adapted using Genetic Improved Particle Swarm Optimization (DE-ABFOA-GIPSO). The developed algorithm was first used to solve the Transmission Constrained Generation Expansion Planning (TC-GEP) problem and then applied in integrated Generation and Transmission Expansion Planning (GTEP) optimization problems.
(ii) Need for better representation of intermittent/variable RES in GTEP formulation and solution: - In this research work, the integrated GTEP problem was formulated and solved taking into account optimal intermittent/variable RES penetration.
(iii) Necessity of considering power loss, thermal limits, voltage and reactive power requirements in the GTEP problem formulation and solution: - This can only be dealt with satisfactorily by employing AC power flow models in the formulations. The TC-GEP and GTEP problems were formulated based on AC-power flow analysis.

(iv) The need to formulate the modern expansion planning problem as practical as possible: - For the first time, this research work formulates and solves the modern Multi-Area Multi-Objective Dynamic Generation and Transmission Expansion Planning (MAMODGTEP) problem employing both intermittent/variable RES and AC power flow constraints.

To meet the set goals for the research work, the formulated objective function of the expansion planning problem incorporated investment cost, operation and maintenance cost, emission cost and outage cost. AC power flow constraints related to system power losses, voltage profiles, thermal limits, real and reactive power flows and power generations were formulated and employed in the optimization. In addition, optimization of vRES penetration was achieved by formulating and inclusion of vRES overutilization and/or underutilization penalties in the objective function. Where applicable, the proposed GTEP formulation and solution methodology was validated by comparing the cost of the obtained expansion plans as well as their technical feasibility (voltage profile, line loading, generator loading etc.) to those obtained by other researchers in this area. IEEE 6-bus [2] & Garver's 6-bus test systems [84] were used for the validation.

3 CHAPTER 3: ADAPTIVE HYBRID METAHEURISTIC APPROACH: DE-ABFOA-GIPSO

3.1 Selection of Power System Expansion Planning Optimization Method

The power system expansion planning problem is a combinatorial optimization problem that aims at finding an optimal solution from a discrete set of feasible solutions. Just like in other combinatorial problems, it is difficult to solve it optimally in reasonable computation time due to its dimensionality and other problem-specific characteristics. Being exact at the expense of computation requirements in such a problem may be meaningless, since one is dealing with not very precise data but only simple simplifications of reality. However, the integrity of the input data, technique used and the solution should be within the acceptable limits [68]. Therefore, meta-heuristic methods are best suited for solving the complex and highly dimensional power system expansion planning optimization problems. This is because among other benefits the meta-heuristic methods are derivative-free (not gradient-based as deterministic methods) which helps them avoid being trapped in local optima (premature convergence). They are also independent of the initial solution, and thus they do not necessarily require convexity in order to be able to solve optimization problems. In addition, unlike heuristic methods that are problem dependent, meta-heuristic methods are not problem-dependent though they both require some fine-tuning of their intrinsic parameters to adapt them to the problem at hand. As evident in recent research, a combination of several approaches into a hybrid has been used to solve drawbacks of individual techniques. Due to this advantage, application of hybrid methods in solving power system expansion planning optimization problems is increasing day by day [31, 73].

In this thesis, a hybrid approach was developed by combining the attributes of Genetic, Particle Swarm, Bacterial Foraging and Differential Evolution Optimization Algorithms in its formulation. Detailed steps in the formulation of each variant of the algorithms employed in the hybridization can be found in [75-80]. In developing the approach, a hybrid of Differential Evolution and Bacterial Foraging Optimization Algorithms was adapted through Genetic Improved Particle Swarm Optimization (DE-ABFOA-GIPSO). The aim was to avoid the weaknesses of individual techniques while capitalizing on their strengths. Table 3-1 gives the attribute(s) of interest for each optimization technique and the reason behind its selection.

Table 3-1: Details on selection of Optimization Techniques

Optimization Technique	Attribute of Interest	Reason for Selection
DE	• Real-valued continuous space application • Differential recombination	• Ease of application to a wide variety of real valued problems with multi-modal, multi-dimensional spaces [71]. • Gives better results in comparison to other EA in most cases [72].
BFOA	• Easily adaptable • Relatively new with increasing application • Powerful among swarm intelligence techniques	• Its formulation accommodates best attributes from other techniques easily (ease of improvement) [79]. • Often outperforms other swarm intelligence techniques [80]
GA	• Cross over • Mutation	• These properties of the GA bring diversity to the candidate solutions thus discouraging premature convergence [76]. • Can provide a good guidance for PSO particles thus improving its efficiency [78].
PSO	• Global best • Individual best	• This attribute can be used to bring the useful social/historical information of particle positions leading to faster convergence [75].

3.2 DE-ABFOA-GIPSO Algorithm Formulation, Hybridization and Adaptation

DE-ABFOA-GIPSO is a novel adaptive hybrid meta-heuristic optimization approach formulated, tested and utilized in solving power system expansion planning problems in this research work. Its formulation is based on the attributes of the four techniques given in Table 3-1. This optimization approach has not being proposed by any other researcher in all the accessed and reviewed works. The following steps outline the procedure employed in the formulation of the proposed optimization algorithm.

Step 1: The parameters for all the techniques are initialized. These include:

(i) *Population size (number of bacteria/particles),* N – This refers to a set of candidate solutions selected from the problem such space.

(ii) *Chemotactic steps,* N_c – These are controlled steps aimed at finding the global optimum solution.

(iii) *Swim length,* N_s - Just like in the chemotactic steps, the movements here are controlled and influenced by the position of the best-fitted candidate.

(iv) *Reproduction steps, K* – The reproduction steps define the number of times the candidate solutions will evolve within the search space.

(v) *Elimination/Dispersal steps, ELL* – This is where unpromising candidate solutions are dropped and the promising ones are allowed to progress with the search for optimal solution.

(vi) *Step-size limits, C_{min} & C_{max}* – These limits control the finite changes in the chemotactic and swim processes.

(vii) *Mutation probability, P_{mut}* – The aim of this step is to introduce some random interruption in the candidate solutions to improve coverage of the search space.

Step 2: The N population is randomly initialized taking into account all relevant constraints for which the already formulated objective function is being optimized (minimized/maximized) subject to.

Step 3: The fitness of each bacterium/particle is evaluated based on the optimization problem objective function. The value of each bacterium P, becomes its personal best denoted, P_{best}. The bacterium with the best fitness in this step is denoted as global best denoted, G_{best}.

$$P_{best}^{i} = P^{i}, \qquad \forall i \tag{3.1}$$

$$G_{best} = P_{best}^{i} \ if \ f\left(P_{best}^{i}\right) = \min\{f\left(P^{i}\right)\}, \qquad i \in N \tag{3.2}$$

Step 4: The iterations are initialized in this stage starting with Elimination/dispersal loop;

$$ell = 1, \ ell \in ELL \tag{3.3}$$

Step 5: Start reproduction loop;

$$k = 1, \ k \in K \tag{3.4}$$

Step 6: Start chemotaxis loop;

$$j = 1, \ j \in N_c \tag{3.5}$$

(i) Unlike in normal BFOA, the chemotactic step here is performed employing an adapted step-size based on GIPSO attributes:

(ii) The chemotactic movement for a classical BFOA is represented in equations (3.6) and (3.7).

$$P_{(j+1,k,ell)}^{i} = P_{j,k,ell}^{i} + C(i)\emptyset(i) \tag{3.6}$$

$$P_{(j+1,k,ell)}^{i} = P_{j,k,ell}^{i} + C(i)\frac{\Delta(i)}{\sqrt{\Delta^{T}(i)\Delta(i)}} \tag{3.7}$$

Where: $P^i_{j,k,ell}$ is the position of the i^{th} bacterium in population *N* at the j^{th} chemotactic step in *Nc* steps, k^{th} reproduction step in *K* steps and ell^{th} elimination in *ELL* elimination steps, $C(i)$ is the step size in the random direction and $\emptyset(\mathrm{i})$ is a unit vector in the random direction.

(iii) In a classical PSO algorithm, the velocity and position are updated based on equations (3.8) and (3.9) respectively.

$$V^i_{j+1} = wV^i_j + c_1 r\left(P_{best_i} - S^i_j\right) + c_2 r\left(G_{best} - S^i_j\right) \tag{3.8}$$

$$S^i_{j+1} = S^i_j + V^i_{j+1} \tag{3.9}$$

Where: V^i_j and S^i_j are the velocity and position of the i^{th} particle in the population, c_1 and c_2 are weight coefficients for each term respectively and r is a random integer between 0 and 1.

(iv) These classical PSO equations are used to improve the chemotactic movement for a classical BFOA by incorporating social behavior between the bacteria. In this case, the new BFOA movement is represented as in equation (3.10);

$$P^i_{(j+1,k,ell)} = P^i_{j,k,ell} + C(i)\{\left(P_{best_i} - P^i_{j,k,ell}\right) + \left(G_{best} - P^i_{j,k,ell}\right)\} \tag{3.10}$$

(v) This social cooperation ensures both exploration and exploitation in the search process. As a result, it enhances the probability of searching/moving towards better areas as good information is fully utilized.

(vi) However, premature convergence may arise when P_{best} and G_{best} are located in the same local optimum. In addition, if P_{best} and G_{best} are located on opposite sides of $P^i_{j,k,ell}$ oscillations will result. To avoid these limitations, the social cooperation analysis is modified using the attributes of Evolutionary Algorithms, i.e., cross-over and mutation. Arithmetic crossover commonly used in Differential Evolution (DE) is performed between the P_{best} of each bacterium and the G_{best} to generate a off-spring P_{ideal_i} which is mutated using a mutation probability, P_{mut} as shown in equations (3.11) and (3.12) respectively:

$$P^i_{ideal} = \begin{cases} \alpha P_{best_i} + (1-\alpha)G_{best}, \text{if } f(P_{best_i}) < f(P_{r,d}) \\ P_{best_i} \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad Otherwise \end{cases} \tag{3.11}$$

$$P_{ideal}^{i} = \begin{cases} P_{ideal}^{i} + r\Delta P_{ideal}^{i}, & \text{if } r < P_m \\ P_{ideal}^{i} & Otherwise \end{cases} \tag{3.12}$$

(vii) Using the P_{ideal}^{i} obtained in equation (3.12) the chemotactic movement given in equation (3.10) becomes:

$$P_{(j+1,k,ell)}^{i} = P_{j,k,ell}^{i} + C(i)\{(P_{ideal}^{i} - P_{j,k,ell}^{i}) \tag{3.13}$$

(viii) To balance between the exploration (diversification) and exploitation (intensification) ability of the DE-ABFOA-GIPSO algorithm, the step size is varied to enhance exploration at earlier stages of chemo-taxis and exploitation at later stages.

$$C_{j,k,ell}^{i} = C_{max} - \frac{(C_{max} - C_{min})}{Nc}.j \tag{3.14}$$

Equation (3.14) ensures larger step size at initial stages to guarantee the exploration ability while as the iteration move towards the stopping criterion smaller step sizes are adopted to intensify search around the promising areas and thus enhance algorithm's convergence.

(ix) The P_{best} and G_{best} for each bacterium and the population respectively are then updated using (3.15) and (3.16).

$$P_{best(j+1,k,ell)}^{i} = \begin{cases} P_{(j+1,k,ell)}^{i} & if\ f(P_{(j+1,k,ell)}^{i}) < f(P_{best(j,k,ell)}^{i}) \\ P_{best(j,k,ell)}^{i} & otherwise \end{cases} \tag{3.15}$$

$$G_{best(j+1)}^{i} = \begin{cases} P_{best(j+1)}^{i} & if\ f(P_{best(j+1)}^{i}) < f(G_{best(j)}^{i}) \\ G_{best(j)}^{i} & otherwise \end{cases} \tag{3.16}$$

(x) Start Swim loop inside the chemotactic step for Ns swims,

$$s = 1, \qquad s \in N_s \tag{3.17}$$

a) Update the position of the bacteria using equation (3.13).

b) Evaluate the fitness of the new bacteria population.

c) Update bacterium's P_{best} and G_{best} using equations (3.18) & (3.19).

$$P_{best(s+1)}^{i} = \begin{cases} P_{(s+1)}^{i} & if\ f(P_{(s+1)}^{i}) < f(P_{best(s)}^{i}) \\ P_{best(s)}^{i} & otherwise \end{cases} \tag{3.18}$$

$$G_{best(s+1)} = \begin{cases} P_{best(s+1)}^{i} & if\ f(P_{best(s+1)}^{i}) < f(G_{best(s)}) \\ G_{best(s)} & otherwise \end{cases} \tag{3.19}$$

d) Increment s, if $s > Ns$ go to step (x) else go to step (a)

(xi) Increment j, if $j > Nc$ go to step (7) else go to step (5)

Step 7: Perform population reproduction. The BFOA reproduction stage is also modified using GA and DE variants.

(i) *Selection:* GA's roulette wheel selection method is used to get the parents from the current population. The probability of a bacterium to be chosen/selected as a parent is given by equation (3.20).

$$p_{(\theta^i)} = \frac{f(P^i_{best(Nc,k,ell)})}{\sum_{i=1}^{N} f(\theta^i_{best(Nc,k,ell)})}, \quad i \in N \tag{3.20}$$

Where, $f(P^i_{best(Nc,k,ell)})$ is the fitness of i^{th} individual in the population.

(ii) *New Population:* Based on DE's arithmetic crossover, the new population is obtained from the parents as given in equations (3.21) and (3.22).

$$P^{i(new_1)}_{Nc,k+1,ell} = \lambda P^{i(old_1)}_{best(Nc,k,ell)} + (1-\lambda) P^{i(old_2)}_{best(Nc,k,ell)} \tag{3.21}$$

$$P^{i(new_2)}_{Nc,k+1,ell} = \lambda P^{i(old_2)}_{best(Nc,k,ell)} + (1-\lambda) P^{i(old_1)}_{best(Nc,k,ell)} \tag{3.22}$$

Where, λ is a random integer between 0 & 1.

Step 8: Increment k, if $k > K$ go to step (9) else go to step (6)

Step 9: Perform Elimination/Dispersal stage: Half of the population (those with the worst fitness) are replaced with randomly assigned new positions in the solution space (similar to the population initialization in step 2) and the other bacteria with the better fitness values are maintained.

Step 10: Increment ell, if $ell > ELL$ go to step (11) else go to step (5).

Step 11: Output the positions and the fitness of all bacteria in the population. The bacteria with the latest G_{best} becomes the optimal solution for the optimization problem.

Figure 3-1 illustrates the main steps of the DE-ABFOA-GIPSO algorithm.

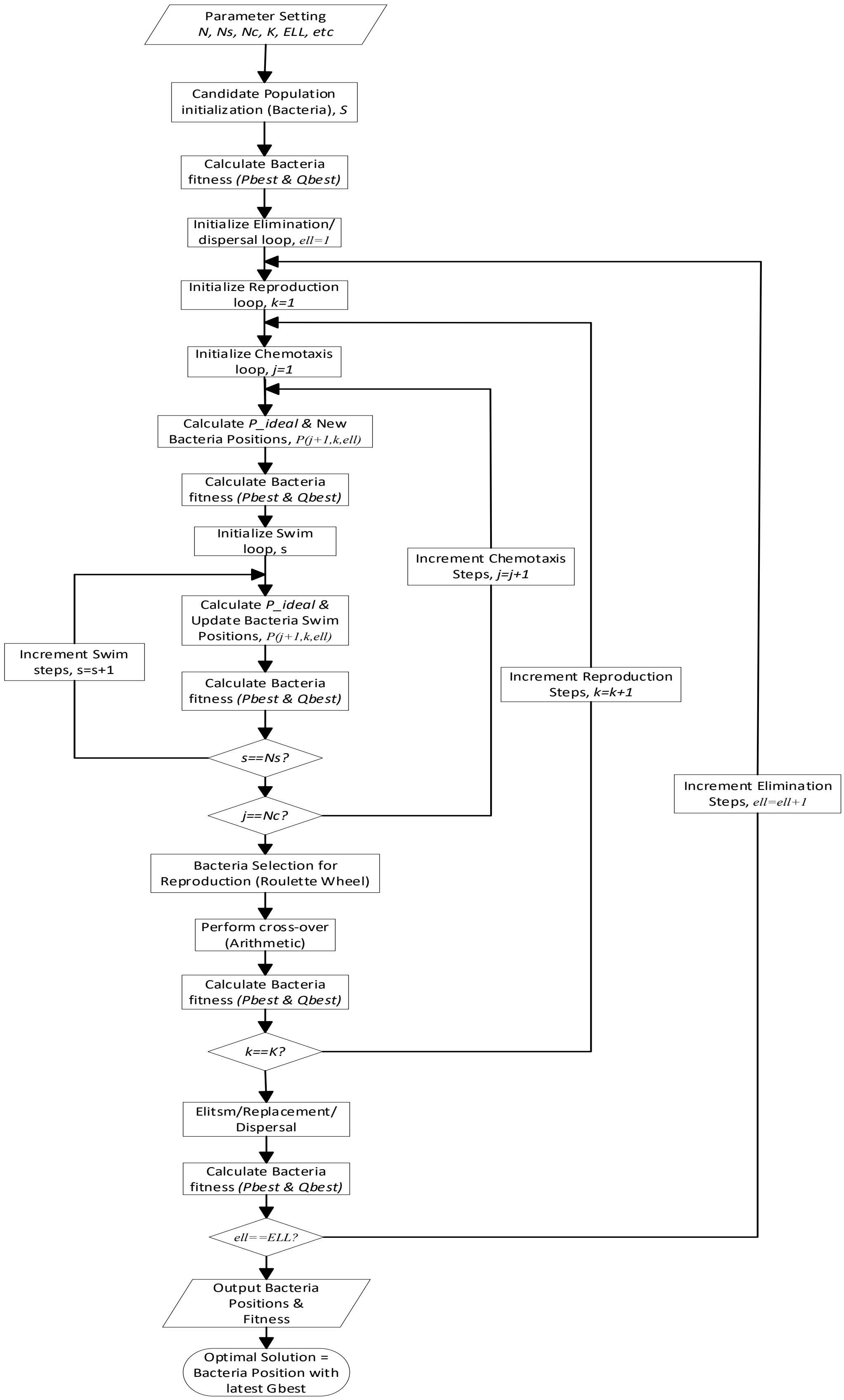


Figure 3-1: Flow Chart of DE-ABFOA-GIPSO Algorithm

3.3 DE-ABFOA-GIPSO Verification and Validation

The formulated meta-heuristic-based adaptive hybrid algorithm was tested on various standard benchmark functions and constrained engineering test problems prior to application in solving the integrated power system expansion planning optimization problem. The developed algorithm and the test problems were programmed on MATLAB 2015b software. The obtained results were compared with those obtained by other researchers using available optimization techniques. The algorithm parameters given in Table 3-2 were used in the test analysis. The parameter values were based on trial and error approach guided by utilized values for BFOA parameters as utilized in [79]. The choice of the parameter values was done to ensure optimal results with the minimum possible iterations.

Table 3-2: DE-ABFOA-GIPSO Parameter Mapping

Parameter	Meaning	Symbol	Value
Population size	Candidate solutions per iteration	N	100
Chemotactic steps	1st stage Exploitation search iterations	N_c	25
Swim length	2nd stage Exploitation search iterations	N_s	4
Reproduction steps	1st stage Exploration search iterations	K	4
Elimination/Dispersal steps	2nd Stage Exploration search iterations	ELL	2
Step-size limits	Limits on change of candidate solution in successive iterations	C_{min} , C_{max}	0.03, 0.07
Mutation probability	Probability of candidate solution alteration during iteration	P_{mut}	0.025

3.3.1 Standard Benchmark Functions

These are functions often used by researchers to examine the performance of developed optimization algorithms/ techniques. In this analysis, both high dimensional and low dimensional test functions were employed. Emphasis was on the high dimensional continuous functions whose dimensionality makes them difficult to solve. Table 3-3 gives a summarized description of these functions.

Table 3-3: Standard Benchmark Functions Characteristics [90]

Name	Function	Modality	Domain	Global Optima
Ackley	$f(x) = -20e^{-0.02\sqrt{D^{-1}\sum_{i=1}^{D} x_i^2}} - e^{D^{-1}\sum_{i=1}^{D}\cos(2\pi x_i)} + 20 + e$	Multimodal	$-35 \le x_i \le 35$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Griewank	$f(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	Multimodal	$-600 \le x_i \le 600$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Rosenbrock	$f(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	Unimodal	$-30 \le x_i \le 30$	$x^* = (1, \dots, 1)$, $f(x^*) = 0$
Schwefel 2.26	$f(x) = -\frac{1}{D}\sum_{i=1}^{D} x_i sin\sqrt{\lvert x_i \rvert}$	Multimodal	$-500 \le x_i \le 500$	$x^* = \pm[\pi(0.5 + k)]^2$ $f(x^*) = -418.983$
Schwefel 2.22	$f(x) = \sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	Unimodal	$-100 \le x_i \le 100$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Schwefel 2.21	$f(x) = \max_{1 \le i \le D} \lvert x_i \rvert$	Unimodal	$-100 \le x_i \le 100$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Schwefel 1.2	$f(x) = \sum_{i=1}^{D} \left(\sum_{j=1}^{i} x_j \right)^2$	Unimodal	$-100 \le x_i \le 100$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Sphere	$f(x) = \sum_{i=1}^{D} x_i^2$	Multimodal	$-100 \le x_i \le 100$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Rastrigin	$f(x) = \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i) + 10)$	Multimodal	$-5.12 \le x_i \le 5.12$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$
Quartic	$f(x) = \sum_{i=1}^{D} i x_i^4 + random[0,1]$	Unimodal	$-1.28 \le x_i \le 1.28$	$x^* = (0, \dots, 0)$, $f(x^*) = 0$

The ten functions are all continuous and scalable. Other than Schwefel 1.2, the rest are differentiable. Additional information on the standard benchmark functions applied here can be obtained in [90 - 92]. For comparison purposes a uniform dimensionality of 20 was adopted in the analysis. Meta-heuristic-based optimization techniques are usually stochastic in nature and thus their performance cannot be judged in a single run [90], as a result an average of 50 runs was used for the comparisons in this thesis. The normalization procedure given in [91] was used to facilitate authentic comparison with results obtained from other algorithms. Table 3.4 gives the comparison between results of the developed meta-heuristic-based adaptive hybrid technique and those of other meta-heuristic algorithms. The comparison uses the best results achieved by each algorithm (Best), the mean of obtained results in the 50 runs (Mean) and the standard deviation of the obtained results (Std dev.).

Table 3-4: Statistical Result Comparison for Benchmark Functions

Benchmark Function [90]	Result Feature	PSO [92]	BBO [92]	DE [92]	FFA [92]	DE-ABFOA-GIPSO
Ackley	Best	0.8561	0.9125	0.1279	0.9878	0.99889
	Mean	0.7351	0.8924	0.0000	0.9733	0.98053
	Std dev.	0.7742	0.2514	0.9875	0.7126	0.54172
Griewank	Best	0.8016	0.9235	0.0001	0.9616	0.96640
	Mean	0.6842	0.9014	0.0000	0.9324	0.91320
	Std dev.	0.5585	0.5197	0.1013	0.9102	0.62140
Rosenbrock	Best	0.9954	0.9672	0.2541	0.9871	1.00000
	Mean	0.9512	0.9201	0.2435	0.9239	0.99255
	Std dev.	0.7649	0.5148	0.3512	0.6284	0.26356
Schwefel 2.26	Best	0.9012	0.8921	0.6214	0.8743	0.93511
	Mean	0.8903	0.8315	0.4240	0.8272	0.87468
	Std dev.	0.5541	0.5148	0.8476	0.7513	0.59305
Schwefel 2.22	Best	0.7549	0.7894	0.6259	0.9006	0.98624
	Mean	0.7158	0.7515	0.3682	0.8851	0.90264
	Std dev.	0.5541	0.8457	0.9845	0.6022	0.63540
Schwefel 2.21	Best	0.8128	0.9459	0.7547	1.0000	0.98973
	Mean	0.7420	0.9025	0.6789	1.0000	0.96246
	Std dev.	0.3518	0.4875	0.8452	0.9638	0.47513
Schwefel 1.2	Best	0.6742	0.9845	0.0000	0.9920	0.99072
	Mean	0.6315	0.9125	0.0000	0.9770	0.95284
	Std dev.	0.6842	0.5148	0.0000	0.7516	0.70122
Sphere	Best	0.7155	0.8965	0.6025	1.0000	1.00000
	Mean	0.6879	0.8823	0.5942	0.9703	0.98564
	Std dev.	0.6658	0.5129	0.9551	0.7125	0.81546
Rastrigin	Best	0.9727	0.9621	0.6745	0.9615	0.97762
	Mean	0.9523	0.9222	0.6424	0.9324	0.94285
	Std dev.	0.5135	0.6541	0.8845	0.9103	0.87583
Quartic	Best	0.9021	0.9925	0.8992	0.9872	0.99925
	Mean	0.8999	0.9401	0.8422	0.9238	0.92856
	Std dev.	0.3513	0.6846	0.6584	0.6284	0.78961

Figure 3-2 gives the comparison of the best solutions from the various optimization algorithms. The developed meta-heuristic-based adaptive hybrid algorithm (DE-ABFOA-GIPSO) produced better results in eight (out of the ten standard benchmark functions) tests when compared to the other meta-heuristic methods in terms of the best obtained solution. Only in F6 (Schwefel 2.21) and F7 (Schwefel 1.2) functions where the developed algorithm was outperformed by the FireFly Algorithm (FFA). The results obtained in these two functions were however very close to those of FFA. In terms of mean solution for the 50 runs, DE-ABFOA-GIPSO was superior, leading in 40% (4 out of the 10 standard benchmark functions) of the tests conducted followed by FFA at 30% and PSO at 20%. Therefore the proposed DE-ABFOA-GIPSO algorithm has a better chance of producing a quasi-optimal result when compared to these other mete-heuristic approaches.

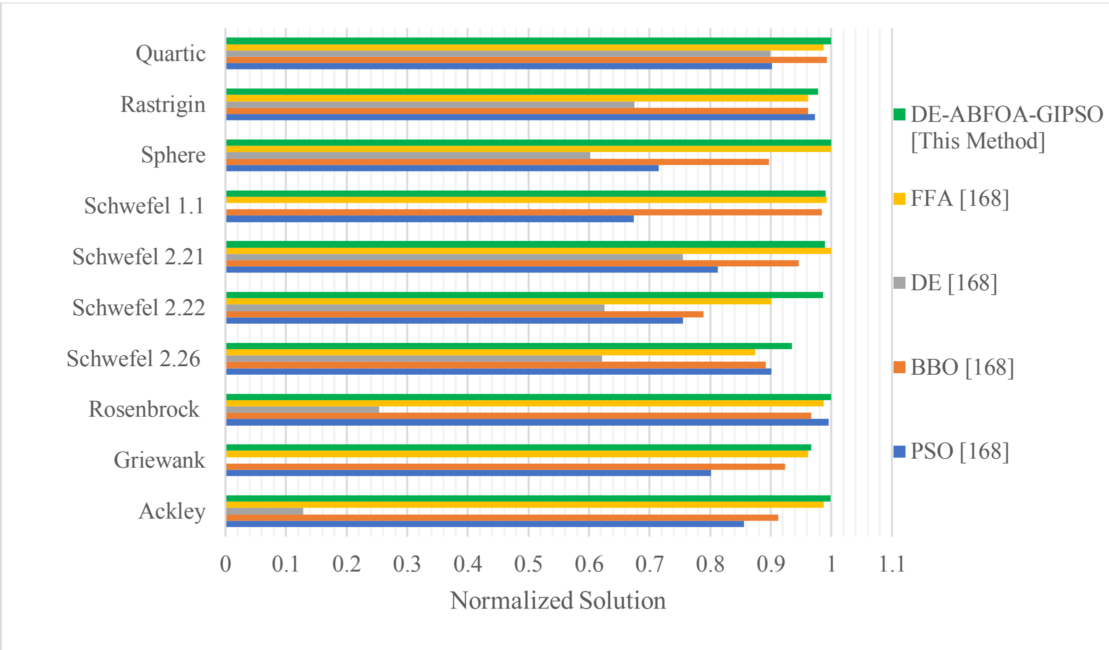


Figure 3-2: Normalized Best Results Comparison

3.3.2 Constrained Engineering Test Problems

The testing of the algorithm performance having shown promising results for the high dimensional standard benchmark functions was extended to selected representative constrained engineering optimization problems. Two constrained engineering problems have frequently been used in open literature to test effectiveness of developed optimization algorithms. These two problems are the pressure vessel design and spring design. Just like in the practical power system expansion planning problem, these test problems are non-linear in nature and constrained in definite operating regions and parameters bounds/limits.

3.3.2.1 Pressure Vessel Design Optimization

Equation (3.23) gives the cost function of the pressure vessel design optimization problem as given in [93].

$$Cost(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^3 + 3.1661x_1^2x_4 + 19.84x_1^2x_3 \tag{3.23}$$

The equation is minimized subject to constraints (3.24-3.27):

$$f_1(x) = (-x_1 + 0.0193x_3) \leq 0 \tag{3.24}$$

$$f_2(x) = (-x_2 + 0.00954x_3) \leq 0 \tag{3.25}$$

$$f_3(x) = \{-(\pi x_3^2x_4^2) - (\tfrac{4}{3}\pi x_3) + 1296000\} \leq 0 \tag{3.26}$$

$$f_4(x) = (x_4 - 240) \leq 0 \tag{3.27}$$

The thickness of the cylinder and head, x_1 and x_2 respectively are discrete variables and can only take integer multiples of 0.0625 inches while the diameter and length of the vessel, x_3 and x_4 are continuous variables. The bounds for x_1 and x_2 are given by $x_1 \geq 1 \times 0.0625$, $x_2 \leq 99 \times 0.0625$ respectively.

The problem is solved in two regions:

Region I: $x_4 \leq 200$ (3.28)

Region II: $10 \leq x_3 \leq 200$ and $10 \leq x_4 \leq 240$ (3.29)

Tables 3-5 & 3-6 give the statistical result comparison between the developed algorithm and other meta-heuristic based algorithms in regions I & II respectively. The new hybrid algorithm produced better results (minimum design cost) in both optimization regions. In region I, the obtained result of 6059.719 was very close to the true global optimum of 6059.714335048436 as obtained using both Mathematical Analysis and Lagrange Multiplier methods [102]. Compared to results from the other techniques and in relation to the true global optimum, the obtained best solution from DE-ABFOA-GIPSO is a superior quasi-optimal solution.

Table 3-5: Result Comparison for Pressure Vessel Design Optimization Problem - Region I

Parameter	Optimization Algorithm				
	PSO [94]	**GA [95]**	**ACO [96]**	**ES [97]**	**DE-ABFOA-GIPSO [This Method]**
Cost (x)	6059.721	6059.946	6059.726	6059.746	6059.719
f1 (x)	-8.8E-07	-2.02E-05	-1.79E-06	-6.9E-06	1.05E-06
f2 (x)	-0.03588	-0.03589	-0.03588	-0.03588	-0.03588
f3 (x)	-521.857	-546.549	-521.682	-518.735	-524.303
f4 (x)	-63.363	-63.346	-63.362	-63.359	-63.364
x1	0.8125	0.8125	0.8125	0.8125	0.8125
x2	0.4375	0.4375	0.4375	0.4375	0.4375
x3	42.0984	42.0974	42.0984	42.0981	42.0985
x4	176.6372	176.6541	176.6378	176.641	176.6364
Best	**6059.721**	**6059.946**	**6059.726**	**6059.746**	**6059.719**
Mean	6440.379	6177.253	6081.781	6850.005	6082.570
Std Dev.	448.471	130.930	67.242	426.000	45.702

Table 3-6: Result Comparison for Pressure Vessel Design Optimization Problem - Region II

Parameter	Optimization Algorithm				
	PSO [98]	**FFA [99]**	**HS [100]**	**EA [101]**	**DE-ABFOA-GIPSO [This Method]**
Cost (x)	5875.166	5850.383	5852.639	5850.383	5849.728
f1 (x)	-0.00340	-7E-08	-0.00031	-7E-08	-0.00019
f2 (x)	-0.00595	-0.00427	-0.00443	-0.00427	-0.00437
f3 (x)	-506.790	-521.510	-523.682	-521.463	-41.152
f4 (x)	-15.910	-18.635	-18.388	-18.635	-18.586
x1	0.7500	0.7500	0.7500	0.7500	0.7500
x2	0.3750	0.3750	0.3750	0.3750	0.3750
x3	38.6840	38.8601	38.8441	38.8601	38.8504
x4	224.09	221.3655	221.6125	221.3655	221.4136
Best	**5875.166**	**5850.383**	**5852.639**	**5850.383**	**5849.728**
Mean	6032.740	5937.338	6083.339	5925.650	5871.985
Std Dev.	315.149	164.547	140.450	150.534	44.514

3.3.2.2 Tension/Compression Spring Design Optimization Problem

Equation (3.30) gives the cost function for the spring design optimization problem while equations (3.31-3.34) give the associated constraints [93].

$$Cost(x) = (x_3 + 2)x_2x_1^2 \tag{3.30}$$

$$f_1(x) = \{1 - (\frac{x_2^3x_3}{7178x_1^4})\} \leq 0 \tag{3.31}$$

$$f_2(x) = \{(\frac{4x_2^2 - x_1x_2}{12566(x_2x_1^3) - x_1^4}) + \left(\frac{1}{5108x_1^2}\right) - 1\} \leq 0 \tag{3.32}$$

$$f_3(x) = \{1 - (\frac{140.45x_1}{x_2^2x_3})\} \leq 0 \tag{3.33}$$

$$f_4(x) = \{\frac{(x_1 + x_2)}{1.5} - 1\} \leq 0 \tag{3.34}$$

The simple bounds for the spring design problem are given by:

$$0.05 \leq x_1 \leq 2.0,\ 0.25 \leq x_2 \leq 1.3 \text{ and } 2.0 \leq x_3 \leq 15.0 \tag{3.35}$$

Table 3-7 gives the comparison between the best solution of the developed DE-ABFOA-GIPSO algorithm and those obtained by various researchers using other metaheuristic-based algorithms. The results from the developed algorithm were superior to those from five different optimization techniques. However, the obtained result of 0.012666 was very close to that obtained by C. Yuksel & K. Hakan (0.012667) using Firefly Algorithm [118]. The best solution obtained by DE-ABFOA-GIPSO algorithm is less (minimum) compared to all those obtained by other reviewed techniques in this minimization optimization problem. Therefore, it can be deduced that the proposed algorithm's solution is closer to the true global optimum than the rest.

Table 3-7: Result Comparison for Tension/Compression Spring Design Optimization Problem

Parameter	Optimization Algorithm					
	GA [114]	PSO [115]	ES [116]	DE [117]	FFA [118]	DE-ABFOA-GIPSO [This Method]
Cost (x)	0.012705	0.012675	0.012698	0.012748	0.012667	0.012666
f1 (x)	-9.034065	-9.008948	-9.018026	-9.000686	-9.001002	-8.990954
f2 (x)	-0.135661	-0.134066	-0.135133	-0.122109	-0.134734	-0.134904
f3 (x)	-4.026318	-4.051307	-4.039301	-4.149707	-4.050127	-4.054598
f4 (x)	-0.731239	-0.727085	-0.728665	-0.689903	-0.728850	-0.728270
x1	0.051480	0.051728	0.051643	0.053862	0.051623	0.051665
x2	0.351661	0.357644	0.355360	0.411284	0.355102	0.355930

Parameter	Optimization Algorithm					
	GA [114]	PSO [115]	ES [116]	DE [117]	FFA [118]	DE-ABFOA-GIPSO [This Method]
x3	11.632201	11.244543	11.397926	8.684380	11.385602	11.331890
Best Solution	**0.012705**	**0.012675**	**0.012698**	**0.012748**	**0.012667**	**0.012666**

3.4 Chapter Conclusion

In this chapter, a new methodology for solving constrained optimization problems was formulated. A systematic procedure used in formulating an adaptive hybrid algorithm in which Differential Evolution (DE) & Bacterial Foraging Optimization Algorithm (BFOA) were hybridized and adapted using both Genetic and Swarm Intelligence operators was outlined. The developed algorithm was tested using the Standard Benchmark Functions and produced superior results. It produced more accurate results than other meta-heuristic methods in eight of the ten high dimensional functions (F1-F10) used. Having produced promising results on the Standard Benchmark Functions the developed algorithm was tested on constrained engineering optimization problems.

The algorithm outperformed other meta-heuristic optimization methods in the two constrained engineering problems solved (Pressure vessel design and tension/compression spring design problem). In the pressure vessel design optimization problem, the obtained result of 6059.719 (region I) was the closest to the true global optimum of 6059.714335048436 obtained using both Mathematical analysis and Lagrange multiplier methods [102]. Likewise, in the tension/compression spring design optimization problem DE-ABFOA-GIPSO produced the minimum solution at 0.012666, very close to 0.012667 obtained by C. Yuksel & K. Hakan using Firefly Algorithm [118]. The results obtained show that the developed adaptive Differential Evolution/Bacterial Foraging Optimization hybrid algorithm (DE-ABFOA-GIPSO) performs better in solving most complex constrained optimization problems. Based on this verification and validation, the developed algorithm was applied in solving the highly dimensional, quite complex and non-linear power system expansion optimization problem as discussed in Chapters 4 and 5.

4 CHAPTER 4: TC-GEP IN INTERMITTENT RES ENVIRONMENT

4.1 Introduction to Transmission Constrained Generation Expansion Planning (TC-GEP)

The Generation Expansion Planning (GEP) problem has been solved in various literature as discussed in Chapter 2. As previously stated, traditionally, single-bus approaches were employed in generation expansion planning. Figure 4-1 gives an illustration of these models where a single node (bus) connection is assumed for all generators. This simplifies the computations by ignoring all constraints related to transmission network [29].

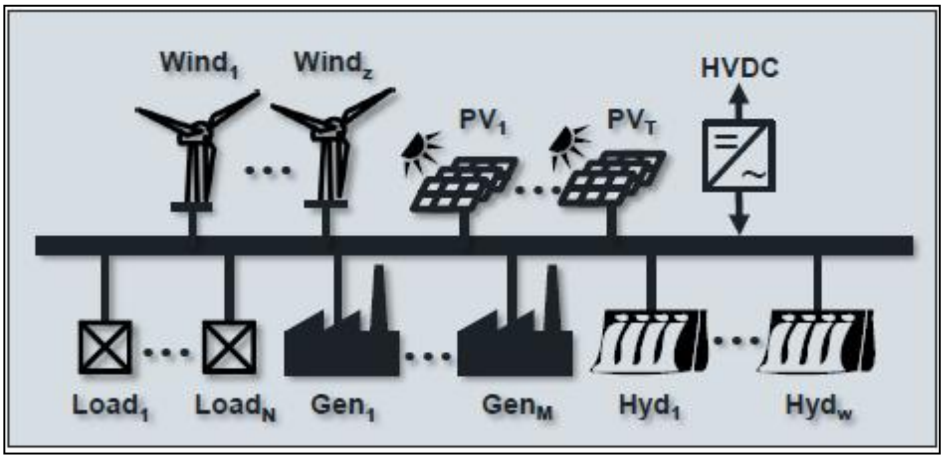


Figure 4-1: Single Busbar Model Representation [29]

With this single-bus approach, the congestion of the required transmission network and the losses in it are not taken into account. The transmission technical and economic constraints that may influence the overall expansion planning are also neglected. These assumptions are not practical in real world and thus they greatly reduce the precision of the problem solution [7].

On the other hand, the multi-bus approach allows for generators and loads in the system to be distributed and allocated in different buses making the generation expansion problem as practical as possible. Here, the transmission related constraints as well as the O&M costs for each geographical area, the interconnection costs and the cost of land among other features can be incorporated in the problem more accurately resulting to a near ideal solution. This multi-bus representation gives rise to the Transmission Constrained Generation Expansion Problem (TC-GEP) in the event that the transmission network is not being expanded in concurrency with the generators [7].

4.2 Classical TC-MOGEP Optimization using DE-ABFOA-GIPSO

In this thesis, the proposed algorithm was first used in solving a classical TC-MOGEP problem in which the formulation was based on DC power flow models and without considering RES penetration. This was important so as to investigate the performance of the proposed DE-ABFOA-GIPSO algorithm in solving power system planning optimization problems. Afterwards, the TC-MOGEP problem was formulated and solved taking into account the AC power flow and RES penetration.

The classical TC-MOGEP problem is mathematically represented as [7]:

$$Min\ (C_{TOTAL}) = Min\ \{C_1(x), C_2(x), C_3(x)\} \tag{4.1}$$

Where $C_1(x)$ represents the cost of investment, C_{Inv} and fixed cost operation, C_f which are power (MW) related. $C_2(x)$ represents the variable cost of operation, C_v including fuel, emissions and system losses and are energy (MWh) dependent. $C_3(x)$ takes account of the cost of not meeting the demand at any time (cost of energy not served, C_{ENS}).

