THE DEVELOPMENT OF AN OPTIMIZATION TECHNIQUE FOR TRANSMISSION EXPANSION PLANNING WITH RENEWABLE ENERGY INTEGRATION

By

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Thesis submitted in fulfillment of the requirements for the degree of

Doctor of Engineering in Electrical Engineering

in the Faculty of Engineering and the Built Environment

at the Durban University of Technology (DUT)

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February 2025

DECLARATION

I affirm that this thesis is the candidate's own creation; all quoted or rephrased content has been properly attributed and has not been previously presented, in whole or in part, for any other academic qualification at this institution or any other.

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05/06/2026

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LIST OF PUBLICATIONS

List of published/ Accepted / under review journals.

1. **N. W. Ndlela**, K. Moloi, and M. Kabeya, "Comprehensive Analysis of Approaches for Transmission Network Expansion Planning," *IEEE Access,* vol. 12, pp. 195778 - 195815, 2024, doi: 10.1109/ACCESS.2024.3519180.
2. **Nomihla Wandile Ndlela,** Katleho Moloi, Musasa Kabeya, "Wind farm integration with the objective of transmission expansion power in South Africa." Indonesian Journal of Electrical Engineering and Computer Science Vol. 40, No. 1, October 2025, pp. 34-46 ISSN: 2502-4752, DOI: 10.11591/ijeecs.v40.i1.pp34-46
3. **N.W. Ndlela**, K. Moloi, and M. Kabeya, "Hybrid Quasi-Dynamic and Probabilistic Method for Analysing Solar and Wind Power Plant Integration and Its Effect on Grid Stability" Sustainable Energy Research – 2026 (Accepted)
4. **N.W. Ndlela**, K. Moloi, M. Kabeya, and E. Ojo "Interconnecting deep rural and urban areas in smart grid using space-based communication – A review" International Review of Electrical Engineering (I.R.E.E.) – 2026 (Under Review)
5. **N.W Ndlela**, M Ntombela, K. Moloi, and M. Kabeya, " Short-Term Transmission Network Expansion Planning With Renewable Energy Integration Using Quasi-Dynamic Simulation," International Journal of Energy Research – 2026 (Accepted)

List of Published/Accepted conference papers

1. **N. Ndlela**, K. Moloi, and M. Kabeya, "Transmission Expansion Planning With The Use Of Renewable Energy Integration " in *International Conference on Electrical, Computer and Energy Technologies* (ICECET), Australia, Sydney, 25 - 27 July 2024:
2. **N. W. Ndlela** and K. Moloi, "Interactional Coordination of High Voltage DC and Flexible AC Transmission System Elements," in *2023 IEEE PES/IAS PowerAfrica*, 2023: IEEE, pp. 1-5.
3. **N. W. Ndlela**, K. Moloi, and M. Kabeya, "Improvement in the Development of the Internet of Things (IoT)," in International Conference on Electrical, Computer and Energy Technologies (ICECET), Sydney, Australia, 25-27 July 2024: IEEE, pp. 1-6.
4. **N. W. Ndlela**, K. Moloi, and M. Kabeya, "Simulating and Analyzing SA Distributed Solar Generating System In Transmission Line Expansion Network," in *2024 IEEE PES/IAS PowerAfrica*, Johannesburg, South Africa, 07-11 October 2024: IEEE, pp. 1-5.
5. **N. W. Ndlela**, K. Moloi, and M. Kabeya "Distributed Renewable Energy Generating System In A Transmission Line Expansion Network" (ICECET 2025) – Accepted

6. **N. W. Ndlela**, K. Moloi, and M. Kabeya, "High-Penetration of Wind Farm in Transmission Expansion Planning," in *2025 IEEE PES/IAS PowerAfrica*, Cairo, Egypt, 28 September 2025 - 02 October 2025: IEEE, pp. 1-6.

7. **N. W. Ndlela**, K. Moloi, and M. Kabeya, "High-Penetration of Solar PV Plant into The Grid" IEEE Africon 2025, Polokwane, South Africa, 10 – 12 December 2025 – Accepted.

8. **Ndlela Nomihla**, Katleho Moloi, and Musasa Kabeya. 2026. "Comprehensive Power Park Design and Analysis of a Wind Farm Using Monte Carlo Simulation" Engineering Proceedings 140, no. 1: 60. https://doi.org/10.3390/engproc2026140060

9. **N. W. Ndlela**, K. Moloi, and M. Kabeya "Analyzing Grid Flexibility and Congestion in Renewable-Integrated Networks Using Quasi-Dynamic Simulation", in International Conference on Electrical, Computer and Energy Technologies (ICECET 2026), Rome, Italy, 6 – 9 July 2026 – Accepted

10. **N. W. Ndlela**, K. Moloi, and M. Kabeya, "Distributed Renewable Energy Generating System In A Transmission Line Expansion Network", in International Conference on Electrical, Computer and Energy Technologies, ICECET 2026, Rome, Italy, 6 -9 July 2026 – Accepted

DEDICATION

This doctoral thesis is dedicated to my family and my kids, Mpilwenhle and Ntsika.

I humbly dedicate my thesis to God Almighty, my source of wisdom, knowledge, and insight, in appreciation for his unwavering support in finishing this thesis.

If I were to cut my PhD degree and present a piece to everyone who has contributed to my life, I would have to cut it into millions of pieces. By that, I am loudly chanting "Izandla zidlula ikhanda"

Lastly, this thesis is dedicated to my late father, TR Ndabandaba. How I wish he was here, how I wish he saw this, how I wish he met me; he should have waited!

ACKNOWLEDGMENT

The author would like to thank the following individuals for their support in finishing this thesis.

I convey my huge appreciation to my primary supervisor, Professor K Moloi, for his unwavering support and guidance in successfully completing my thesis and for his numerous valuable contributions. This research project would not have been feasible without his professional and career development advice.

I am endlessly grateful to my co-supervisor, Professor M Kabeya, for his contributions, constructive thoughts, and recommendations he made in this study.

I am grateful to my doctoral study partner, Dr. ME Ntombela, for his constructive contributions and daily support to ensure the completion of this study.

I thank the DUT EPE team for their valuable contributions to my engineering education and professional development. I also appreciate Mr. KW Ntuli for his helpful support in this journey.

I would like to express my gratitude to DUT and the Grow Our Own Timber (GOOT) initiative for their trust in me and their financial support and flexibility, which significantly contributed to the timely completion of my dissertation.

I express my gratitude to DIgSILENT PowerFactory for supplying the software that enabled me to get the necessary results from my research.

I am grateful to the Erasmus exchange program for the opportunity to participate in a semester-long exchange program at Huelva University in Spain. This experience has significantly enhanced my research.

I would like to express my thanks to Mrs. Bongiwe Khumalo, who passed away during COVID-19, for raising my daughter, which contributed significantly to my receiving my first qualification.

Finally, I extend my gratitude to my family, particularly my mother, Thandi Ndlela, and my aunt, Ntombikayise Ndlela, for their firm trust in me and steadfast support, as well as to my friends for their constant encouragement.

ABSTRACT

The demand for electrical energy is rapidly increasing due to various socioeconomic factors, including industrialization, population growth, urbanization, and the advancement of modern technologies within the context of the Fourth Industrial Revolution. The rapid increase in energy demand poses a significant challenge to the power system. The desire for sustainability is driving significant changes in the global energy sector. Keeping the global average temperature within bounds is a critical concern, prompting countries to take tangible steps to reduce energy system dependence on fossil fuels. Recently, transmission network expansion planning (TNEP) was studied. Power network planning requires TNEP to determine the locations, timing, and quantity of additional transmission lines while ensuring grid stability to guarantee all equipment performs within limitations. Renewable energy (RE) is used in grid connectivity, small businesses, and photovoltaic (PV) solar systems in homes. This research proposes adding RE resources to transmission line expansion to enhance capacity. Studies have examined RE inclusion into power grid expansion plans. South Africa's electricity system uses solar and wind. However, the integration of RE in power systems can cause instability as most of the renewable energy has an intermittent nature. Therefore, this problem is discussed to provide an effective solution for generation and TEP. The first part of this study is the comprehensive analysis of Approaches for TNEP, which includes various approaches, methodologies, and technologies utilized in the expansion process, highlighting their advantages, limitations, potential implications, and reliability in transmission expansion planning (TEP), distributed generation, electrical markets, insecurity, line congestion, and reactive power planning (RPP). It also analyzes innovative transmission expansion planning models that integrate renewable energy sources (RES) utilizing improved optimization methods. The second case study shows the importance of TEP and is divided into sub-sections. The first, Tie Open Point Optimisation (TOPO) techniques in conjunction with Genetic Algorithm (GA), denote switchable connections among network segments, allowing system operators to reorganize a network for improved reliability, efficiency, minimal losses, and cost-effectiveness. After that, hosting capacity development and RE integration evaluate and upgrade the power grid's capacity to accommodate distributed energy resources (DERs) such as solar and wind while maintaining reliability to add more RE without strengthening the network. Reliability assessment with contingency is proposed, which examines the network response to any possible faults. The short and long-term TEP with load and generator forecasts predicts grid

behavior in different seasons over a year and over many years, when load growth increases with RE uncertainty, such as wind farms and solar PV plants. To assess network performance over time, quasi-dynamic simulation uses load flow computations at specified times. Finally, probabilistic analysis in conjunction with Quasi-Monte Carlo simulation (QMCS) is suggested to evaluate system performance under uncertainty, determine the best location for additional lines to maintain grid stability, and analyze system behavior, demand growth, generation availability, and network restrictions. It helps decision-makers evaluate expansion possibilities and mitigate power system development risks throughout time. A power park analysis tool evaluates wind farm profitability, losses, and energy. Basic energy analysis and probabilistic analysis using the QMCS are employed. The network with hybrid renewable plant integration was successfully constructed through both short-term and long-term transmission planning amidst various uncertainties. The optimal techniques employed for transmission expansion planning effectively maintained system stability over 15 years, as shown in Figure 6.38 and Table 6.10 / different conditions, as shown in Figure 6.23 and Table 6.9 with minimal losses under reliability assessment.

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LIST OF ABBREVIATIONS

ACOPF	AC Optimal Power Flow
ACIT	Average Customer Interruption Time
ACO	Ant Colony Optimization
ARO	Adaptive Robust Optimization
ATC	Available transfer capability
AIS	Artificial Immune System
ANN	Artificial Neural Networks
BCA	Bee Colony Algorithm
BESS	Battery Energy Storage System
BB	Branch And Bound
BD	Benders Decomposition
COA	Chaos Optimal Algorithm
CHA	Constructive Heuristic Algorithm
CHP	Combined Heat and Power
CNNs	Convolutional Neural Networks
DEA	Differential Evolution Algorithm
DLR	Dynamic Line Rating
DR	Demand-Responsive
DERs	Distributed Energy Resources
EENS	Expected Energy Not Supplied
ESS	Energy Storage Systems
FACTS	Flexible AC Transmission System
FERC	Federal Energy Regulatory Commission
FSCs	Fixed Series Compensators
GTEP	Generation and Transmission Expansion Planning
GA	Genetic Algorithm
GRASP	Greedy Randomized Adaptive Search Procedure
GF	Growth Factor
HSA	Harmony Search Algorithm

HVDC	High Voltage Direct Current
HC	Hosting Capacity
IC	Investment Cost
IPM	Interior Point Method
LP	Linear Programming
LODF	Line Outage Distribution Factors
LTTEP	Long-Term Transmission Expansion Planning
LF	Load Factor
LOLE	Loss of Load Expectation
ML	Machine Learning
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
MIQP	Mixed Integer Quadratic Programming
MCS	Monte Carlo simulation
MOTP	Multi-Objective Transmission Planning
OF	Objective Function
OASIS	Open Access Same-Time Information System
OTS	Optimal Transmission Switching
PSO	Particle Swarm Optimization
PSTs	Phase-Shifting Transformers
PV	Photovoltaic
PDF	Probability Distribution Function
QMCS	Quasi-Monte Carlo simulation
RPP	Reactive Power Planning
RE	Renewable Energy
RDG	Renewable Distributed Generators
REDG	Renewable Energy Distributed Generators
REs	Renewable Energy Source
RO	Robust Optimization
SA	Simulated Annealing
SAIFI	System Average Interruption Frequency Index

SAIDI	System Average Interruption Duration Index
Statcom	Static Synchronous Compensators
SSSCs	Static Synchronous Series Compensators
SVC	Static Var Compensators
SDDP	Stochastic Dual Dynamic Programming
SP	Stochastic Programming
SFLA	Shuffled Frog Leaping Algorithm
SHCs	Shunt Compensators
SVM	Support Vector Machines
TS	Tabu Search
TCSCs	Thyristor-Controlled Series Compensators
TEP	Transmission Expansion Planning
TNEP	Transmission Network Expansion Planning
TSO	Transmission System Operator
TS	Transmission Switching
TOP	Tie Open Point
TOPO	Tie Open Point Optimisation
VGT	Variable Generation Technologies
VSM	Voltage Security Margin
WF	Wind Farms

CHAPTER 1 INTRODUCTION

TEP is essential in contemporary power networks, particularly due to the rising integration of RES such as wind and solar power. The incorporation of these sporadic and decentralized energy supplies has distinct issues regarding grid stability, efficiency, and cost-effectiveness. Optimization strategies are essential in overcoming these issues by guaranteeing economic and technological viability.

1.1 Background and significance of TEP

The primary goal of TEP is to enlarge and strengthen the transmission network to meet the growing future energy demand and to incorporate new power plants to ensure the system operates efficiently [1]. TEP is the process of choosing which parts of equipment, like overhead or underground lines, underground and/or underwater cables, and transformers, will be placed and where they will go. It also plans when they will be put into service [2]. The transmission network plays a crucial role in the power system and is presently facing significant challenges due to the profound revolution occurring in the energy industry. Specifically, the rise in the use of renewable energy sources and the merging of markets necessitate the development of new pathways and enhancements to the current power grid [3]. It is a crucial aspect of power system planning that involves determining the quantity, timing, and placement of additional transmission lines to be added to the existing network [4]. Thus, it is a challenging, extensive, and extremely complex optimization problem that can be addressed using conventional, unconventional, or heuristic approaches [5].

Long-term planning in power transmission network development involves strategically expanding power equipment and facilities to satisfy the projected demand for electric energy while maintaining an acceptable level of reliability [6, 7]. The primary objective of the TEP problem is to minimize the overall investment costs while ensuring compliance with a range of techno-economic constraints, including both equality and inequality constraints [8]. The TEP model specifically focuses on two main concerns: (i) determining which facilities should be included in the transmission network, and (ii) deciding their optimal locations [6, 9]. To address the intricacy of present and future electrical networks, it is necessary to employ more precise models for solving the TNEP problem. In order to address this problem, the research community has put forth formulations that rely on AC network equations [10]. Figure 1.1 depicts a comprehensive overview of transmission expansion planning, encompassing all the crucial factors that must be considered while developing the expansion of transmission lines, with parameters being transmission parameters and devices being transmission devices. With the rising penetration of renewable producing units, particularly in distant places where load demand is not well connected, there is a growing significance in co-optimizing generation and transmission expansion planning (GTEP) in power networks[11]. Other models include investment and operating costs when determining which transmission lines to build. The AC power flow equations are non-convex and non-linear, making the TEP model a complicated optimization problem. Several strategies have been proposed in published literature to achieve a definitive and practical systematic state of the arts [12]

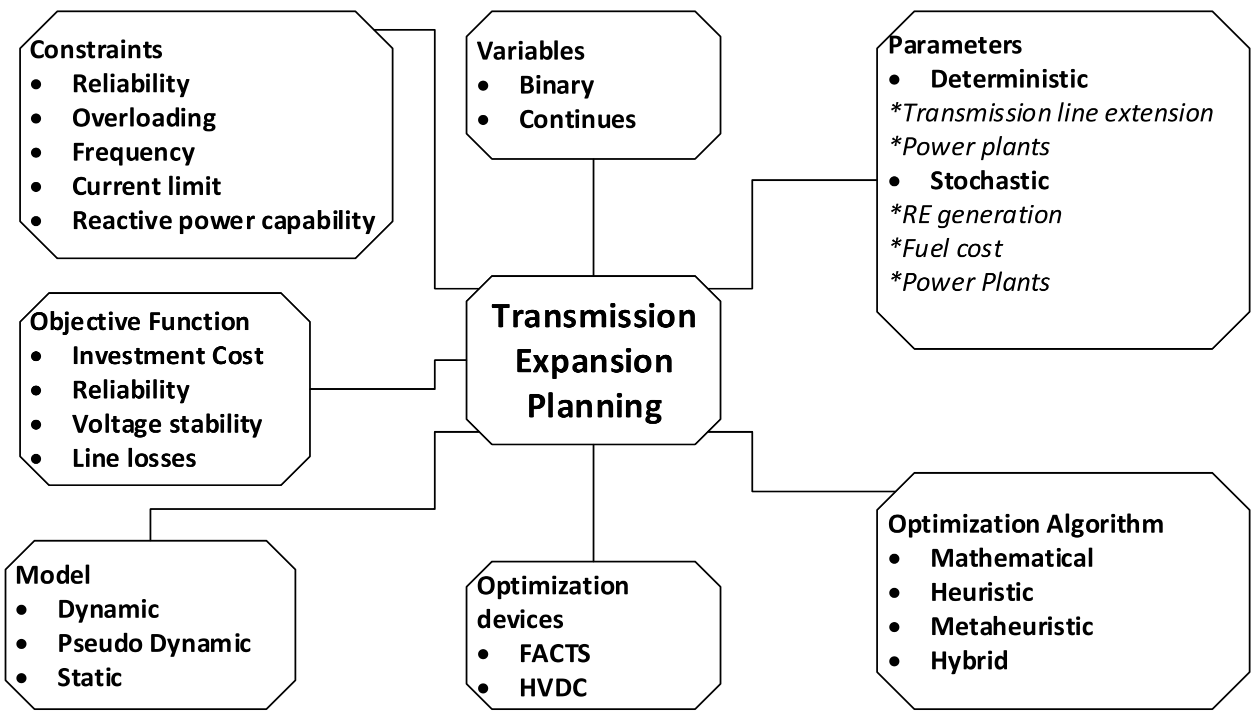


Figure 1. 1 Visual overview of transmission expansion planning.

Due to the rising presence of RES, particularly in isolated regions with limited connection to power demand, there is a growing focus on co-optimizing production and transmission expansion planning in power networks [13]. The TEP problem in modern power networks is a complex, non-linear, mixed-integer, and non-convex problem [14]. It aims to develop and fortify the transmission network to satisfy the projected increase in energy needs, incorporate new power plants, and guarantee efficient system operation [1, 15]. TEP aims to increase power system capacity to meet future demand. Its objective is to identify the most efficient circuit arrangement that can be implemented in the network to fulfill the load requirement and operational restrictions. In 1970, Garver became the pioneer in solving the TNEP issue, which involves determining the most efficient paths between power supply sources and loads [16]. Garver utilized a transportation model to determine the TNEP, focusing solely on the active power balance at each bus. Subsequently, other researchers enhanced the direct current power flow by using the Kirchhoff voltage law for each basic loop [17]. The TEP specifies the location, timing, and number of new power lines needed to meet network demand. Current and future electrical networks require more precise models to address the TNEP issue due to their complexity [10, 16, 18]. Optimal network expansion is a crucial topic in power system planning. Expansion of the power system occurs in the generating, transmission, or distribution sectors [19, 20]. The South African electricity grid needs to be expanded to fulfill the demand growth and the RE integration objective [21] Additionally, in recent years, devices such as Flexible AC Transmission System (FACTS) devices have been developed. These include, but are not limited to, phase-shifting transformers (PSTs), Thyristor Controlled Series Compensators (TCSCs), and Static Synchronous Series Compensators (SSSCs) [22]. Power flows across the grid can be dynamically rerouted by FACTS devices by simulating a change in line impedances. Thus, it makes sense to use such technology in TNEP assessments, as it may reduce operating and investment costs while enhancing the grid's long-term stability [22]. In certain articles, transmission and generation planning is integrated into a system known as GTEP. GTEP involves strategically installing new components such as generators, transmission lines, Combined Heat and Power (CHP), and furnaces ensuring a reliable and cost-effective supply of electricity and heat within a specific time frame [23, 24].This study aims to employ optimal techniques to identify suitable locations for additional transmission lines to meet future demand and accommodate the increased power resulting from the integration of renewable energy (RE). Furthermore, this study utilizes optimal methods to ascertain suitable locations for new power generated from RE. Additionally, it forecasts the network's behavior for both short-term and long-term transmission expansion planning, which is crucial for maintaining a robust grid over time under varying dynamics.

1.2 Overview of challenges faced in traditional approaches

The AC models are highly nonconvex and nonlinear, causing severe obstacles in finding a high-quality solution via commercial solvers [8]. Applying the AC model in TEP issues leads to nonconvex mixed-integer nonlinear programming (MINLP) models. This situation worsens, and existing heuristic-based techniques also struggle with convergence [25]. Utilizing only conventional deterministic data, the optimal plans generated from expansion planning exercises will be the most suitable for this precise input data. However, these plans may lack robustness as they may not effectively handle minor fluctuations that impact the input data [26].

1.3 South African power system

The majority of South Africa's energy is generated by Eskom's coal-fired power stations situated in the coalfields of the Mpumalanga Highveld near Lephalale. However, the power generating scenario is undergoing a fast transformation [27]. The transmission network connects power suppliers and consumers, making it the most important aspect of electrical power [28]. Most power sources are located on terrain far from the city. Reliable transmission networks are necessary for connecting power sources to load centers [29, 30]. Eskom is a state-owned power company that operates as a vertically integrated entity. It is responsible for producing almost 95 percent of the energy consumed in South Africa, and it also plays a significant role in generating electricity across the African continent. It engages in power exchange with seven countries: Botswana, Lesotho, Mozambique, Namibia, Eswatini, Zimbabwe, and Zambia [31-33].

In the late 19th century, small power networks with restricted geographic reach initiated the generation, transmission, and distribution of electricity to supply modest load centers. Concurrent with the proliferation of technological advancements and the growth of electricity demand and consumer centers, there was a concurrent expansion of electric networks [34]. Determining the optimal timing and location for the installation of transmission lines, cables, and transformers onto the power grid is the objective of the TEP problem [35]. TNEP is a crucial aspect of power system planning and optimization, focused on expanding the current network. The process involves the incorporation of modern power units, strengthening the current power infrastructure, establishing new transmission pathways, and/or installing more power lines to anticipate the growing energy requirements to uphold the reliability and effectiveness of the system [36]. The transmission expansion capacity is driven by several considerations, including the need to meet the rising electricity demand, enhance system reliability, reduce transmission line losses, and ensure that consumers have fair access to affordable generation [37]. The proposed model is expressed as a four-objective optimization to provide adaptable, secure, and reliable power to the transmission line [38, 39]

1.4 Research problem

The growing integration of RES, including wind and solar power, introduces novel issues for power system design and operation. The continuous demand growth introduces additional issues that threaten grid stability, as well as alterations in the generating network, such as generator failure or insufficient power supply. TEP is an essential procedure designed to guarantee the stable, cost-efficient, and effective growth of the power grid to meet increasing energy demand with high penetration of RE, all while preserving system security, stability, and minimal losses. The apparent answer to this problem is TEP, resulting in a significant need for transmission lines that can provide sufficient power and maintain stability in the face of unexpected disruptions that may arise in the grid, as well as the losses that occur over long distances.This study aims to enhance transmission line capacity through both long-term and short-term planning to optimize grid stability. Additionally, while integrating renewable energy into the grid, it is essential to consider the losses, energy output, and profitability of wind farms. Therefore, this study intends to analyze wind farms to assess the power generated by the plant under various system dynamics.

1.5 Aim and objectives of the research

The aim is to identify optimal techniques for determining the optimum position of additional RES and transmission lines to address system instability arising from load growth/ load variation, variable nature of RES, and fluctuating generators under a quasi-dynamic network, thereby ensuring a reliable and stable power transmission system with minimal losses over a short and long period

1.5.1 Research objectives

- To present a comprehensive analysis of approaches for TEP
- To propose a technique that minimizes losses in the network.

- To propose a tool that effectively locates the best position and size of RE such as wind farms and solar Plants that can be integrated into the system without the need for reinforcement.
- To develop a network that varies in load, wind turbines, solar PV systems, and generators under quasi-dynamic conditions. Furthermore, techniques that specify the available power that can be transferred from the wind farm to the rest of the network.
- To develop an optimization technique that is best known to handle networks with RE that produce unpredictable power, to locate the best location for reinforcement over a long-term period. Moreover, evaluate the wind farm's losses, energy, and profit.

1.6 Research contribution and motivation

It is imperative that we do not delay our focus on RE until coal reserves are exhausted. The significance of transmission lines cannot be overstated, as they connect the generation and distribution sectors, ensuring that load demand is satisfied without jeopardizing grid stability. Therefore, it is crucial to explore optimal methods for expanding transmission lines to facilitate the integration of new power sources and meet increasing demand. The motive and contribution of this study are listed below:

- determine the optimal techniques for the placement of additional RES without requiring reinforcement.
- to identify the best possible locations for additional transmission lines while ensuring system reliability and minimal losses in a network experiencing increased integration of hybrid renewable energy systems (wind farm and solar PV plant), together with fluctuating generators, while accommodating short- & long-term load variation/growth in a system.
- To use TOPO in conjunction with GA to minimize losses and reliability configuration in elements such as transformers, lines, and busbars that analyze network response to possible faults and give possible stochastic results.
- To employ methods that quantify the transferable power from the wind farm to the broader network.

- To evaluate losses, profits, and energy in a wind farm utilizing two methods, which are basic power park analysis and probabilistic using QMCS analysis, which is an efficient approach to managing uncertainty.

1.7 Organization of the thesis

The following chapters will serve as the basis for the organization of the thesis.

Chapter 1: Introduction

Chapter 2: Literature Review

Chapter 3: South African Power Grid with RE Integration

Chapter 4: Proposed Mathematical Modeling

Chapter 5: 39 Bus New England System with Solar Plant and Wind Farm Model Development

Chapter 6: Short & Long-Term Transmission Expansion Planning with RE Integration

Chapter 7: Conclusion and Future Recommendation

CHAPTER 2 LITERATURE REVIEW

2.1 Background reviews on TNEP

TNEP identifies the optimal locations, timing, and types of transmission assets (such as lines, transformers, converters, and conversions from HVAC to HVDC) to construct, ensuring the grid meets future demand, reliability requirements, and policy objectives while minimizing overall costs. It may be static, which is single year or dynamic, which is a multi-year investment decision [40]. Power networks are extensive and intricate interconnected systems, spanning large geographical areas. They consist of several lines that are interconnected in a web-like fashion and are managed by a single network operator [41]. The efficient construction timelines of projects utilizing variable generation technologies (VGTs) such as PV and wind generation, combined with increasing obstacles in constructing new transmission lines due to socio-environmental regulations, have presented fresh obstacles in the advancement of sustainable power systems [42]. Multiple options exist for the installation of transmission lines and generators, including both traditional and sustainable energy sources, at various levels of the system [43]. The evolution of energy systems is rapidly accelerated by advances in technology and the introduction of novel operational and market design paradigms.

The worldwide need for sustainability is specifically propelling the shift towards a significant makeover [44]. Integrated RE is being implemented on a large scale, and other innovative advancements, like distributed energy resources, demand response, energy storage technologies, and local energy markets, are also being included into modern energy systems. Within this ever-changing environment, the task of designing and implementing energy policies has encountered fresh obstacles. To facilitate this crucial process, expansion planning models and tools can be of indispensable assistance [45, 46]. The subject of TEP is complex and has been addressed using many models and technologies. The scientific community has recently focused significant attention on bio-inspired metaheuristics because of their extraordinarily effective performance in tackling highly difficult and combinatorial issues [2]. Figure 2.1 illustrates the potential lines that may be included in the system to enhance the transmission network for various objectives.

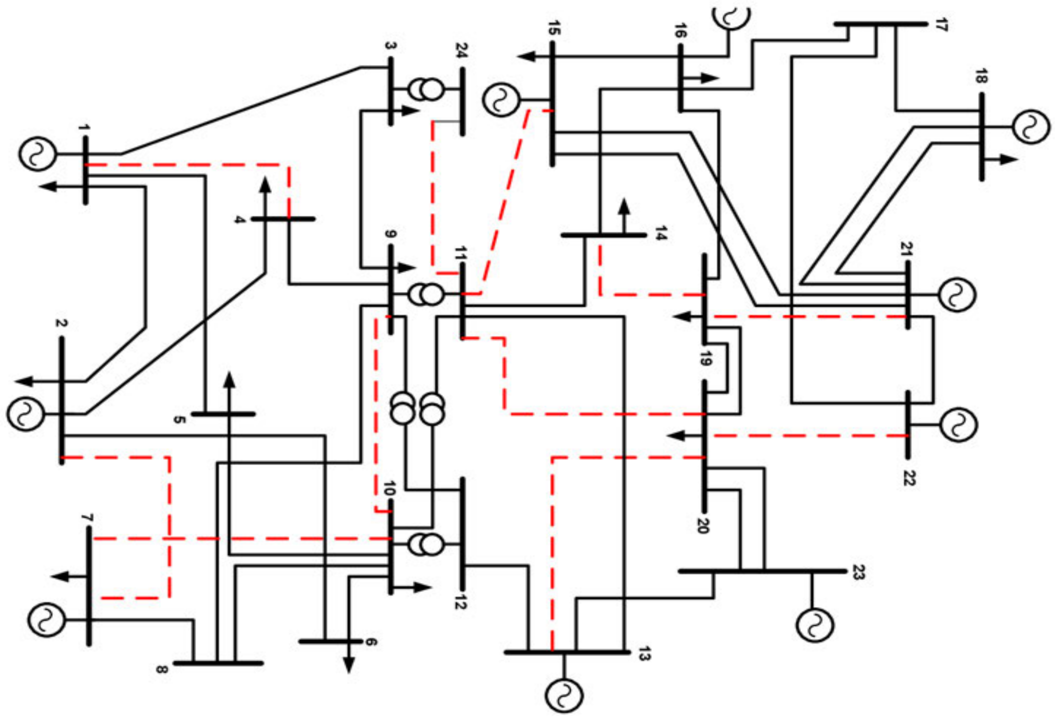


Figure 2. 1Illustration of a possible line candidate for TEP

2.1.1 Generation and Transmission Expansion Planning (GTEP)

Over twenty years of experience with the deregulated operation of electricity markets, the need to synchronize investment decisions for generating and transmission has been identified as a significant issue, especially given the anticipated high integration of renewable energy sources in the next years [47]. The absence of adequate coordination poses risks for investors involved in both operations. The traditional centralized structure of electrical networks assigned the duty of producing and transmitting growth decisions to vertically integrated utilities, hence facilitating coordinated optimization of both aspects [48]. Nevertheless, due to the deregulation of the sector, the process of generating and transmitting electricity has been separated, making it impossible to achieve combined optimization [47]. Computational approach to generating composites and plan transmission extension, taking into account reliability and cost evaluation. The suggested approach integrates a virtual database to mitigate the repeated computation required by the optimization solution. Moreover, TEP involves identifying the timing, locations, and methods for enhancing or enlarging the power transmission infrastructure to reliably, affordably, and securely satisfy future energy demand. It evaluates technical, economic, and environmental factors to guarantee the transmission grid can adapt to fluctuations in demand, generation (particularly renewables), and system contingencies [49] .

2.1.2 TEP constraints.

TEP requires the optimization of new transmission line development to accommodate increasing energy demand while maintaining reliability, efficiency, and sustainability. Numerous restrictions must be taken into account in TEP, including the following constraints:

- Power equilibrium for every individual node.
- Transport network model or AC/DC power flow.
- Power constraints imposed on transmission lines.
- Security limitations (N − 1 or other calculation method).
- Limitations in cost [44].

2.2 TNEP challenges

An inherent difficulty in TEP is in selecting suitable conditions to evaluate prospective transmission networks [50]. When assessing reliability and cost, it is essential to consider many scenarios accounting for the variability in demand and renewable generation. Nevertheless, the computational complexity of including an excessive number of possibilities in an optimization process becomes overwhelming [9]. Indicated in Figure 2.2 are the occurrences that lead to difficulties in transmission lines, emphasizing the pressing necessity of building TEP.

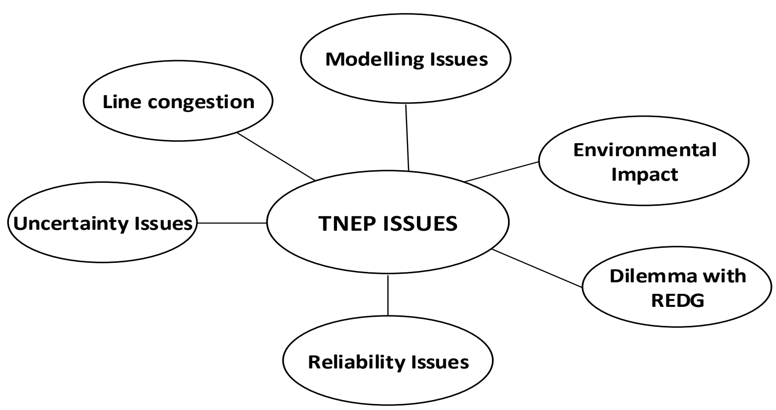


Figure 2. 2 TNEP challenges

2.2.1 Uncertainty in TEP

Management of uncertainty is crucial when assessing the economic and environmental consequences of various energy policy tools: ambiguity could heighten the risks linked to investments and the total ensuing expenses in the long run [44]. Power systems are susceptible to uncertainties, which need to be factored into various sorts of research and models [51]. The issues of sustainability and climate change have led to a substantial increase in the use of RE in conjunction with smart grid technology. The transmission system operator (TSO) planning has significant challenges in dealing with several variables [52]. Moreover, there exist many sources of uncertainty: the unpredictable characteristics of non-dispatchable technologies such as solar and wind, whose output can oscillate greatly within time periods ranging from seconds to months [53]; electricity demand, which is influenced by several socio-economic and technological factors; technology costs, which are influenced by several non-electrical factors; fuel costs, which fluctuate annually; and water availability, which is crucial for systems heavily reliant on hydropower [54]. The inclusion of uncertainties, particularly in long-term models, is a crucial matter to mitigate the danger of implementing growth strategies that are overly vulnerable to the uncertainties in given data [26]. Typically, uncertainties are dealt with using probabilistic models and, more recently, by fuzzy notions that were first presented in the influential work of Zadeh [55]. Probabilistic models are particularly suitable for random occurrences when the occurrence may be replicated under identical circumstances, whatever number of times is needed [56]. The proliferation of DERs including smart grid technology has led to heightened levels of uncertainty in the transmission system [57]. In order to mitigate uncertainties in large-scale renewable energy integration, a probability-based multi-objective model with risk-control techniques has been created [58]. This model addresses overload hazards for wind power integration. Moreover, the uncertainty associated with modeling is shown in Table 2.1

Table 2. 1TEP modeling uncertainty

Factors affecting the Grid	Effect in TEP
load growth [59].	Variations in future power consumption.
Large scale RE [60].	Distributed Solar & Wind power uncertainty
Market price [16].	Volatile energy costs and regulations
Demand response [43].	fluctuating demand patterns
Technology advancement [43].	Grid upgrades, storage, and microgrids can disrupt transmission planning.

2.2.2 Reliability issues

The power blackout in the operation of the electrical grid under a restructured environment is primarily caused by voltage instability. Therefore, to reduce the impact and ensure safety, it is advisable to take necessary measures to enhance the performance of the power system by improving voltage and frequency instabilities [61]. The reasonableness of atypical power system design is assessed in two distinct stages: macro and micro. The macro stage pertains to the examination of planning from a strategic policy perspective, whereas the micro stage focuses on researching planning from an engineering feasibility standpoint [62]. The examination of adequacy, security, and dependability pertains to the macro level, whereas fault analysis and stability analysis pertain to the micro level [63]. The rate of power outages is used to measure how reliable a power system is. This includes the number of outages per customer per year, the average time it takes to fix a failure, the chance of a power outage lasting longer than a certain amount of time, and the total amount of time it is expected to be down each year [6]. Incorporating reliability assessment is essential in any comprehensive long-term planning, such as TNEP, to provide a dependable power supply. Therefore, a well-designed plan must meet all reliability criteria [64]. The following features of a reliable power grid highlight the need to promote TEP: The grid that is resilient to the failure of a single transmission line, The acceptable voltage level in each busbar of the system, the importance of avoiding overloading components like transformers, generators, and transmission lines. The generating capacity must consistently exceed the load demand. Regular occurrences of blackouts or power outages are a clear indication of an electric grid that cannot be relied upon [65].

2.2.3 Line congestion

One of the biggest obstacles to future power system planning and expansion is the power system's increasing energy consumption. According to investigations, one practical and efficient solution to deal with this problem in the power system is to reduce the line capacity of the power system [66]. The goal of paper 1 is to present a cost-effective method for achieving the minimal voltage security margin (VSM) index using Transmission Switching (TS) while reducing the active/reactive power capacity of the transmission lines. It should be noted that this effort has the potential to significantly lower the power system's operating costs in addition to lowering the system's line loading and loss reduction [67]. Transmission network overload or congestion is a byproduct of the expansion of deregulated power systems. Power systems are negatively impacted by congestion, even to the point of significant system damage. Transmission networks become congested when they are unable to distribute power according to load demand. Congestion management techniques are used to address these issues, and they are crucial in the present deregulated electricity networks. A number of strategies have been put out to control congestion as shown in Figure 2.3[68].

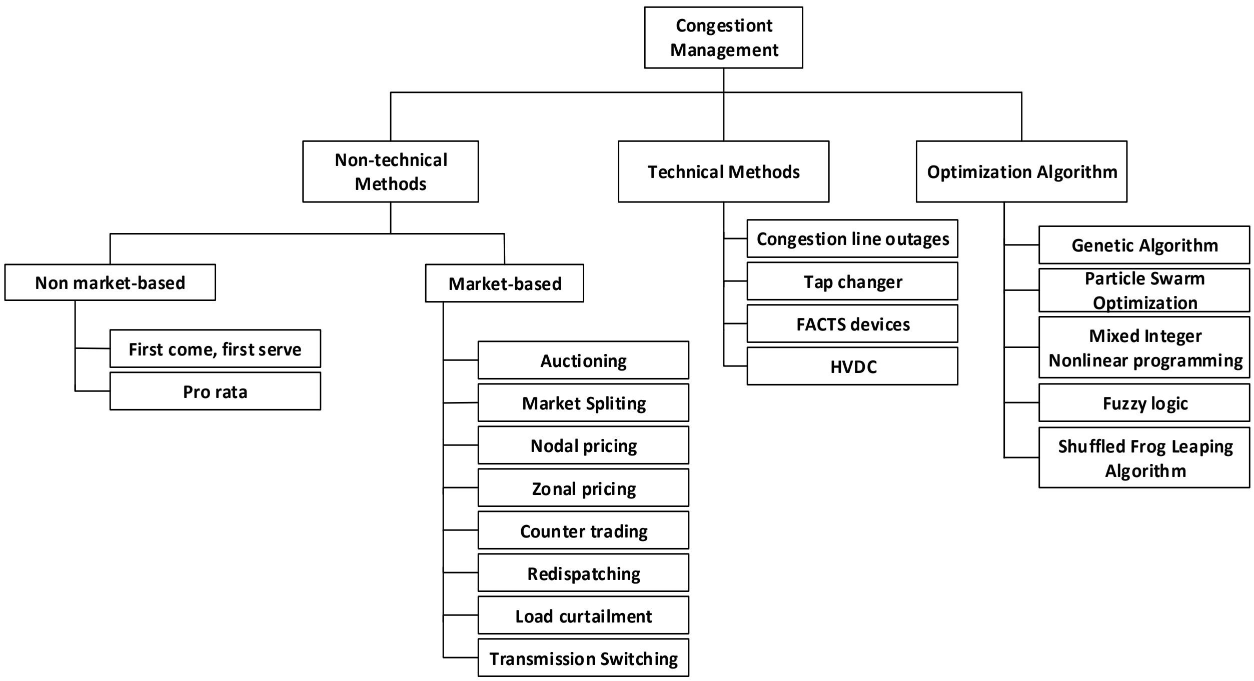


Figure 2. 3TEP congestion management

Congestion occurs when the transmission line's capacity to provide electricity is beyond its thermal, voltage, or stability limits, causing it to become limited and restrict power flow [69]. The emergence of deregulated electricity systems has led to the problem of transmission networks becoming overloaded or congested [68]. Congestion has significant ramifications for power systems, including substantial system harm. It arises when transmission networks are unable to efficiently transport electricity in accordance with the demand load [67]. Therefore congestion management approaches are utilized to address these issues, and they have a significant impact on modern deregulated electricity systems [70].

Due to the economic, social, and political issues associated with expanding transmission infrastructure, there is a need for new transmission topologies that can effectively make use of the current infrastructure [71]. However, wind power generation is rising worldwide. A major obstacle to large-scale wind power generation is network congestion owing to inadequate capacity making a need to propose a co-optimized optimal transmission switching (OTS) and dynamic line rating (DLR) approach to optimize system resources by reducing network congestion and optimizing wind power accommodation [72]. Distributed Generation (DGs) can decrease the demand on the local grid. As a result, they can alleviate congestion in transmission and distribution networks and delay the need for investments in transmission and distribution infrastructure [35]. According to Article [73], the suggested transmission congestion identification technique identifies major congestion lines and provides an economically reliable expansion planning scheme. Wind power access sites affect transmission congestion and economic comparisons, requiring quantitative reliability evaluation and probabilistic economic analysis before finalizing development plans.

2.2.4 Dilemma with Renewable Energy Distributed Generation (REDG)

REDG refers to a power station that generates electricity using hydro, solar, wind, biomass, or certified co-generation methods. The power plant has an installed capacity of 10MW or less[74]. As REDG reaches higher levels, REDG agents have the ability to participate in the spot market and engage in energy trading through the transmission grid. This can lead to an increase in congestion on the transmission lines, which may need further expenditures on transmission equipment [75]. The integration of RE into transmission lines leads to intermittent and unreliable power supply, grid infrastructure and capacity challenges, regulatory and policy barriers, cost implications, and technological advancements [71, 76].

2.2.5 TEP environmental impacts

Considering the growing severity of environmental issues such as global warming, it is imperative to articulate the economic advantages of the environment via market mechanisms. A carbon price is a market-based mechanism used to mitigate environmental damage by reducing emissions [77]. The need to include carbon pricing policies in transmission design due to the rise of environmental issues is emphasized in [78]. The equilibrium between the natural surroundings and financial considerations is examined in [79]. Implementing a carbon fee that reflects the cost of pollution is an effective incentive and optimizes societal well-being in a scenario of perfect competition. However, in a Cournot oligopoly, a carbon charge diminishes societal well-being since it results in less consumption and increased market dominance [80].

2.2.6 Line modelling issues

Several types of line modeling include the AC model, DC model, transportation model, and Disjunctive model as detailed in Figure 2.4 [81]. Transmission expansion is inherently a multi-stage problem in which the planner makes judgments at several time horizons. Furthermore, the expansions have a significant influence not only on the functioning of the system but also on other aspects such as its dynamic behavior or market dominance [47].

The transportation model, introduced by Garver in 1970, uses linear programming [82]. Article [83] proposes an optimum transmission network expansion planning approach. The transmission network is modeled as a transportation network. Hierarchical Benders decomposition is used to solve the problem by dividing it into master and slave subproblems. Figure 2.4 was synthesized from several sources to illustrate the characteristics of all TEP line model choices [6, 59, 83, 84].

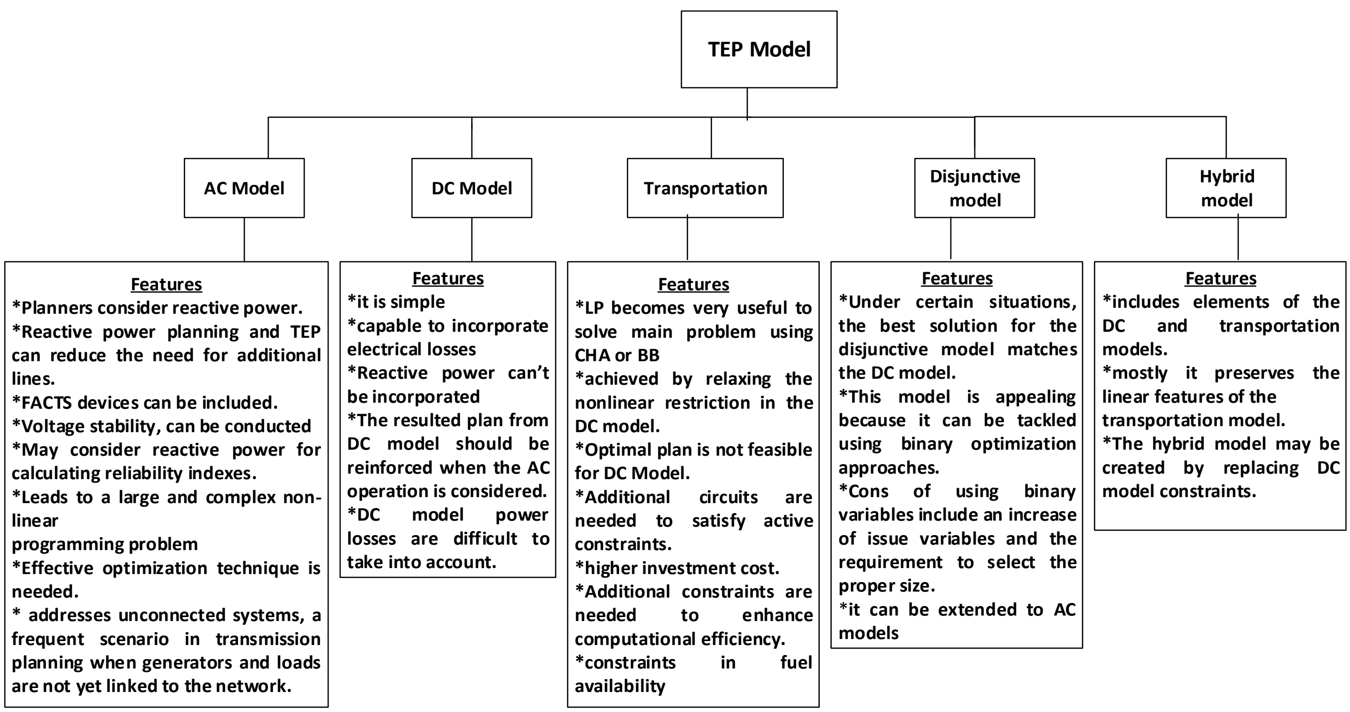


Figure 2. 4Different types of TEP line modeling and their features

2.2.7 Time horizon TEP

TEP may be classed into two types based on the planning horizon: static (single-stage) planning and dynamic (multi-stage) planning [25]. In static planning, the planner aims to find the most efficient plan for a certain year within the planning horizon. The planner's task is to determine the necessary transmission facilities to be added to the network and their specific installation locations

[85]. When it comes to dynamic planning, it is necessary to take into account multiple years and planners aim to find the most effective strategy for the whole planning period. Put simply, despite fixed planning, planners must determine the timing of transmission facility installation within the planned horizon. The dynamic planning problem is highly intricate, as it considers not only the dimensions and arrangement but also the temporal aspect [35]. Figure 2.5 illustrates the planning time for TEP, both in terms of static and dynamic TEP

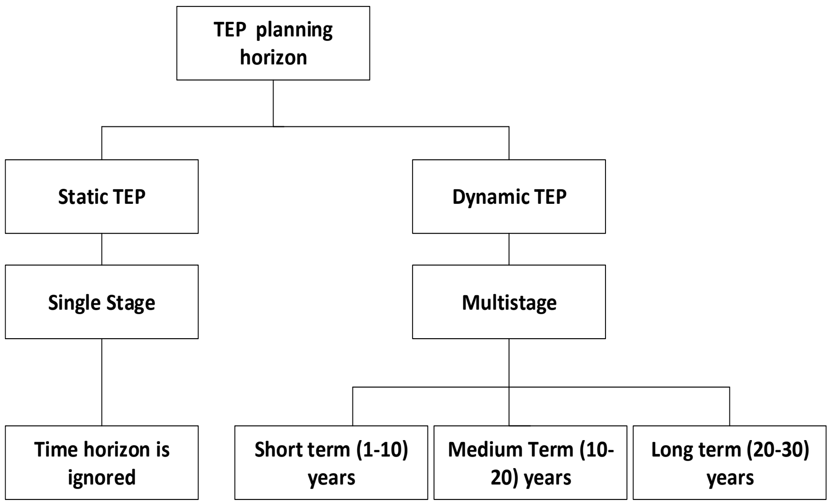


Figure 2. 5TEP planning horizon

Single-stage planning ignores the time horizon and evaluates the best plan for one phase. In dynamic planning, each year's horizon is assessed, and new lines are built separately. This makes dynamic planning more complicated and time-consuming. The TEP can also be categorized into short-term, mid-term, and long-term planning. Long-term planning involves decades (usually 20-30 years), medium-term planning involves 10-20 years, and short-term planning involves issues that must be addressed within 10 years [86].

To address the dynamic multiyear TEP challenge, this research introduces a novel and promising approach structured in two parts. Specifically, the initial phase is focused on reducing the size of the search space and is carried out using a new constructive heuristic algorithm (CHA) [2]. article in [26] introduces a multiyear dynamic model for the TEP issue. The model aims to determine the optimal collection of projects and their scheduling throughout the planning horizon. The candidate plans are assessed using a fitness function that takes into account both operating and investment expenses, as well as a series of penalty terms.

2.2.8 TEP security constraints

An efficient TEP is crucial for the smooth functioning of a power system, especially when considering security constraints [86]. Traditional TEP approaches, which solely consider N-1 static security, may not guarantee the security of numerous contingencies and transient stability in a situation where wind power is integrated on a wide scale [87]. According to an article [88], integrating N-k based static constraints and dynamic constraints, such as differential-algebraic-equations-(DAEs)-based transient stability requirements, in TEP can lead to a significant increase in computing workload and make the TEP model difficult to solve.

2.2.9 Reactive Power Planning (RPP)

RPP is essential in TEP as it ensures voltage stability, regulates reactive power flow, and enhances overall grid resilience [89]. TEP focuses on the development and optimization of new transmission lines or enhancements to accommodate future demand increases and assure dependability. Nevertheless, whereas TEP conventionally emphasizes active power (real power), incorporating reactive power concerns is crucial for attaining an efficient and stable power system [90]. Reactive power ensures that power can be transmitted over long distances without significant voltage drops by maintaining voltage levels throughout the transmission network. In contrast to active power, which is responsible for the "real work," reactive power is essential for the maintenance of the system's voltage profile, the regulation of power flow, and the prevention of voltage collapse or instability [91]. Table 2.2 below details each element of RPP.

Table 2. 2TEP Reactive Power Planning (RPP) aspects

Element	Function in TEP
Voltage stability	Reactive power regulates the voltage. Capacitors, synchronous condensers, and FACTS must be strategically positioned in the network to avert voltage collapse under high load [92].
Distributed Reactive Power Compensation	To regulate voltage and maximize power flow, reactive power compensating devices like shunt capacitors or reactors are placed across the grid at important spots [93].
Loss Minimization	An effectively orchestrated reactive power distribution diminishes losses in the transmission system by reducing the necessity for reactive power flow across extensive distances [94].

Economical Operation	Incorporating reactive power sources during TEP minimizes the expenses associated with maintaining grid stability by decreasing the necessity for expensive real-time voltage management measures [9, 35].
FACTS	FACTS devices, including Static Var Compensators (SVC) and Static Synchronous Compensators (STATCOM), are frequently incorporated in reactive power planning due to their provision of dynamic reactive support and their ability to augment the power transfer capacity of existing transmission lines [95].
Power Flow Optimization	The appropriate allocation of reactive power sources enhances the efficient distribution of real and reactive power, alleviating congestion and optimizing the use of the transmission network [96].

2.2.10 TEP insecurity

Insecurity in TEP denotes the uncertainties and vulnerabilities that may emerge during the expansion of a power transmission network. This may result from various sources, including technical, economic, environmental, and societal dangers. These vulnerabilities must be meticulously addressed to guarantee a reliable and robust electricity grid [7]. Transmission expansion is contingent upon future demand projections. The over- or under-sizing of infrastructure can result from inaccurate demand forecasts, which are influenced by unanticipated economic growth, changes in energy consumption patterns, or the introduction of disruptive technologies [97]. The increasing incorporation of renewable energy sources introduces fluctuation in generation, such as sun and wind, resulting in uncertainty over power availability for transmission. This impacts the grid's stability and capacity requirements [71]. Modifications in energy policies, regulatory structures, or environmental legislation might pose risks to long-term transmission planning. Policy changes regarding carbon emissions, incentives for renewable energy, or mandates for system upgrading can profoundly influence the planning process [37]. Insecurity in transmission expansion planning is complex, encompassing both external uncertainties and internal difficulties. Mitigating these concerns necessitates a thorough and flexible planning strategy that reconciles short-term requirements with enduring resilience.

2.3 Contingency analysis

Contingency analysis in power systems serves the objective of conducting a security analysis to evaluate the power system and identify any overloads or issues that may hinder its functioning [98]. During atypical conditions in the power system, such as contingency situations, the entire system or a portion of it may become congested, leading to unanticipated changes in the loads [99]. Contingency ranking and eventual selection are implemented by performing load flow following the interruption of each transmission line on the test networks [100]. Effective MILP models for solving the multistage Contingency-Constrained TEP issue are discussed in [101]. An iterative algorithm using Line Outage Distribution Factors (LODF) screens worst-case scenarios in existing or candidate lines and dynamically adds security constraints to TEP formulation, reducing decision variables and simulation times compared to alternative approaches. The approach was tested on Garver's system, IEEE 118-bus, and 300-bus systems, the suggested method was to prevents underinvestment in network capacity due to transmission losses, security, and flexibility restrictions. An indispensable technique in power system management operations is contingency analysis (CA). The goal is to pinpoint the crucial contingencies that may impact the reliability of the system [72].

2.4 Transient stability

Transient stability refers to the power system's capacity to sustain synchronization during disruptions [88]. Traditional security limits the primary focus of TEP to static security, which makes it challenging to fulfill transient stability requirements. To enhance the security of the system and minimize the likelihood of widespread failures and power outages, it is important to examine the transient stability of the TEP [102]. Innovative methods for addressing strategic expansion issues between generating and transmission businesses are discussed in [103] . It considers the security limitations of the power network, including transient stability and voltage stability. The suggested technique establishes the voltage stability index and security stability index as security constraints of the system initially and subsequently utilizes PSO to optimize the objective function.

2.5 Grid code requirements for TEP

The South African Grid Code (SAGC) defines the technical and operational stipulations for all entities linked to the national electrical grid, guaranteeing the dependable and efficient functioning of the power system [104]. The Grid Code has many parts, including the Network Code, which delineates the technical requirements for connection to and operation within the transmission and distribution networks. When expanding a transmission line, it is crucial to adhere to the technical standards outlined in the grid regulations established by the distribution system operator. Therefore, an examination of the current grid codes (Transmission and Distribution) is conducted. Assessing the generating limitations is essential for ensuring the sustainability and security of the system, in accordance with planning and operational standards [105].

2.6 Reason to optimize TEP

TEP is a challenge that necessitates forecasts of demand behavior, generation profile, and annual budget to guarantee the quality of supply service. If, on one hand, the minimization of anticipated financial resources must be effectively managed by taking into account all the limitations associated with the budget, grid structure, and service quality, on the other hand, the future operational circumstances must also be guaranteed by a dispatch process [2]. Table 2.3 breaks down the several categories of objective functions that must be considered while expanding transmission lines.