For a dynamic GEP problem these costs can be given by;

$$C_{Inv} = \sum_{t=1}^{T}(1+d)^{-t}\sum_{q=1}^{Q}\varepsilon_{q,t}P_{q,t}(IC_q - S_q) \tag{4.2}$$

$$C_f = \sum_{t=1}^{T}(1+d)^{-t}\left\{\sum_{e=1}^{E}P_{k,t}FC_k + \sum_{q=1}^{Q}\varepsilon_{q,t}P_{q,t}FC_q\right\} \tag{4.3}$$

$$C_v = \sum_{t=1}^{T}(1+d)^{-t}\sum_{l=1}^{L}\left\{\begin{matrix}\sum_{e=1}^{E}\mu_{e,l,t}(H_{l,t}G_{e,l,t}VC_e+\lambda_e Emi(H_{l,t}G_{e,l,t}))\\ +\sum_{q=1}^{Q}\mu_{q,l,t}(H_{l,t}G_{q,l,t}VC_q+\lambda_q Emi(H_{l,t}G_{q,l,t}))\end{matrix}\right\} \tag{4.4}$$

$$C_{ENS} = \sum_{t=1}^{T}\sum_{l=1}^{L}(1+d)^{-t}H_{l,t}DNS_{l,t}C_{(DNS),l,t} \tag{4.5}$$

$$DNS_{l,t} = D_{max,l,t} - \{\sum_{e=1}^{E}\mu_{e,l,t}G_{e,l,t} + \sum_{q=1}^{Q}\mu_{q,l,t}\,G_{q,l,t}\} \tag{4-6}$$

Where;

- d is the interest rate used for discounting, T is the total number of years in the planning horizon, L is the total number of load blocks in each year and H_l is the number of hours in load block l. DNS_l is the unmet demand in MW in load block l, $C_{(DNS),l}$ is the cost of not satisfying the demand for load block l while $D_{max,l}$ is the maximum demand at period l.
- E & Q is total number of existing and new generation investment options available in the planning period, ε_q, IC_q & S_q represent the investment decision (0,1), investment and the

salvage costs per MW of new unit type q, P_t & G_l represent the maximum available plant capacities in MW in year t and the committed capacities in each load block respectively.

- FC_e & FC_q, VC_e & VC_q, λ_e & λ_q are the fixed operational and maintenance cost per MW, variable cost per MWh, emission cost factors existing and new generation units respectively
- $\mu_{e,l}$, & $\mu_{q,l}$, $G_{e,l}$, & $G_{q,l}$, $C_{(ED)e,l}$ & $C_{(ED)q,l}$, $Emi(H_l G_{e,l})$ & $Emi(H_l G_{q,l})$ are the unit commitment decisions (0,1), committed capacities, fuel costs per MWh (if not included in the variable cost), emissions from committed existing and new units in load block l respectively.

The multi-objective function in Equation (4.1) is minimized subject to the following constraints:

$$(1 + x_{res,l,t})D_{max,l,t} \leq \sum_{\substack{e=1\\q=1}}^{E,Q}(\mu_{e,l,t}G_{e,l,t} + \mu_{q,l,t}G_{q,l,t}) \tag{4.7}$$

$$0 \leq P_{q,t}^{invest} \leq P_{q,t}^{max} \quad for\, \forall t, \forall q \in (Q) \tag{4.8}$$

$$G_{g,min} \leq G_g \leq G_{g,max} \quad , \forall g \in (E, Q) \tag{4.9}$$

Equations (4.7) to (4.9) represent the reserve constraints, plant capacity and plant generation limits respectively. In addition to the constraints in equations (4.7) to (4.9), DC power flow analysis is adopted in formulating the transmission constraints as given in equations (4.10) to (4.13) and Appendix B.

$$P_{ij,t} = -b_{ij}(\theta_{i,t} - \theta_{j,t}) \;\; , \;\forall t \;\&\; i,j \in nb \tag{4.10}$$

$$PG_{j,t} + \sum_i^{nb} P_{ij,t} - \sum_i^{nb} PL_{ij,t} = PD_{j,t} \;\; , \;\forall t, j \in nb \tag{4.11}$$

$$P_{ij,l,t} \leq P_{ij,max} \, , \;\; \forall l, \;\forall t \;\&\; i,j \in nb \tag{4.12}$$

$$\sum_g^G PG_{g,t} = \sum_i^{nb} PD_{i,t} + \frac{1}{2}\sum_i^{nb}\sum_j^{nb} PL_{ji,t} \, , \;\forall t, \;\; G \in (E, Q) \tag{4.13}$$

Where nb is the total number of buses, b_{ij} is the ij^{th} susceptance while θ_i & θ_j are the i^{th} and j^{th} bus voltage phase angles. P_{ij} and PL_{ji} represent power flow and system active power losses in ij^{th} transmission corridor (branch), PG_j and PD_j are the total generation and electricity demand at the j^{th} node/bus and PG_g is the generation output of the g^{th} generation unit.

Equations (4.10) to (4.13) give the power flow representation, nodal balance constraint, branch thermal limits and power balance constraints respectively.

The formulated TC-MOGEP optimization problem was solved using the proposed solution methodology and compared to results obtained by other researchers in [2]. The comparison works were based on IEEE Six-Bus Test System and thus it was adopted in this analysis. The network configuration is as given in Figure 4-2.

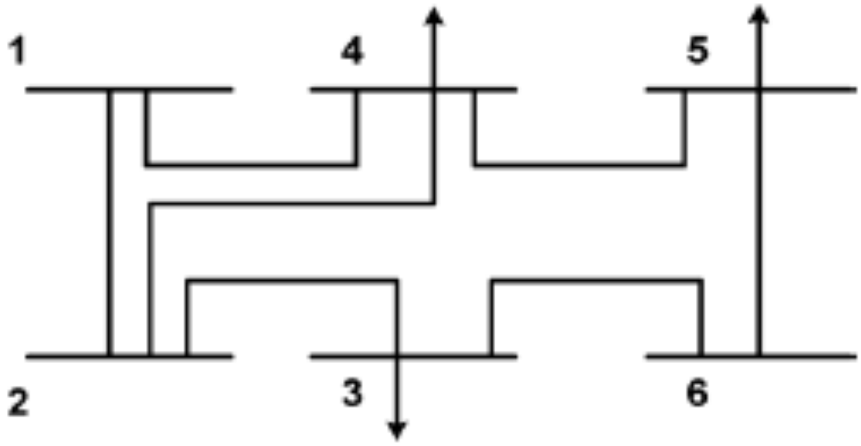


Figure 4-2: Single Line Representation of IEEE 6-Bus Test System [2]

System load is distributed among buses 3, 4 and 5 in the ratios of 40%, 30% and 30% respectively. This study assumed a one-year planning horizon with the load curve approximated into five load segments (load blocks) of 1510hrs, 2800hrs, 2720hrs, 1120hrs and 610hrs whose respective system load factors are 50%, 65%, 80%, 90% and 100%. Additional system data for the six-bus test system is given in [2] and Appendix A.1. This includes details on data on existing transmission network, existing and candidate generator capacities, costs, outage rates etc.

Starting with an annual system peak load of 30MW, a load growth of 5MW was adopted in order to test the dynamics of the system requirements at different loading. This assisted in determining the maximum amount of load that the system can supply when considering GEP only without transmission investments. After getting an infeasible solution, the peak load was reduced by 1MW stepwise to determine the maximum allowable peak load.

4.2.1 TC-MOGEP Optimization Results and Discussions

Based on the TC-MOGEP formulation above and the network data given in Appendix A.1, the parameters given in Table 4-1 were adopted for the optimization.

Table 4-1: TC-MOGEP Parameter Mapping

Parameter Meaning	Symbol	Value
Number of existing generators	E	4
Number of new generator units	Q	13
Planning Horizon	T	1 (with 5MW load increments)
Number of Load blocks	L	5
Transmission line loading limit	$P_{ij,max}$	100% (No contingency) 120% (N-1 contingency)
Generator minimum output limits	P_{min}	0
Generator maximum output limits	P_{max}, & $P_{j,i,t}^{max}$	100% of capacity
Generation Reserve Margin	$x_{res,l,t}$	10MW (calculated)

The DE-ABFOA-GIPSO parameters discussed and presented in Chapter 3 were employed in this optimization process. Three scenarios were studied:

4.2.1.1 Scenario A: TC-MOGEP Assuming No System Contingencies and Ignoring Spinning Reserve Requirements in the System.

In this scenario, system contingencies were ignored. Both generator and transmission line forced outage rates (FOR) were equal to zero. Therefore, in each optimization step, all existing and committed generation units and transmission lines were assumed available.

Table 4-2 gives a comparison between the results obtained using the proposed methodology and those obtained using other techniques including BFOA, one of the best performing meta-heuristic algorithms [80]. In the initial case of 30MW, even with the all the existing generators available there was an overload of 16% observed on the transmission line section between buses 2 & 3 at system peak. Therefore, the proposed algorithm committed a generator at bus 6 (B8) to control this overload. Other than at the initial case of 30MW and at 35MW (in which additional generators were committed to mitigate overloads), the proposed methodology produced better results (least cost expansion plans) as compared to those of BFOA and MILP_PM (Mixed Integer Liner Programming-based Probabilistic Model) [2]. The existing transmission network was able to accommodate up to 52MW while considering generation expansion options only (without constructing any new lines). Above this amount of annual peak load, reinforcement of the transmission network is required. This value is very close to the 53.328MW obtained in [2].

Table 4-2: TC-MOGEP Results Comparison _ Scenario A

Annual Peak Load	*TC-MOGEP Methodology*	*Constructed Generators*	*No. of generators constructed*	*Total Cost (10^6\$)*
30MW	MILP_PM [2]	-	0	5.035
	BFOA	B8	1	5.102
	DE_ABFOA_GIPSO	B8	1	5.102
35MW	MILP_PM [2]	B5	1	6.461
	BFOA	B3,B4,B5	3	6.865
	DE_ABFOA_GIPSO	B4,B7	2	6.543
40MW	MILP_PM [2]	A5,B4,B5	3	7.682
	BFOA	B3,B4,B5	3	7.053
	DE_ABFOA_GIPSO	B3,B4,B7	3	6.853
45MW	MILP_PM [2]	A5,B3,B5	3	8.884
	BFOA	A5,B3,B4,B5	4	9.001
	DE_ABFOA_GIPSO	B3,B4,B6	3	8.625
50MW	MILP_PM [2]	A1,A5,B2, B3,B4,B5	6	10.860
	BFOA	A5,B1,B2, B3,B4,B6,B7	7	10.335
	DE_ABFOA_GIPSO	A5,B1,B2, B3,B4,B7	6	9.710
52MW	BFOA	A5,B1,B2, B3,B4,B6,B7	7	10.478
	DE_ABFOA_GIPSO	A5,B1,B2, B3,B4,B7,B8	7	9.807
55MW	MILP_PM [2]	infeasible	infeasible	infeasible
	BFOA	infeasible	infeasible	infeasible
	DE_ABFOA_GIPSO	infeasible	infeasible	infeasible

Figure 4-3 shows the cost comparison for the three TC-GEP optimization approaches studied. The comparison covers expansion costs from 30MW to 50MW load level where all the solution techniques were feasible. The proposed DE_ABFOA_GIPSO methodology reduced the cumulative TC-GEP expansion cost by approximately 5% and 4% in comparison to MILP_PM and BFOA based approaches respectively.

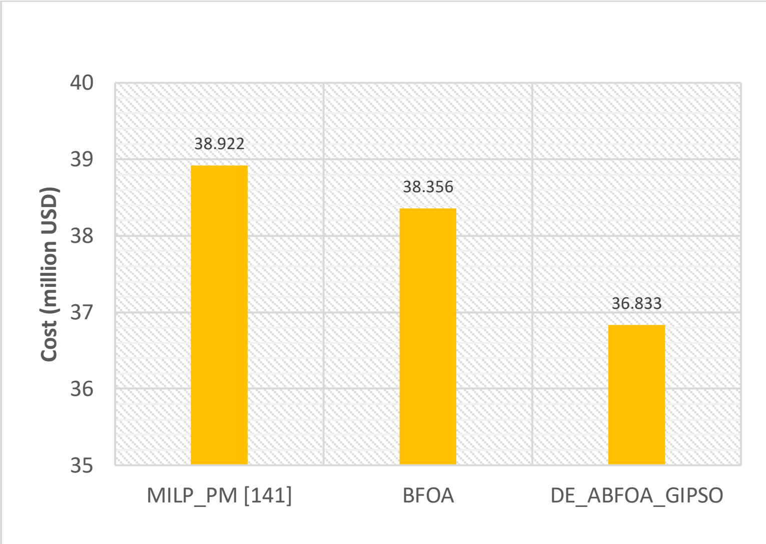


Figure 4-3: Cumulative Cost Comparison (Up to 50MW load)

Table 4-3 gives the obtained line loadings in each expansion plan at peak load. There were no overloads in all the transmission line sections up to a peak load of 52MW. At this load an additional generator B8 was committed in Bus 6. This increased the flow of power from Bus 6 to the loads in Buses 5 (TE6) and 3 (TE7) considerable while reducing the flow between Buses 4 and % (TE5) to only 1%. TE2 (corridor 2-3) and TE6 (corridor 5-6) were loaded at 100% at this peak load. Above this load, the proposed algorithm could not give any feasible expansion plans no matter the number of generators committed. This was due to transmission network constraints; majorly thermal limit violations.

Table 4-3: Bus Voltages for Scenario A

Line	Corridor	Percentage Loading at Annual Peak Load					
		30MW	35MW	40MW	45MW	50MW	52MW
TE1	1-2	23	16	18	27	27	28
TE2	2-3	96	85	95	98	98	100
TE3	1-4	82	77	74	90	90	89
TE4	2-4	79	81	74	84	84	83
TE5	4-5	33	8	24	20	2	1
TE6	5-6	96	99	81	98	98	100
TE7	3-6	4	44	62	88	45	72

4.2.1.2 Scenario B: TC-MOGEP Taking into Account System Contingencies while Ignoring Spinning Reserve Requirements in the System.

This scenario considers both generator and line forced outage rates (FOR) in coming up with the feasible expansion plans especially in the calculation of the unserved energy (DNS_l) and in checking adherence to transmission constraints. A probabilistic approach was employed to analyze N-1 contingency situation in which the second and third terms in Equation (4.1) were given by:

$$Operational\ Cost = C_2(x) = \rho_0 C_v + \rho_1 C_v \tag{4.14}$$

$$Cost\ of\ EENS = C_3(x) = \rho_1 \sum_{l=1}^{L} H_l DNS_l C_{(DNS),l} \tag{4.15}$$

Where ρ_0 and ρ_1 represent the probability for no contingency and that for occurrence of N-1 contingency. The scenario ignored spinning reserve requirements. A 120% loading limit was used for all transmission lines under contingency situation.

Table 4-4 gives the TC-GEP result comparison between proposed methodology and MILP_PM [2] for this scenario. The consideration of the N-1 contingencies resulted to increase in the investment cost of generators since more units needed to be committed to supplement any single element outage in the network.

The results obtained matched very closely to those obtained in [2]. In some cases, the results were the same though in most of the annual peak load cases considered the proposed methodology produced least cost results. It is however important to note that the proposed methodology could not produce results for 50MW annual peak load and above due to the overloads expected on some line sections during N-1 contingencies.

Table 4-4: TC-MOGEP Results Comparison _ Scenario B

Annual Peak Load	*TC-MOGEP Methodology*	*Constructed Generators*	*No. of generators constructed*	*Total Cost (10^6\$)*
30MW	MILP_PM [2]	A4,A5,B4,B8	4	6.355
	DE_ABFOA_GIPSO	B2,B3,B4,B8	4	6.215
35MW	MILP_PM [2]	A5,B2,B3, B4,B8	5	7.259
	DE_ABFOA_GIPSO	A5,B2,B3, B4,B8	5	7.259

Annual Peak Load	*TC-MOGEP Methodology*	*Constructed Generators*	*No. of generators constructed*	*Total Cost (10^6\$)*
40MW	MILP_PM [2]	A5,B2,B3, B4,B5,B8	6	8.525
	DE_ABFOA_GIPSO	A5,B1,B2,B3, B4,B8	6	8.420
45MW	MILP_PM [2]	A5,B1,B2,B3 B4,B5,B8	7	9.911
	DE_ABFOA_GIPSO	A5,B1,B2,B3, B4,B6,B8	7	9.562
50MW	MILP_PM [2]	A5,B1,B2,B3 B4,B5,B8	7	11.69
	DE_ABFOA_GIPSO	Infeasible	infeasible	Infeasible
55MW	MILP_PM [2]	Infeasible	infeasible	Infeasible
	DE_ABFOA_GIPSO	Infeasible	infeasible	Infeasible

Figure 4-4 gives the cumulative TC-MOGEP cost comparison for zero and N-1 contingency cases up to the 45MW load level. Considering N-1 contingency increased the DE_ABFOA_GIPSO optimized cumulative expansion cost by 16% from 27.12 million USD (zero contingency) to 31.46 million USD. However, even with N-1 contingency criterion, DE_ABFOA_GIPSO optimized TC-MOGEP results had lower investment cost requirements compared to MILP_PM costs of 32.05 million USD in the same load range. This represents a cost reduction of approximately 2%.

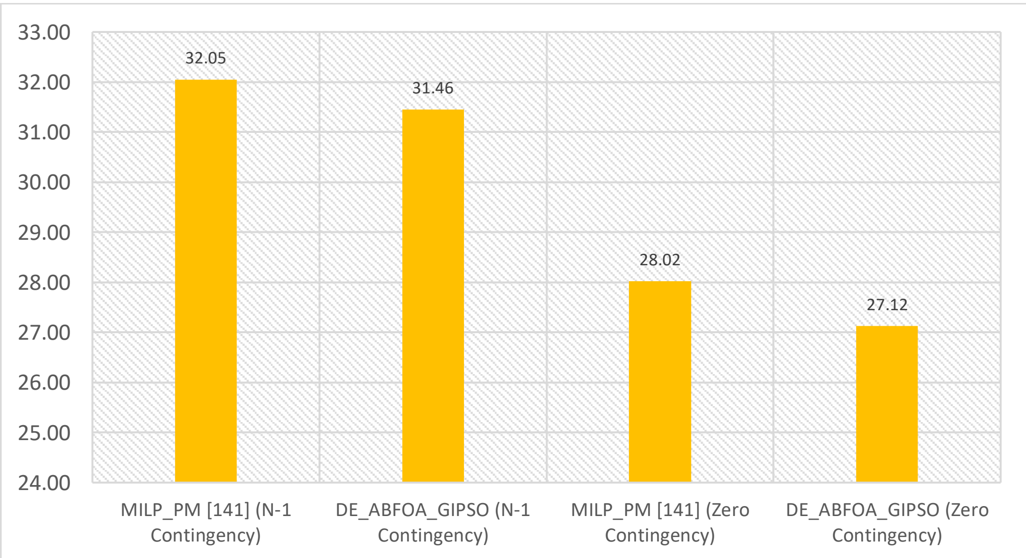


Figure 4-4: Zero and N-1 Cost Comparison (Up to 45MW load)

4.2.1.3 Scenario C: TC-MOGEP Taking into Account System Contingencies and Spinning Reserve Requirements in the System.

This scenario considers both the effect of the system contingencies and the spinning reserve requirements. Though the research work used for validation in Tables 4-2 & 4-4 as given in [2] considered N-1 contingency, spinning reserve requirements were ignored. The spinning reserve [29] is calculated using Equation (4.16) and applied in calculating the constraint given in Equation (4.7).

$$R_{sp} = max\begin{cases} R_{peak} \\ P_{gen\_max} \end{cases} \tag{4.16}$$

$$R_{peak} = \{\sqrt{(10L + 150^2)} - 150\} \tag{4.17}$$

Where, L is the annual peak load and P_{gen_max} is the largest generating unit in service during peak load. Table 4-5 gives the results obtained in this scenario. There were no changes in the results previously obtained in scenario B (accounting for N-1 contingency while ignoring reserve requirements). This is because in all the expansion plans obtained in scenario B there was an excess committed generation of more than 10MW, the required spinning reserve as given by equation (4.16).

Table 4-5: TC-MOGEP results for Scenario C

Annual Peak Load	*Constructed Generators*	*No. of generators constructed*	*Total Cost (10^6\$)*
30MW	B2,B3,B4,B8	4	6.215
35MW	A5,B2,B3, B4,B8	4	7.259
40MW	A5,B1,B2,B3, B4,B8	6	8.420
45MW	A5,B1,B2,B3, B4,B6,B8	7	9.562
50MW	infeasible	infeasible	infeasible
55MW	infeasible	infeasible	infeasible

4.3 AC Power Flow-based TC-MOGEP Optimization Considering Intermittent RES

Figure 4-5 represents a possible power balance representation when evaluating the penetration of intermittent RES in the system.

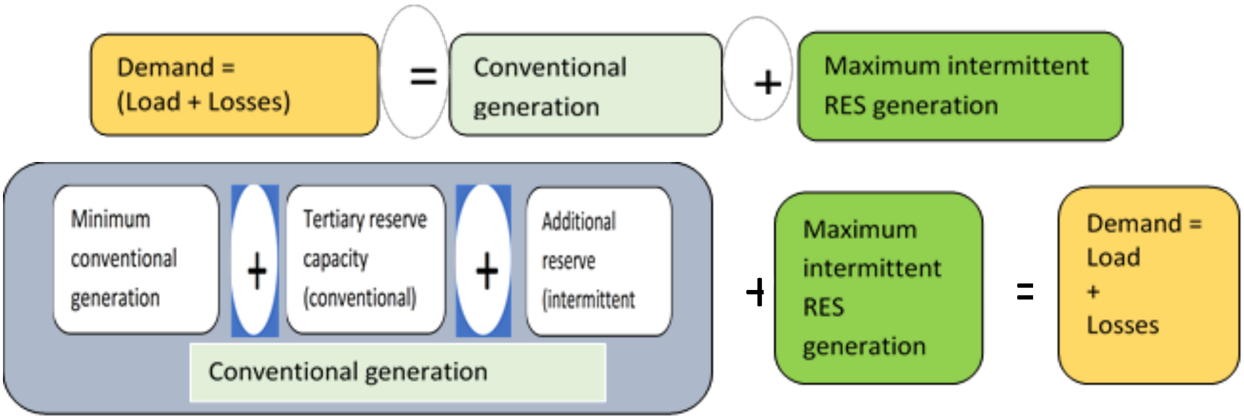


Figure 4-5: Power Balance Representation

The reserve requirements in presence of intermittent RES are evaluated as [29];

$$R_{sp}^{res} = max\begin{cases} R_{peak} \\ P_{gen\_max} \\ E_{f\_total\_max} \end{cases} \tag{4.18}$$

The formula in Equation (4.18) is very optimistic, for a more pessimistic evaluation the possibility of having maximum forecast error and generator outage concurrently is formulated as;

$$R_{sp}^{res} = max\begin{cases} (R_{peak} + E_{f\_total\_\max}) \\ (P_{gen\_max} + E_{f\_total\_\max}) \end{cases} \tag{4.19}$$

With;

- $R_{peak} = \{\sqrt{(10L + 150^2)} - 150\}$ is the recommended value for the secondary reserve in MW during peak load as given in [55];
- P_{gen_max} is the largest generating unit in service during peak load;
- $E_{f\_total\_max}$ is the maximum forecast error in MW.

For a dynamic GEP problem taking into account intermittent RES and emissions the optimization problem is formulated as;

$$C_{TOTAL} = C_{inv} - C_{sal} + C_f + C_v + C_{ENS} \tag{4.20}$$

Where;

$$C_{inv} = \sum_{t=1}^{T}(1+d)^{-t}\{\sum_{q=1}^{Q} \varepsilon_{q,t}P_{q,t}(IC_q - S_q) + \sum_{r=1}^{R} \varepsilon_{r,t}RES_{r,t}(IR_r - S_r)\} \tag{4.21}$$

$$C_f = \sum_{t=1}^{T}(1+d)^{-t}\{\sum_{e=1}^{E} P_{e,t}FC_e + \sum_{q=1}^{Q} \varepsilon_{q,t}P_{q,t}FC_q + \sum_{r=1}^{R} \varepsilon_{r,t}RES_{r,t}FC_r\} \tag{4.22}$$

$$C_v = \sum_{t=1}^{T} \sum_{l=1}^{L} (1+d)^{-t} \left\{ \begin{array}{c} \sum_{e=1}^{E} \mu_{e,l,t} (H_{l,t} G_{e,l,t} VC_e + \lambda_e Emi(H_{l,t} G_{e,l,t})) \\ + \sum_{q=1}^{Q} \mu_{q,l,t} (H_{l,t} G_{q,l,t} VC_q + \lambda_q Emi(H_{l,t} G_{q,l,t})) \\ + \sum_{r}^{R} \mu_{r,l,t} (H_{l,t} RES_{r,l,t} VC_r + \lambda_r Emi(H_{l,t} RES_{r,l,t})) \end{array} \right\} \tag{4.23}$$

$$C_{ENS} = \sum_{t=1}^{T} \sum_{l=1}^{L} (1+d)^{-t} H_{l,t} DNS_{l,t} C_{(DNS),l,t} \tag{4.24}$$

The variable O&M cost is expanded to include the economic dispatch, $\mathrm{C}_{(ED)}$ (fuel cost), the unit commitment, $\mathrm{C}_{(UC)}$ (start-up and shut-down costs), variable maintenance cost, $C_{(M)}$ and the emission cost, $C_{(Emi)}$ separately as;

$$C_v = \sum_{t=1}^{T} \sum_{l=1}^{L} (\mathrm{C}_{(ED)l,t} + \mathrm{C}_{(UC)l,t} + C_{(M)l,t} + C_{(Emi)l,t}) \tag{4.25}$$

Where the unit commitment cost is calculated as given in Equation (4.26);

$$C_{(UC)} = \sum_{t=1}^{T} \sum_{l=1}^{L} (1+d)^{-t} \left\{ \begin{array}{c} \sum_{e=1}^{E} (su_{e,l,t}\, C_{(ST)e,l,t} + sd_{e,l,t}, C_{(SD)e,l,t}) \\ + \sum_{q=1}^{Q} (su_{q,l,t}\, C_{(ST)q,l,t} + sd_{q,l,t}, C_{(SD)q,l,t}) \\ + \sum_{r}^{R} (su_{r,l,t}\, C_{(ST)r,l,t} + sd_{r,l,t}, C_{(SD)r,l,t}) \end{array} \right\} \tag{4.26}$$

In cases where the emission rates of the existing and candidate generating units are known then the emission cost are calculated as;

$$C_{(Emi)Total} = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{x=1}^{X} (1+d)^{-t} \left\{ \begin{array}{c} \sum_{e=1}^{E} \mu_{e,l,t} \lambda_e \big(H_{l,t} G_{e,l,t} Emi_{e,x}\big) + \\ \sum_{q=1}^{Q} \mu_{q,l,t} \lambda_q \big(H_{l,t} G_{q,l,t} Emi_{q,x}\big) + \\ \sum_{r=1}^{R} \mu_{r,l,t} \lambda_r (H_{l,t} RES_{r,l,t} Emi_{r,x}) \end{array} \right\} \tag{4.27}$$

Where;

- *E, Q* and *R* are the total number of existing units, new conventional and new intermittent RES generation units committed in the planning horizon respectively;
- $C_{(ED)e,l,t}$, $C_{(ED)q,l,t}$ and $C_{(ED)r,l,t}$ are the fuel costs per MWh for existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* in load block *l* in the t^{th}planning period if not included in the variable cost;
- $su_{e,l,t}$, $su_{q,l,t}$ and $su_{r,l,t}$ are the total number of start-up decisions for existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* in load block *l* in the t^{th}planning period;
- $sd_{e,l,t}$, $sd_{q,l,t}$ and $sd_{r,l,t}$ are the total number of start-up decisions for existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* in load block *l* in the t^{th}planning period;

- $C_{(ST)e}$, $C_{(ST)q}$ and $C_{(ST)r}$ are the start-up costs per incidence for existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* respectively;
- $C_{(SD)e}$, $C_{(SD)q}$ and $C_{(SD)r}$ are the shut down costs per incidence for existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* respectively;
- λ_e, λ_q and λ_r are respective emission cost factors for emissions from existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* respectively.
- *X* is the total number of emission types considered;
- $Emi_{e,x}$, $Emi_{q,x}$ and $Emi_{r,x}$ are the emission rates for emission type *x* per MWh generated from existing conventional unit type *e,* new conventional unit type *q* and new intermittent RES type *r* respectively.

Employing AC-power flow model formulation in an intermittent RES environment, the above objective function is minimized subject to the below constraints in addition to the previous ones in Equations (4.9, 4.11 & 4.38):

$$(1 + x_{res,l,t})D_{max,l,t} \leq \sum_{\substack{e=1\\q=1\\r=1}}^{E,Q,R} (\mu_{e,l,t}G_{e,l,t} + \mu_{q,l,t}G_{q,l,t} + \mu_{q,l,t}RES_{r,l,t}) \tag{4.28}$$

$$0 \leq P_{t(g)}^{invest} \leq P_{t(g)}^{max} \quad \text{for } \forall t, \forall g \in (E, Q, R) \tag{4.29}$$

$$P_{t(g)}^{max} = \begin{cases} P_{t(g)}^{max}, & for\ t \leq lifetime_g \\ 0, & for\ t > lifetime_g \end{cases} \quad \forall t \in T \tag{4.30}$$

$$V_{min} \leq V_{i,t} \leq V_{max} \ , \ \forall t, \ \forall i \in nb \tag{4.31}$$

$$\theta_{min} \leq \theta_{i,t} \leq \theta_{max} \ , \ \forall t, \ \forall i \in nb \tag{4.32}$$

$$PG_g^2 + QG_g^2 \leq S_{g,max}^2 \ , \ \forall g \in (E, Q, R) \tag{4.33}$$

$$QG_{g,min} \leq QG_g \leq QG_{g,max} \ , \ \forall g \in (E, Q, R) \tag{4.34}$$

$$P_{ij,t}^2 + Q_{ij,t}^2 \leq S_{ij,max}{}^2 \ , \ \forall t, \forall i, j \in nb \tag{4.35}$$

$$0 \leq RES_{r,l,t} \leq cf_{r,l,t}RES_{r,l,t}^{max} \ , \ \forall r \in R \ , \forall l \ \in L \ \& \ \forall t \ \in T \tag{4.36}$$

$$R^{avail}_{sp,l,t} \geq R^{res}_{sp,l,t} \;,\; \forall l \in L \;\&\; \forall t \in T \tag{4.37}$$

$$R^{avail}_{sp,l,t} = min\begin{cases}\sum_{i=1}^{M} \mu_{i,l,t}(\,G_{i,l,t} - G^{min}_{i,l,t}) \\ \sum_{i=1}^{M} \mu_{i,l,t}(G^{max}_{i,l,t} - G_{i,l,t})\end{cases} \text{ for } \forall l \in L, \forall t \in T \text{ and } M \in (E, Q) \tag{4.38}$$

Equations (4.28) to (4.30) represent the reserve constraints, plant investment and retirement constraints. AC power flow constraints are given by nodal voltages and angles constraints in equations (4.31) & (4.32), real and reactive power generation and line flows limits in equations (4.33)-(4.35) while intermittent RES related constraints on available capacities and reserve requirements are given in equations (4.36) to (4.38) respectively. In determining constraints in (4.11), (4.13), (4.35) and other AC-power flow analyses, the real and reactive power flow and power loss for the ij^{th} branch (transmission corridor) of the power system are calculated as given in equations (4.39) to (4.43).

$$P_{ij} = V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_{ij}) - V_i^2 Y_{ij} cos\theta_{ij} \tag{4.39}$$

$$Q_{ij} = -V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_{ij}) + V_i^2 Y_{ij} sin\theta_{ij} - \frac{V_i^2 Y_{sh}}{2} \tag{4.40}$$

$$P_{L(ij)} = g_{ij}(V_i^2 + V_j^2 - 2V_i V_j cos\delta_{ij}) \tag{4.42}$$

$$Q_{L(ij)} = -b^{sh}_{ij}(V_i^2 + V_j^2) - b_{ij}(V_i^2 + V_j^2 - 2V_i V_j cos\delta_{ij}) \tag{4.43}$$

When planning for large electricity networks, computation time may be a challenge due to the increased combinations of possible solutions. In order to improve on the computation time, use of power flow and power loss sensitivity factors in prioritizing the candidate locations for new generators is proposed. In this case the fitness of a bus to be selected as a candidate location for a new generator is proportional to the estimated impact it has on line flows and system losses. The power flow and power loss sensitivity factors are based on the resultant network jacobian matrix as given in Equations (4.44) and (4.45) respectively. Detailed formulation of the sensitivity factors is given in [106] and Appendix C.

$$\begin{bmatrix}\frac{\partial P_{ij}}{\partial P_n} \\ \frac{\partial P_{ij}}{\partial Q_n}\end{bmatrix} = [J^T]^{-1}\begin{bmatrix}\frac{\partial P_{ij}}{\partial \delta} \\ \frac{\partial P_{ij}}{\partial V}\end{bmatrix} \;\&\; \begin{bmatrix}\frac{\partial Q_{ij}}{\partial P_n} \\ \frac{\partial Q_{ij}}{\partial Q_n}\end{bmatrix} = [J^T]^{-1}\begin{bmatrix}\frac{\partial Q_{ij}}{\partial \delta} \\ \frac{\partial Q_{ij}}{\partial V}\end{bmatrix} \tag{4.44}$$

$$\begin{bmatrix} \frac{\partial P_{L(ij)}}{\partial P_n} \\ \frac{\partial P_{L(ij)}}{\partial Q_n} \end{bmatrix} = [J^T]^{-1} \begin{bmatrix} \frac{\partial P_{L(ij)}}{\partial \delta} \\ \frac{\partial P_{L(ij)}}{\partial V} \end{bmatrix} \quad \& \quad \begin{bmatrix} \frac{\partial Q_{L(ij)}}{\partial P_n} \\ \frac{\partial Q_{L(ij)}}{\partial Q_n} \end{bmatrix} = [J^T]^{-1} \begin{bmatrix} \frac{\partial Q_{L(ij)}}{\partial \delta} \\ \frac{\partial Q_{L(ij)}}{\partial V} \end{bmatrix} \tag{4.45}$$

Where;

- $\frac{\partial P_{ij}}{\partial P_n}$ & $\frac{\partial P_{ij}}{\partial Q_n}$ are the real power flow sensitivities in the ij^{th} corridor related to real and reactive power injections in the n^{th} bus respectively.
- $\frac{\partial Q_{ij}}{\partial P_n}$ & $\frac{\partial Q_{ij}}{\partial Q_n}$ are the reactive power flow sensitivities in the ij^{th} corridor related to real and reactive power injections in the n^{th} bus respectively.
- $\frac{\partial P_{L(ij)}}{\partial P_n}$ & $\frac{\partial P_{L(ij)}}{\partial Q_n}$ are the real power loss sensitivities in the ij^{th} corridor related to real and reactive power injections in the n^{th} bus respectively.
- $\frac{\partial Q_{L(ij)}}{\partial P_n}$ & $\frac{\partial Q_{L(ij)}}{\partial Q_n}$ are the reactive power loss sensitivities in the ij^{th} corridor related to real and reactive power injections in the n^{th} bus respectively.

The four sensitivities are column vectors whose dimension is the number of buses in the network under consideration.

4.3.1 TC-MOGEP Optimization in a RE Environment using DE-ABFOA-GIPSO

The formulated TC-MOGEP optimization problem in Section 4.3 was applied on IEEE 6-bus test system and solved using the developed adaptive hybrid meta-heuristic approach formulated and tested in Chapter 3. To discourage selection of candidate GEP plans that do not meet some AC-power flow based transmission constraints (for example voltage or line loading violations) but with converging power flow analysis, a large violation penalty cost was applied. The solution methodology was as illustrated in Figure 4-6.

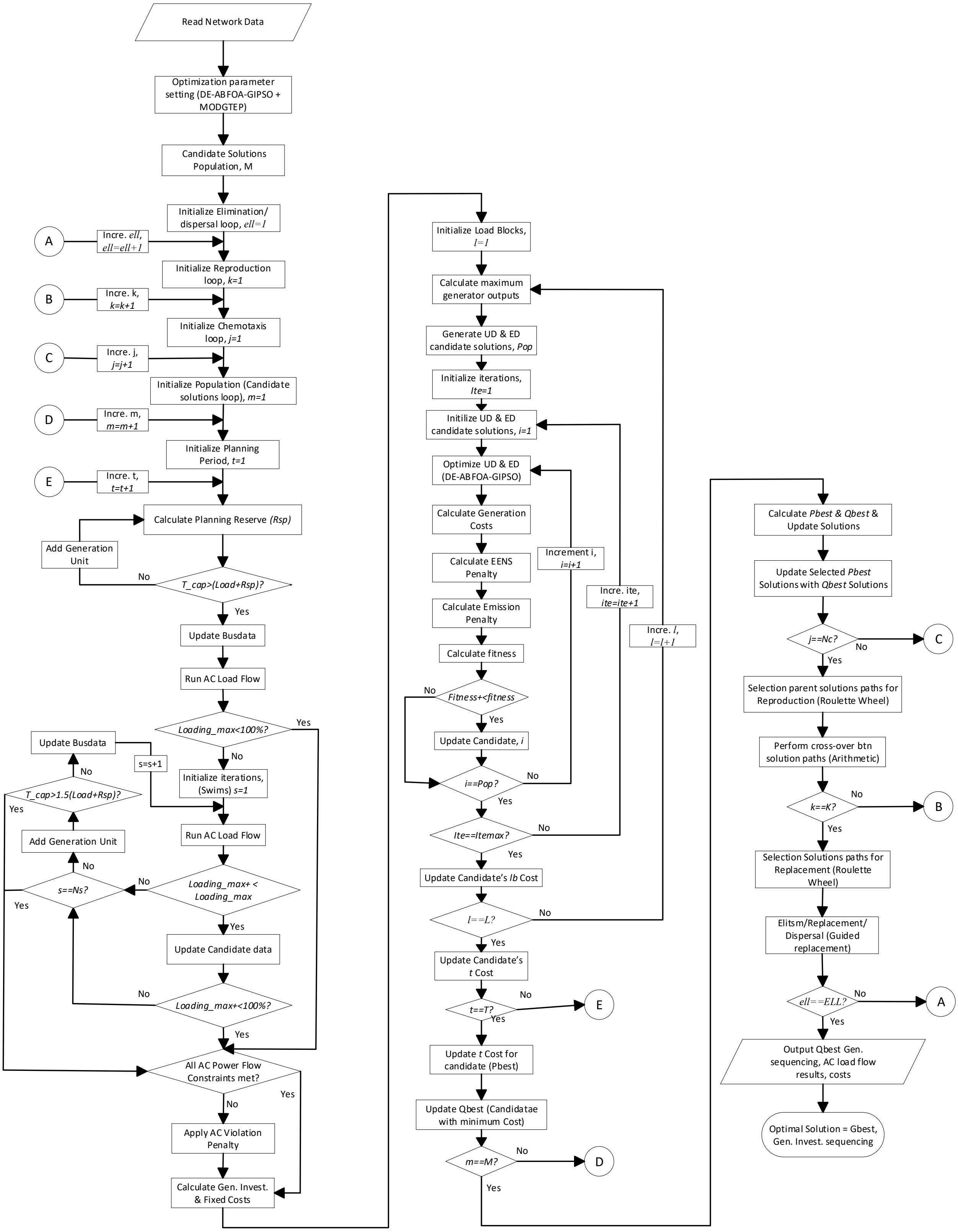


Figure 4-6 : Flow Chart of TC_MODGEP Optimization Methodology

The network configuration and data for the six-bus test system is as described in section 4.2 and detailed in Appendix A.1. To incorporate emission and vRES consideration, the existing and candidate generator data was updated to include typical generator technologies as given in Figure 4-7 and Appendix A.2.

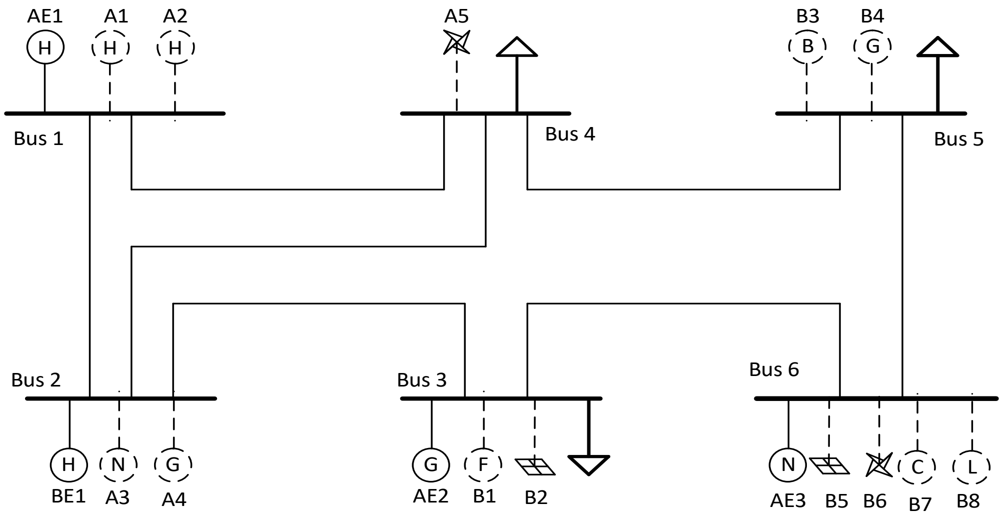


Figure 4-7: IEEE 6-Bus Test System SLD with Candidate vRES

Table 4-6 gives a summary of the generator technology assignment.