Table 2. 3Different types of objective functions in TEP

Type	description	Objective function to:
Investment and operation [82].	Decreases the overall capital expenditure for new transmission lines and mitigates fuel expenses, maintenance expenditures, and generator dispatch costs.	Minimize
Energy loss cost [106].	The purpose of designing an objective function for reducing energy loss costs in transmission expansion planning is to improve the design and expansion of the transmission network, decreasing energy losses and minimizing the resulting expenses.	Minimize
Power congestion [107].	Mitigates bottlenecks and facilitate improved market functionality.	Minimize

System Reliability [59].	To maximize system reliability in transmission expansion planning, it is necessary to include several aspects that contribute to the overall dependability of the power system while creating an objective function. The target function must include both the technical and economic factors of dependability, including the reduction of power outages, the optimization of the location and capacity of new transmission lines, and the guarantee of system resilience against unforeseen events.	Maximize
Load Shedding [59].	Offers demand fulfillment by reducing unsupplied energy.	Minimize
System Security	Improves stability under unforeseen events (e.g., N-1 security criteria).	Maximize
Expected Energy Not Supplied (EENS)	Decreases the probability and intensity of power disruptions.	Minimize

2.7 Traditional methods of TEP

If only traditional deterministic data is utilized, the optimal plans obtained from expansion planning exercises will be suitable for the crisp input data, but they may lack robustness in handling slight variations that may impact the input data [108]. Hence, it is crucial to consider uncertainties, particularly in long-term models, as a means of mitigating the risk associated with implementing growth plans that heavily rely on uncertain input data [26]. The approach involves employing decomposition techniques to solve a relaxed version of the original integer issue. In this relaxed form, the integer investment possibilities are replaced by continuous variables. They aim to identify global optimum solutions using this method. However, these methods often need significant computational resources, which poses challenges when attempting to apply them to medium and large systems, such as genuine transmission networks [35]. Mathematical optimization techniques have been used to solve many real-world issues for decades. There is an increasing interest in utilizing mathematical programming methods to address generation expansion planning issues [109]. This study also covers several mathematical optimization strategies for TNEP issues, up to the current state of the art [110, 111]. Mathematical optimization is a traditional strategy used in Engineering, Mathematics, Computer Science, and Management Science (Operation Research) to choose the most optimal solution to a problem or pick the best option among several alternatives based on certain criteria. It might be considered the first form of optimization techniques [6]. The approach involves using an algorithm or a set of algorithms to address engineering problems. This notion encompasses additional resources like high-speed computers and other equipment, making it broader than an algorithm. An algorithm is a collection of instructions for achieving desired outputs in a finite number of steps using input data [13, 101]. Despite significant advancements in optimization techniques, finding an optimal solution to a problem of this kind remains challenging [14]. Researchers provided formulations based on AC network equations to address this issue. Existing AC formulations are ineffective when dealing with a high volume of potential transmission pathways, various planning situations, due to convergence concerns, or when solutions are not viable [18, 112]. Nevertheless, the task of identifying an optimal solution only by mathematical methods might prove to be highly tough and time-consuming, owing to the intricate nature of TNEP situations [5]. GTEP and demand response were investigated to help planners make investment decisions for power systems to satisfy anticipated energy demand, resulting in an optimal expansion strategy. The model evaluates the influence of DR penetration on system performance by assessing many degrees of penetration in the planning system. The suggested multi-period multi-objective GTEP model is a Mixed Integer Quadratic Programming (MIQP) problem. CPLEX 12.8.1 solver was used to test the proposed MIQP on two actual case studies: IEEE 24-bus and the Nigerian power system. A sensitivity study of the proposed model found that increasing DR resource penetration in planning decreases power generation, emissions, and system costs, while improving RES use in the power system [113].

2.7.1 Existing traditional techniques

Linear programming technique shows improved computing speed; it has the drawback of not explicitly providing the inverse of matrix B[6]. Mixed integer linear programming (MILP) is used to ensure feasibility; a planner must incorporate operating decision-making into the planning model due to the instability of renewable energy [13]. The MILP Generation and TEP model is described in the article [114], which generally consists of millions or tens of millions of variables.

This large number of variables makes the model unsolvable by commercial solvers without additional steps. Article [14] used a linearized power flow model for TEP on the IEEE 118-bus test system. This work proposes a MILP technique that accounts for losses, generator costs, and security limitations in multi-stage TEP. Simulation findings demonstrate the suggested approach's accuracy and efficiency, making it suitable for large-scale power system planning. To tackle the computational complexity of the TEP issue, we suggest using a nested BD approach and a tailored BD technique that makes use of the specific structure of the GTEP problem [13]. Both techniques partition the planning issue by year. The nested Benders' decomposition (BD) method sequentially solves each year, first moving forward and then backward [115]. BD is a method that involves a master problem that focuses on investment decisions, as well as several subproblems that reflect operating decisions for a certain year. computer investigations, the tailored BD technique outperforms the nested BD approach [9]. The branch and bound (BB) approach is commonly employed to achieve the global solution of MILP problems. However, the standard BB structure is not successful in solving nonconvex MINLP problems because of the nonlinearity and nonconvexity of the feasible region [116]. Using a constructive heuristic algorithm, at each iteration of the algorithm, a sensitivity index is utilized to include a circuit (either a transmission line or a transformer) into the system [117].

The stochastic dual dynamic programming (SDDP) method is used to account for uncertainties, and the complete model was resolved using the BD methodology [118]. Existing approaches cannot guarantee finding the best global solution [119]. The TEP problem is a complicated and non-convex problem that is both nondeterministic and polynomial time (NP)-hard. It may be expressed as a MINLP problem [86]. Traditional techniques such as linear programming (LP) and BD rely only on mathematical concepts. However, their drawback lies in the fact that when dealing with large-scale problems, it becomes exceedingly challenging to obtain precise and rational answers [120].

The MINLP problem can be addressed by the utilization of mathematical methods that employ commercial solvers or through the application of metaheuristic algorithms such as genetic algorithm (GA), tabu search (TS), PSO, and others [121]. Furthermore, stochastic programming (SP) or robust optimization (RO) may be employed to consider the pertinent uncertainties associated with the TEP problem, including power consumption, pricing, and RES, among other factors [122]. The incorporation of security and Reliability aspects into the TNEP problem has been addressed through the development of several approaches [123]. Table 2.4 examines traditional approaches to TEP issues, elucidating their problem-solving techniques and the TEP models employed in these approaches.

Table 2. 4Traditional optimization algorithm in TNEP problems

Mathematical Algorithm and year to TEP	**Controls**	**Applications**	**Contributions**	**Drawbacks**	**Models**
Linear programming [6, 85, 124]. (1970)	Capacity shortages	optimal solution for low and medium-sized systems	Optimize resource allocation	Lacking explicit matrix B inversion is a drawback.	Garver's six-bus
Nonlinear programming [116, 125, 126]. (2000)	maximize the social welfare function of market participants, constraints that include corona power loss	Large-scale, Electricity market,	Minimize investment cost, and prioritize transmission line reinforcement. Significantly decreases the intricacy and computing load of the TEP problem	Struggle to detect the infeasibility subproblem	-Garver's six bus -IEEE 24-bus -IEEE 662-bus
Mixed Integer programming [127-130]. (1999)	guide transmission equipment investment.	Static planning optimizes the size and location of new transmission.	Minimize total investment cost, supply spatial forecasted load	It lacks additional network constraints, Absence of an investment execution sequence	-Garver 6 bus -IEEE 30 bus
Mixed Integer Linear Programming [13, 14, 119, 131, 132]. (2001)	Investments, operational cost. where to build or reinforce transmission lines	Multi-scale TEP issue	Examines losses, generator costs, and security constraints	It has computational challenges	-ERCOT -IEEE 30 Bus
Mixed- Integer Non-Linear Programming (MINLP) [116, 133, 134]. (2005)	determine the optimal sub-transmission system expansion planning	Complex, multi-stage model	Reduces cost	The power output of DG units is constrained.	-A case study of 5 current and 17 proposed substations feeding 62 load locations. -Garver's system -IEEE 24-bus Southern Brazilian reduced system.
Second-order conic programming	used to convexify the nonconvex lower-level	Optimum solution for small and medium-scale systems	computational efficiency, naturally convex	The price offered by generators and its correlation can	-IEEE-118 bus - EEE 24-bus

(SOCP) [124, 135]. (2012)	optimization problem.			significantly impact the ideal plan for transmission planning.	
Bender's decomposition [13, 16, 136-139]. (1988)	Addresses computational challenges	Small and medium-scale power systems	It can cope with large-scale problems, investment master problem, time cost reduction	Huge computational burden may be a challenge	-Garvers 6 bus -6 bus - IEEE 118 bus -IEEE RTS 79 -IEEE RTS 96 -Realistic sized test system.
Branch-bound method (BB) [16, 116, 127, 131]. (1974)	Force convergence of integer variables	outperforms commercial and open-source solvers for nonconvex MINLP problems, particularly when using LOQO to obtain the best-known solutions for all instances of the TNEP problem.	The planning findings are globally optimum and achievable under AC power flow restrictions.	Struggles with innovative, practical solutions and identifying the next subproblem.	-IEEE 30 bus -93-bus Colombian system
Game theory [140-143]. (1997)	Addresses investment and operational planning challenges.	makes decisions on investment in the transmission network while predicting the results of a completely competitive energy market.	It can predict results for the electricity market	It has been applied to small networks and has no trace of any large network.	-3 bus system -9 bus system -IEEE 14 bus
Monte Carlo simulation [8, 43, 138, 144, 145]. (2005)	Addresses uncertainties, planning investment, risk analysis, option pricing, spare capacity	uses random variables to describe the likelihood of multiple outcomes in a process or system that cannot be anticipated	Long-term horizon planning, Generates stochastic disruptions in the electric power system. Lowest cost.	The computation time for the The scenario-based problem depends on the number of scenarios, leading to high computational time, Trade-off between accuracy and computational flexibility.	-IEEE RTS 24-bus -6 bus + 10 nodes -36 node system
Adaptive Robust Optimization [6, 135, 146-149]. (2015)	price uncertainties from generators	A large network, stochastic model	Considers long-term and short-term Uncertainties	It leads to a rise in the investment cost while aiming to reduce the overall cost across the iterations.	-IEEE 118 bus test -IEEE 24-bus RTS
Constructive Heuristic algorithm based on sensitivity	Solves the short-term TNEP problems, solves security constraints	Consider several generating possibilities in a competitive power market.	achieves a satisfactory resolution using an iterative procedure,	Existing methods could fail to foster competition in the power sector.	-Modified Garver System. -IEEE 24 bus

index [117, 150-152]. (2004)			finds high-quality solutions		
Hierarchical decomposition [153-155]. (1994)	Can effectively plan collaborative expansion for transmission and distribution with a restricted investment budget.	Both in large and small networks, generation-transmission expansion	Reduce investment cost, cope with nonconvexity, Able to find the global optimal.	It does not consider uncertainties	-45 bus -Garver's 6-bus -IEEE 118-Bus
Dynamic programming [6, 118, 156]. (2016)	Addresses uncertainty.	Applied to determine best expansion plans for various load scenarios.	It solves discrete sequential issues like the TNEP issue, which is a sophisticated finite Markovian sequential process over time, robustly.	The technique is frequently constrained by the restricted number of steps and possibilities that are considered.	-Revised IEEE 24 bus -Revised IEEE RTS-96 Test
Kernel Oriented Algorithm [6, 157, 158]. (2000)	Transmission cost, cost allocation	A central cost allocation, deregulated networks, multi-agent system, decentralized manner.	It combines equilibrium and transparency in calculating final assignments.	However, the technique has not resolved sunk cost allocation.	-6 bus Garver -IEEE 24
Stochastic programming [131, 135, 137, 159]. (2007)	Address multiple uncertainties, Risk-averse approach, uncertainties related to demand and wind	A large network, multistage TNEP	Cost-effectiveness, reliability, decreased computational time.	Considers short-term uncertainties only, integer variables are unrestorable, making them intractable.	-6-bus -118-bus -IEEE 30 bus -21 node network
Interior Point Method (IPM) [6, 134, 160]. (2004)	It addresses a subsidiary issue inside the primary TNEP problem.	Short-term TEP, TEP sub-problem.	It identifies high-quality solutions for systems of medium scale.	Multiple predictor-corrector and multiple centrality correction approaches were utilized to tackle the nonlinear programming issue in each step.	-Garver's 6 bus
Dual decomposition [131]. (2020)	Address future demand uncertainty, reliability, operation and investment cost.	Long-term horizon planning, multi-stage stochastic programming.	Cost reliability, cost operation, cost investment. convey optimal decision, achieve economical use of time	Shortcoming in integer variable convergence, not able to realize adequate reliability cost, not able to analyse power system flexibility for newly constructed lines	-IEEE 30 bus

2.7.2 Benefits of traditional methods

Mathematical optimization models solve TEP by mathematically describing the problem and computing the optimal growth plan [161]. The ideal solution is often precise and has a short solving time. An appropriate convergence is achieved [23].

2.7.3 Drawback of traditional methods

It is challenging to include power system equations in an optimization programming model [162]. To include a new constraint, it is necessary to reorganize the model and incorporate additional equations. Static studies can be conducted, but dynamic studies, such as stability analysis, are not possible [59]. Traditional approaches such as LP and BD rely only on mathematical concepts. However, their main challenge is in the difficulty of finding correct and appropriate solutions when dealing with large-scale problems [4].

2.8 Metaheuristic methods in TEP Problems

Metaheuristic Optimization techniques are techniques that have attained a high level of maturation in recent years and are employed in a broad range of industries, including the electrical, construction, automotive, chemical, aerospace, and manufacturing industries [6]. They are widely used as a fundamental approach in the search for an optimal solution to a complicated problem [163]. Commonly referred to as nature-inspired algorithms, have demonstrated their efficacy in tackling a wide range of optimization problems, particularly in the context of TNEP [6, 164]. Figure 2.6 illustrates the utilization of some existing metaheuristic methods in addressing TEP issues.

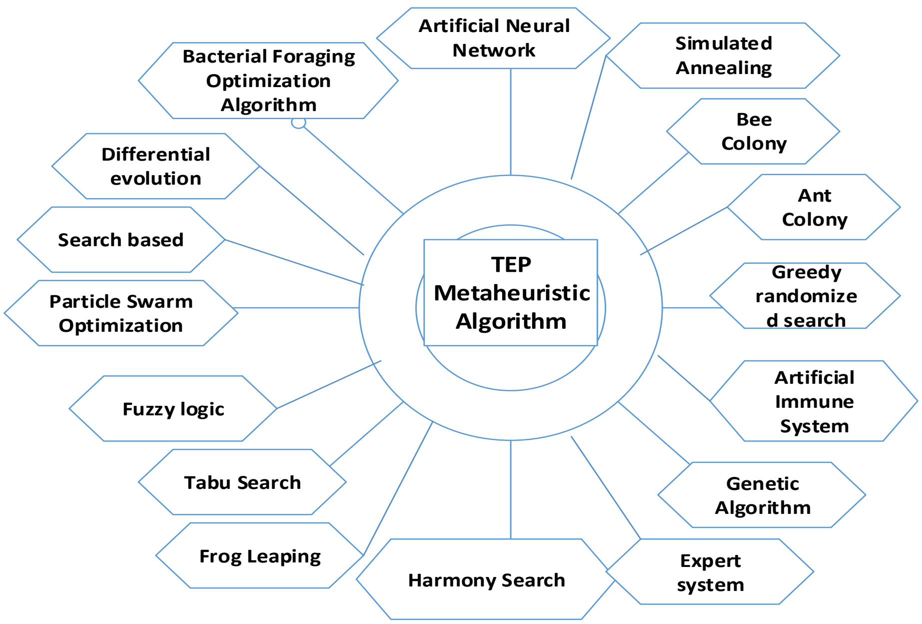


Figure 2. 6Metaheuristic optimization algorithm

2.8.1 TEP metaheuristic optimization algorithm

A confined meta-heuristic multi-year TNEP model, utilizing Ant Colony Optimization (ACO), is introduced in the article [5, 42]. One key feature of the model is its ability to concurrently examine other extension possibilities, such as line reconductoring, voltage uprating, and the addition of series compensation to lines [165]. The ACO model was evaluated using Garver's 6-bus test system and a modified version of the IEEE 118-bus test system, with a substantial integration of VGTs. The results from a 15-year planning task demonstrate that the model performs exceptionally well in terms of solution quality and computational times when compared to the traditional MILP approach. Additionally, incorporating line uprating options in the multi-year TNEP yields substantial benefits, including reduced total investment and congestion costs for the system, as well as a decrease in the number of lines that need to be constructed[42]. This article investigates the improvement of an existing metaheuristic algorithm in the field of TEP. It also examines the rationale for the improvements made to these approaches, which are listed below.

2.8.2 Improvement on Genetic Algorithm (GA)

1. Improved Genetic algorithm (IGA)

GA is a heuristic search technique commonly employed in the fields of artificial intelligence and computation. It is mostly utilized to discover optimum solutions for non-linear problems [166, 167]. The long-term transmission expansion planning (LTTEP) problem is addressed by the utilization of an advanced genetic algorithm (EGA) [168]. An evolutionary programming genetic method is suggested for optimizing the position, size, and charge/discharge operation in power flow regulation [169-171]. Various approaches have been implemented using MATLAB and DigSilent PowerFactory software, which utilize an intelligent automated data exchange mechanism to find the ideal solution [169]. GAs are utilized in large-scale power distribution systems to enhance efficiency and reduce power loss [172, 173]. The suggested EGA for solving the static and multistage LTTEP issue is characterized by the following features: (1) the production of an initial population through the utilization of quick and efficient heuristic algorithms, (2) the improved implementation of the local improvement phase, and (3) the efficient solution of LP problems [174]. The GA formulation encompasses several factors inside it. The population size, selection method, crossover parameters, goal function, probability parameters, and mutation method in GA need to be carefully defined based on the specific optimization issue and desired outcomes [166].

2. Decimal-coded GA

The research paper [175] presents an evolutionary algorithm that uses decimal codification to address the TNEP problem, considering the financial consequences of line maintenance. The objective is to prolong the lifespan of the aging transmission lines to decrease the financial expenditure required for expanding the transmission network and enhance the value of the overall transmission system [175, 176]. The method was assessed using the IEEE reliability test system. The evaluation of the findings showed that including the impact of line maintenance on the TNEP problem can lead to substantial cost reductions in the entire system [175]. The study in [166] GA was employed in a modified 33-bus to simulate the power flow. The objective is to optimize the location and size of the PV and Battery Energy Storage System (BESS) while considering power loss. This is achieved using the integrated Python in DIgSILENT PowerFactory.

3. Real-coded GA

To address the complex and nonlinear character of the Dynamic TEP issue, as well as the inclusion of Fixed Series Compensators (FSCs) and Shunt Compensators (SHCs), the paper [177] utilizes the Real Coded GA (RCGA) to get the optimal solution. The simulations conducted on the IEEE 24-bus test system demonstrate the satisfactory performance of the proposed model, considering the FSCs and SHC.

4. Chue and Beasley GA

This technique has been applied to 6-Bus Garver, IEEE 24-bus, and South Brazilian 46-bus systems to account for active power loss, it converts MINLP into LP [178] [179]. The research in [180] utilizes the Chu-Beasley GA (CBGA), originally developed for the generalized assignment issue, to address the transmission network expansion planning problem that involves unpredictable demand. The CBGA exhibits special features in comparison to GA. It does not eliminate individuals that are not possible. During the initial stages of the calculation process, unfeasible people are included in the population until convergence is reached, at which time all individuals become feasible [181].

5. Non-dominated Sorting GA II

The model was tested on both a simulated system and a real-world system, and it demonstrated a greater level of social welfare compared to the design with distinct networks. The multi-objective optimization model is solved using the Elitist Non-dominated Sorting GA II (NSGA-II) to accurately identify the best Pareto front [182]. Paper [183] focuses on three optimization objectives: investment cost, cost of density, and reliability. To address this non-convex and mixed integer problem, the multi-objective GA and NDSGAII were employed in an IEEE 24-bus system. The "VDS-NSGA-II" is a virtual database-supported NDSGAII that is specifically built to address the challenges of the multi-year multi-objective dynamic generation and transmission expansion planning (MMDGTEP) framework. In paper [184], the MMDGTEP is presented as a bi-objective optimization problem. The objective functions were to minimize the overall cost and to minimize the anticipated energy not supplied (EENS) at the hierarchy level II.

2.8.3 Improvement in particle swarm optimization (IPSO)

PSO is inspired by the foraging and social behavior of swarms [185]. It was introduced by Eberhart and Kennedy in 1995 specifically for optimizing continuous linear functions [186, 187]. This approach is founded upon a collective of particles that actively seek optimal food sources. Every particle hunts for the ideal fitness position by comparing its fitness value and adjusting its own velocity [188]. PSO is computationally efficient regarding memory and performance and may be simply implemented through computer programming [189, 190].

1. Multi-objective PSO

Multi-Objective PSO (MOPSO) is one of the suitable meta-heuristic algorithms to solve complex optimization problems because of its robustness in controlling parameters and its flexible applications [191, 192]. A multi-objective optimization approach, utilizing PSO, seeks to simultaneously reduce two objective functions. The technique employs various weighting factors and random coefficients to compute the velocity and displacement of individual particles, with the objective of identifying the global optimum point through iterative processes.

2. Improved PSO

Enhancing the efficacy of the PSO algorithm necessitates increasing the probability of the search space [193, 194]. The simulation results demonstrate that the IPSO method is superior to the PV smoothing mode in finding the optimal operating of the BESS and reducing PV voltage fluctuations in the microgrid. The IPSO algorithm may be developed using MATLAB and DIgSILENT PowerFactory, both of which utilize a dynamic data interchange file called "Switch.csv" [195].

3. Novel binary PSO (NBPSO)

The NBPSO algorithm successfully identifies the TEP solution in an IEEE 24 bus system, achieving the lowest investment and operational costs without violating any power system limits [196]. Paper [197] suggests using NBPSO to decide which transmission line to connect to the power system. There are two scenarios in this simulation. Consider transmission power losses first, then regardless. The NBPSO approach yields optimum results in a fast calculation period. Compared to the first scenario, the second scenario involves fewer new lines but higher power losses, leading to significant costs.

4. Discrete evolutionary PSO

Evolutionary PSO (EPSO) is a meta-heuristic that was first suggested in 2002. It is based on evolutionary principles [26]. Paper [26] presented a concept for multiyear transmission expansion planning that involves both integer and non-integer variables. The difficulty was resolved by employing a discrete iteration of the EPSO algorithm, referred to as DEPSO. The TEP formulation is characterized by its dynamic multiyear nature, which ensures that all periods within the planning horizon are considered in a single run of the planning process [198]. Paper [199] presents a hybrid tool for addressing the TEP issue in the IEEE 24 bus. The tool consists of two phases. In the first phase, a Constructive Heuristic Algorithm (CHA) is used to pick a list of equipment candidates. In the second phase, a DEPSO approach is employed for the final planning. Results demonstrate that swarm intelligence-based techniques in smaller search areas may uncover high-quality solutions with minimal computing effort. The first PSO was designed for continuous values. However, discrete PSO was created in 1997 for discrete optimization problems [197].

2.8.4 Enhanced modified shuffled frog leap algorithm (EMSFLA)

An improved method for guiding frogs (solutions) to food (the best global solution) is introduced in this work; it is called EMSFLA. The TEP problem is optimized using the provided technique. The suggested approach has the benefit of avoiding local minimum and achieving convergence with a reduced number of iterations. To skew the intermediate outcomes towards the optimal solution on a global scale, EMSFLA specifically considered population formation and evolution [200]. The local search process is modified to expedite the progression of memeplexes into their fully developed state. The overall processing time while employing EMSFLA does not show any improvement compared to MSFLA, which is currently the method that takes the least amount of time [201]. Table 2.5 presents an analysis of the use of metaheuristic optimization in TNEP issues, including instances where they can potentially be applied and the aspects they regulate in TEP problems.

Table 2. 5Metaheuristic optimization algorithm in TNEP problems

Metaheuristic Algorithm and year	**Inspiration**	**controls**	**Applications**	**Benefits**	**drawbacks**	**Used Models**
Tabu Search (TS) [202-204]. (1997)	Prohibitions, also known as Tabu, are used to discourage the search from revisiting ideas that have already been explored.	It controls numerous costs.	Small and large-scale network, dynamic nature, Multi-stage planning.	The least cost solution, addresses financial investment, transmission losses	Encounters difficulties in identifying the most efficient solution, it does not address uncertainty.	-England 39 bus -6 bus Garver -6 bus test system -18 bus
Ant Colony Optimization (ACO)[42, 165, 205, 206]. (2009)	The method is derived from the behavior of an ant colony in search of a path to food that is near optimal.	Minimizes investment cost, addresses security constraints,	Multi-objective function, Multi-year TNEP, Multiple load generation profiles. Dynamic TNEP	Evaluate further expansion alternatives like line reconductoring, voltage uprating, and series compensation concurrently. Optimal solution with appropriate computing time.	It is advisable to enhance the method to decrease the amount of time it takes to compute.	-3 bus -Garver 6 -bus - 46 -South Brazilian bus -IEEE 118-bus
Genetic algorithm (GA) [16, 61, 168, 207, 208]. (2000)	inspired by evolution, including the concepts of mutation, natural	It is preferred for its rapidity and purity of solution. to determine the most efficient	solve the static, multistage LTTEP, and multi-objective TNEP optimization	Reduce power loss, improve efficiency, improve voltage stability, Global	The computing cost is high, resulting in a huge number of variables and	-Garver 6 -bus -IEEE 24 bus -South Brazilian

	selection, inheritance, and crossover.	solution for intricate optimization issues.		optimal solution, and flexible structure.	sluggish convergence.	
Particle Swarm Optimization (PSO) [6, 187, 209, 210]. (1995)	birds seeking to find the best food	Entails deciding on the placement and quantity of additional transmission lines.	Large scale, Multi-stage TNEP issue, multi-year Dynamic model.	Performance and robustness, Optimal planning, Improve the expense associated with TEP.	The variety diminishes rapidly in the subsequent cycles, leading to a suboptimal solution.	-IEEE 118- bus -IEEE 30 -bus
Artificial Immune System (AIS) [6, 211-213]. (2009)	influenced by theoretical immunology and vertebrate immune systems	Find the solution with the lowest cost. Reduces the number of lines and length of transmission lines to be built. transmission loss and investment cost	Multi-stage nature TEP, large scale network, Optimization of candidate line costs	AISA's performance with fewer lines and longer new lines, especially for higher load and generation, suggests its appropriateness for long-term TEP. The AISA is more efficient than GA and BFOA in determining the cost of new transmission lines following TEP.	The method has not undergone testing in an actual extensive transmission network.	-small test system -133 bus TNS
Artificial Neural Networks (ANN) [6, 214]. (2002)	Human brain's neural structure.	Better suited for predicting applications.	Short-term load forecasting	quick when conducting a local search	It has specifically operated as a decision support system, utilizing other algorithms addressing the TNEP problem. Optimal neural network architectures or training methods are needed to enhance predicting accuracy.	-single line diagram 11kV network
Bee Colony Algorithm (BCO)[215-218]. (2010)	The foraging activity of honeybees when searching for a high-quality food source.	Address transmission investment costs,	For static TNEP issues, for security constraints	Reduces investment cost.	It discovers more precise solutions for the given problem in comparison to PSO or GA.	-Garver's 6 bus -IEEE 24- bus -IEEE 25 -bus
Chaos Optimal algorithm (COA) [6, 219]. (2008)	To use the ergodic property of chaotic maps to improve	Increase branch load factor distribution while	Stochastic TEP	The structure is straightforward and	It has not been applied in large networks. The	-modified Garver's 6-bus

	the solution's effectiveness.	reducing investment.		conducive to easy interpretation.	investment may exceed that of traditional methods in the planning model.	
Differential Evolution Algorithm (DEA) [220-222]. (2006)	Darwin's theory of evolution	Determine the optimal location of the new transmission lines while minimizing costs.	Market-based, deregulated market environment, multi-stage problem.	Excellent proficiency in producing a comparable and superior solution. Another benefit of utilizing DEA is its ability to initiate seemingly unattainable solutions.	The technique is very resilient for small and medium-sized test systems. However, it is advisable to employ additional ways in conjunction with this one to enhance findings for large networks.	-Garver's 6 bus -IEEE 25- bus -IEEE 24 -bus -IEEE 30 -bus
Expert system [223, 224]. (1993)	Human expert.	Minimize investment cost.	Short-term TEP, large networks.	Capable of determining feasible options for the growth of the electrical transmission system, capable of identifying and assessing further reinforcements	Unable to achieve the precise best solution.	-5 -bus -500 bus Electrical system network.
Shuffled Frog Leaping algorithm (SFLA) [200, 225-227]. (2003)	Frog's behaviour in finding food	Reduce Investment, Maintenance cost	Multi-Objective function, Static TEP	Minimize cost investment, congestion cost, and load curtailment	The uncertainties related to demand and generation projections are not considered. Implementing heuristic strategies for selecting suitable rights-of-way can speed up the suggested process for big power systems.	-Garver's 6 bus -IEEE RTS 24-bus test network
Bacterial Foraging Optimization [228-231]. (2010)	Social behavior of Escherichia coli.	Address operational cost, network adequacy restriction	A multi-objective, Deregulated market environment, considers real-world network limitations.	To acquire the Pareto approximation set of solutions. The BFO algorithm has yielded superior outcomes in comparison to the DEA and ABC	The significance of computational time is not taken into account.	-IEEE 6- bus -Colombian 93-bus. -IEEE 24 bus RTS

				algorithms. Fast convergence.		
Fuzzy logic[232] [233, 234]. (1998)	Degrees of truth.	Level of reliability of the components	Short-term uncertainty, identify critical scenarios	maintain a high degree of reliability	Requires the implementation of alternative algorithms, such as BB and CHA for the purpose of determining the ultimate choice.	-Garver's 6 -bus -IEEE 24 bus
Greedy randomized adaptive search procedure (GRASP) [16, 235-237]. (2001)	It seeks to find and choose the best option at each problem-solving stage.	Optimization of transmission expansion and reliability costs based on bus load loss.	Multi-stage and static TEP issue.	Reducing variables and combinatorial search space. Can give cost-effective, realistic solutions quickly.	The local search process in this approach makes comparison trimming challenging.	-3 -bus
Harmony Search Algorithm (HSA) [238] [239, 240]. (2010)	The musical process of seeking the ideal state of harmony	Addresses security constraints, and low cost.	Static and Dynamic TNEP issue	It is more resilient and computationally effective when compared to other meta-heuristic algorithms such as GA and BFOA.	The precise and efficient potentials of applying it to a large-scale power system have not yet been proven in a real-world context.	-Garver's 6-bus -IEEE 24 bus -46 bus South Brazilian 93-bus Colombian.
Simulated Annealing (SA) [16, 241-243]. (1995)	Annealing process in metallurgy	Optimize the investment and LOL	Long-term planning, large-scale network	This tool possesses the capability to evade local optima by temporarily tolerating subpar answers and actively seeking superior alternatives within its immediate vicinity.	The approach has not been used on a large scale in network simulations, resulting in a lack of assurance of convergence towards a globally optimum solution in large networks.	-Garver's 6 - bus -6 -bus system-
Cuckoo Search [6, 244]. (2009)	Cuckoo's behavior & their egg laying strategy	Investment cost	Large actual electrical system	To reduce investment cost	The best solution for the AC-TNEP model remains a formidable task.	-46 -bus system
chaotic grasshopper optimization algorithm [245]. 2017	Grasshopper swarm behavior	The investment plan, and planning horizon, minimize costs by decreasing the peak	Multi-model, GTEP, to optimize the results	Lower the total cost, and explore low-emission and cost plans.	No evidence of its use with other uncertainty-reducing approaches.	-IEEE 24-bus RTS

Teaching learning-based optimization [246-249]. (2010)	The impact of a teacher on the performance of students in a classroom.	account for a 24-hour prediction of future power consumption, sun irradiation, temperature, and wind speed.	Static TEP, multi-area economic dispatch problem.	The results confirm that the suggested tweak significantly improves the algorithm's performance.	Several other optimization algorithms, such as CSA, ABC, and GWO, have been proven to outperform TLBO in terms of performance.	-Garver's 6 bus -46 bus Southern Brazilian System -IEEE 6 -bus -IEEE 89 -bus

2.9 Hybrid optimization techniques in TEP

Several meta-heuristic approaches and hybrid algorithms have been developed to tackle the TNEP problem while minimizing computational challenges [10, 42]. The main purpose of hybridizing several algorithms is to exploit the advantages of each method when they are combined to achieve a particular aim that cannot be achieved by a single algorithm alone. An example of addressing the issue of slow convergence in GA and the tendency of GA to become trapped in local optima in high-dimensional spaces, as well as the low rate of convergence in the iterative process of PSO, is the combination of GA and PSO [6]. A new modeling framework and solution method that combines SP and RO to address numerous uncertainties in coordinated mid and long-term power system planning is suggested in [23] . The problem is presented as a multi-year generation and transmission planning problem from the viewpoint of an independent system operator (ISO) with the aim of reducing expansion and operational costs while considering both binary and continuous uncertainties, such as system component contingency and load/generation fluctuation [106]. N-1 contingencies are accounted for in RO by applying the revised contingency criteria. Load/generation uncertainty is addressed in SP integrated with RO by utilizing operational scenarios derived from historical data with spatiotemporal correlations [250]. Table 2.6 explores the existing Hybrid Optimization algorithm in TEP, which encompasses the combining of two or more algorithms, such as mathematical, heuristic, and metaheuristic algorithms. Furthermore, it elucidates the rationale of hybridization, as seen below.

Table 2. 6Hybrid optimization algorithm characteristics in TEP

Hybrid Algorithm and year	controls	hybridization	Applications	Improvements	Future work	models

SP& RO [146, 147, 250, 251]. (2017)	Transmission system operator	To improve the uncertainty	Multi-year TNEP Problem	Reduce both expansion and operational cost	Incorporate uncertainty sets like ellipsoidal sets to efficiently model correlation.	IEEE 118-bus
GA & Fuzzy Logic [252, 253]. (2012)	Adress transmission lines	Adapts to the non-linear multi-objective optimization issue	Multi-objective, multi-period TEP, real-life network	Explores new deregulated environment requirements, prioritizes stakeholders, uses a cost-benefit approach, includes value-based reliability assessment, and considers transmission line and PST combinations for a secure solution.	is to integrate this hybrid into large networks and long-term planning.	-IEEE 30-bus -IEEE 24-bus -IEEE 6 -bus
RGA and IPM [254]. (2013)	Concurrent transmission network expansion and reactive power planning (TEPRPP) solution.	Capability and practicality of the suggested approach using the AC model for TEPRPP in real-world situations.	A multi-objective optimization problem using AC model.	Reduce active and reactive power generating costs and VAR investments.	To enhance the suggested approach, consider adding new indices to identify weak busses and install reactive sources.	-EEE 24-bus -46-bus South Brazilian -Southeast Network of Iran (SNI)
GA & LP [6, 207, 255]. (2011)	Uncertainties including demand, oil pricing, environmental difficulties, precipitation, renewable generation, and production failures are addressed.	demonstrates a swift convergence on the test issues when compared to the exclusive usage of GA	Multi-year TEP under deregulated market	The flexible structure demonstrates a swift convergence on the test issues.	Offers an equitable and effective TNEP solution within a highly competitive market.	-Garver 6-bus -IEEE 24-bus -South Brazilian test
NSGA II and Fuzzy decision-making [256-258]. (2011)	Considers minimizing investment, load-shedding, and congestion	To find the Pareto optimum solutions for TEP goals and the ultimate	multi-objective transmission planning, deregulated	Simultaneous minimization.	Additional MOTEP advancements, such as short-circuit analysis, can be used to optimum systems to identify stability difficulties.	-43 Node Reduced Luzon Grid -IEEE 24 bus -Iranian 400kV

	costs simultaneously.	optimal solution.			Techniques that include uncertainty must be considered.	transmission grid.
NSGA II and Probabilistic optimal power flow (POPF) [259]. (2014)	Investment cost and reliability of the system	Determine best Pareto solutions for power system uncertainty.	Multi-stage, multi objectives	An NSGA II-based POPF established trade-offs between reliability, private investment absorption, and installation costs for several systems.	To minimize simulation time for large-scale networks with unknown variables, consider parallel processing, fewer contingencies, and clever GA initialization.	-IEEE 24-bus RTS
NSGA II and point estimation method [260]. (2016)	considering wind power generation uncertainty.	To solve the multi-objective TNEP expected value model, the NSGA II algorithm is used, and an upgraded PEM evaluates objective functions	Multi objectives TNEP	High precision in handling linked wind power generating uncertainty. To speed up calculations.	The proposed improved PEM will evaluate objective functions and consider wind power generation uncertainty.	-IEEE 24-bus
NSGA II, PEM & PDIP [182]. (2016)	Controls the total production cost.	Determine the optimal Pareto front, objective function evaluation.	Multi objectives TNEP, stochastic nature, The test system and real-life system yield better social welfare than the design with separate networks.	Validation of the proposed model and approach utilizes a modified IEEE 24-bus electrical network, a 15-node natural gas system, and a real-world system in Hainan province.	Using fuzzy decision-making, decision-makers may choose the ideal answer from the optimal Pareto front depending on their preferences. Also the consideration of different uncertainty.	-IEEE 24 -bus + 15 nodes NG - Real-world system in Hainan province
Fuzzy logic and branch & bound and PSO [261]. (2019)	Address different uncertainties, predict load	To handle uncertainties, compute the number of new lines per corridor, and verify planning scheme security.	Multistage robust TNEP, dynamic model	Reduces planning model complexity and boosts computational performance.	A triangular fuzzy number is used to represent the projected load, however the comparable planning model conversion procedure is not limited by membership function type. TNEP can use an arbitrary	-modified IEEE RTS 24-bus system -231-bus system

					fuzzy membership function that aligns with the fuzzy characteristic of the unsure factor.	
MILP-Exact Based Heuristic (EBH) [25]. (2022)	Address investments	Improve metaheuristic and MILP solution quality significantly.	Single and multi-stage TEP model	Reduce investment costs using an evolutionary computation solution for single- and multi-stage TEPs.	Significant findings indicate that comparing and improving contemporary heuristic algorithms for complete TEP models and exact-based solutions for approximated TEP models can enhance reliability.	-RTS 24 bus -IEEE 118 -bus
Probabilistic Neural Networks and Harmony Search [238]. (2012)	Consider the uncertain role of loads	Minimize the expenses associated with expansion.	Large-scale system	Economical and effective, reduces active losses, reduces expansion cost	It has only been tested in a small network	-Gaver's 6-bus
MCS MSFLA-MPSO-MTLBO [8]. (2020	Controls Intermittent nature.	capable of achieving superior results compared to other algorithms.	TEP with RE integration.	Reduces cost. Good lower bound	There is no evidence of its implementation on a large-scale network.	-IEEE RTS 24-bus test
PSO and GA [262, 263]. (2016)	Global optimum cost, reduces investment cost	The PSO algorithm exhibits immature convergence, whereas the GA algorithm has a poor convergence speed.	Dynamic TEP problem.	It provides efficient solutions in a shorter amount of time compared to PSO.	Additional approaches can be incorporated into the network to minimize uncertainty.	-Garver's 6 -bus -IEEE 14 -bus - IEEE 24-bus
GA-TS-ANN [264]. (2002)	Minimize the transmission investment cost	superiority in solving large-scale problems with exponentially growing search spaces.	Small and large network systems	Based on final solution quality and computational speed, the approach was suitable for complex optimization problems.	Hybridization can turn out complex.	-IEEE 24 bus -6- bus -Saudi Arabian network

GA - TS [265]. (2017)	Address the outage cost and investment cost.	GTHA reduces calculation time by one-third compared to earlier methods and converges quicker than GA and Tabu algorithms.	Applied in the generation-transmission network.	Potential benefits outweigh the drawbacks of separate planning, such as poor consideration of the power grid effect during generation planning or insufficient transmission system design without generation information.	Hybridization may be complicated.	-50 bus offshore
MINLP - Benders decomposition [266, 267]. (2015)	evaluate system reliability	Using Benders decomposition, the MINLP formulation was transformed into a MILP master problem and an LP sub-problem.	Dynamic expansion planning	To improve calculation speed and eliminate nonlinear limitations	incorporating uncertainty and the impact of renewable energy sources on the expansion problem.	-IEEE 30 -bus -6 -bus

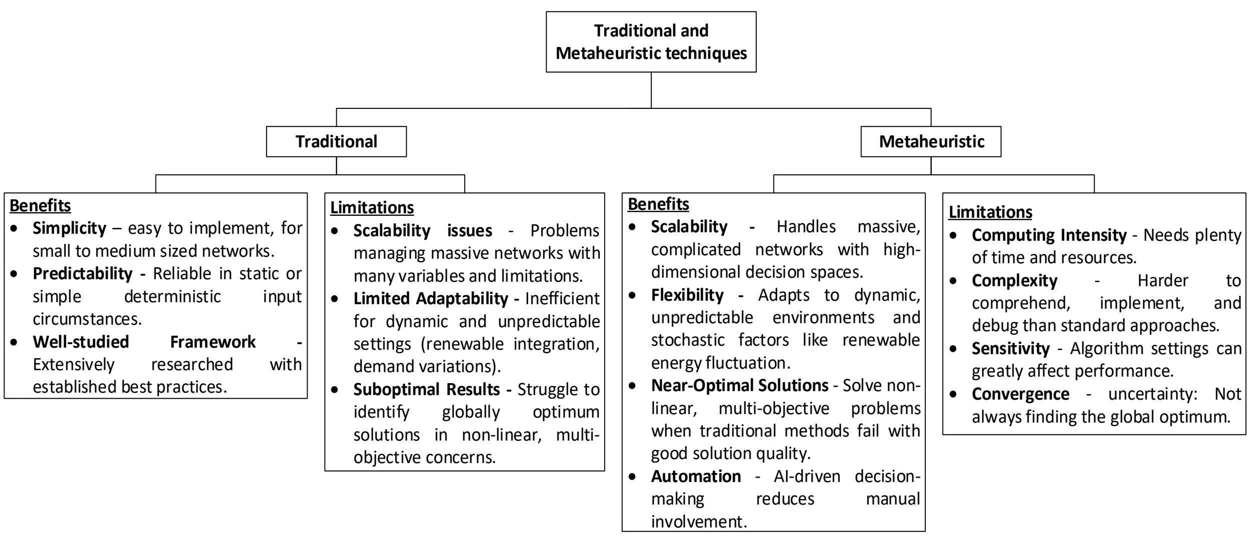


Figure 2. 7 Traditional and Metaheuristic techniques

Figure 2.7 differentiates between traditional methods and metaheuristic techniques, illustrating the advantages and disadvantages gathered from various sources [268-270].

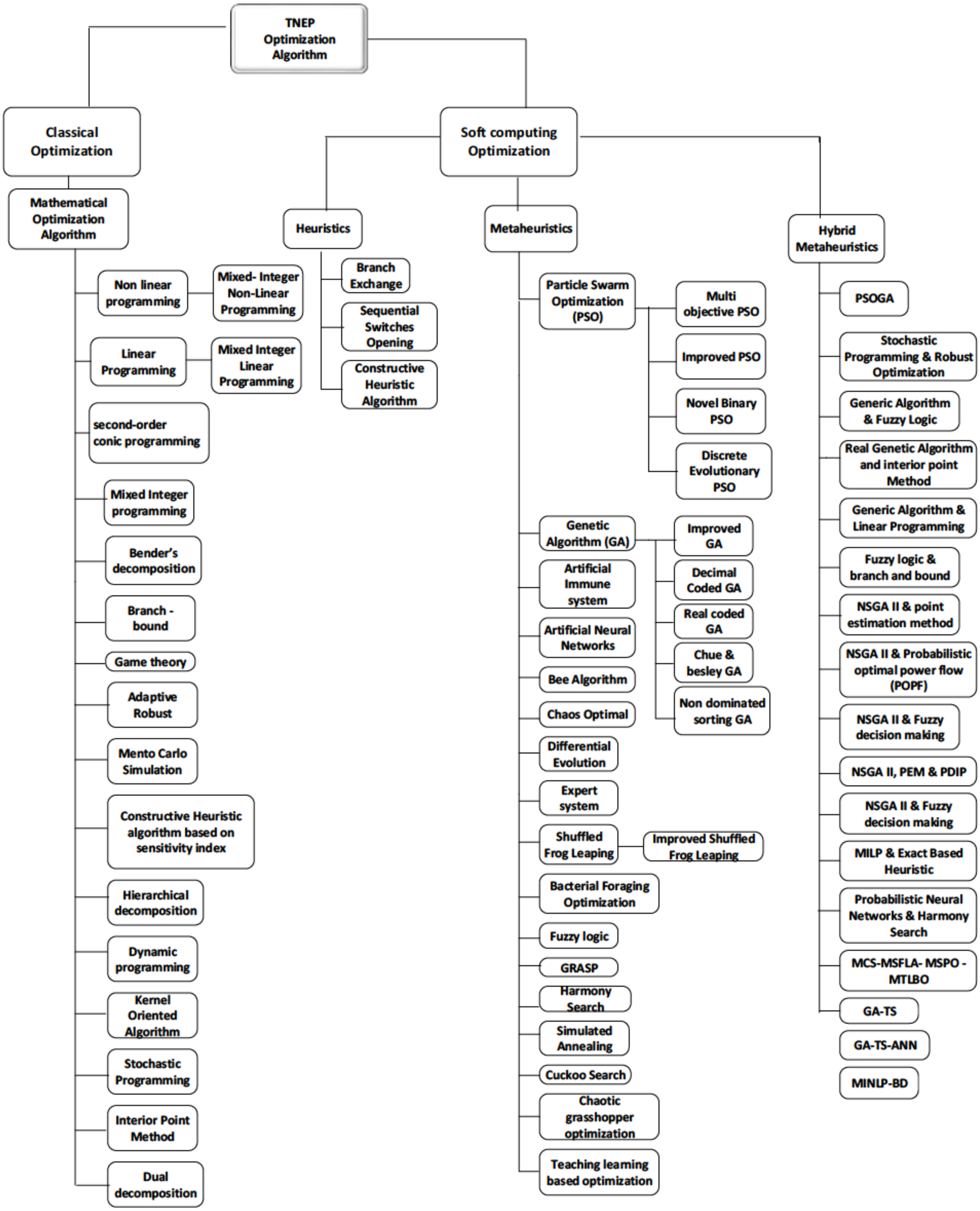


Figure 2.8 Optimization techniques for TEP Problems

In summary, Conventional TNEP methodologies depend on deterministic or heuristic strategies to enhance network development according to established criteria such as cost reduction and demand fulfillment. As demonstrated in Table 2.7, it comprises techniques such as LP, MIP, and Metaheuristics.

Advanced algorithms utilize state-of-the-art computational methods, frequently including artificial intelligence (AI), metaheuristics, and probabilistic modeling to address intricate and evolving TNEP challenges [6]. This encompasses approaches including GA, PSO, ML, SO through MCS or RO, and Hybrid methods. Conventional TNEP methods continue to be pertinent for uncomplicated, deterministic situations or as foundational solutions [6]. Advanced algorithms are essential for contemporary power systems confronting issues like renewable energy integration, dynamic loads, and escalating system complexity [271]. Nonetheless, their computational and implementation constraints need meticulous evaluation of trade-offs. A hybrid methodology that integrates conventional techniques with sophisticated algorithms typically yields the optimal equilibrium of efficiency and resilience. Figure 2.8 illustrates the comprehensive TNEP optimization techniques, which are categorized into classical and soft computing methods. This figure was created based on the literature review and Tables 2.4 to 2.6, showcasing the algorithm's enhancements from classical to heuristic to metaheuristic to hybrid approaches, as depicted in Figure 2.8.

Table 2. 7Comparison between traditional and metaheuristic techniques

Element	Traditional	Metaheuristic
Problem Scale	Small to medium networks	Large and complex networks
Solution Quality	Deterministic, possibly suboptimal	Excellent, near-optimal solutions
Flexibility	Static and deterministic environments	Uncertain, stochastic, and dynamic circumstances
Computational Demand	Moderate to low	High (depending on the algorithm)
Easy Implementation	Simple and straightforward	Complex, expert-needed

Key Application	Traditional power grids	Integration of renewable energy, smart grids

Based on the literature review and Tables 2.4 to 2.6, showcasing the algorithm's enhancements from classical to heuristic to metaheuristic to hybrid approaches, as depicted in Figure 2.8. Table 2.7 further analyzes the distinction between traditional and metaheuristic approaches as discussed in the literature.

2.10 Optimization and constraints formulas in TEP

The TEP problem primarily focuses on two key objectives: IC performance and reliability. The operating and maintenance (O&M) cost is typically disregarded in TEP problems [272]. The equations (1) and (2) for the Objective functions to minimize the investment cost of new installation, which in this case is generating units and transmission lines, and for a generating unit, it will be renewable energies such as solar and wind. and can be utilized for the previously mentioned ideal techniques. The equations provided are applicable to Static TEP. However, they can also be utilized for Dynamic TEP, as it encompasses numerous years and includes the element of time.

$$\text{Min.OF}_g = \sum_{i=1}^{Ncg} \alpha_i \text{ICG}_i \text{P}_{\max_i} \tag{2.1}$$

$P_{\max_i}$ is the maximum capacity of the candidate generator. α_i is the number of candidates generating units (0-1). Ncg is the number of candidates generating units. ICG_i is the investment cost of the candidate generating unit.

$$\text{Min.OF}_{Tl} = \sum_{j=1}^{N_{line}} \beta_j \times \text{ICL}_j \times \text{Tl}_j \tag{2.2}$$

Whereby, β_j is the status of the candidate transmission line $(0-1)$. N_{line} is the number of candidate transmission lines. ICL_i is the investment cost of the candidate transmission line unit. Tl_i is the length of the transmission line.

The expression used to calculate the IC of newly installed lines is as follows:

$$\text{Minimize(IC)}: f_1(x) = \sum_{ij}(c_{ij} \times n_{ij}) \tag{2.3}$$

Where $f_1(x)$ is the total investment cost (IC), $c_{i.j}$ is the IC associated with adding a new line between busses $i \& j$ and $n_{i.j}$ is the number of added lines between buses $i \& j$

$$T.Min.OF = \sum_{i=1}^{Ncg} \alpha_i ICG_i P_{max_i} + \sum_{j=1}^{N_{line}} \beta_j \times ICL_j \times Tl_j \tag{2.4}$$

Equation (2.4) is the total Objective functions to minimize the investment cost of new installation taken from equations (2.1) and (2.2)

Power flow calculations and constraints are shown from equation (2.5) to (2.10).

$$P_{ji} = \frac{\delta_j - \delta_i}{X_{ji}} \tag{2.5}$$

Whereby P_{ji} is the power flow between buses i and j, δ_j and δ_i are the voltage angle of the bus i and j, X_{ji} is the reactance between bus i and j.

Below are the constraints of Power line and voltage as shown in (2.6) and (2.7)

$$0 < P_{Line,l} < P_{max,l} \qquad \forall l \in N_{line} \tag{2.6}$$

$$V_t^{min} \le V_t \le V_t^{max} \qquad \forall t \in N_{bus} \tag{2.7}$$

The maximum current limits of lines are represented by (2.8)

$$-I_t^{max} \le I_t \le I_t^{max} \tag{2.8}$$

For solving the TEP problem, the following constraints should be regarded:

$$(n_{i.j}^0 + n_{i.j})P_{i.j}^{max} \ge |P_{i.j}| \tag{2.9}$$

$$0 \le n_{i.j} \le n_{i.j}^{max} \tag{2.10}$$

$n_{i.j}^0$ is the number of network lines connecting bus i and j. $P_{i.j}^{max}$ is the maximum power flow between bus i and j. P_{ij} is the power flow between bus i and j. $n_{i.j}^{max}$ indicates the maximum number of lines that can be installed between the buses [208, 272, 273].The equations provided above are essential for utilizing metaheuristic algorithms to determine the objective function of an optimization solution.

2.11 Summary

The TNEP problem is fundamentally a large-scale, nonlinear, and non-convex issue that has garnered interest from both academic and industrial sectors. Identifying an optimal solution to the TNEP problem over a planning horizon necessitates the incorporation of various extensive parameters, including candidate circuits, the network topology of the base year, investment limits, and forecasts for electricity demand and generation. These factors augment the complexity of the TNEP problem. This study provides a thorough review of TEP, including all essential variables that must be considered in the development of transmission line extension, as seen in Figure 3.4. The existing electrical transmission network encounters numerous problems as it adapts to the requirements of contemporary power generating and consumption trends. The obstacles can be categorized into technical, economic, regulatory, and environmental issues, including aging infrastructure that results in frequent outages and diminished reliability. The incorporation of renewable energy, frequently situated in remote locations, necessitates enhancing transmission networks for long-distance power distribution. Congestion in transmission lines as demand increases and energy production escalates. Resilience to natural disasters, including extreme weather events such as storms, heat waves, and floods, poses dangers to transmission networks.

Table 2.4 breaks down the literature on traditional methods employed in TEP, including their control methods, applicable contexts, utilized network models, initial implementation year in TEP, contributions, and limitations. Most traditional approaches use deterministic inputs and struggle to handle uncertainty as the system becomes larger. The integration of renewable energy sources, changing demand patterns, and dynamic market mechanisms make modern power systems uncertain. Large, complex systems may make traditional methods computationally intractable. Traditional approaches are less adaptive to modern power networks, especially as renewable energy and distributed generation grow. SP, RO, and machine learning-based methodologies are being added to the current TEP to address these issues. Table 2.5 breaks down all the metaheuristics employed in TEP, similarly to Table 2.4, adding the inspiration behind each algorithm. According to the literature, metaheuristic approaches have demonstrated significant efficacy in addressing TEP challenges by providing flexibility, global optimization potential, and adaptability to diverse uncertainties in contemporary power systems. Though flexible, metaheuristic approaches demand a lot of computational commands, especially for large-scale TEP problems. Some of these strategies require domain expertise to tune parameters like mutation rate and crossover rate in GA.

When the problem is complex or non-convex, metaheuristic approaches may converge prematurely.

Table 2.6 breaks down all existing hybrid algorithms employed in TEP, analogous to Tables 2.5 and 2.4, but includes improvements it made, future developments or gaps, and the rationale for hybridizing the algorithm. It integrates diverse optimization strategies to capitalize on their advantages and mitigate the shortcomings of singular approaches. TEP is an essential function in power systems aimed at strategically developing the transmission network for the future in a cost-efficient, reliable, and secure manner, while addressing rising needs, renewable energy incorporation, and uncertainties. The primary benefit of hybrid algorithms in TEP is their ability to handle large-scale systems by combining global search heuristics with local refining. Robustness in uncertainties and nonlinearities than single methods, Enhanced Solution Quality using complementary methods like global and local optimization enhances convergence and solution correctness. Flexibility allows environmental, economic, and technical restrictions to be integrated. Hybrids can find good answers faster than standard methods by combining algorithm strengths. In light of the fact that this study places an emphasis on the incorporation of RE, the author also advises the use of techniques such as ARO and MCS that successfully deal with the uncertainty that is associated with RE. This study additionally presents the optimization formulas and constraints typically employed in TEP to minimize or optimize specific objectives, including losses, costs, reliability, power congestion, load curtailment, and power outages. Moreover, it provides an overview of the current renewable energy landscape, and the obstacles associated with integrating renewable energy into transmission lines, while simultaneously highlighting the significance of this integration and the techniques available for its implementation.

Assessing the efficacy of TEP approaches is crucial to ensure they fulfill technical, economic, and environmental goals, including the cost-effectiveness of investments, operations, and maintenance throughout the planning period. the network's reliability and resilience, particularly its operation under N-1 contingency as delineated in the literature. Adaptability and flexibility to accommodate demand increase and renewable energy integration. mitigation of greenhouse gas emissions. Furthermore, technical performance includes loss minimization, voltage stability, and transfer capability. By evaluating these measures against historical data, simulations, or comparative analyses of different methodologies, one can assess the efficacy of present TEP methods and pinpoint areas for enhancement.

CHAPTER 3 SOUTH AFRICAN POWER GRID WITH RE INTEGRATION

South Africa's electricity grid is a sophisticated network that is predominantly dependent on coal-fired power plants. The government is striving to move to a more sustainable energy balance by including renewable energy sources, such as solar, wind, and hydropower. This chapter analyzes the configuration of South Africa's power system, the obstacles and prospects of renewable energy integration, and the policies facilitating this change. South Africa has considerable renewable energy potential, especially solar and wind energy. The nation has instituted the Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) to promote private-sector participation in renewable energy initiatives. Consequently, renewable energy capacity has expanded considerably during the last ten years. This research utilizes South Africa's existing RE as a case study to demonstrate the integration of RE into the transmission network without compromising long-term grid stability.