Table 4-6 : Generator Technology Assignment

Generator Technology / Load	**Symbol**	**IEEE Six Bus Generator Units**
Hydropower	H	AE1, BE1, A1, A2
Geothermal	G	AE2, A4, B4
Natural Gas	N	AE3, A3
Solar PV		B2, B5
Wind		A5, B6
Coal	C	B7
Biomass	B	B3
HFO Thermal	F	B1
Gasoil Thermal (LFO)	L	B8
Loads		Load in Buses 3,4 & 5
All technologies	———	Existing
All technologies	— — —	Candidate

Average cost factors per technology were obtained from [85] while the emission factors for the different generator technologies were obtained from open literature [37, 119 & 128]. Start up and shut down costs were ignored in the analysis. Several emissions are expected from power generation such has Carbon Dioxide (CO_2), Sulphur Dioxide (SO_2) Nitrogen Oxides (NO_x), particulate matter, and hazardous air pollutants. However, this thesis focused on CO_2 due to its high radiative force (global warming influence) when compared to other environmental pollutants. CO_2 emissions are expected to account for approximately 63% of the cumulative radiative force by year 2025 [130]. The CO_2 emission factors were averages for the entire lifecycle of the given technology covering equipment production, power plant construction and operation as well as decommissioning and disposal. A carbon dioxide cost of 0.035USD/kg was used. This was the average weighted carbon price as at June 2021 [89].

Table 4-7: Costs and Emission Factors per Technology

Generator Technology	Invest Cost (USD/kW)	Fixed O&M Cost (USD/kW/ month)	Variable O&M Cost (USD/MWh)	Fuel Cost (USD/MWh)	CO_2 Emission (kgs/MWh)
Hydropower	3,200	2.25	0.5	0	10
Geothermal	2,100	5.95	10.6	2	122
Natural Gas	860	1.74	12.5	90	433
Solar PV	1,100	2.2	0.5	0	25
Wind	1,750	6.34	0.5	0	11
Coal	2,400	5.75	1.4	50	960
Biomass	3,000	12.5	3.5	5	230
HFO Thermal	1,500	2.63	8.8	85	900
Gasoil Thermal	1,250	1.74	12.5	240	900

The load and transmission network data was as described in Section 4.2, however resistive component of the transmission lines were considered at a quarter of the given reactive component. The updated transmission data is given in Appendix A.2. An average load power factor of 0.95 was adopted. Table 4-8 gives the parameter mapping for the TC-MODGEP optimization problem considering variable RES sources.

Table 4-8: TC-MODGEP Parameter Mapping in vRES Environment

Parameter Meaning	Symbol	Value
Number of buses	nb	6
Number of existing lines	nl	7
Number of existing generators	E	4
Number of candidate Conventional generator units	Q	9
Number of candidate vRES units	R	4
Generator units with reserve provision capability	M	All committed conventional generator units
Projected vRES forecast errors (for all solars & wind plants)	f_{solar} & f_{wind}	15%
Planning Horizon	T	6 years
Annual load growth	D_g	+5MW
Load power factor	pf	0.95
Discount rate	d	10%
Number of Load blocks	L	5
Transmission line loading limit	$S_{ij,max}$	100%
Generator minimum output limits	$PG_{g,min}$	0% for natural gas, HFO, gasoil, biomass, wind & Solar 50% for Geothermal & Coal 25% for Hydropower
Generator maximum output limits	$PG_{g,max}$ & $P_{t(g)}^{max}$	100% of capacity
Voltage limits	V_{min} & V_{max}	$\pm 5\%$
Phase angle limits	θ_{min} & θ_{max}	$\pm 30\%$
Generator power factor	pf_g	± 0.9
Emission penalty (CO_2)	λ	0.035 USD/kg
AC power flow violation Penalty	AC_{pen}^{vio}	$1\text{x}10^{12}$ USD
Cost of Unserved Energy (uniform in all load blocks)	$C_{(DNS)}$	$1\text{x}10^{4}$ USD/MWh

Table 4-9 gives the duration in hours as well as the load and vRES output characteristics in each of the five load blocks in a year. Similar load factors and vRES capacity factors were adopted for all the studied years.

Table 4-9: Load and vRES Characteristics per Load block

Load Block	Block 1	Block 2	Block 3	Block 4	Block 5
Time segment duration (hrs)	1510	2800	2720	1120	610
Load factor (lf_l)	50%	65%	80%	90%	100%
Solar capacity factor ($cf_{solar,l}$)	0%	30%	80%	30%	0%
Wind capacity factor ($cf_{wind,l}$)	80%	45%	25%	30%	55%

For comparison purposes two scenarios were simulated;

Scenario I: Base Case without vRES – In this scenario the vRES in buses 3, 4 & 6 (Table 4.6) were replaced with thermal power plants i.e. HFO based plants for candidates A5, B2 and B5 and Gasoil based plant for candidate B6.

Scenario II: vRES Case – Here the candidate power plants were as outlined in Table 4.6 with vRES replacing some of the thermal units in bus 3, 4 and 6.

The next sections of this chapter summarizes the obtained results. Detailed results are given in Appendix D.

4.3.1.1 Generation Investments Decisions

In both scenarios, expansion optimization was feasible for the first four years (up to a peak demand of 45MW). Optimal TC-GEP expansion results could not be realized for years five (50MW) and year six (55MW) due to divergence of the AC-based power flow analysis. The cause of the divergence was due to unsatisfied constraints majorly overloading of existing transmission lines. Therefore, it can be concluded that practically the existing transmission network can only accommodate up to 45MW even with increased generation.

Table 4-10 gives the required generator investments in the four-year horizon for the two scenarios studied. Without vRES a total of 58MW of generation capacity is required at the end of the four years at total investment cost of 2.42 million USD. With vRES consideration in the optimization, a slightly higher capacity of up to 60MW was committed. This is because vRES require additional reserve capacity to ensure reliability and security of supply. The total investment cost in this case is 2.48 million USD representing an increase of 2.5%.

Table 4-10: AC-based MODGEP Investment Decisions with & without vRES Consideration

Year / Load	Scenario I: Without vRES	Scenario II: With vRES
Year 1 (30MW)	B3_Biomass, B7_Coal B4_Geothermal	B2_Solar PV, B3_Biomass B4_Geothermal, B8_Gasoil
Year 2 (35MW)	B1_HFO B8_Gasoil	A2_Hydro, B1_HFO
Year 3 (40MW)	A2_Hydro	A5_Wind
Year 4 (45MW)	A5_HFO	B7_Coal
Year 5 (50MW)	Infeasible	infeasible
Year 6 (55MW)	Infeasible	infeasible
TOTAL COST (USD)	**2,421,961**	**2,479,664**

Figure 4-8 and 4-9 give the installed capacities, peak load and reserve requirements for a case without and with vRES respectively. The figures show that the installed capacities was adequate to supply the loads as well as provide enough reserve for any contingency situations in all the four years studied. It was observed that, committed vRES in scenario II replaced coal committed in years 1 (moved to 4) and one of the HFO units committed in year 4 (scenario I). When considering vRES, the new hydropower and gasoil units were considered one year earlier. This can be explained by the fact that additional flexible generation was required to cater for additional vRES reserve requirements.

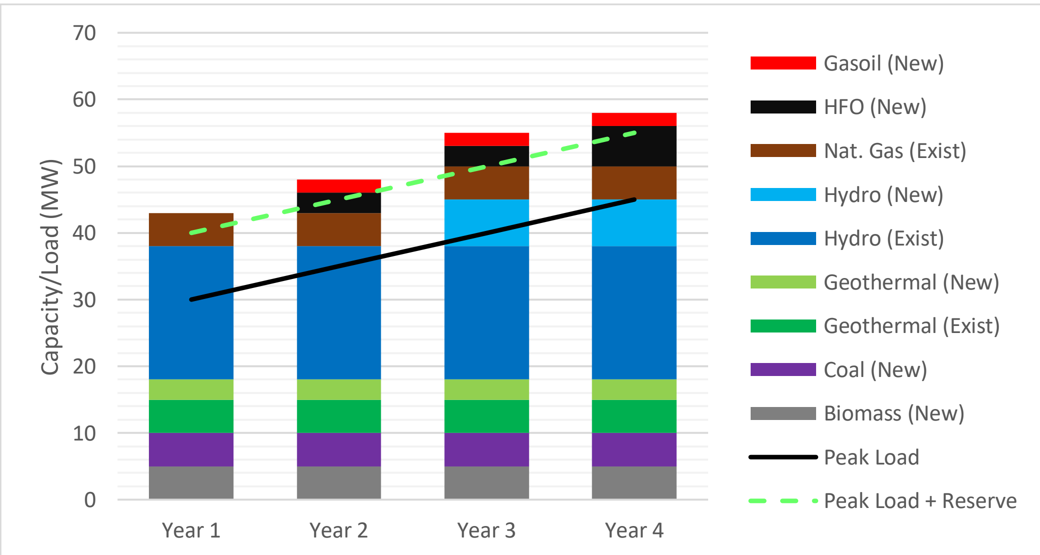


Figure 4-8: Installed Capacity vs Peak plus Reserve - Scenario I: Without vRES

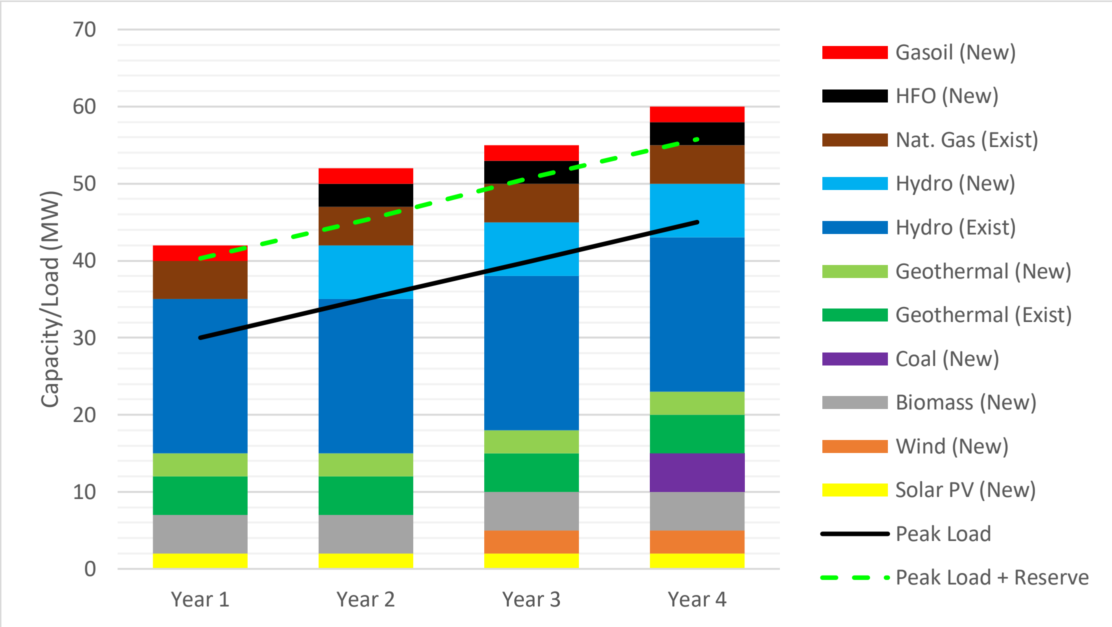


Figure 4-9: Installed Capacity vs Peak plus Reserve - Scenario II: With vRES

An analysis of the committed installed capacities for the case considering vRES penetration gave an average vRES share of 6.5% as given in Table 4-11. The highest vRES share was in year 3 at 9.1%. This share is expected to increase if transmission expansion is concurrently optimized with generation expansion planning. This is because some limitation to increased vRES penetration are due to transmission constraints like line overloads which can be solved by integrated planning.

Table 4-11: Share of vRES Penetration in Total Installed Capacity

	Installed Capacity (MW)	Conventional Sources (MW)	Intermittent RES (MW)	vRES Share (%)
Year 1	42	40	2	4.8%
Year 2	52	50	2	3.8%
Year 3	55	50	5	9.1%
Year 4	60	55	5	8.3%

Even though there was an increase of approximately 2.5% in investment cost when vRES were included, other costs decreased substantially resulting to an overall decrease in total network expansion and operation cost as shown in Figure 4-10. The highest decrease in cost was on the generation cost that reduced from 7.12 million USD without vRES to 3.57 million USD with vRES signifying a 50% reduction. The cumulative expansion and operation cost decreased by approximately 3.88million USD (19% reduction).

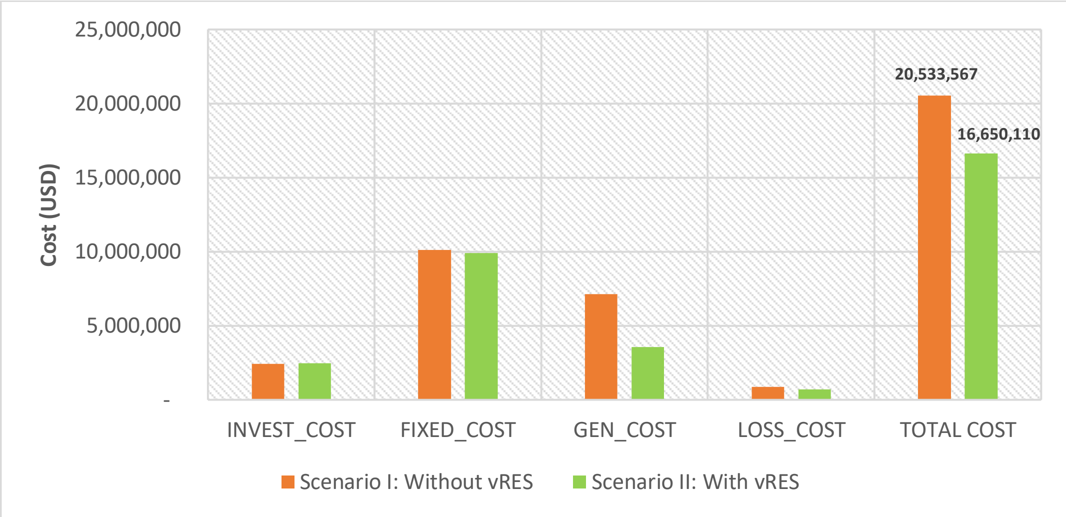


Figure 4-10: Specific & Cumulative Costs Comparison

4.3.1.2 Generated Energy Mix and Emissions Comparison

Figures 4-11 & 4-12 give the annual generated energy mix per plant for cases without and with vRES respectively. In both scenarios, the optimized generation mix did not result to any unserved energy in the entire planning period. Cumulatively, hydropower had the largest share in the energy mix at 71% and 75% in scenario I and II respectively. With vRES consideration, the share of Coal in the energy mix reduced from 9% in scenario I to 2% in scenario II. Cumulatively, vRES contributed approximately 5% of the entire generation in scenario 2.

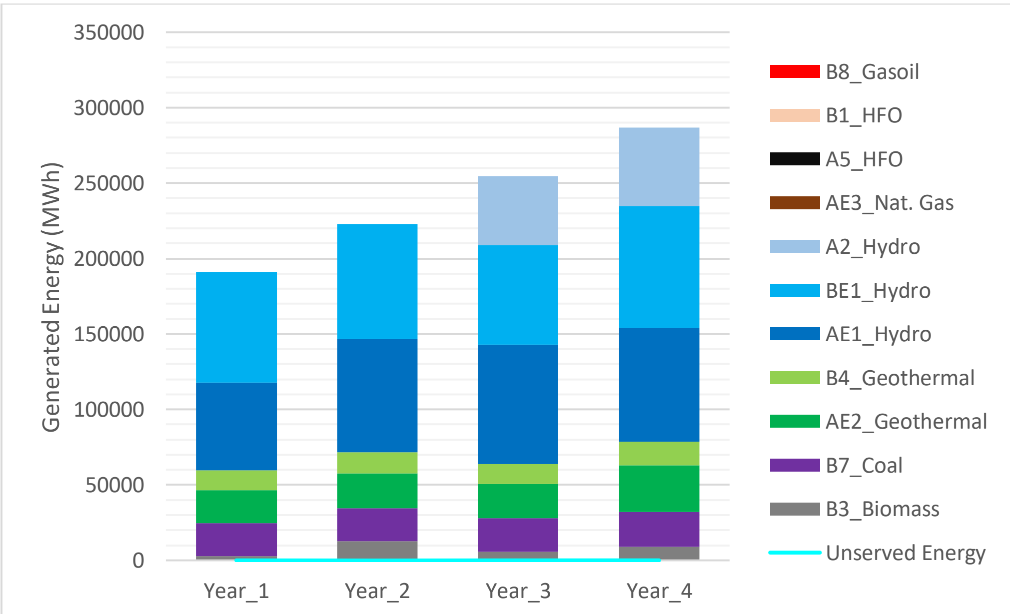


Figure 4-11: Annual Generation Mix - Scenario I: Without vRES

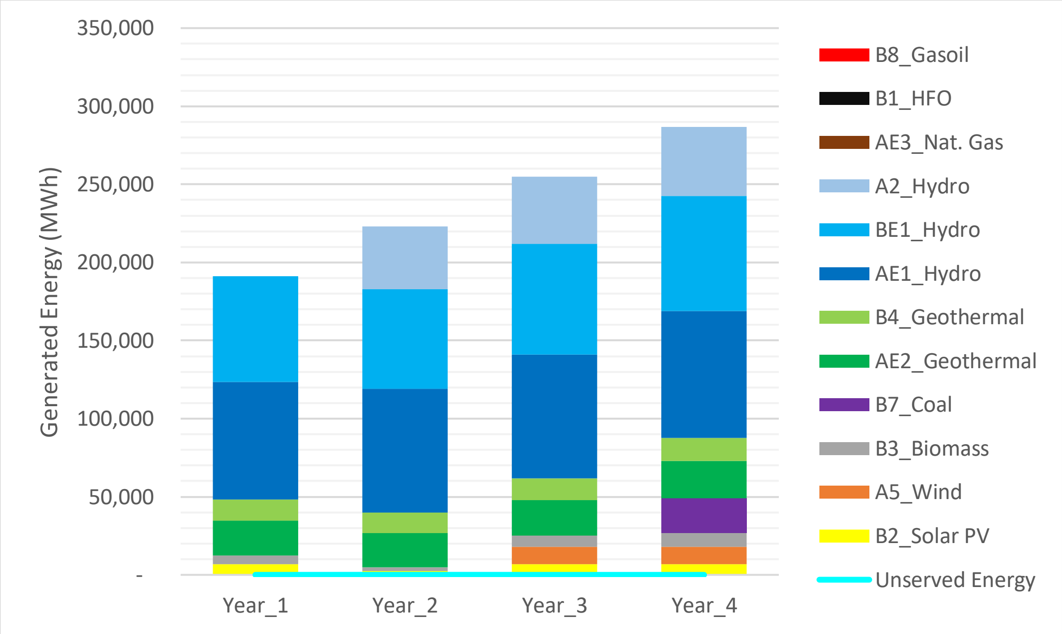


Figure 4-12: Annual Generation Mix - Scenario II: With vRES

The annual shares of vRES output in the generation mix are given in Table 4-12. An average annual vRES generation share of 4.5% was obtained with the highest penetration of 7.1% observed in the third year. Assumption of a higher emission cost penalty (more than 0.035USD/kg) will significantly increase this share by giving vRES an advantage over the conventional sources in the optimization.

Table 4-12: Share of vRES Generation in Energy Mix

	Total Energy (MWh)	Conventional Sources (MWh)	Intermittent RES (MWh)	vRES Share (%)
Year 1	191,068	184,364	6,704	3.5%
Year 2	222,914	220,562	2,352	1.1%
Year 3	254,758	236,596	18,162	7.1%
Year 4	286,605	268,450	18,155	6.3%

Consideration of vRES in the TC-MOGEP optimization resulted in significant reduction in CO_2 emissions as shown in Figure 4-13. There was generally a reduction of emissions in each year of study with vRES penetration. The overall reduction was 55% from 118,140 tons to 52,754 tons of carbon dioxide.

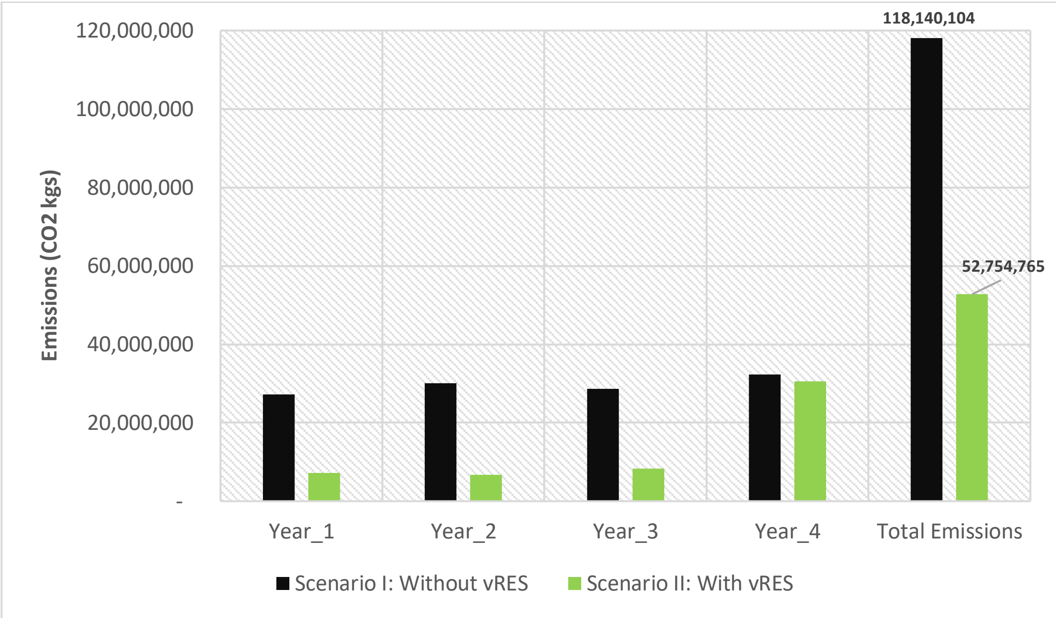


Figure 4-13: Annual & Cumulative CO_2 Emission Comparison

Figures 4-14 and 4-15 give the annual CO_2 emission per technology for the two cases under investigation. The highest contributor to emissions in both cases is the coal power plant at 72% and 41% in scenario I and II respectively. Committed vRES in scenario II contributed approximately 2% of the total CO_2 emissions in the entire planning period.

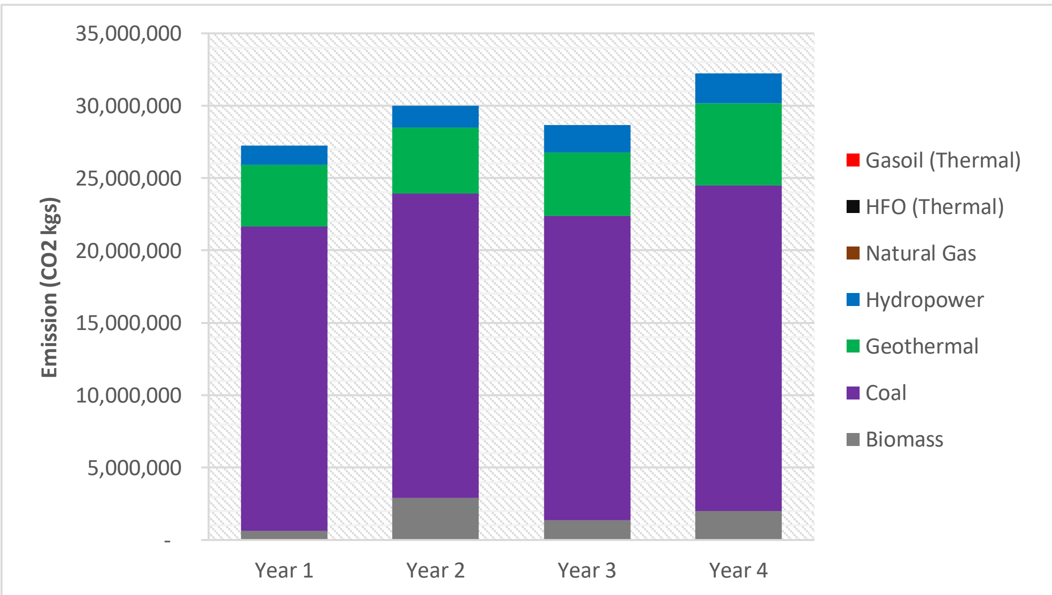


Figure 4-14: Annual Emission Mix - Scenario I: Without vRES

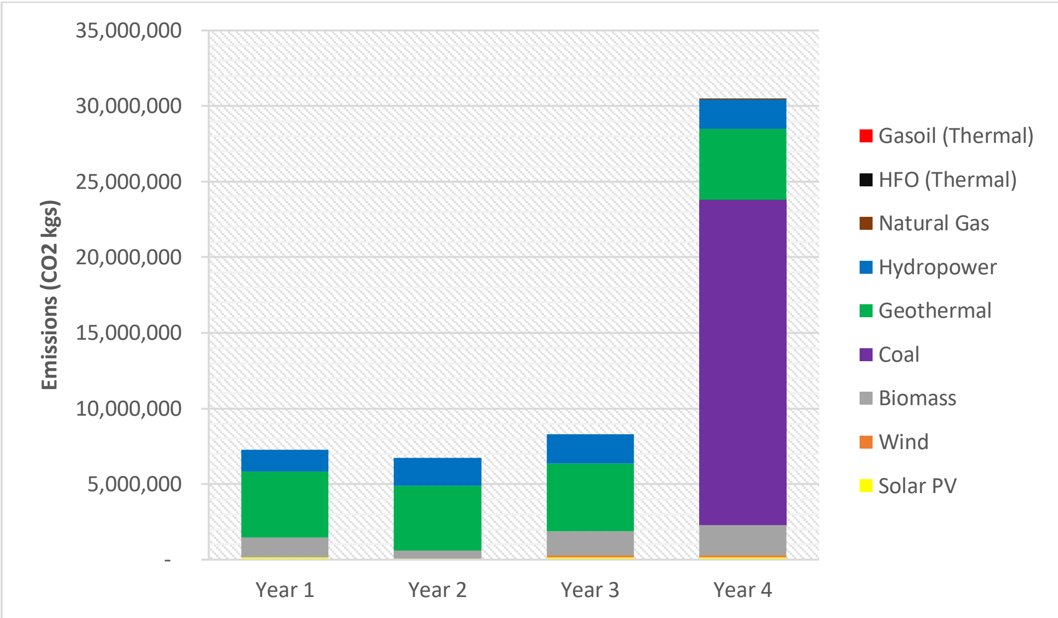


Figure 4-15: Annual Emission Mix - Scenario II: With vRES

4.3.1.3 Transmission Loss and Constraints Comparison

Active transmission line losses for the two scenarios studied were as given in Figure 4-16. Higher system losses were observed for the scenario without vRES penetration (scenario I). This is because the vRES that replaced High Fuel Oils (HFO) and Low Fuel Oils (LFO)/gasoil-based units in the candidate plants for optimization of scenario II were favored for investment and dispatch due to low investment and operational costs. On the other hand, majority of the original HFO and LFO (gasoil) based units in scenario I were not selected for investment and the few selected were not favored during dispatch due to their expensive generation (variable and fuel) costs. Thus, commitment of the vRES units in scenario II resulted to a more evenly distributed generation in the network reducing the system loses. Inclusion of vRES in the TC-MODGEP optimization problem reduced the total system losses for the four-year period from 854.13MWh in scenario I to 699.15MWh in scenario II, an 18% reduction.

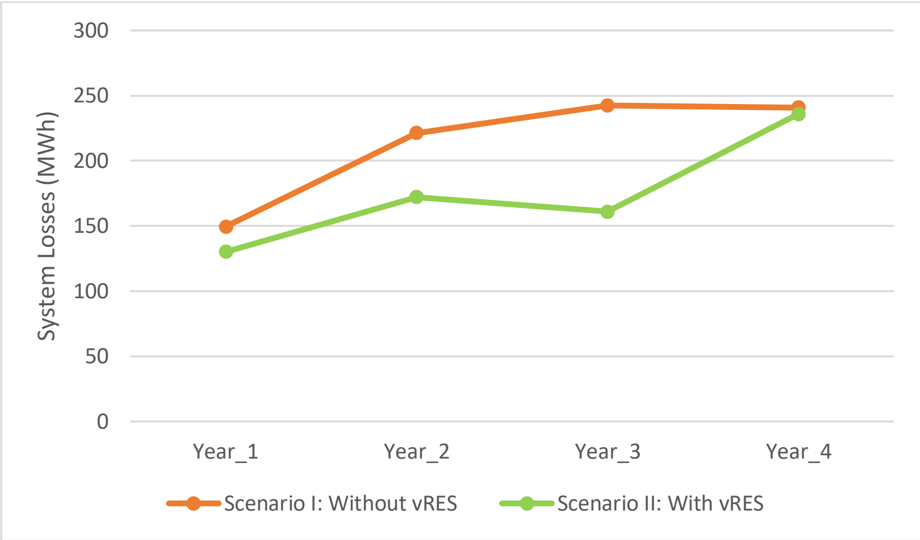


Figure 4-16: Active System Loss Comparison

The following transmission constraints were considered in both scenarios: transmission line overloading, voltage violation limits, phase angle limits as well as generator overloading. As previously stated, the overloading of transmission lines resulted to infeasible results for year 5 (50MW load) and year 6 (55MW load). All the other constraints were still within their acceptable ranges. The percentage line loadings for years 1 to 4 for the two scenarios are given in Figure 4-17 and 4-18. As observed, there are no line overloads in this horizon. Commitment of generators A5 in Bus 4 and A2 in Bus 1 greatly reduces the loading of corridor (4,5) due to reduction of power flow to this bus from the generators in Bus 5. Likewise commitment of generator B7 in Bus 6 reduces the power flow in corridor (1,2) towards the load in Bus 3 but increased the load in corridor (3,6). The highly loaded line in both scenarios is the one between buses 5 and 6.

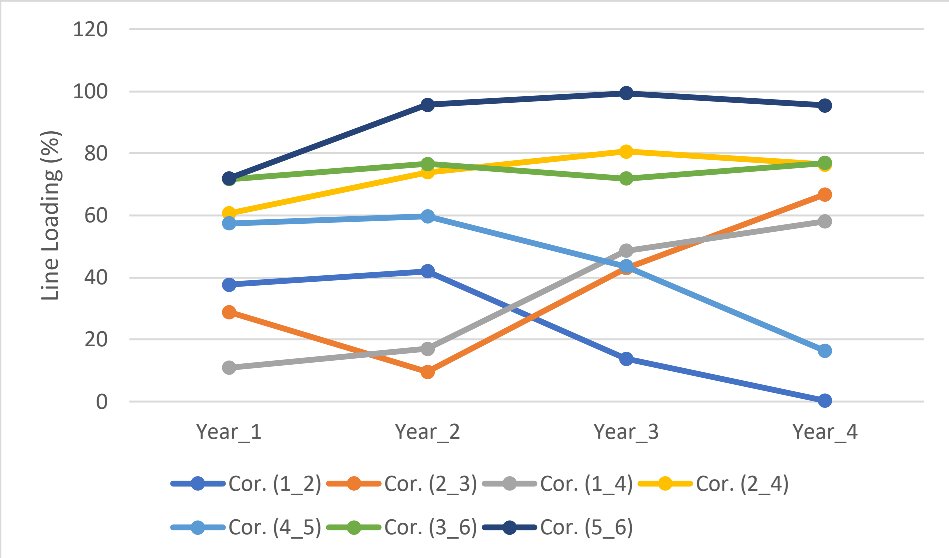


Figure 4-17: Annual Peak Line Loading - Scenario I: Without vRES

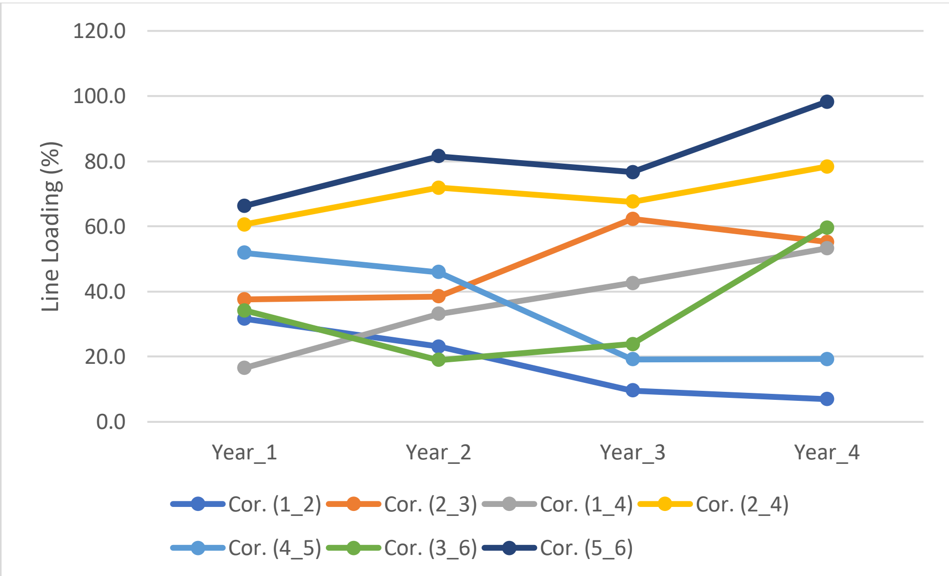


Figure 4-18: Annual Peak Line Loading - Scenario II: With vRES

4.4 Chapter Conclusion

In this chapter, the adaptive hybrid meta-heuristic optimization approach (DE-ABFOA-GIPSO) formulated and tested in Chapter 2 was applied in solving the TC-MOGEP problem using the IEEE six-bus test system. First, the classical TC-MOGEP problem was solved in various study scenarios to investigate the effect of contingencies and system reserve requirements on the expansion plans. To verify the accuracy and superiority of the developed optimization approach, the obtained results were compared to those obtained by other researchers in this area. The proposed DE_ABFOA_GIPSO methodology reduced the cumulative TC-GEP expansion cost by approximately 5% and 4% in comparison to MILP_PM and BFOA based approaches respectively. Consideration of N-1 contingency increased the expansion cost significantly. The DE_ABFOA_GIPSO optimized TC-MOGEP cost in this case increased by 16%.

The TC-MOGEP problem was then formulated in a dynamic environment and utilizing the AC-power flow analysis. The formulated AC-power flow based TC-MODGEP problem was solved using DE_ABFOA_GIPSO approach. There were no transmission constraint violations up to the fourth year of optimization (45MW) after which no feasible solutions could be obtained even with increased investment in generation sources. The formulation was extended to consider intermittent/variable RES in the generation expansion options. vRES inclusion in the optimized expansion plans slightly increased the generation investment cost by 2.5% however, it significantly reduced the operational cost by approximately 50%. An overall cost reduction of up to 19% was obtained when vRES were considered in TC-MODGEP. The average share of vRES in the installed capacity was 6.5% while the average penetration level in the energy mix was 4.5%. This penetration level resulted to a 55% reduction in CO_2 emissions.

5 CHAPTER 5: GTEP CONSIDERING OPTIMAL INTERMITTENT RES PENETRATION

5.1 Introduction to Integrated Generation and Transmission Expansion Planning (GTEP)

The formulation of the integrated GTEP problem has been done mostly using DC power flow models [2, 38, 61, 107, 110, etc.], which are usually over simplified leading to less accurate expansion results [60]. As a matter of fact, in practice the expansion plans obtained using DC power flow models need to be tested further to ensure that they do not violate voltage and thermal limits or result to high system losses [84]. AC power flow based formulations solve this problem but have not been exhaustively studied due to their complexity in formulation and solution.

The existing AC power flow based GTEP formulations need to be revised and improved by considering combined AC power flow related constraints and optimal vRES penetration constraints such as additional reserve capacity requirements or overutilization and underutilization risks. None of the reviewed research works has considered these important features.

5.2 MODGTEP Formulation

5.2.1 AC Power Flow-Based MODGTEP Formulation

The objective function of an integrated GTEP problem aims at minimizing the total investment and operation costs for both generators and transmission lines in the system as given in (5.1).

$$Min\ (C_T) = Min\ \{C_1(x), C_2(x), C_3(x)\} \tag{5.1}$$

Where, C_T is the total cost, $C_1(x)$ and $C_2(x)$ represent the investment and operation/production costs of generation stations and transmission system respectively while $C_3(x)$ is the outage cost. For a dynamic IGTEP:

$$C_T = \sum_{t=1}^{T} (1+d)^{-t} \{(ICG_t + PCG_t) + (ICT_t + PCT_t) + OC_t\} \tag{5.2}$$

Where, IC & PC are the investment & production costs per generation/transmission unit respectively, G_t & T_t is number of generation & transmission units committed in time *t* and OC_t is the outage cost in period *t*.

$$ICG_t = \sum_{q=1}^{Q} \varepsilon_{q,t} P_{q,t} (IC_q - S_q) \tag{5.3}$$

$$PCG_t = PCG_{Fixed,t} + PCG_{Var,t} \tag{5.4}$$

$$PCG_{Fixed,t} = \sum_{e=1}^{E} P_{e,t}FC_e + \sum_{q=1}^{Q} \varepsilon_{q,t}P_{q,t}FC_q \tag{5.5}$$

$$PCG_{Var,t} = \sum_{l}^{L} \begin{Bmatrix} \sum_{e=1}^{E} \mu_{e,l,t}(H_{l,t}G_{e,l,t}VC_e)+ \\ \sum_{q=1}^{Q} \mu_{q,l,t}(H_{l,t}G_{q,l,t}VC_q) \end{Bmatrix} \tag{5.6}$$

$$ICT_t = \sum_{i}^{nl} \eta_{q(i)}LEN_{q,t(i)}(ICT_{(i)} - S_{(i)}) \tag{5.7}$$

$$PCT_t = PCT_{Fixed,t} + PCT_{Var,t} \tag{5.8}$$

$$PCT_{Fixed,t} = \sum_{i}^{nl}(\eta_{e(i)}LEN_{e,t(i)}FCT_{e(i)} + \eta_{q(i)}LEN_{q,t(i)}\, FCT_{q(i)}) \tag{5.9}$$

$$PCT_{Var,t} = PCT_{Var,t}^{exist} + PCT_{Var,t}^{new} \tag{5.10}$$

$$PCT_{Var,t}^{exist} = \sum_{i}^{nl}\{Bra_{ld,t(i)}\, \eta_{e(i)}\alpha_{e(i)}RATE_{e,t(i)}VCT_{e(i)} * 8760\} \tag{5.11}$$

$$PCT_{Var,t}^{new} = \sum_{i}^{nl}\{Bra_{ld,t(i)}\, \eta_{q(i)}\alpha_{q(i)}RATE_{q,t(i)}VCT_{q(i)} * 8760\} \tag{5.12}$$

$$\alpha_{e(i)} = 1 - FOR_{e(i)} \text{ and } \alpha_{q(i)} = 1 - FOR_{q(i)} \tag{5.13}$$

$$OC_t = \sum_{l=1}^{L} H_{l,t}DNS_{l,t}C_{(DNS),l,t} \tag{5.14}$$

$$DNS_{l,t} = D_{max,l,t} - \{\sum_{e=1}^{E} \mu_{e,l,t}G_{e,l,t} + \sum_{q=1}^{Q} \mu_{q,l,t}\, G_{q,l,t}\} \qquad 5.15)$$

Where;

- *d* is the interest rate used for discounting;
- *L* is the total number of load blocks in year *t* of the planning period,
- $H_{l,t}$ is the number of hours in load block *l* of year *t*;
- E & Q is total number of existing and new generation investment options available in the planning period;
- $\varepsilon_{q,t}, IC_q$ & S_q represent the investment decision (0,1), investment and the salvage costs per MW of new generation unit type q in year *t* respectively;
- $P_{e,t}$ & $P_{q,t}$ are the capacities in MW of existing and new units in year *t* respectively;
- FC_e & FC_q, VC_k & VC_e are the fixed operational and maintenance cost per MW; variable cost per MWh for existing and new generation units respectively.
- $\mu_{e,l,t}$, & $\mu_{q,l,t}$, $G_{e,l,t}$, & $G_{q,l,t}$ are the unit commitment decisions (0,1) and committed capacities for committed existing and new units in load block *l* in year *t* respectively.

- nl is the total number of branches (transmission lines and transformers),
- $\eta_{e,t(i)}$ and $\eta_{q,t(i)}$ are the number of existing and new transmission circuits in i^{th} corridor in time t respectively;
- $LEN_{e,t(i)}$ and $LEN_{q,t(i)}$ are the lengths of existing and new transmission circuits in i^{th} corridor in time t respectively;
- $FCT_{e(i)}$ and $FCT_{q(i)}$ are the fixed cost per unit length (km) of existing and new transmission circuits in i^{th} corridor respectively;
- $VCT_{e(i)}$ and $VCT_{q(i)}$ are the variable cost per unit energy flow (MVAh) of existing and new transmission circuits in i^{th} corridor respectively;
- $RATE_{t(i)}$ and $Bra_{ld,t(i)}$ and represent the MVA rating and the percentage loading of transmission circuits in the in i^{th} corridor in time t respectively;
- $FOR_{e(i)}$ and $FOR_{q(i)}$ are the forced outage rates of the existing and new transmission circuits in i^{th} corridor respectivel;
- $D_{max,l,t}$ and $DNS_{l,t}$ is the total demand and the amount of unmet demand in MW in load block l of year t.
- $C_{(DNS),l,t}$ is the cost of not satisfying the demand for load block l in year t..

In this case, the objective function in (5.1) is minimized subject to the constraints given in (5.16) to (5.33) as follows:

$$(1 + x_{res,l,t})D_{max,l,t} \leq \sum_{\substack{e=1 \\ q=1}}^{E,Q} (\mu_{e,l,t}G_{e,l,t} + \mu_{q,l,t}P_{q,l,t}) \quad \forall t, \forall l \in L \tag{5.16}$$

$$V_{min} \leq V_{i,t} \leq V_{max} \;, \forall t, \forall i \in nb \tag{5.17}$$

$$\theta_{min} \leq \theta_{i,t} \leq \theta_{max} \;, \forall t, \forall i \in nb \tag{5.18}$$

$$0 \leq P_{t(g)}^{invest} \leq P_{t(g)}^{max} \quad for\, \forall t, \forall g \in G \tag{5.19}$$

$$PG_{g,min} \leq PG_g \leq PG_{g,max} \quad , \forall g \in G \tag{5.20}$$

$$PG_g^2 + QG_g^2 \leq S_{g,max}^2 \;, \forall g \in G \tag{5.21}$$

$$PG_{g,min,new} \leq PG_{g,new} \leq PG_{g,max,new} \quad , \forall g \in G \tag{5.22}$$

$$PG_{g,new}^2 + QG_{g,new}^2 \leq S_{g,max,new}^2 \ ,\forall g \in G \tag{5.23}$$

$$0 \leq \eta_{i,t} \leq \eta_{i,t}^{max} \ \ for\, \forall i \in nl \tag{5.24}$$

$$P_{ij,t}^2 + Q_{ij,t}^2 \leq (S_{ij,max} + u_{ij,t}S_{ij,max,new})^2 \ ,\forall t, \forall i,j \in nb \tag{5.25}$$

$$PG_{j,t} + \sum_i^{nb} P_{ij,t} - \sum_i^{nb} PL_{ij,t} = PD_{j,t} \ \ , \ \forall t, j \in nb \tag{5.26}$$

$$P_{ij} = V_iV_jY_{ij}\cos(\theta_{ij} + \delta_{ij}) - V_i^2Y_{ij}cos\theta_{ij} \ , \ \ \forall i,j \in nb \tag{5.27}$$

$$P_{L(ij)} = g_{ij}(V_i^2 + V_j^2 - 2V_iV_jcos\delta_{ij}), \ \ \forall i,j \in nb \tag{5.28}$$

$$QG_{j,t} + \sum_i^{nb} Q_{ij,t} - \sum_i^{nb} QL_{ij,t} = QD_{j,t} \ \ , \ \forall t, j \in nb \tag{5.29}$$

$$Q_{ij} = -V_iV_jY_{ij}\sin(\theta_{ij} + \delta_{ij}) + V_i^2Y_{ij}sin\theta_{ij} - \frac{V_i^2Y_{sh}}{2}, \ \ \forall i,j \in nb \tag{5.30}$$

$$Q_{L(ij)} = -b_{ij}^{sh}(V_i^2 + V_j^2) - b_{ij}(V_i^2 + V_j^2 - 2V_iV_jcos\delta_{ij}), \ \ \forall i,j \in nb \tag{5.31}$$

$$\sum_g^G PG_{g,t} = \sum_i^{nb} PD_{i,t} + \frac{1}{2}\sum_i^{nb}\sum_j^{nb} PL_{ji,t} \ , \ \forall t \tag{5.32}$$

$$\sum_g^G QG_{g,t} = \sum_i^{nb} QD_{i,t} + \frac{1}{2}\sum_i^{nb}\sum_j^{nb} QL_{ji,t} \ , \ \forall t \tag{5.33}$$

The constraint related to the reserve requirement is formulated in equation (5.16), nodal voltages and angles constraints are in equations (5.17) & (5.18), real and reactive power generation limits are in equations (5.19) - (5.23), limit on number of lines and line flows are in equations (5.24) & (5.25) while equations (5.26) to (5.33) give the power flow balance constraints.

To allow for trade-off between constraint violations and total cost, the effects of these violations are included in the objective function of the integrated GTEP problem as penalties. In this research work, several AC-based power flow penalties were formulated and included in the objective function. These include bus voltage violation penalty, branch overload penalty, generator overload penalty and system losses penalty.

5.2.2 Penalty Formulations

Formulation of the respective cost penalties was as follows:

Bus Voltage Violation Penalty: For each candidate expansion plan, a penalty cost was included for all buses whose voltages were outside the recommended ranges of 0.95-1.05pu for transmission networks. This was done for the worst-case scenario when the power system is operating at peak load. Equation (5.34) was formulated for calculating this penalty:

$$V_{pen,t}^{cost} = v_{pen}^{vio}\{\sum_{i=1}^{nb}(V_{abs(i)} - 0.05)\} \quad \text{for} \quad V_{abs(i)} > 0.05 \tag{5.34}$$

Where;

$$V_{abs(i)} = \left|1 - V_{t(i)}\right| \quad \text{for} \quad i \in nb \;\&\; t \in T \tag{5.35}$$

$V_{t(i)}$ is the voltage of the i^{th} bus at peak load scenario in year t in the planning horizon, and,

v_{pen}^{vio} is the voltage violation penalty cost associated with one per unit voltage violation.

Branch Overload Penalty: The percentage loadings of individual branches were calculated based on their respective power flows at peak load scenario against their thermal ratings. Overloaded branches in each candidate expansion plan were penalized as given in equation (5.36):

$$Bra_{pen,t}^{cost} = bra_{pen}^{ovl}\{\sum_{i=1}^{nl}(Bra_{ld,t(i)} - 100\%)\} \quad \text{for} \quad Bra_{ld,t(i)} > 100\% \tag{5.36}$$

Where;

bra_{pen}^{ovl} is the branch overload penalty cost per one percent of branch overload.

Generator Overload Penalty: Generators producing more than their capacities were also penalized as follows:

$$Gen_{pen,t}^{cost} = gen_{pen}^{ovl}\{\sum_{i=1}^{ng}(Gen_{ld,t(i)} - 100\%)\} \quad \text{for} \quad Gen_{ld,t(i)} > 100\% \tag{5.37}$$

Where;

ng is the total number of committed generators in the system,

$Gen_{ld,t(i)}$ is the percentage loading of the i^{th} generator at peak load in year t and,

gen_{pen}^{ovl} is the generator overload penalty cost per one percent of branch overload.

System Losses Penalty: System losses reduce profit margins of power system operators since they lead to increased investments in both generation and transmission facilities as well as need for additional generation outputs to cater for them. As a result, a good expansion planning process should take into consideration their impact. In this research work, active power losses were incorporated in the formulation of the objective function as follows:

(i) The annual active power losses, $P_{Loss,t}$ at system peak were obtained from the ac-based load flow analysis

(ii) The annual system Load Factor (LF) was used to calculate the Loss Load Factor (LLF) as given in equation (5.38).

$$LLF_t = (a \times LF_t) + [b \times (LF_t)^2] \tag{5.38}$$

Where; $a + b = 1,$ a ranges between 0.2 and 0.3 and b ranges between 0.7 and 0.8

(iii) Using the obtained LLF the energy losses for the respective year were calculated;

$$Energy_{loss,t} = P_{Loss,t} \times LLF_t \times 8760 \tag{5.39}$$

(iv) The system loss penalty cost $PLoss_{pen}^{cost}$ was calculated based on the active power loss penalty cost per MWh, $Ploss_{pen}^{cost}$.

$$PLoss_{pen,t}^{cost} = Ploss_{pen}^{cost} \times Energy_{loss,t} \tag{5.40}$$

These costs formed part of the variable operation cost in the objective function to be minimized. The formulated multi-objective function for solving the integrated GTEP problem becomes:

$$C_T = \sum_{t=1}^{T} \begin{Bmatrix} (ICG_t + PCG_t) + (ICT_t + PCT_t) + \ OC_t + \\ V_{pen,t}^{cost} + Bra_{pen,t}^{cost} + Gen_{pen,t}^{cost} + PLoss_{pen,t}^{cost} \end{Bmatrix} \tag{5.41}$$

In practice, suitable penalty cost factors should be selected based on planners experience and the specific operating conditions. Generally, loading and voltage violation penalties should be large enough to discourage violation of respective constraints. When choosing system loss penalty, several factors such as the operational cost of the most expensive generator or the marginal cost of supply are taken into consideration.

Equation (5.41) can be rearranged by grouping the investment and operation costs separately as given in (5.42).

$$C_T = \sum_{t=1}^{T} \begin{Bmatrix} (ICG_t + ICT_t) + (PCG_t + PCT_t + OC_t + \\ V_{pen,t}^{cost} + Bra_{pen,t}^{cost} + Gen_{pen,t}^{cost} + PLoss_{pen,t}^{cost}) \end{Bmatrix} \tag{5.42}$$

It is important to consider the impact of system contingencies on integrated expansion plans. This is because system elements (e.g. transformers, lines, generators etc.) experience both planned and unplanned outages. To consider this the formulated integrated MODGTEP objective function is adapted to ensure the adherence to N-1 redundancy in the system. The proposed multi-objective function becomes:

$$C_T = \sum_{t=1}^{T} \begin{Bmatrix} (ICG_t + ICT_t) + \rho_0 (PCG_t + PCT_t + V_{pen,t}^{cost} + Bra_{pen,t}^{cost} + \\ Gen_{pen,t}^{cost} + PLoss_{pen,t}^{cost}) + \rho_1 (PCG_t + PCT_t + OC_t + \\ V_{pen,t}^{cost} + Bra_{pen,t}^{cost} + Gen_{pen,t}^{cost} + PLoss_{pen,t}^{cost}) \end{Bmatrix} \tag{5.43}$$

Where ρ_0 and ρ_1 represent the probability for no contingency and that for occurrence of N-1 contingency. Equations (5.44) and (5.45) are used to calculate the probabilities.

$$\rho_0 = \prod_{z=1}^{Z} (1 - p_z FOR_z) \tag{5.44}$$

$$\rho_k = p_k FOR_k \prod_{\substack{z=1 \\ z \neq k}}^{Z} (1 - p_z FOR_z) \tag{5.45}$$

Where Z is the number of existing and new components (i.e., generators and lines) in the system at each planning period, p_z is the state of component z (0,1) depending on whether it is available or unavailable and FOR_z is the forced outage rate for component z.

5.3 MODGTEP Optimization using DE-ABFOA-GIPSO

The formulated Integrated Multi-Objective Dynamic Generation and Transmission Expansion Planning (MODGTEP) optimization problem was applied on the Garver's 6-bus test system and solved using the developed Adaptive Hybrid Meta-Heuristic Approach. The problem was programmed using MATLAB R2015b. The single line diagram of the test system is given in Figure 5-1. The data for this test system is as given in [84] and Appendix A.3. Bus 6 is assumed to be a pre-planned bus.

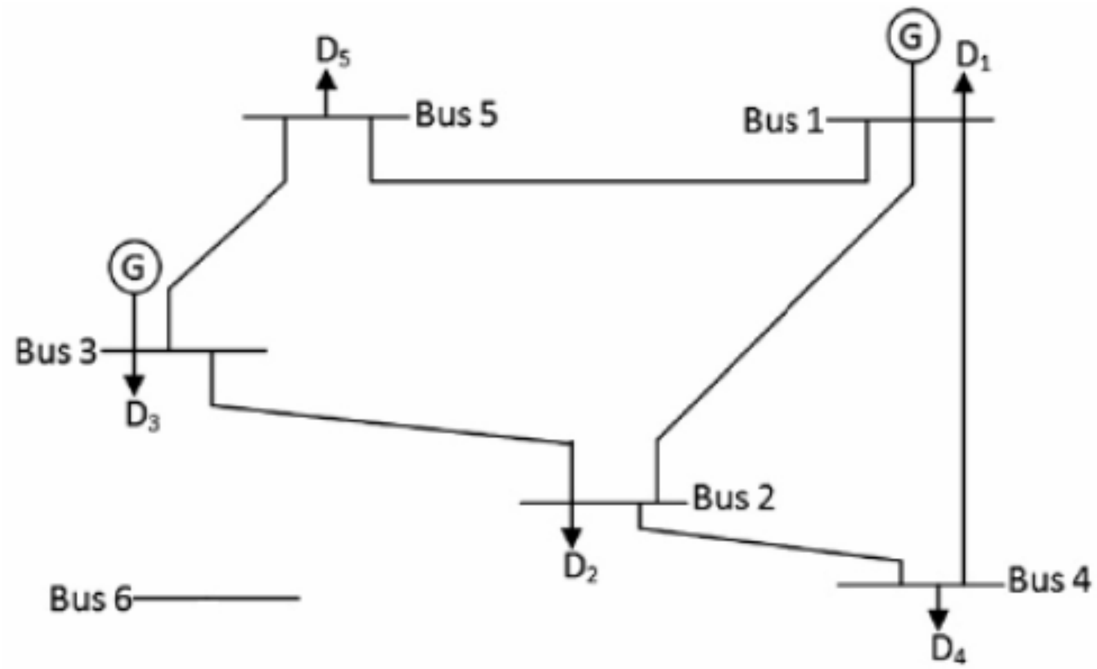


Figure 5-1: Single Line Representation of Garver's 6-Bus Test System [84]

Table 5-1 gives the parameter mapping for the MODGTEP optimization problem based on the formulations above and the network data given in Appendix A.3.

Table 5-1: MODGTEP Parameter Mapping

Parameter Meaning	**Symbol**	**Value**
Number of buses	nb	6
Number of existing generators	E	2
Number of new generator units	Q	2 types (multiple usage)
Circuit limit per corridor	$\eta_{ij,t}^{max}$	2
Planning Horizon	T	5 years
Annual load growth	L_g	10%
Discount rate	d	0%
Number of Load blocks	L	1
Transmission line loading limit	$S_{ij,max}$	100% (No contingency) 120% (N-1 contingency)
Generator minimum output limits	$PG_{g,min}$	0
Generator maximum output limits	$PG_{g,max}$ & $P_{t(g)}^{max}$	100% of capacity
Voltage limits	V_{min} & V_{max}	$\pm 5\%$

Parameter Meaning	Symbol	Value
Phase angle limits	θ_{min} & θ_{max}	$\pm 30\%$
Generator power factor	pf_g	± 0.9
Active power loss penalty	$Ploss_{pen}^{cost}$	$10M\$/MW$
Voltage violation penalty	v_{pen}^{vio}	$100M\$/\Delta V$
Cost of Unserved Energy	$C_{(DNS)}$	$10M\$/MW$

A planning period of 5 years was adopted in this study. Candidate generators were considered only in buses 5 and 6 while candidate transmission lines are considered on all existing and pre-planned transmission corridors. The outage cost at peak load was assumed to be 10M$/MW. The active power losses and the voltage violations were penalized at rates of 10M$/MW and 100M$ per one percent drop/increase from the lower and upper limits respectively. Transmission corridors were limited to a maximum of two circuits. The study involved two cases as described in Sections 5.3.1 and 5.3.2.

5.3.1 Case A: MODGTEP Optimization Results with No Contingency Situation

In this case, FOR for existing and committed system components were ignored to enable fair comparison of obtained results with those given in [84]. Table 5-2 shows the yearly generation and transmission investment decisions and total investment & operation cost (excluding active power loss and voltage violation penalties) for the three approaches under comparison. The proposed methodology required commitment of additional lines on corridors 3-6 (year 1) and 4-6 (year 4) over and above the DC power flow based investment decisions. Moreover, the commitment of the first circuit in corridor 4-6 was brought earlier by one year to year 1. As a result, the AC power flow based GTEP co-optimization resulted to an additional cost of M$ 398. Since the proposed methodology uses AC power flow-based formulations the extra investments committed are to take care of thermal and voltage violations in the system which could not be handled exhaustively using DC power flow. Compared to the MINLP approach given in [84], the proposed methodology reduced the total MODGTEP investment and operation cost by 7%.

Table 5-2: MODGTEP Result Comparison for Case A

Year	DC Power Flow Analysis [84]	MINLP Method [84]	DE-ABFOA-GIPSO
Year 1	1x{(2-3), (3-5)}	1x{(1-5), (3-5), (4-6)}, 2x(2-3)	1x{(3-5), (2-3), (3,6), (4-6)}
Year 2	G3, 1x(4-6)	G3, G4, 1x(3-6)	G3
Year 3	-	-	-
Year 4	-	-	1x(4-6)
Year 5	-	-	-
TOTAL COST (M$)	**22,202**	**24,272**	**22,600**

Table 5-3 gives breakdown of the costs obtained using the proposed AC power flow based approach. As evident, ac-power flow based transmission penalties were highly optimized and contributed only 2.5% of the total cost.

Table 5-3: MODGTEP Cost Distribution for Case A

Year	$IC_t + PC_t$ (M$)	P_{Loss} (MW)	$PLoss_{pen}^{cost}$ (M$)	ΔV_{vio} (pu)	V_{pen}^{cost} (M$)
Year 1	3411.0	8.1	81	0.02	20
Year 2	4675.5	9.1	91	-	-
Year 3	4198.5	10.2	102	-	-
Year 4	4905.0	13.1	131	-	-
Year 5	5410.0	15.7	157	-	-
TOTAL (M$)	**22,600**	**56.2**	**562**	**0.02**	**20**
	23,182				

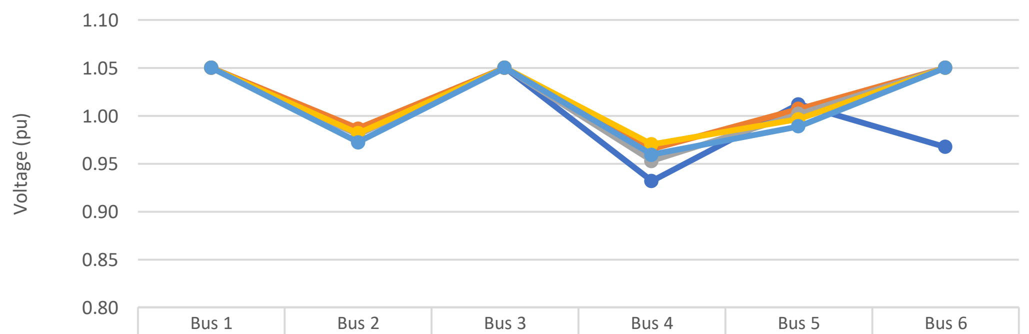
The 5-year generator and transmission line loadings at peak load were as given in Tables 5-4 and 5-5 respectively while Figure 5-2 gives the system voltage profile in the planning period. The obtained optimized MODGTEP results did not experience any severe voltage or thermal violations in the entire planning period, as is the case with the DC power flow-based results. Generator G1 was always fully loaded at peak load times throughout the planning period. The highest loaded transmission corridor was (2-3) with 98% loading in year 3. In the first year, slight under-voltages were experienced in bus 4 at 0.93pu.

Table 5-4: Generator loading in Case A

Generator	*Generator Loading at Annual Peak Load (%)*				
	Year 1	Year 2	Year 3	Year 4	Year 5
G1	100	100	100	100	100
G2	96	100	100	85	95
G3	-	6	13	37	41
G4	-	-	-	-	-

Table 5-5: Per Circuit Loading in Case A

Corridor	*Per Circuit Loading at Annual Peak Load (%)*				
	Year 1	Year 2	Year 3	Year 4	Year 5
1-2	34	33	33	35	34
1-4	57	52	45	17	18
1-5	44	43	46	67	64
2-3	85	92	98	82	96
2-4	34	31	21	30	29
3-5	61	70	79	78	92
3-6	39	33	6	50	48
4-6	39	56	84	89	97



	Bus 1	Bus 2	Bus 3	Bus 4	Bus 5	Bus 6
Year 1	1.05	0.99	1.05	0.93	1.01	0.97
Year 2	1.05	0.99	1.05	0.97	1.01	1.05
Year 3	1.05	0.98	1.05	0.95	1.00	1.05
Year 4	1.05	0.98	1.05	0.97	1.00	1.05
Year 5	1.05	0.97	1.05	0.96	0.99	1.05

Figure 5-2: System Voltage Profile in 5-year Planning Period - Case A

Figures 5-3 to 5-6 show load flow comparison of AC and DC power flow based GTEP co-optimization results. The following can be deduced:

(i) When compared to AC power flow, DC power flow based GTEP co-optimization results are inferior and may be operationally infeasible (could not converge in years 4 & 5).

(ii) AC power flow based GTEP co-optimization results to significant active power loss saving. From Figure 5-3, a cumulative loss saving of 10% was realized in the first three years of planning. In the third year, the annual peak load losses were reduced by 14% (from 11.83MW to 10.2MW) as shown in Figure 5-4.

(iii) Even in years with converging DC power flow based GTEP optimization results there is likelihood of experiencing severe system voltage violations and thermal overloads of network elements as shown in Figures 5-5 & 5-6. In the 1st year, DC power flow based expansion plan resulted to severe voltage violations in bus one (up to 0.86pu compared to the recommended minimum of 0.95pu).

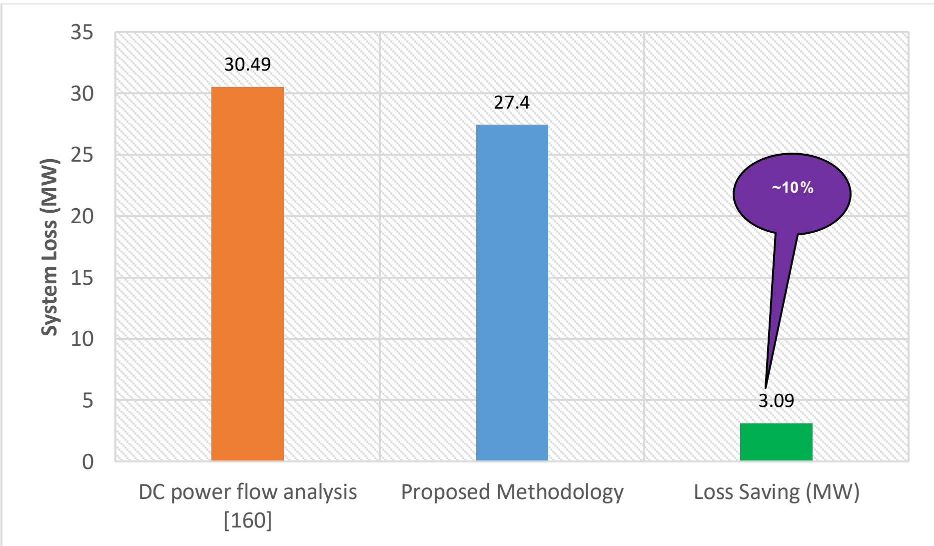


Figure 5-3: 3-year cumulative System Loss Reduction

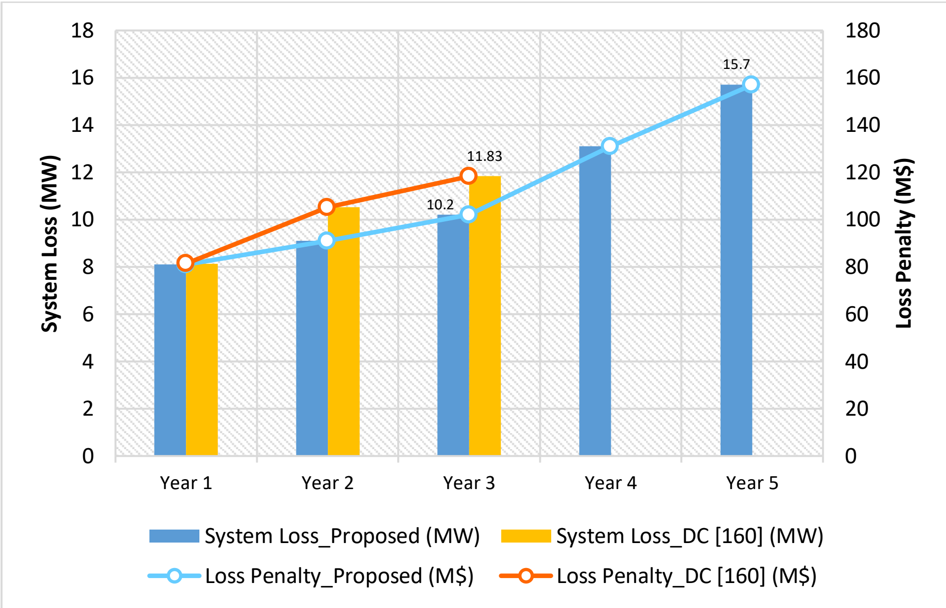


Figure 5-4: System Loss Comparison

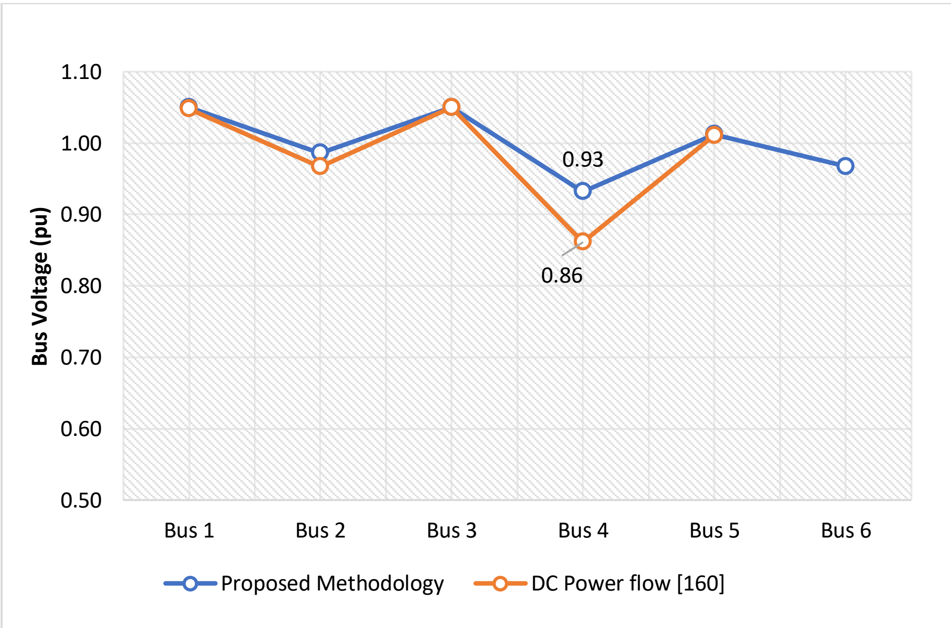


Figure 5-5: Voltage Profile Comparison – Year 1

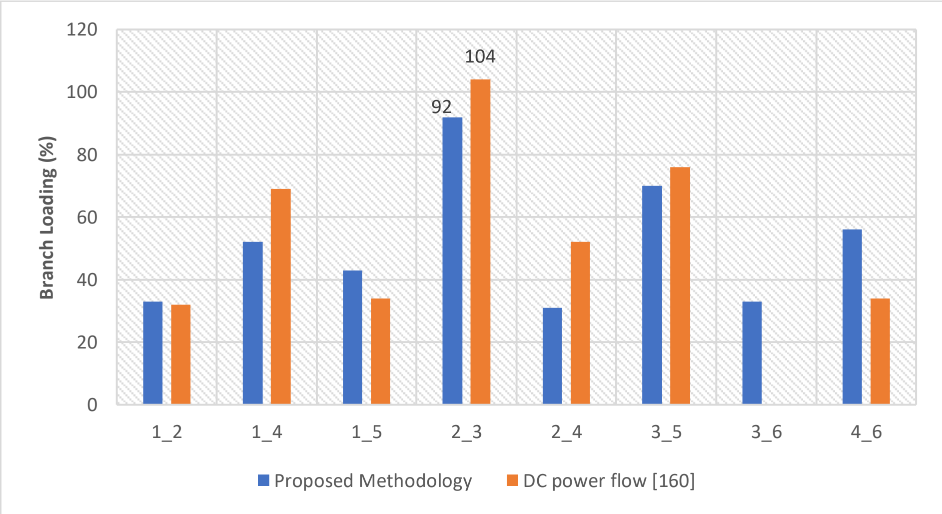


Figure 5-6: Branch Loading Comparison - Year 2

5.3.2 Case B: MODGTEP Optimization under N-1 Contingency Situation

This case assumed FOR values of 3% and 1% for generators and transmission lines (both existing and committed) in the system respectively. The spinning reserve constraint given by equation (5.16) was also considered. A 120% loading limit was used on the transmission lines and the candidate transmission corridor (2-6) was included as in [74]. Table 5-6 gives the optimized expansion results. Inclusion of the N-1 redundancy criterion in the MODGTEP optimization resulted to an increase on the number of transmission lines and generators committed in the planning period. There was also a shift on the years some units were required in the system. As a result, the optimized total generation and transmission expansion cost for the 5-year planning period increased by approximately 9% from 22,600 million USD (zero contingency case) to 24,650 million USD.

Table 5-6: MOGTEP Result Comparison for Case B

Year	DE-ABFOA-GIPSO	
	Zero Contingeny	N-1 Contigency
Year 1	1x{(3-5), (2-3), (3,6), (4-6)}	G3, 1x{(3-5), (2-3), (3,6), (4-6)}
Year 2	G3	1x{(4,6), (2,6)}
Year 3	-	G4
Year 4	1x(4,6)	(1-5)
Year 5	-	-
TOTAL COST (M$)	**22,600**	**24,650**

5.4 MODGTEP in Intermittent RES Environment

5.4.1 MODGTEP Formulation for Optimal Intermittent RES Penetration

In addition to the AC power flow based penalties included in the MODGTEP objective function formulation in Section 5.2.2, the proposed methodology sought to optimize the utilization of committed intermittent RES in the power system. To achieve this, penalty costs for not using the entire available vRES generation was introduced in the formulated objective function. In each load block, the penalty cost was calculated as given in equations (5.46) to (5.48).

$$vRES_{pen,t}^{under} = \sum_{l}^{L} vres_{pen}^{under}\left(vRES_{total,l,t}^{avail} - vRES_{total,l,t}^{com}\right) \text{ for } vRES_{total,l,t}^{com} < vRES_{total,l,t}^{avail} \tag{5.46}$$

$$vRES_{total,l,t}^{com} = \sum_{i=1}^{nS} u_{solar,l,t(i)} RES_{solar,l,t(i)}^{com} + \sum_{i=1}^{nW} u_{wind,l,t(i)} RES_{wind,l,t(i)}^{com} \text{ for } l \in L \;\&\; t \in T \tag{5.47}$$

$$vRES_{total,l,t}^{avail} = \sum_{i=1}^{nS} cf_{solar,l,t(i)} RES_{solar,l,t(i)}^{max} + \sum_{i=1}^{nW} cf_{wind,l,t(i)} RES_{wind,l,t(i)}^{max} \text{ for } l \in L \;\&\; t \in T \tag{5.48}$$

Where;

- nS and nW are the total numbers of existing and candidate solar and wind power plants in each year of optimization respectively;
- T and L is the total number of years in the planning horizon and load blocks (time slices) in each year of optimization respectively;
- $vRES_{total,l,t}^{com}$ and $vRES_{total,l,t}^{avail}$ are the total committed and total available vRES capacities in load block *l* in year *t* respectively;
- $vres_{pen}^{under}$ is the vRES under-utilization penalty cost per MWh;
- $RES_{solar,l,t(i)}^{com}$ and $RES_{solar,l,t(i)}^{max}$ are the committed and maximum capacities for i^{th} solar power plant in load block *l* in year *t* respectively;
- $RES_{wind,l,t(i)}^{com}$ and $RES_{wind,l,t(i)}^{max}$ are the committed and maximum capacities for i^{th} wind power plant in load block *l* in year *t* respectively;
- $u_{solar,l,t(i)}$ and $u_{wind,l,t(i)}$ are commitment decisions for i^{th} solar and wind power plants in load block *l* in year *t* respectively;
- $cf_{solar,l,t(i)}$ and $cf_{wind,l,t(i)}$ are the respective forecasted capacity factors for i^{th} solar and wind power plants in load block *l* in year *t*. These factors are based on respective solar irradiance and wind speeds.

Though the unit commitment and economic dispatch optimization was constrained to the maximum available capacities of the existing and candidate generators based on their respective capacity factors at each load block as given in equations (5.20) & (5.22), it was necessary to ensure that introduction of vRES does not lead to power system instability problems. To achieve this a penalty cost relating to additional spinning reserve requirements in case of vRES over-commitment was introduced in the formulated objective function:

$$vRES_{pen,t}^{over} = \sum_{l}^{L} vres_{pen}^{over} (vRES_{reserve,l,t}^{req} - vRES_{reserve,l,t}^{avail}) \text{ for } vRES_{reserve,l,t}^{req} > vRES_{reserve,l,t}^{avail} \quad (5.49)$$

$$vRES_{reserve,l,t}^{req} = \sum_{i=1}^{nS} f_{solar(i)} u_{solar,l,t(i)} RES_{solar,l,t(i)}^{com} + \sum_{i=1}^{nW} f_{wind(i)} u_{wind,l,t(i)} RES_{wind,l,t(i)}^{com} \quad (5.50)$$

$$vRES_{reserve,l,t}^{avail} = min \begin{cases} \sum_{i=1}^{M} u_{conv,l,t(i)} (GEN_{conv,l,t(i)}^{max} - GEN_{conv,l,t(i)}^{com}) \\ \sum_{i=1}^{M} u_{conv,l,t(i)} (GEN_{conv,l,t(i)}^{com} - GEN_{conv,l,t(i)}^{min}) \end{cases} \text{for } l \in L \,\&\, t \in T \quad (5.51)$$

Where,

- M is the total number of generating units in load block l in year t with capability of generating reserve capacity. Mostly the conventional generators.
- $vRES_{reserve,l,t}^{req}$ and $vRES_{reserve,l,t}^{avail}$ are the required and available reserve capacities in load block l in year t with respect to the committed vRES capacities.
- $vres_{pen}^{over}$ is the vRES over-utilization penalty cost per MWh;
- $f_{solar(i)}$ and $f_{wind(i)}$ are the projected forecast errors for the i^{th} solar and wind power plants in load block l in year t respectively.
- $u_{conv,l,t(i)}$ is the commitment decision for the i^{th} generating unit capability of generating reserve capacity in load block l in year t.
- $GEN_{conv,l,t(i)}^{com}$, $GEN_{conv,l,t(i)}^{max}$ and $GEN_{conv,l,t(i)}^{min}$ are the committed generation, technical & operational maximum and minimum operating capacities from the i^{th} generating units capability of generating reserve capacity in load block l in year t respectively.

These costs formed part of the variable operation cost in the objective function to be minimized and were optimized in each economic dispatch and unit commitment stage in the proposed methodology. In this research work, the variable cost of the most expensive committed generator (usually the flexible peaking power plant) was adopted as both the vRES underutilization and overutilization penalty cost per MWh.

The formulated multi-objective function given in equation (5.42) was adapted to include these vRES optimization penalties as given in equation (5.52).

$$C_T = \sum_{t=1}^{T} \begin{Bmatrix} (ICG_t + ICT_t) + (PCG_t + PCT_t + OC_t + V_{pen,t}^{cost} + Bra_{pen,t}^{cost} \\ +Gen_{pen,t}^{cost} + PLoss_{pen,t}^{cost} + vRES_{pen,t}^{under} + vRES_{pen,t}^{over}) \end{Bmatrix} \quad (5.52)$$

5.4.2 MODGTEP Optimization for Optimal Intermittent RES Penetration using DE-ABFOA-GIPSO

In this section, the formulated MODGTEP problem was solved using the adaptive hybrid meta-heuristic approach (DE-ABFOA-GIPSO) developed in Chapter 2. The adopted solution methodology is as illustrated in Figure 5-7. A similar customized IEEE 6-bus test system network data as described in Section 4.3.1 was used employing typical generator technologies and characteristics as given in Figure 5-8 and Appendix A.2. Candidate transmission circuits were considered in all existing transmission corridors.

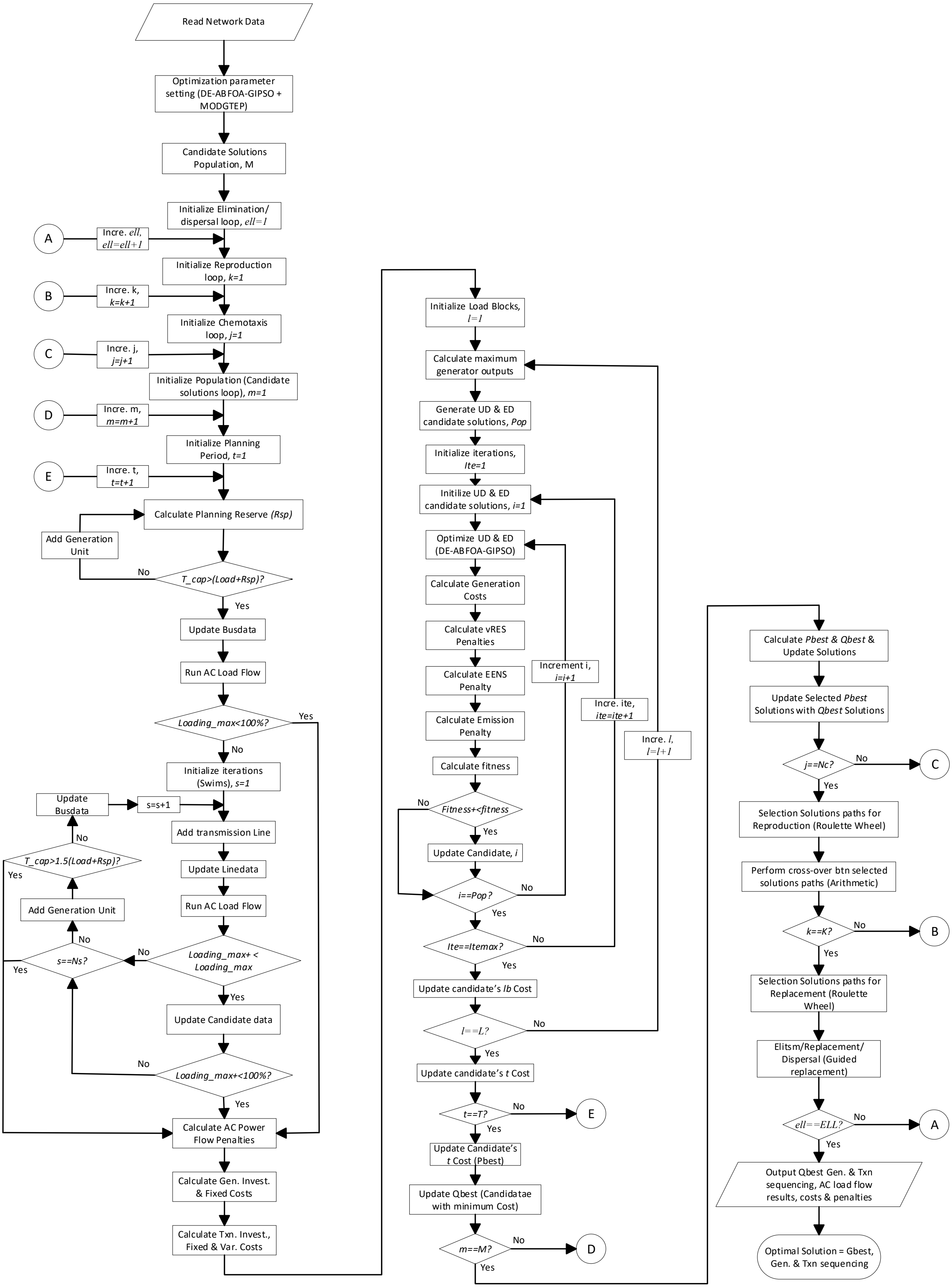


Figure 5-7: Flow Chart of MODGTEP Optimization Methodology

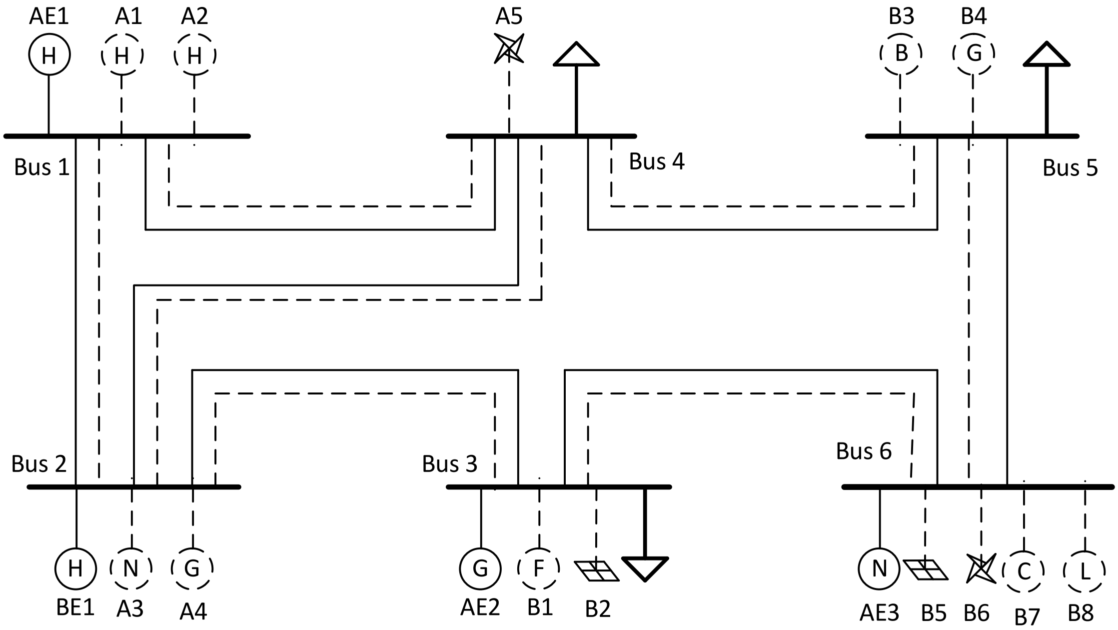


Figure 5-8: IEEE 6-Bus Test System SLD with Candidate vRES & Candidate Transmission Lines

Table 5-7 gives the parameter mapping for the MODGTEP optimization problem for optimal RES penetration as per the formulations in this chapter and the test data.