3.1 Existing power system

The power grid is a complex network often represented as a combination of ring and radial network topology [274]. Interconnected networks are highly vulnerable to catastrophic failures for this reason: As the interconnections between components strengthen, the behavior of system components can have a substantial impact on or impair the functioning or operation of other components [275]. The rising amount of RES in today's power system, together with their fluctuating nature, significantly add to the grid's expanding complexity [12]. Electric power utilities strive to meet both system loads and customer demands by minimizing operational costs while maintaining acceptable quality and uninterrupted energy supply [276]. The development of the electrical sector has witnessed a shift from centralized power generation to decentralized electricity generation. Subsequently, this transition has led to compromises in protection philosophies [277]. Therefore, it is imperative to ensure that transmission lines are adequately protected. In contemporary times, there has been a notable shift in the manner in which energy is produced, with a majority of individuals now relying on the grid [46]. The grid refers to an extensive and interconnected network encompassing expansive regions, wherein power generation and consumption are facilitated [53, 278]. In recent years, the electricity system has transitioned into a new era of technology. The growing dedication to wind farms (WFs) and energy storage systems (ESSs), along with the need for demand-side flexibility, necessitates significant alterations to the current power system architecture and procedures [279]. Storage owners and demand-responsive (DR) actors play a substantial role in the present power system since they are at the forefront of a paradigm change from passive grid consumers to active prosumers.[280, 281]. The major components of the existing power system are presented in the following sub-section

3.1.1 Power grid equipment

1. Generators

The evaluation of generator systems in power flow analysis often includes the assessment of both active power and reactive power. Active power dispatch is often predetermined according to the economic dispatch via the P-V bus or the generator bus. The required reactive power must be within the capacity of the generator to ensure appropriate regulation of generator voltage, avoiding exceeding the maximum voltage level. This research employs generators to illustrate the available power in the network and the types of resources utilized. Three-phase synchronous generators provide substantial amounts of power. Generators are regarded as sources of both reactive power (MVAr) and real power (MW) [282]. The fundamental concept of a controlled synchronous machine designed for load flow analysis is presented in Figure 3.1.

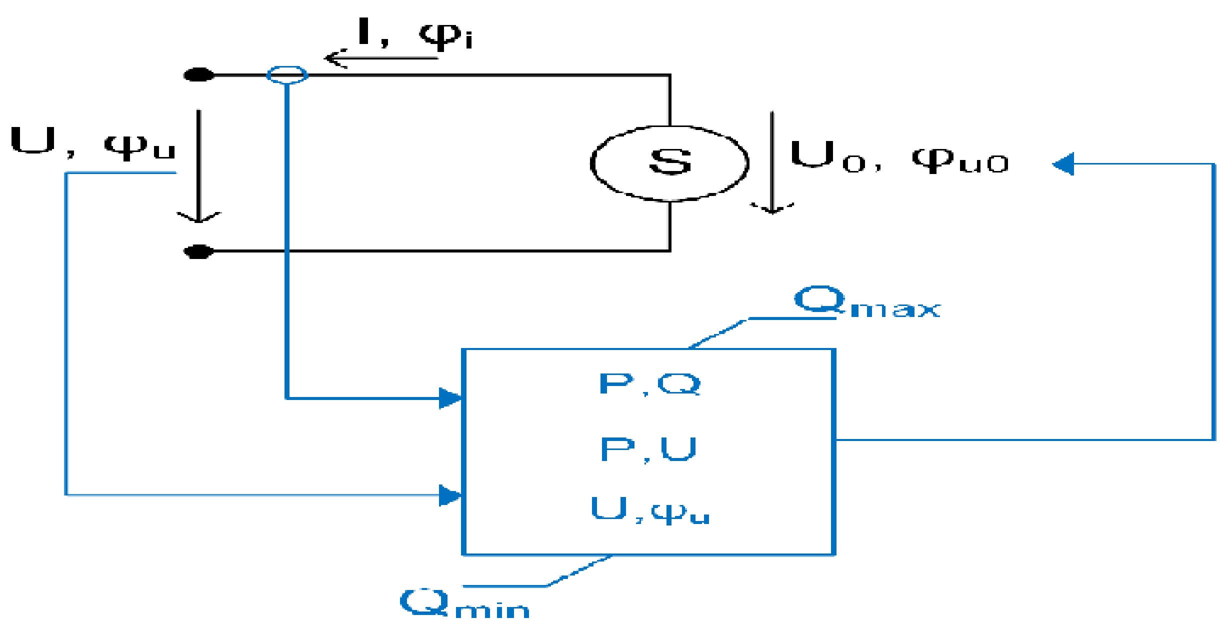


Figure 3. 1 Synchronous generator control

DigSILENT PowerFactory provides six local controllers for synchronous generators: Constant V/U, voltage Q-droop, Constant Cosphi, Constant Q, Q(P)-Characteristics, and Voltage iq-Droop. This project employs Constant V and Constant Q, with Constant V being utilized for big synchronous generators in major power plants operating in voltage control mode ("PV" mode), while Constant Q is typically applied to smaller synchronous generators (PQ mode). This control method allows for the specification of the generator's active and reactive power. Furthermore, there's a reference machine that functions as a slack bus for the preservation of reserve power.

The actual active power of each generator is determined by (3.1):

$$P = P_0 + K_{pf}.\Delta F \tag{3.1}$$

Whereby P is the actual power in MW, P_0 is the active power set point in MW, K_{pf} is the primary frequency bias in MW/Hz and ΔF is the frequency deviation in Hz.

2. Power transformer

Electricity transformers are constructed at power stations to raise the voltage of the electricity to a level appropriate for long-distance transmission. Typically, these transformers increase the voltage from 11kV to 22 kV to 220 kV, 275 kV, 400 kV, or 765 kV and then transmit the electricity to Eskom's national grid. Finally, this voltage is reduced to a level that is suitable for use by the consumer. Large factories may operate at 11 kV, while businesses and houses may be supplied with 380/220 volts [283]. The transformer load must not surpass 100% of its thermal limit under any operating conditions. Figure 3.2 illustrates the positive sequence (per-unit) equivalent circuit of the transformer. The leakage reactance and winding resistances are incorporated on both the high- and low-voltage sides, while the magnetizing branch represents core losses.

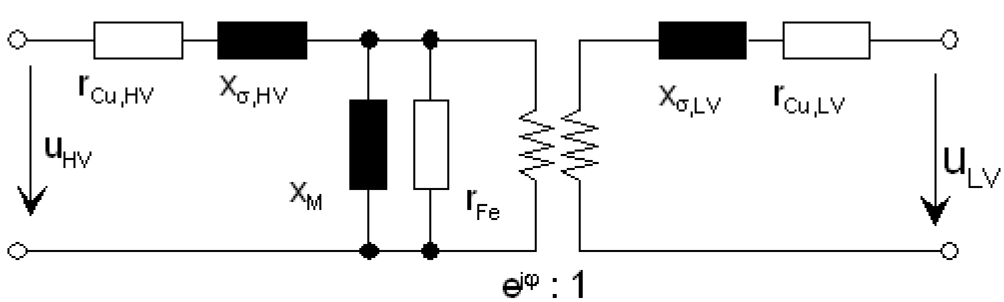


Figure 3. 2 Equivalent circuit of the two-winding transformer

The specified impedances are provided by (3.2):

$$Z_r, HV = \frac{U_r, HV^2}{S_r}\Omega \tag{3.2}$$

The specified currents are provided by (3.3):

$$I_r = \frac{S_r}{\sqrt{3}.U_r} kA \tag{3.3}$$

Following the two-port network theory, the L, M, and H parameters can be defined as shown in (3.4) to (3.6), whereby t_k is the Off-nominal turns ratio of an in-phase transformer

$$M = t_k Y_k \tag{3.4}$$

$$LV = t_k(t_k - 1)Y_k \tag{3.5}$$

$$HV = (1 - t_k)Y_k \tag{3.6}$$

Consequently, the equations for real and reactive power flow in the transformer with a real turns ratio t_k are derived as in (3.7) and (3.8):

$$P_k^{ij} = (t_k V_i)^2 G_k - t_k V_i V_j (G_k \cos\theta_k + B_k \sin\theta_k) \tag{3.7}$$

$$Q_k^{ij} = -(t_k V_i)^2 (B_k + B_{k0}) + t_k V_i V_j (B_k \cos\theta_k - G_k \sin\theta_k) \tag{3.8}$$

If the turns ratio of a transformer matches the ratio of the nominal rated voltages of its corresponding network sections, then t_k = 1.

3. Transmission lines

Power transmission lines serve as the crucial connections between generating stations and distribution networks, constituting a vital component of the Electrical Power System.

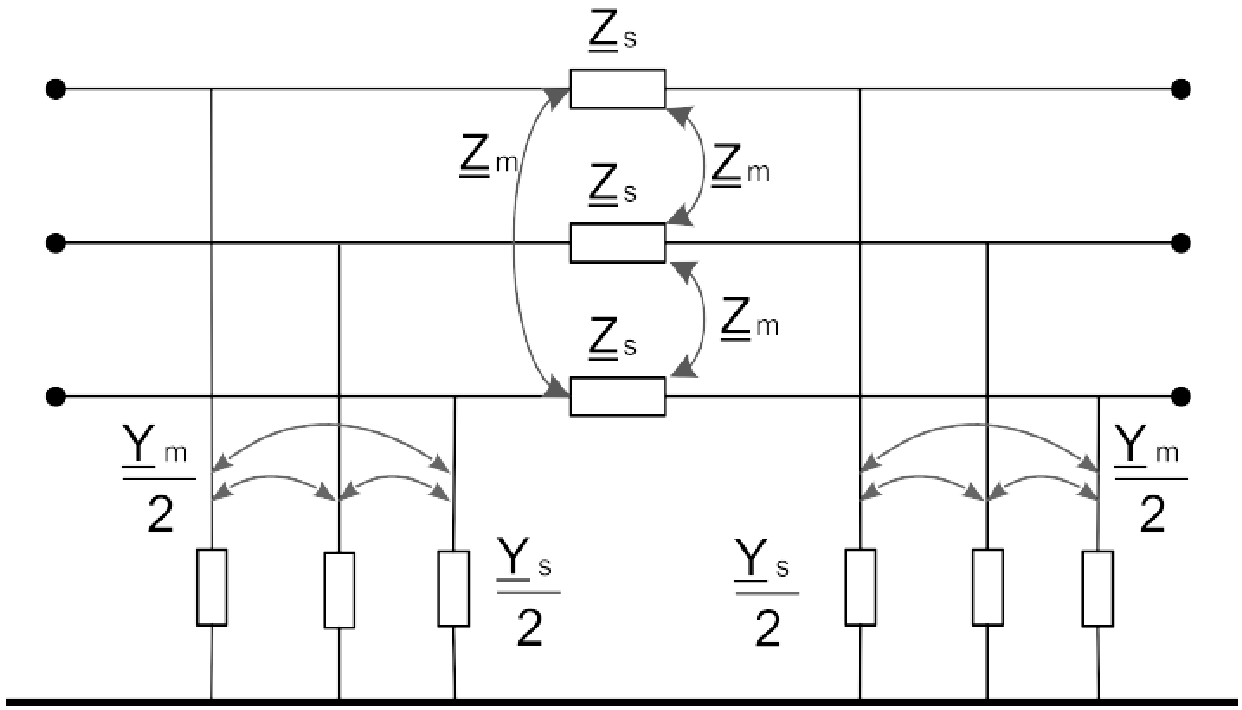


Figure 3. 3 Equivalent circuit of the three-phase transmission line

The assessment of line losses, voltage drop, and efficiency constitutes the primary considerations in the design and operation of electricity transmission lines. The transmission network is primarily characterized by the Y-Bus (Admittance Matrix), which consists of various transmission system elements. The impedance (Z) is the sum of the resistance (R) and reactance (X), whereas the admittance (Y) is the sum of susceptance (B) and conductance (G) [284].

Admittance, being the mathematical inverse of impedance, is expressed in equation (3.11).

$$Z = R + jX \tag{3.9}$$

$$Y = G + jB \tag{3.10}$$

$$Y = \frac{1}{Z} = \frac{1}{R + jX} = \left(\frac{R}{R^2 + X^2}\right) + j\left(\frac{-X}{R^2 + X^2}\right) \tag{3.11}$$

Whereby

$$G = \left(\frac{R}{R^2 + X^2}\right) \text{ and } B = \left(\frac{-X}{R^2 + X^2}\right) \tag{3.12}$$

$$R = rline.(1+\alpha.(temp-20) \tag{3.13}$$

Whereby the coefficient of temperature α depends on the line type or conductor material. The subsequent formula in (3.14) is employed to ascertain the loading of the line.

$$loading = \max\left(\frac{|I_{bus_i}|}{I_{nom(bus_i)}}, \frac{|I_{bus_j}|}{I_{nom(bus_j)}}\right).100[\%] \tag{3.14}$$

The cumulative losses of the lines are calculated as shown in (3.15) and (3.16)

$$P_{loss} = P_{bus_i} + P_{bus_j} - P_{lineloads} \tag{3.15}$$

$$Q_{loss} = Q_{bus_i} + Q_{bus_j} - Q_{lineloads} \tag{3.16}$$

4. Load model

The importance of load modeling in power system analysis cannot be overstated, as the primary purpose of power generation is to meet the load demands. Load modeling has garnered increased attention over the past decade owing to the integration of renewable energy, demand-side management, and smart metering technologies. The difficulties and unpredictability in modeling power system loads arise from the multitude of varied load components, weather-dependent and time-varying compositions, intricate load data, and inadequate measurements. In power transmission network design and steady-state power flow analysis, MVA is typically employed as the standard unit for system load. The basic load model resembles that of shunt devices, with the exception that the load is represented as a sink of constant active and reactive power, independent of variations in bus voltage magnitude, as illustrated in (3.17)

$$S_d = P_d + jQ_d \tag{3.17}$$

where P_d and Q_d represent the active and reactive components of the load, respectively, and are both constants.

In power systems, the term "shunts" refers to reactive power compensation devices connected at buses, specifically indicating "phase to ground." By alternating the shunt devices, a broader spectrum of control over the bus voltage magnitude can be attained.

The modeling of shunts parallels the modeling of loads. The primary difference in modeling is that the reactive power a shunt device can either supply or absorb is contingent upon voltage. In data files, shunt data are often represented as reactive power at the nominal voltage. The real reactive power that a shunt device can either supply or absorb

$$S_d = jQ_d V_i^2 \tag{3.18}$$

5. Busbars

Bus bars are conductors that gather electricity from incoming feeders and send it to outgoing feeders; thus, they serve as an electrical junction for all incoming and outgoing electrical currents. The bus bars function under specific voltage limitations. Transformers, generators, and line thermal loads must range from 80% to 100%, as indicated in Table 3.1.

Table 3. 1 Network condition for modelling

Network condition	**Voltage limit**
System healthy	0.95 – 1.05 p.u.
Lower voltage range	≥ 0.95 p.u.
Upper voltage range	≤ 1.05p.u.
Thermal loading	80% - 100%

3.1.2 HVAC load flow analysis with the Newton-Raphson method

The Newton-Raphson technique is favored for its efficacy in solving non-linear equations. The fundamental premise of power flow derived from the Newton-Raphson approach is the determination of the voltage magnitude and phase angle (V & δ) at all system buses, along with the reactive and real power (Q & P) through each line.

Table 3. 2 Features of various buses

Bus type	**Specified**	**Not specified**
Slack	$V = 1.0$p.u. & $\delta = 0.0$	
PQ bus	P, Q	δ, V
PV bus	P, V	δ, Q

This approach solves power flow by first assessing the system's data, getting the known and unknown variables in the system, which completely depends on the kind of bus, which are slack bus, PQ bus, which is a load bud, and PV bus, which is a generator bus, as shown in Table 3.2.

The Newton-Raphson method is being used in this study to investigate load flow in a system.

$$S_i = V_i \sum_{j=1}^{n} Y_{ij}^* V_j^* = \sum_{j=1}^{n} | V_i || Y_{ij} | \angle(\delta_i - \delta_j - \theta_{ij}) \tag{3.19}$$

Whereby

$$Y_{ij} = | Y_{ij} | \angle\theta_{ij}, \quad V_i = | V_i | \angle\delta_i \text{ and } V_j = | V_j | \angle\delta_j \tag{3.20}$$

This formula in (3.21) and (3.22) calculates each bus's active and reactive power in a power network.

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos\left(\delta_i - \delta_j - \theta_{ij}\right) \tag{3.21}$$

$$Q = -\sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\delta_i - \delta_j - \theta_{ij}) \tag{3.22}$$

Thermal loading is determined by dividing the load current by the rated current.

$$\text{Thermal.loading} = \frac{I_{load}}{I_{rated}} X100\% \tag{3.23}$$

The load current for each phase is calculated as shown in (3.24)

$$I_1 = \frac{S_{13\phi}^*}{3V_1^*} \tag{3.24}$$

3.1.3 Grid code compliance

When extending a transmission line, it is important to consider the technical criteria specified in the grid codes by the distribution system operator. Therefore, an examination of the current grid codes (Transmission and Distribution) is conducted. Assessing the generating limitations is essential for ensuring the sustainability and security of the system, in accordance with planning and operational standards [105]. It is necessary to consider the technical requirements specified in grid codes by the distribution system operator. Therefore, an examination of the current grid codes

(Transmission and Distribution) is conducted. It is crucial to evaluate the generation constraints to ensure sustainability and assess the system's security in accordance with planning and operational criteria. To alleviate the adverse consequences arising from the incorporation of Office National de l'Électricité et de l'Eau Potable (ONEE), it has established criteria and implemented initiatives to integrate wind power into the electrical system. These factors encompass flickers, harmonics, voltage regulation, and frequency deviation. Flicker is a widely used metric for assessing power quality. This phenomenon arises because Voltage-induced variations lead to fluctuations in the light. Measurement of electrical light intensity [105].

3.2 Power system reliability and security

The reliability of a power system quantifies the grid's or network's capacity to endure disruptions, including unforeseen interruptions like generator failures or sudden demand surges, along with other unpredictable occurrences. Security and system stability must be consistently upheld [285]. The North American Electric Reliability Corporation designated this idea as the operational reliability of power systems. There is an immediate necessity to satisfy the growing demand for power, and each grid must be reliable. The characteristics of a reliable grid network are as follows:

- System busbars must be voltage compliant.
- No transformer, generator, or transmission line overloading.
- Its producing capacity must always surpass the load.
- Stability during short circuits
- Ability to maintain stability after a generator failure

Frequent power outages indicate a vulnerable electric grid. Connected power grids are very secure and dependable, but their complexity means that unforeseen events like insufficient connections, human mistakes, malfunctions, or protective strategy failures can cause a cascade of equipment failure [286].

3.3 Overview of renewable energy

The integration of RESs necessitates a power network that can effectively manage the unpredictable situations that may arise in the system [287]. The utilization of renewable hydrogen is often seen as crucial in facilitating the shift towards a carbon-neutral trajectory. The reason for its designation as an energy vector is attributed to its capacity for spatio-temporal storage and sector coupling [288]. The study of the operational strategies and financial aspects of a power system with significant RE integration is highly regarded by both academic and industrial sectors [289, 290]. Power networks are gradually becoming decarbonized, mostly via the use of RES. They exhibit significant variability and poor controllability, making them difficult to anticipate. RES such as wind and solar include uncertainty. In the power system, the uncertainty of wind speed and solar radiation has a great impact on the planning problems. If wind turbines and PV modules are considered in the energy hub, the impact of their uncertainty should be investigated on the planning results [291, 292]. PV and wind energies are sporadic sources of energy and are not consistently accessible throughout the day, especially at nighttime for solar energy. Ensuring power system stability and sufficient reserve margins is of utmost importance. By 2050, there will still be a need for fossil fuel-powered facilities to address these limitations [293].

The paper in [113] study evaluates the possible effects of RES and DR on the GTEP problem. It is crucial to improve the integration of RES into power networks to ensure long-term energy security and reduce emissions. The optimization process should involve the joint execution of GTEP processes. However, due to the deregulation of the power industry in many countries and the existence of diverse decision factors in the planning systems, these processes have been studied independently by various researchers [294]. The findings in paper [295] demonstrate that including solar power into the expansion planning issue, while accounting for contingencies in both the electrical and gas networks, leads to a reduction in costs.

3.3.1 Drawbacks and benefits of RE in TEP

There are still several unanswered matters pertaining to the widespread implementation of hydrogen, including the cost-effectiveness of production, the most advantageous location for facilities, and the broader impact on power and energy networks [296, 297]. The incorporation of a significant share of RESs is an unavoidable trajectory in future power system planning, mostly driven by conventional energy deficiencies and concerns over environmental pollution. Nevertheless, due to the unpredictable, intermittent, and uncontrolled nature of RESs, TEP will encounter additional obstacles [136]

Table 3. 3Uncertainty in RE

Renewable Energy	Uncertainty

Solar [298].	Local solar irradiance directly impacts solar production, which is often handled by Beta.
Wind [299].	The wind speed directly affects wind generation, frequently represented by the Weibull distribution.
Hydro [300].	Hydropower plant production is influenced by hydrological and hydraulic conditions.

Table 3.3 outlines the factors causing uncertainty in TEP due to the introduction of RE. Whereby Table 3.4 provides a description of the different forms of RE and their respective advantages and limitations. These characteristics make them essential for integration into transmission lines to facilitate power development, sourced from many references [301-309].

Table 3. 4Types of RE, benefits, and drawbacks

Renewable Energy	Benefits	drawbacks
Hydropower	*Maintenance costs are low * Electricity and water flow are simply adjusted. * Environmentally non-polluting. * Use lake water for agriculture. * Dams are built to endure decades. * Once built, a dam generates electricity continuously. * Hydropower is safer than fossil fuels and nuclear.	*Power plants are expensive to build. * Large dams impact Earth's geology. * Floods harm the ecosystem by flooding big areas. * Large dams influence water table levels. * Its availability depends on drought-related power and energy production. Drought may alter this. *Limited reservoirs:

	* Hydropower reservoirs strengthen local economies.	
Solar Energy	*Most easily accessible source. * Lowers non-renewable resource utilization. *Reduces power bill. *Energy independence. *Long-term savings. *Low Maintenance cost.	*High upfront cost. *Low efficiency. *Intermittency. *Sunlight dependent. *Space constraints. *Environmental impact of manufacturing
Biomass	* As a renewable energy source, biomass is easily accessible. *Carbon neutral. *Reduces the overreliance of fossil fuels. *Costs less than fossil fuels. * Manufacturers profit from biomass production. *Less landfill waste.	*Expensive * Requires a lot of space. * Still emits greenhouse gasses. * Inefficient energy use to generate power.
Wind Energy	*Lower operating cost. *Cleanest form of energy. *Free fuel.	*Wind variability *High upfront cost. *Noisy

	*Advances in Technology.	*Dangerous to Some Wildlife
Geothermal	* Environmentally Friendly. * Sustainability *Huge potential. * Rapid Evolution. *Fuel free.	* Location Restricted. * Environmental Side Effects. * Expensive resource to tap into. * Risk of triggering earthquakes. * Sustainability requires management.

3.3.2 Renewable energy into transmission lines

The implementation of distributed generation requires coordination and interaction between transmission and distribution levels. This need is especially important when planning for RE generation [43]. The incorporation of intermittent and variable energy sources into the grid presents novel problems for power system dependability and stability [71].

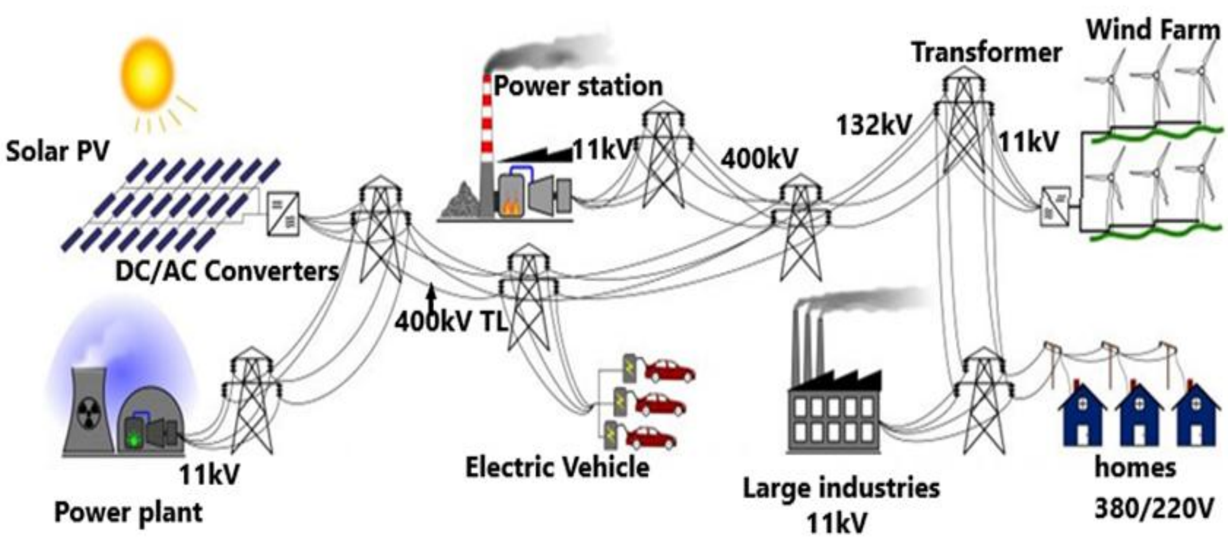


Figure 3. 4Transmission network with RE integration

The power system experiences a significant rise in operational states when there is a high penetration of RE. Hence, it is important to take into account extensive operating scenarios in TEP to accurately assess the influence of RE on power system performance [139]. Incorporating large-scale variable renewable energy sources (VRES), specifically wind and solar, into the transmission system. The primary difficulties under consideration include the accessibility of the grid over vast distances, the ability to adapt and respond to changing conditions, the maintenance of stability and dependability, and the capacity to withstand and recover from disruptions [71, 310].

3.3.3 Types of RE into transmission lines

It is essential to consider the influence of wind farms on TEP, which is a critical component of power system planning [225]. Wind energy has been widely utilized over time to provide environmentally friendly and dependable electricity [311]. Wind energy possesses inherent attributes of stochasticity, intermittent nature, and inherent unpredictability [136]. TEP in competitive power markets, the suggested technique in [312] combines GEP and TEP simultaneously, taking into account wind farm unpredictability. The problem is modeled using a normal probability distribution function (PDF) and MCS to account for uncertainty. For the hydropower study paper [313] a technique was created to calculate the backbone voltage level using economic and technological factors. There were two voltage levels to consider: 275 and 500 kV. Multiple factors were used to select the backbone voltage level, including economic voltage, line-loading limit, N-1 contingency, short circuiting, transient stability, voltage stability, and tiny signal stability. Candidates for backbone voltage must meet all criteria. Simulations were run in base- and high-demand scenarios, taking into account future economic growth fluctuations. The load flow and dynamic analysis were simulated in a DIgSILENT Power Factory. The 2022-built 275 kV backbone failed to meet three criteria: economic voltage, N-1 contingency, and voltage stability. Paper [314] conducted a case study of twelve reservoir hydropower stations and two open-loop pumped hydro stations, including freestanding and cascaded systems in six river basins. The research assesses the extra production and storage needed to replace the hydropower fleet with high VRES penetration, and the consequent cost increases from these expenses. Additionally, the study approximates Hydro Power Plants (HPP) storage capacity and examines how simplified HPP modeling affects system functioning and investment decisions. The findings emphasize the need to reevaluate hydro rule curves for high VRES penetration and the role of HPPs in the energy transition toward carbon neutrality. The incorporation of RES into microgrids is seeing a significant global surge. All classifications of RE are shown in detail in Figure 3.5.

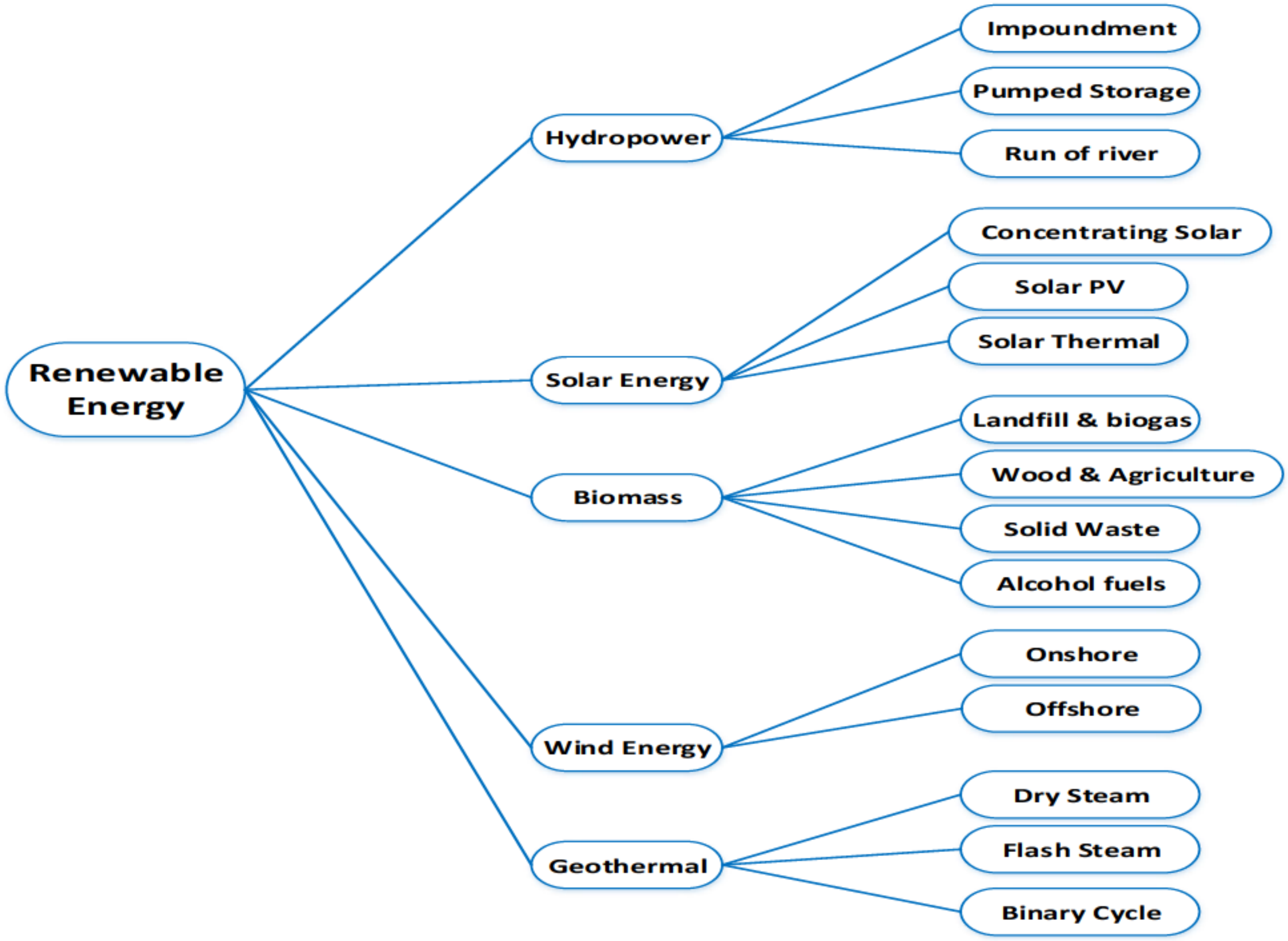


Figure 3. 5Classification of RE

PV is a widely favoured kind of RE since it is environmentally beneficial and financially viable. Therefore, this study aims to explore the usage of PV in transmission lines [315]. The variation in PV power generation can be attributed to the unpredictability and intermittency of light intensity, which is influenced by cloud movement and meteorological conditions [209]. Other publications indicate that a microgrid with a high PV penetration can have a significant impact on the issue of voltage fluctuations in the microgrid [316]. The BESS is a device that may be employed to mitigate fluctuations in PV output and improve the adaptability of the microgrid [209]

1. Cost reduction

The findings in an article [317] indicate that introducing renewable energy sources leads to a decrease in energy expenses, while simultaneously causing an increase in costs within the reserve market due to uncertainty. TEP often relies on long-term projections of the peak load, which is considered the most severe situation. Nevertheless, as renewable energy becomes more prevalent, the peak demand may no longer be the sole factor used to determine investment needs [299]. Unforeseen bottlenecks might arise from a combination of high off-peak load conditions and insufficient renewable output.

2. Climate change mitigation

The growing utilization of RE in TEP actively aids in the reduction of climate change. Nevertheless, the widespread integration of these systems into the electricity grid presents technological obstacles because of the sporadic nature of these resources [105]. To safely utilize these environmentally friendly energy sources for electricity generation, utilities can employ many control methods, including energy storage systems, demand side management, RE curtailment, and transmission switching [318].

3. Power improvement

Enhancing and enlarging the transmission grid is the optimal technological approach to achieve high levels of VRES integration [319]. A robust transmission infrastructure is essential for accessing high-quality, plentiful energy supplies and delivering them to demand centers [320].

3.3.4 Renewable energy potential in SA

The rapidly growing energy demand has resulted in the significant use of fossil fuels and the inevitable escalation of energy costs. Moreover, the environmental impact of fossil fuels necessitated the use of RE to satisfy the increasing energy demand [321]. While coal-based power generation is more convenient for coal-rich South Africa, there is a growing requirement for a larger proportion of large-scale renewable energy (such as solar and wind) due to environmental considerations [322].The vast array of renewable energy sources holds promise for a transformative power industry that minimizes environmental impact [323]. Renewable energy technologies are becoming more widely accepted as alternative energy sources to fossil fuels in several countries [324]. Utilizing multi objectives optimization approaches to assess the size, placement, and maintenance of distributed energy resources is crucial to reducing system costs and mitigating power shortages during contingency situations [325]. In order to decrease greenhouse gases and effectively handle load needs, a utility company must aim to achieve a complete reliance on renewable sources for electrical power generation [326].

Figure 3.6 illustrates the installed capacity in South Africa, with thermal power having the highest installed capacity. Consequently, the majority of our power plants utilize coal as the primary source for energy generation. The figure clearly indicates that oil and diesel are currently not utilized as sources of electricity in South Africa. Once again, there has been a rise in the potential of renewable energy sources, such as solar and wind power. This research proposes that the utilization of RE is necessary to enhance power accessibility in the transmission line. The data utilized in Figure 3.6 was gathered from many sources [31, 327, 328].

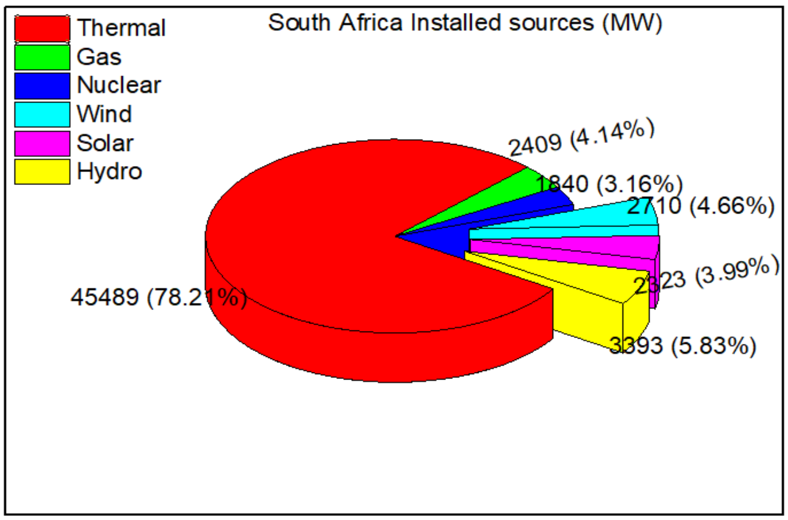


Figure 3. 6SA installed capacity

South Africa is revamping its Integrated Resource Plan (IRP) to solve persistent power difficulties through integrated planning techniques that balance supply and demand. The revised IRP, encompassing forecasts through 2050, seeks to integrate new data indicative of enhancements in Eskom's performance and to tackle grid limitations within the transmission network. The government plans to submit this amended proposal to the cabinet for approval. Collaboration between transmission and generation planning is a major aspect of these initiatives. The updated IRP aims to improve coordination by incorporating new data and resolving current grid limitations. Although these activities demonstrate a dedication to enhancing the alignment of transmission and generation planning, the efficacy of these measures will rely on their execution and continuous supervision. Attention on RE must be prioritized without waiting for coal sources to be depleted. Presently, academia and business are placing considerable emphasis on the usage of RE. Several families have installed PV solar panels as a secondary power source, while others have attached geysers to them to directly heat water using solar energy.

1. Solar PV in SA

A renewable energy provider predicts a substantial increase in solar photovoltaic (PV) capacity in South Africa [329]. This growth is expected to continue as more households and companies transition to solar power, gradually replacing traditional energy sources that rely on fossil fuels [330]. Similar to wind generating facilities, the majority of solar farms are situated in the Cape provinces. Nevertheless, a few can be found sporadically in the center and northern regions of the nation, such as in Free State, North West, and Limpopo. These provinces also get abundant sunshine year-round in several regions [331]. Given the increasing complexity of the system, it is crucial to examine the effects of dispersed generators, intermittent renewable sources, and mobile loads across different dynamics [332]. The incorporation of renewable energy sources into microgrids is seeing a significant global surge. PV is a widely favored kind of renewable energy since it is environmentally beneficial and financially viable. Therefore, this study aims to explore the usage of PV in transmission lines [315]. The variation in PV power generation can be attributed to the unpredictability and intermittency of light intensity, which is influenced by cloud movement and meteorological conditions [209]. Other publications indicate that a microgrid with a high PV penetration, can have a significant impact on the issue of voltage fluctuations in the microgrid [316]. The battery energy storage system (BESS) is a device that may be employed to mitigate fluctuations in PV output and improve the adaptability of the microgrid

2. Wind farm in SA

Over time, the pervasiveness of wind assets throughout South Africa has functioned as an indispensable source of power. As enthusiasm increases, it becomes more prevalent [333]. Presently, electricity is frequently generated using wind energy, which is a renewable, non-polluting, and limitless source of power. The implementation of wind energy on a large scale necessitates the use of expansive land areas and sizable, disruptive turbines [334]. Globally deployed wind capacity stands at 651 GW, of which onshore wind accounts for approximately 95% [335-338]. Offshore wind technology is an alternative method of generating sustainable electricity that provides South Africa with a significant opportunity for power security and decarbonization [339]. Although it is projected that onshore wind will maintain its dominance for the next three decades, owing to technological advancements and declining costs [340]. The objective of this study, as seen in Table 3.5, is to incorporate a wind farm into the current network.

Table 3. 5South African wind farms

Name	Installed Capacity (MW)	WTGs	Rating (MW)	OEM	Status	location	Year of commissioning	Type
Amakhala Wind Farm	134,4	56	2,4	Nordex	Fully active	Eastern Cape	2016	Onshore
Chaba Wind Farm	21	7	3	Vestas	Fully Active	Eastern Cape	2015	Onshore
Cookhouse Wind Farm	138,6	66	2,1	Suzlon	Fully Active	Eastern Cape	2014	Onshore
Copperton	107.1	34	3,15	Acciona	under construction	Northern Cape	2021	Onshore
Dassiesklip Wind Farm	27+27,4	9	3,0	Sinovel	Partially active	Western Cape	2014	Onshore
Dorper Wind Farm	100 + 446.4	40	2,5	Nordex	Partially Active	Eastern Cape	2020	Onshore
Excelsior	32	13	2,5	Goldwind	Under construction	Western Cape	2020	Onshore
Garob	144.9	46	3,15	Acciona	Fully active	Northern Cape	2022	Onshore
Gibson Bay Wind Farm	111	37	3	Nordex	Fully active	Eastern Cape	2017	Onshore
Golden Valley	120	48	2,5	Goldwind	Under construction	Eastern cape	2021	Onshore
Gouda Wind Farm	138	46	3	Acciona	Fully active	Western Cape	2015	Onshore
Grassridge Wind Farm	60	20	3	Vestas	Fully active	Eastern Cape	2016	Onshore
Hopefield Wind Farm	66,6	37	1,8	Vestas	Fully active	Western Cape	2013	Onshore
Jeffreys Bay Wind Farm	138	60	2,3	Siemens	Fully active	Eastern Cape	2014	Onshore
Kangnas	140.3	61	2,3	Siemens	Fully active	Northern cape	2020	Onshore
Karusa	147	35	4,2	Vestas	Under construction	Western Cape	2022	Onshore
Khobab Wind Farm	140,3	61	2,3	Siemens	Fully active	Northern Cape	2018	Onshore
Kouga Wind Farm	80	32	2,5	Nordex	Fully active	Eastern Cape	2015	Onshore
Loeriesfontein 2 Wind Farm	140,3	61	2,3	Siemens	Fully active	Northern Cape	2017	Onshore
Longyuan Mulilo De Aar 1 Wind Farm	100,5	67	1,5	United Power	Fully active	Northern Cape	2017	Onshore
Longyuan Mulilo De Aar 2 Wind Farm	144	96	1,5	United Power	Fully active	Northern Cape	2017	Onshore
Metro Wind Farm	27	9	3	Sinovel	Fully active	Eastern Cape	2014	Onshore
Noblesfontein Wind Farm	73,8	41	1,8	Vestas	Fully active	Northern Cape	2014	Onshore
Nojoli Wind Farm	88	44	2	Vestas	Fully active	Eastern Cape	2016	Onshore
Noupoort Wind Farm	80,5	35	2,3	Siemens	Fully active	Northern Cape	2016	Onshore
Nxuba	148.05	47	3,15	Acciona	Fully active	Eastern Cape	2020	Onshore
Oyster Bay	140	41	3,6	Vestas	Under construction	Eastern Cape	2021	Onshore
Perdekraal East	110.4 + 140	48	2,3	Siemens	Partially active	Western Cape	2021	Onshore
Roggeveld	147	47	(40)x3,15 + (7)x3	Acciona	Under construction	Western Cape	2021	Onshore
Soetwater	147	35	4,2	Vestas	Fully active	Northern Cape	2022	Onshore
Tsitsikamma Community Wind Farm	93	31	3	Vestas	Fully active	Eastern Cape	2016	Onshore
Waainek Wind Farm	24	8	3	Vestas	Fully active	Eastern Cape	2016	Onshore
West Coast 1 Wind Farm	94	47	2	Vestas	Fully active	Western Cape	2015	Onshore
Phezukomoya	140	23	6		Under construction	Northern Cape	-	Onshore
Fully Operational (Total)						2710.65MW		
In construction (Total)						1306.9MW		

It is evident from the table that the majority of wind farms are located in the northern, Western Cape, and western capes [333, 341]. The information regarding the potential of wind energy and the operational status of wind farms in South Africa, including their installed capacity and year of commissioning, was gathered from various sources [342]. The Soetwater wind farm has Vestas V136-4.2 MW wind turbines, the biggest on the African continent to date [343]. Table 3.5 displays the existing and currently underway wind farms in South Africa. It is evident from the table that South Africa does not presently have any offshore wind farms. The majority of the wind farms are situated in the Eastern Cape, Northern Cape, and Western Cape regions. The OEM in this table refers to the Original Equipment Manufacturer, whereas the Wind Turbine Generators are abbreviated as WTGs.

3.4 Challenges of integrating RE in TEP

Variability, intermittency, or fluctuation refers to the alteration in generation output caused by changes in meteorological conditions. Forecasting is essential for ensuring the dependability of the grid. The fluctuating nature of renewable energy generation results in an uncorrelated supply with a demand pattern [71]. Lack of predictability, which is the inability to forecast generation output changes in timing and amplitude (seconds, hours, days). Real-time RE generation forecasts diverge, causing output uncertainty and scheduling issues. RE generators' abrupt generation inrush at high-resource-potential locations causes local grid congestion [344, 345]. Availability, diversity, or location limit: The geographic distribution of VRES is uneven, and potential generating locations with high-VRE resources are usually in areas with low energy demand. Offshore and deserts have significant wind and solar resources [346]. RE generators are nonsynchronous; therefore, their substantial penetration can induce rotational inertia loss and damping torque, impairing synchronous power system inertial response. This decreases transient stability, causes voltage instability, quicker frequency excursions in supply-demand imbalances, and complicates problem identification [347].

Wind and solar energy are characterized by their volatility and non-storable nature. Unlike hydroelectricity or biomass, they cannot be easily controlled or stored in reservoirs for future use. The volatile and ephemeral character of the fast-changing and uncertain environment necessitates the implementation of an energy storage system as a buffering mechanism to adapt to it [348]. Transmission networks and VRES are vulnerable to weather conditions, and with the current climate change, there is an increased likelihood of experiencing extreme weather events that are more intense and frequent. Furthermore, VRES sites and extensive transmission networks are susceptible to enduring catastrophic calamities [349]. Offshore wind farms and desert solar plants are far from load centers, demanding long-distance transmission and accelerating transmission line congestion [71]. The approach is to construct new transmission lines or enhance existing ones to support the augmented renewable capacity or utilize Dynamic Line Rating (DLR) to enhance the efficiency of existing transmission lines through real-time monitoring and optimization of power flow [350].

The integration of RE and the expansion of the transmission network can result in substantial expenditures, such as grid modernization, infrastructure enhancements, and balancing services [30]. Comprising the methodology employing comprehensive economic modelling to reconcile the expenses associated with network expansion with the long-term advantages of reduced operational costs and environmental impacts, from the literature, it is observed that integrating RE into TNEP entails a confluence of technological, financial, regulatory, and sociological obstacles. Addressing them necessitates careful planning, cutting-edge technologies, and synchronized policy frameworks to guarantee that the grid stays reliable and economically viable during the transition to a more sustainable energy future.

3.5 Solution TEP with RE challenges

Scenario-based optimization incorporates several renewable generation and demand scenarios to account for unpredictability and uncertainty, utilizing historical weather and demand data to model various operational conditions [351, 352]. Probabilistic and stochastic models depict renewable generation and demand as probabilistic distributions instead of deterministic values. Integrate stochasticity in model parameters to optimize transmission strategies under fluctuating situations [353]. The time-series modeling, which utilizes high-resolution time-series data (e.g., hourly or sub-hourly) for renewable generation and demand, aims to accurately represent real-time variations. They facilitate the identification of short-term grid congestion and the necessity for dynamic adaptability [354].

3.6 Impact of RE on the grid

Abrupt declines in generation, such as those caused by cloudy conditions or little wind, can disrupt the grid, particularly when renewable sources constitute a substantial share of the supply. Energy storage technology, such as batteries and grid interconnections, alleviate these impacts by storing surplus energy and dispersing it as required [355]. The integration of RES might complicate the maintenance of the grid's optimal frequency and voltage, hence increasing the danger of imbalances and potential blackouts, Advanced inverter technology and rapid-response energy storage provide frequency and voltage stabilization, mitigating fluctuations. [71]. The demand for grid flexibility is escalating, necessitating investments in technology that facilitates real-time load balancing and demand response, including smart grids and sophisticated monitoring systems, DERs, microgrids, and demand-response initiatives to facilitate the dynamic regulation of supply and demand, enhancing system resilience [356]. RE integration threatens grid stability due to fluctuation, however storage, grid flexibility, and real-time control can help. The transition can boost efficiency and resilience, making the grid more sustainable and resilient if managed well. The use of RE in TEP yields substantial environmental advantages, especially for carbon mitigation and general sustainability [357]. Hydropower, solar, and wind generate minimal to no greenhouse gas emissions. Including these in TEP minimizes fossil fuel use and carbon emissions. Large-scale renewable integration can dramatically reduce the carbon intensity of the power grid, resulting in annual CO_2 emission reductions proportionate to the extent of deployment [358]. Renewable sources reduce coal and natural gas depletion by using abundant natural resources. This change aligns energy production with natural system regenerative capacities for long-term sustainability [359]. Incorporating renewables into TEP systems is a crucial measure for decarbonizing the energy industry and attaining sustainable development objectives. Despite existing hurdles, advancements in technology, legislation, and system management can alleviate these issues, establishing renewable energy as a fundamental element of a sustainable future.

3.7 RE Integration to TEP cost and benefits

The integration of RE into TEP entails both immediate and long-term consequences. The analysis examines two principal categories, namely Costs: These encompass capital expenditures, operational expenses, and prospective integration obstacles and benefits: These include ecological benefits, sustained operating savings, and improved grid reliability [15, 266]. Capital Expenditures refer to the investments necessary for renewable energy projects, encompassing generating and grid integration, including substations, storage systems, and transmission enhancements [360]. Operating Savings pertain to diminished dependence on fossil fuels and reduced operating expenses resulting from decreased fuel and maintenance requirements [361]. Environmental advantages that diminished greenhouse gas (GHG) emissions and ensured adherence to climate policies. Social benefits include job creation and enhanced energy availability in neglected areas. Table 3.6 illustrates the preliminary cost-benefit analysis, encompassing total costs and total benefits [362, 363]. Initial capital investment, although the initial expenses are considerable, they are predominantly counterbalanced by operating savings and enduring advantages [364]. Environmental impact significant advantages from the decrease of greenhouse gas emissions and the alignment with climate objectives. The social impact of renewables includes employment creation and energy equity. Integration enhances grid stability, hence improving reliability and minimizing expensive outages. The comprehensive cost-benefit analysis highlights the strategic importance of integrating renewable energy into transmission expansion planning. Despite the substantial initial expenditure, the long-term advantages, financial, environmental, and social exceed the costs, supporting sustainability objectives and improving grid resilience.

Table 3. 6Preliminary cost benefit analysis

Parameter	description	Cost ($Million)	Benefits ($Million)	Remarks
Capital Investments	Investment in renewable energy and grid.	1200	-	Includes wind/solar farms and grid integration upgrades
Transmission Upgrades	Transmission line expansion	800	-	Includes capacity and infrastructure costs.
Energy Storage Systems	Battery storage for grid stability	400	-	Essential for balancing intermittent renewables
Operational Savings	Reduced fossil fuel usage	-	1000	Reduced fuel procurement savings over 20 years
GHG Emission Reductions	Renewable adoption reduces emissions	-	500	Using carbon offset values
Increased Grid Reliability	Distributed supply reduces outages	-	300	Climate-induced disruption resilience improved
Social and Job Benefits	Renewable energy jobs	-	200	Job creation during construction and operation
	Total Costs ($)		2,400 Million	
	Total Benefits ($)		2,000 Million (Direct) + 300 Million (Indirect)	

3.8 Summary

Incorporating RE into South Africa's power system is essential for enhancing energy security, diminishing dependence on coal, and mitigating load shedding. This document provides an overview of essential elements for integrating renewable energy into the South African electricity system. Eskom dominates the power grid, generating around 80%–85% of electricity predominantly from coal. The deterioration of infrastructure and insufficient investment in maintenance have resulted in recurrent failures, leading to load shedding (rolling blackouts). Independent Power Producers (IPPs) enhance the grid, yet have issues related to grid connectivity and legislation. The Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) has promoted the expansion of renewable energy; yet, grid limitations hinder its implementation.

The obstacles challenging the existing grid include Grid Stability Concerns. The national grid was constructed for centralized coal facilities, rendering it less flexible for intermittent renewable sources like solar and wind. Limitations of Transmission Infrastructure, The optimal renewable energy resources in the Northern Cape, Eastern Cape, and Western Cape, as shown in Table 3.5, are situated at a considerable distance from the demand centers of Gauteng and KwaZulu-Natal. Grid modernization, enhancement of transmission lines, and expansion of network capacity to include additional renewable energy sources are advocated. Battery Energy Storage Systems (BESS), such as the Eskom BESS effort, can facilitate the storage of surplus renewable energy and enhance grid stability. Decentralized generation and microgrids, including municipalities and enterprises investing in their own renewable energy generation, can diminish dependence on Eskom. Furthermore, flexible power sources, together with the expansion of natural gas and hydropower, can mitigate the intermittency of RE. Policy reforms and market liberalization, enhancing private sector involvement and optimizing licensing for renewable energy projects.

CHAPTER 4 PROPOSED MATHEMATICAL MODELING

This mathematical model establishes a framework for incorporating renewable energy into the transmission network, reducing losses and assuring reliability. Advanced optimization techniques are employed to improve planning decisions in uncertain circumstances for both short and long-term TEP.

4.1 TEP model based on AC

Present transmission networks are mostly alternating current systems. The AC Optimal Power Flow (ACOPF), grounded on the conventional AC power flow equations (4.2) and (4.3), uses the most precise network model; however, the ensuing optimization problem is significantly nonlinear and nonconvex. Whereby G_k and B_k Susceptance of line k p.u (equal to the inverse of reactance). The AC power flow equation in its complex version is expressed as in (4.1)

$$S_k = P_k + jQ_k \tag{4.1}$$

The active and reactive components P_k and Q_k from bus i to bus j of each branch may be computed as follows.

$$P_k = V_i^2 G_k - V_i V_j (G_k \cos\theta_k + B_k \sin\theta_k) \tag{4.2}$$

$$Q_k = -V_i^2 B_k + V_i V_j (B_k \cos\theta_k - G_k \sin\theta_k) \tag{4.3}$$

The series resistance of each branch in the network results in active power losses, whilst the reactive power losses in each branch are complicated by the simultaneous generation and consumption of reactive power along the line. In practical scenarios, the active power losses in each branch of the network may be expressed as (4.4)

$$PL_k = P_k^{ji} + P_k^{ij} = (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_k) G_k \tag{4.4}$$

Power losses in the network adversely affect generation and operational costs, primarily due to harmonics within the system. These losses can lead to increased maintenance expenses for aging equipment and a reduction in the accuracy of the system's measuring instruments.

4.2 TOP optimization

Minimizing losses through TOP optimization in a power distribution network generally entails establishing an objective function that reduces overall active power losses while adhering to operational restrictions. The standard representation of the objective function can be articulated as

$$\min .P_{Loss} = \sum_{i=1}^{N} I_i^2 R_i \tag{4.5}$$

Subject to

$$P_i = P_{load,i} = \sum_{j \in Ni} P_{ij} \tag{4.6}$$

Whereby P_i is the power injected at node i, $P_{load,i}$ is the power demand at node i, P_{ij} is the power flow between node i and j, and Ni is the set of neighboring nodes of i. voltage and current limits are shown in (4.7) and (4.8)

$$V_{min} \le V_i \le V_{max}, \qquad \forall i \in N \tag{4.7}$$

$$I_i \le I_{max,i} \tag{4.8}$$

The restructured network must maintain a radial configuration (without loops). Ensure the connection of all nodes. The limits for Transformer and Line Capacity are specified in section (4.9).

$$S_i \le S_{max,i,} \qquad \forall i \in N \tag{4.9}$$

Whereby S_i is the apparent power in branch i, and $S_{max,i}$ is the maximum capacity of the branch

4.3 Reliability assessment

The commonly used indices which will be discussed in the results section include the following:

SAIFI: System Average Interruption Frequency Index [1/customer/a] indicates how often the average customer experiences a sustained interruption during the period specified in the calculation as shown in (4.10).

$$\mathrm{SAIFI} = \frac{\sum \mathrm{ACIF}_i . \mathrm{C}_i}{\sum \mathrm{C}_i} \quad (4.10)$$

Whereby ACIF: Average Customer Interruption Frequency, expressed as $[1/a]$. Which is calculated as shown in (4.11)

$$\mathrm{ACIF}_i = \sum_k \mathrm{Fr}_k \cdot \mathrm{frac}_{i,k} \quad (4.11)$$

C_i is the Number of clients serviced by load point i, i is the load point index, k is the contingency index, Fr_k Occurrence frequency of contingency k, and $frac_{i,k}$ which is The proportion of the load that is diminished at load point i, for contingency k

Annual Average Interruption Frequency (Contracted Power), in $[1/a]$. which denotes the frequency of contracted power interruptions during the computation period.

$$\mathrm{SAIFI\_P} = \frac{\sum \mathrm{TPCONTIF}_i}{\sum \mathrm{PCONTRACT}_i} \quad (4.12)$$

Whereby TPCONTIF is the Total Contracted Power Interruption Frequency in [MWh/a] which is calculated as:

$$\mathrm{TPCONTIF}_i = \sum_k \mathrm{Fr}_k \cdot \mathrm{frac}_{i,k} \cdot \mathrm{Pc}_i \quad (4.13)$$

Of which Pc_i is the Acquired active power at load point i

SAIDI: System Average Interruption Index [h/customer/a] indicates the total duration of interruption for the average customer during the period in the calculation

$$\mathrm{SAIDI} = \frac{\sum \mathrm{ACIT}_i \cdot \mathrm{C}_i}{\sum \mathrm{C}_i} \quad (4.14)$$

Whereby ACIT is the Average Customer Interruption Time, in $[h/a]$. which is calculated by

$$\mathrm{ACIT}_i = \sum_k 8760 \cdot \mathrm{Pr}_k \cdot \mathrm{frac}_{i,k} \quad (4.15)$$

Of which Pr_k is the probability of occurrence of contingency k.

Annual Average Interruption Duration (Contracted Power), in $[h/a]$. It indicates the cumulative duration of contracted power outages within the computation period.

$$SAIDI\_P = \frac{\sum TPCONTIT_i}{\sum PCONTRACT_i} \tag{4.16}$$

Whereby $TPCONTIT$ is the Total Contracted Power Interruption Time, in [MWh/a] which is calculated as shown in (4.17)

$$TPCONTIT_i = \sum_k 8760.Pr_k.frac_{i,k}.Pc_i \tag{4.17}$$

ENS: Energy Not Supplied [MWh/a] is the total amount of energy on average not delivered to the system loads which is calculated as shown in (4.18)

$$ENS = \sum LPENS_i \tag{4.18}$$

Whereby LPENS is the load point energy not supplied in [MWh/a] as shown in (4.19)

$$LPENS_i = ACIT_i \cdot (Pd_i + Ps_i) \tag{4.19}$$

Where Pd_i represents the weighted average power disconnected at load point i, and Ps_i indicates the weighted average power shed at load point i.