Table 5-7: MODGTEP Parameter Mapping for Optimal RES Penetration

Parameter Meaning	**Symbol**	**Value**
Number of buses	nb	6
Number of existing lines	nl	7
Number of existing generators	E	4
Number of candidate Conventional generator units	Q	9
Number of candidate vRES units	R	4
Generator units with reserve provision capability	M	All committed conventional generator units
Number of solar PV plants	nS	2
Number of wind power plants	nW	2
Projected vRES forecast errors (for all solars & wind plants)	f_{solar} & f_{wind}	15%
Circuit limit per corridor	$\eta_{i,t}^{max}$	2
Planning Horizon	T	6 years
Annual load growth	D_g	+5MW

Parameter Meaning	Symbol	Value
Load power factor	pf	0.95
Discount rate	d	10%
Number of Load blocks	L	5
Transmission line loading limit	$S_{ij,max}$	100%
Generator minimum output limits	$PG_{g,min}$	0% for natural gas, HFO, gasoil, biomass, wind & Solar 50% for Geothermal & Coal 25% for Hydropower
Generator maximum output limits	$PG_{g,max}$ & $P_{t(g)}^{max}$	100% of capacity
Voltage limits	V_{min} & V_{max}	$\pm 5\%$
Phase angle limits	θ_{min} & θ_{max}	$\pm 30\%$
Generator power factor	pf_g	± 0.9
Capacity margin (planning reserve) penalty	R_{pen}^{res}	1×10^8 USD/MW
Active system loss penalty	$Ploss_{pen}^{cost}$	252.5 USD/MWh
Voltage violation penalty	v_{pen}^{vio}	1×10^6 USD/ΔV_{vio}
Branch overload penalty	bra_{pen}^{ovl}	1×10^8 USD/$\%S_{ovl}$
Generator overload penalty	gen_{pen}^{ovl}	1×10^6 USD/MW
vRES under-utilization penalty	$vres_{pen}^{under}$	252.5 USD/MWh
vRES under-utilization penalty (vRES reserve violation penalty)	$vres_{pen}^{over}$	252.5 USD/MWh
Emission penalty (CO_2)	λ	0.035 USD/kg and 1,000 USD/kg
Cost of Unserved Energy (uniform in all load blocks)	$C_{(DNS)}$	1×10^4 USD/MWh

Similar load factors and vRES capacity factors as given in Chapter 4 (Table 4-9) were adopted for all the studied years.

Two scenarios were studied:

a) **Scenario 1: Low Emission Penalty Scenario** – This scenario employed a carbon dioxide emission penalty of 0.035USD per kilogram (weighted carbon price as at June 2021 [89]). This scenario was used as the reference scenario to explore the optimal penetration of vRES in business as usual power system expansion planning case.

b) **Scenario 2: High Emission Penalty Scenario –** In this scenario, a high carbon price of 1000USD per kilogram was used. The objective of the scenario was to investigate the competitiveness of variable Renewable Energy Sources in power generation in the era of climate change mitigation. However, this vRES competitiveness and penetration was studied in an optimally constrained environment to ensure electricity demand is met at least cost while ensuring security of supply.

The obtained results are as summarized in the next sub-sections. The detailed results are given in Appendix D.

5.4.2.1 Generation and Transmission Investments

Table 5-8 gives the optimal generation and investment decisions for the MODGTEP problem for the two scenarios while considering optimal vRES penetration. Only vRES plants (B2_Solar and B5_Solar) are selected in scenario 1 that considers low carbon price as compared to three vRES plants in the high carbon price scenario 2 (B2_Solar, B5_Solar and B6_Wind). The two scenarios had similar transmission investment requirements with scenario 2 (high carbon price) having an extra investment in between buses 5 and 6. Overall, scenario 2 resulted to a higher investment cost of 2.94 million USD compared to 2.61 million USD in scenario 1, an increase of 12.5%.

Table 5-8: MODGTEP Investment Decisions Considering Optimal vRES Penetration

Year/Load	Scenario 1: Low Carbon Price		Scenario 2: High Carbon Price	
	Generation	**Transmission**	**Generation**	**Transmission**
Year 1 (30MW)	A1_Hydro, B8_Gasoil	(2,3), (2,4)	A1_Hydro, A2_Hydro, B2_Solar	(2,3), (2,4)
Year 2 (35MW)	A2_Hydro, B2_Solar	-	B5_Solar	(3,6)
Year 3 (40MW)	B1_HFO, B5_Solar	(3,6)	-	-
Year 4 (45MW)	-	-	B1_HFO	-
Year 5 (50MW)	-	(1,4)	B6_Wind	(5,6)
Year 6 (55MW)	A4_Geothermal	-		(1,4)
TOTAL COST (USD)	**2,614,611.27**		**2,940,731.29**	

The higher carbon price in scenario 2 (1,000USD/kg compared to 0.035USD/kg in scenario 1) made vRES more competitive in the generation expansion optimization problem in the entire planning horizon. The share of vRES in the installed generation capacity increased from 13% to 20% as shown in Figure 5-9.

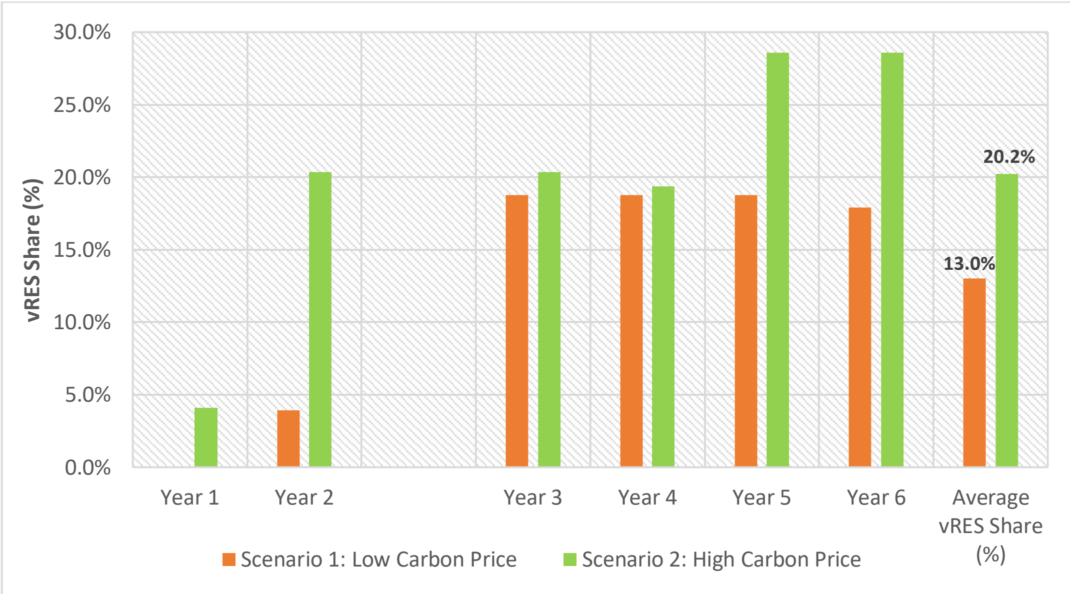


Figure 5-9: vRES Penetration in Installed Capacity

Figures 5-10 and 5-11 illustrate the comparison between installed capacity and peak load plus reserve margin for the low and high carbon price scenarios respectively. The high share of committed vRES in scenario 2 resulted in higher installed capacity (70MW compared to 67MW in scenario 1) since some conventional sources that would have otherwise been replaced were still needed to offer the required additional vRES related reserve capacity that is key for system security and reliability. There are no capacity gaps in both scenarios and reserve margins are adequately covered. Scenario 1 had slightly higher energy losses than scenario 2. Both scenarios had the lowest system losses at years with largest impact investments (investments in 10MW candidate B5_Solar and transmission corridor (3, 6)). These were the 3rd year for scenario 1 and 2nd year for scenario 2.

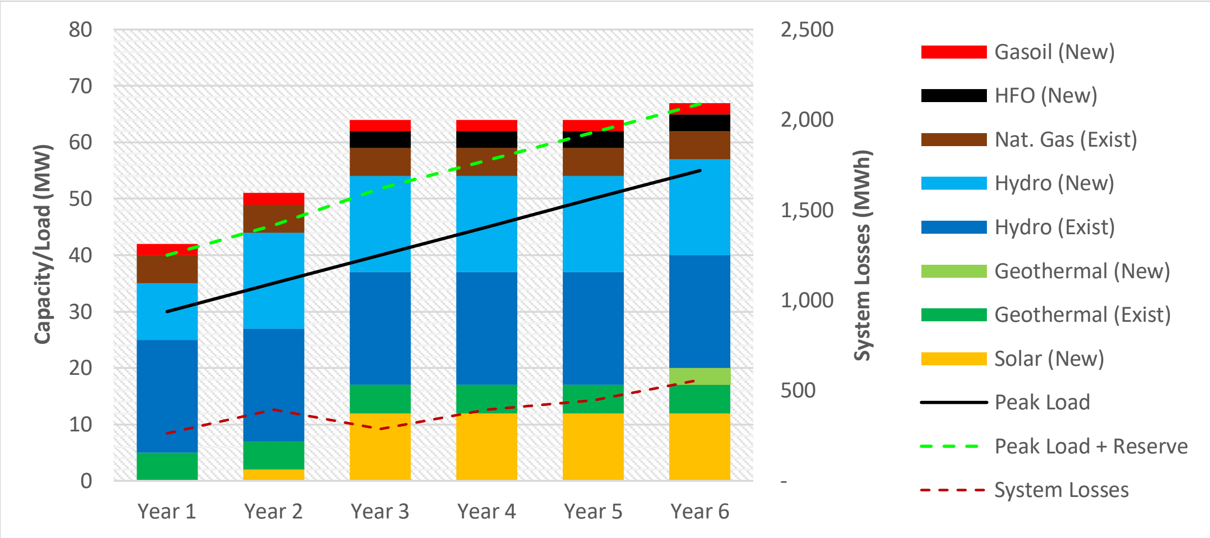


Figure 5-10: Installed Capacity Vs Peak Load plus Reserve – Scenario 1 (Low Carbon Price)

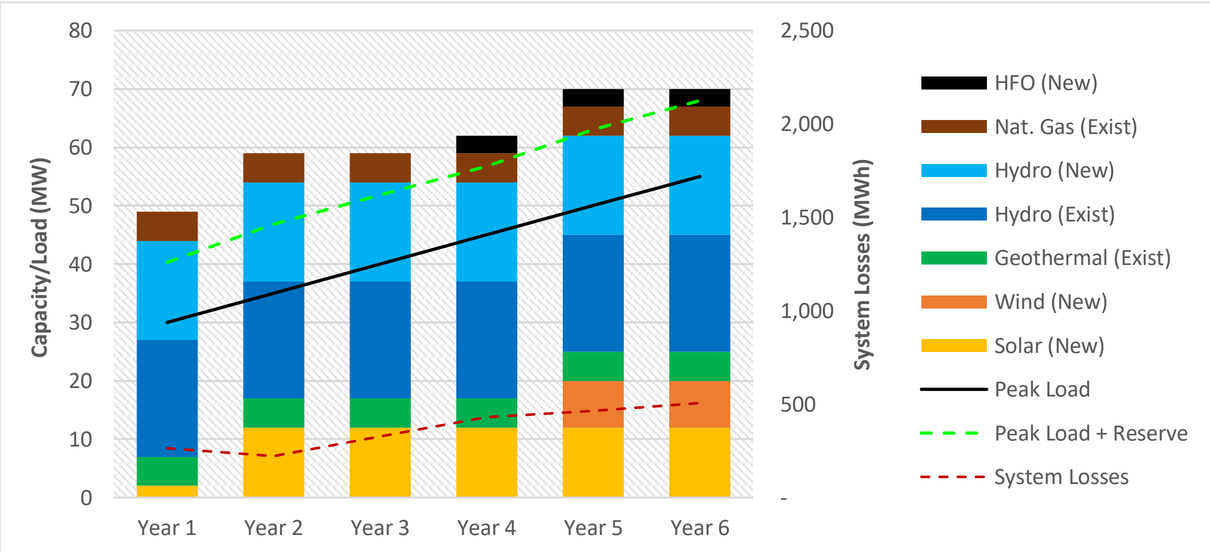


Figure 5-11: Installed Capacity Vs Peak Load plus Reserve – Scenario 2 (High Carbon Price)

5.4.2.2 Generation and Energy Mix Comparison

Figure 5-12 gives a comparison for vRES penetration in the energy mix for the two studied scenarios. The higher emission penalties in scenario 2 favored generation from the less pollutant vRES compared to fossil fuel based energy sources. This resulted to increased energy mix penetration of vRES in this scenario when compared to the low carbon price case in scenario 1. The average share of vRES in the energy mix increased from 7.6% in scenario 1 to 12.8% in scenario 2.

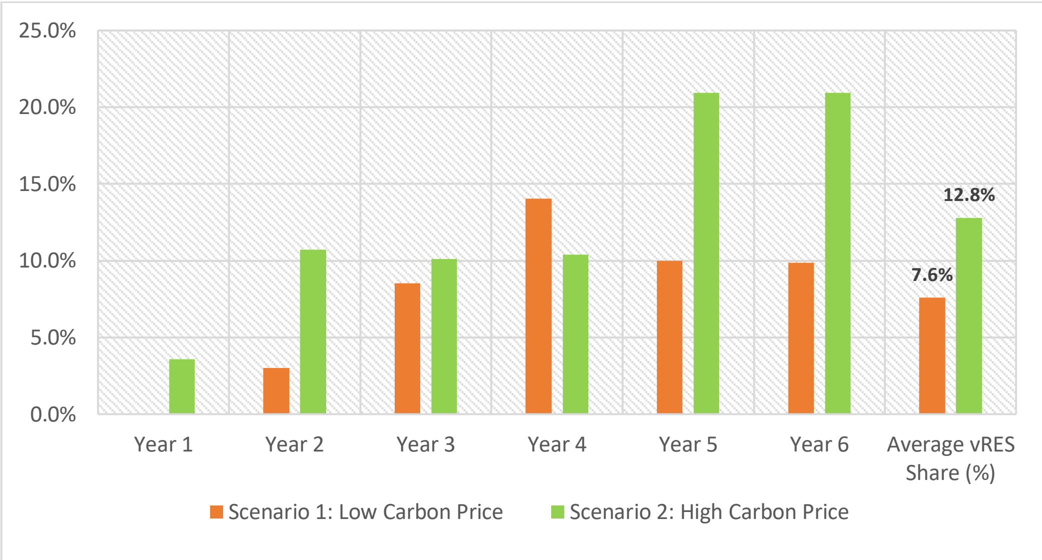


Figure 5-12: Annual & Cumulative vRES Share Comparison in Energy Mix

The obtained annual generation mix per plant for scenario 1 and 2 were as given in Figures 5-13 and 5-14 respectively while Figures 5-15 and 5-16 give the respective energy mix per technology. As explained the high carbon tax resulted to increased vRES penetration in scenario 2. This however resulted to noticeable unserved energy of up to 3.7% (12.5GWh) at the end of the planning period as shown in Figures 5-14 and 5-16 when compared to the Figures 5-13 and 5-15 (scenario 1). This is because of increased uncertainty in the power demand-supply balance caused by aggravated vRES output fluctuations as per their changing capacity factors in each load block studied. Compensating these increasing output fluctuations while at the same time trying to avoid over-utilization or under-utilization of committed vRES makes demand-supply balancing challenging. In the entire planning period, unserved energy in scenario 2 (high vRES penetration) was 2.5% compared to 0.002% in scenario 1 (low vRES penetration). This alludes to an increased risk of not meeting all the demand at all times with increased vRES penetration.

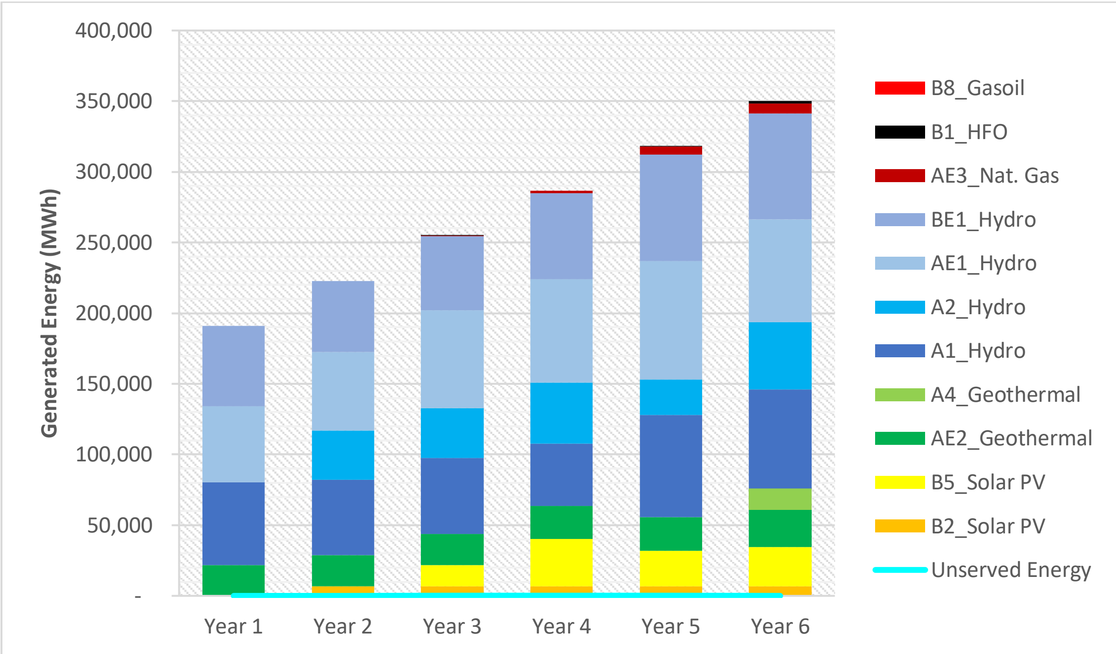


Figure 5-13: Annual Generation per Plant – Scenario 1 (Low Carbon Price)

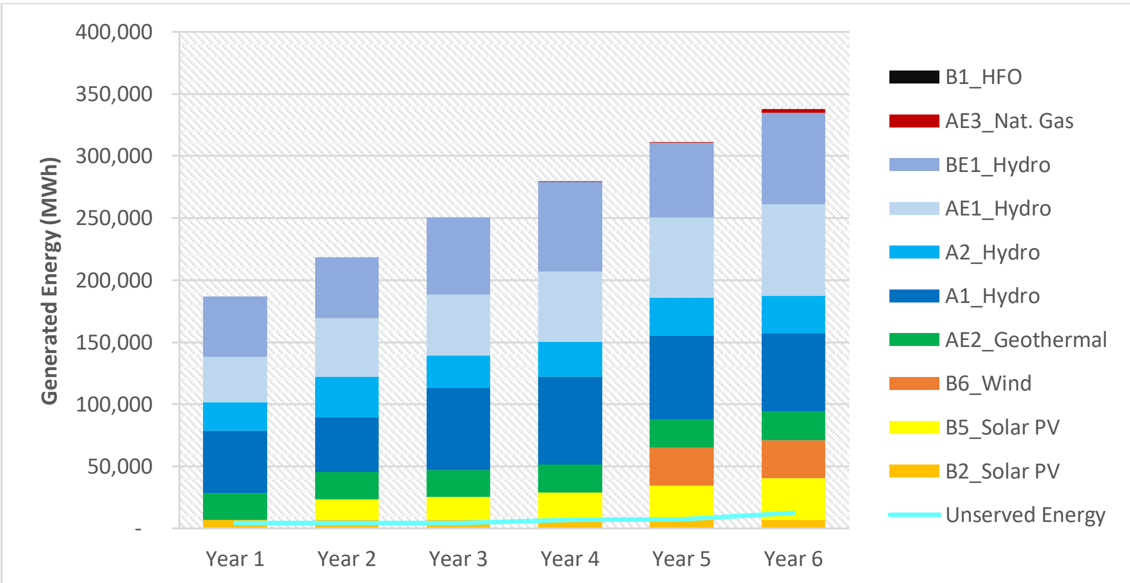


Figure 5-14: Annual Generation per Plant – Scenario 2 (High Carbon Price)

The annual generation mix in both scenarios was majorly from hydropower plants contributing 75.8% and 71.3% for scenarios 1 and 2 in the last year of the planning period respectively. This is because hydropower plants has lower operating costs of 0.5USD/kWh (same vRES) compared to 12.6USD/kWh, 93.8USD/kWh, 102.5USD/kWh and 252.5USD/kWh for Geothermal, Natural gas, HFO and Gasoil based power plants.

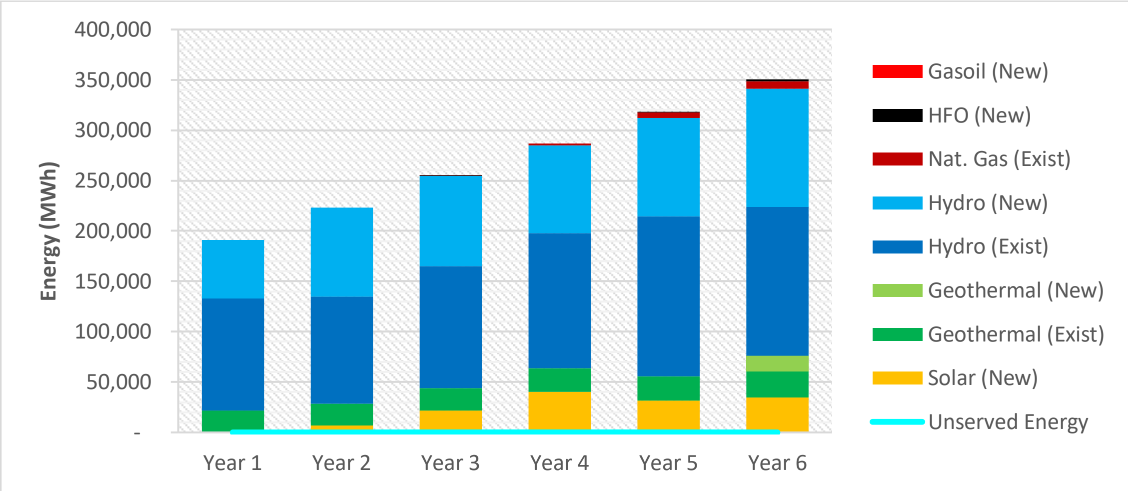


Figure 5-15: Annual Generation per Technology– Scenario 1 (Low Carbon Price)

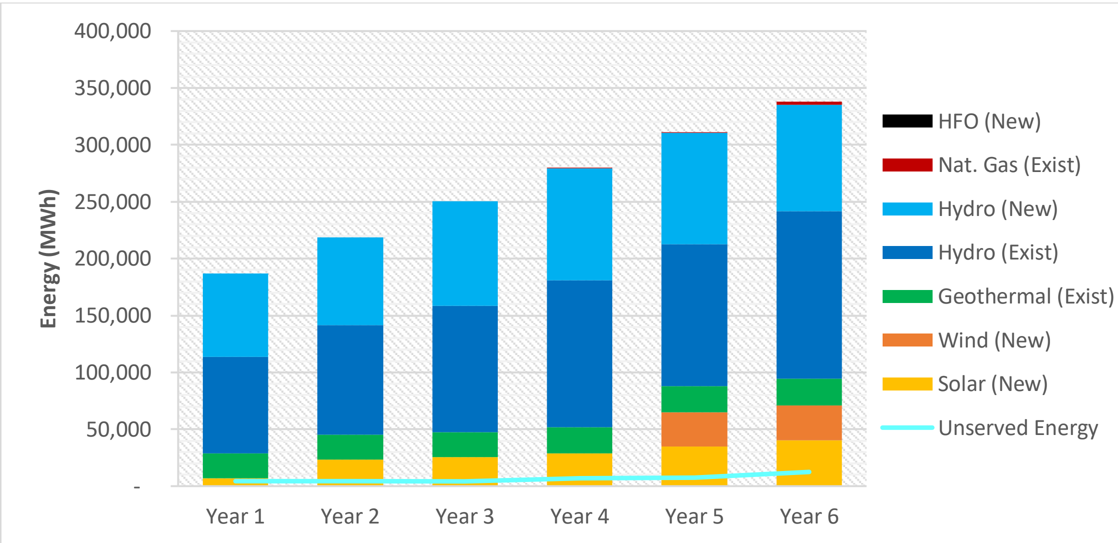


Figure 5-16: Annual Generation per Technology– Scenario 2 (High Carbon Price)

Figures 5-17 & 5-18 gives the cumulative energy mix per load block in the entire planning period for the low and high carbon price scenarios respectively. Hydropower contributed approximately 81% and 77% of the entire generation in the low and high carbon price scenarios respectively. As observed, in both scenarios solar PV generation is only in load blocks 2, 3 and 4 due to the respective capacity factors given in Table 4-9. Solar PV has 0% capacity factors for load blocks 1 and 5 representing night hours.

The fossil fuel based generators that are not only expensive in operation cost but also more pollutant were mostly utilized in load block 5 and not in the rest of the load blocks. This is because load block 5 had a load factor of 100% representing the peak load times. During these times, flexible generators with overall competitive costs at low utilization levels are preferred in addition to the available base and intermediate generation capacity. This load block (peak load time) also has the high risk of experiencing unserved energy situations.

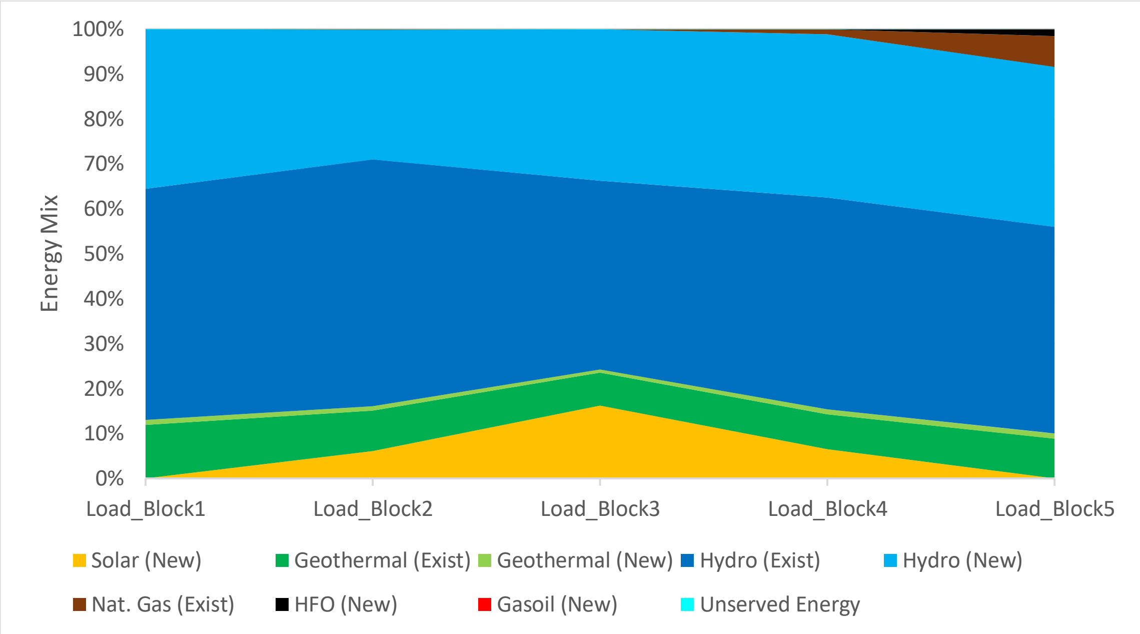


Figure 5-17: Cumulated Load Block Energy Mix – Scenario 1 (Low Carbon Price)

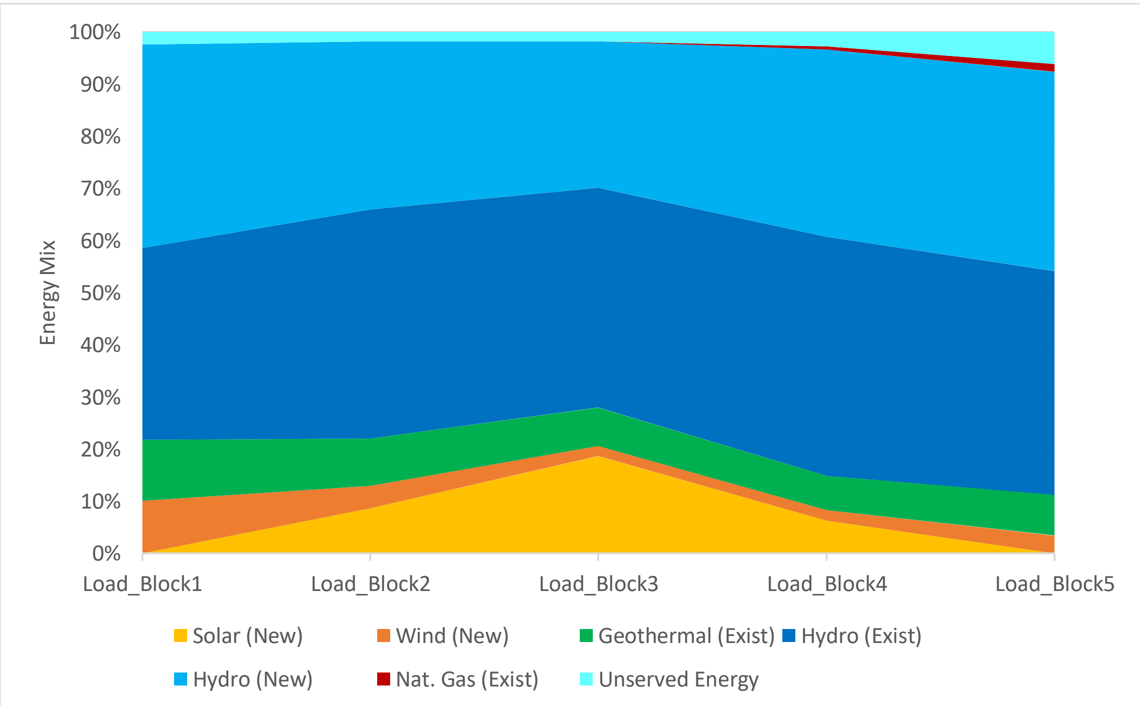


Figure 5-18: Cumulated Load Block Energy Mix – Scenario 2 (High Carbon Price)

5.4.2.3 Emission Results and Comparison

The high carbon price scenario resulted to significantly low CO_2 emissions compared to the low carbon price scenario due to increased vRES penetration in the energy mix. The vRES have low carbon dioxide emission factors of 11kg/MWh and 25kg/MWh for wind and solar respectively compared to committed fossil-fueled plants with Natural gas at 433kg/MWh while both HFO and gasoil plants produce approximately 900kgs of CO_2 per MWh. The total CO_2 emissions reduced from 44,076 tons to 35,393 tons a reduction of 19.7% as shown in Figure 5-19.

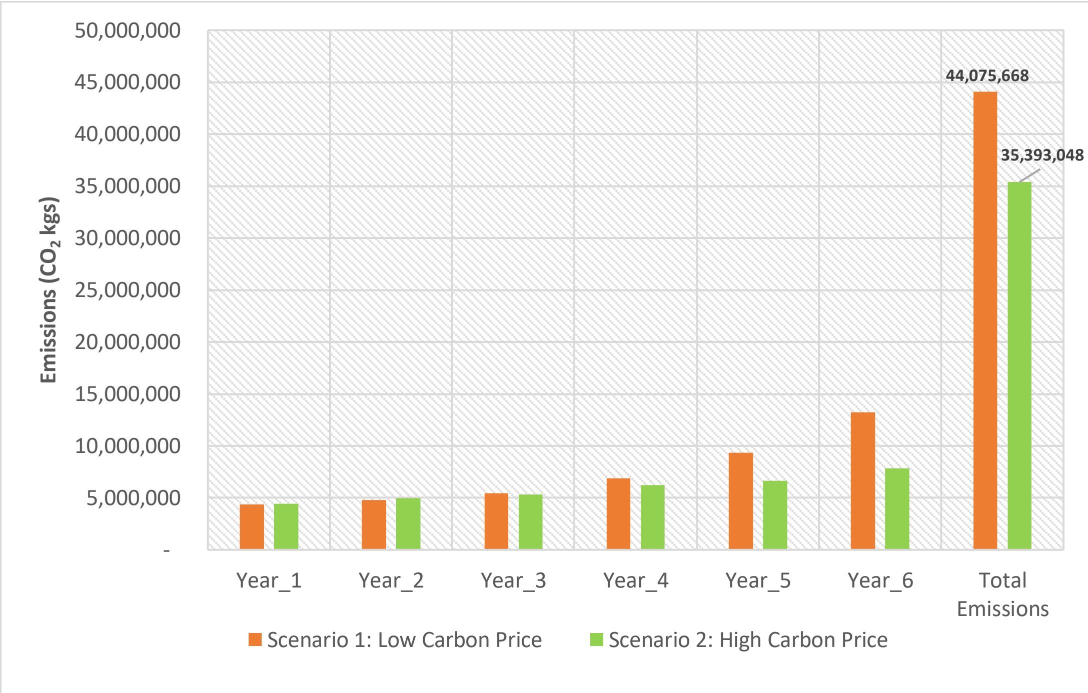


Figure 5-19: Annual & Cumulative Emission Comparison

Figures 5-20 & 5-21 show the annual emission mix per plant for scenario 1 and 2 respectively. Comparing the emission trends in both scenarios, there is a noticeable decrease in the build-up of CO_2 emissions in scenario 2 especially towards the end of the planning period (years 4, 5 and 6) due to increased vRES penetration. On the other hand, there is increased fossil-based generation in scenario 1 in the same period resulting to exponential increase in CO_2 emissions. Though being a highly pollutant technology, the HFO emissions in Scenario 2 were very minimal since its generation was significantly lower when compared to Scenario 1.

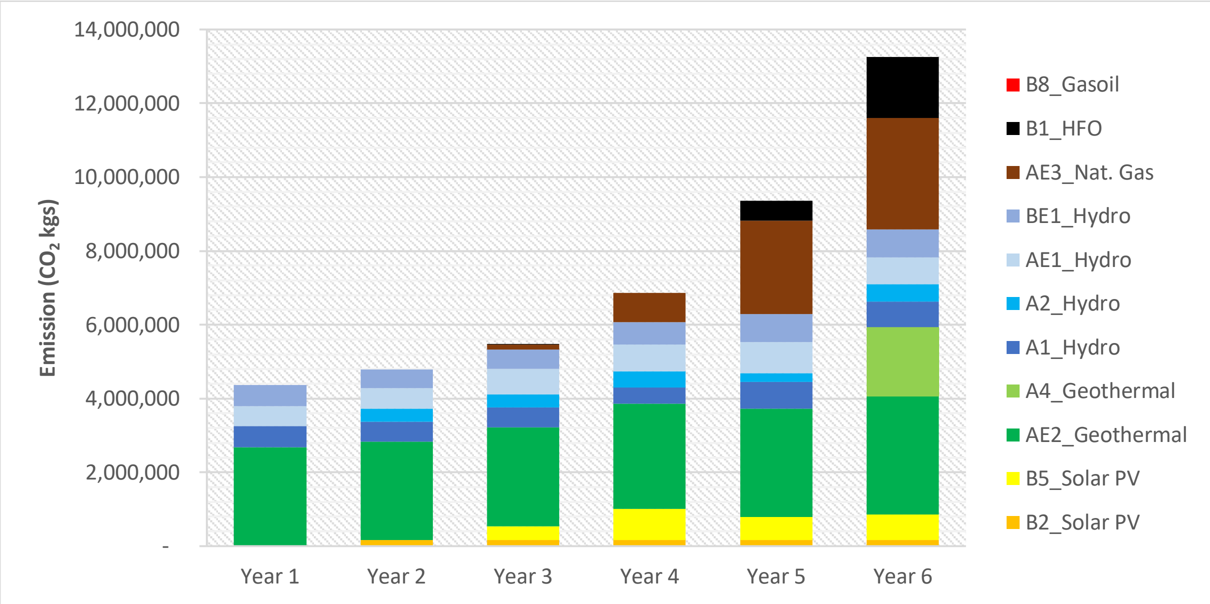


Figure 5-20: Annual Emission per Plant - Scenario 1 (Low Carbon Price)

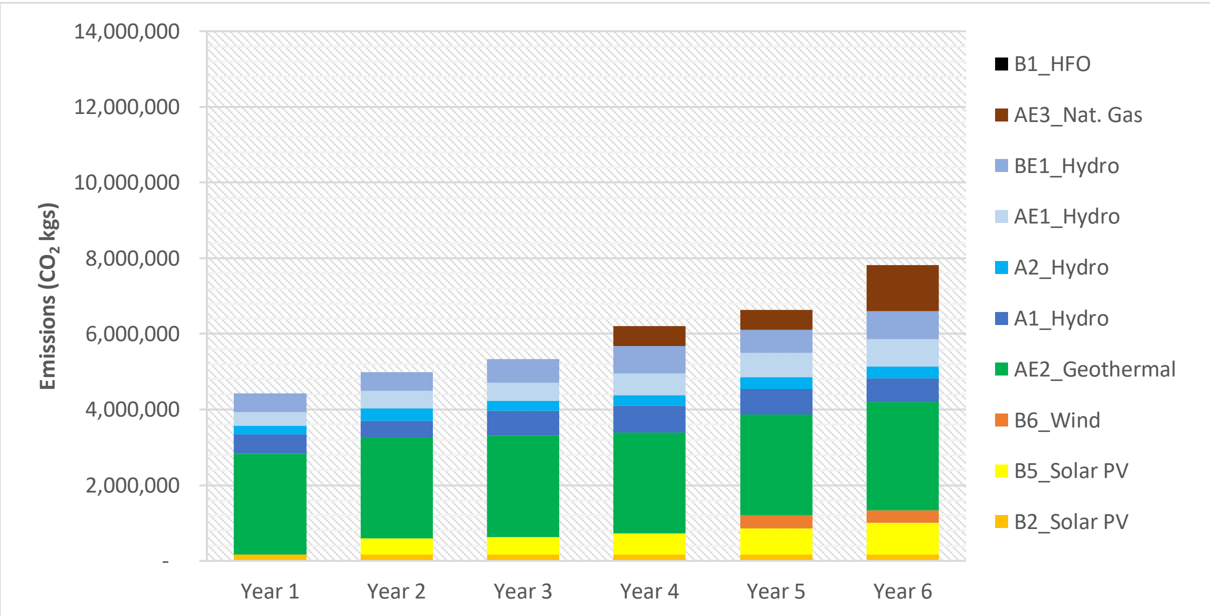


Figure 5-21: Annual Emission per Plant - Scenario 2 (High Carbon Price)

In scenario 1 (low carbon price), annual emissions increased exponentially from 4,364 tons of CO_2 in the start of the planning period to 13,248 tons at the end of the planning period as shown in Figure 5-22. The average annual growth in CO_2 emission in this scenario was 25%. On the other hand, annual CO_2 emissions in the high carbon price scenario (Scenario 2) grew at an average rate of 12% to reach 7,814 tons at the end of the planning period as illustrated in Figure 5-23. As previously stated, the HFO emissions in Scenario 2 were minimal due to the significantly reduction in HFO generation in this scenario.

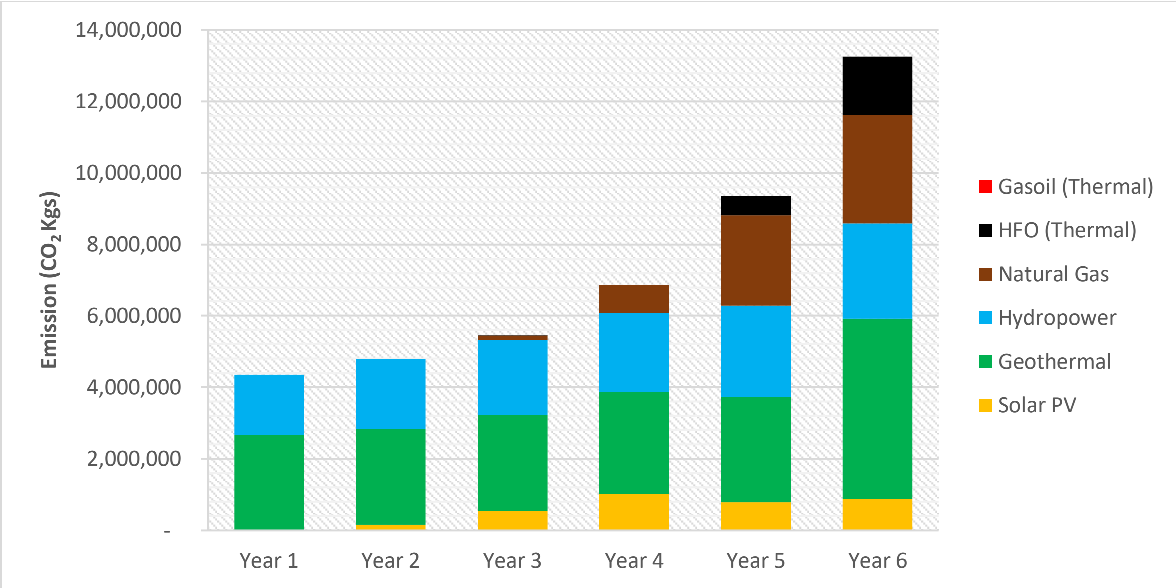


Figure 5-22: Annual Emission per Technology - Scenario 1 (Low Carbon Price)

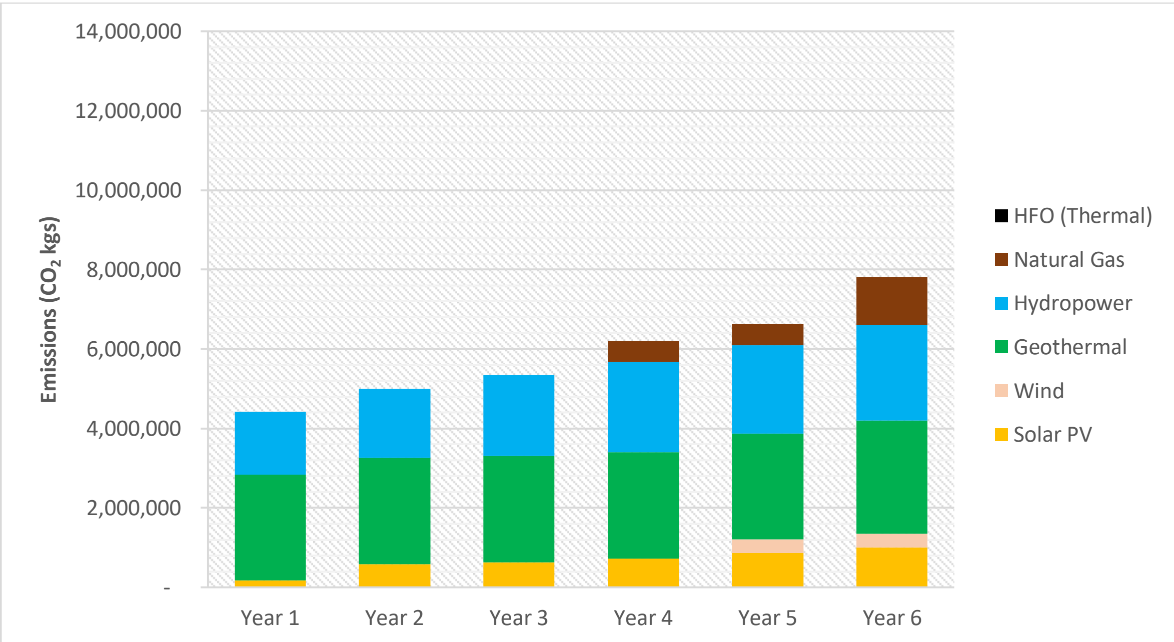


Figure 5-23: Annual Emission per Technology - Scenario 2 (High Carbon Price)

Figures 5-24 and 5-25 give the cumulative CO_2 emission mix for the low and high carbon price scenarios in the entire planning period. For both scenarios, geothermal and hydropower though having lower emission factors than the fossil-fueled generators contributed the highest amount of CO_2 emissions. This was because these technologies were used to supply base and intermediate loads and thus have high share in the generation mix (more than 80% combined). As expected, the fossil-fueled generators (Natural gas, HFO and gasoil in this case) had a substantial share of emissions in load block five. This load block represented the peak load times with an annual load factor of 100% in all the study years. During peak load, such plants were suited for fast peaking with short utilization period due to their flexibility, low investment and fixed costs but high variable (operation) costs. The fossil-fueled generators contributed approximately 20% and 6% of the CO_2 emissions produced in scenario 1 and 2 respectively. The emission contribution from vRES (solar and wind) was at 8% (scenario 1) and 13% (scenario 2).

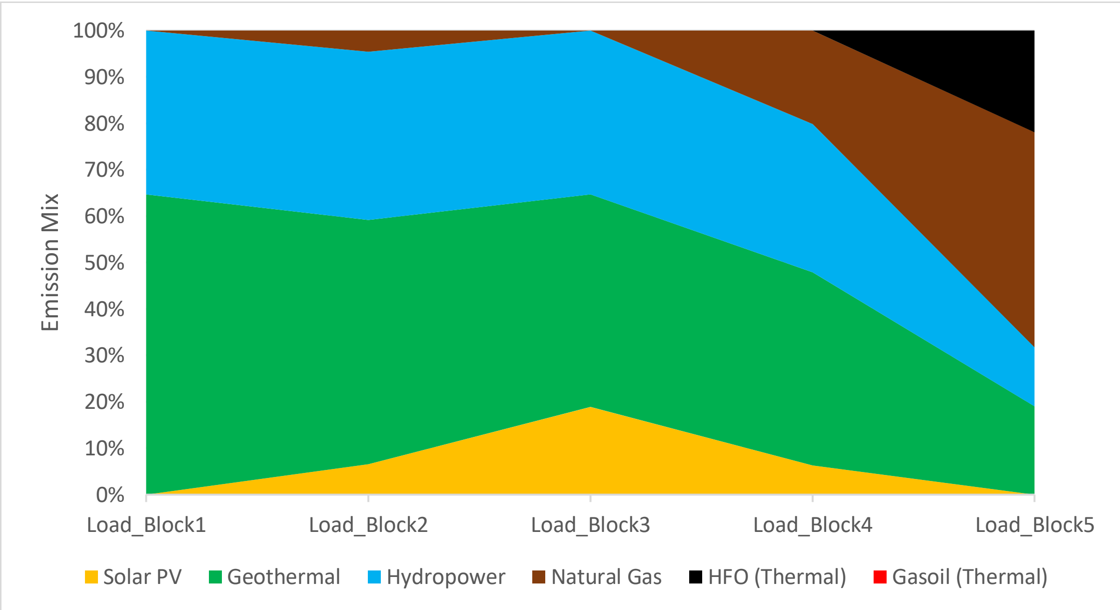


Figure 5-24: Cumulated Load Block Emission Mix – Scenario 1 (Low Carbon Price)

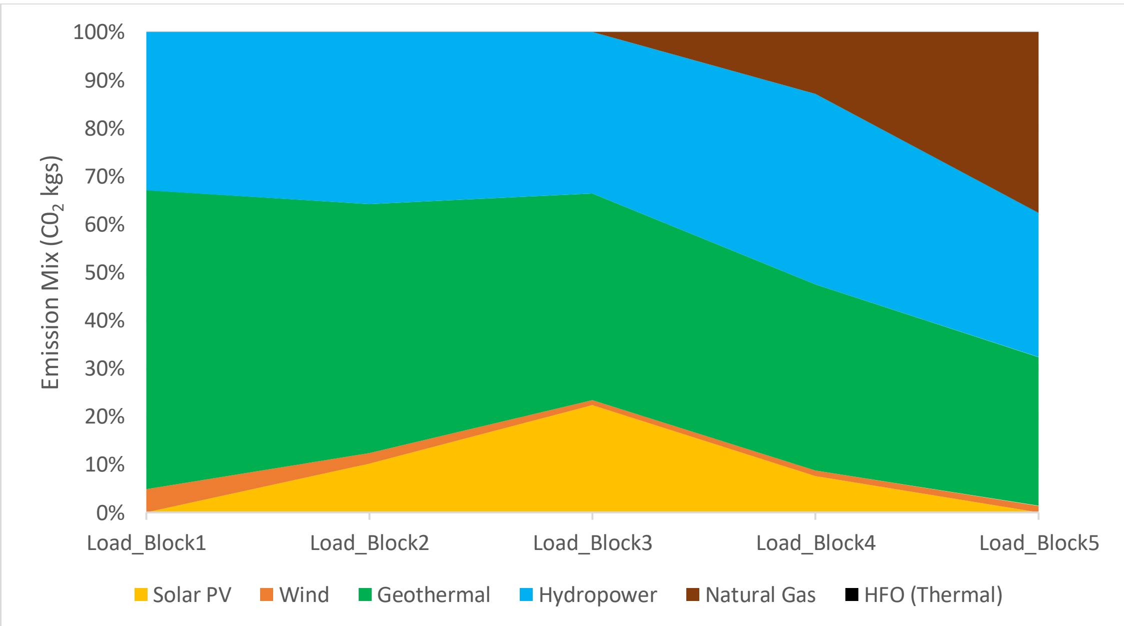


Figure 5-25: Cumulated Load Block Emission Mix – Scenario 2 (High Carbon Price)

5.4.2.4 Investment, Operation Costs and Penalties

The investment and operation cost comparison for the low and high carbon price scenarios is given in Figure 5-26. Scenario 2 (high carbon price scenario) has relative higher investment and fixed costs of 2.94 million USD and 12.2 million USD compared to 2.61 million USD and 11.1 million USD in scenario 1 (low carbon price scenario). However, the increased vRES penetration in scenario 2 reduced the operation cost significantly to 2.9 million USD in comparison to 4.4 million USD scenario 1, representing a 34% reduction. The transmission variable and loss costs were almost the same. Overall, the total investment and operation cost for the two scenarios were very close at 19.5 million USD and 19.4 million USD for scenario 1 and 2 respectively.

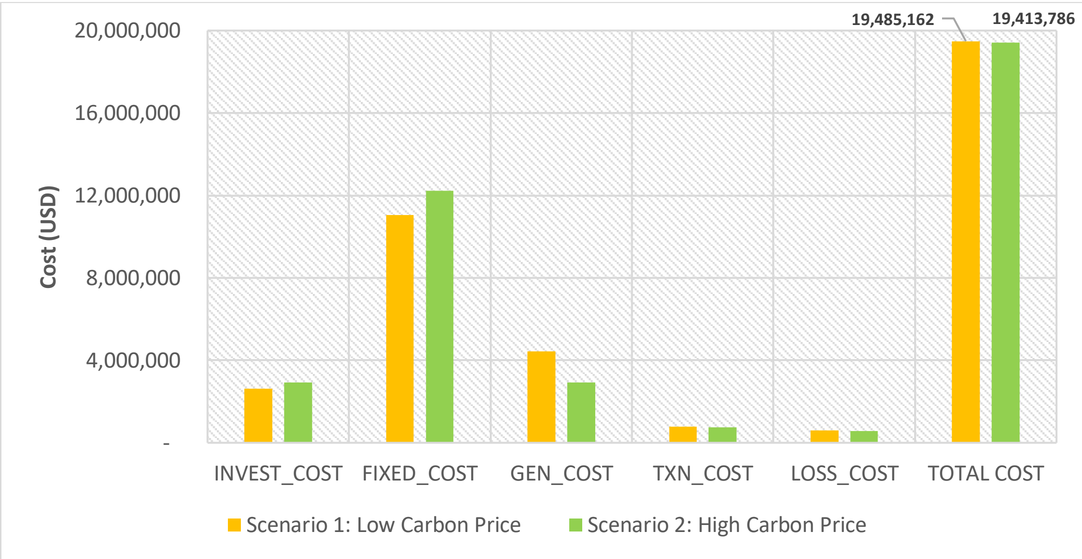


Figure 5-26: Specific and Total Cumulative Cost Comparison

Figure 5-27 and 5-28 give the trends in annual investment and operation costs for the low and high carbon price scenarios respectively. In scenario 1, the generation cost increases exponentially from year 4 reaching 1.56 million USD in year 6. This can be attributed to commitment of substantial generation capacity from fossil-fueled generators whose operating cost is high. On the other hand, the generation cost in scenario 2 that has high vRES penetration increases gradually throughout the planning period to reach 0.74 million USD in year 6.

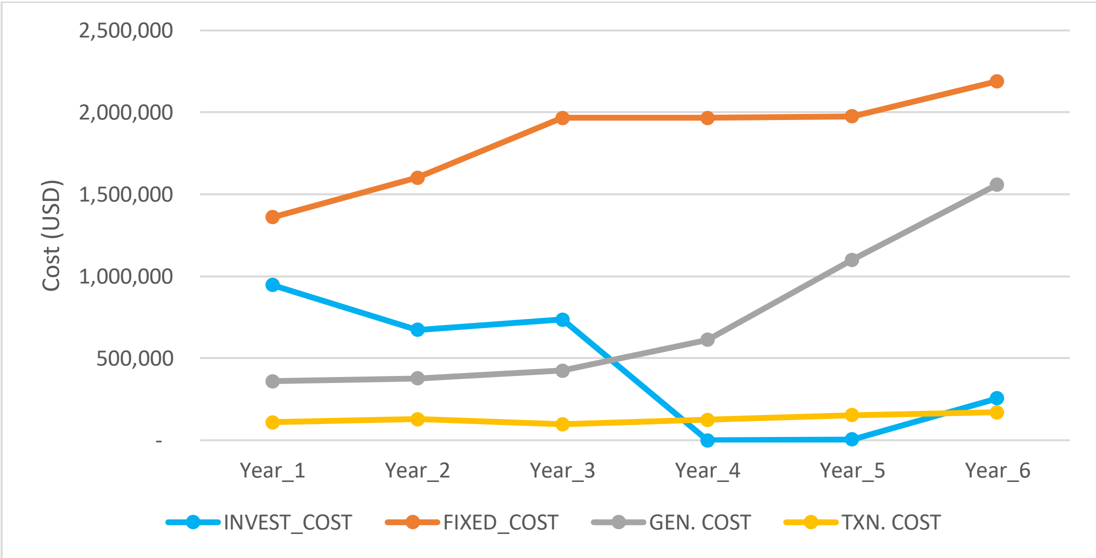


Figure 5-27: Investment and Operation Costs - Scenario 1 (Low Carbon Price)

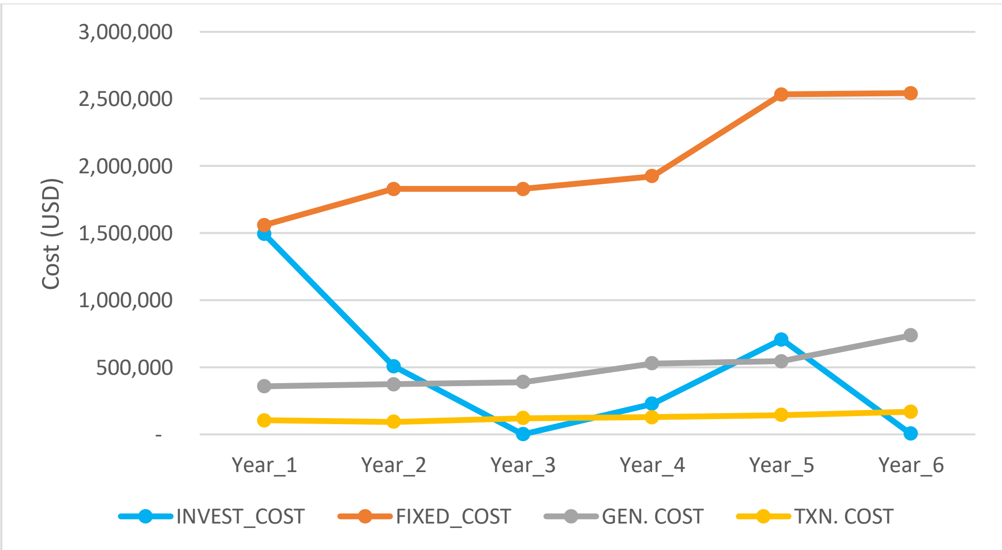


Figure 5-28: Investment and Operation Costs - Scenario 2 (High Carbon Price)

The penalties formulated and monitored in this optimization for scenarios 1 and 2 behaved as illustrated in Figure 5-29 and 5-30 respectively. There were no branch or generator overloads in the optimized generation and transmission expansion plan. vRES penalties were observed towards the end of the planning period in both scenarios. These were majorly due to inadequate vRES reserve capacities especially in load block 5 (peak load times) when the committed conventional generators were producing at near maximum capacities leaving little room for compensating vRES downward output fluctuations. As expected higher vRES penalties were experienced in scenario 2 (high carbon price scenario) due to increased vRES penetration. This phenomenon elevates the risk of unserved energy. As a result, higher vRES reserve and unserved energy were experienced concurrently in scenario 2.

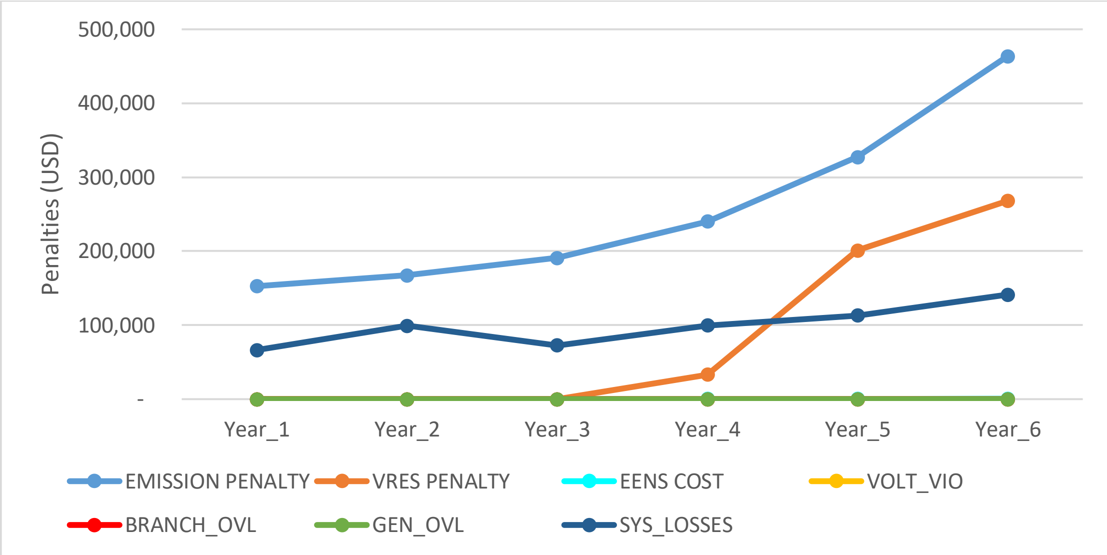


Figure 5-29: Incurred Penalties - Scenario 1 (Low Carbon Price)

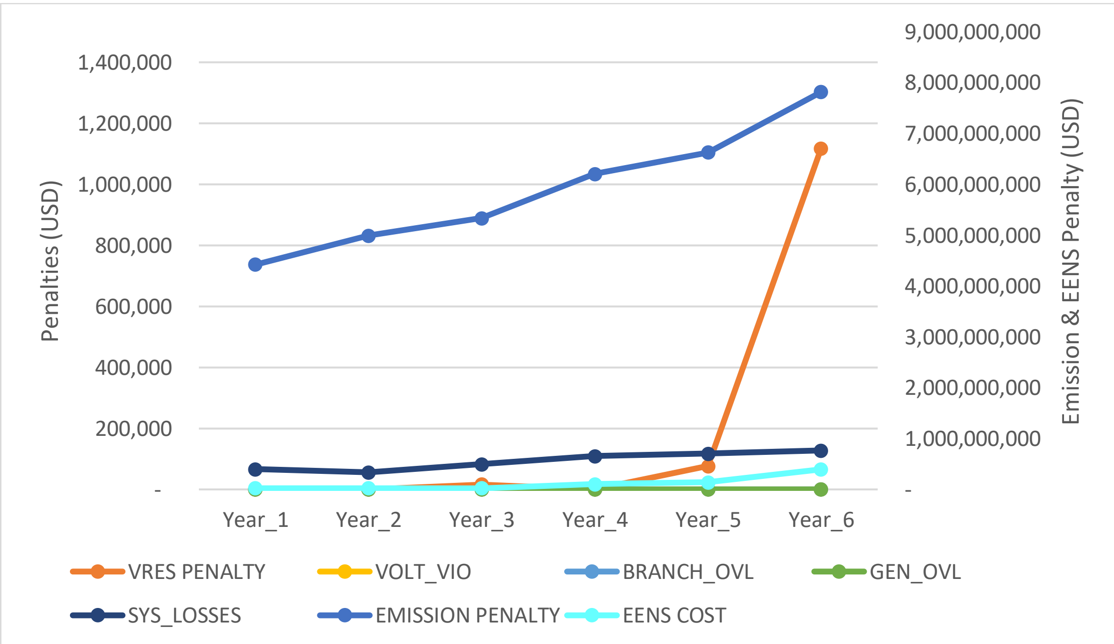


Figure 5-30: Incurred Penalties - Scenario 2 (High Carbon Price)

5.5 AC-Power Flow Based MAMODGTEP with Optimal Intermittent RES Penetration

Electric power systems have been expanding at a high rate around the world due to increasing electricity demand especially in the developing countries. As a result, such huge networks are subdivided into specific smaller areas/clusters based on the features being studied. In practice, when dealing with electric power generation and transmission infrastructure expansion planning, networks under investigation are usually subdivided into geographical areas within a country, group of countries or even continentally. Different geographical regions are best suited for specific generation technologies due to certain favourable factors. For example, just like in many other countries, in Kenya generation technologies utilizing imported fuels are usually located along the coastal regions. On the other hand, locations for renewable energy sources such as wind, solar, hydro and geothermal are mainly dictated by resource availability.

To capture this practical power system planning phenomenon, the formulation of the Multi-Objective Generation and Transmission Expansion Planning optimization problem was extended to cover a Multi-Area environment. In formulating the Multi-Area Multi-Objective Dynamic Generation and Transmission Expansion Planning (MAMODGTEP) problem the mathematical procedure and equations detailed in section 5.2 and 5.3 were utilized. To capture the multi-area characteristics the following features were included:

(i) Loads in all the buses in a specific area are lumped to obtain the area total load. Similarly, interconnections between buses in one area are ignored. However, transmission lines interconnecting various study areas are explicitly defined with specific line parameters, costs and lengths. The same transmission related formulations in equations (5.7) to (5.13) are applied in the optimization though based on respective areas and not buses.

(ii) Rather than optimizing the different generation units, optimization is usually done based on generation technology and constrained to the available resource or exploitation capability in each area. As a result, for a given planning year fixed and variable generation cost are given as in equations (5.53) to (5.56).

$$ICG_t = \sum_a^A \{ \sum_{q=1}^{NT} \varepsilon_{q,a,t} P_{q,a,t} (IC_{q,a} - S_{q,a}) \} \tag{5.53}$$

$$PCG_t = PCG_{Fixed,t} + PCG_{Var,t} \tag{5.54}$$

$$PCG_{Fixed,t} = \sum_a^A \{ \sum_{e=1}^{ET} P_{e,a,t} FC_{e,a} + \sum_{q=1}^{NT} \varepsilon_{q,a,t} P_{q,a,t} FC_{q,a} \} \tag{5.55}$$

$$PCG_{Var,t} = \sum_a^A \sum_l^L \begin{Bmatrix} \sum_{e=1}^{ET} \mu_{e,a,l,t} (H_{l,t} G_{e,a,l,t} VC_{e,a}) + \\ \sum_{q=1}^{NT} \mu_{q,a,l,t} (H_{l,t} G_{q,a,l,t} VC_{q,a}) \end{Bmatrix} \tag{5.56}$$

Where, ET and NT represent the total number of existing and candidate generation technologies while A is the number of power system areas.

(iii) In this optimization, the cost of unserved energy was calculated as follows;

$$OC_t = \sum_{l=1}^{L} H_{l,t} DNS_{l,t} C_{(DNS),l,t} \tag{5.57}$$

$$DNS_{l,t} = D_{max,l,t} - \sum_a^A \{\sum_{e=1}^{ET} \mu_{e,a,l,t} G_{e,a,l,t} + \sum_{q=1}^{QT} \mu_{q,a,l,t}\, G_{q,a,l,t}\} \tag{5.58}$$

(iv) Equations (5.19) to (5.23) representing generator related constraints were customized as below;

$$0 \leq P_{q,a,t}^{invest} \leq P_{q,a,t}^{max} \quad \text{for } \forall t \in T, \forall q \in NT \tag{5.59}$$

$$PG_{g,a,t,min} \leq PG_{g,a,l,t} \leq PG_{g,a,t,max}\ , \forall g \in (ET\ \&\ NT), \forall l \in L \tag{5.60}$$

$$P_{g,a,t,max} \leq \ (P_{g,a,t-1,max} + P_{g,a,t}^{invest}) \tag{5.61}$$

$$PG_{g,a,l,t}^2 + QG_{g,a,l,t}^2 \leq S_{g,a,l,t,max}^2 \tag{5.62}$$

Equation (5.59) constraints the maximum possible generation investment for candidate technology q in the t^{th} year to the maximum available resource or exploitation capability in area a as at that year. Equations (5.60) and (5.62) are generator operational limits in each load block while equation (5.61) constraints maximum generator capacity in each year to the existing capacity plus the invested capacity in that year.

(v) Generally, intermittent/variable renewable energy resources (vRES) in a particular area have similar capacity factor characteristics due to correlated solar irradiance and/or wind speeds. The penalties for underutilization or overutilization of vRES in equations (5.46) to (5.51) were thus re-introduced as below:

$$vRES_{pen,t}^{under} = \sum_l^L vres_{pen}^{under} (vRES_{total,l,t}^{avail} - vRES_{total,l,t}^{com}) \text{ for } vRES_{total,l,t}^{com} < vRES_{total,l,t}^{avail} \tag{5.63}$$

$$vRES_{pen,t}^{over} = \sum_l^L vres_{pen}^{over} (vRES_{reserve,l,t}^{req} - vRES_{reserve,l,t}^{avail}) \text{ for } vRES_{reserve,l,t}^{req} > vRES_{reserve,l,t}^{avail} \tag{5.64}$$

$$vRES_{total,l,t}^{com} = \sum_a^A \sum_{i=1}^{nS} u_{solar,a,l,t(i)} RES_{solar,a,l,t(i)}^{com} + \sum_{i=1}^{nW} u_{wind,a,l,t(i)} RES_{wind,a,l,t(i)}^{com} \tag{5.65}$$

$$vRES_{total,l,t}^{avail} = \sum_a^A \sum_{i=1}^{nS} cf_{solar,a,l,t(i)} RES_{solar,a,l,t(i)}^{max} + \sum_{i=1}^{nW} cf_{wind,a,l,t(i)} RES_{wind,a,l,t(i)}^{max} \tag{5.66}$$

$$vRES_{reserve,l,t}^{req} = \sum_a^A \sum_{i=1}^{nS} f_{solar,a(i)} u_{solar,a,l,t(i)} RES_{solar,a,l,t(i)}^{com} + \sum_{i=1}^{nW} f_{wind,a,(i)} u_{wind,a,l,t(i)} RES_{wind,a,l,t(i)}^{com} \tag{5.67}$$

$$vRES_{reserve,l,t}^{avail} = min \begin{cases} \sum_a^A \sum_{i=1}^{M} u_{conv,a,l,t(i)} (GEN_{conv,a,l,t(i)}^{max} - GEN_{conv,a,l,t(i)}^{com}) \\ \sum_a^A \sum_{i=1}^{M} u_{conv,a,l,t(i)} (GEN_{conv,a,l,t(i)}^{com} - GEN_{conv,a,l,t(i)}^{min}) \end{cases} \tag{5.68}$$

5.5.1 MAMODGTEP Optimization Results

To explore the integrated generation and transmission expansion planning optimization problem in a multi-area, multi-objective and dynamic environment the adapted 6-bus IEEE test network data described in Appendix A.2 and Sections 4.3.1 and 5.4.2 of this research work was utilized. Each bus represented a specific area while the existing and candidate generation technologies were distributed among the areas as given in Tables 5-9 and 5-10. Areas 2 and 3 were assumed to have abundance in solar resource while Area 6 was suitable for wind power plants and geothermal exploitation. The maximum capacities for each technology in an area were a cumulative total for all the power plants previous connected to the buses forming that area as given in the original 6-bus IEEE test system data [2].

Table 5-9: Existing Generation Technology Distribution

Area	Buses	Technology	Maximum Capacity (MW)
Area 1	Bus 1	Hydropower	10
Area 2	Bus 2	Hydropower	10
Area 3	Bus 3	Geothermal	5
Area 6	Bus 6	Natural Gas	5

Table 5-10: Candidate Generation Technology Distribution

Area	Buses	Technology	Maximum Capacity (MW)
Area 1	Bus 1	Hydropower	17
Area 2	Bus 2	Solar PV	8
Area 3	Bus 3	Solar PV	5
Area 4	Bus 4	HFO (Thermal)	3
Area 5	Bus 5	Natural Gas	8
Area 6	Bus 6	Geothermal	7
		Wind	18

As mentioned on Chapter 4, the loads for IEEE 6-bus test system are located in buses 3, 4 and 5. In this research work, similar load characteristics were assumed for all areas. However, different capacity factors were considered for vRES sited at different locations as given in Table 5-11.

Table 5-11: Area Load and vRES Characteristics

Load Block		Block 1	Block 2	Block 3	Block 4	Block 5
Time segment duration (hrs)		1510	2800	2720	1120	610
Load factor (lf_l)	All	50%	65%	80%	90%	100%
Solar capacity factor ($cf_{solar,a,l}$)	Area 2	0%	35%	65%	45%	0%
Solar capacity factor ($cf_{solar,a,l}$)	Area 3	0%	30%	80%	30%	0%
Wind capacity factor ($cf_{wind,a,l}$)	Area 6	80%	45%	25%	30%	55%

The mapping parameters given in Table 5-7 were used in optimizing the MAMODGTEP problem. The MAMODGTEP optimization employed a carbon dioxide emission penalty of 0.035USD per kilogram (average weighted carbon price as at June 2021 [89]). The obtained results were as summarized in Sections 5.5.1.1 to 5.5.1.7.

5.5.1.1 MAMODGTEP Investment Decisions

Table 5-12 gives the optimal investment decisions for the formulated ac-power flow based integrated generation and transmission expansion planning problem while considering optimal vRES penetration. The total investment cost was approximately 3 million USD. Only renewable energy sources were preferred in this case against the fossil-fuel sources with hydropower and solar PV dominating the cumulative invested capacities at 17MW and 10.5MW respectively. The transmission investment decisions were similar to those for the low carbon price scenario in section 5.3.2 save for the fact that the investment years for corridors (1, 4) and (3, 6) were interchanged.

Table 5-12: MAMODGTEP Generation and Transmission Investments

Year/Load	Generation	Transmission
Year 1 (30MW)	Hydro_8.5MW (Area 1), Solar PV_2.5MW (Area 3)	(2,3), (2,4)
Year 2 (35MW)	Hydro_8.5MW (Area 1), Solar PV_4MW (Area 2)	-
Year 3 (40MW)	-	(1,4)
Year 4 (45MW)	Geothermal_3.5MW (Area 6)	-
Year 5 (50MW)	Wind_9MW (Area 6)	(3,6)
Year 6 (55MW)	Solar PV_4MW (Area 2)	-
TOTAL COST (USD)	**3,024,242**	

As shown in Figure 5-31, most of the new generation investments were made in areas one (17MW of hydropower), two (8MW of solar) and six (9MW wind and 3.5MW geothermal). From the load data for IEEE 6-bus test system, loads are located in areas (buses) 3, 4 and 5 at 40%, 30% and 30% ratios respectively. Only one solar power plant was invested in area 3 with no generation investments made in areas 4 and 5 despite being substantial load centers. Investigations showed that this was because the candidate generators in these areas were fossil fuel based (HFO in area 4 and Natural gas in area 5) as described in Table 5-10. As a result, it was cheaper to invest in cheaper and cleaner sources in other areas as well as an additional transmission lines and transmit power to these locations.

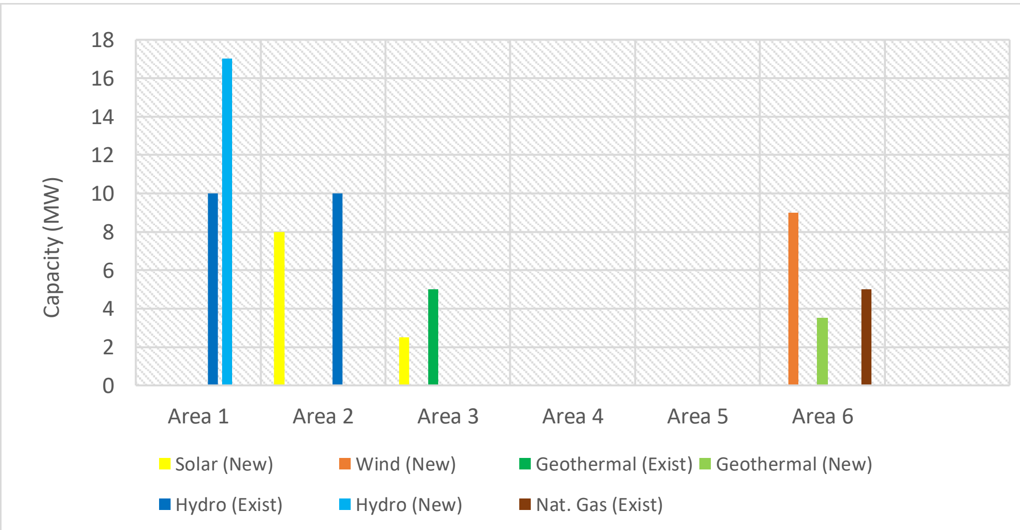


Figure 5-31: Area distribution of generation sources

The annual installed capacity per technology was as given in Figure 5-32. The figure also compares the annual installed capacities to the peak load plus the reserve requirements. There were no capacity gaps in the optimized MAMODGTEP plan and the installed capacities surpassed the sum of peak load and reserve margin in all the studied years.

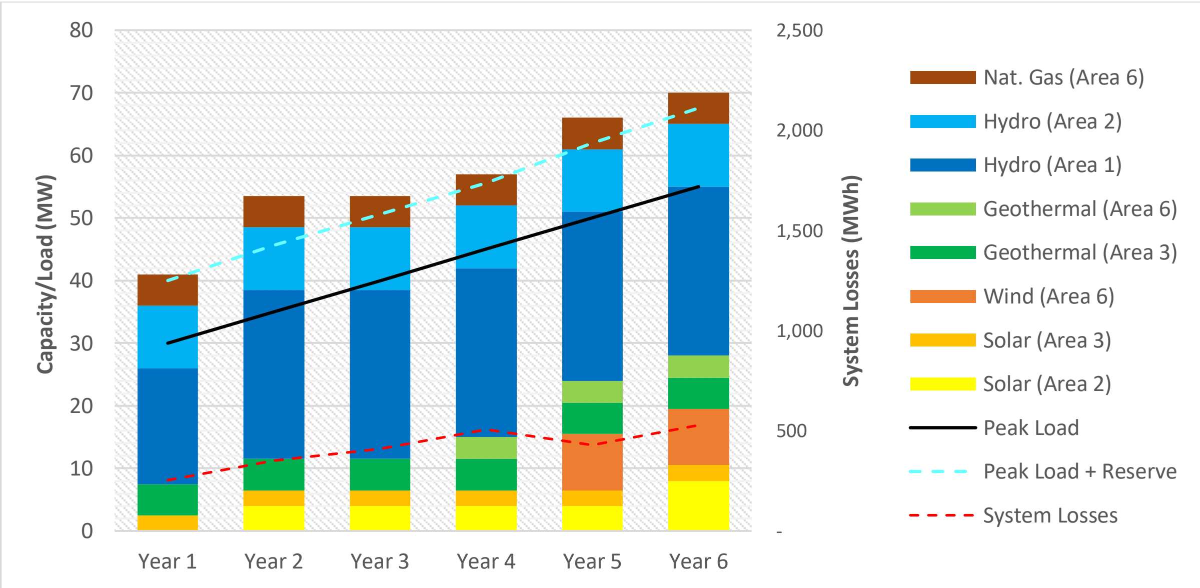


Figure 5-32: Annual Installed Capacity vs Peak Load plus Reserve

5.5.1.2 Investment & Operation Costs and Penalties

Figure 5-33 gives the yearly distribution of various costs in the optimization. Transmission operation cost was fairly constant throughout the planning period while generation costs increased gradually from 0.38 million USD to almost one million USD at the end of the planning period. As additional generation and transmission investments were committed, the annual fixed costs increased from 1.34 million USD in year 1 doubling to 2.73 million USD at the end of the planning period.

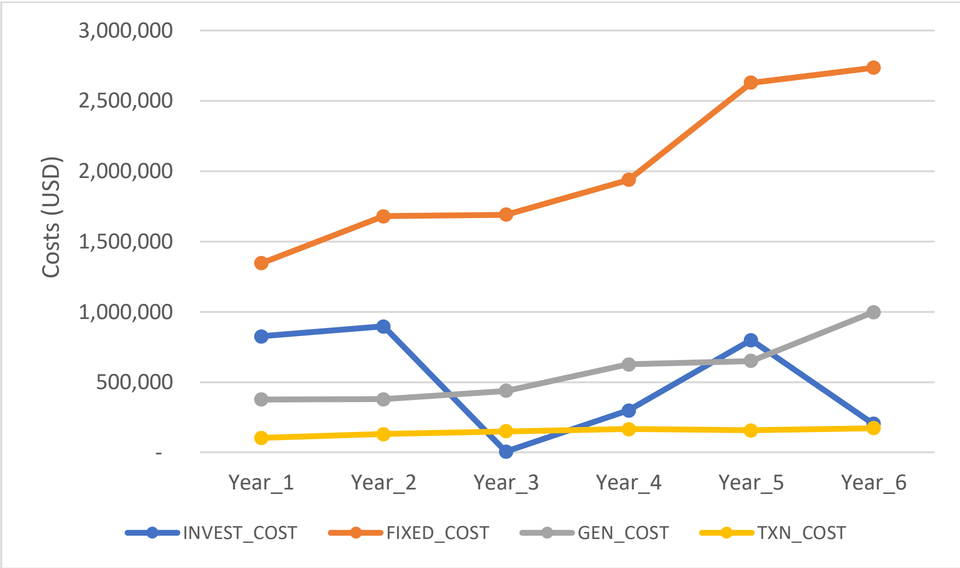


Figure 5-33: MAMODGTEP Investment, Fixed and Operation Costs

The annual trends of the various penalties in the optimization were as illustrated in Figure 5-34. The CO_2 emissions and system loss penalties increased gradually across the planning years to reach 0.36 million USD and 0.13 million USD in the sixth year respectively. There were no generator or transmission line overloads in the optimized MAMODGTEP plan while the unserved energy was minimal with an annual cumulative maximum of 10MWh in the last year of study. With increased share of vRES generation towards the end of the planning period, vRES utilization penalties increased to reach half a million USD. This was majorly due to vRES overutilization penalization, which occurs when the already committed conventional sources lack adequate spare capacities to compensate for expected vRES output fluctuations.