4.4 RE integration into a 39-bus system

The 39 Bus New England System is a simplified model of the high voltage transmission network in the northeastern United States (New England region). It was first introduced in 1970 and has since been frequently utilized for academic research and publications [365]. This study utilizes the 39 bus as a case study to demonstrate the significance of expanding transmission lines for short-term and long-term objectives, particularly with the substantial integration of renewable energy. The growing recognition of the significant pollutants generated by coal, as well as the depletion of these sources, has compelled energy firms to explore alternative and sustainable energy sources, known as RERs which may play a big role in reducing load shedding [8, 366, 367]. Load shedding is a form of time theft that deprives Africa's most industrialized economy of valuable chances. It involves intentionally disconnecting energy from paying consumers to inhibit a complete failure of the power infrastructure [368]. The transmission capacity of electricity systems must be modified in response to shifting generation infrastructure and consumption patterns as these systems progress [369]. RES is being explored as a viable alternative to the depleting and environment-unfriendly fossil fuels [28, 370]. They are being introduced to reduce emissions, and lower maintenance, storage capabilities, and costs associated with generation facilities [371, 372]

The proposed project will initially incorporate sustainable energy sources like solar and wind into transmission lines in order to enhance the power of the system.

4.4.1 Wind power uncertainty

The small-scale wind power also originates from wind speed defined as unpredictable and stochastic generation. The wind speed follows a Weibull distribution, and the probability density function (PDF) is applied to the wind variations.

$$f(v)=\left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^{k}} \tag{4.20}$$

The scaling index c may be determined from the average wind speed at a location as shown in (4.21).

$$v_m=\int_0^{\infty} vf(v)dv=\int_0^{\infty}\left(\frac{2v^2}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right]dv=\frac{\sqrt{\pi}}{2}c \tag{4.21}$$

Consider the wind speed, form factor, and scale factor, denoted as v, k and c, respectively, where, $k>0, v>0$ and $c>1$ Then, the wind power output can be stated as

$$P_w=\begin{cases} 0 & 0\le v<V_{ci} \\ P_w^0(A+Bv+Cv^2) & V_{ci}\le v<V_r \\ P_w^0 & V_r\le v<V_{co} \\ 0 & v\ge V_{co} \end{cases} \tag{4.22}$$

V_{ci}, V_r and V_{co} are known to be cut in wind speed, rated wind speed, and cut out wind speed respectively. P_w^0 is the rated power of a wind unit.

The probability of each state is defined by the following equation:

$$\pi_s^w=\int_{v_{1,s}}^{v_{2,s}} f(v)dv=\int_{v_{1,s}}^{v_{2,s}}\left(\frac{2v}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right]dv \tag{4.23}$$

Whereby

$$v_s=\frac{v_{2,s}+v_{1,s}}{2} \tag{4.24}$$

where $v_{2,s}$ and $v_{1,s}$ represent the velocity restrictions in state w

4.4.2 Uncertainty in distributed solar power

The stochastic illumination intensity dominates the primary factor of solar production. Several studies have demonstrated that the PDF conforms to the Beta distribution as

$$f(R) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma\beta}\left(\frac{R}{R^{max}}\right)^{\alpha-1}\left(\frac{R}{R^{max}}\right)^{\beta-1} \tag{4.22}$$

Whereby Γ stands for Gamma function, α and β are the considerations, R is the illumination intensity, R^{max} is the maximum value. They communicate between the illumination intensity and the output power of a solar unit can be described as

$$P_s = \begin{cases} P_s^0 \frac{R}{R_r} & \begin{cases} 0 \le R \le R_r \\ R > R_r \end{cases} \\ P_s^0 & \end{cases} \tag{4.23}$$

Where R_r represents the rated value and P_s^0 represents the rated output power of the solar unit.

4.5 Available transfer capability (ATC) on the wind farm

To enhance competition in contemporary power systems, the Federal Energy Regulatory Commission (FERC) has mandated open access nondiscriminatory transmission services and the Open Access Same-Time Information System (OASIS) [373]. The ATC must be published on OASIS to ensure competition is fair and effective. This network uses the boundary to calculate the available transfer capability of the wind farm excluding the rest of the network, this is done to calculate the losses, profit, and energy of the wind farm.

$$ATC = TTC - TRM - CBM - ETC \tag{4.25}$$

TTC is the total transfer capability which is less than the transmission reliability margin (TRM), which is less than the capacity benefit margin (CBM), and less than the sum of existing transmission commitments (ETC). This study does not address TRM or CBM. Therefore, the ATC may be derived by subtracting the TTC from the ETC

$$ATC = TTC - ETC. \tag{4.26}$$

Whereby

$$TTC = \sum_{i \in \sin k} P_{Di}(\lambda \max) - \sum_{i \in \sin k} P_{Di}^{0} \tag{4.27}$$

Subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} B_{ij}\theta_{ij} = 0 \tag{4.28}$$

Where B is the sets of all buses, P_{Gi} is the active power at the generator I, and P_{Di} is the active power demand at bus i, θ_{ij} is the voltage phase angle between the bus i and λ is the scalar parameter.

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{4.29}$$

$$P_{ij} \leq P_{ij}^{max} \tag{4.30}$$

$$P_{Gi} = P_{Gi}^{0}(1 + \lambda k_{Gi}) \tag{4.31}$$

$$P_{Di} = P_{Di}^{0}(1 + \lambda k_{Di})$$

This approach is for computing the ATC utilizing Monte Carlo simulations alongside a sensitivity analysis.

4.6 Load forecast and quasi-dynamic

Quasi-Dynamic Simulation toolbox is a dedicated time-varying load flow calculation tool that can be used for short-, medium-, and long-term simulation studies. This tool completes a series of load flow simulations spaced in time, with the user given the flexibility to select the simulation. period and the simulation step size. Statistical overview of observed variables. PowerFactory efficiently computes summary statistics for each monitored variable in the Quasi-Dynamic simulation. The subsequent quantities are ascertained automatically. Such as Average (mean), time of maximum or minimum, range, and standard deviation which is the population standard deviation calculated as shown in (4.31)

$$\sigma = \sqrt{\frac{\sum (x - \bar{x})^2}{n}} \tag{4.32}$$

Where the Variance = σ^2

This section presents the concurrent forecasting of peak load and maximum production capacity of renewable energy sources for the proposed network in the planning years. Per the IEEE 1547 standard, the primary function of renewable energy sources (RESs) is active power generation; hence, its reactive power regulation capability is underutilized in networks. The formula below is used to calculate the annual peak value of net power demand ($\overline{P}^{D}$). Moreover, w is the indices and set of scenario samples, t is the indices and set of hours, and y & y_0 are the indices and set of planning history year.

$$\overline{P}^{D}_{i,y,w} = \max(P^{D}_{i,1,y,w}, P^{D}_{i,2,y,w}, \ldots, P^{D}_{i,N,y,w}) \tag{4.33}$$

Whereby

$$P^{D}_{i,t,y,w} = P^{CL}_{i,1,y.w} - \sum_{rt} P^{RES}_{i,rt,t,y,w} \qquad \forall i, t, y, w \tag{4.34}$$

Of which P^{RES} is the RES active power and P^{CL} is the consumption active load

$$P^{RES}_{i,rt,t,y,w} = \overline{P}^{RES}_{i,rt,y} PR_{rt,t,w} \quad \forall i, rt, t, y, w \tag{4.35}$$

The hourly power rate (PR) varies throughout the year for different types of renewable energy sources (RESs). Consequently, subscript rt is the RES type and it is employed for P^{RES} and PR in formulations (4.33) - (4.34) to facilitate the observation of disparities in power generation curves among various types of RES inside the Network. N_y is the total number of planning years

$$\overline{P}^{RES}_{i,rt,y} = \overline{P}^{RES}_{i,rt,y-1} + \frac{HC^{RES}_{i,rt}}{N_y} \qquad \forall i, rt, y, \qquad \overline{P}^{RES}_{i,rt,0} = \overline{P}^{RES}_{i,rt,N_{Y0}} \tag{4.36}$$

From equation 4.35 HC^{RES} represents the Hosting capacity of renewable energy sources that must be implemented in the future.

$$P^{CL}_{i.1,y,w} = LF_{t,w} \overline{P}^{CL}_{i,y} \qquad \forall i, t, y, w \tag{4.37}$$

Whereby LF is the load power factor, GF is the growth factor, e is the load forecasting error in MW, and a & b are the decision-making variables in the time series-based logistic method, and N_{Y0} being the total number of historical years

$$\overline{P}_{i,y}^{CL} = \frac{GF_i \overline{P}_{i,N_{Y0}}^{CL}}{1 + a_i e^{-b_i y}} \qquad \forall i, y \tag{4.38}$$

$$GF_i = \frac{\overline{P}_{i,N_{Y0}}^{CL}}{\overline{P}_{i,y0=1}^{CL}} \qquad \forall i \tag{4.39}$$

4.7 Probabilistic analysis

The probabilistic analysis tool facilitates network evaluation utilizing probabilistic input data instead of assessing specific operational situations or conducting time sweep analysis. It becomes crucial after the input parameters are established as random or when one intends to recreate the grid at a future time with forecast inaccuracies.

This function defines the infinitesimal probability at any position x. The region between the probability density function $f(t)$ and the x-axis from point a to point b represents the probability of obtaining a value within that interval as shown in (4.40)

$$F(a \le X \le b) = \int_a^b f(t)dt \tag{4.40}$$

This distribution can be utilized to represent real-valued random variables (such as amounts with measurement errors) when the distribution is unknown. The probability density function of this distribution, characterized by the parameters μ (mean) and σ (standard deviation), can be articulated as:

$$\mu = \exp(\mu_L + \frac{\sigma_L^2}{2}) \tag{4.41}$$

Whereby μ_L is the mean of logarithm and σ_L is the standard deviation of the log

$$\sigma = \sqrt{(\exp \sigma_L^2 - 1)\exp(2\mu_L + \sigma_L^2)} \tag{4.42}$$

Under Markov assumptions, the probability of state i, P_i, is defined by the equality of frequencies and the condition that the total of all state probabilities equals one, leading to the following equation:

$$P_i = \frac{\lambda_i}{\mu_i} = \lambda_i . r_i \tag{4.43}$$

Whereby λ and μ indicate the failure and repair rates, respectively, of a system with n components, where S signifies the successful state and i = 1, 2, … n represents the failure states. r_i specifies the mean repair duration of component i. If P_s represents the probability of state S, the system failure frequency f_{Syst} and unavailability U_{Syst} are approximately expressed as:

$$f_{Syst} = P_s . \sum_{i=1}^{n} \lambda_1 \cong \sum_{i=1}^{n} \lambda_i \tag{4.44}$$

$$U_{Syst} \cong \sum_{i=1}^{n} \lambda_i . r_i \tag{4.45}$$

These predictions are accurate provided that:

$$\sum_{i=1}^{n} \lambda_i \cdot r_i \ll 1 \tag{4.46}$$

Such that P_s is about equal to 1. The mean time of system disruptions can be determined as

$$r_{Syst} = U_{Syst} / f_{Syst} \tag{4.47}$$

This interpretation will be significant in the testing functions of the proposed QMCS and the algorithm itself. Ultimately, note that the aforementioned customer load point (individual) and system reliability indices can be readily computed from these estimates.

4.7.1 Quasi-Monte Carlo method

The Quasi-Monte Carlo approach employs specific sequences to achieve a more uniform spatial coverage compared to the Monte Carlo method. The convergence rate of a Quasi-Monte-Carlo simulation is defined by (4.48)

$$O(\ln(N)^d / N \tag{4.48}$$

which, for a substantial quantity of samples N, exhibits behavior analogous to 1/N, d is the dimension that determines the convergence rate.

Quasi-Monte Carlo simulation is very adaptable, enabling the modeling of non-exponential residence durations, which is particularly advantageous for time-dependent systems. In the context of a simulation period T, the operational history of system states is derived using stochastic models of components (i.e., equipment) and the load model. After evaluating each state, reliability indices are calculated based on the expected values, $\tilde{E}[G]$, derived from the relevant test functions $G(yj)$, as detailed in (4.49):

$$\tilde{E}[G] = \frac{1}{NY}\sum_{j=1}^{NY} G(yj) \tag{4.49}$$

where NY represents the quantity of simulated years and yj is a series of system states in year j

4.8 Expansion strategy presented

An expansion plan refers to a series of investments in infrastructure networks that are strategically arranged over a certain planning horizon. Investments must be chosen based on several variables and evaluated as a cohesive unit in a coordinated manner. New transmission lines or transformers can be constructed in existing corridors or substations, as well as in new corridors, to link additional demand or generating centers. Regardless, it is acknowledged that the cost of each project is known and that there are no prior projects or connections between them. In addition to their expenses and network connections, each project will be assigned a certain timeframe for when it will become operational as a consequence of the TEP exercise. It should be noted that the MOTP (Multi-Objective transmission planning) is a non-convex nonlinear mixed integer problem. Currently, numerous heuristic techniques have been used to improve the performance of this determination problem.

4.8.1 The TEP problem formulation

In TEP, enhancing reliability entails ensuring that the transmission network can accommodate load demand during diverse situations while reducing breakdowns and preserving system stability. The goal function must equilibrate investment costs, operating expenses, and reliability measurements, like Loss of Load Expectation (LOLE), Expected Energy Not Supplied (EENS), or system security indices.

Two objectives, which are to minimize losses and improve reliability, are identified for the TEP problem as outlined in (4.50):

$$OF = \min(w_1 EENS + w_2 P_{loss}) \tag{4.50}$$

P_{loss} is the total power loss in the transmission network, w_1, w_2 are the weighting factors to balance the reliability and loss minimization. EENS - A reliability metric indicating the anticipated quantity of energy not delivered as a result of network limitations and outages.

The proposed approach aims to maximize the reliability of the system. This objective can be accomplished by reducing the total amount of EENS. To compute the EENS reliability measure at load demand j during a contingency k, and time frame t, the following formulas are employed.

$$0 \le g_{itk} \le u_i g_i^{max} \qquad \forall i, \forall t, \forall k \tag{4.51}$$

$$\sum_{j\in\Psi_n^D}' \Gamma_{jtk} = \sum_{j\in\Psi_n^D}' d_{jt} - \sum_{i\in\Psi_n^G}' g_{itk} + \sum_{\substack{l:s(l)=n \\ l\notin\xi_k}}' f_{ltk} - \sum_{\substack{l:r(l)=n \\ i\notin\xi_k}}' f_{ltk} \qquad \forall n, \forall t, \forall k \tag{4.52}$$

From equation (4.51) g_{it} is the power output at the generator i through the demand interval t (MW), $u_i g_i^{max}$ being the binary variable which is equal to 1 if unit i is implemented and 0 if otherwise. Γ_{jtk} which is the unintentional load shedding of jth demand during the demand interval t as a result of contingency k (MW). Ψ_n^D which is the set of demands located at bus n. d_{jt} which is the power demand j in the demand t (MW). Ψ_n^G being the set of generating units at bus n. f_{lt} Which is the power flow over line l during the demand period t (MW). And ξ_k indicates the failed equipment due to contingency k.

Subjected to:

$$0 \le \Gamma_{jtk} \le d_{jt} \quad \forall j, \forall t, \forall k \tag{4.53}$$

$$f_{ltk} = B_{l\chi l}(\theta_{s(l)tk} - \theta_{r(l)tk}) \qquad \forall l, \forall t, \forall k \tag{4.54}$$

Whereby B_l is the susceptance of line l, χ_l is the binary variable that is 1 if line i is constructed and 0 if otherwise. θ_s, θ_r for voltage angle for sending and receiving line. f_l^{max} being the maximum capacity of line l.

$$f_{ltk} \le f_l^{max} \qquad \forall l, \forall t, \forall k \tag{4.55}$$

$$f_{ltk} \ge -f_l^{max} \qquad \forall l, \forall t, \forall k \tag{4.56}$$

Constraint (4.51) restricts unit generation to their capacity limit. The total load reduced from the demand at the bus n during the jth demand at period t is specified by the nodal balance equality constraint (4.52). Load shedding is constrained by (4.53). Transmission line constraints are dictated by equations (4.54)–(4.56).

Assume that the condition of system components is

$$v_1 xK = [v_e v_n] \tag{4.57}$$

where v_e signifies the status of existing components, represented by 1, and v_n indicates the condition of new units and lines, which may be produced or not, thus potentially equating to one or zero. Considering two potential states for system components (lines and units), either accessible or unavailable, and assuming that the random variables are statistically independent, results in probability definitions grounded on the Bernoulli distribution [374]. The odds of no contingency and the occurrence of a single contingency are presented in (4.58) and (4.59), respectively:

$$\rho_0 = \prod_{\alpha \in \vartheta} (1 - v_\alpha U_\alpha) \tag{4.58}$$

$$\begin{aligned}
\rho_k &= v_k U_k \prod_{\substack{w \neq k \\ w \in \vartheta}} (1 - v_w U_w) \\
&= v_k U_k (1 - U_k)^{-1} \prod_{w \in \vartheta} (1 - v_w U_w) \qquad \forall k \\
&= v_k U_k (1 - U_k)^{-1} \rho_0
\end{aligned} \tag{4.59}$$

Whereby ϑ indicates the set of all existing and newly installed components in the system such as transmission lines and generators. ρ_0 is the probability of no contingency state. And ρ_k is the probability of contingency k. where U_k is the forced outage rate of the element k. Equations (4.58) and (4.59) specifically delineate the likelihood of random outage events in relation to the G&TEP variables, employing a nonlinear approach. This analysis focuses on non-contingent and single contingent situations because of their elevated probability. Nonetheless, higher-order contingencies such as double contingencies can be similarly articulated and integrated into the model if necessary. It is now feasible to articulate the EENS at load demand j, within a specified time interval, and during contingencies k, in relation to the probability and magnitude of load shedding during such contingencies.

$$EENS_{jtk} = \rho_k \Gamma_{jtk} du_t \qquad \forall j, \forall t, \forall k \tag{4.60}$$

$$P.loss = \sum_{i.j=1}^{ns} r_{ij}^{t} \cdot (I_{ij}^{t})^2 \tag{4.61}$$

$$I_{ij}^{t} = \frac{|f_{ij}^{t}|}{\sqrt{3} \cdot V_L} \tag{4.62}$$

The inequality constraints are outlined below:

The active power generation limits of generators are expressed in the following equation, where st denotes the scenario time, Gen is the generator, and L is the line

$$P_{Gen}^{min} \le P_{Gen,st} \le P_{Gen}^{max} \tag{4.63}$$

$$-P_{L}^{max} \le P_{L,st}^{0} \le P_{L}^{max} \tag{4.64}$$

$$P_i - P_{di} = \sum_{j \in N} P_{ij}, \qquad \forall i \in N \tag{4.65}$$

P_i being the power generation, P_{di} being the power demand and P_{ij} being the power flow between buses.

4.9 Summary

Mathematical modeling for TEP is essential for the design of efficient, cost-effective, and dependable transmission networks. Diverse optimization methodologies, restrictions, and uncertainty management strategies assist utilities in making informed decisions while maintaining grid stability and operating efficiency. It entails formulating plans to augment electricity transmission networks to improve reliability and reduce losses while guaranteeing cost-effectiveness and operational viability. Key aspects of mathematical modeling involve the selection of new transmission lines or the strengthening of existing ones. Optimal positioning and dimensioning of new network components. Modifications to power flow for enhanced network efficiency. The main objective of this research is to enhance network dependability and minimize losses while increasing the transmission line to meet network dynamics.

CHAPTER 5 39 BUS NEW ENGLAND SYSTEM WITH SOLAR PLANT AND WIND FARM MODEL DEVELOPMENT

This study employs 39-Bus England test systems utilizing DIgSILENT PowerFactory software to demonstrate the necessity of increasing transmission lines to meet anticipated demand when incorporating RE into the existing system. This section also illustrates the design and integration of solar PV plants and wind farms into the system to improve electricity accessibility, while accounting for the inherent power unpredictability associated with these sources.

5.1 39 bus England test system

The present study uses the 39-bus England test system. The present version pertains to the global TNEP academic literature. The data utilized for the IEEE 39-bus test system to evaluate TNEP from 2024 to 2039 is presented in tables 5.1 to 5.7.

Table 5.1 outlines the components that comprise the entire network and lists the total number of components. Table 5.1 indicates that this study employs four voltage levels, a fact corroborated by Figure 5.1 in the small box.

Table 5. 1 39Bus New England system parameters

Parameter	**Value**
No of Transmission lines	34
No of buses	39
No of loads	19
No of generators	10
Transformers – 2 Winding	12
Number of Voltage levels	4

Figure 5.1 below displays a schematic of a single line in the IEEE 39-bus test system [365]. This is the case study that was utilized in this study to illustrate the significance of expanding the transmission line while integrating RE into the network and ensuring the system network is healthy and working under permitted table values. This research used a slack bus, commonly referred to as a swing bus.

This research utilizes a reference bus, designated as G 01, in a load flow analysis to stabilize the network. It maintains a constant voltage magnitude and angle, enabling it to either absorb or provide power to achieve system balance.

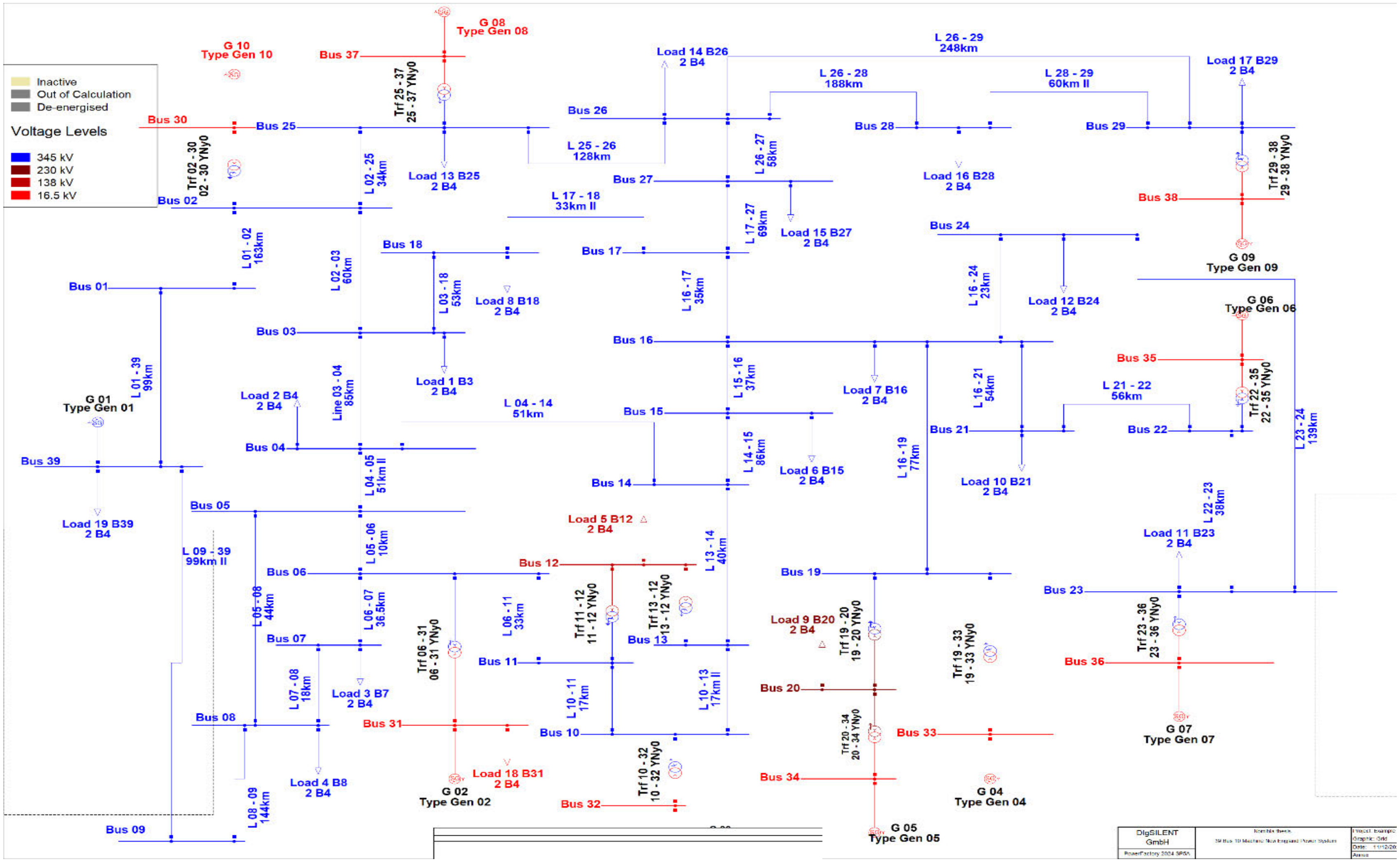


Figure 5. 139 Bus New England system network diagram

5.2 Tie Open Point Optimization

The open switches that separate adjacent feeders are known as tie open points. In this network, the feeders are predefined, as illustrated in Figure 5.1. In this network, the TOPO function optimizes a radial system of connected feeders by identifying the optimal location for network open points. The TOPO utility has the capability to relocate an open point by opening and closing switches on the networks that are to be optimized. This network has three feeders and two open tie points, as indicated by the little circle in Figure 5.2. Each feeder originates at the substation and terminates at an open point. The open points in this network are not inherently the optimal open points. For instance, it may be more economical (i.e., reduced network losses and/or diminished outage impact) to relocate these open points by deactivating the open switches and activating two switches at distinct locations on the feeds. The TOPO tool aims to automatically identify these optimal open sites. The TOPO tool can autonomously account for network voltage and temperature limitations; for example, relocating an open point may be economically advantageous for minimizing system losses, although it could lead to cable overload. Figure 5.1 illustrates the network containing three feeders starting from the terminal point of the line. The TOPO tool necessitates the definition of feeders for the portion designated for optimization; the selected feeders must not be congested or exhibit voltage issues. The network with selected tie open points with small circles in a radial network is depicted in Figure 5.2. These points are selected with the objective of minimizing the network's losses.

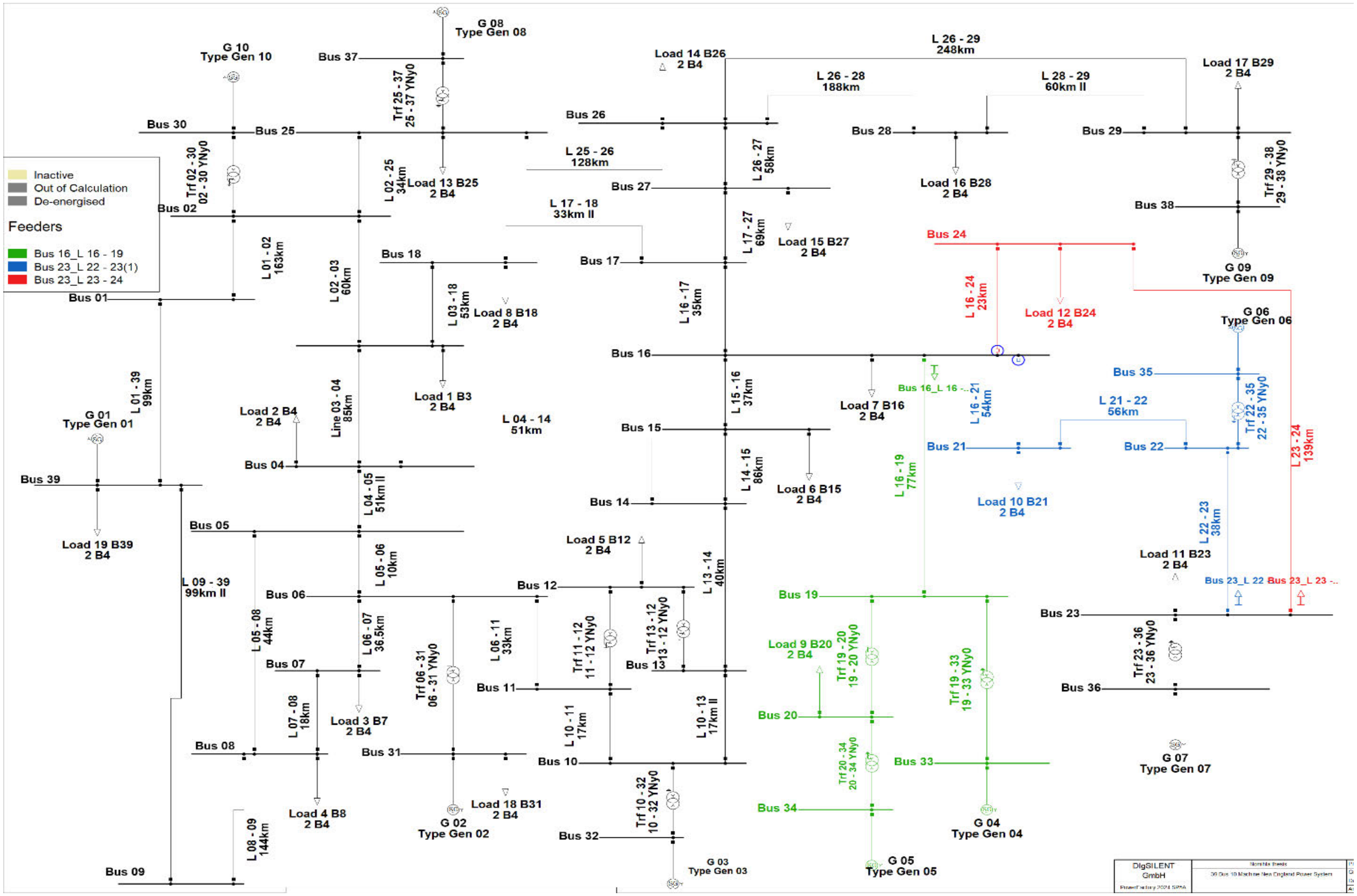


Figure 5. 2Network simulation with feeders

The TOPO is performed using a Genetic Algorithm (stochastic optimization) using the following steps:

1. Create feeders
2. Configure the TOPO command
3. Configure constraints for TOPO
4. Configure switching points
5. Configure reliability options
6. Configure scenario/ time sweep
7. Configure output results

Table 5.2 defines the parameters used in TOPO, along with its objective function and the employed approach, which is GA stochastic optimization. The objective of this optimization strategy is to reduce losses by repositioning the tie open point and identifying the optimal location.

Table 5. 2TOPO settings

TOPO Settings	
Objective Function: Minimisation of losses	**Method**: Genetic Algorithm (Stochastic Optimisation)
Constraints	
Thermal constraints	Max thermal loading of components: 100%
Consider Voltage Constraints	Lower Limit of Voltage 0.95p.u
	Upper limit of allowed Voltage 1.05p.u

5.3 Hosting capacity development and RE integration

The Hosting Capacity tool enables the assessment of the effects of incorporating generation (Distributed Energy Resource (DER) Capacity) or load (Spare Load Capacity) into a power system. It is typically described as the quantity of new generation or consumption that can be integrated into the grid without infringing upon system restrictions (e.g., power quality for connected consumers) and without necessitating any network expansion. All limitations employed to ascertain the extent of potential generation or load accommodation can be assessed by the performance index. This index may connect with voltage violations, loading violations, and protection configurations. It may be construed as the system's robustness.

5.3.1 Hosting capacity development

This chapter employs hosting capacity analysis within the IEEE 39 bus network to ascertain the maximum additional load or distributed energy resources (DER) that may be included as a source without contravening system limits or necessitating development. PowerFactory's hosting capacity analysis tool enables fast automated evaluation by combining load flow protection harmonic analysis in a single workflow, resulting in a systematic and efficient approach to DER and consumer integration. The system limits are specified above for equipment loading and voltage p.u.

Method

1. Select hosting sites: Feeders, Groupings, Grids, or sites
2. Calculative objective: DER Capacity or Spare Load Capacity
3. The calculation method is AC Load Flow, balanced, positive sequence in a standard Load Flow
4. Thermal constraints, same as load flow constraints
5. Configuration: Specified Static generator

In this command area, constraints are considered during calculation. The following constraints exist:

- Thermal limits
- Voltage limits
- Protection limits
- Power quality limits
- Short-circuit contribution limits

The initial power must be less than any power that violates constraints, as indicated in the table. Otherwise, the algorithm will fail to identify a solution.

Table 5. 3Voltage constraints for power

Voltage level in kV	Initial Power
< 9.5	5kW

< 39.5	200kW
< 100	1MW
≥ 100	10MW

initial conditions: The initial step size can be specified in this category. The first step is computed by multiplying the initial power by the initial step size as shown in the formula below

$$P_{new} = P_{ini}.(1 + step_{ini} / 100\%) \tag{5.1}$$

5.3.2 RE integration

This section integrates two sources of renewable energy: wind farms and solar PV plants into the network infrastructure. These RE plants are operational facilities situated in South Africa's Northern Cape, intended to facilitate the country's transition to clean energy production. The incorporation of RE plants into the IEEE 39-bus system is essential for analyzing and enhancing renewable penetration in real power networks. It enhances grid reliability, lowers expenses, diminishes emissions, and promotes the study of existing power networks. Table 5.4 shows the parameters of the wind turbine.

Table 5. 4Parameters of the wind turbine

Element	**Value**
Number of Wind turbines	11
Rated Apparent Power	2.778MVA
Wind Speed	16m/s
Rated Power Factor	0.9

Figure 5.3 illustrates the wind power curve applicable to all wind turbines used in this study; from this curve, it is evident that the turbines achieve maximum power generation at a wind speed of 16 m/s.

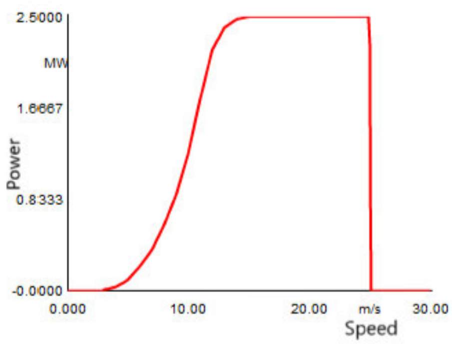


Figure 5. 3Speed of wind turbine

The wind power capability curve, which represents the capability curve of an electrical generator, outlines the constraints of the active and reactive power that the generator can supply. The curve delineates the limit of all operational points as shown in Figure 5.4.

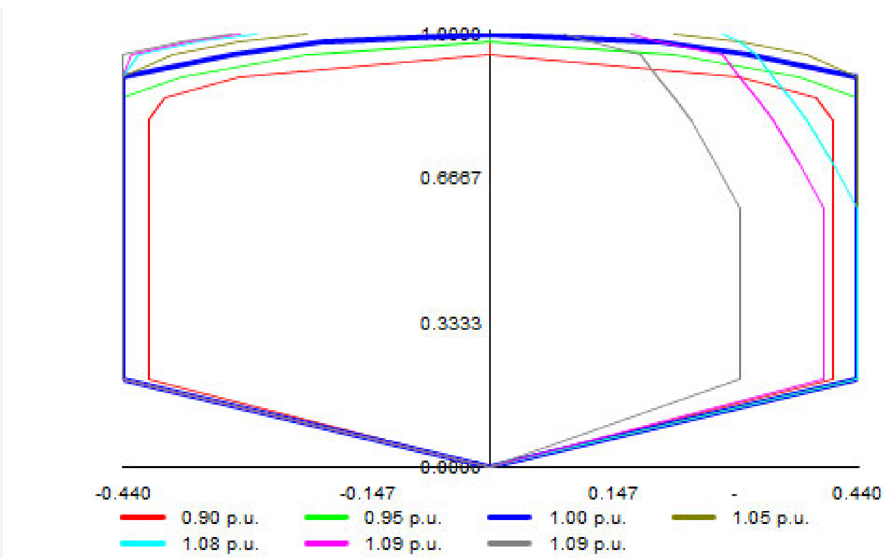


Figure 5. 4Wind power capability curve

Figure 5.5 shows the wind farm integrated into the 39 bus England System, consisting of 11 wind turbines, each rated at 2.778 MVA with a power factor of 0.9. These wind turbines are interconnected with an 11kV busbar with a 1km cable between them.

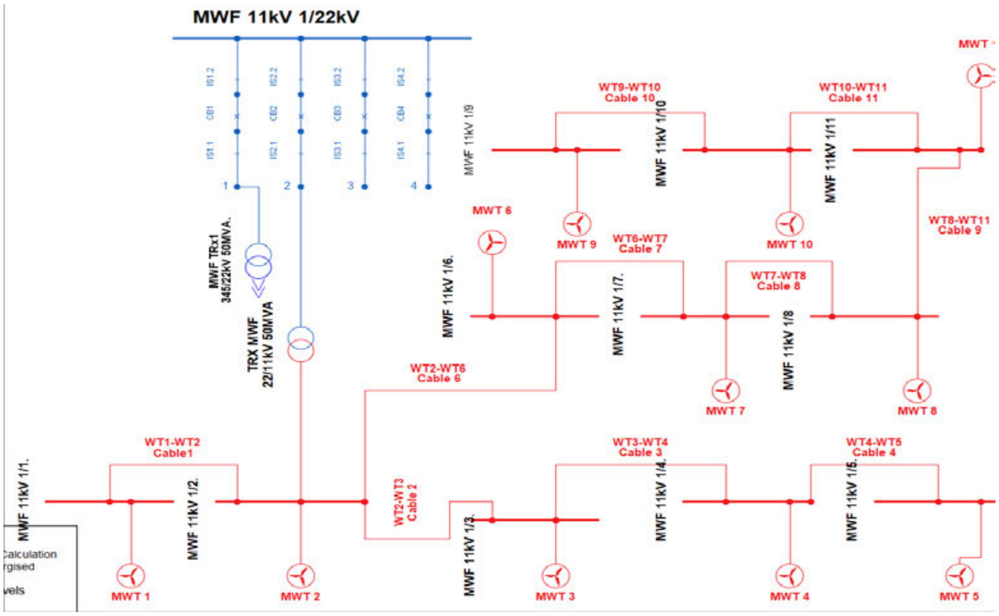


Figure 5. 5Metro wind farm network diagram

The 22/11KV step-up transformer is used to step up the voltage to 22kV MWF as shown in Figure 5.5

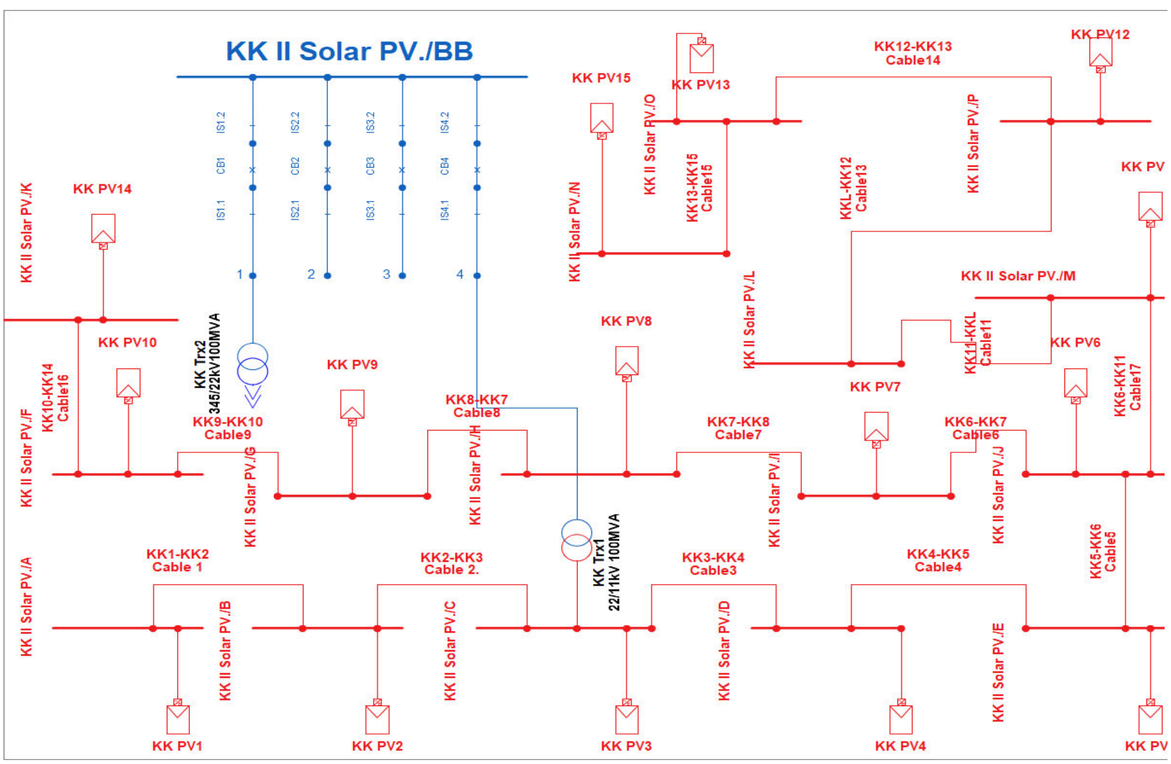


Figure 5. 6Konkonsies Solar PV plant network diagram

Figure 5.6 displays the Konkonsies II solar PV plant, which consists of 15 solar PV units, each generating 5MW, with an apparent power of 7MVA and a power factor of 0.9, using active power input to produce power. These solar PV are connected by an 11kV busbar and a 1km cable. Furthermore, a step-up transformer rated 100MVA and a voltage of 11/22kV is utilized to step up the voltage to 22kV in KK II Solar PV, as illustrated in Figure 6.4.

Table 5.5 illustrates the parameters incorporated into the expanded network. A comparison with Table 5.1 reveals an increase in the number of busbars from 39 to 73. Additionally, transmission lines have been introduced due to the cables linking the busbars. The newly integrated components in the system include 15 Solar PV units and 11 wind turbines.

Table 5. 5Components of the expanded network

Components of 39 Bus with RE Integration	**value**
No. of Transmission lines	61
No. of buses	73
No. of loads	19
No. of generators	10
Transformers – 2 Winding	16
Number of Voltage levels	6
No. of PV systems	15
No of Wind Generators	11

Figure 5.7 depicts the whole network of the 39-bus system, including the solar PV plant and wind farm. The diagram shows that the voltage levels have been increased by incorporating two RE power plants, marked by a circle and a square, referring to substations. This is shown in the small box with voltages when compared with Figure 5.1

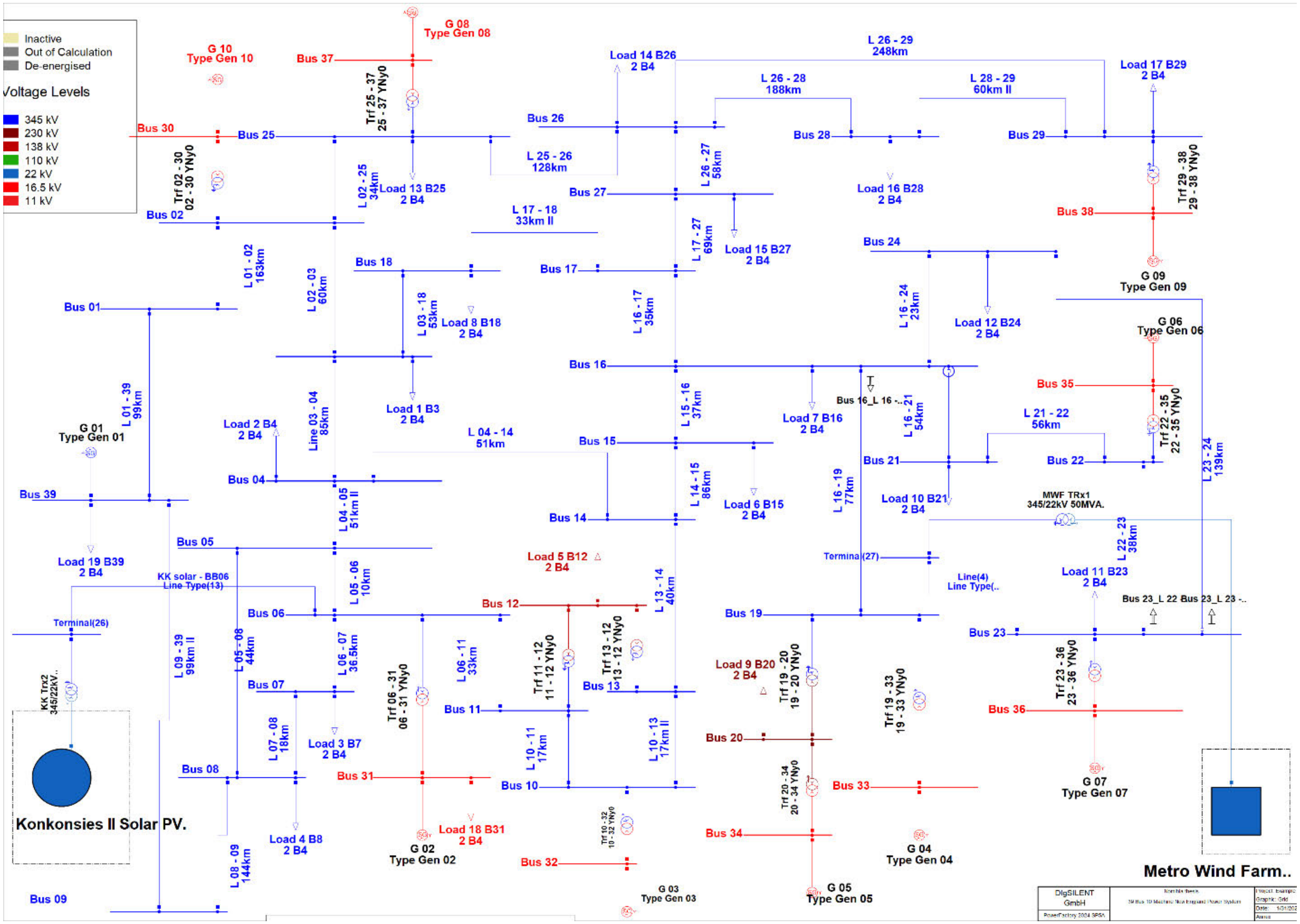


Figure 5. 739-bus New England with wind and solar RE power plant network diagram

5.4 Reliability assessment

The network's response to potential faults is evaluated through reliability assessment, which quantifies the reliability of the customer's supply in terms of standard indices. Faults are analyzed stochastically, indicating that individual fault events cannot be anticipated; nevertheless, the likelihood of such events can be modeled using failure rate data. Upon the occurrence of a fault, three actions must transpire:

1. A protection mechanism activates and opens the circuit breaker to eliminate the fault.

2. The faulty equipment must be segregated from the rest of the network.

3. Re-switching may occur to restore maximum demand while maintaining the isolation of the faulty component.

The expenses related to loads are established using global costs for loads contingent upon the duration of the outage. The illustration in Figure 5.8 depicts the cost structure related to loads. Reliability evaluation employs identical constraints as load flow analysis. Figure 5.8 shows the global cost curve for all loads, which defines the cost associated with losses based on the outage duration

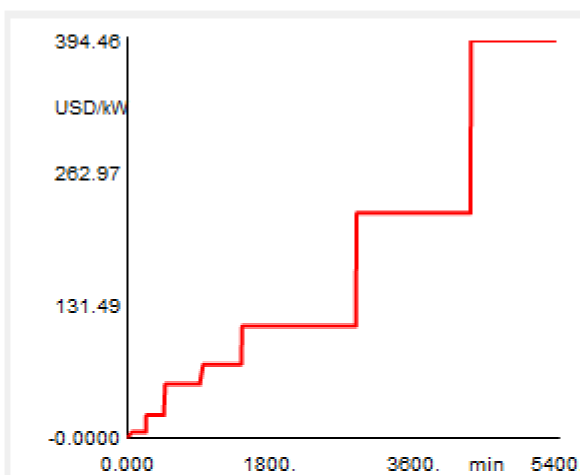


Figure 5. 8Time tariff

Table 5.6 is the failure rate data used to calculate the probability of events for lines, transformers, and busbars, which is configured on the reliability section of each element, since the contingency will examine failures based on these elements for the full network. The faults are selected to be cleared using switches with protection devices; this is done on the reliability section of all the switches in the network.

Table 5. 6Element failure rate data

Element	Failure Frequency		Repair duration (h)
Line	0.02329453	1/(a*km)	10
Line	0.07838819	1/(a*km)	10
Transformers	0.177	1/a	16
Busbars/ Terminal	0.0104	1/a	20
Busbars/ Terminal	0.00475	1/a	60

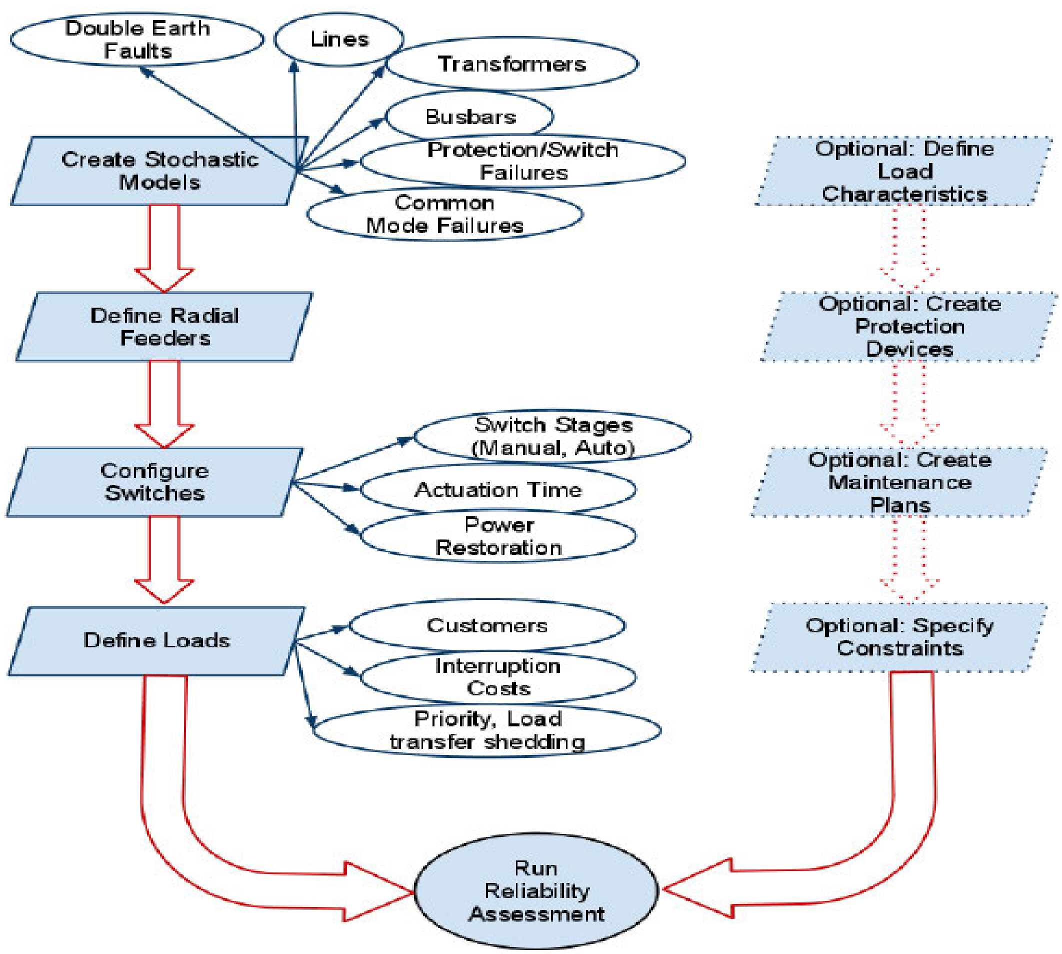


Figure 5. 9Procedure for reliability assessment

The fundamental user protocol for doing a reliability evaluation comprises the subsequent phases, as illustrated in Figure 5.9. The stages on the left are mandatory, but the steps on the right are discretionary and may be employed to enhance the calculation's detail.

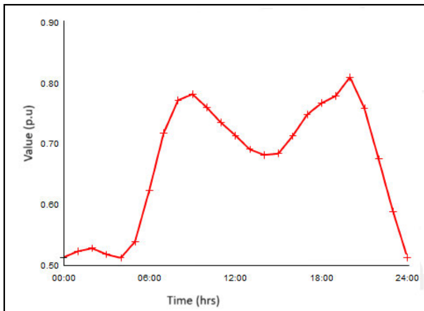
5.5 39-Bus system under load forecast and quasi-dynamic conditions

For modeling systems that exhibit both static and dynamic behaviors, it makes use of a technique known as quasi-dynamic simulation, which is traditionally utilized in engineering as well as in other domains. A fully static technique (time-invariant) would not be able to capture key temporal effects, but it is frequently used in cases where full dynamic simulation (which involves tracking every minor change over time) would be computationally expensive or superfluous.

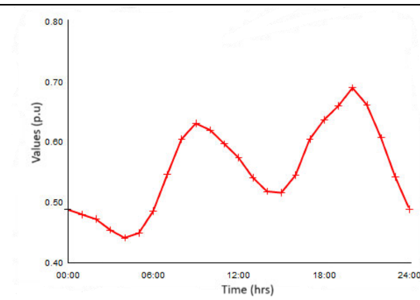
5.5.1 Load forecast for 1 year and 15 years

Case A: Load forecast for 1 year

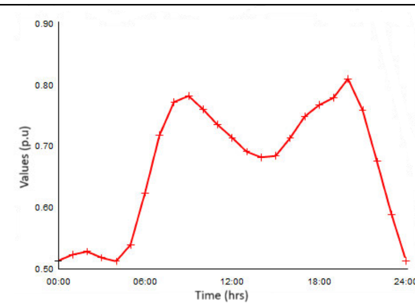
Figure 5.10 illustrates the annual variation of the load used in this study, which is the global load characteristics profile, enabling an evaluation of system performance during peak demand and the identification of potential network reinforcement requirements.