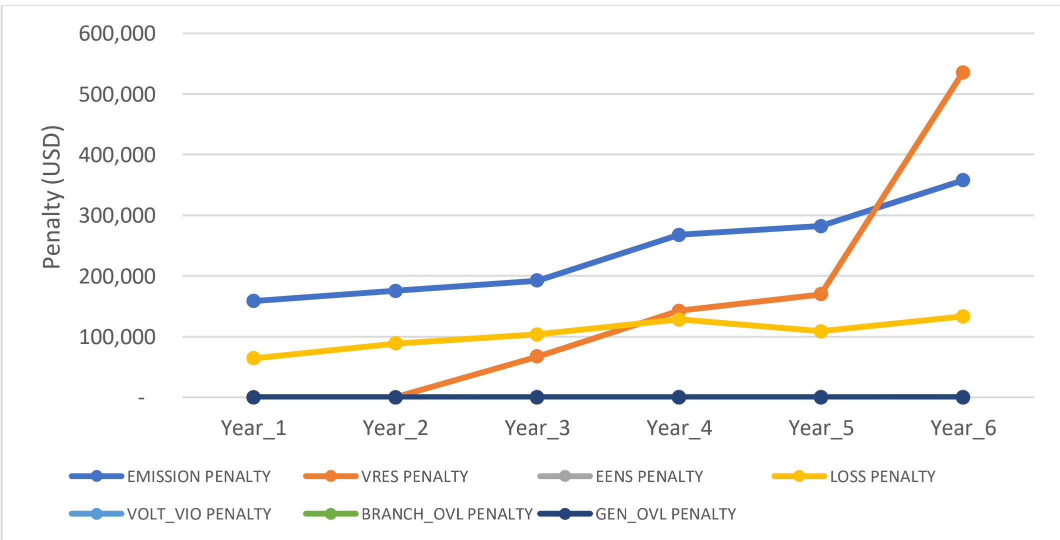


Figure 5-34: Annual Penalty Trends

5.5.1.3 AC-Power Flow Results

As previously noted, there were no transmission constraint violations in the obtained MAMODGTEP results. Figure 5-35 shows the transmission line loadings at annual peak loads. In the last year, the highest loaded transmission corridor was (5, 6) at 96%. The annual voltage profiles at peak load were as given in Figure 5-36. All the area voltages were within the recommended 0.95-1.05 pu range.

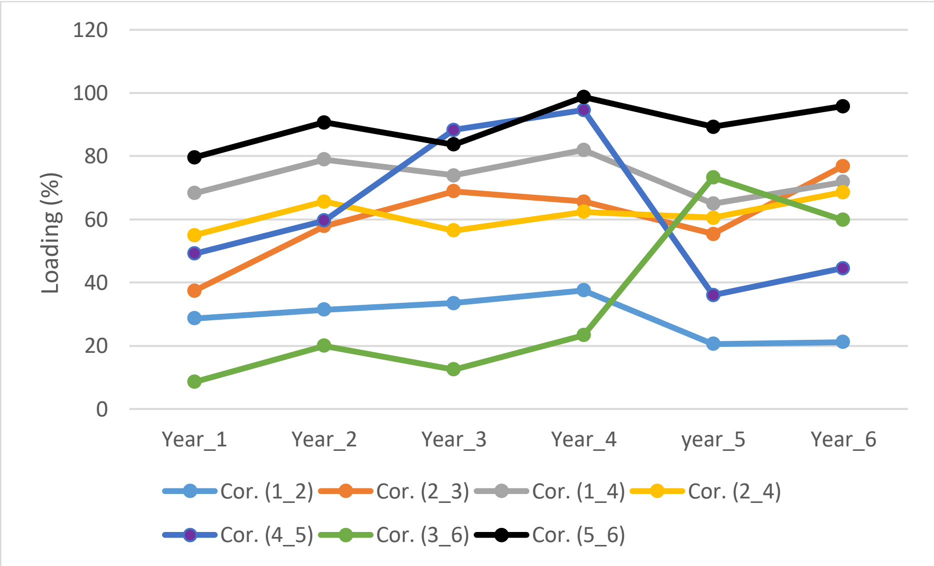


Figure 5-35: Annual transmission line loadings

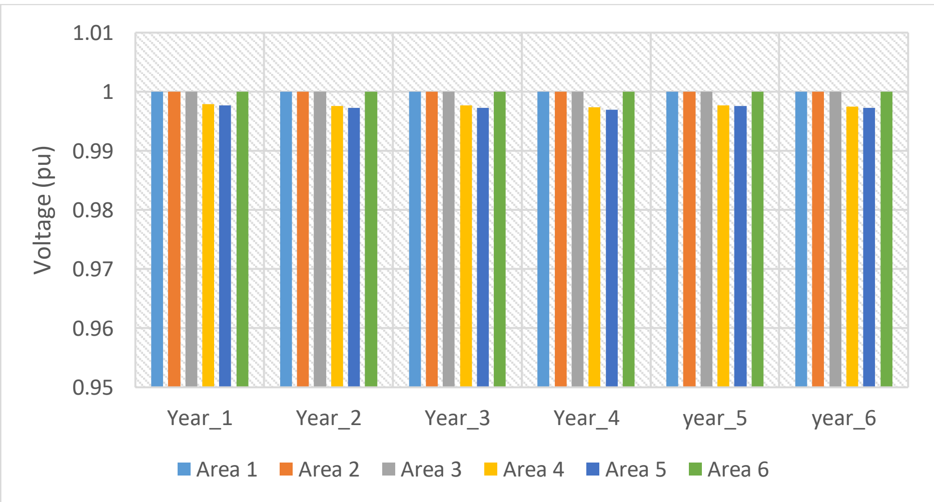


Figure 5-36: Area annual voltage profiles at peak load

5.5.1.4 Area Generation and Demand Comparison

Figure 5-37 gives a comparison of the generation energy and the demand at each area in the last year of study. Most of the energy was generated in areas 1 and 2 that were hydropower dominated. This explains the necessity of the additional transmission circuits invested in corridors (2, 3), (2, 4) and (1, 4) to facilitate transmission of the generated energy to the load centers in areas 3, 4 and 5. There is a slight energy gap of 10MWh (unserved energy in year 6) due to the increased vRES penetration causing difficult in supply-demand balancing while ensuring optimal vRES penetration by avoiding underutilization or over-utilization of the committed intermittent renewable energy sources.

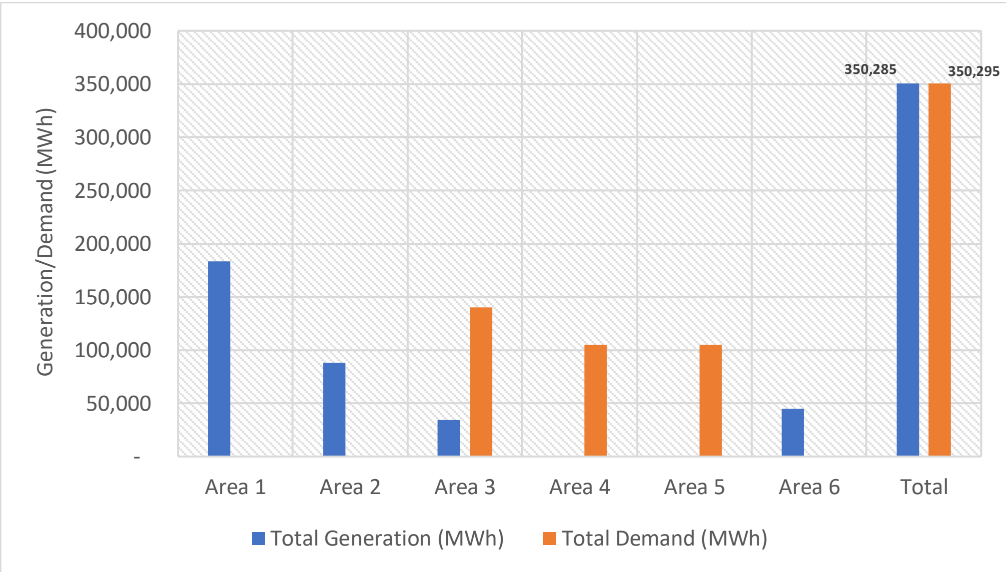


Figure 5-37: Area Generation vs Demand – Year 6

5.5.1.5 vRES Penetration Comparison

Figure 5-38 gives the share of vRES in the annual installed capacities and the respective energy mix. In the last years of planning both shares increase considerably to reach 28% and 17% in the 6^{th} year for installed capacity and energy mix respectively. The penetration of vRES is majorly limited by reserve availability from conventional generators to compensate for their expected output fluctuations. This limited reserve availability results to high vRES utilization penalties.

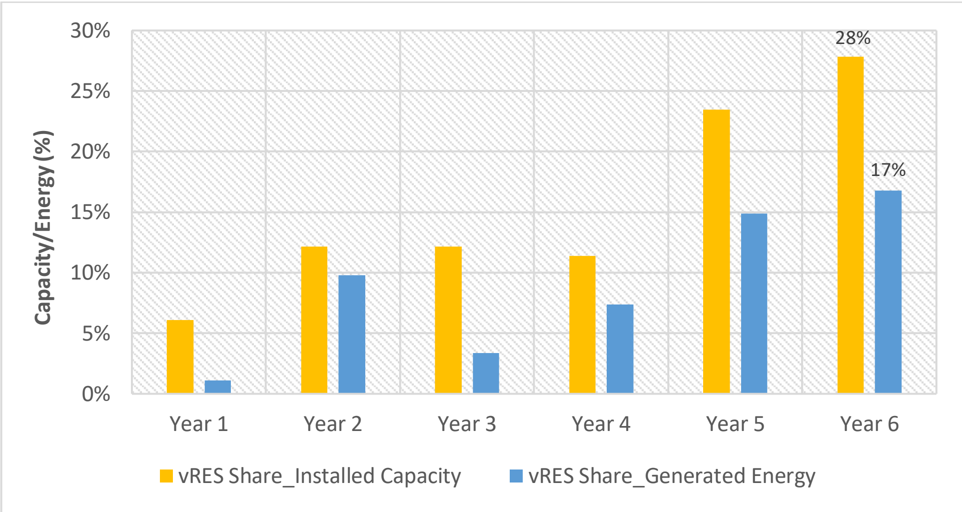


Figure 5-38: vRES share in Installed capacity and Energy mix

5.5.1.6 Generation Mix Results

The annual generation mix results were as given in Figure 5-39. The figure also gives the obtained unserved energy that was minimal throughout the planning period with some years showing slight excess generation. Both under and over generation situations were penalized in the optimization to avoid overinvestment or underinvestment. The annual unserved/excess energy was between -3MWh in year three (excess energy) to +10MWh in year six (unserved energy). Hydropower contributed the highest share of the energy mix in each of the studied years with a share of approximately 70% in the final year. This is due to its benefits of flexibility in operation, low operation cost as well as low CO_2 emission contribution per unit energy generation.

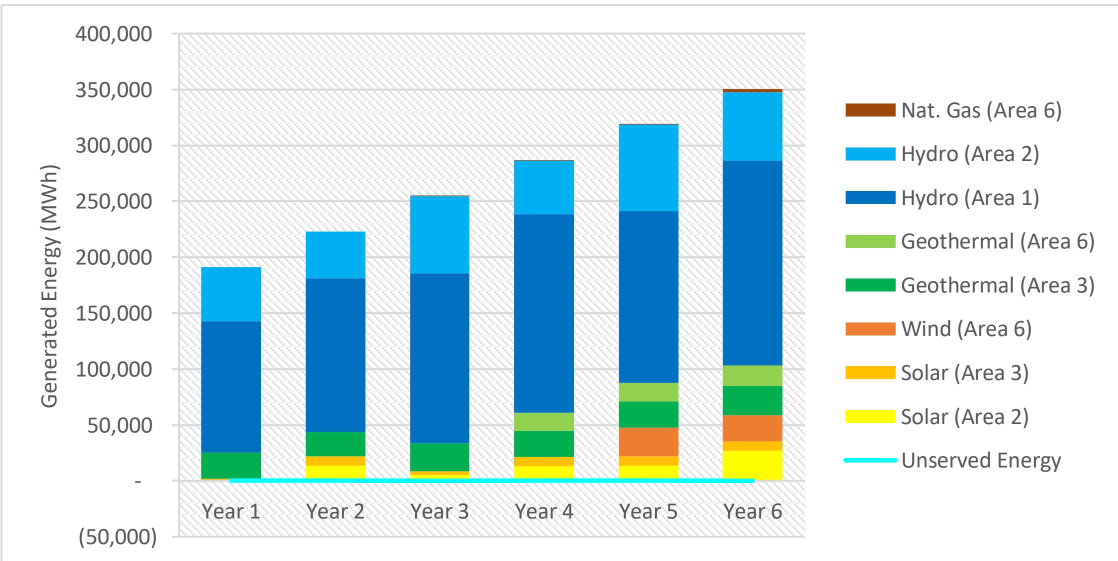


Figure 5-39: Annual generation Mix and Unserved Energy

Figure 5-40 gives the cumulative energy mix in the entire planning period per load block. vRES contribution to the energy mix are highest at load block 3 at 15% due to the high solar PV capacity factors in this load block. Fossil fuel-based generation (the existing Natural gas unit) was majorly utilized in the fifth load block (peak load time) contributing 2% of the load block generation mix.

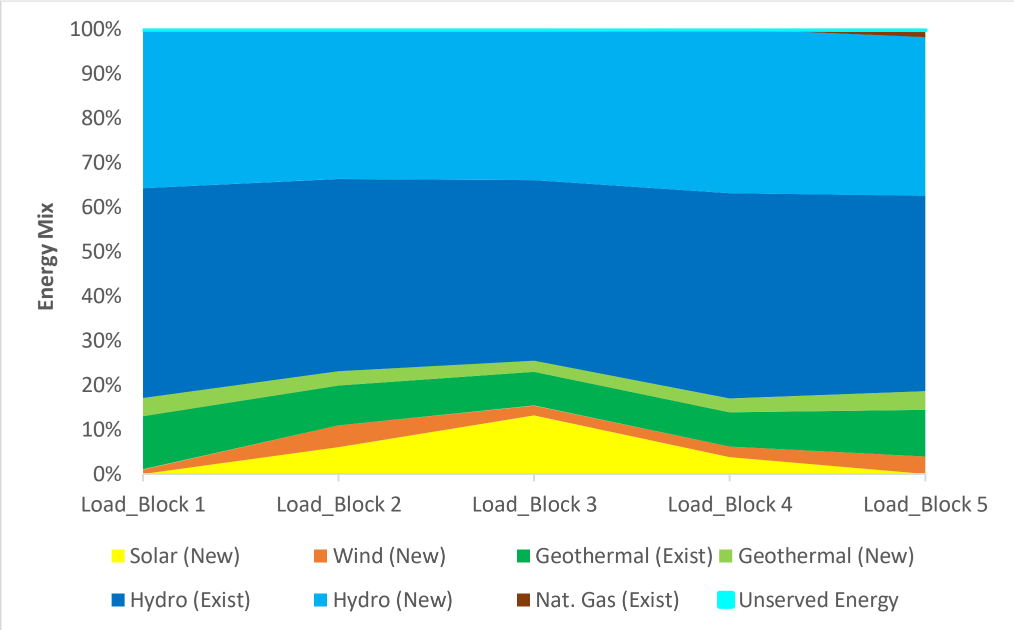


Figure 5-40: Cumulative Load block Energy Mix

5.5.1.7 Emission Results

The annual CO_2 emissions per technology in each area are given in Figure 5-41. Geothermal power plants contributed the highest share of emissions in all the studied years. This is because geothermal was the second largest contributor to the annual energy mixes throughout the entire planning period after hydropower. Therefore, since geothermal has a higher CO_2 emission factor of 122kgs/MWh compared to hydropower's 10kgs/MWh it produced the highest emissions reaching 53% in the final year of optimization. The total annual CO_2 emission increased from 4,531 tons in the first year to 10,219 tons in the 6th year.

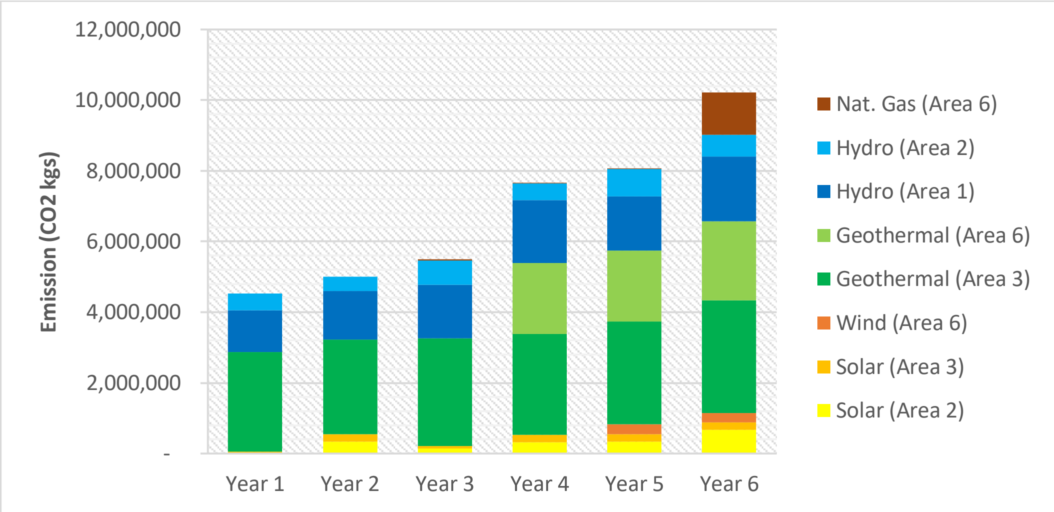


Figure 5-41: Annual Emission Mix

Figure 5-42 gives the cumulative CO_2 emission mix per load block. There was a considerable share of emissions from the fossil-fueled generators (Natural gas) in load block five. Load block five represented the peak demand scenario with a load factor of 100% as previously given in Table 5-11. Therefore, fossil-fuel generators were committed in the system to provide peaking capacity. In addition, the capacity factor of Solar PV plants was 0% and thus no available solar generation in this load block. Natural gas contributed approximately 23% of the CO_2 emissions in this load block despite generating only 2% of the required energy. This is due to its high emission factor of 433kg/MWh. vRES had the lowest CO_2 emission contribution of 8% having generated approximately 10% of the total energy in the planning period.

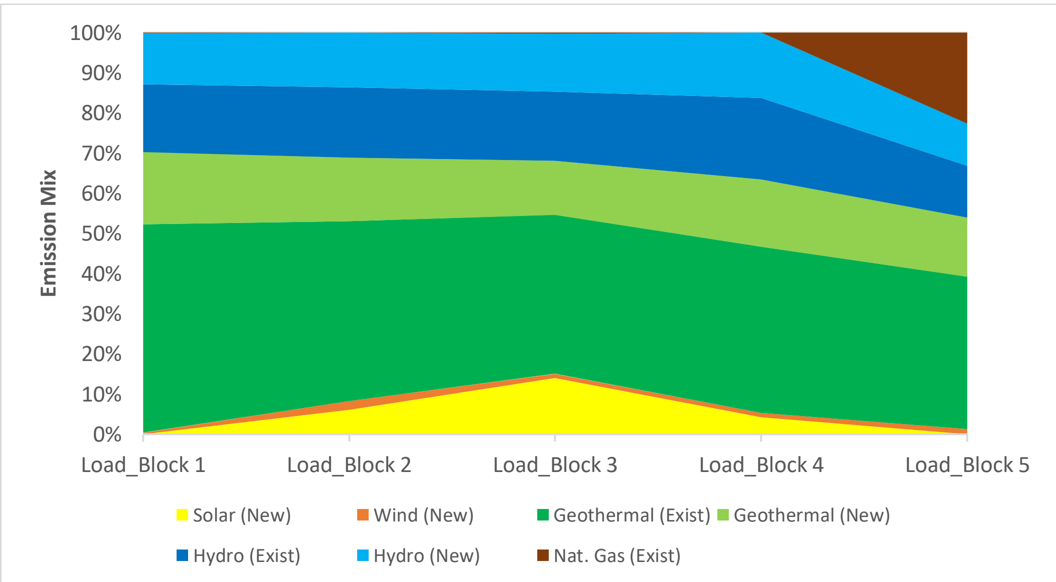


Figure 5-42: Cumulative Load block Energy mix

5.6 Chapter Conclusion

In this chapter, the integrated Generation and Transmission Expansion Planning (GTEP) optimization problem was formulated in a multi-objective and dynamic environment. The formulation was based on the more accurate AC power flow network representation. The multi-objective function developed took into account the investment, production and outage costs as various ac-power flow based transmission network constraints including penalties related to active power losses, voltage profile violation, line and generator overloads. The impact of N-1 redundancy criterion was also studied. The formulated problem was solved using the developed adaptive hybrid meta-heuristic approach. The obtained results showed the superiority of the proposed MODGTEP optimization problem formulation and solution methodology to other reviewed solution techniques. The proposed formulation and solution methodology reduced total MODGTEP investment and operation cost by 7% compared to the MINLP approach. In addition, the obtained optimized plan did not experience any severe voltage or thermal violations, as is the case with the DC power flow-based results. A 10% reduction in three-year cumulative system losses were also observed. Inclusion of the contingency analysis showed that the committed components (generators and transmission lines) increase to ensure sufficient redundancy. This results to an increase in the obtained expansion cost by approximately 9%.

The formulated ac-based MODGTEP was extended to consider optimal vRES penetration. This was achieved by formulating and integrating vRES underutilization and overutilization penalties to the overall objective function. Two scenarios, assuming different carbon prices were simulated. The high carbon price scenario resulted to a 12.5% increase in the combined generation and transmission investment cost as well as a high share of vRES penetration at 20% of installed capacity compared to 13% in the low carbon price scenario. A 19.7% reduction in total CO_2 emissions was achieved in the high carbon price scenario.

The MODGTEP problem was then formulated in a multi-area environment with various energy sources distributed amongst the areas. The obtained results showed that renewable energy sources were preferred to fossil-fueled generators especially when considering emission penalty in the optimization. A maximum of 28% and 17% annual vRES penetration in installed capacity and energy mix respectively was optimally achieved. The penetration level was majorly limited by vRES reserve requirement penalties as well as the risk of unserved energy at high levels of vRES integration. Both challenges occurring due to the variability of vRES power outputs. Inclusion of grid-scale energy storage and demand side management as recommended in advancement of this research will have a positive impact on vRES penetration. The role of vRES in climate change adaptation and mitigation was vivid. In the 6-year planning period, vRES contributed the lowest CO_2 emissions at 8% having generated approximately 10% of the total energy compared to the fossil-fueled gas power plants that contributed 23% of the emissions with only 2% share of generated energy at peak load.

6 CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary of Research Outcomes and Conclusions

6.1.1 Power System Expansion Planning Review

In this thesis, the recent research works in integrated Generation and Transmission Expansion Planning (GTEP) were reviewed in detail. The findings of the reviewed GTEP works showed that only 15% of the works were formulated in a dynamic multi-objective planning environment. Among the reviewed works only 3% had employed AC power flow analysis in formulating a multi-objective dynamic GTEP optimization problem. These works however linearized the AC power flow constraints by adopting assumptions similar to those made in DC power flow analysis. They assumed that angular separation between buses is very small, that is $(\theta_i - \theta_j) < 6^{\circ}$ such that $Cos(\theta_i - \theta_j) = 1, Sin(\theta_i - \theta_j) = (\theta_i - \theta_j)$ and $|V_i| = |V_j| = 1.0$ thus $|V_i||V_j| = 1.0$. These assumptions are only applicable in ideal networks but not realistic with most practical networks especially weakly interconnected grids. In addition, the review showed that vRES inclusion (consideration of both solar PV and wind) in GTEP optimization problems is still very low (below 10%). Only 9% of the reviewed research works had considered vRES in a multi-objective dynamic environment. Though 6% of them considered both wind and solar PV concurrently their formulations were based on the unreliable and over simplified DC power flow. In addition, there was no optimized penetration of the considered vRES. Based on this review, there was no research work that explored optimized vRES (solar PV and wind) penetration in MODGTEP problem using the most practical and reliable AC power flow analysis.

6.1.2 Adaptive Hybrid Meta-heuristic Approach

A new methodology for solving constrained optimization problems was formulated in which an hybrid of DE & BFOA optimization techniques were hybridized and adapted using both Genetic and Swarm Intelligence operators. The developed algorithm was tested using the Standard Benchmark Functions and constrained engineering optimization problems. It performed better than other meta-heuristic methods in eight of the ten high dimensional functions (F1-F10) used. In the pressure vessel design optimization problem, a value of 6059.719 was obtained, which was the closest to the true global optimum of 6059.714335048436 among the compared meta-heuristic algorithms. Likewise, in the tension/compression spring design optimization problem the developed DE-ABFOA-GIPSO algorithm produced the minimum solution at 0.012666. Based on this verification and validation, the developed algorithm was ready for application in solving the highly dimensional, complex and non-linear power system expansion optimization problem.

6.1.3 AC Power Flow Based TC-MODGEP Optimization in vRES Environment

First, the classical TC-MOGEP problem using the developed DE_ABFOA_GIPSO methodology and results compared with those of other researchers. The proposed methodology reduced the cumulative TC-GEP expansion cost by approximately 5% and 4% in comparison to MILP_PM and BFOA based approaches respectively. When N-1 contingency criterion was incorporated in the optimization, the total expansion cost increased significantly. The DE_ABFOA_GIPSO optimized TC-MOGEP cost in this case increased by 16%. This shows system expansion costs would increase substantially with increased system redundancy requirement.

The TC-MODGEP problem was then formulated utilizing AC-power flow analysis and considering intermittent/variable RES constraints. Inclusion of vRES in the optimization resulted to slight increase in generation investment cost by 2.5%. However, it significantly reduced the operational cost by approximately 50% resulting to an overall cost reduction of up to 19%. The average share of vRES in the installed capacity was 6.5% and while the average penetration level in the energy mix was 4.5%. This penetration level resulted to a 55% reduction in CO_2 emissions. Based on these results, the following conclusions are drawn:

(i) The proposed DE_ABFOA_GIPSO approach was able to solve the AC power flow based TC-MODGEP problem optimally in presence of vRES. This approach produced the least cost expansion options compared to the other algorithms studied.

(ii) Inclusion of vRES in the TC-MODGEP problem results to overall reduction in investment and operation cost as well as significant reduction in CO_2 emissions.

6.1.4 AC Power Flow based MAMODGTEP Optimization Considering Optimal vRES Penetration

The GTEP optimization problem was formulated in a multi-objective and dynamic environment based on the more accurate AC power flow network representation. In addition to investment, production and outage costs, the formulated multi-objective function took in consideration various AC-power flow based transmission network constraints including penalties related to active power losses, voltage profile violation, line and generator overloads. The impact of N-1 redundancy criterion was also studied. The formulated problem was solved using the developed adaptive hybrid meta-heuristic approach. Compared to the MINLP approach, the proposed methodology reduced total MODGTEP investment and operation cost by 7% without subjecting the system to any severe voltage or thermal violations, as is the case with the compared DC power flow-based results. Compared to DC power flow based results a system loss reduction of 10% was achieved. N-1 contingency analysis increased MODGTEP cost by approximately 9%.

Optimal vRES penetration was achieved by formulating and integrating vRES underutilization and overutilization penalties to the overall objective function. Low and high carbon price scenarios were studied. High carbon price favoured vRES penetration reaching 20% of installed capacity compared to 13% in the low carbon price scenario. In addition, a 19.7% reduction in CO_2 emissions was achieved. However, the high carbon price scenario increased the combined generation and transmission investment cost by 12.5%. The MODGTEP problem was then formulated in a multi-area environment (MAMODGTEP) with various energy sources distributed amongst the areas. Renewable energy sources were preferred to fossil-fueled generators. The proposed optimization methodology achieved up to a maximum of 28% and 17% annual vRES penetration levels in installed capacity and energy mix respectively. With a total energy share of 10%, vRES contributed only 8% of the emission compared to the natural gas power plant which contributed 23% of the emissions with only 2% share of generated energy.

Based on these results, the following is deduced:

(i) The proposed DE_ABFOA_GIPSO approach solves the AC power flow based MAMODGTEP problem adequately even when considering optimal vRES penetration. The results from this approach did not result in any transmission constraint violations.

(ii) vRES optimization in integrated GTEP problem is very key. Low utilization of committed vRES would reduce vRES associated benefits while high vRES penetration levels would result to the risk of unserved energy due to inadequate operating reserves to compensate for vRES output fluctuations. The formulated vRES overutilization and underutilization factors ensured that optimal vRES penetration levels are achieved.

(iii) Optimal utilization of vRES will greatly enhance the strategies towards climate change adaptation and mitigation by reducing emissions produced from power generation while ensuring security and reliability of the electricity grid.

6.2 Contributions to Knowledge

The following are the major contributions of this thesis:

(i) Formulation, testing and adoption of a new adaptive hybrid meta-heuristic approach [DE-ABFOA-GIPSO] in optimizing multi-objective expansion planning problems.

(ii) An AC Power Flow-based formulation and solution of the integrated generation and transmission expansion planning problem. This results in improved accuracy and reliability of obtained GTEP results.

(iii) A novel approach for considering optimal penetration of vRES in integrated generation and transmission expansion planning. This ensures that vRES benefits are reaped without subjecting the grid to adverse effects.

(iv) Application of the developed meta-heuristic approach in solving an AC Power Flow-based MAMODGTEP problem while considering optimal penetration of vRES.

The general formulation and solution architecture of the proposed AC power flow based GTEP considering optimal vRES penetration and employing the developed DE-ABFOA-GIPSO optimization approach is as given in Figure 6-1.

The key beneficiaries of the knowledge contribution in this thesis include:

(i) Energy Policy Makers and Regulatory Bodies.

(ii) Utility Companies integrating vRES into the grid.

(iii) Integrated Generation and Transmission Utilities.

(iv) Energy Researchers in Power System Operation and Planning.

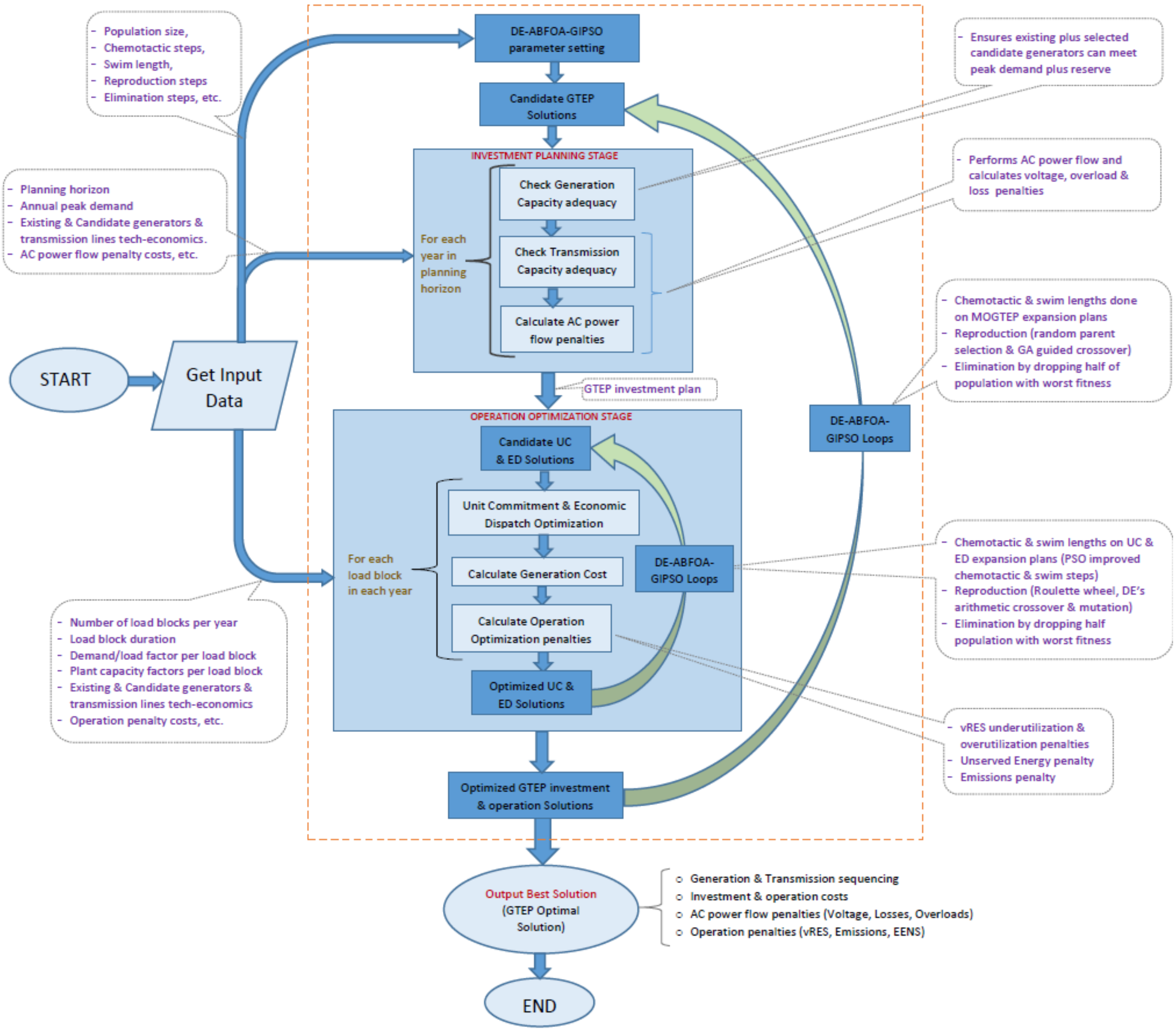


Figure 6-1: AC-Power Flow based MODGTEP with vRES Optimization using DE-ABFOA-GIPSO

6.3 Recommendations and Results Adoption

6.3.1 Recommendations for Further Work

In this research work, the MAMODGTEP optimization problem and its sub-problems were formulated and solved using a new adaptive hybrid meta-heuristic optimization approach (DE-ABFOA-GIPSO). Though the developed DE-ABFOA-GIPSO hybrid optimization approach outperformed other meta-heuristic and deterministic techniques commonly applied by researchers in solving power system expansion planning problems, testing and comparison can be expanded to cover other hybrid and recently developed metaheuristic approaches not considered in this research work. The GTEP formulation was AC power flow based and considered optimal vRES penetration. Various objectives and constraints were included in this research work, however, there is need to incorporate more industry related objectives and constraints (e.g. consideration of must-runs, obligatory plants, generator interdependency etc.) in the formulation and solution of the expansion problem. Moreover, additional research in this area can take into account some of the latest developments in the energy sector that influence accuracy of GTEP results. These include Distributed generation, Energy storage, Demand Side Management among others. Inclusion of these recent developments in power system expansion planning, especially grid-scale energy storage will greatly enhance optimal uptake of vRES.

In addition to the constraints introduced in this thesis, when integrating vRES in the generation mix it would be necessary to incorporate an assessment of flexibility adequacy of available conventional generators used for providing operating reserves. This can only be dealt with adequately by considering the ramping requirements of the system with vRES against the ramping capabilities of these conventional generators. This is another area of furthering this work. Inclusion of vRES in the generation mix displaces a considerable share of synchronous conventional generators in the grid thus reducing system inertia. Even with the emerging possibility of emulating inertia in vRES, insufficient inertia in vRES dominated grid is a major challenge. Reduced inertia has direct negative impact on system stability. Therefore, this research works can be extended to consider inertia constraints in the formulation. In formulating the objective function, emissions were considered as a penalty affecting the minimized total cost. Further research work can accommodate various environmental policies such as allowable emission targets as well as other types of emissions in a similar manner as the CO_2.

Though reliable results were obtained in all test cases and studied TC-GEP and GTEP scenarios employing the IEEE 6-bus and Garver's six bus test systems, there is need to further test both the proposed formulations and solution methodologies in large electricity networks. This testing will pave way for application in solving real life power system expansion planning problems in existing electricity grids. Application of the AC-power flow based optimization methodology in large networks will require high computation capacity. Therefore, simplification of the AC power flow models for GTEP formulation to reduce the complexity, memory and computation requirements while ensuring integrity of the expected results is another area of further research.

6.3.2 Adoption of Results

The proposed formulations and solution methodology produced good results for both the TC-GEP and GTEP optimization problems using the IEEE 6-bus and Garver's six bus test systems. As recommended, further testing and evaluation on relatively large electricity networks is key so as to facilitate their adoption and application in solving practical power system planning optimization problems.

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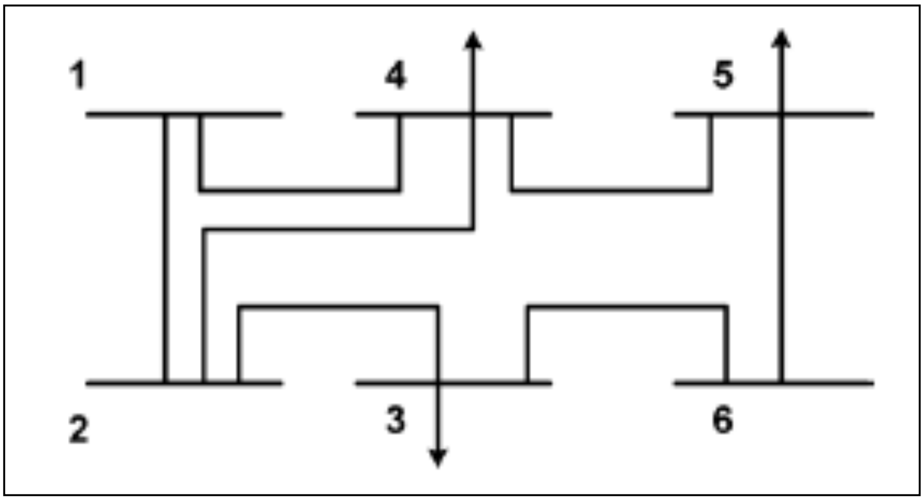
APPENDICES

A. Test Networks Data

A.1 Classical IEEE 6-Bus Test System

(i) Single Line Diagram



(ii) Existing Line Data

Line Name	From Bus	To Bus	Capacity (MW)	FOR (%)	X (pu)
TE1	1	2	10	1.0	0.170
TE2	2	3	7	1.0	0.037
TE3	1	4	7	1.0	0.258
TE4	2	4	7	1.0	0.197
TE5	4	5	7	1.0	0.037
TE6	5	6	7	1.0	0.140
TE7	3	6	7	1.0	0.018

(iii) Existing Generator Data

Unit Name	Bus No.	Capacity (MW)	FOR (%)	Operating Cost ($/MWh)
AE1	2	10	3	25
AE2	3	5	3	35
AE3	6	5	3	37
BE1	1	10	3	25

(iv) Candidate Generator Data

Unit	Bus	Capacity (MW)	FOR (%)	Operating Cost ($/MWh)	Investment Cost ($/kW/yr)
A1	1	10	3	22	100
A2	1	7	3	30	80
A3	2	5	5	35	60
A4	2	3	3	40	30
A5	4	3	5	40	40
B1	3	3	2	40	45
B2	3	2	1	55	20
B3	5	5	5	35	70
B4	5	3	3	40	35
B5	6	10	3	22	110
B6	6	8	3	29	85
B7	6	5	5	35	50
B8	6	2	1	55	15

(v) Bus Load Distribution

Bus	Bus 3	Bus 4	Bus 5
Percentage Load	40%	30%	30%

(vi) Load Factors

Time segment duration (hrs)	1510	2800	2720	1120	610
Load factor	50%	65%	80%	90%	100%

A.2 Customized IEEE 6-Bus Test System Data

(i) Customized Existing Generator Data

Unit Name	Technology	Max. Capacity (MW)	Min. Generation (MW)	Location (Bus)	Remaining Plant Life (Years)	Fuel cost (USD/MWh)	Fixed O&M Cost (USD/kW/month)	Variable O&M Cost (USD/MWh)	Scheduled & Forced Outages (days/year)	Emission (CO2 kgs/MWh)
AE1	Hydropower	10	2.5	1	30	0	2.25	0.5	10.95	10
AE2	Geothermal	5	2.5	3	15	2	5.95	10.6	10.95	122
AE3	Natuaral Gas	5	0	6	10	90	1.74	12.5	10.95	433
BE1	Hydropower	10	2.5	2	30	0	2.25	0.5	10.95	10

(ii) Customized Candidate Generator Data

Unit Name	Technology	Max. Capacity (MW)	Min. Generation (MW)	Location (Bus)	Investment Cost (USD/kW)	Plant Life (Years)	Fuel cost (USD/MWh)	Fixed O&M Cost (USD/kW/month)	Variable O&M Cost (USD/MWh)	Scheduled & Forced Outages (days/year)	Emission (CO2 kgs/MWh)
A1	Hydropower	10	0	1	3200	40	0	2.25	0.5	10.95	10
A2	Hydropower	7	0	1	3200	40	0	2.25	0.5	10.95	10
A3	Natural Gas	5	0	2	860	20	90	1.74	12.5	18.25	433
A4	Geothermal	3	1.5	2	2100	25	2	5.95	10.6	10.95	122
A5	Wind	3	0	4	1750	20	0	6.34	0.5	10.95	11
B1	HFO (Thermal)	3	0	3	1500	20	85	2.63	8.8	7.3	900
B2	Solar PV	2	0	3	1000	20	0	2.2	0.5	10.95	25
B3	Biomass	5	0	5	3000	25	0	12.5	8.5	18.25	230
B4	Geothermal	3	1.5	5	2100	25	2	5.95	10.6	10.95	122
B5	Solar PV	10	0	6	1000	20	0	2.2	0.5	10.95	25
B6	Wind	8	0	6	1750	20	0	6.34	0.5	10.95	11
B7	Coal	4	2.5	6	2400	30	50	5.75	1.4	18.25	960
B8	Gasoil (Thermal)	2	0	6	1250	20	240	1.74	12.5	3.65	900

(iii) Customized Transmission Data

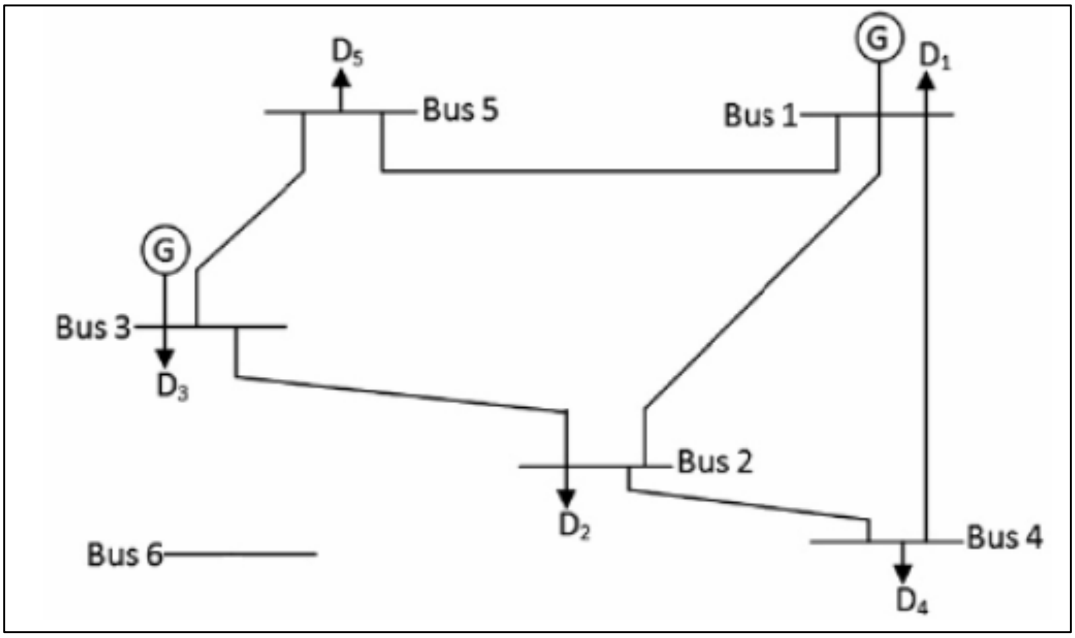
From Bus	To Bus	R (pu)	X (pu)	Rating (MW)	Number of Circuits	Length (km)	Invest. Cost (USD/km)	Fixed O&M Cost (USD/km)	Var O&M Cost (USD/MVAh)
1	2	0.04	0.17	10	1	94	1200	120	0.6
2	3	0.01	0.04	7	1	14	1000	100	0.5
1	4	0.06	0.26	7	1	100	1000	100	0.5
2	4	0.05	0.20	7	1	76	1000	100	0.5
4	5	0.01	0.04	7	1	14	1000	100	0.5
5	6	0.04	0.14	7	1	54	1000	100	0.5
3	6	0.00	0.02	7	1	7	1000	100	0.5

(iv) Annual Peak Load data

Year	MW	MVAr
Year 1	30	7.50
Year 2	35	8.75
Year 3	40	10.00
Year 4	45	11.25
Year 5	50	12.50
Year 6	55	13.75

A.3 Classical Garver's 6-Bus Test System

(i) Single Line Diagram



(ii) Existing and Candidate Generator Data

Gen No.	S_{max} (MVA)	Location at Bus	Operation cost(M$/MW)	Construction cost(M$)
1	173	1	5	-
2	390	3	7	-
3	642	6	8.5	1000
4	400	5	10	2000

(iii)Peak Load Data

Bus No.	PD (MW)	QD (MVAr)
1	55	11
2	164	32.8
3	27	5.4
4	109	21.8
5	164	32.8
6	0	0

(iv) Existing and Candidate Transmission Line Data

Corridor	r_{ij}(p.u)	x_{ij}(p.u)	Capacity(MVA)	Cost(M$)
1-2	0.04	0.4	100	40
1-4	0.06	0.6	80	60
1-5	0.02	0.2	100	20
2-3	0.02	0.2	100	20
2-4	0.04	0.4	100	40
3-5	0.02	0.2	100	20
3-6	0.048	0.48	100	48
4-6	0.03	0.3	100	30

B. Key Simplifications in DC Power Flow Analysis

(i) Transmission Lines

In DC power flow analysis, resistances of transmission lines are assumed to be very small compared to respective reactances, that is, $r \ll x$.

The admittance is given by:

$$y = \frac{1}{z} = \frac{1}{r+jx} = \frac{r-jx}{r^2+x^2} = g + jb \tag{b.1}$$

Therefore;

$$g = \frac{r}{r^2+x^2} \quad \text{and} \quad b = \frac{-x}{r^2+x^2} \tag{b.2}$$

Using the above assumption, the conductance g becomes very small and is usually ignored; while the susceptance b becomes the reciprocal of the reactance;

$$g = 0 \quad \text{and} \quad b = \frac{-1}{x} \tag{b.3}$$

The real part of all Y-bus elements is thus zero. This is not realistic in practice since lossless power systems are theoretical and do not exist in real world.

The accuracy level of this assumption significantly decreases with increase in length of transmission lines and/or adoption of smaller conductor sizes.

The AC-power flow based equations are given by;

$$P_{ij} = \sum_{j=1}^{nb} |V_i||V_j| G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \tag{b.4}$$

$$Q_{ij} = \sum_{j=1}^{nb} |V_i||V_j| G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j) \tag{b.5}$$

This approximation simplifies the equations to:

$$P_{ij} = \sum_{j=1}^{nb} |V_i||V_j| B_{ij} \sin(\theta_i - \theta_j) \tag{b.6}$$

$$Q_{ij} = \sum_{j=1}^{nb} |V_i||V_j| \{-B_{ij} \cos(\theta_i - \theta_j)\} \tag{b.7}$$

(ii) Node voltage angles

The second key assumption is that the difference in voltage phase angles $(\theta_i - \theta_j)$ at two connected busses is very small (small angular separation $(\theta_i - \theta_j) < 15°$).

This leads to the conclusion that;

$$Cos(\theta_i - \theta_j) = 1; \tag{b.8}$$

$$Sin(\theta_i - \theta_j) = (\theta_i - \theta_j) \tag{b.9}$$

This is only applicable for well interconnected networks but not with weakly interconnected grids. In practice, angular separations of more than 30° are usually realized especially in areas interconnected by long and/ or radial transmission lines.

The above power flow equations are further approximated to:

$$P_{ij} = \sum_{j=1}^{nb} |V_i||V_j|\{B_{ij}(\theta_i - \theta_j)\} \tag{b.10}$$

$$Q_{ij} = \sum_{j=1}^{nb} |V_i||V_j|(-B_{ij}) \tag{b.11}$$

If $i \neq j$, then $B_{ij} = -b_{ij}$; where B_{ij} is ij^{th} element of the Y-bus matrix and $-b_{ij}$ is the susceptance of ij^{th} circuit.

If $i = j$, then $B_{ij} = b_i + \sum_{j=1, j\neq i}^{nb} b_{ij}$;

Considering this the power flow equations become;

$$P_{ij} = \sum_{j=1, j\neq i}^{nb} |V_i||V_j|\{B_{ij}(\theta_i - \theta_j)\} \tag{b.12}$$

$$Q_{ij} = -|V_i|^2 b_i + \sum_{j=1, j\neq i}^{nb} |V_i||b_{ij}|(|V_i| - |V_j|) \tag{b.13}$$

(iii) Node voltage magnitudes

In addition, the nodal voltage magnitudes in all the buses are assumed to be very close to 1.0 pu such that:

$$|V_i| = |V_j| = 1.0 \quad \text{(b.14)}$$

$$|V_i||V_j| = 1.0 \quad \text{(b.15)}$$

This is only close to reality for very well interconnected grid with evenly distributed generators. Locations for generators and loads are influenced by different factors and in most cases there is no even distribution in the grid. Some areas have geographical or locational advantages compared to others.

With this simplification, the power flow equations are reduced to:

$$P_{ij} = \sum_{j=1, j\neq i}^{nb} \{B_{ij}(\theta_i - \theta_j)\} \quad \text{(b.16)}$$

$$Q_{ij} = -b_i + \sum_{j=1, j\neq i}^{nb} |b_{ij}|(|V_i| - |V_j|);\ Q_{ij} \approx -b_i \quad \text{(b.17)}$$

This DC power flow simplifications leads to the conclusion that $Q_{ij} \ll P_{ij}$ and hence ignored. This affects the optimization results of GTEP results especially where vRES are involved.

C. Power Flow and Power Loss Sensitivity Factors

The power flow or loss sensitivity of a given transmission line in a power system in relation to power injection in a particular bus is the change in power flow or loss in that line due to unit change in the power injected at the specified bus in the system.

Equations (c.1) and (c.2) give the real and reactive power flows in the ij^{th} corridor respectively.

$$P_{ij} = V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_{ij}) - V_i^2 Y_{ij} cos\theta_{ij} \tag{c.1}$$

$$Q_{ij} = -V_i V_j Y_{ij} \sin\left(\theta_{ij} + \delta_{ij}\right) + V_i^2 Y_{ij} sin\theta_{ij} - \frac{V_i^2 Y_{sh}}{2} \tag{c.2}$$

Where;

V_i and V_j are the voltage magnitudes at buses i and j respectively

δ_{ij} is the voltage angle difference between buses i and j

Y_{ij} is magnitude of the ij^{th} element of the Y_{Bus} matrix

θ_{ij} is the angle of the ij^{th} element of the Y_{Bus} matrix

Y_{sh} is the shunt charging admittance of ij^{th} line.

Real and reactive power flow sensitivities can be mathematically expressed as:

$$\frac{\Delta P_{ij}}{\Delta P_n} \text{ and } \frac{\Delta Q_{ij}}{\Delta Q_n} \tag{c.3}$$

Using Taylor series approximation while ignoring second and higher order terms the change in real and reactive line flow can be expressed as:

$$\Delta P_{ij} = \frac{\partial P_{ij}}{\partial \delta_i} \Delta\delta_i + \frac{\partial P_{ij}}{\partial \delta_j} \Delta\delta_j + \frac{\partial P_{ij}}{\partial V_i} \Delta V_i + \frac{\partial P_{ij}}{\partial V_j} \Delta V_j \tag{c.4}$$

$$\Delta Q_{ij} = \frac{\partial Q_{ij}}{\partial \delta_i} \Delta\delta_i + \frac{\partial Q_{ij}}{\partial \delta_j} \Delta\delta_j + \frac{\partial Q_{ij}}{\partial V_i} \Delta V_i + \frac{\partial Q_{ij}}{\partial V_j} \Delta V_j \tag{c.5}$$

Equations (c.4) and (c.5) can be arranged in matrix form and expressed as;

$$\begin{bmatrix} \Delta P_{ij} \\ \Delta Q_{ij} \end{bmatrix} = \begin{bmatrix} \frac{\partial P_{ij}}{\partial \delta} & \frac{\partial P_{ij}}{\partial V} \\ \frac{\partial Q_{ij}}{\partial \delta} & \frac{\partial Q_{ij}}{\partial V} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} \tag{c.6}$$

From Newton Raphson method we have;

$$\begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = [J]^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{c.7}$$

Using equation (c.7), equation (c.6) becomes,

$$\begin{bmatrix} \Delta P_{ij} \\ \Delta Q_{ij} \end{bmatrix} = \begin{bmatrix} \frac{\partial P_{ij}}{\partial \delta} & \frac{\partial P_{ij}}{\partial V} \\ \frac{\partial Q_{ij}}{\partial \delta} & \frac{\partial Q_{ij}}{\partial V} \end{bmatrix} [J]^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{c.8}$$

Equation (c.8) can be expanded and re-arranged to get real and reactive power flow sensitivity factor matrices given in equation (c.9).

$$\begin{bmatrix} \frac{\partial P_{ij}}{\partial P_n} \\ \frac{\partial P_{ij}}{\partial Q_n} \end{bmatrix} = [J^T]^{-1} \begin{bmatrix} \frac{\partial P_{ij}}{\partial \delta} \\ \frac{\partial P_{ij}}{\partial V} \end{bmatrix} \quad \& \quad \begin{bmatrix} \frac{\partial Q_{ij}}{\partial P_n} \\ \frac{\partial Q_{ij}}{\partial Q_n} \end{bmatrix} = [J^T]^{-1} \begin{bmatrix} \frac{\partial Q_{ij}}{\partial \delta} \\ \frac{\partial Q_{ij}}{\partial V} \end{bmatrix} \tag{c.9}$$

The real and reactive power loss sensitivity factors are obtained in a similar manner using equations (c.10) and (c.11) respectively.

$$P_{L(ij)} = g_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}) \tag{c.10}$$

$$Q_{L(ij)} = -b_{ij}^{sh}\left(V_i^2 + V_j^2\right) - b_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}) \tag{c.11}$$

Where we get:

$$\begin{bmatrix} \frac{\partial P_{L(ij)}}{\partial P_n} \\ \frac{\partial P_{L(ij)}}{\partial Q_n} \end{bmatrix} = [J^T]^{-1} \begin{bmatrix} \frac{\partial P_{L(ij)}}{\partial \delta} \\ \frac{\partial P_{L(ij)}}{\partial V} \end{bmatrix} \quad \& \quad \begin{bmatrix} \frac{\partial Q_{L(ij)}}{\partial P_n} \\ \frac{\partial Q_{L(ij)}}{\partial Q_n} \end{bmatrix} = [J^T]^{-1} \begin{bmatrix} \frac{\partial Q_{L(ij)}}{\partial \delta} \\ \frac{\partial Q_{L(ij)}}{\partial V} \end{bmatrix} \tag{c.12}$$

The respective sensitivities are thus calculated from the jacobian matrix and the partial derivatives of power flow equations (c.1 & c.2) and power loss equations (c.11 & c.12) with respect to variables δ and V.

D. TC-GEP and GTEP Optimization Results

D.1 TC-MOGEP with & without vRES (Section 4.3.1) Results

Scenario I: TC-MOGEP Without vRES

(i) Candidate Generator Investment Sequencing

PLANT_SEQUENCING													
	A1_Hydro	A2_Hydro	A3_Nat. Gas	_Geothermal	A5_HFO	B1_HFO	B2_HFO	B3_Biomass	B4_Geothermal	B5_HFO	B6_Gas oil	B7_Coal	B8_Gasoil
Year_1	0	0	0	0	0	0	0	1	1	0	0	1	0
Year_2	0	0	0	0	0	1	0	1	1	0	0	1	1
Year_3	0	1	0	0	0	1	0	1	1	0	0	1	1
Year_4	0	1	0	0	1	1	0	1	1	0	0	1	1

(ii) Annual Investment and Operation Costs (million USD)

COSTS	INVEST_COST	FIXED_COST	GEN. COST	LOSS COST
Year_1	1,269,350.23	2,310,600	1,655,776.68	150,994.89
Year_2	353,686.63	2,447,040	1,777,795.43	223,431.11
Year_3	571,554.58	2,636,040	1,723,930.88	244,858.41
Year_4	227,369.98	2,730,720	1,967,036.16	243,382.35

(iii) Annual Generation Costs per Load block (million USD)

GENERATION_COST	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	276556.5	519119.9	510407.9	216320.1	133372.2
Year_2	278444.0	523669.9	548468.9	259164.1	168048.5
Year_3	280331.5	528219.9	521287.9	239280.1	154811.4
Year_4	282219.0	532769.9	608462.4	291300.1	252284.7

(iv) Annual Excess/Unserved Energy per Load block (MWh)

EENS_TOTAL	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	-0.064175478	-0.119	-0.1155983	-0.9267993	-0.504774984
Year_2	-0.064175963	-0.11901	-2.2508311	-0.9337776	-0.514534865
Year_3	-0.064151793	-0.1189	-0.1157646	-0.93028	-0.521932968
Year_4	-0.064353504	-0.10604	-2.7767563	-0.943414	-2.59251469

(v) Bus Voltages at Peak Load (pu)

PEAK_VOLTAGES				
Bus	Year_1	Year_2	Year_3	Year_4
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	0.999744	0.999699	0.999653	1
5	1	1	1	1
6	1	1	1	1

(vi) Line Loadings at Peak Load (%)

PEAK_LOADING					
From_bus	To_bus	Year_1	Year_2	Year_3	Year_4
1	2	37.7042	41.93724	13.82705	0.284141
2	3	28.88073	9.593798	42.95352	66.73636
1	4	10.88172	16.96381	48.55144	58.05542
2	4	60.63379	73.83355	80.61722	76.38225
4	5	57.3904	59.70454	43.59045	16.38371
3	6	71.62237	76.55183	71.90789	76.84286
5	6	71.91902	95.68403	99.32409	95.39323

Scenario II: TC-MOGEP With vRES

(i) Candidate Generator Investment Sequencing

PLANT_SEQUENCING													
Horizon	A1_Hydro	A2_Hydro	A3_Nat. Gas	A4_Geothermal	A5_Wind	B1_HFO	B2_Solar PV	B3_Biomass	B4_Geothermal	B5_Solar PV	B6_Wind	B7_Coal	B8_Gasoil
Year_1	0	0	0	0	0	0	1	1	1	0	0	0	1
Year_2	0	1	0	0	0	1	1	1	1	0	0	0	1
Year_3	0	1	0	0	1	1	1	1	1	0	0	0	1
Year_4	0	1	0	0	1	1	1	1	1	0	0	1	1

(ii) Annual Investment and Operation Costs (million USD)

COSTS	INVEST_COST	FIXED_COST	GEN. COST	LOSS COST
Year_1	1,090,490.26	2,060,160	572,789.49	131,358.29
Year_2	798,924.56	2,343,840	554,957.05	173,928.43
Year_3	265,264.97	2,572,080	624,454.88	162,564.47
Year_4	324,983.96	2,917,080	1,818,942.17	238,291.62

(iii) Annual Generation Costs per Load block (million USD)

GENERATION_COST	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	84,408.97	162,819.94	164,287.94	90,824.12	70,448.52
Year_2	86,296.47	167,369.94	169,727.96	71,847.98	59,714.71
Year_3	88,183.97	171,919.97	175,167.94	105,720.13	83,462.87
Year_4	282,219.32	532,769.94	531,926.72	270,972.28	201,053.91

(iv) Annual Excess/Unserved Energy per Load block (MWh)

EENS_TOTAL	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	-0.064175321	-0.11899914	-0.1156	-0.9268	-0.5145351
Year_2	-0.064174874	-0.11830017	-0.14771	-0.0442	-0.504775
Year_3	-0.056400185	-0.12147787	-0.1131	-0.9277	-0.5145356
Year_4	-0.042238196	-0.11745528	3.502821	-0.93137	-2.5922201

(v) Bus Voltages at Peak Load (pu)

PEAK_VOLTAGES				
Bus	Year_1	Year_2	Year_3	Year_4
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	0.9997437	0.9996987	1	1
5	1	1	1	1
6	1	1	1	1

(vi) Line Loadings at Peak Load (%)

PEAK_LOADING					
From_bus	To_bus	Year_1	Year_2	Year_3	Year_4
1	2	31.64278	23.1284899	9.58612674	6.974311
2	3	37.574126	38.4968024	62.28342286	55.2181
1	4	16.532228	33.0846567	42.5590864	53.25465
2	4	60.603814	71.8152457	67.554734	78.34233
4	5	51.83343	45.9228216	19.1484622	19.22168
3	6	34.213284	18.933219	23.86379812	59.64386
5	6	66.263463	81.5332315	76.60624375	98.23414

D.2 MODGTEP Considering Optimal vRES Penetration (Section 5.3.2) Results

Scenario 1: Low Carbon Price

(i) Candidate Generator Investment Sequencing

PLANT_SEQUENCING													
Horizon	A1_Hydro	A2_Hydro	A3_Nat. Gas	A4_Geothermal	A5_Wind	B1_HFO	B2_Solar PV	B3_Biomass	B4_Geothermal	B5_Solar PV	B6_Wind	B7_Coal	B8_Gasoil
Year_1	1	0	0	0	0	0	0	0	0	0	0	0	1
Year_2	1	1	0	0	0	0	1	0	0	0	0	0	1
Year_3	1	1	0	0	0	1	1	0	0	1	0	0	1
Year_4	1	1	0	0	0	1	1	0	0	1	0	0	1
Year_5	1	1	0	0	0	1	1	0	0	1	0	0	1
Year_6	1	1	0	1	0	1	1	0	0	1	0	0	1

(ii) Candidate Transmission Investment Sequencing

TXN_SEQ.	Cor_(1_2)	Cor_(2_3)	Cor_(1_4)	Cor_(2_4)	Cor_(4_5)	Cor_(3_6)	Cor_(5_6)
Year_1	0	1	0	1	0	0	0
Year_2	0	1	0	1	0	0	0
Year_3	0	1	0	1	0	1	0
Year_4	0	1	0	1	0	1	0
Year_5	0	1	1	1	0	1	0
Year_6	0	1	1	1	0	1	0

(iii) Annual Investment and Operation Costs (million USD)

	INVEST_COST	FIXED_COST	GEN. COST	TXN. COST
Year_1	946,283.25	1,360,153.36	360,524.81	108,643.67
Year_2	672,607.90	1,601,953.36	376,447.31	128,171.24
Year_3	735,378.35	1,966,059.71	424,262.97	97,661.41
Year_4	-	1,966,059.71	612,865.06	124,310.42
Year_5	5,052.67	1,976,059.71	1,101,304.49	152,710.65
Year_6	255,289.10	2,190,259.71	1,559,905.73	171,091.59

(iv) Annual Generation Costs per Load block (million USD)

GEN_COST	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	57,002.47	111,999.94	114,919.94	48,999.98	27,602.49
Year_2	58,889.97	116,549.94	120,359.94	51,519.98	29,127.49
Year_3	59,937.47	120,508.49	127,681.75	54,375.97	61,759.29
Year_4	62,664.97	125,649.94	131,239.94	56,559.98	236,750.24
Year_5	64,552.47	130,199.94	136,679.94	225,779.96	544,092.18
Year_6	93,846.47	303,701.04	191,487.95	289,284.10	681,586.18

(v) Annual Excess/Unserved Energy per Load block (MWh)

EENS_TOTAL	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	-0.064175044	-0.1190003	-0.1156	-0.0476	-0.025925
Year_2	-0.064174658	-0.119001	-0.1156	-0.0476	-0.025925
Year_3	-0.064175104	-0.1192698	-2.517384	-0.041391	-0.041772
Year_4	-0.064175181	-0.1189547	-0.115859	-0.047529	-5.265978
Year_5	-0.06417456	-0.1189072	-0.116634	-0.956122	-5.49915
Year_6	-0.064174807	-6.8473398	-0.11452	-0.944637	-5.499149

(vi) VRE Underutilization Penalty Cost (million USD)

VRES_UNDER_	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	0	0	0	0	0
Year_2	0	0	0	0	0
Year_3	0	0	0	0	0
Year_4	0	0	0	0	0
Year_5	0	0	0	9.20572E-05	0
Year_6	0	0	0.00026974	0	0

(vii) VRE Overutilization Penalty Cost (million USD)

VRES_OVER_U	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	0	0	0	0	0
Year_2	0	0	0	0	0
Year_3	0	0	0	0	0
Year_4	0	0	0	0	33260.371
Year_5	0	0	0	0	200997.55
Year_6	0	0	0	0	268097.55

(viii) AC Power Flow Constraint Penalty Costs (million USD)

AC PENALTIES	VOLT_VIO	BRANCH_OVL	GEN_OVL	SYS_LOSSES
Year_1	0	0	0.00000017	66,426.03
Year_2	0	0	0.00000011	99,107.01
Year_3	0	0	0.00000003	72,593.65
Year_4	0	0	0.00000011	99,740.70
Year_5	0	0	0.00000040	112,916.06
Year_6	0	0	0.00000023	141,322.10

(ix) Bus Voltages at Peak Load (pu)

PEAK_VOLTAGES						
Bus	Year_1	Year_2	Year_3	Year_4	year_5	year_6
1	1	1	1	1	1	1
2	1	1	1	1	1	1
3	1	1	1	1	1	1
4	0.9979065	0.997545655	0.99783656	0.997557042	0.997669464	0.997428463
5	0.9976771	0.997279462	0.99784374	0.997568856	0.997552486	0.997301887
6	1	1	1	1	1	1

(x) Line Loadings at Peak Load (%)

PEAK_LOADING							
From_bus	To_bus	Year_1	Year_2	Year_3	Year_4	year_5	Year_6
1	2	32.18699342	48.7682197	1.071511752	28.99980364	31.67019	37.7220007
2	3	41.35013209	46.3997073	10.67334955	28.71272704	38.78847	58.839796
1	4	70.54539245	90.8773911	45.09710254	75.24240412	71.61694	81.8970889
2	4	53.63242853	60.2400295	60.33706671	63.6872076	55.81472	61.976286
4	5	48.63576326	60.395791	6.145205813	9.406029276	39.79589	51.1814359
3	6	20.38947606	10.2927851	67.01362194	60.3889956	69.69477	59.0537442
5	6	80.12958905	89.9456865	88.72707029	91.93462504	87.47071	92.6513448

Scenario 2: High Carbon Price

(i) Candidate Generator Investment Sequencing

PLANT_SEQUENCING													
Horizon	A1_Hydro	A2_Hydro	A3_Nat. Gas	A4_Geothermal	A5_Wind	B1_HFO	B2_Solar PV	B3_Biomass	B4_Geothermal	B5_Solar PV	B6_Wind	B7_Coal	B8_Gasoil
Year_1	1	1	0	0	0	0	1	0	0	0	0	0	0
Year_2	1	1	0	0	0	0	1	0	0	1	0	0	0
Year_3	1	1	0	0	0	0	1	0	0	1	0	0	0
Year_4	1	1	0	0	0	1	1	0	0	1	0	0	0
Year_5	1	1	0	0	0	1	1	0	0	1	1	0	0
Year_6	1	1	0	0	0	1	1	0	0	1	1	0	0

(ii) Candidate Transmission Investment Sequencing

TXN_SEQ.	Cor_(1_2)	Cor_(2_3)	Cor_(1_4)	Cor_(2_4)	Cor_(4_5)	Cor_(3_6)	Cor_(5_6)
Year_1	0	1	0	1	0	0	0
Year_2	0	1	0	1	0	1	0
Year_3	0	1	0	1	0	1	0
Year_4	0	1	0	1	0	1	0
Year_5	0	1	0	1	0	1	1
Year_6	0	1	1	1	0	1	1

(iii) Annual Investment and Operation Costs (million USD)

	INVEST_COST	FIXED_COST	GEN. COST	TXN. COST
Year_1	1,492,575	1,560,193	358,335	105,476
Year_2	508,008	1,829,620	374,257	92,353
Year_3	-	1,829,620	390,179	121,445
Year_4	227,370	1,924,300	529,347	127,839
Year_5	707,726	2,533,637	544,948	143,463
Year_6	5,053	2,543,637	736,723	168,777

(iv) Annual Generation Costs per Load block (million USD)

GEN_COST	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	56,624.98	111,299.96	114,239.97	48,719.99	27,449.99
Year_2	58,512.50	115,849.97	119,679.97	51,239.99	28,974.99
Year_3	60,399.98	120,399.96	125,119.97	53,759.99	30,498.87
Year_4	62,287.48	124,949.97	130,559.97	56,000.00	155,550.00
Year_5	64,175.00	129,499.97	135,999.97	58,381.53	156,892.00
Year_6	66,062.48	134,049.97	140,423.71	220,080.00	176,107.00

(v) Annual Excess/Unserved Energy per Load block (MWh)

EENS_TOTAL	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	-755.037708	-1400.07003	-1360.06806	-560.027981	-305.0152681
Year_2	-755	-1400.06998	-1360.06792	-560.028023	-305.0152167
Year_3	-755.037753	-1400.07005	-1360.06794	-560.027993	-307.2519191
Year_4	-755.037747	-1400.06998	-1360.06809	-1120	-2135
Year_5	-755	-1400.06988	-1360.06814	-1396.94798	-2501
Year_6	-755.037854	-1400.07	-3392.58807	-2912	-4026

(vi) VRE Underutilization Penalty Cost (million USD)

VRES_UNDER	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	0	0	0	0	0
Year_2	0	0	0	0	0
Year_3	0	0	0	0	0
Year_4	0	0	0	0	0
Year_5	0	0	0	70672.13872	0
Year_6	0	0	1009392.344	3.28271E-10	0

(vii) VRE Overutilization Penalty Cost (million USD)

VRES_OVER	Block_1	Block_2	Block_3	Block_4	Block_5
Year_1	0	0	0	0	0
Year_2	0	0	0	0	0
Year_3	0	0	0	0	16609.85926
Year_4	0	0	0	0	0
Year_5	0	0	0	0	5368
Year_6	0	0	0	19096	89243

(viii) AC Power Flow Constraint Penalty Costs (million USD)

AC PENALTIES	VOLT_VIO	BRANCH_OVL	GEN_OVL	SYS_LOSSES
Year_1	0	0	0.000000284	66,307.14
Year_2	0	0	0.000000057	56,069.44
Year_3	0	0	0.000000654	82,970.72
Year_4	0	0	0.000000171	108,727.31
Year_5	0	0	0.000000909	117,055.82
Year_6	0	0	0.000000796	127,773.59

(ix) Bus Voltages at Peak Load (pu)

PEAK_VOLTAGES						
Bus	Year_1	Year_2	Year_3	Year_4	Year_5	Year_6
1	1	1	1	1	1	1
2	1	1	1	1	1	1
3	1	1	1	1	1	1
4	0.997906185	0.998111245	0.997832697	0.99755391	0.99728111	0.997433829
5	0.99767713	0.998118032	0.997843918	0.997568126	0.997292461	0.997302775
6	1	1	1	1	1	1

(x) Line Loadings at Peak Load (%)

PEAK_LOADING							
From_bus	To_bus	Year_1	Year_2	Year_3	Year_4	Year_5	Year_6
1	2	31.94990673	1.307187917	31.37517905	41.80365964	20.07429014	23.1182362
2	3	40.447118	19.98323925	38.02020117	38.93955214	13.66327436	23.6720597
1	4	70.87815154	41.62230528	71.83049983	86.29113181	73.42278497	70.4034669
2	4	54.33825644	52.95051043	56.2964783	62.63260942	72.10634544	64.5328849
4	5	50.40769949	2.789765243	12.76547972	18.38225825	2.855215657	33.3406827
3	6	7.256333642	63.12030231	56.50283733	39.93663491	59.97007826	64.6888743
5	6	78.40774504	76.37871209	79.59582962	87.61583159	96.8260811	99.282158

E. Details on Published Works from the Thesis

E.1 Publications in International Journals

1. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Metaheuristic-based Adaptive Hybrid Algorithm for solving Constrained Optimization Problems",** ***European Journal of Advances in Engineering and Technology, 2020, 7(6):57-65, Volume 7, Issue 6,*** **2020.**

   Abstract: In this paper a novel Adaptive Hybrid Optimization technique based on Evolutionary and Swarm Intelligence Meta-heuristic methods is formulated and tested in solving complex optimization problems. The hybrid utilizes some of the mostly studied and applied metaheuristic methods in the hybridization and adaptation process with the aim of suppressing their individual weaknesses while taking advantages of the associated individual strengths. The proposed approach combines the strengths of Differential Evolution (DE) and Bacterial Foraging Optimization Algorithms (BFOA) in the hybridization while their weaknesses are mitigated by the introduction of important Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) characteristics in the algorithm formulation. The developed algorithm is tested on the high dimensional Standard Benchmark Functions (F1-F10) as well as two constrained engineering optimization problems (Pressure vessel design and tension/compression spring design). The obtained results are compared with those obtained by other researchers using other well-known metaheuristic optimization methods. When subjected to solving the standard benchmark functions the developed algorithm outperformed the rest of the optimization methods in eight out of the ten test functions. In addition, the developed algorithm produced superior results for the two constrained engineering optimization problems when compared to other meta-heuristic methods.

2. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Integrated Generation & Transmission Expansion Planning Optimization in Power Systems: A Review",** ***International Journal of Emerging Technology and Advanced Engineering*****, Volume 9, Issue 7, July 2019.**

   Abstract: The unbundling and liberalization of the power system in the recent past resulted to separate GEP and TEP optimizations. This separation has caused many challenges which have forced network planners and researchers to reconsider going back to the integrated planning scenario. This is a new developing area of research which has much potential of bringing positive impact to the power system sector. This paper gives a detailed review of the previous research works on the integration of GEP and TEP optimization with the aim of identifying research gaps in this area of research. In addition to the general review of previous works, a comparison is done among the reviewed works. The paper ends by identifying and clearly explaining the research gaps which the authors feel need to be studied further so as to improve on previous obtained research results and make them more applicable to real-life industry situations.

3. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "AC Power Flow-Based Integrated GTEP with optimal penetration of Intermittent RES",** ***IEEE Journal of Power and Energy, 2023*** **(submitted).**

   Abstract: The paper presents a new approach for optimizing the integrated Generation and Transmission Expansion Planning (GTEP) problem that takes into account the more accurate AC power flow network representation. The multi-objective function considers investment, production and outage costs, as well as AC power flow-based transmission network constraints and associated violation penalties. The formulation is extended to consider optimal intermittent/variable Renewable Energy Sources (vRES) penetration by integrating vRES underutilization and overutilization penalties to the overall objective function. In this analysis, two scenarios assuming different carbon prices were simulated representing low and high carbon price scenarios. While the high carbon price scenario results to a higher share of vRES penetration, it led to a 12.5% increase in the total investment cost. The operation cost however reduced by 34% in this scenario compared to the low carbon price scenario. Overall, the total GTEP investment and operation costs for both scenarios were quite similar, with a percentage difference of less than 1%. The percentage of vRES in the energy mix increased from 7.6% to 12.8% between low and high carbon price scenarios. Additionally, the high carbon price scenario led to a 19.7% reduction in total CO2 emissions.

E.2 Conference Papers

1. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "AC Power Flow-based Transmission Constrained Generation Expansion Planning with Intermittent RES",** ***2023 IEEE AFRICON,*** **September 2023.**

   Abstract: Transmission Constrained Generation Expansion Planning (TC-GEP) optimization has been solved majorly using the less reliable DC power flow analysis. In this paper, the TC-MOGEP problem is formulated based on AC-power flow analysis and considering presence of variable/intermittent Renewable Energy Sources (vRES). vRES related constraints in terms of resource availability and variability are considered to ensure reliability and security of supply. The paper studies the dynamics brought about by inclusion of both AC-power flow analysis and vRES in TC-GEP optimization. When considering AC power flow constraints, feasible TC-GEP results were achieved up to the fourth year of optimization (45MW). Beyond this load, no feasible solutions could be obtained even with increased investment in generation sources due to divergence of the AC-based power flow analysis. The divergence was caused by unsatisfied constraints majorly overloading of existing transmission lines. Though penetration of vRES in the optimized expansion plans slightly increased the generation investment cost by 2.5% it significantly reduced the operational cost by approximately 50% resulting to an overall cost reduction of up to 19%. Using the proposed formulation and solution methodology a 6.5% and 4.5% annual average share of vRES were realized in installed capacity and energy mix respectively. This penetration level resulted to a 55% reduction in CO2 emissions.Federal and state

2. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Co-optimized Generation & Transmission Expansion Planning in Kenya: A Drive Towards Realization of Affordable Quality Electricity Supply"** ***Ketraco 3rd Annual Conference*****, July 2022.**

Abstract: Federal and state government agencies as well as utilities have been using optimization models in evaluating their power system expansion plans. In the recent past, the separation of Generation Expansion Planning (GEP) and Transmission Expansion Planning (TEP) optimization processes has caused many challenges which have forced network planners and researchers to reconsider going back to the integrated planning approach. The scenario is not different in Kenya. In this research paper a detailed literature review is done on the commercially available GTEP co-optimization software giving a recommendation for Kenyan application. The literature review also covers the justification for co-optimization of GEP and TEP processes and the benefits which Kenya can realize. A shift to Generation & Transmission Expansion Planning (GTEP) co-optimization can make the country save between 10% and 30% on its total power generation and transmission expansion costs. From the review, PLEXOS software was strongly preferred due to its competitive features. However, just like many commercially available software, its main weakness is in the adoption of DC power flow based formulation. A detailed analysis of recent trends on GTEP co-optimization show increasing adoption of AC power flow based formulations. An analysis based on a simple GTEP co-optimization algorithm developed by the authors showed that AC power flow based GTEP co-optimization results in a total cost savings of between 2% (well interconnected electricity grid) and 10% (weakly interconnected electricity grid) when compared to DC power flow based results considering penalties due to load flow constraint violations. The research paper ends by recommending a phased out adoption process for co-optimizing GEP and TEP processes in Kenya.

3. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "Security Constrained MODGTEP using Adaptive Hybrid Meta-Heuristic Approach",** ***IEEE PES & IAS, Power Africa Conference,*** **August 2020.**

Abstract: Due to the ever-increasing electricity demand, network expansion solutions from the Transmission Constrained Generation Expansion Planning (TC-GEP) process may not be adequate and

thus the transmission network needs be expanded together with the generation system. Separation of the two processes of network expansion whose results must be combined during implementation will often lead to sub-optimal expansion plans. This concern has given rise to the integrated Generation and Transmission Expansion Planning (GTEP) optimization problem. In this paper the GTEP problem is formulated in a multi-objective and dynamic environment. The multi-objective function considers investment, production and outage costs as well as penalties related to system voltage violations and active power loss. In addition, the proposed formulation considers system redundancy. To increase on the reliability of the results the formulations are based on AC power flow models. The formulated MOGTEP problem is optimized using adaptive hybrid meta-heuristic approach. This approach is suitable for handling the highly dimensional and complex problem. The obtained results showed the superiority of the proposed MODGTEP formulation and solution methodology to other reviewed solution techniques. The proposed methodology produced less costly and more reliable expansion plans. Inclusion of the contingency analysis led to increase in the committed elements (generators and transmission lines) so as to account for any planned and forced outages in the system.

4. **Julius Kilonzi Charles, Peter Musau Moses, Jackson Mwangi Mbuthia, "An Adaptive Hybrid Meta-Heuristic Approach for Transmission Constrained MOGEP",** ***IEEE PES & IAS, Power Africa Conference,*** **August 2020.**

   Abstract: Meta-heuristic methods are characterized by their combination of both mathematical optimizations with heuristic concepts. The combination of both concepts helps to suppress the limitations associated with either deterministic or heuristic approaches while taking advantage of their individual strengths. This paper presents a novel Adaptive Hybrid Meta-heuristic approach for solving the highly dimensional and complex Transmission Constrained Multi-Objective Generation Expansion Planning (TC-MOGEP). The algorithm combines both evolutionary and swarm intelligence meta-heuristic techniques in its formulation. The proposed algorithm is tested on the IEEE six-bus test system in three scenarios. In Scenario A, both system contingencies and reserve margin requirements are ignored, Scenario B takes into account N-1 contingency while ignoring reserve margin requirements and Scenario C considers both N-1 contingency and reserve margin requirements. The obtained results are compared to those obtained by other researchers in the area. The proposed adaptive hybrid meta-heuristic approach gives better expansion plans for most of the considered system load levels; thus it can be confidently applied in solving the power system expansion optimization problems.

F. Biography

Julius Kilonzi Charles received his BSc. & MSc. degrees in Electrical and Electronics Engineering from the University of Nairobi, Kenya in 2011 & 2014 respectively. His research interests are in Optimization of Electric Power Systems Operations and Planning as well as Renewable Energy Integration.

He is currently working as a Power System Planning Engineer in Kenya Power & Lighting Company Plc, the sole Electricity Distributor and System Operator in Kenya. Julius has vast experience in power system operation & planning and is proficient in various Power System Simulation Software including PSSE, DigSILENT Powerfactory, PSS SINCAL, OseMOSYS, IRENA Flextool, LIP OP/XP among others.

Julius is a registered Professional Engineer by the Engineers Board of Kenya (EBK) and a Corporate Member of the Institution of Engineers of Kenya (IEK). He is also an active Student Member of the Institute of Electrical and Electronic Engineers (IEEE). His hobbies are travelling and watching football.