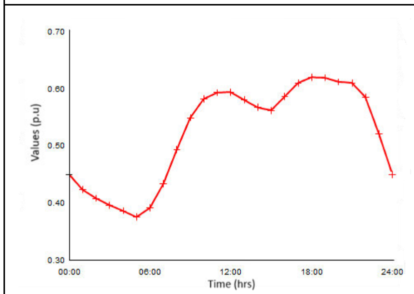
(a) Spring Sunday



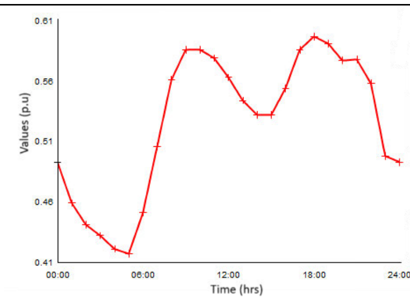
(b) Spring Saturday



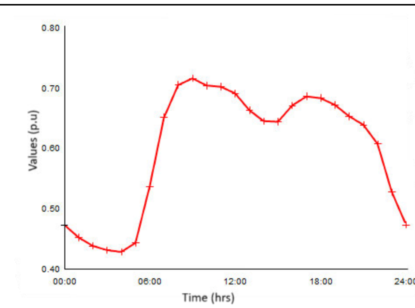
(c) Spring Weekdays



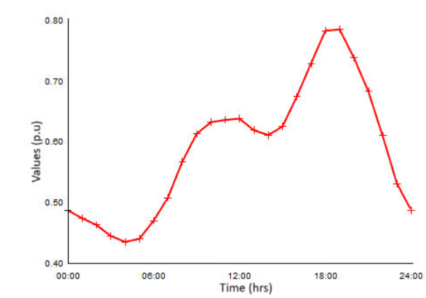
(d) Summer Sunday



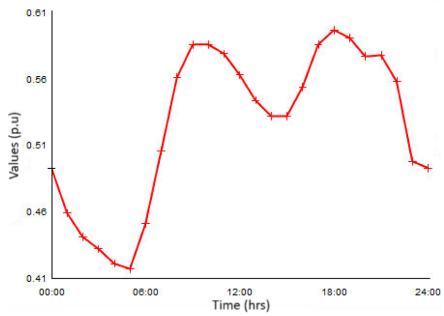
(e) Summer Saturday



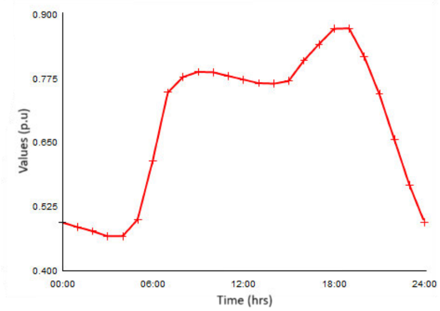
(f) Summer weekdays



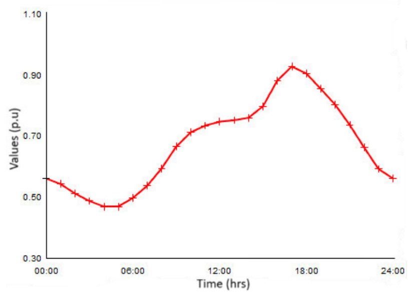
(g) Autumn Sunday



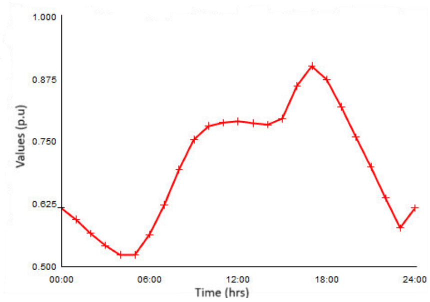
(h) Autumn Saturdays



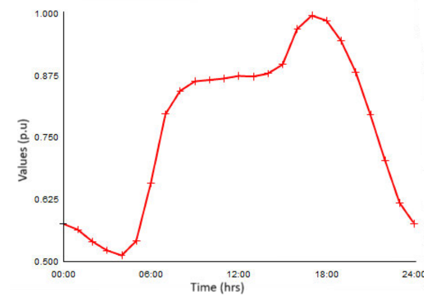
(i) Autumn Weekdays



(j) Winter Sunday



(k) Winter Saturdays



(l) Winter Weekdays

Figure 5. 10Load characteristic profile for a year

Figure 5.11 illustrates the comprehensive load variance across the entire year, as depicted in Figure 5.10

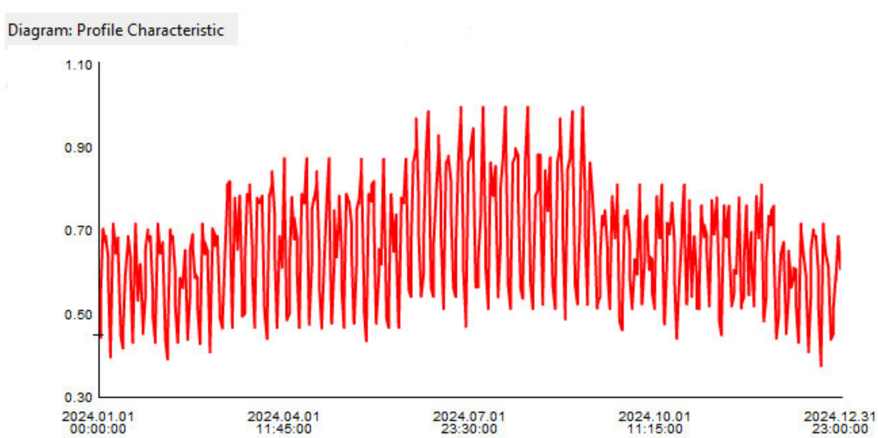


Figure 5. 11Complete load profile characteristics for a year

Case B: Load forecast for 15 years

A load projection is conducted for a medium-term planning horizon of 15 years, assessing the system's response to increasing load demand to accommodate growth as shown in Figure 5.12.

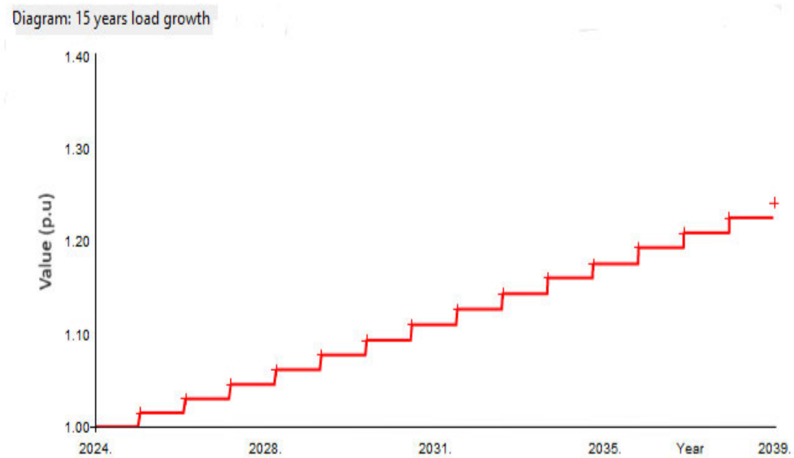
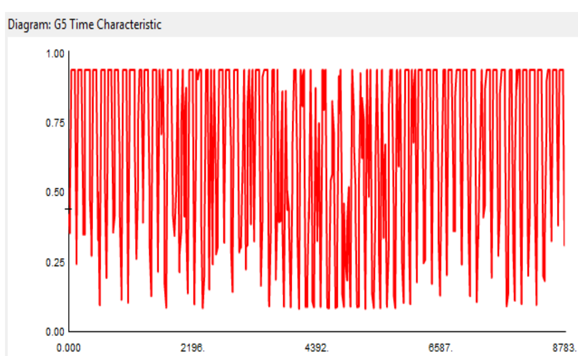


Figure 5. 1215 years of Load Growth

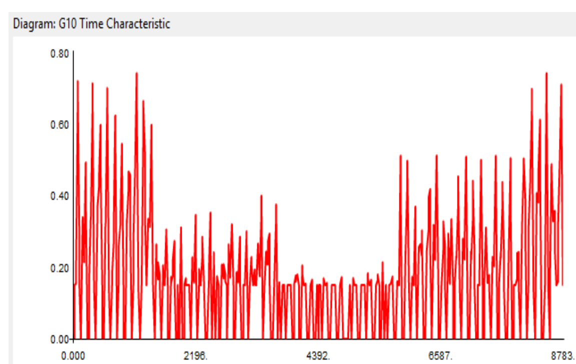
5.5.2 Quasi-Dynamic condition for 1 year and 15 years

A. Generator characteristics

Figure 5.13 represents the various features applied to the generators G5 and G10 in the Transmission network to adapt the power produced by each generator for each hour of the year.



(a) Generator G5

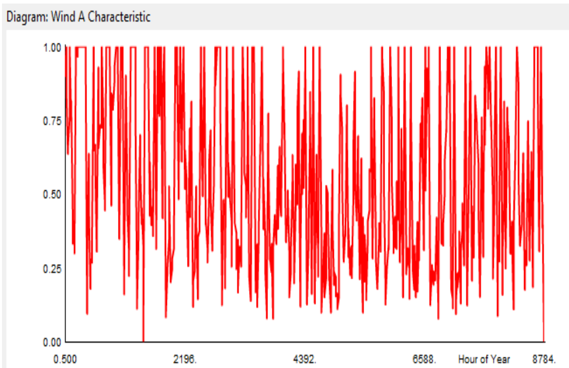


(b) Generator G10

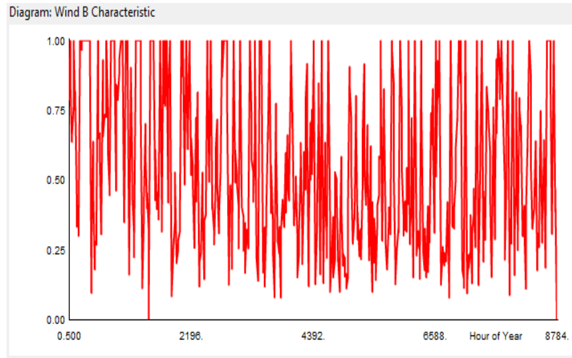
Figure 5. 13Time characteristics of generators

B. Wind turbine characteristics

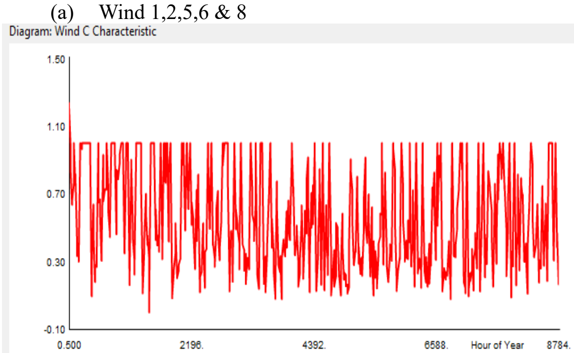
The following are the wind turbine characteristics that determine the amount of wind produced, which vary 2 times each hour throughout the year. Winds 1 and 8 have the same time characteristics as shown in Figure 5.14, as do winds 2, 3, 4, and 9.



(a) Wind 1,2,5,6 & 8



(b) Wind 3,9 & 10

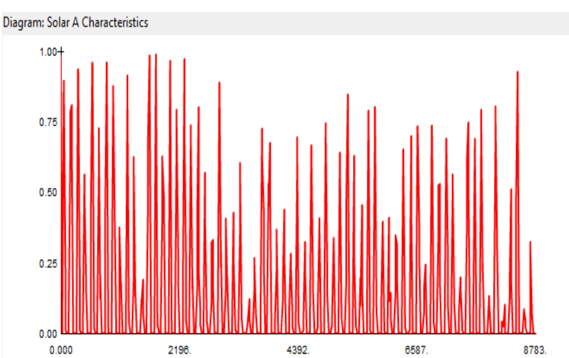


(c) Wind 4, 7 &11

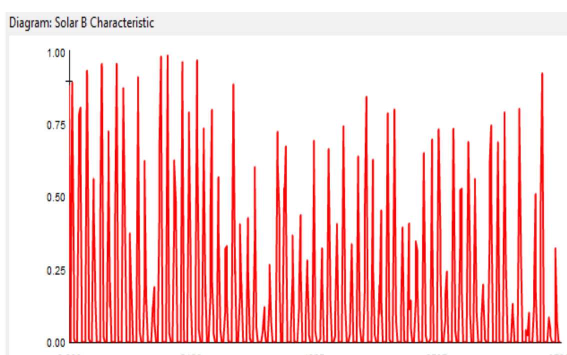
Figure 5. 14Wind generator time characteristics

C. Solar PV characteristics

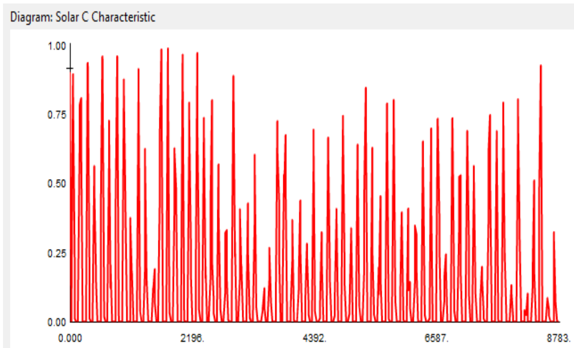
The periodic features of solar PV for the KK II solar PV Plant fluctuate bi-hourly throughout the year, leading to significant unpredictability in the output power generated by the solar facility as shown in Figure 5.15.



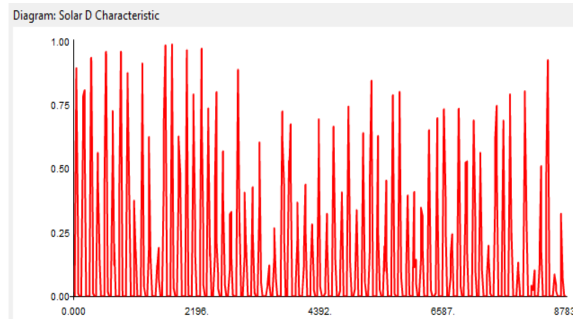
(a) PV 1, 14 & 9



(b) PV 2, 5, 8, 10 and 13



(c) PV 3, 7, 11, 12 & 15



(d) PV 4 and 6

Figure 5. 15PV solar characteristics

5.6 Implementation of probabilistic analysis using Quasi-Monte Carlo simulation

TEP with RE Integration utilizing QMCS Simulation is an innovative approach for assuring a reliable and economical power grid while integrating variable RES such as wind and solar. Conventional MC techniques are extensively employed for uncertainty analysis in TEP. Nonetheless, MC techniques depend exclusively on random sampling, which may be inefficient. QMC approaches enhance MC by employing low-discrepancy sequences (e.g., Sobol, Halton, Faure sequences) to more uniformly span the uncertainty space. It lowers variance and enhances convergence speed, resulting in more precise results with fewer simulations. Furthermore, it facilitates enhanced incorporation of stochastic renewable power models in planning. The advantages of QMCS in TEP with RES minimize computational expense and attain near-optimal solutions with fewer iterations. Enhanced uncertainty representation guarantees the capturing of infrequent yet significant grid circumstances. Enhanced integration of renewables enables optimal transmission design for high RES penetration. Probabilistic analysis allows network evaluation using probabilistic input data, providing an alternative to assessing individual operational scenarios. It is beneficial when input parameters are inherently random or when simulating the grid for future conditions while considering forecast errors. Examples of extreme scenarios that may necessitate network reinforcement include **Low load high infeed**, where the loads have been scaled to around 20% of their nominal power, at which point the generators yield their nominal output. The second scenario is **high load no infeed**, where all loads maintain their operational setpoint while generation is reduced to zero.

Figure 5.16 illustrates the characteristics applied to both sources and loads; specifically, Figure 5.16 (a) illustrates the transformed distribution allocated to the wind turbine, which integrates wind speed and the Weibull curve. Figure 5.16 (b) illustrates the distribution of prediction errors allocated to generators and solar photovoltaic systems to predict potential future inaccuracies. Figure 5.16 (c) illustrates the distribution predicated on load increase for the network throughout a 15-year expansion period. Figure 5.16 (d) illustrates the distribution of load fluctuation throughout the year, accounting for seasonal differences, which is utilized for short-term TEP.

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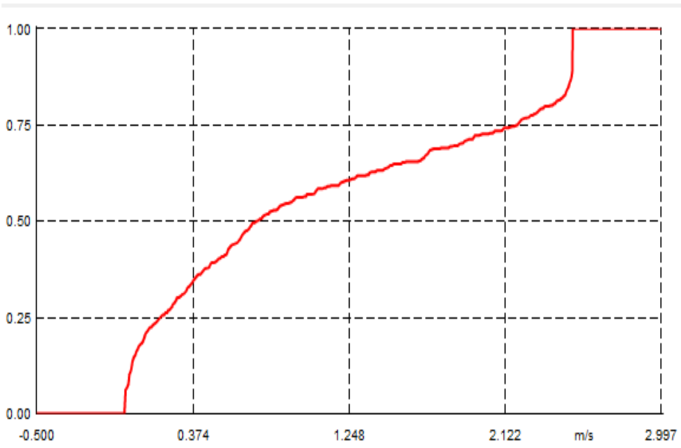
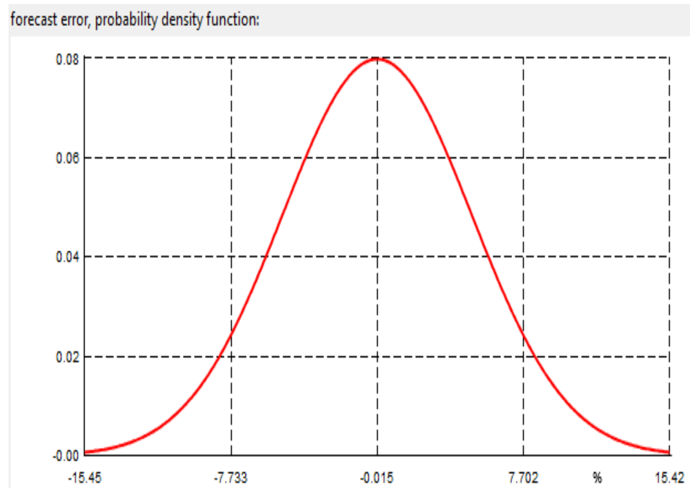
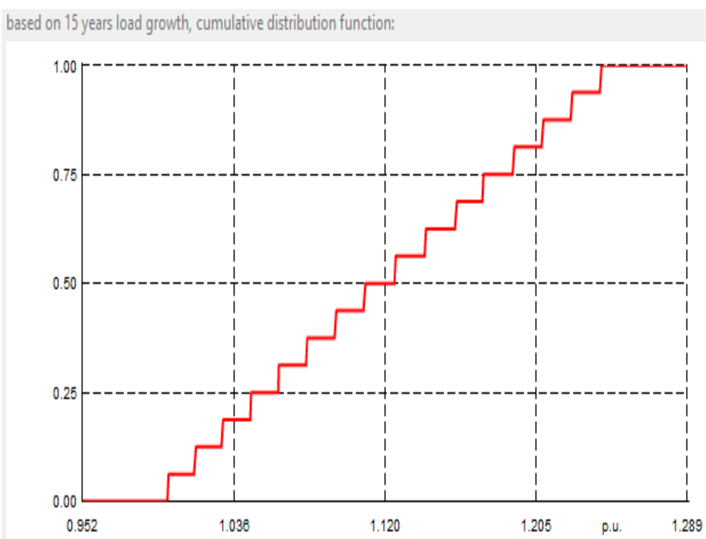


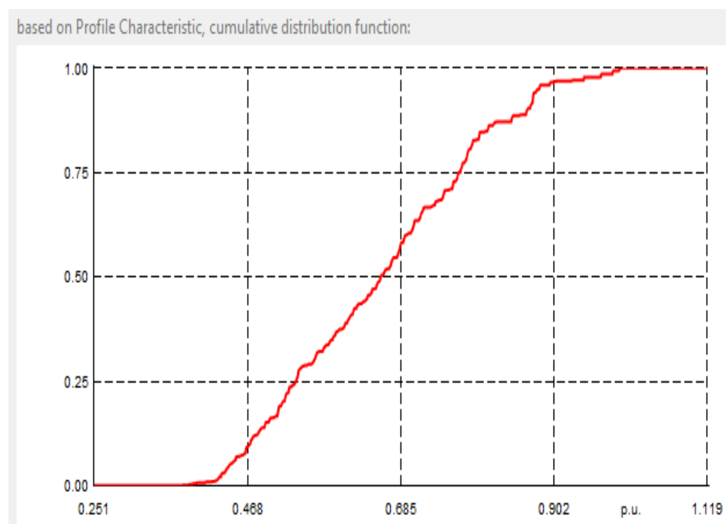
(a) Transformed distribution



(b) Forecast error



(c) Characteristics based on load growth for 15 years



(d) Characteristics based on load characteristics

Figure 5. 16Characteristics distribution on loads and sources

5.7 Transmission expansion method

The techno-economic calculation function is an economic evaluation that proposes a network expansion project. The investment costs of the specific strategy are contrasted with the financial advantages derived from the reduction of costs associated with system losses and anticipated interruptions. These quantities are determined during the techno-economic analysis utilizing a load flow or quasi-dynamic simulation in conjunction with reliability assessment.

5.8 Power park (RE wind farm) analysis

Power Park energy analysis evaluates the profitability of power parks, such as wind farms, through load flow calculations, enabling the determination of critical variables such as energy, profit, and loss based on network calculation findings. It employs the power park analysis function, and two distinct methodologies will be employed. Power Park analysis evaluates the profitability of power parks such as wind farms using a tool based on load flow calculations. Using network calculation results, you can easily estimate critical amounts of energy as well as profit and loss for a power park. This section compares basic energy analysis with probabilistic energy analysis. The wind farm consists of 11 wind turbines that are identically designed. This part uses the wind turbine with wind speed input, as seen before, and assigns the wind power curve based on the wind speed PowerPoint. The agreed-upon active connection power for this network is 27MW, which is the maximum power of all wind turbines linked to the farm. It is used as a reference for the calculation of the full load. The power park employs the boundary element named wind farm to define the boundary between the wind farm and the rest of the network. Table 5.7 shows the data for a single Weibull curve for the distribution function of the wind farm, wind speed. Table 5.8 delineates the specifications of the feed-in tariff and consumer tariff.

Table 5. 7Weibull curve data

Parameter	Value
Scale factor	10m/s
Shape factor	2
Confidence level	0.99999
Wind speed step size	0.1m/s

Table 5. 8Tariffs

Tariffs	Value (USD/kWh)
Feed-in tariff	0.05

Consumer tariff	0.25

Figure 5.17 illustrates the Weibull distribution applied to wind speed, with the shape and scale parameters detailed in Table 5.7. Figure 5.18 represents the distribution correlation utilized to determine the relationship among the 11 wind turbines in the wind farm, with the correlation coefficient established at 0.99. A higher coefficient signifies a stronger correlation, indicating that a value of 1 represents a perfect correlation. This is done for the second method which is probabilistic analysis using quasi-Monte Carlo simulation.

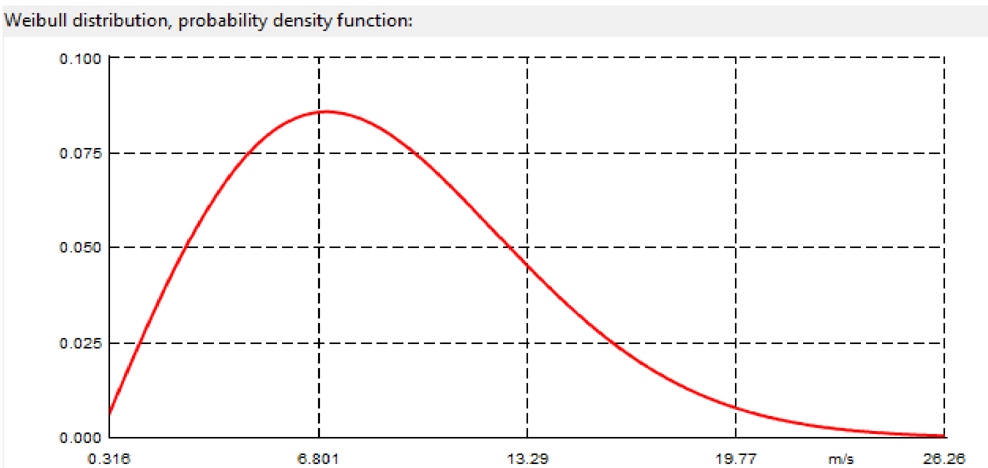


Figure 5. 17Weibull distribution

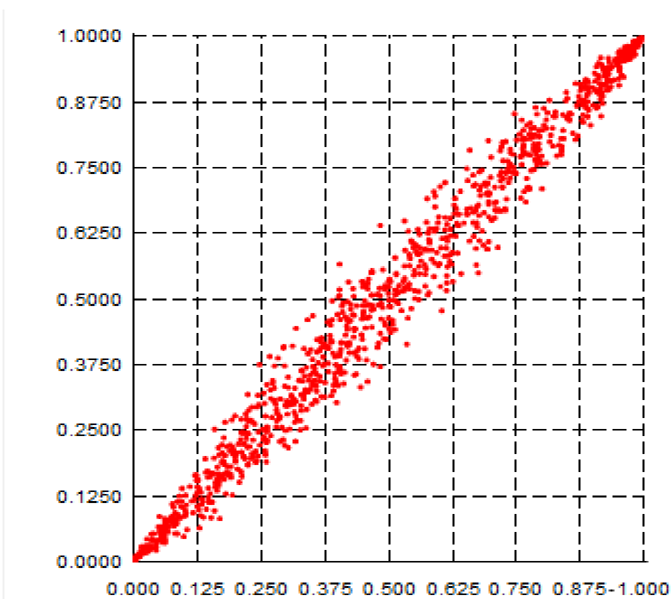


Figure 5. 18Wind speed correlation

Figure 5.19 illustrates the flowchart of the proposed methodology employed in this study to effectively integrate renewable energy into the existing network, accommodating load demand under varying conditions for both short- and long-term periods, while ensuring minimal losses and maintaining grid stability.

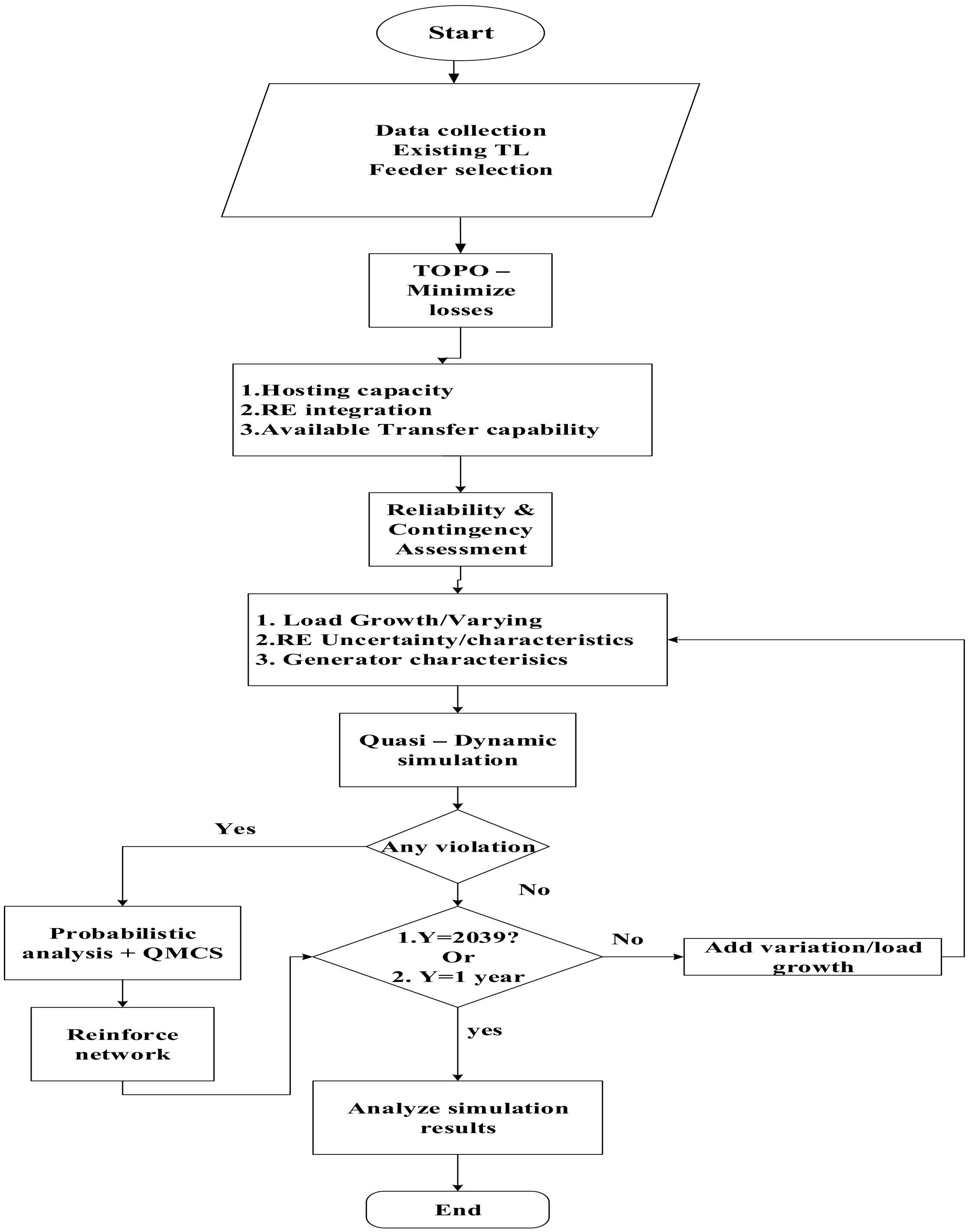


Figure 5. 19Flowchart of the proposed methodology for S&L term TEP with RE Integration

5.9 Summary

This chapter defines the methods employed to proficiently create a model incorporating a solar PV plant and a wind farm into a transmission network, aimed at accommodating long-term load expansion through the utilization of renewable energy. Furthermore, to efficiently identify the ideal locations for the installation of new transmission lines. This chapter presents the parameters, limitations, features, and distribution employed. Moreover, Figure 5.19 illustrates the comprehensive framework of the proposed technique for both short-term and long-term transmission expansion planning with renewable energy integration.

CHAPTER 6 SHORT & LONG-TERM TRANSMISSION EXPANSION PLANNING WITH RE INTEGRATION

TEP entails the design and enhancement of the electrical grid to satisfy present and future energy requirements while maintaining reliability and efficiency. Planners have unique obstacles when incorporating RES due to the fluctuating and sporadic characteristics of resources such as solar and wind power. Effective TEP ensures a stable, sustainable, and economically efficient power system capable of adapting to the changing dynamics of RE integration.

6.1 39-Bus New England system case study

This research employs 39-bus systems from DIgSILENT PowerFactory software, as shown in Figure 6.1. The network works under permissible values, as indicated in the small box, with permissible voltage p.u. and thermal loading.

The loading from the little box must not exceed 100%, as displayed in red. The voltage should not exceed 1.1 p.u., also marked in red, and must not fall below 0.9 p.u., indicated in blue.

Table 6.1 presents the power summary, encompassing the total power from all generators, the active power generated, the overall system losses, and the reactive power

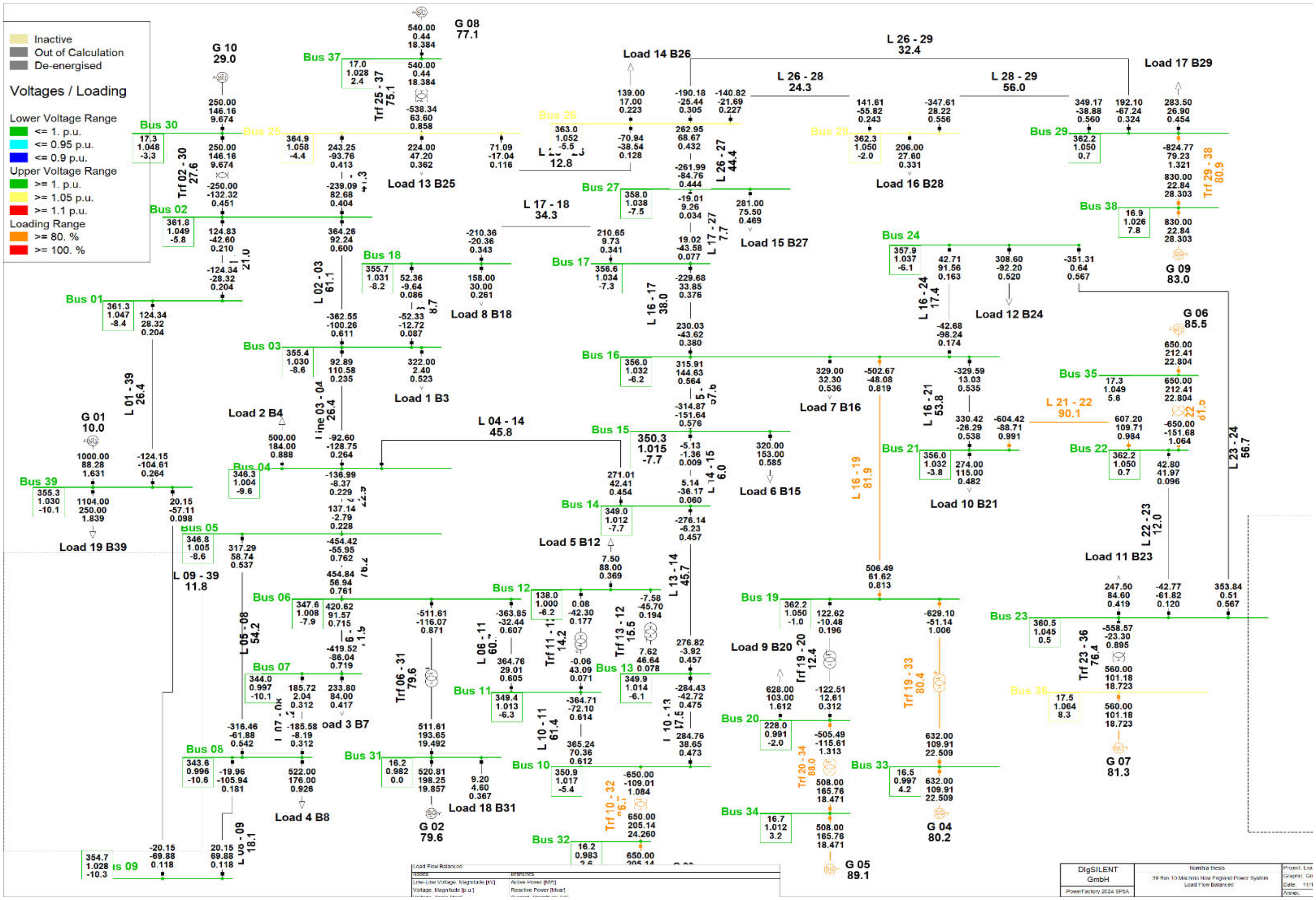


Figure 6. 1 39-Bus New England system network simulation results

Table 6. 1Power summary of 39-Bus New England System

Power Summary		
Generators, Active Power	Generators, Reactive Power	Generators, Apparent Power
6140.8MW	1250.4MVAr	6266.8MVA
Generators, Nominal Active Power	Generators, Nominal Reactive Power	Generators, Nominal Apparent Power
14535.0MW	9008.0Mvar	17100.0MVA
Generators, the difference between the maximum and actual active power	Generators, the difference between the maximum and actual reactive power	
8394.2MW	10619.6MVAr	
Loads, Active power	Loads, Reactive power	Loads, Apparent Power
6097.1 MW	1408.9 MVAr	6257.8MVA
Loads, Nominal Active Power	Loads, Nominal Reactive Power	Loads, Nominal Apparent Power
6097.1 MW	1408.9 MVAr	6257.8MVA
Loads, the difference between nominal and actual active power MW	Loads, the difference between nominal and actual reactive power MVAr	
0	0	
Losses, Active Power	Losses, Reactive Power	
43.7MW	-158.5MVAr	

Table 6.2 presents the maximum and minimum voltages within the system, as well as a maximum load of 90.1%, which remains within permissible limits. This loading is observable in the network along line L21-22.

Table 6. 2Equipment loading

Thermal Loading	
Maximum voltage of all terminals (p.u) – 1.064	Minimum voltage of all terminals (p.u) – 0.982
Maximum Loading (%) – 90.1	

Figure 6.2 portrays the voltage p.u for all the busbars in the system. It can be seen from the figure that this system comprises 39-buses all running at a permissible value.

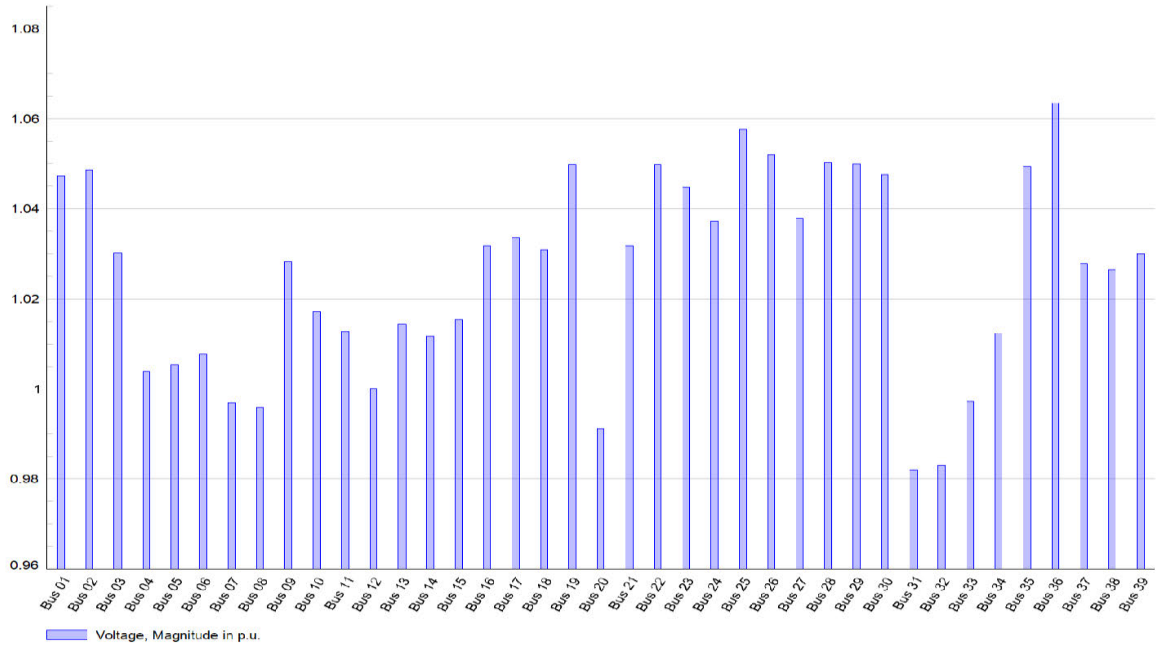


Figure 6. 2Busbar voltages in p.u. for a 39-bus New England System

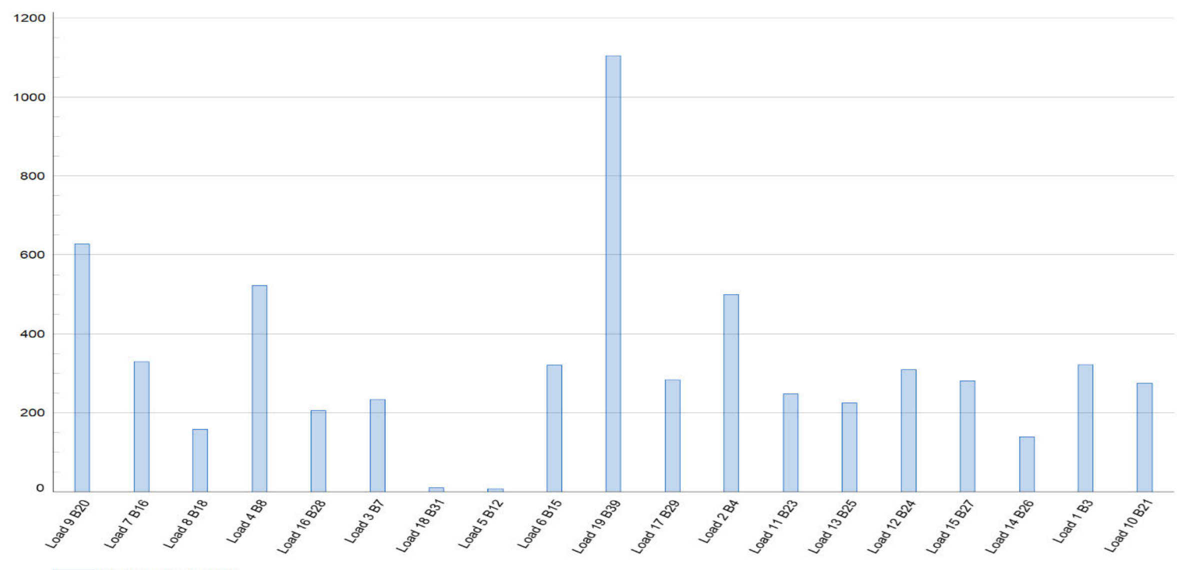


Figure 6. 3Active power in each busbar for a 39-Bus New England

Figure 6.3 illustrates the active power consumption of all system loads, with load 19 exhibiting the highest demand relative to other loads, while loads 18 and 5 demonstrate the lowest demand.

Figure 6.4 illustrates the active and reactive power generated by each generator within the network, with G01 yielding the highest output and G10 the lowest.

Figure 6. 4Active for 39-Bus New England

The 39-bus New England system is evaluated in 6.1 as the base case. This network will be utilized in this study to illustrate the necessity of increasing transmission lines with the integration of diverse renewable energy and guaranteeing the stability of the network.

6.2 Tie Open Point optimization Results

The tie open points are randomly chosen in the radial network to minimize network losses by selecting the ideal position for network open points. The selected tie open point may not be the optimal open point to reduce network losses; so, the TOP relocates this open point by deactivating it and activating the perfect open point. The TOPO was executed, and the open points were repositioned upon comparing Figure 6.5 with Figure 5.2, which is the figure with open points before the optimization to reduce losses. This strategy suggests relocating the open point from bus 16 to bus 23.

This optimization strategy may lead to the overloading of components, including lines, transformers, and busbars, posing a risk to network stability. As illustrated in lines 05-06 of the network, the line loading has escalated, with overloading indicated by the red line.

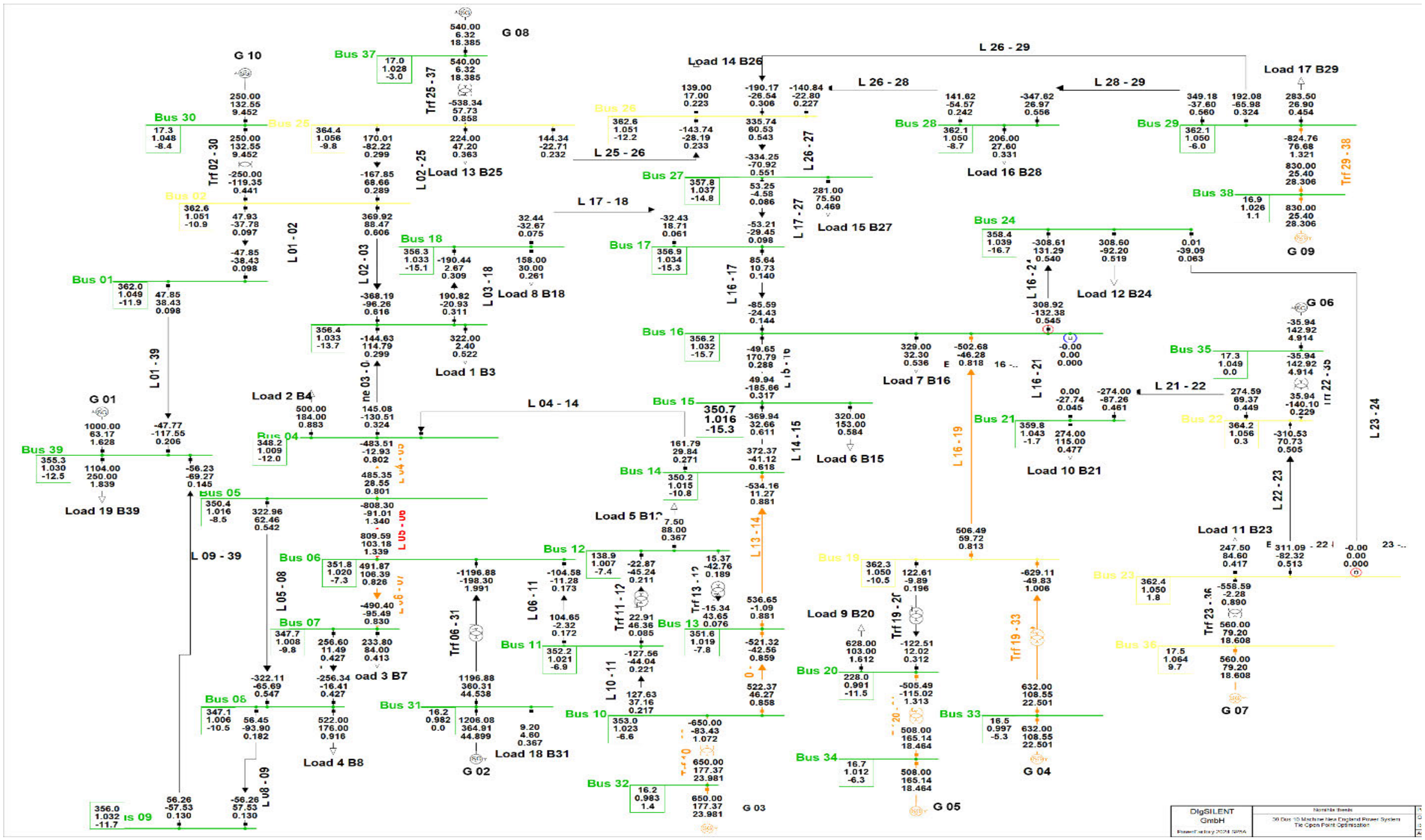


Figure 6. 539-Bus New England system under TOPO

Table 6.3 indicates that losses in the improved segment of the network were reduced from 12.1 MW to 10.5 MW. This technique is performed in DIgSILENT PowerFactory under the tool Distribution Network Optimization. Moreover, Appendix A shows the number of objective function evaluations, the number of modified elements, and the losses before and after optimization

Table 6. 3Comparison of losses before and after TOPO

Optimization	Total losses (MW)
Before Optimisation	12.1MW
After Optimisation	10.5MW
Absolute difference	1.7MW

6.3 Hosting capacity analysis and RE integration

This technique examines the extent of additional DER that can be integrated in relation to the supplementary consumer load. The coloration is depicted in accordance with the little box in the image below, illustrating the permissible power addition for each busbar without contravening system restrictions or necessitating any development or reinforcement inside the system. This is undertaken to enhance the network's capacity without compromising system stability; it is crucial to identify optimal methods for effectively integrating renewable energy into the network to meet the increasing population and future demand.

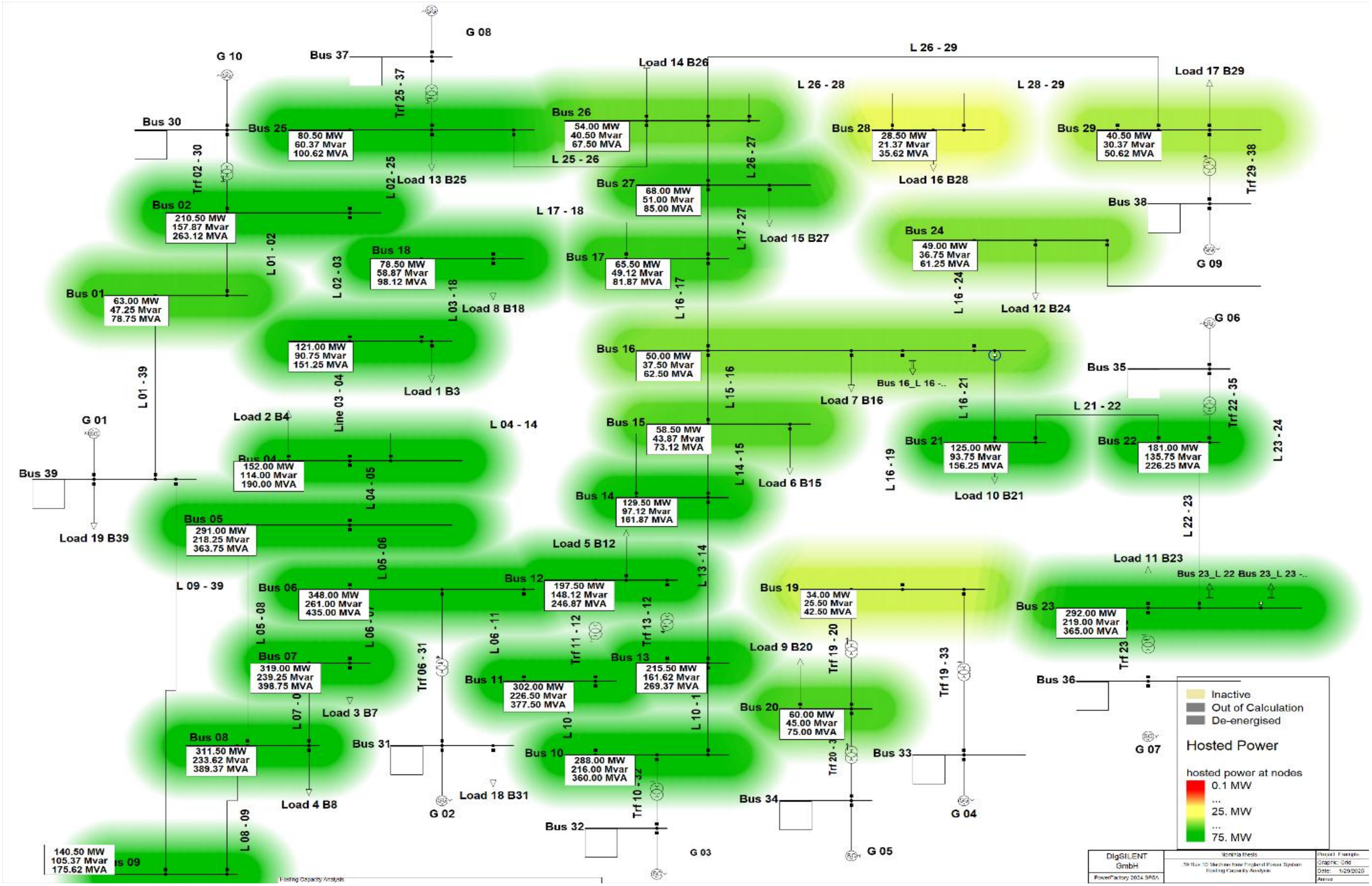


Figure 6. 639-Bus New England system under hosting capacity analysis

6.3.1 Hosting capacity analysis

Figure 6.6 illustrates the network, indicating the maximum power that can be added to each busbar without compromising network stability or necessitating reinforcement. Bus 06 is designated as the busbar capable of accommodating the largest capacity relative to all other busbars, while busbar 28 is identified as having the smallest capacity in comparison to the other busbars.

Table 7.5 displays the maximum active power that may be allocated to each busbar and the maximum loading, indicating that voltage is the limiting constraint for all busbars, with a maximum voltage of 1.05 p.u. Furthermore, it identifies the limiting components that constrain the hosting capacity.

Table 6. 4Maximum hosting power with its limiting components

Terminals	Max Active Power kW	Max Loading (%)	Max / Min Voltage p.u	Limiting components
1. Bus 28	28.50000	88.27173	1.049959	Bus 28
2. Bus 19	34.00000	88.05137	1.049969	Bus 19
3. Bus 29	40.50000	88.27642	1.049984	Bus 29
4. Bus 24	49.00000	88.01340	1.049991	Bus 19
5. Bus 16	50.00000	88.02035	1.049984	Bus 19
6. Bus 26	54.00000	88.17022	1.049957	Bus 26
7. Bus 15	58.50000	87.95923	1.049982	Bus 19
8. Bus 20	60.00000	92.03264	1.049984	Bus 19
9. Bus 01	63.00000	88.26175	1.049946	Bus 01
10. Bus 17	65.50000	87.96071	1.049989	Bus 19
11. Bus 27	68.00000	88.03544	1.049985	Bus 26
12. Bus 18	78.50000	87.95721	1.049995	Bus 19
13. Bus 25	80.50000	88.20609	1.049994	Bus 25
14. Bus 03	121.0000	87.95753	1.049993	Bus 19
15. Bus 21	125.0000	88.30901	1.049928	Cub 5
16. Bus 14	129.5000	87.95788	1.049999	Bus 19
17. Bus 09	140.5000	88.21810	1.049964	Bus 09
18. Bus 04	152.0000	87.95673	1.049998	Bus 19
19. Bus 22	181.0000	88.30901	1.049975	Bus 22
20. Bus 12	197.5000	88.03803	1.049922	Bus 12
21. Bus 02	210.5000	88.02712	1.049987	Bus 25
22. Bus 13	215.5000	87.95732	1.049999	Bus 19
23. Bus 10	288.0000	98.35424	1.049998	Bus 19
24. Bus 05	291.0000	87.95902	1.049998	Bus 19
25. Bus 23	292.0000	97.61356	1.049996	Bus 22
26. Bus 11	302.0000	92.92618	1.049999	Bus 19
27. Bus 08	311.5000	87.95717	1.049999	Bus 19
28. Bus 07	319.0000	87.95681	1.049998	Bus 19

29. Bus 06	348.000	87.95681	1.049998	Bus 19

6.3.2 Integration of wind farm and solar Plant

This study aims to integrate two renewable energy sources: the Metro Wind farm, with an installed capacity of 27.5 MW, and the Konkonsies II solar PV plant, with an installed capacity of 75 MW. These two renewable energy facilities are operational plants situated in the Northern Cape of South Africa. This study aims to integrate them into the transmission line to enhance electricity accessibility.

Figure 6.7 illustrates the simulated Metro wind farm, which includes 11 identical wind turbines, each generating 2.5 MW, which is 90% of their maximum capacity at a wind speed of 16 m/s. The total power produced is 27.39 MW, with minimal losses accumulated in the cables. This network indicates that the plant is operating under normal operating conditions, as evidenced by the small box.

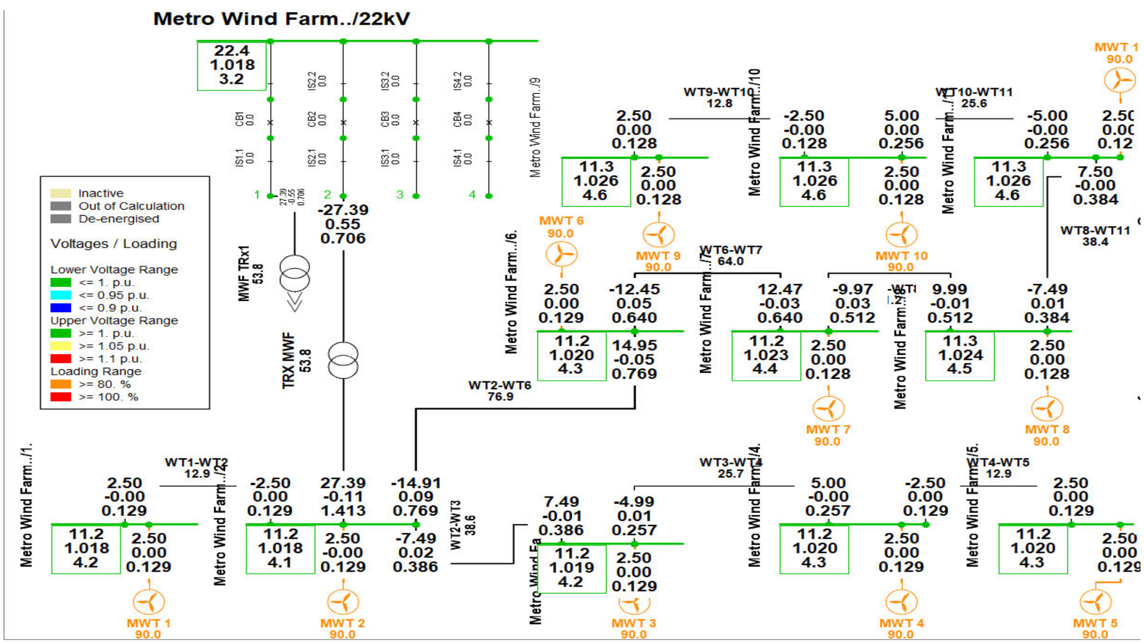


Figure 6. 7Metro wind farm simulation network

Figure 6.8 illustrates the KK II solar PV plant, with 15 identical solar PV units, each producing 5MW, which is 71.4% of their full capacity. The aggregate power output is 73.26MW, with 1.74MW wasted in the cabling connecting the busbars. The KK II solar PV power is functioning within acceptable parameters, hence enhancing system stability.

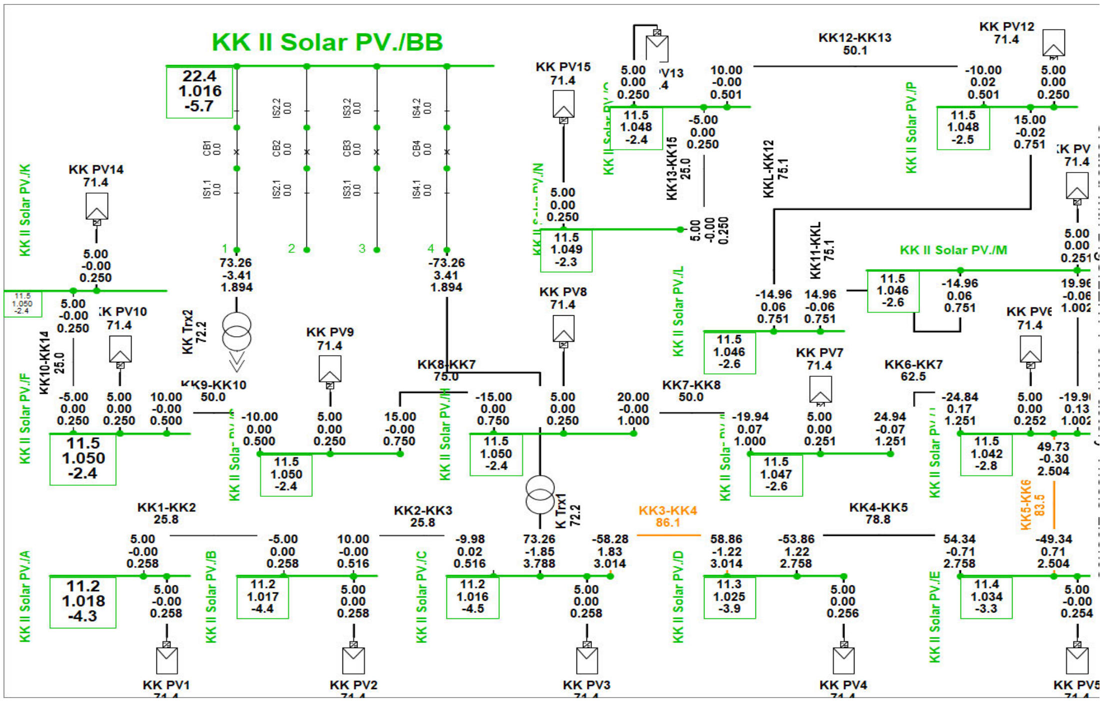


Figure 6. 8Konkonsies II Solar PV simulation network results

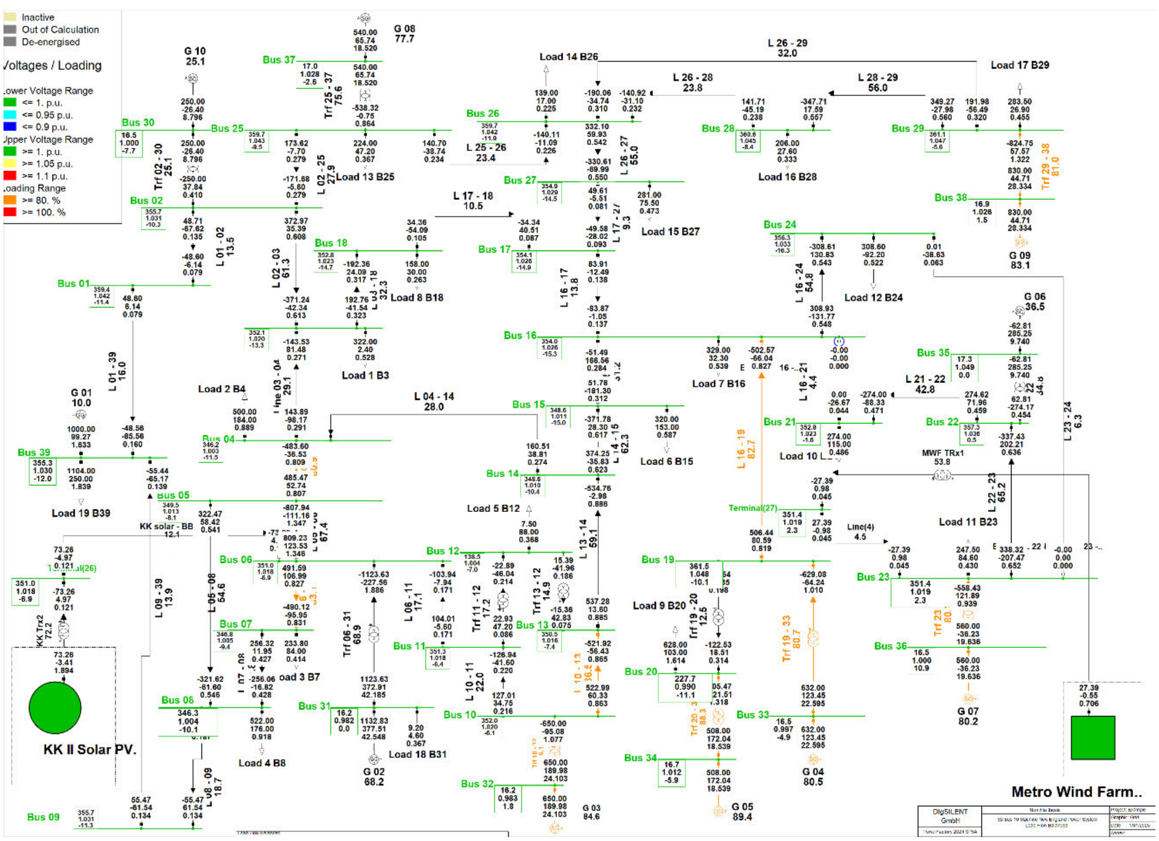


Figure 6. 939-Bus New England with wind and solar PV simulation network

Figure 6.9 shows the complete network after the integration of the Wind and Solar PV plant. The network is working under normal conditions, as advised by the hosting capacity for the best location of added RE.

Table 6.5 presents the power summary of the 39-bus systems with Renewable Energy (RE) Integration. An additional 1.7 MW of active power is attributed to losses incurred during network expansion. The demand for load remains the same. The nominal active power has increased due to the addition of more power to the system.

Table 6. 5Power summary of 39-Bus with RE integration

Power Summary with RE Integration		
Generators, Active Power	Generators, Reactive Power	Generators, Apparent Power
6142.5MW	1295.3MVAr	6277.6MVA
Generators, Nominal Active Power	Generators, Nominal Reactive Power	Generators, Nominal Apparent Power
15549.5MW	9620.2Mvar	18284.80MVA
Generators, the difference between the maximum and actual active power	Generators, the difference between the maximum and actual reactive power	
9400MW	11309.7MVAr	
Loads, Active power	Loads, Reactive power	Loads, Apparent Power
6097.1 MW	1408.9	6257.8MVA
Loads, Nominal Active Power	Loads, Nominal Reactive Power	Loads, Nominal Apparent Power
6097.1 MW	1408.9	6257.8MVA
Loads, the difference between nominal and actual active power MW	Loads, the difference between nominal and actual reactive power MVAr	
0	0	
Losses, Active Power	Losses, Reactive Power	
45.4MW	-113.6MVAr	

Table 6.6 presents the maximum loading of all network components, together with the maximum and minimum voltage per unit of all busbars inside the network. Figure 7.7 illustrates the 90%

maximum loading of the wind turbine. It can be observed from the table that the network constraints are not violated

Table 6. 6 Thermal loading of a 39-bus system with RE integration

Thermal Loading with RE Integration	
Maximum voltage of all terminals (p.u) – 1.05	Minimum voltage of all terminals (p.u) – 0.982
Maximum Loading (%) – 90	

6.4 Reliability analysis

The reliability evaluation was conducted through contingency analysis of terminals, lines, and transformers across the whole network. The fault must be cleared by switches with a protection device. Figure 6.10 illustrates the network findings of the reliability assessment, with colors indicating the annual interruption time calculated for loads. The regions marked in red are expected to endure more than one hour of supply disruption annually.

Figure 6.10 is shaded to represent the annual interruption duration computed for loads; the regions shown in red are expected to endure over one hour of supply disruption each year.

Table 6.7 presents the indices for several component types utilized to signify reliability, indicating that terminals are the primary contributors to annual supply interruption modes.

Table 6. 7Contributions of component groups to system indices

Components	**SAIFI (1/Ca)**	**SAIDI (h/Ca)**	**ASIFI (1/a)**	**ASIDI (h/a)**	**ENS (MWh/a)**
Lines	0.4340	4.3399	0.7188	7.1882	43826.89
Transformers	0.0373	0.4472	0.0406	0.5217	3180.5
Terminals	4.5379	140.2840	4.6768	127.88	2882.22
Equipment	**SAIFI %**	**SAIDI%**	**ASIFI%**	**ASIDI%**	**ENS%**
Lines	8.6638	2.9915	13.2229	5.3013	5.3013
Transformers	0.7439	0.3082	0.7460	0.3847	0.3847
Terminals	90.5923	96.7002	86.0311	94.3140	94.3140

Figure 6.11 illustrates many components of the network, detailing each component's contribution to the indices. It serves to identify which components have the most influence on each index when applied to the entire network. Moreover, the possible outages are shown in Appendix B where they were calculated to be 148.

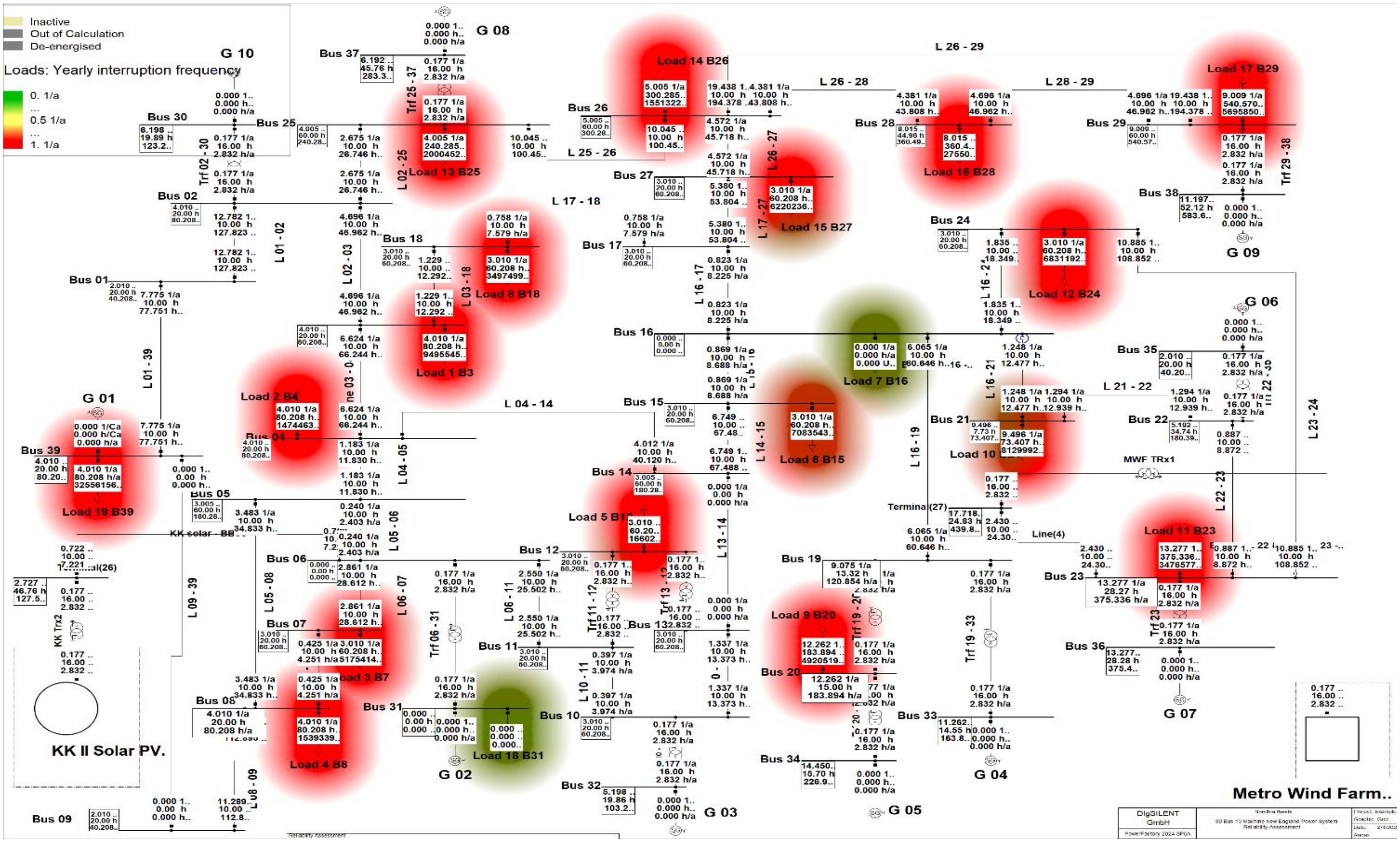


Figure 6. 10Network simulation under reliability assessment

Minimum Contr. 0.000000 % of c:C_SAIFI

	Name	In Folder	Contribution to SAIFI [1/Ca]	C_SAIFI [%]	C_SAIFI [%]	Contribution to SAIDI [h/Ca]	C_SAIDI [%]	C_SAIDI [%]	Contribution to ENS [MWh/a]	C_ENS [%]	C_ENS [%]
9	Bus 39	Grid	0.211074	4.213747		4.221473	2.909936		88549.627991	10.710873	
10	Bus 25	Grid	0.210776	4.207811		12.646578	8.717508		53823.836975	6.510477	
11	Bus 29	Grid	0.210776	4.207811		12.646578	8.717508		68120.793672	8.239822	
12	Bus 07	Grid	0.158442	3.163043		3.168842	2.184338		14076.630850	1.702695	
13	Bus 12	Grid	0.158442	3.163043		3.168842	2.184338		451.560009	0.054620	
14	Bus 15	Grid	0.158442	3.163043		3.168842	2.184338		19266.560364	2.330464	
15	Bus 18	Grid	0.158442	3.163043		3.168842	2.184338		9512.864180	1.150666	
16	Bus 19	Grid	0.158442	3.163043		3.168842	2.184338		37810.624714	4.573535	
17	Bus 20	Grid	0.158442	3.163043		3.168842	2.184338		37810.624714	4.573535	
18	Bus 21	Grid	0.158442	3.163043		3.168842	2.184338		16496.992311	1.995459	
19	Bus 24	Grid	0.158442	3.163043		3.168842	2.184338		18580.189518	2.247441	
20	Bus 27	Grid	0.158442	3.163043		3.168842	2.184338		16918.448319	2.046438	
21	Bus 28	Grid	0.158442	3.163043		3.168842	2.184338		12402.848234	1.500236	
22	Bus 36	Grid	0.105811	2.112338		2.110920	1.455094		9926.601581	1.200712	
23	L 21 - 22	Grid	0.068100	1.359502		0.680997	0.469423		3545.271337	0.428832	
24	L 22 - 23	Grid	0.046697	0.932230		0.466970	0.321890		2195.924293	0.265617	
25	Trf 22 - 35	Grid	0.018632	0.371950		0.149518	0.103066		703.344904	0.085076	
26	Trf 19 - 20	Grid	0.009316	0.185975		0.149053	0.102745		1778.496011	0.215125	
27	Trf 23 - 36	Grid	0.009316	0.185975		0.148587	0.102424		698.729629	0.084518	
28	KK1-KK2	KK II Solar PV.	0.000000	0.000000		0.000000	0.000000		0.000000	0.000000	

Figure 6. 11Contribution of each component to indices

6.5 Load forecast and Quasi-Dynamic simulation

Load forecasting is an essential procedure for anticipating future energy requirements across regions and power networks, assisting utilities in ensuring that energy supply always aligns with demand. It employs diverse models to forecast short-term requirements (such as daily or hourly consumption) and long-term trends extending over years or even decades. This study encompasses two load prediction analyses: an annual load forecast segmented by seasons—summer, spring, autumn, and winter—and it also incorporates weekends and holidays to predict demand under varying situations. The second section encompasses a load prediction spanning 30 years, with an escalation in load growth.

6.5.1 Load forecast and quasi-dynamic for 1 year

Case A: Load forecast for 1 year

This section shows how the system behaves under different conditions throughout the year. Various characteristics have been assigned to loads based on different seasons, holidays, and weekends, as illustrated in Figure 6.12. The network used for load forecast over a year is the same as the base network the only thing that has been added is four load demands.

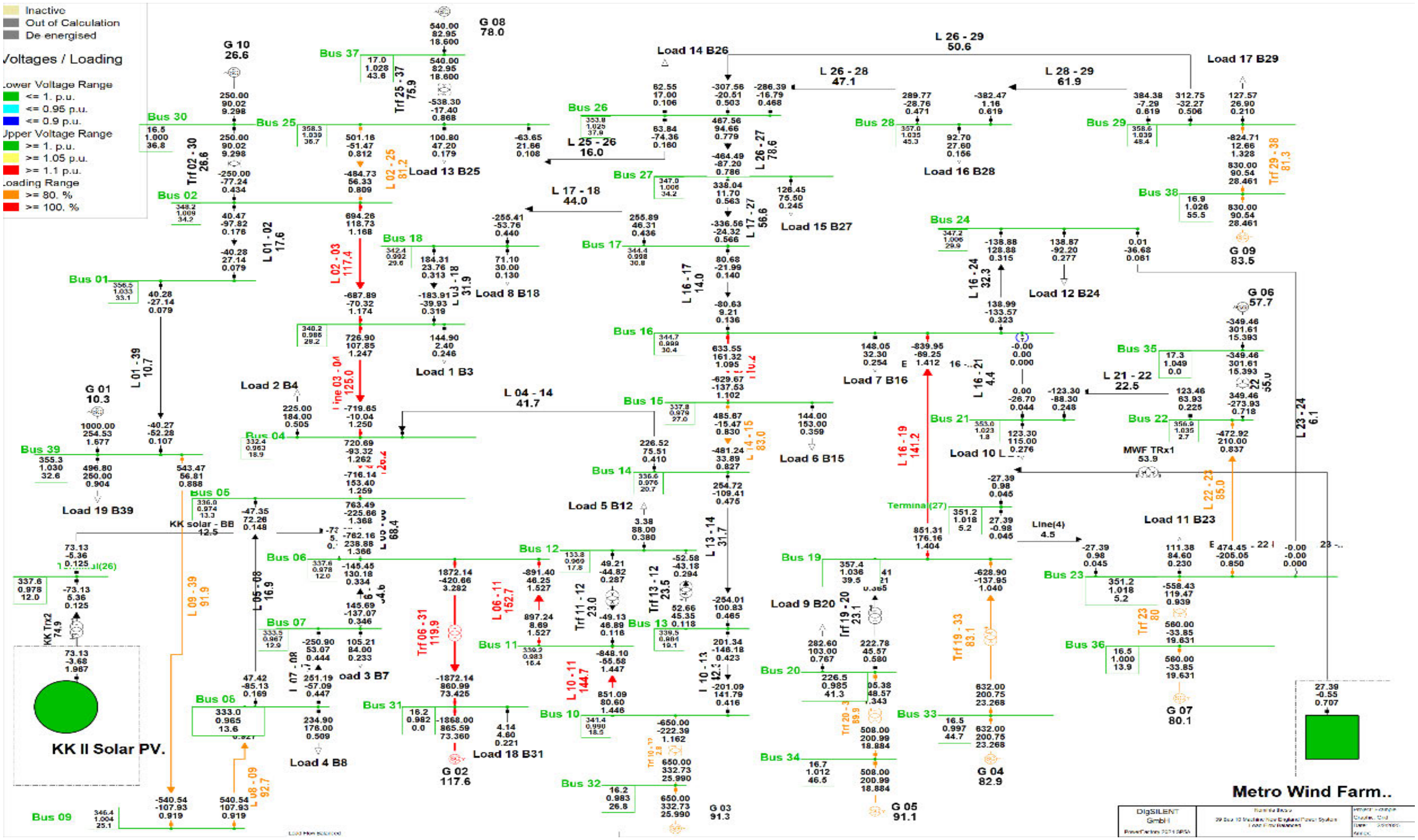
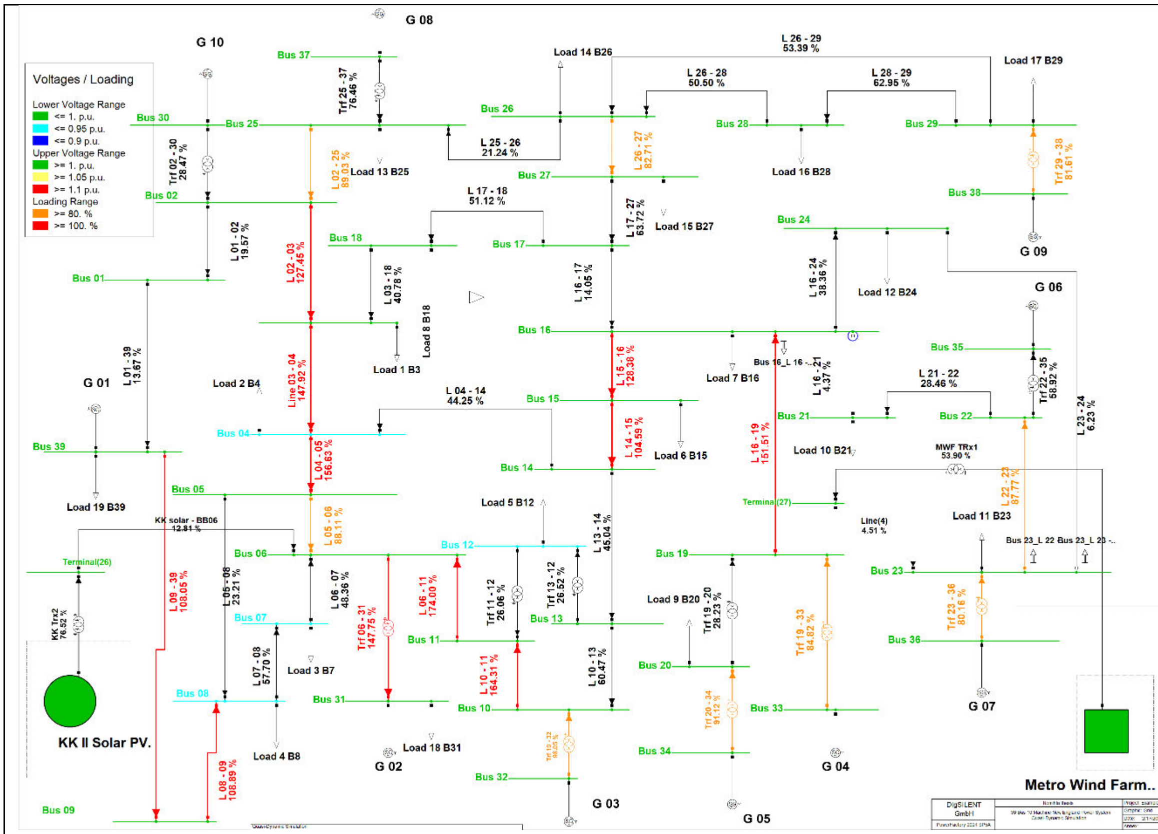


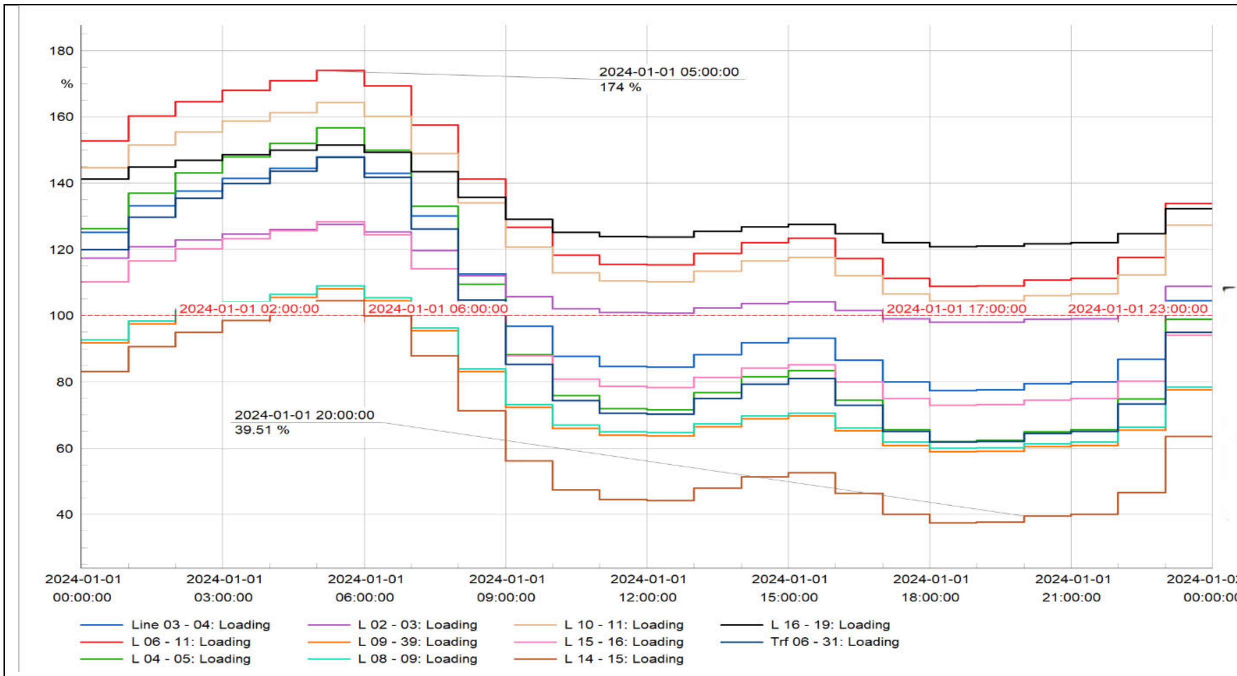
Figure 6. 12Load flow analysis under load forecast

Figure 6.12 illustrates the whole network with load demand fluctuating throughout several seasons. It is evident that owing to the variable load, certain components require reinforcement to address overloading issues, as shown by line L06-11, which experiences loading above 100%.

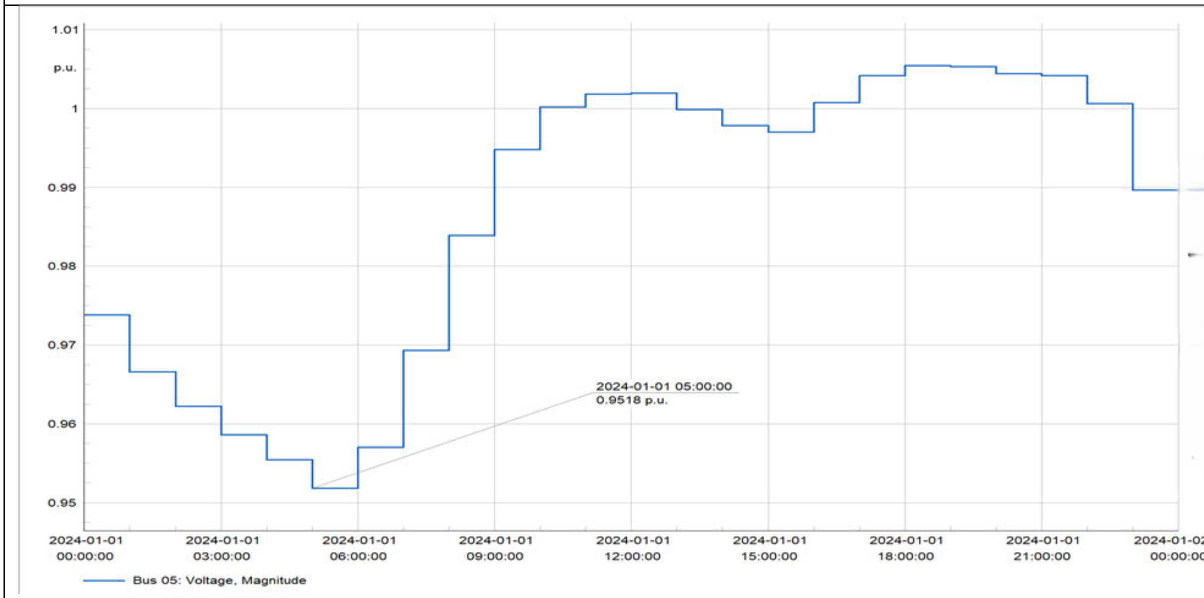
Figure 6.13 (a) illustrates the variation of loading throughout the day. The figure includes all lines that exceed permissible loading, allowing for the identification of times when loading exceeds 100% and the duration of such occurrences, enabling informed decisions to maintain grid stability. Figure 6.13(b) illustrates the per unit voltage for busbar 05, indicating that the voltage is at its minimum when line loading is elevated, as seen in Figure 6.13(a), attributable to increased demand. The voltage per unit is functioning within permissible limits.



(a) Network under load forecast for 1 day



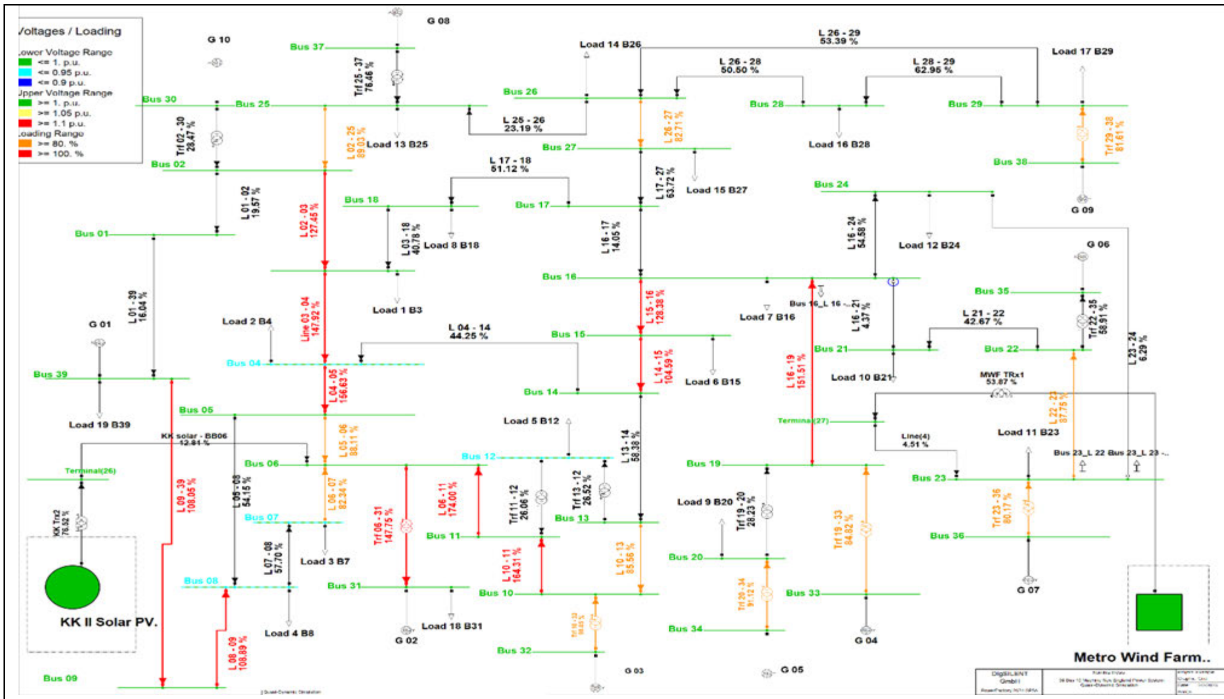
(b) Thermal loading under load forecast (1 Day)



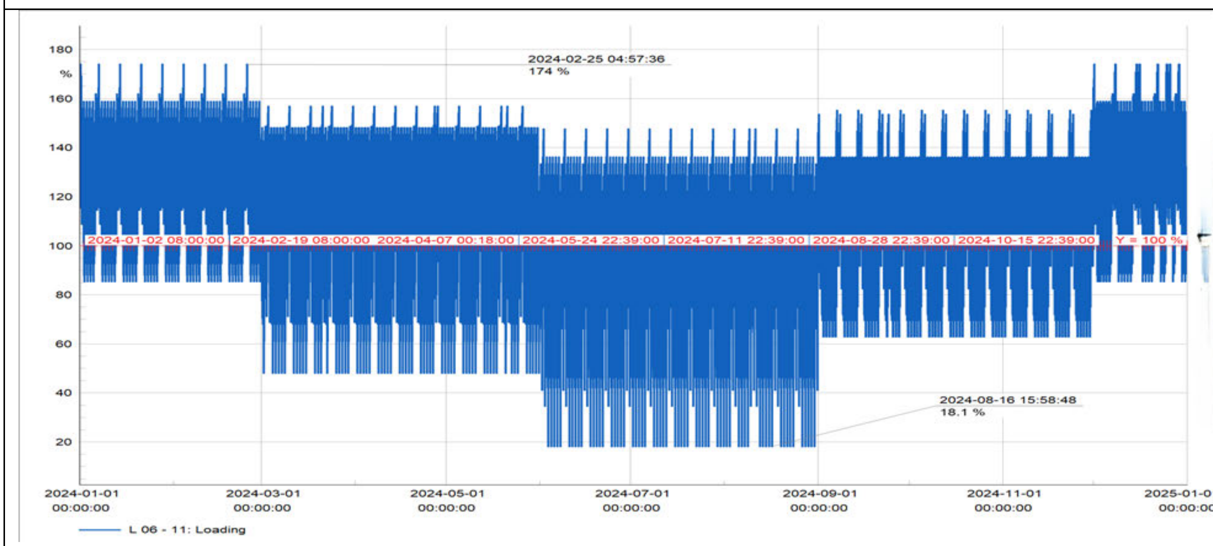
(c) Voltage p.u (1 day) for Bus 5

Figure 6. 13Effect of load forecast for 1 day

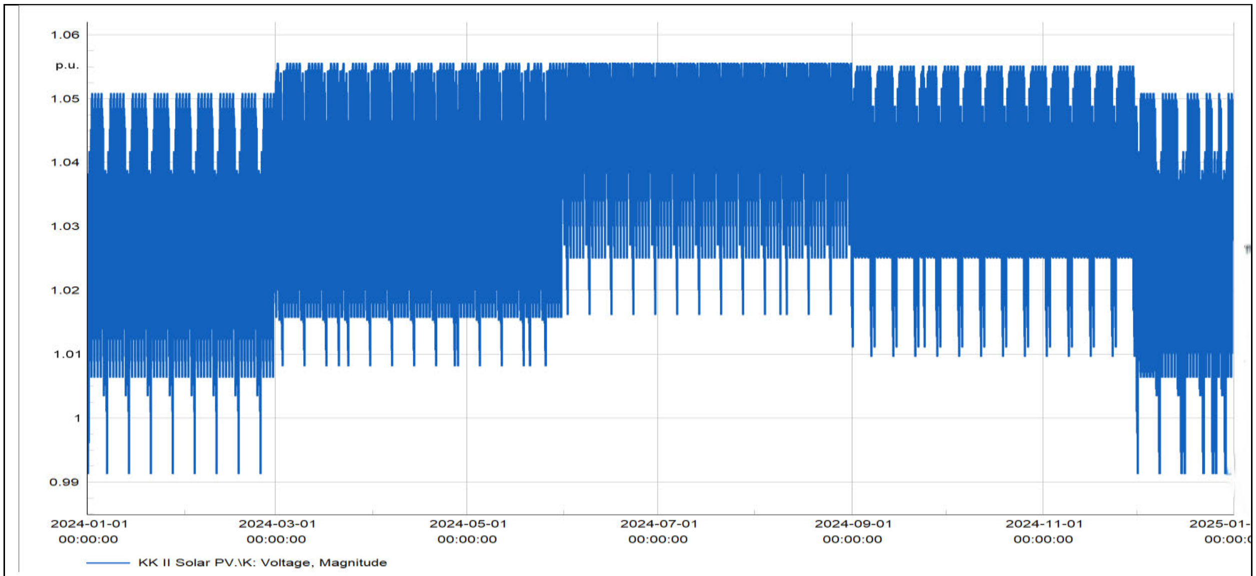
Upon comparing Figure 6.10 and Figure 6.14(a), it is evident that the same lines and transformers require strengthening, with the addition of two lines, specifically L08-09 and L09-39. This figure represents the load projection for one year, taking into consideration hourly load variations. Figure 6.14 (b) illustrates the thermal loading over one year for L06-11, which exhibits the highest loading compared to other lines. This figure depicts the times when this line surpasses permissible loading, denoted by Y=100%. Figure 6.14(c) illustrates the per unit voltage over the course of one year for the busbar in the wind farm. Despite variations, all busbars within the network function within constrained limitations, as seen in Figure 6.14(a).



(a) Load forecast for 1 year



(b) L06-11 thermal loading for 1 year



(c) KK II solar Busbar Voltage p.u for 1 year

Figure 6. 14Load forecast for 1 year

The thermal loading for May 2024 for line L06-11 increases significantly on Sundays, as seen in Figure 6.15, where it reaches 156.8%. Additionally, the impact of the holiday is evident on May 21, with a loading of 154.1%.

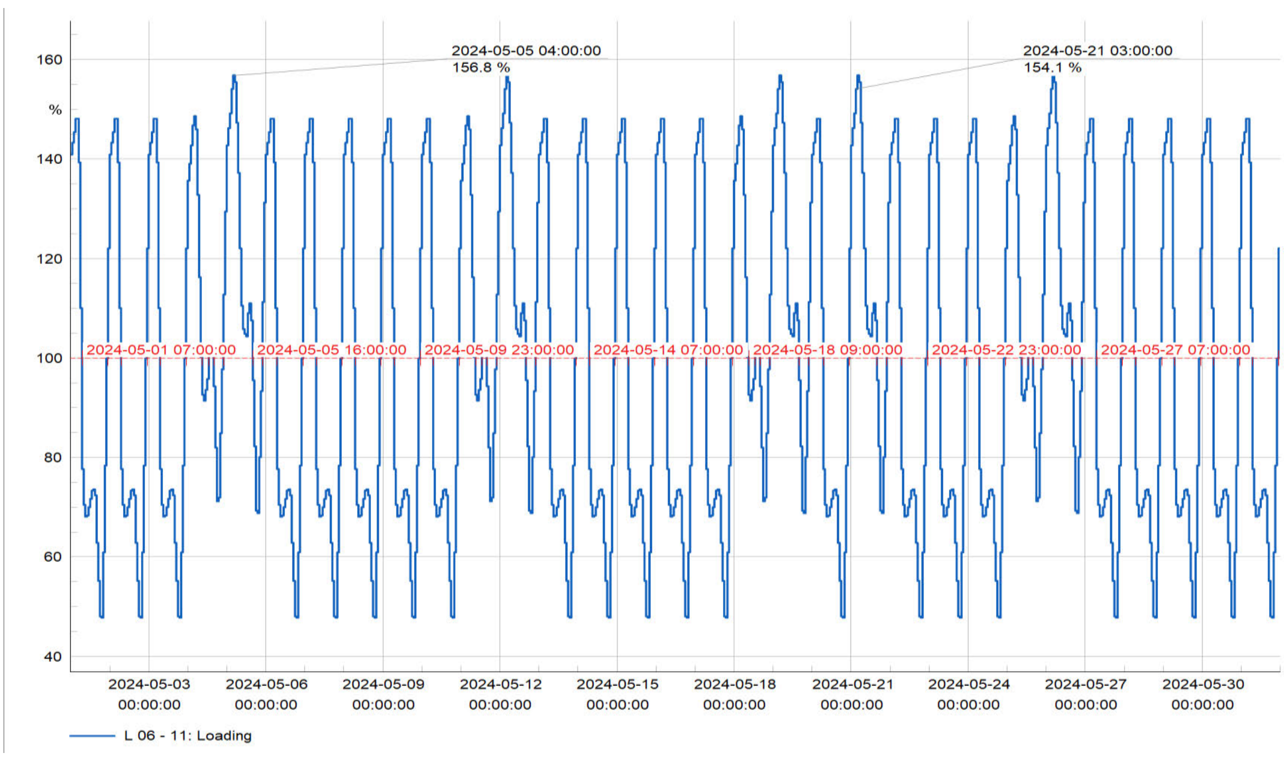


Figure 6. 15L06-11 line loading for May 2024

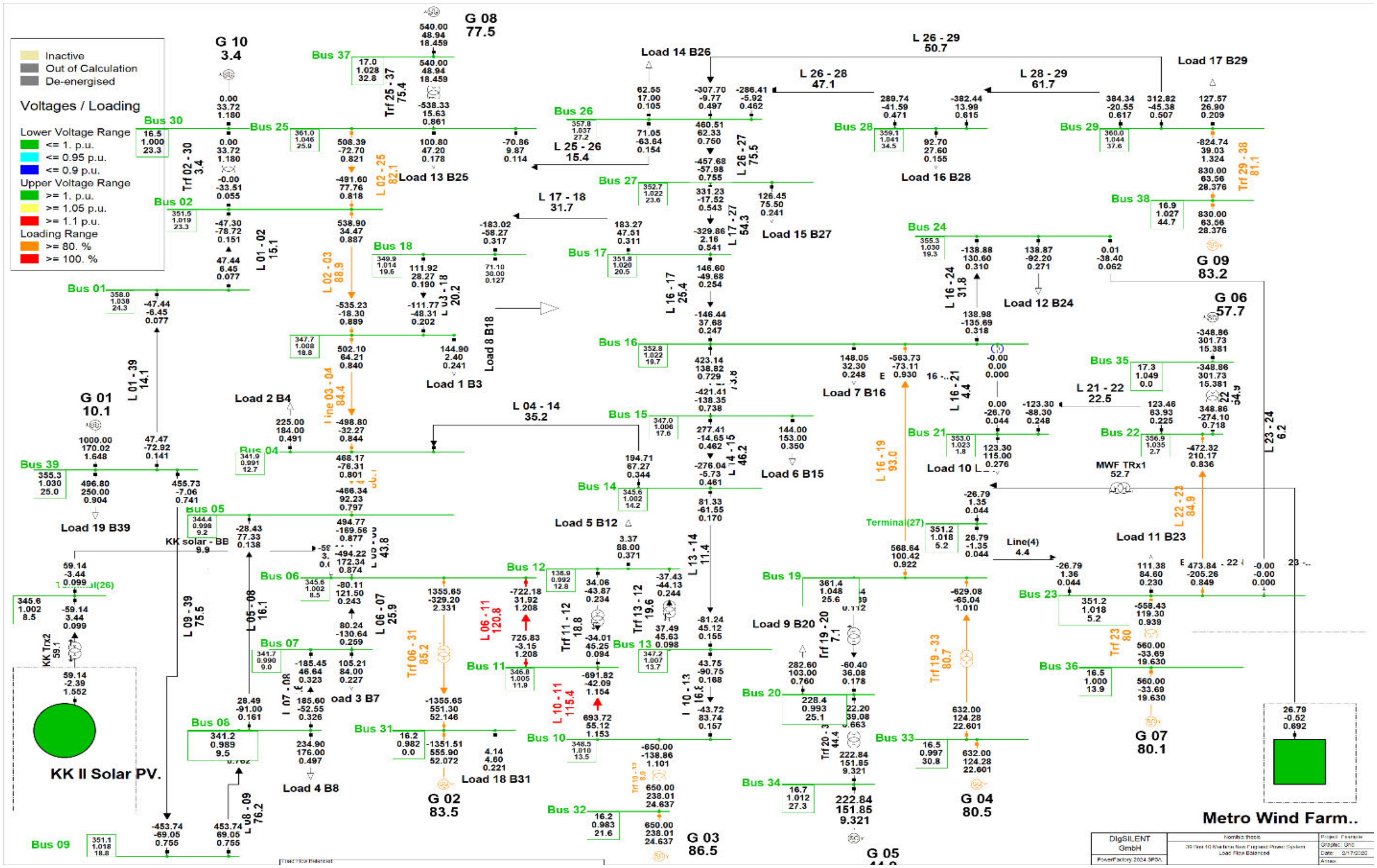
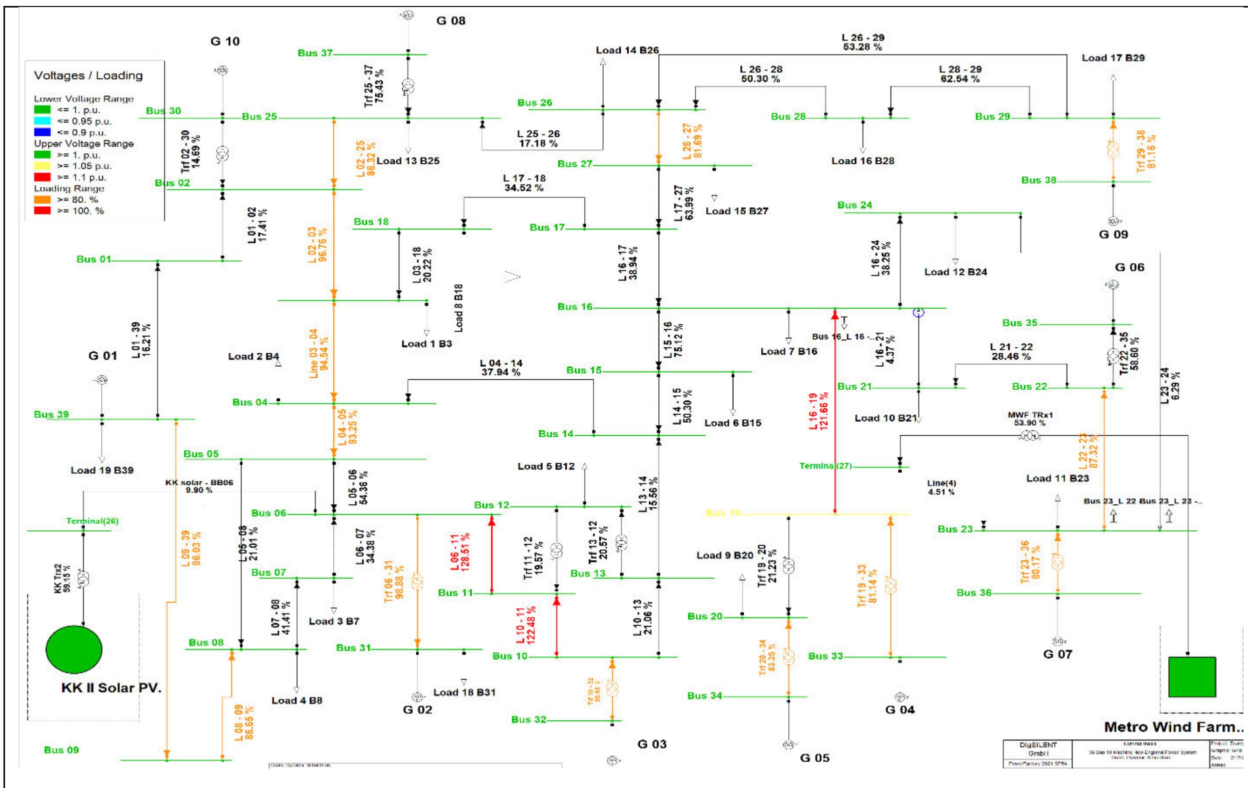


Figure 6. 16Load flow analysis under a quasi-dynamic network

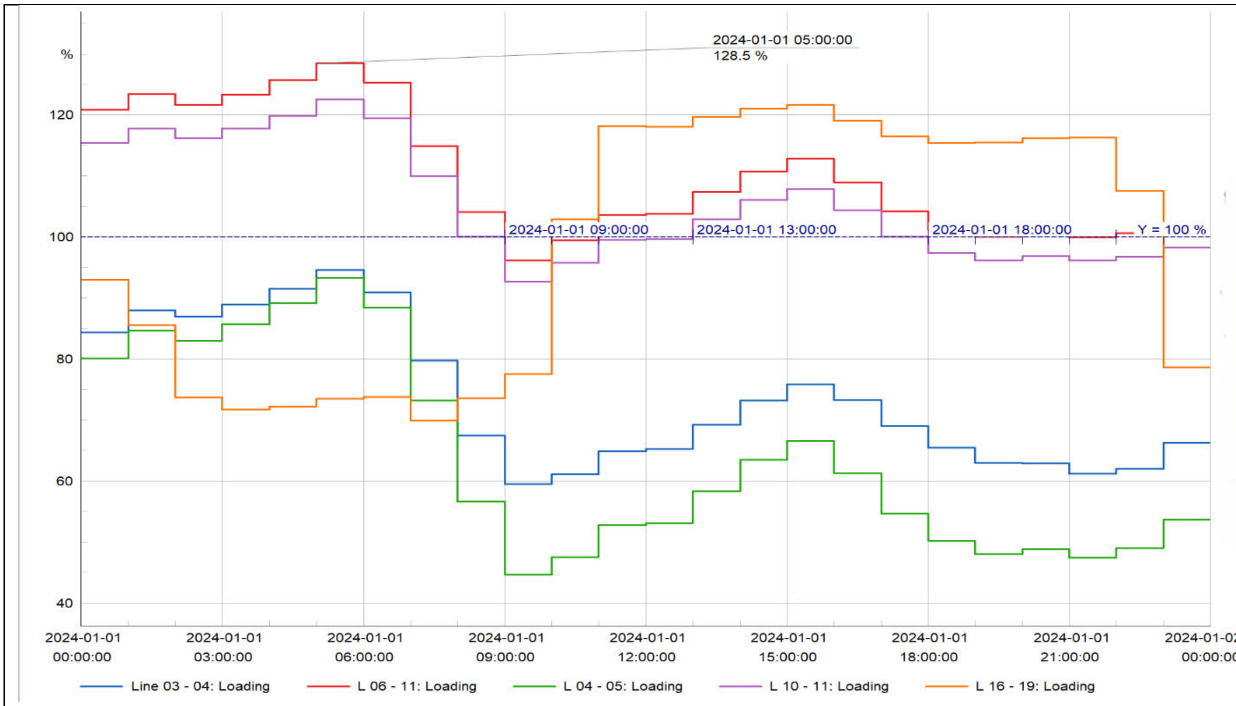
Case B - Quasi-dynamic simulation for 1 year

Figure 6.16 below illustrates the load flow analysis influenced by both load projections for a year, incorporating the fluctuating power output from the wind farm and solar PV plant, which fluctuate bi-hourly throughout the year, along with two generators that vary hourly during the year. The network's instability, in contrast to Figure 6.12 where only the load fluctuates, has improved due to the reduced production from the wind farm, solar PV plant, and two generators with variable power output which comes from G5 and G10, resulting in reduced congested lines currently.

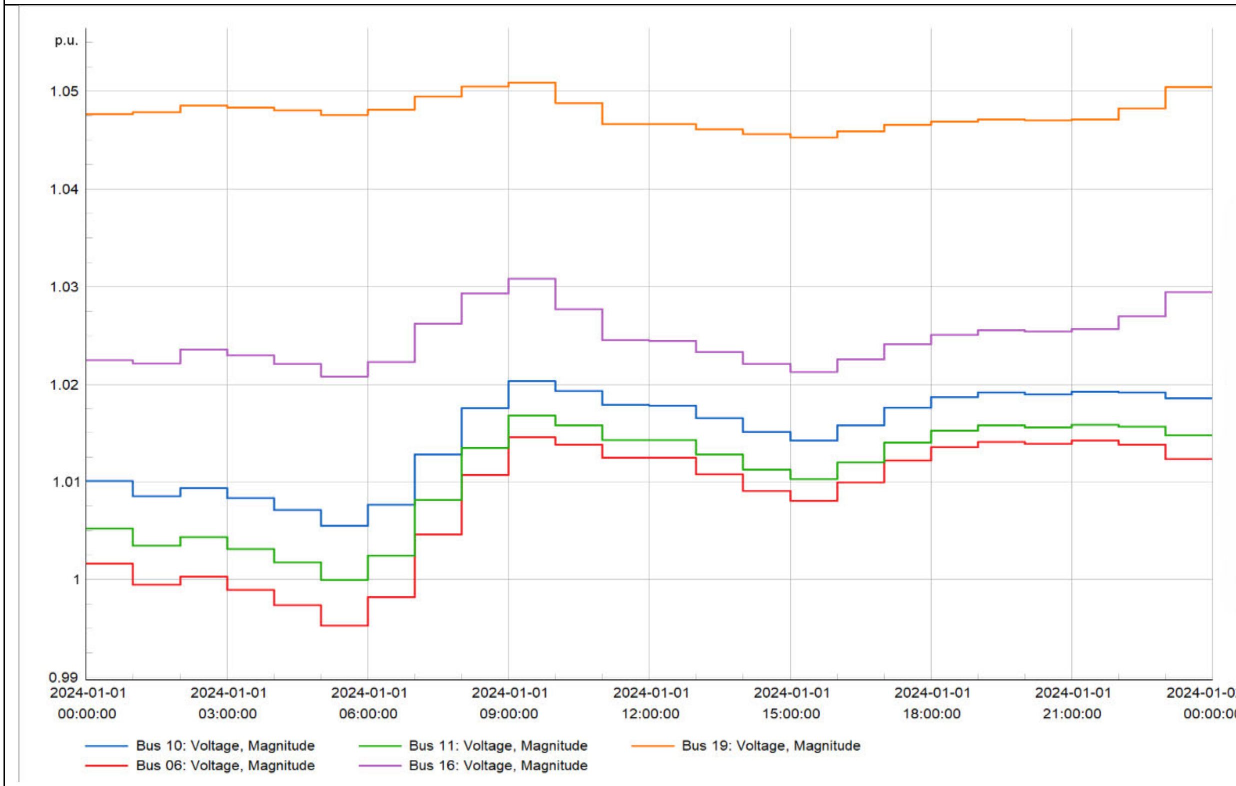
Figure 6.17 shows the network under quasi-dynamic simulation for a duration of one day, as seen in Figures 6.17 b and c. The uncertainty associated with RE is evident since the graph exhibits a non-uniform shape in contrast to Figure 6.13 b, which represented only variations in load. Furthermore, the loading has diminished in comparison to Figure 6.13 (b), when only the loads varied seasonally.



(a) Quasi-dynamic for 1 day



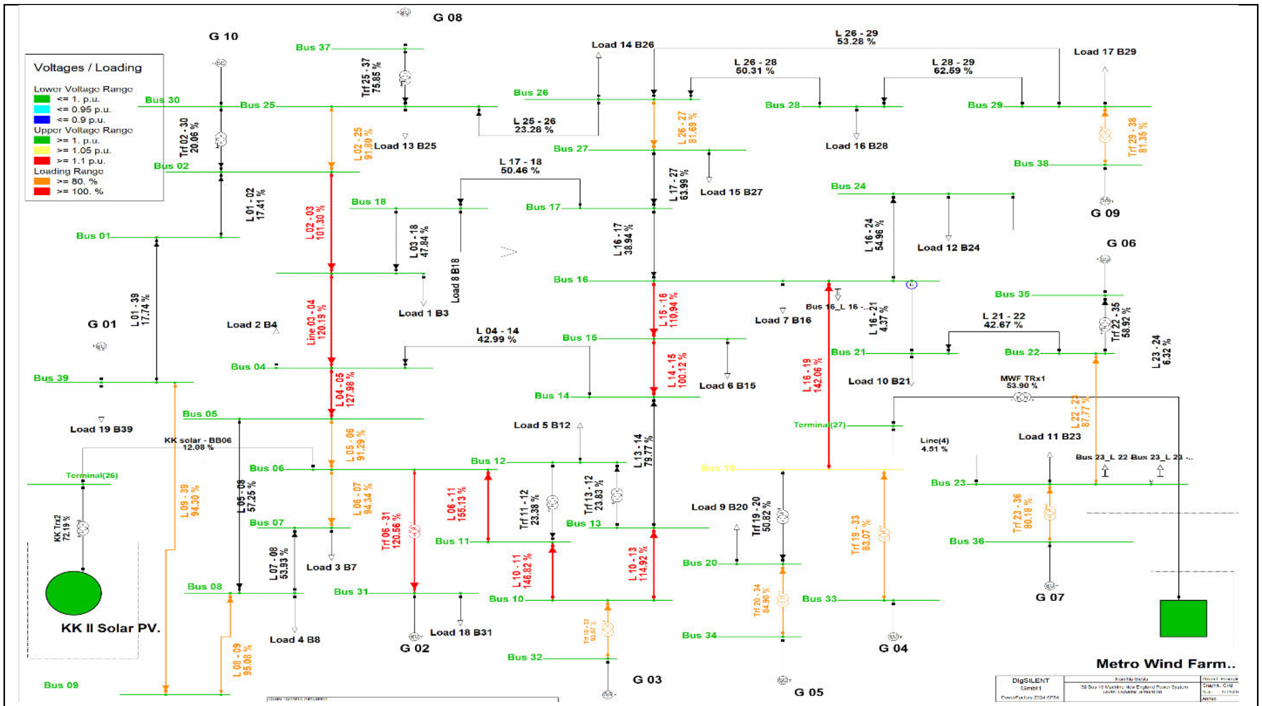
(b) Line loading for 1 day under quasi-dynamic



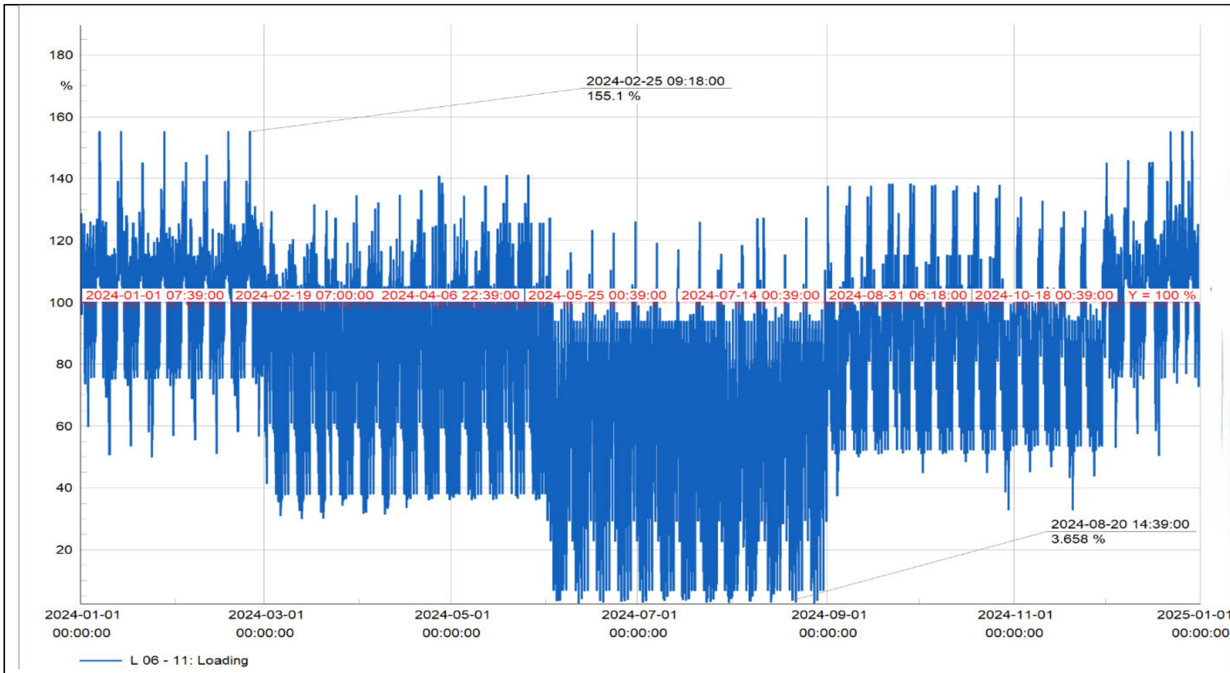
(c) Busbar Voltage (p.u) for 1 day under quasi-dynamic

Figure 6. 17Quasi-dynamic simulation for 1 day

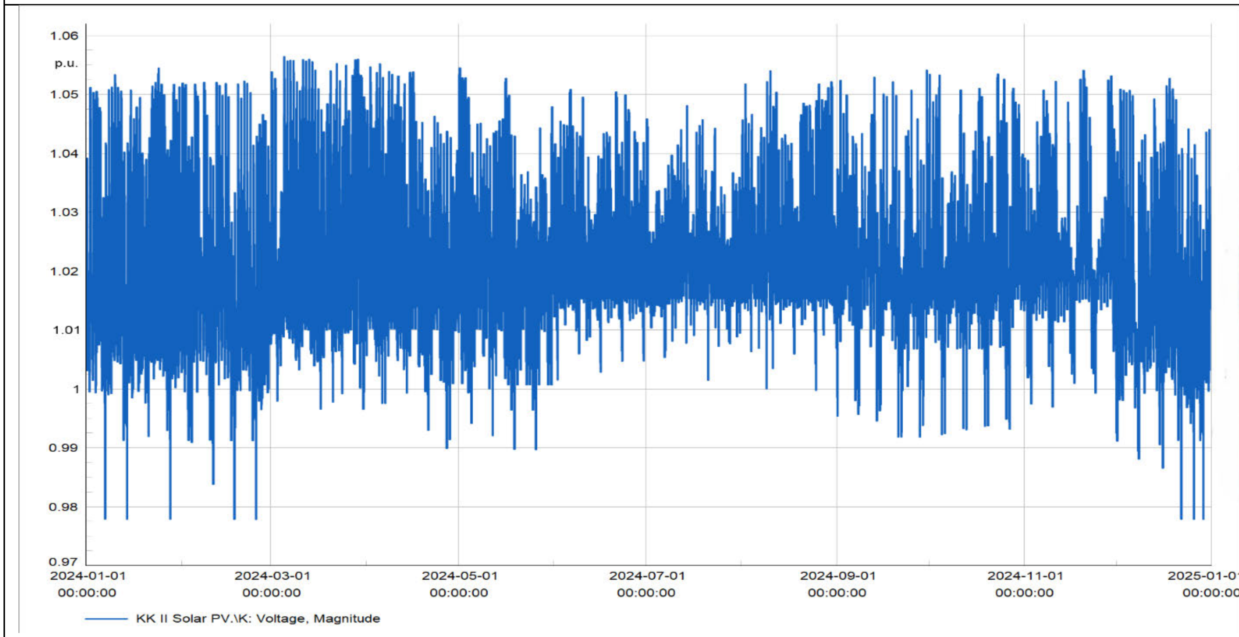
Figure 6.18 illustrates the network and the impact of quasi-dynamic conditions over a one-year period. It is evident from 6.18 (a) that the number of lines experiencing overloading increased, which is attributable to elevated variability in the system resulting from both load fluctuations and diverse source types, However, in comparison to figure 6.14 (a), the loading is now lower and the number of overloaded lines has reduced from 10 to 9. Figure 6.18 (b) illustrates the loading of line L06-11, indicating a decrease from 174% to 155.1%. The variability in loading, evidenced by the non-uniform shape, contrasts with Figure 6.14 (b), suggesting an anomaly in the voltage at busbar K in Figure 6.18 (b).



(a) Quasi-dynamic for 1 year



(b) Line loading for 1 year under quasi-dynamic



(c) Busbar Voltage (p.u) for 1 year under quasi-dynamic

Figure 6. 18Network under quasi dynamic for 1 year

Figure 6.19 illustrates the impact of quasi-dynamic simulation on May 2024. Notably, there is uncertainty arising from various sources, as evidenced by the consistent timing on all Sundays;

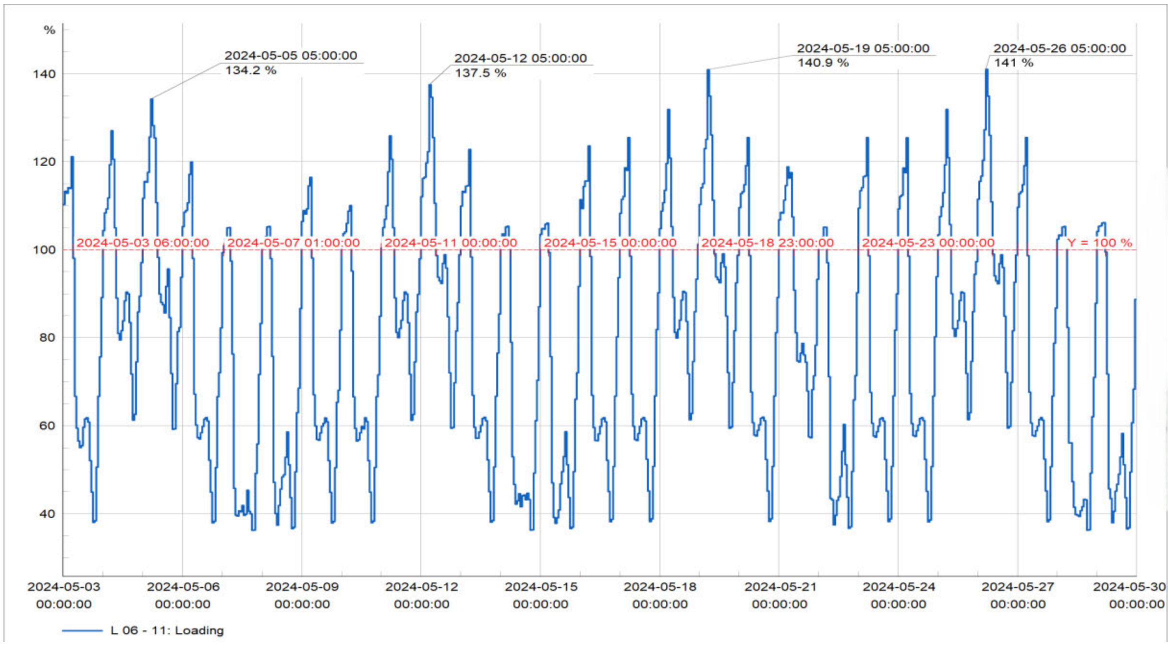


Figure 6. 19L06-11 quasi-dynamic simulation for May 2024

However, the loading varies due to power fluctuations occurring twice per hour from renewable energy sources and two generators that alter output power hourly throughout the year.

Figure 6.20 illustrates the line loading for line L06-11 in December 2024, indicating that the network is undergoing increasing variable loading, significantly contributing to grid instability.

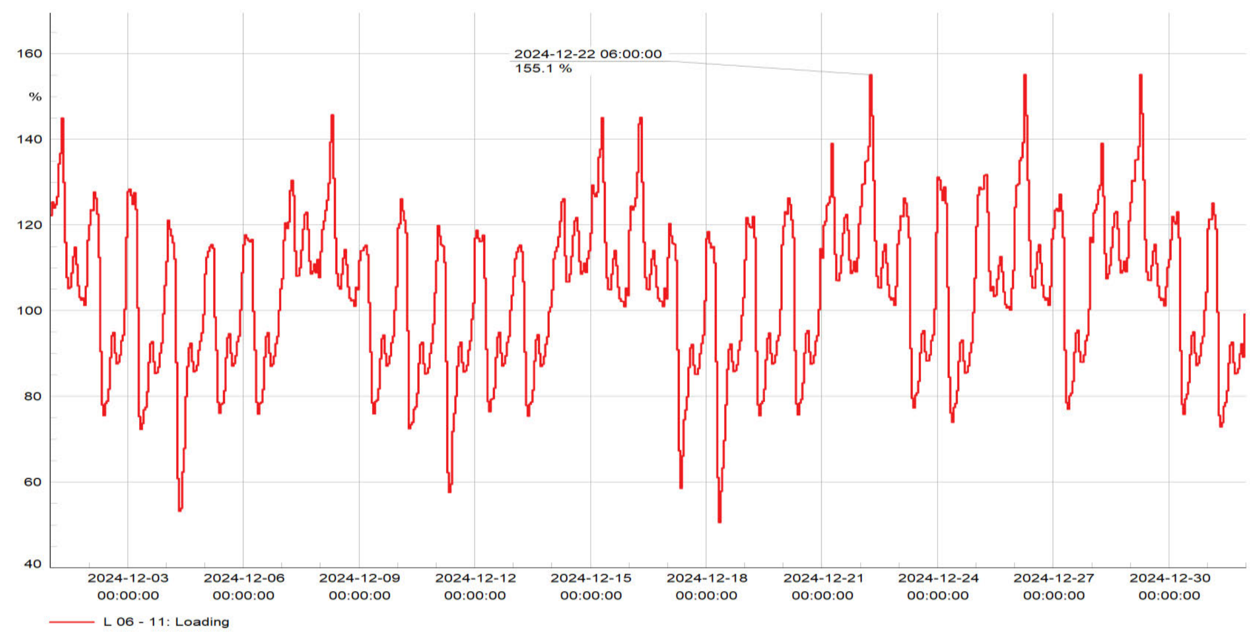


Figure 6. 20L06-11 line loading for December 2024 under quasi-dynamic

Table 6.8 presents the power summary subsequent to the assignment of characteristics for both loads and generators, as illustrated in Figures 5.10, 5.11, 5.13, 5.14, and 5.15. This power summary defines the load flow analysis for the application, showing characteristics that fluctuate either bi-hourly or hourly throughout the year. The network losses increased from 45.4 MW, as indicated in Table 6.5, to 78.1 MW, although demand decreased. This variation is attributed to the characteristics applied to loads, which adjust to accommodate various seasons and circumstances throughout the year.

Table 6. 8Power summary after Quasi

Power Summary		
Generators, Active Power	Generators, Reactive Power	Generators, Apparent Power
2821.8MW	1654.3MVAr	3270.9MVA
Generators, Nominal Active Power	Generators, Nominal Reactive Power	Generators, Nominal Apparent Power
15549.5MW	9620.2Mvar	18248.8MVA
Generators, difference between maximum and actual active power	Generators, the difference between maximum and actual reactive power	
12705.5MW	10950.7MVAr	
Loads, Active power	Loads, Reactive power	Loads, Apparent power
2743.7 MW	1408.9MVAr	3084.3MVA
Loads, Nominal Active Power	Loads, Nominal Reactive Power	Loads, Nominal Apparent Power
2743.7 MW	1408.9 MVAr	3084.3MVA
Losses, Active Power	Losses, Reactive Power	
78.1MW	-245.4MVAr	

6.6 1-year probabilistic analysis using QMCS

The unpredictability and uncertainty of renewable sources such as wind and solar complicate planning, necessitating probabilistic strategies to manage variations. This study used Monte Carlo methods, which utilize random sampling; however, QMCS methods employ low-discrepancy sequences to enhance convergence and improve accuracy in probabilistic analysis with a reduced number of samples when compared with Monte Carlo Figure 6.21 illustrates the network subjected to probabilistic analysis using QMCS, in contrast to Figure 6.18.

The network demonstrates nine lines that are overloaded under QMCS over the span of one year. While one could focus solely on alleviating the overload on these lines, probabilistic analysis using QMCS serves as a robust instrument for addressing the uncertainties associated with fluctuating sources, such as wind turbines or solar PV plants. It identifies the specific segments of the network requiring reinforcement to prevent congestion. Figure 6.21 indicates that the reinforcement of 10 lines is necessary to guarantee the network's stability.

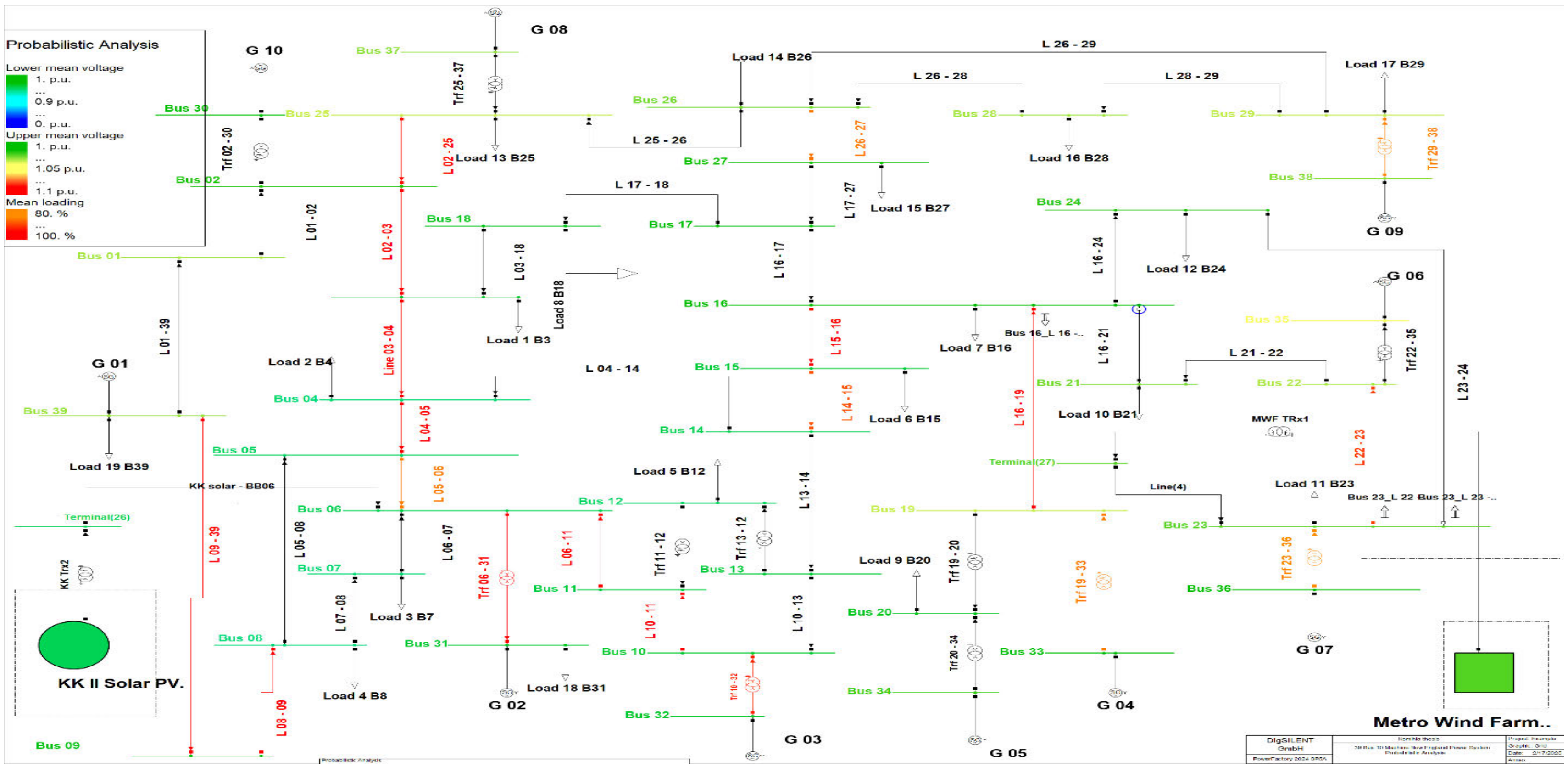


Figure 6. 21Network under probabilistic analysis using QMCS

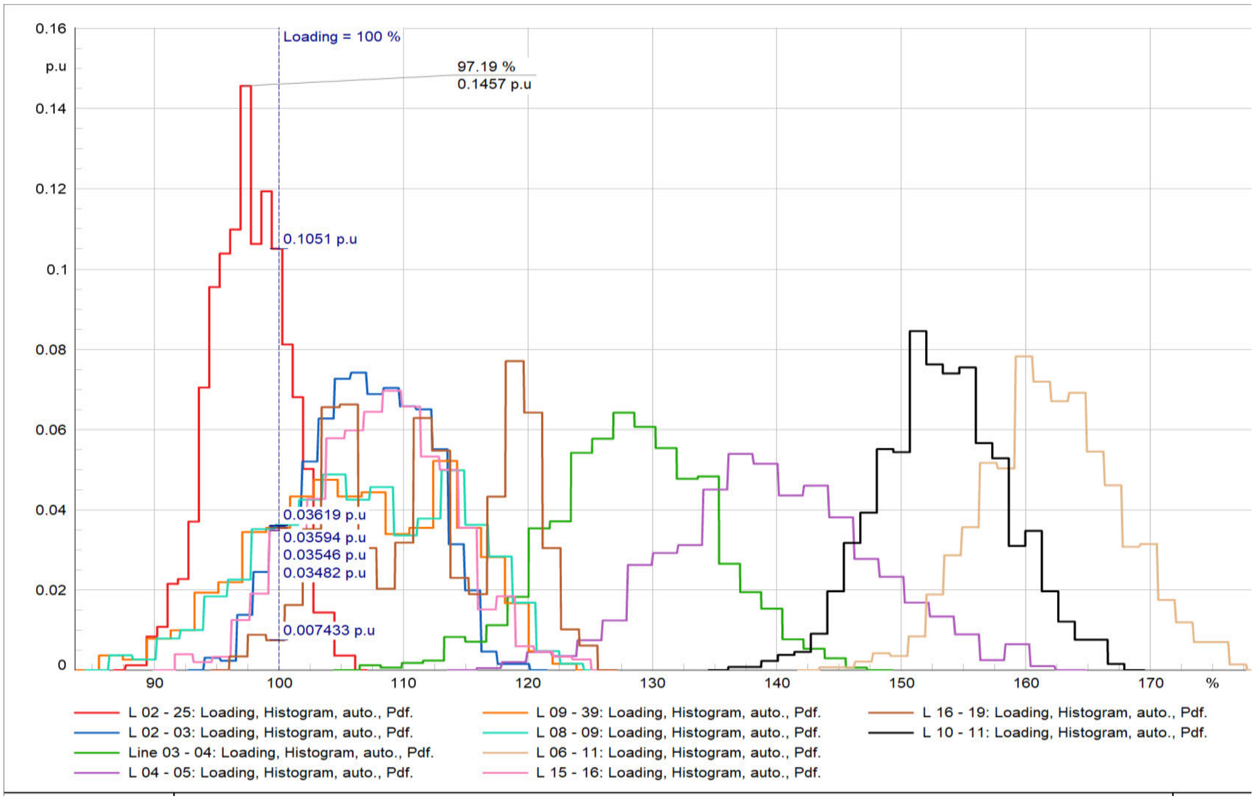
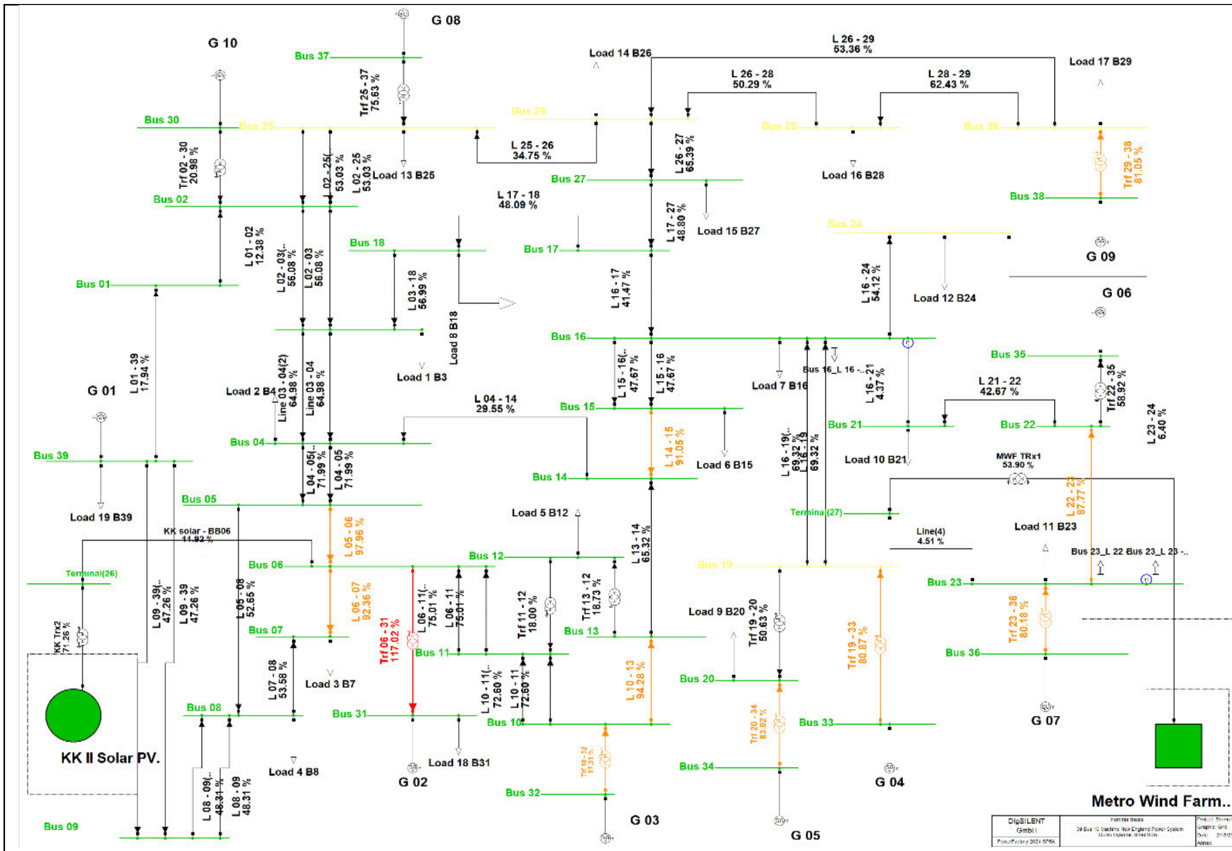


Figure 6. 22Distribution estimation for 1 year

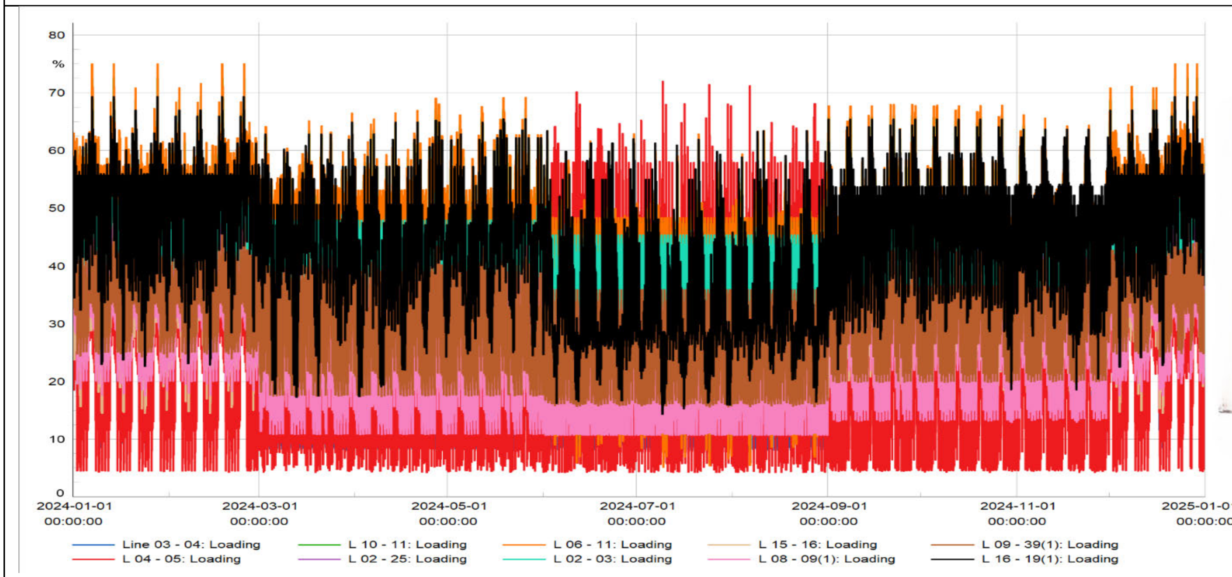
Figure 6.22 illustrates the distribution estimation of all lines proposed by probabilistic analysis, with line L02-25 exhibiting the largest quantity slightly over 100%, and line L16-19 demonstrating the maximum loading, approaching 180%.

6.7 Transmission expansion planning for 1 year

Figure 6.23(a) illustrates the network post-expansion, as recommended by probabilistic analysis in conjunction with QMCS. Ten lines were added in parallel to those requiring reinforcement. It is evident that following the expansion, all lines are functioning within permissible values, with no lines exceeding 100% capacity. Furthermore, the variability associated with renewable energy and demand fluctuations is seen in Figure 6.23(b), where the graph exhibits a lack of uniformity.

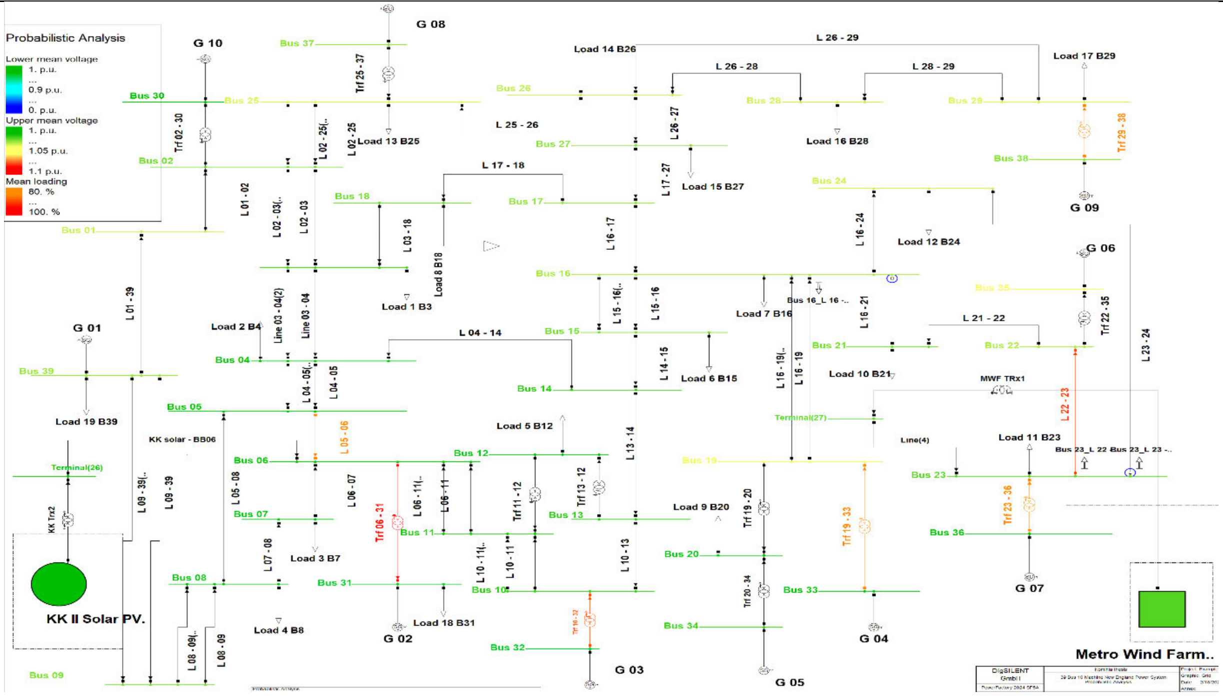


(a) Transmission network for 1 year after expansion using Quasi dynamic simulation

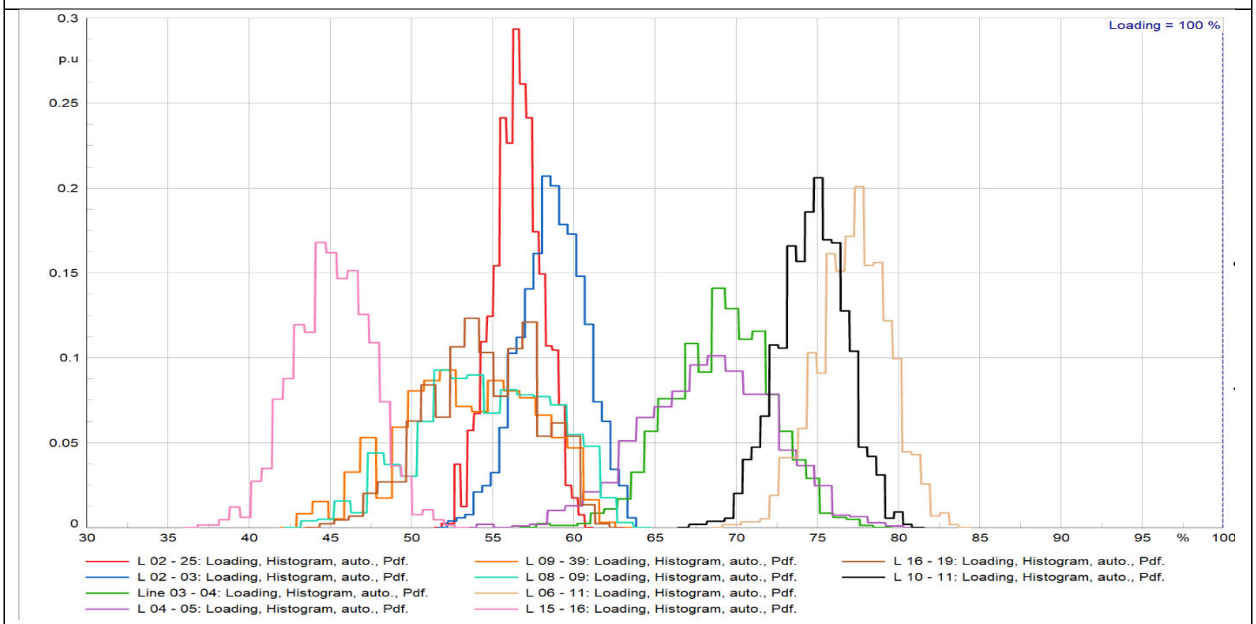


(b) Line loading for 1 year after expansion

Figure 6. 23Quasi-Dynamic simulation for 1 year after Transmission expansion planning



(a) 1 year probabilistic analysis after expansion



(b) 1 year distribution estimation after TEP

Figure 6. 241 year probabilistic analysis after TEP

Figure 6.24 is the probabilistic analysis after the expansion of transmission lines to ensure that there is no longer a need to expand the network and to see that the network will stand healthy under all dynamic changes throughout the year, from Figure 6.24(a) it can be seen that there is no need now to reinforce transmission lines. Figure 6.24 (b) is the distribution estimation showing that all the lines are operating within permittable values.

Table 6.9 presents the power summary for a one-year scenario post-expansion. It is evident from this figure that losses have diminished from 78.1 MW to 56.6 MW. The load remains unchanged; however, the generator's active power has dropped.

Table 6. 9Power summary after 1 year of expansion

Power Summary		
Generators, Active Power	Generators, Reactive Power	Generators, Apparent Power
2800.3MW	1062.5MVAr	2995.1MVA
Generators, Nominal Active Power	Generators, Nominal Reactive Power	Generators, Nominal Apparent Power
15549.5MW	9620.2Mvar	18248.8MVA
Generators, the difference between the maximum and actual active power	Generators, the difference between the maximum and actual reactive power	
12727MW	11542.5MVAr	
Loads, Active power	Loads, Reactive power	Loads, Apparent power
2743.7MW	1408.9MVAr	3084.3MVA
Loads, Nominal Active Power	Loads, Nominal Reactive Power	Loads, Nominal Apparent Power
2743.7 MW	1408.9 MVAr	3084.3MVA
Losses, Active Power	Losses, Reactive Power	
56.6MW	-346.4MVAr	

6.7.1 Load forecast and Quasi-Dynamic Simulation for 15 years

Case A: Load forecast for 15 years

This section illustrates the system's behavior over an extended period as the load escalates.

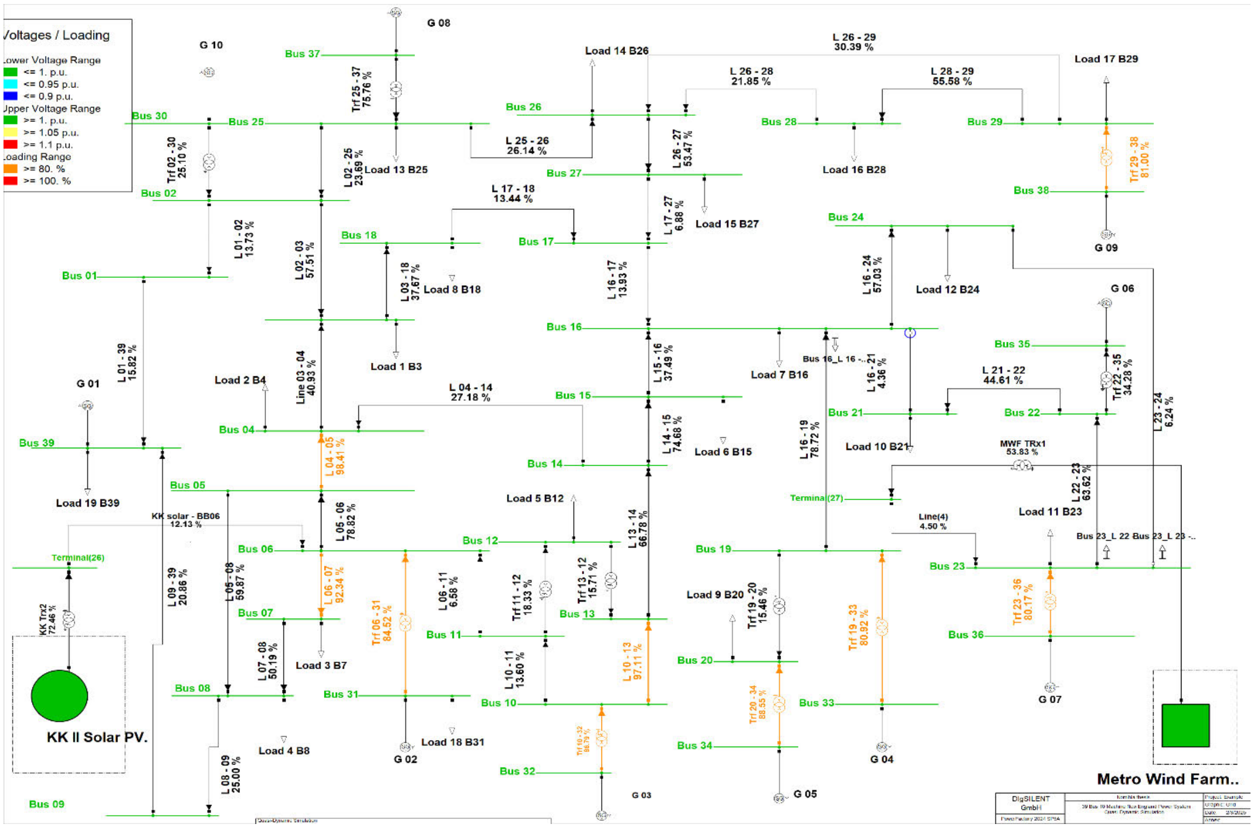


Figure 6. 25Load forecast for the year 2027

It is crucial for predicting load demand to meet anticipated requirements and to strategize for optimal system operation within accepted parameters, ensuring that no lines experience congestion and all busbars function under acceptable conditions. Figure 6.29 indicates that load increase begins in 2025, with a value of 1 p.u in 2024.

Figure 6.25 shows the whole network under quasi-dynamic simulation; the thermal loading has increased, as shown in line L04-05 at 98.41% and Line L10-13 at 97.11%, but it is still running within permittable limits.

Figure 6.26 depicts the effect of load increase for the year 2028; it can be seen that the load growth has influenced the thermal loading of Lines L10-13 and L04-05, exceeding 100%, which is the highest permissible limit.

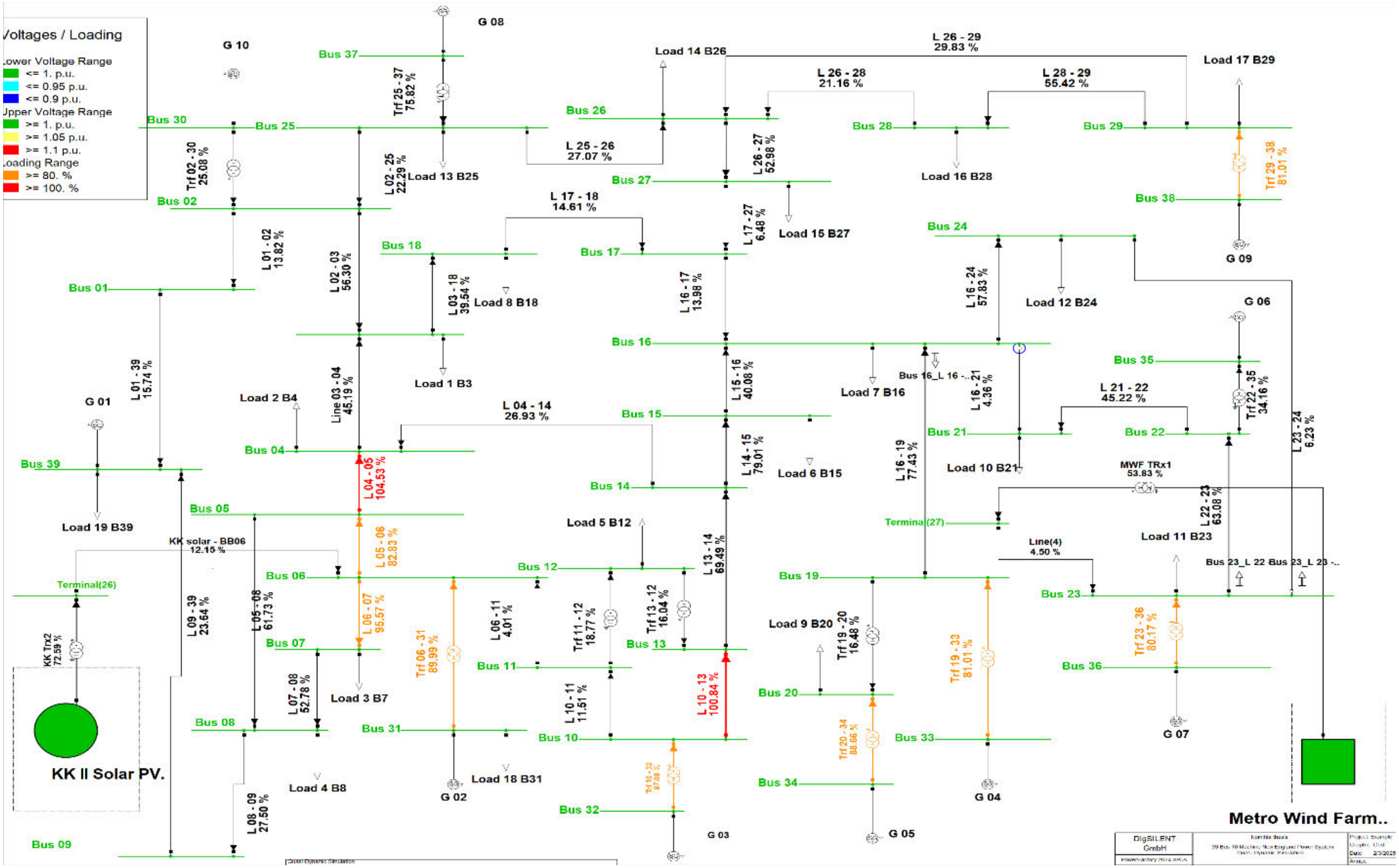
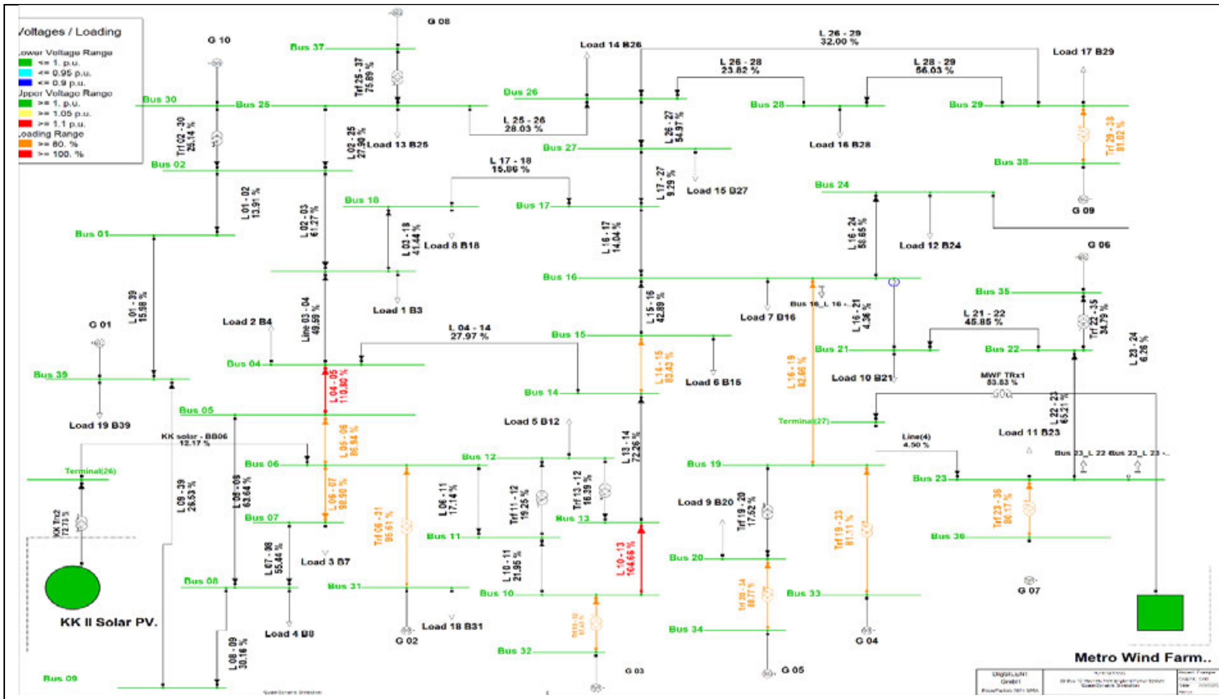
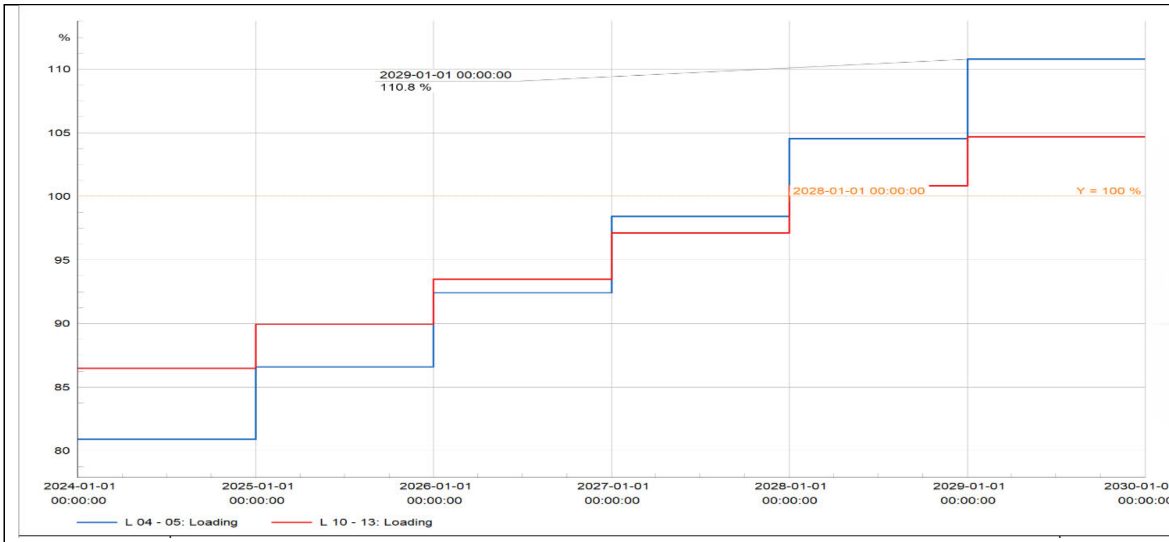


Figure 6. 26Load forecast for the year 2028

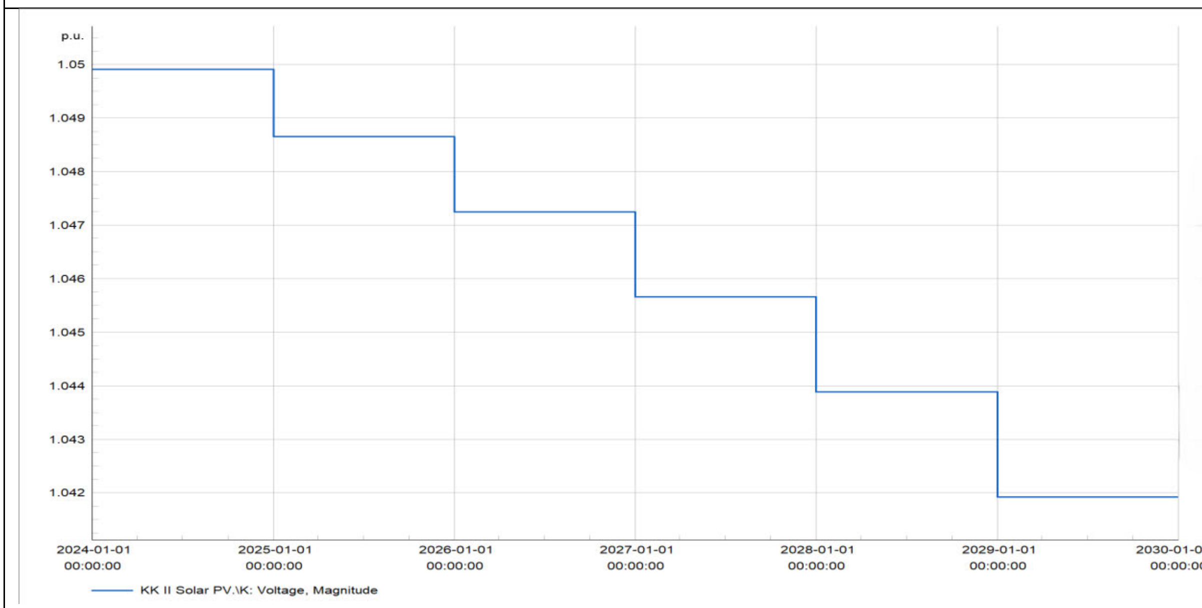
Figure 6.27 (a) shows the effect of load increase over a five-year period, with two lines above 100%. Additionally, the thermal loading of the transformer Trf 06-31 is noted to be increasing when compared to the aforementioned Figures. Figure 6.27 (b) illustrates the line loading of two lines. The figure indicates when the loading exceeds permissible limits, as seen by the y-intersection, and also depicts the highest loading attained. Figure 6.27(c) illustrates the busbar voltage p.u, indicating that all busbar voltages remain within permissible limits. Additionally, it is observed that voltage decreases as load demand escalates, most notably compared to Figure 6.27(b)



(a)Load growth after 5 years



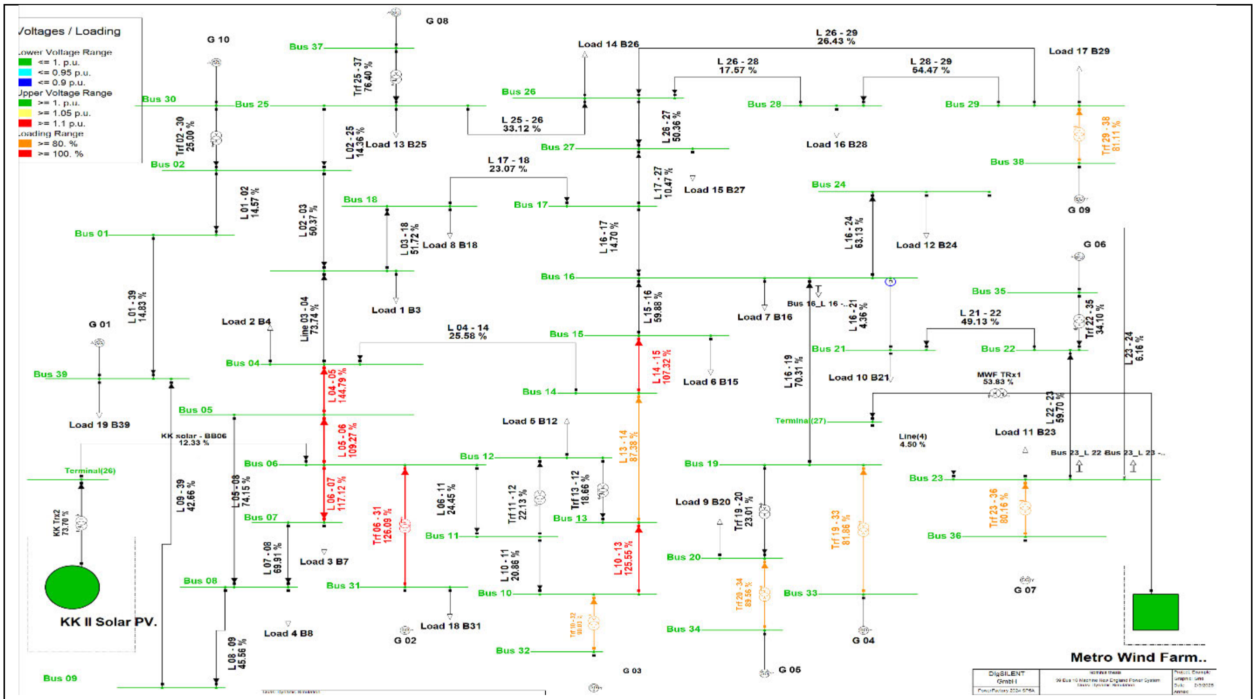
(b)Line loading for the period of 5 years with Load growth



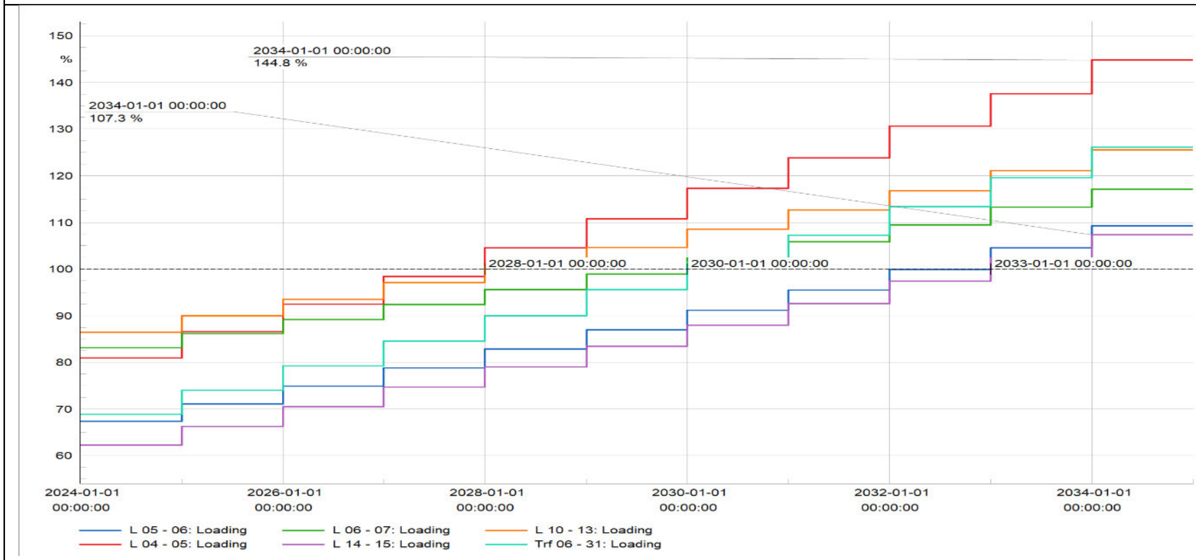
(c) Busbar Voltage (p.u.) for five years

Figure 6. 27Effect of Load growth over 5 year period

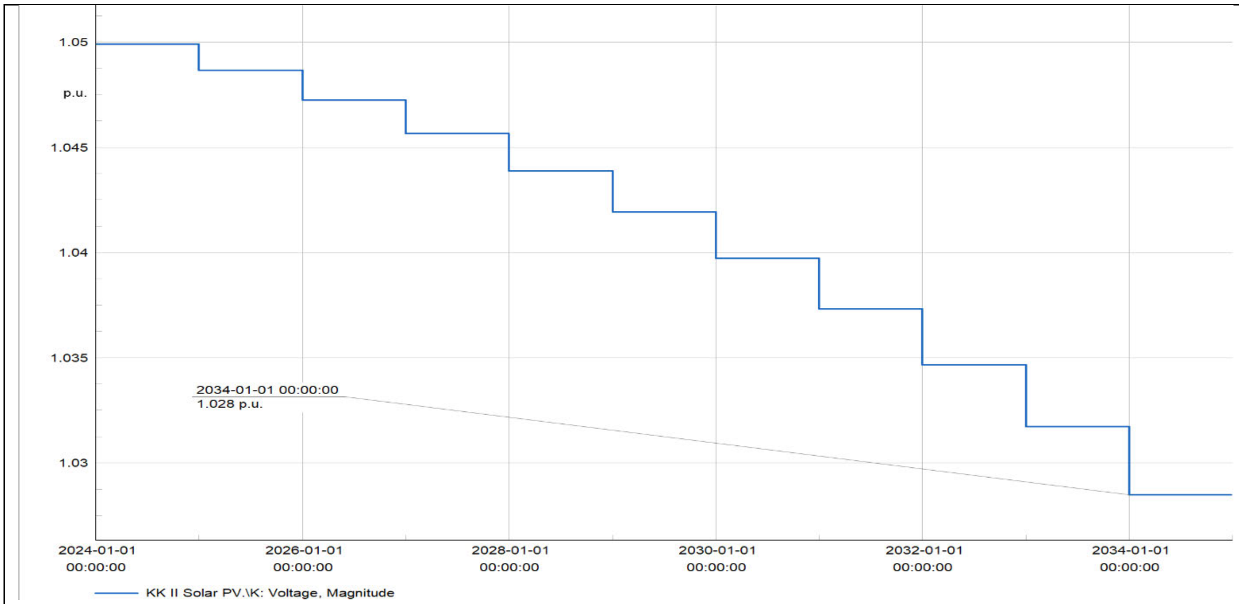
Figure 6.28 illustrates the impact of load increase over a ten-year period. In 6.28 (a), the whole network is depicted, with five lines over the permissible loading threshold highlighted in red, along with a transformer operating above 100% capacity.



(a) Effect of load growth after 10 years



(b) Line loading for the period of 10 years with load growth

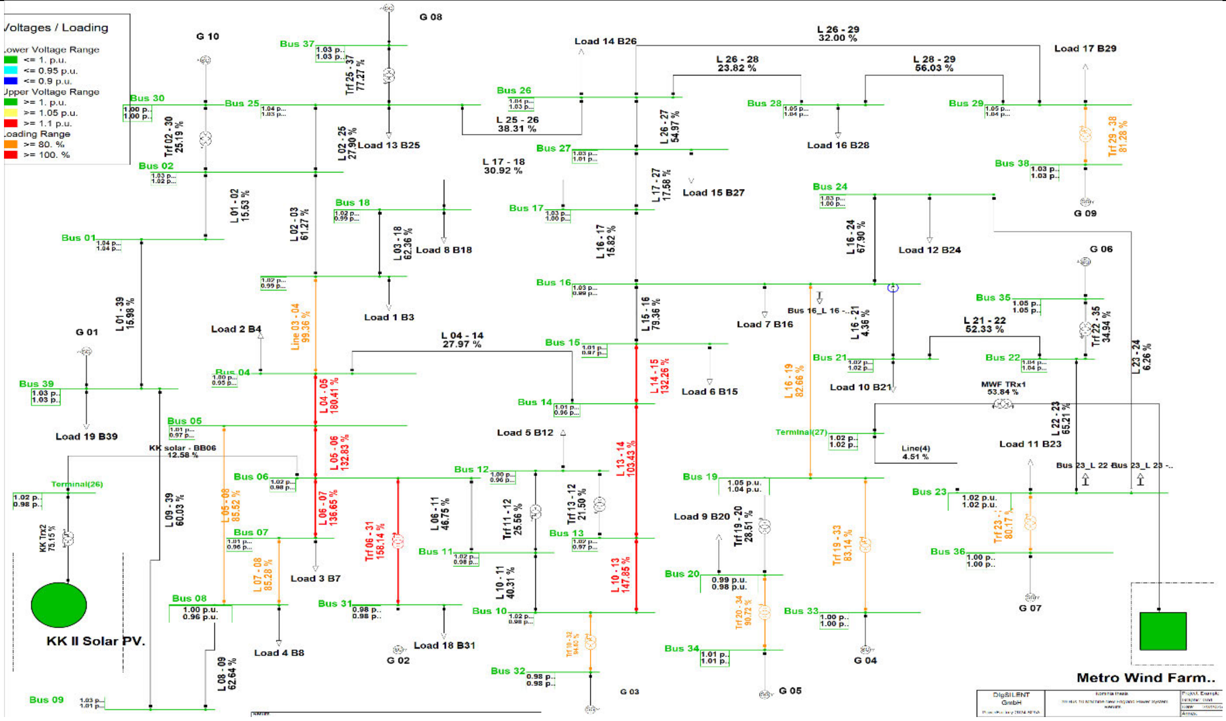


(c) Busbar Voltage (p.u) for 10 years

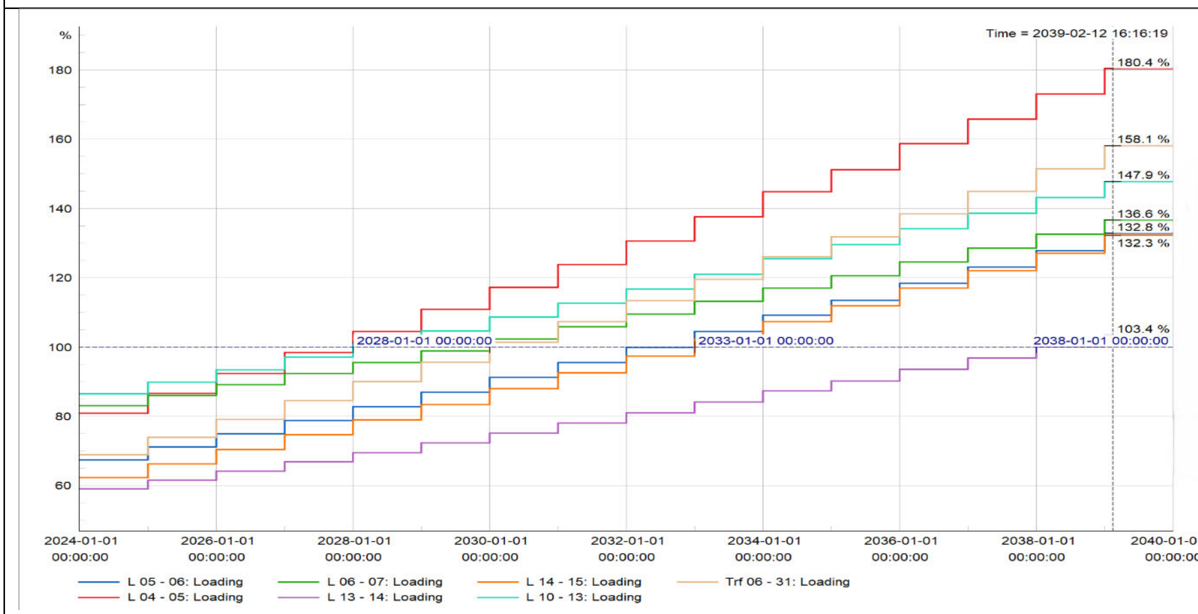
Figure 6. 28Load forecast over 10 year period

Figure 6.28 (b) shows the graph for lines that surpass 100% loading; from the graph, it is possible to observe when these transmission lines reach 100%. Figure 6.28 (c) displays the line voltage in p.u., which is still within permissible limits despite having increased in comparison to Figure 6.27(c).

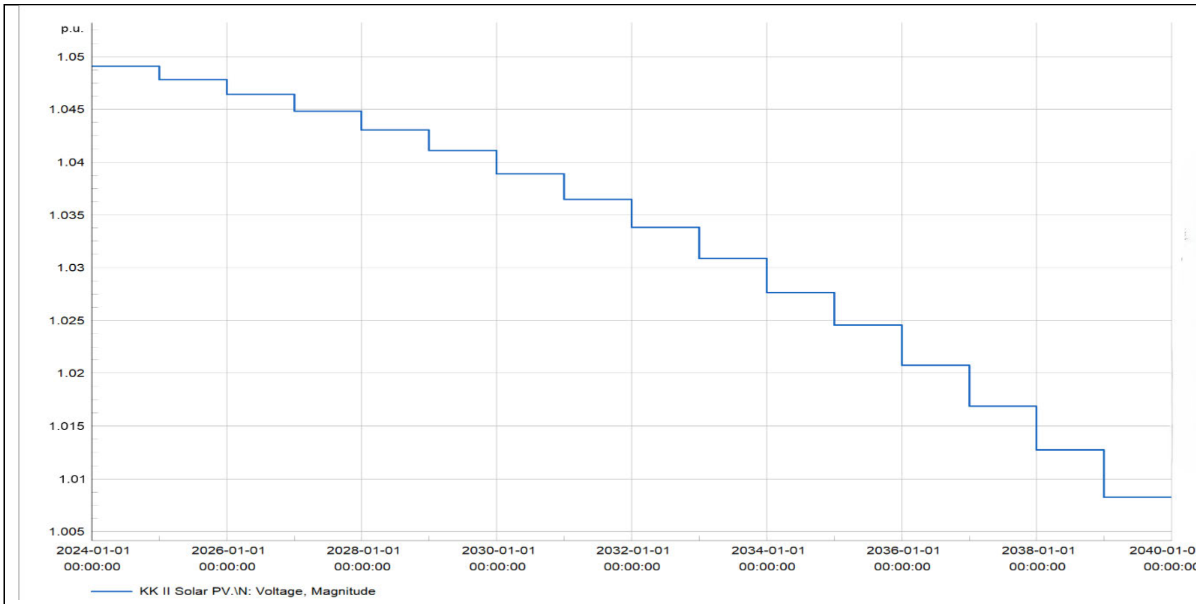
Figure 6.29 shows the effect of load growth over 15 years, which is the maximum duration for this study. Figure 6.29(a) is the network simulation; it can be observed that the same lines are affected in 6.29(a), but the loading continues to increase as the load growth increases. Figure 6.29(b) shows a noticeable rise in loading, with a maximum loading of 180.4%. Figure 6.29(c) shows a bus bar different from Figures 6.27 and 6.26, but it is still clear that the busbar voltage p.u is not violated.



(a) Effect of load growth after 15 years



(b) Line loading for the period of 15 years with load growth



(c) Busbar Voltage (p.u) for 15 years

Figure 6. 29Effect of load growth over 15 years period

Case B: Quasi Dynamic simulation for 15 years

Figure 6.30 illustrates the entire network, with load characteristics detailed in Chapter 5.

The second set of characteristics applies to the wind farm, which varies every half hour throughout the year, introducing uncertainty associated with renewable energy. The third set of characteristics is assigned to solar power plants, also presented in Chapter 5, to demonstrate the erratic nature of solar supply. Furthermore, the characteristics attributed to generators 5 and 10 cause these generators to fluctuate hourly throughout the year, whilst all other generators maintain a steady power output annually. The network forecasts a load expansion over 15 years; nonetheless, it is evident that lines 04-05 and 10-13 are currently experiencing overload.

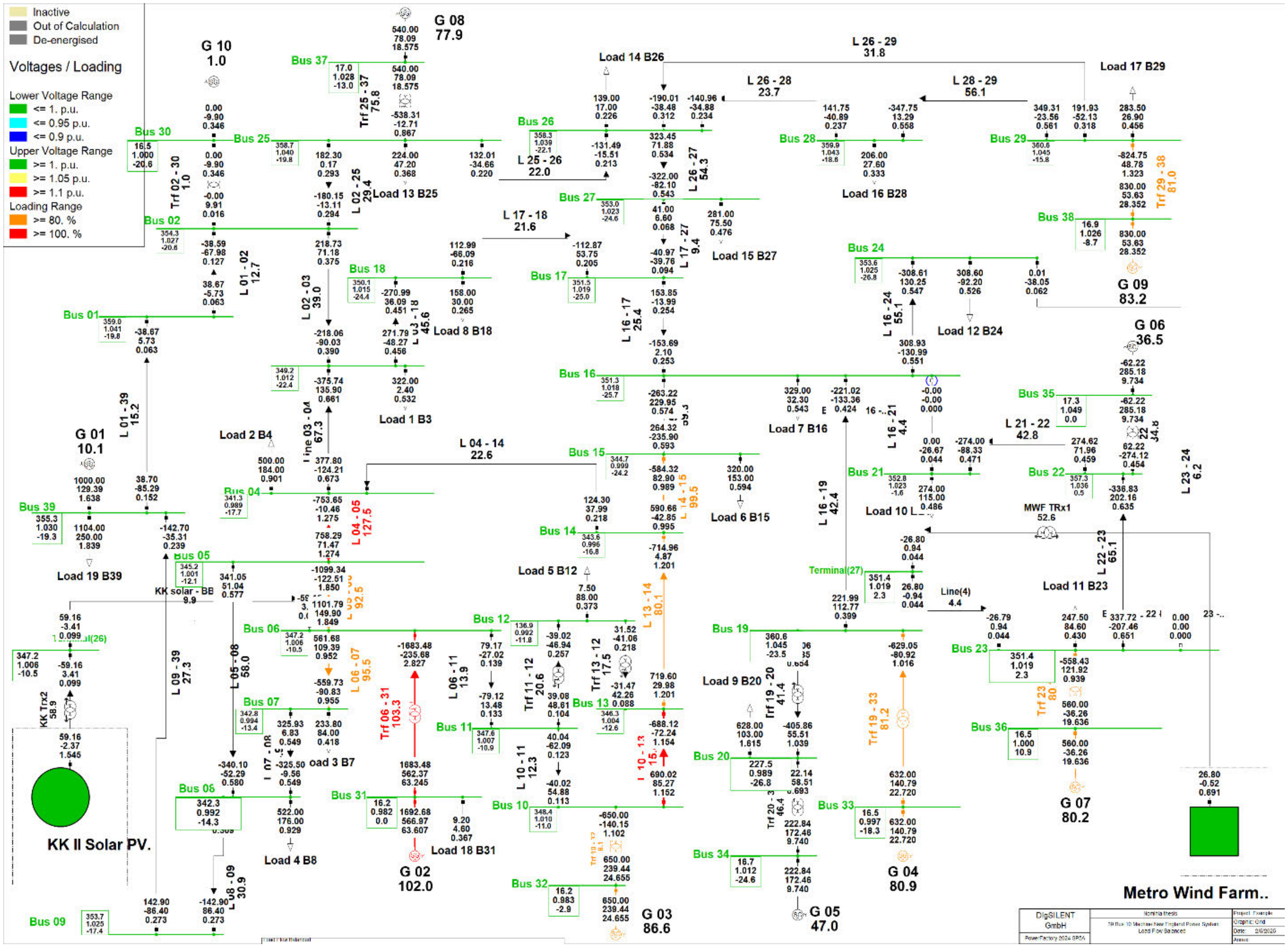


Figure 6. 30Network under quasi-dynamic simulation

Figure 6.31 illustrates the metro wind farm undergoing quasi-dynamic simulation. Each wind turbine is assigned distinct characteristics as detailed in Chapter 5, resulting in variations every half hour throughout the year. As depicted in Figure 6.31, WT1 exhibits differing active power levels compared to WT2 and WT3.

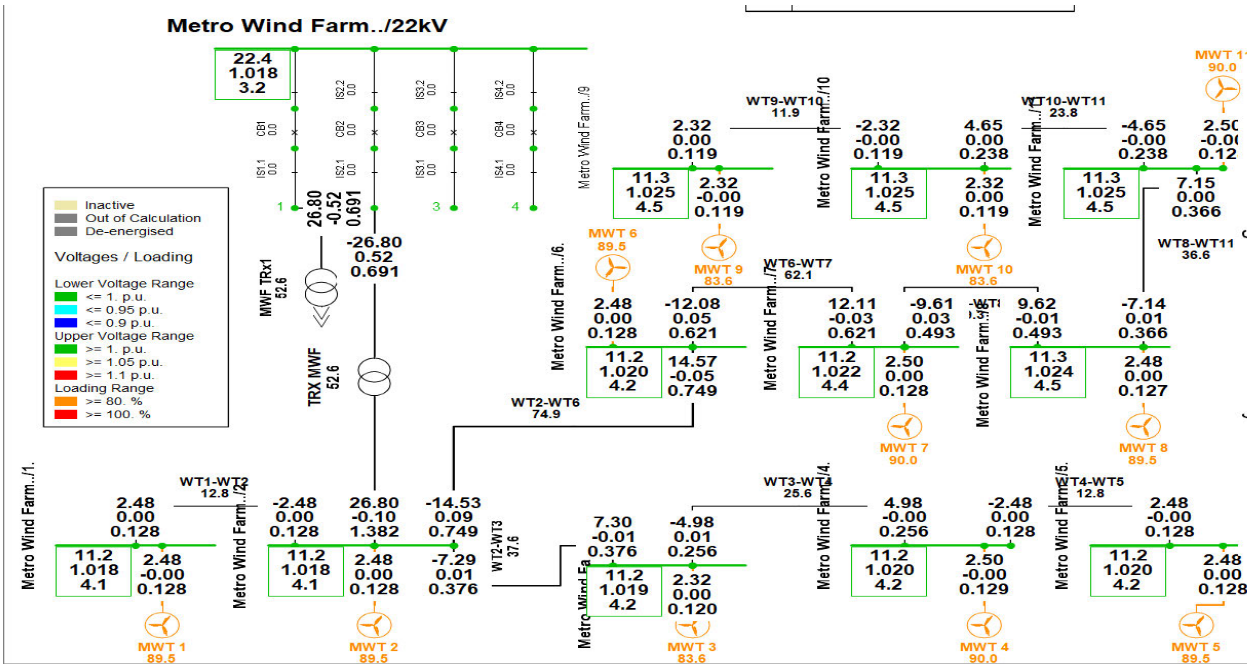


Figure 6. 31Metro wind farm under quasi dynamic simulation

Figure 6.32 illustrates the solar power plant under quasi-dynamic simulation, containing 15 solar PV units with distinct characteristics, as previously detailed in Chapter 5. The figure demonstrates that PV1 differs from PV2 and PV3, highlighting the inherent uncertainty associated with renewable energy. Furthermore, in contrast to Figure 6.8, the PV plant is currently generating a total output of 59.16 MW.

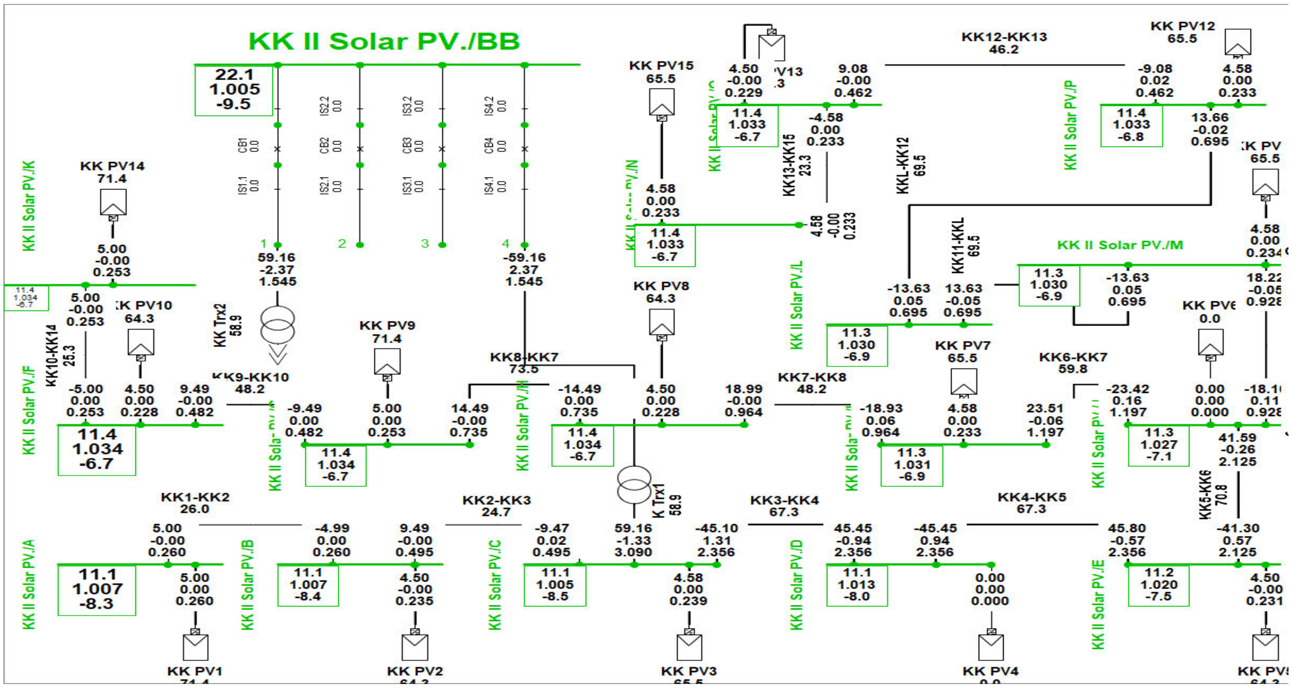
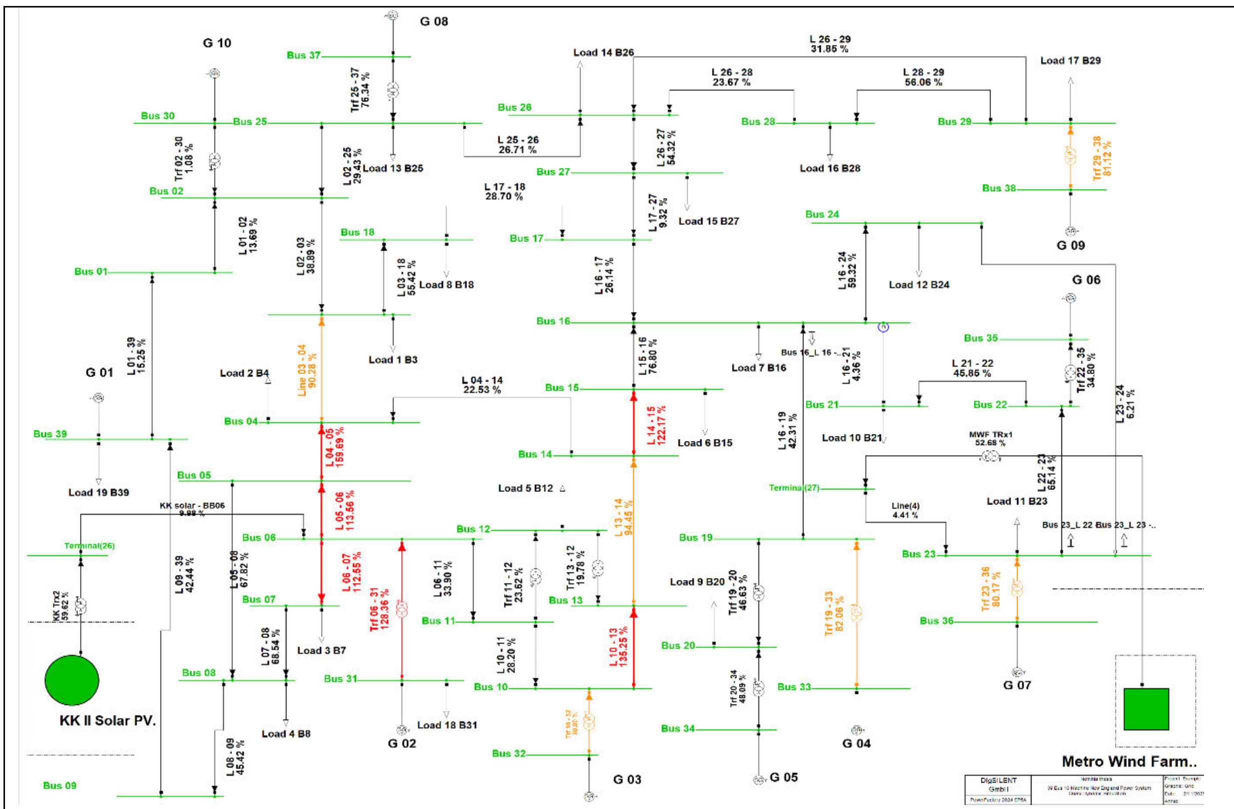
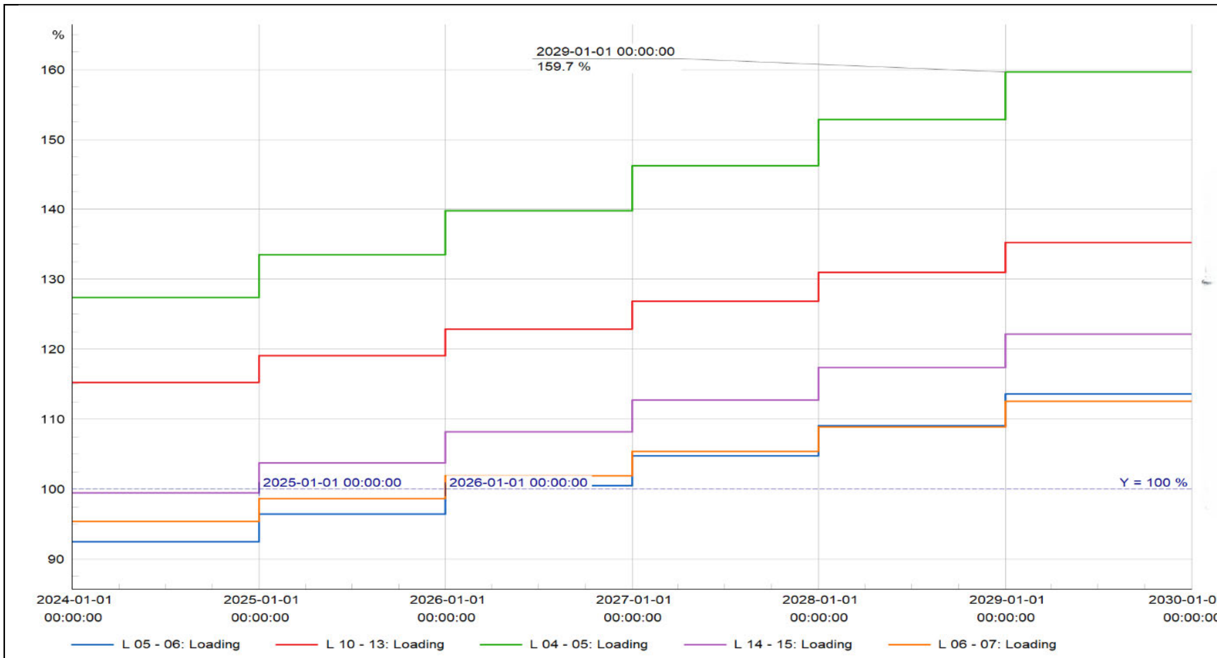


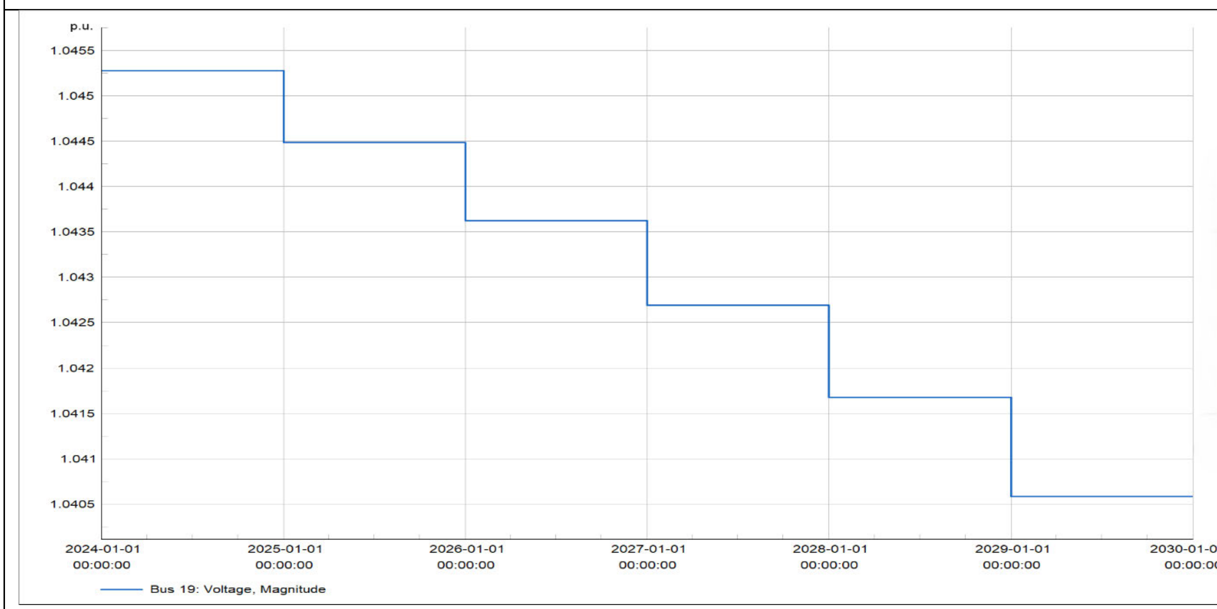
Figure 6. 32KK II solar PV under quasi dynamic simulation



(a) Effect of quasi-dynamic after 5 years



(b) Line loading for 5 years with quasi-dynamic

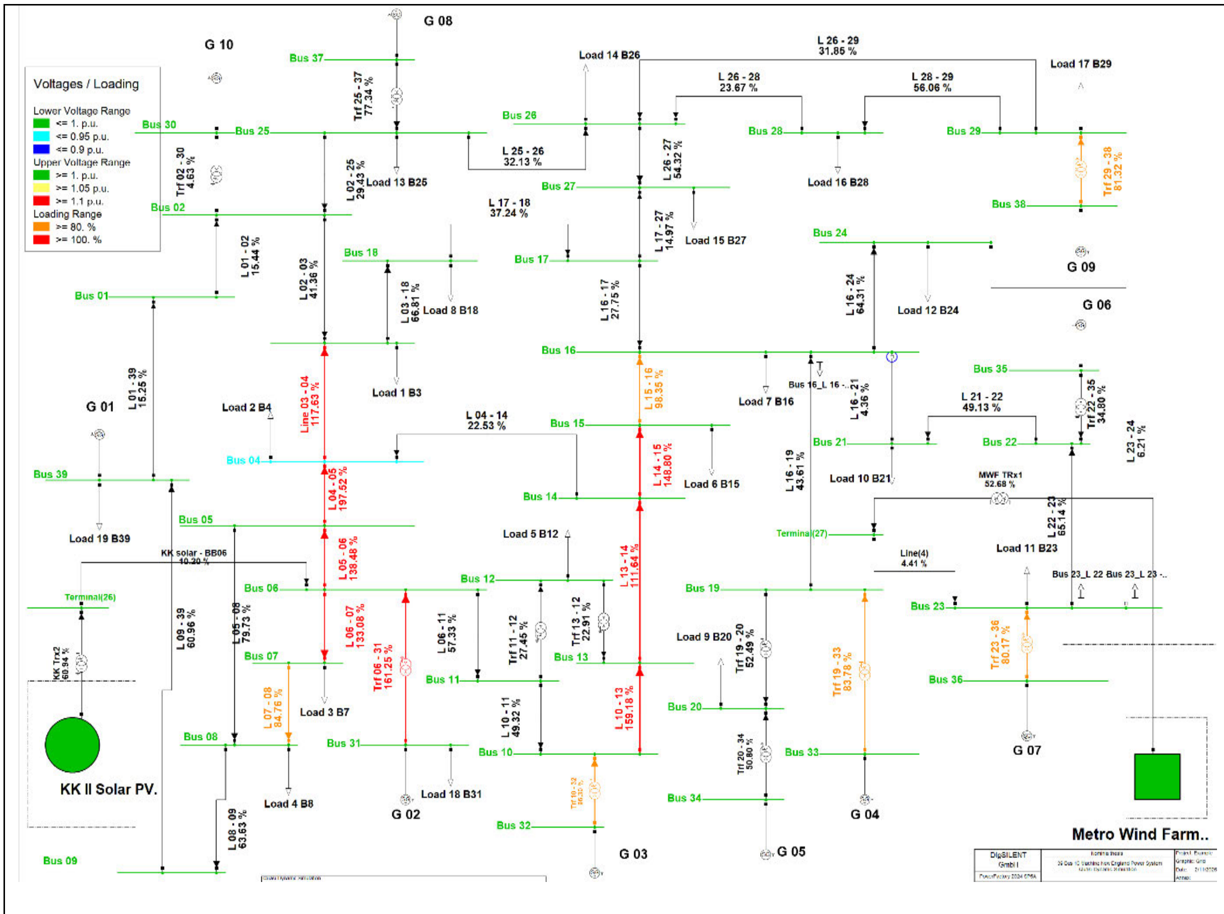


(c) Busbar voltage (p.u) for 5 years under quasi-dynamic

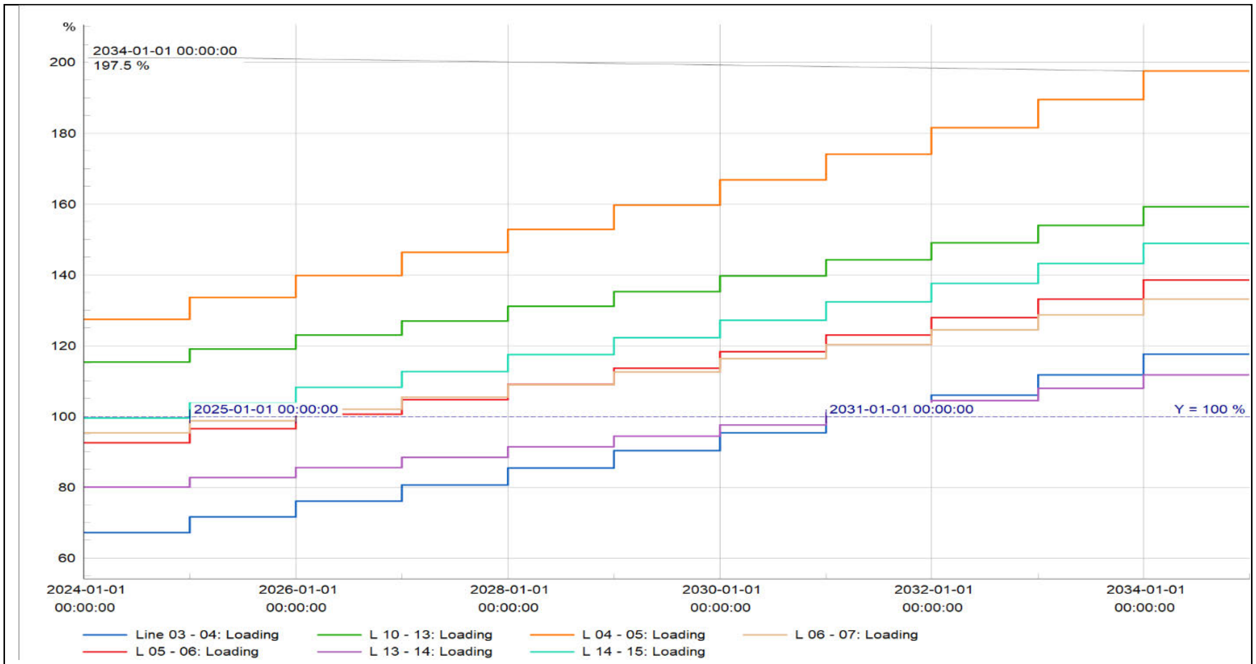
Figure 6. 33Quasi-Dynamic simulation for 5 years

Figure 6.33 (a) illustrates the network system under quasi-dynamic simulation during a five-year period. In comparison to Figure 6.30, it is evident that the overloading of lines 04-05 has intensified, and the total number of lines suffering overloading has risen alongside the growth in load. Figure 6.33 (b) shows an increase in line loading, with a highest level of 159.7% in the network, which worsens system instability. Additionally, Figure 6.33(c) indicates that as load demand grows, the p.u voltage diminishes; however, all busbar voltages remain within permissible limits.

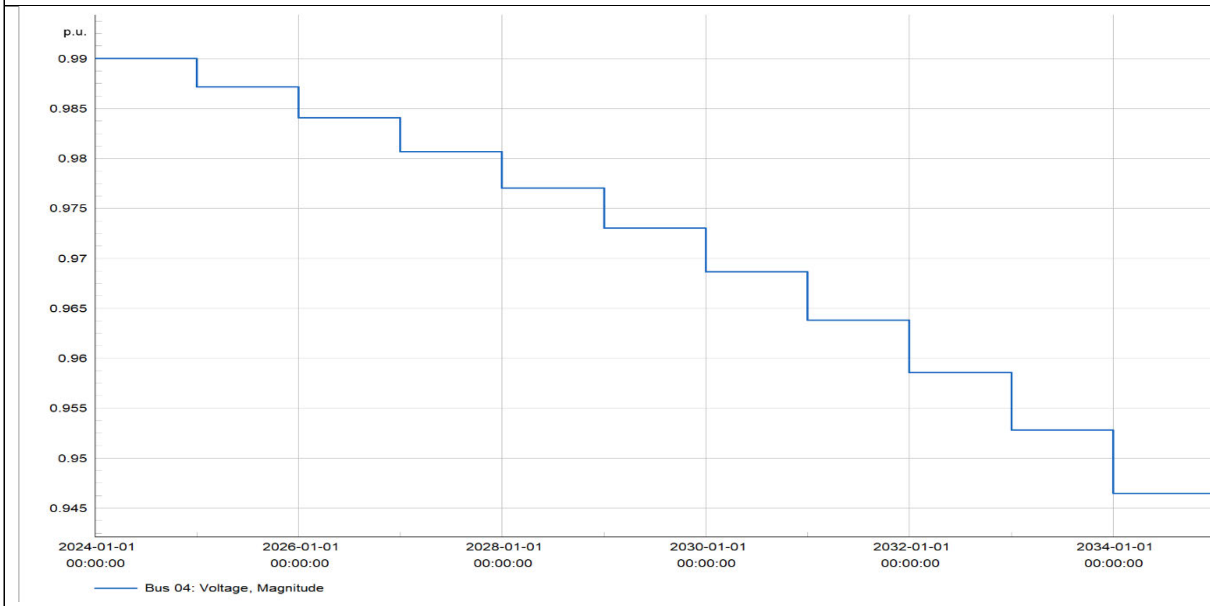
Figure 6.34 (a) depicts the network under quasi-dynamic simulation for a duration of 10 years, culminating in the year 3034. The inline loading has once again escalated, resulting in an increased number of lines suffering overloading, indicating that this network would encounter issues after the 10-year period. Figure 6.34 (b) illustrates the line loading of all lines subjected to overloading, with the maximum loading recorded at 197.52%. Figure 6.34 (c) illustrates the per unit voltage of bus 4, which is the busbar with the lowest voltage. It is evident from 6.34 (a) that this busbar is undergoing voltage instability, however, it remains within permissible limits.



(a) Effect of quasi-dynamic after 10 years



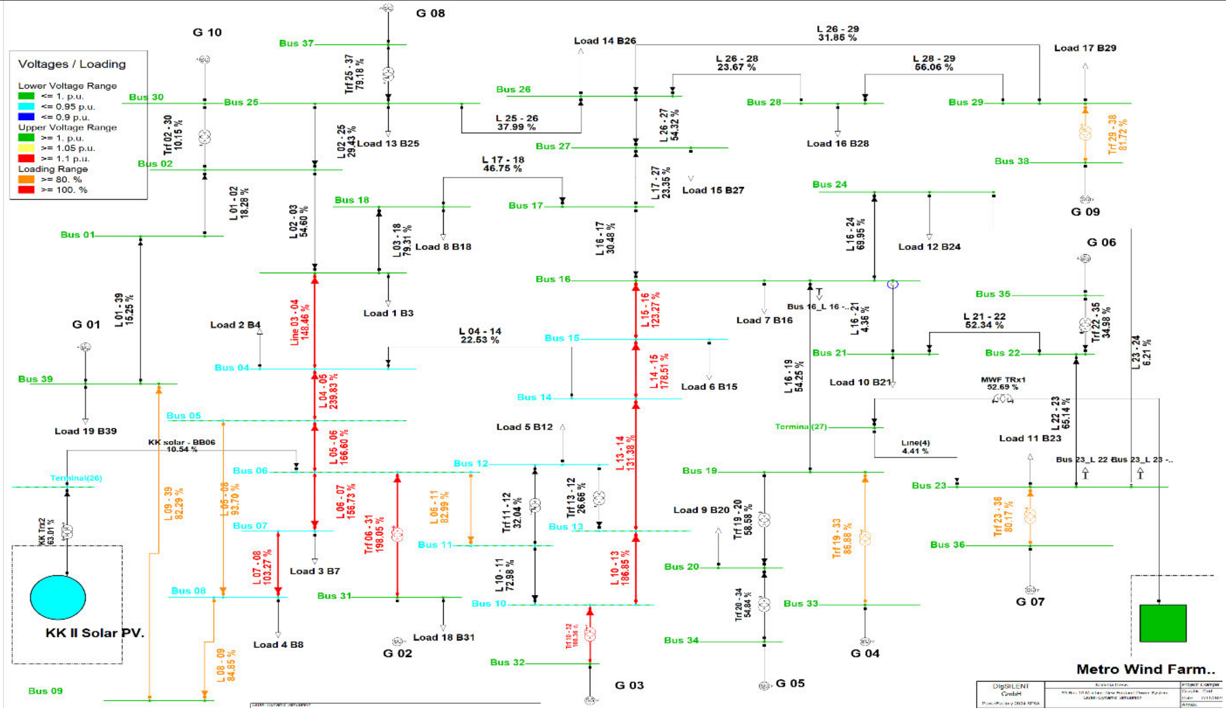
(b) Line loading for 10 years with quasi dynamic



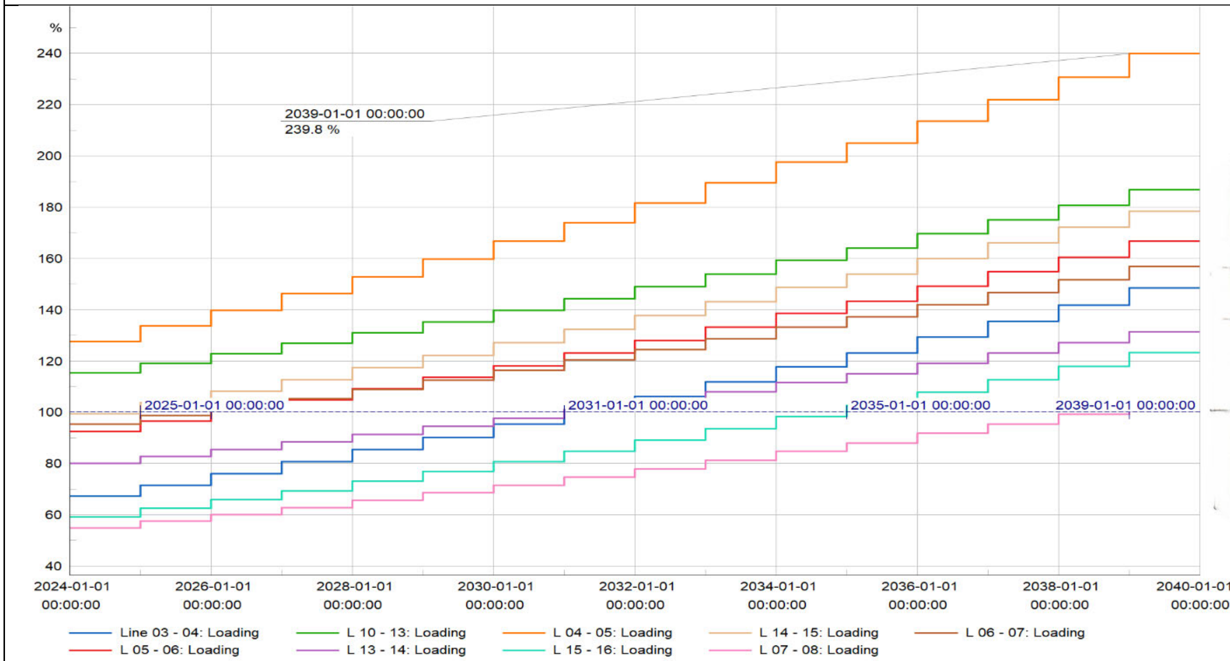
(c) Busbar voltage (p.u) for 10 years under quasi-dynamic

Figure 6. 34Quasi-dynamic simulation for 10 years

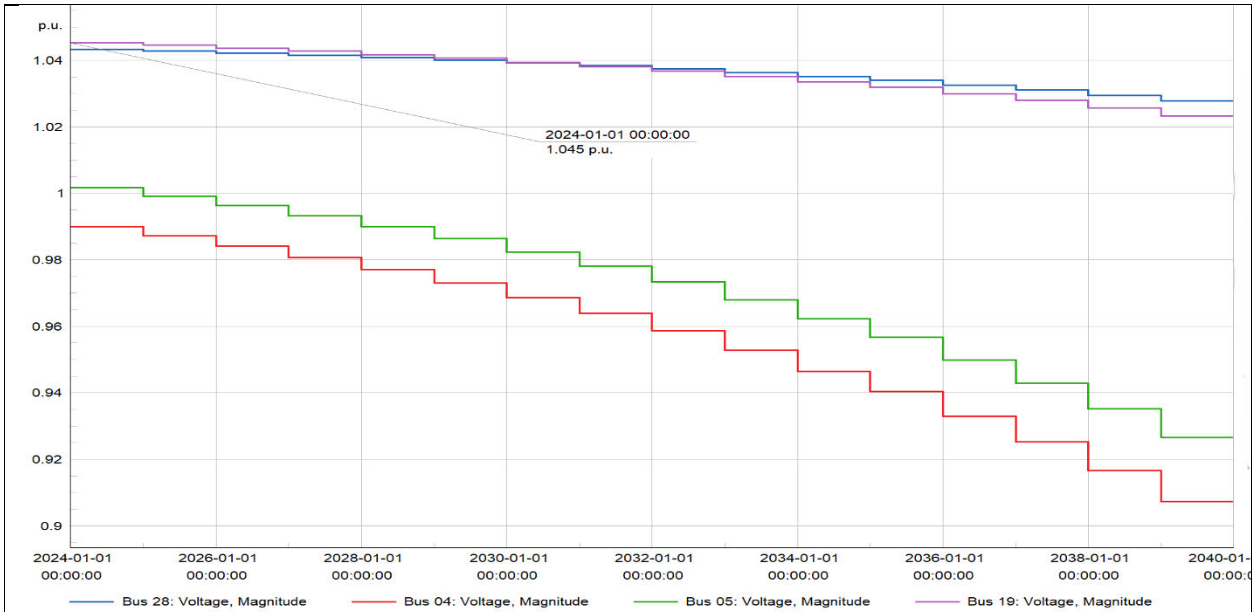
Figure 6.35 presents the quasi-dynamic simulation for a 15-year forecast period. In Figure (a), the entire network is shown, revealing a maximum loading of 239.83%, which is unacceptable for a robust grid. Additionally, the number of overloaded lines in the system has escalated, indicating a detrimental trend for grid health over the 15-year forecast, suggesting that the system will not sustain the anticipated load growth.



(a) Effect of quasi-dynamic after 15 years



(b) Line loading for 15 years with quasi-dynamic



(c) Busbar voltage (p.u) for 15 years under quasi-dynamic

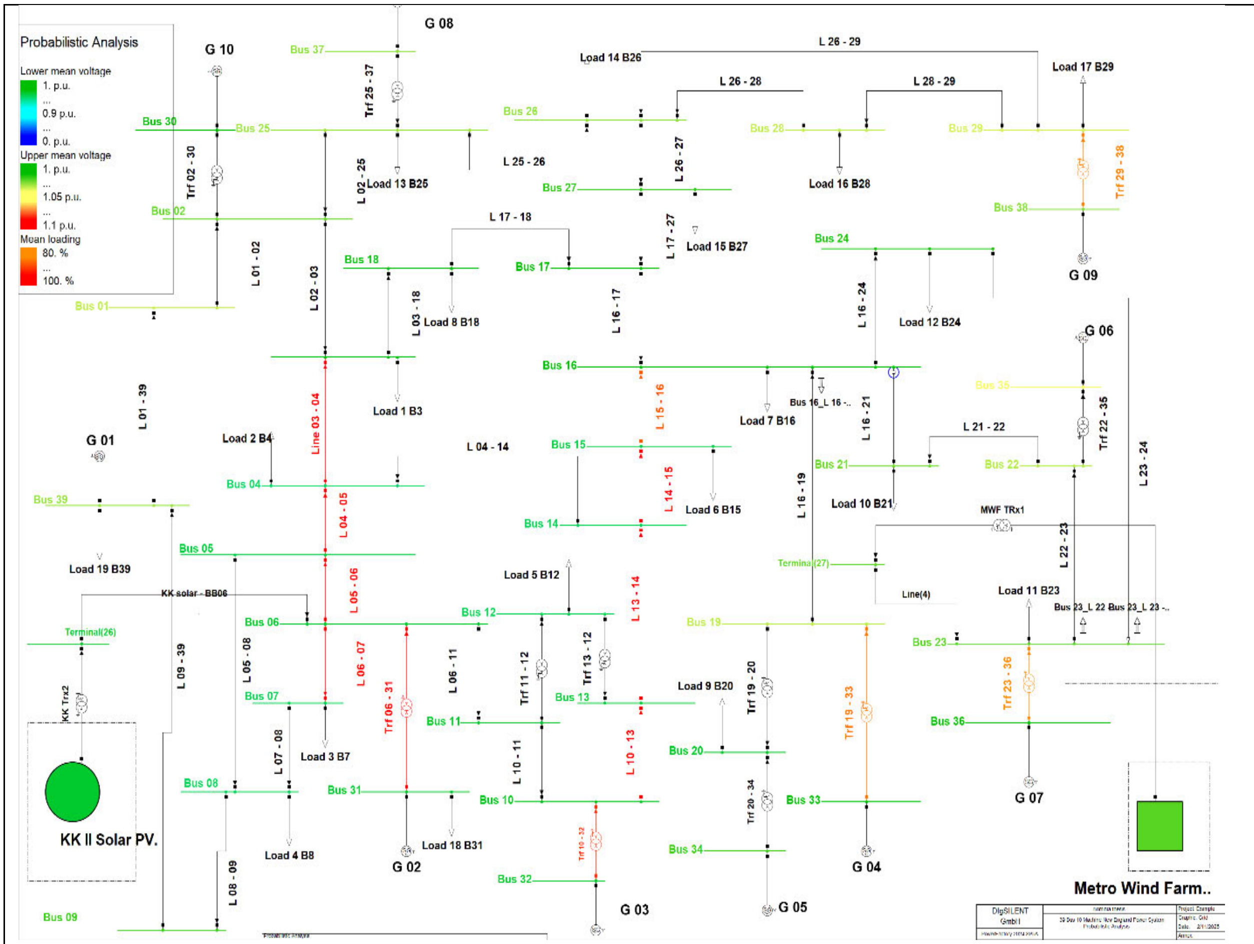
Figure 6. 35Quasi-dynamic simulation for 15 years

Figure 6.35 (b) illustrates the line loading, indicating all instances when the line is over the permissible value. Additionally, the line loading provides insight into the specific moments when this line exceeds the allowable value. Figure 6.35 (c) presents the voltage per unit for the busbars. While certain busbars indicate potential voltage instability, they remain within acceptable limits.

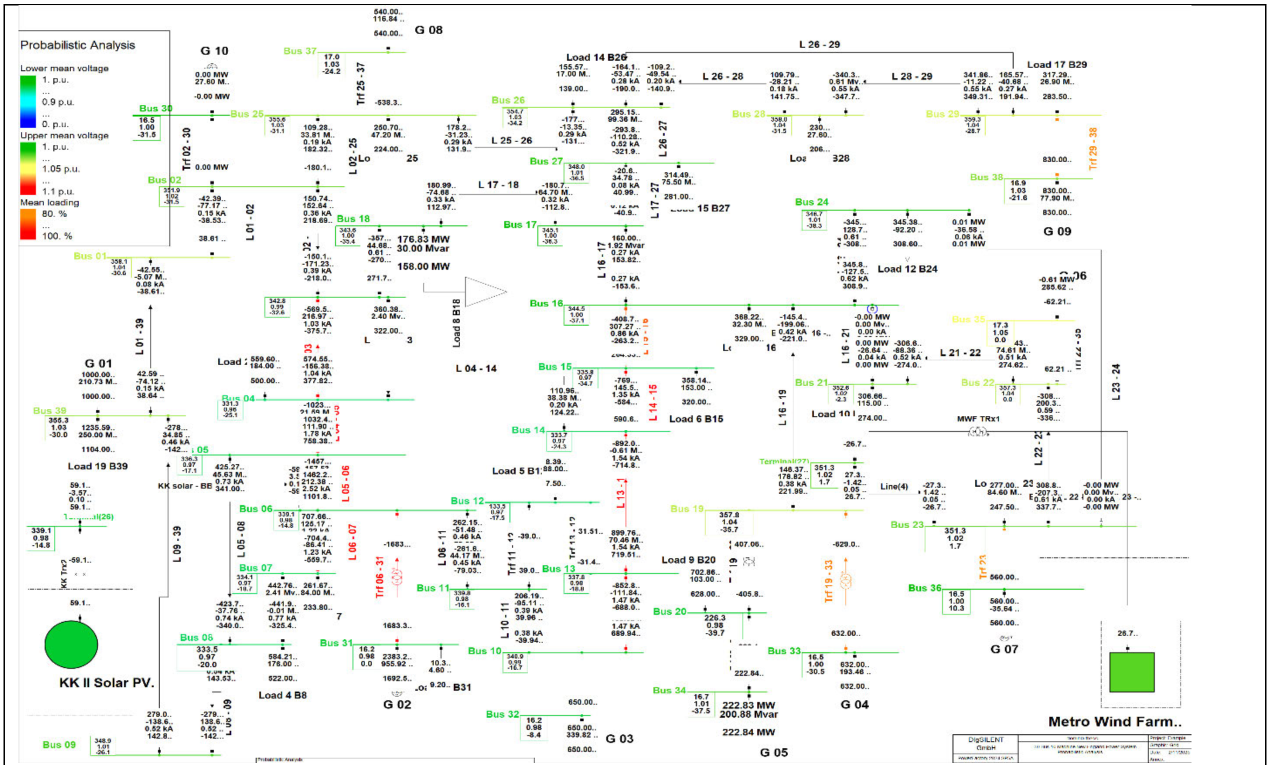
6.8 Probabilistic using Quasi Monte Carlo simulation

This section proposes a probabilistic methodology utilizing QMCS to identify the optimal location for network reinforcement. The methods used employ probabilistic input data represented as distributions, resulting in stochastic outcomes; hence, the results are not singular values but rather distributions from which statistical metrics may be derived. This section applies characteristics and distributions to generators and loads, allowing probabilistic analysis to account for several probable scenarios. All loads possess characteristics that account for load increase over 15 years, as detailed in Chapter 5. Similarly, wind turbines have features that enable them to vary every half hour throughout the whole year. Distributions are generated for probabilistic analysis, enabling the examination of several potential situations by random sampling of values from the distribution.

While the quasi-dynamic simulation network shows overloaded lines as load growth escalates, it remains challenging to identify which segments of the network require reinforcement to mitigate loading instability and which areas significantly contribute to increased instability. A probabilistic analysis technique utilizing QMCS is proposed to identify network components requiring expansion and to demonstrate its influence on grid stability threats. Figure 6.36(a) illustrates the simulation network under probabilistic analysis, demonstrating the lines that contribute to voltage instability over a 15-year period. In contrast, Figure 6.35 (b) identifies 9 lines exceeding the permissible threshold of 100% during the same timeframe; however, the probabilistic tool in conjunction with QMCS indicates that 7 lines require reinforcement to address the network's overloading. Figure 6.36(b) illustrates the necessary average power for each load and generator to operate within permissible limits following strengthening.



(a) Network simulation showcasing overloaded lines using probabilistic analysis & QMCS



(b) Network simulation showcasing average powers.

Figure 6. 36Network simulation under probabilistic analysis using the QMCS

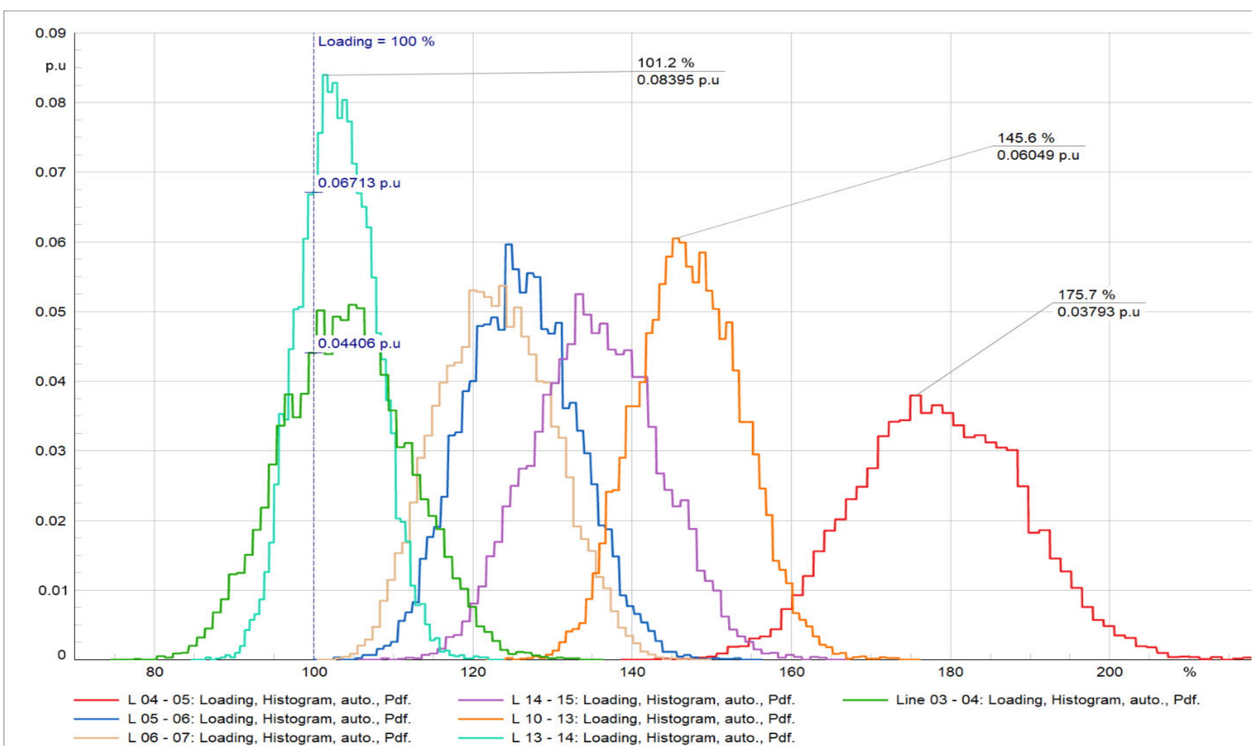


Figure 6. 37Line distribution estimation

Figure 6.37 is the distribution estimation for the suggested lines in a histogram shape, showing the impact of this line it has on the grid, as it can be seen in line L13-14, which has the highest quantity being 0.08395p.u exceeding 100%, also line 04-05 has the most loading exceeding 200% showing that the line reinforcement must be doubled as the permissible value is 100%.

6.9 Transmission expansion network for 15 years

This section expands transmission lines as suggested by Figures 6.36 and 6.37. The new transmission lines are placed in parallel to the lines that needed reinforcement. Line L04-05 shows an overloading of above 200% when using distribution estimation, which shows that if we add the line with the same parameters, we need to add two lines to ensure reinforcement, since the maximum thermal loading should not exceed 100%. Figure 6.38 is the loadflow analysis network after expansion, showing all the lines added.

Figure 6.39 illustrates the probability analysis following the network extension seen in Figure 6.38. The study indicates that the network can now support a load growth of 15 years without grid instability or the necessity for reinforcement. Figure 6.40 illustrates the distribution estimation of the lines requiring strengthening, indicating that all lines are currently functioning within acceptable thermal loading parameters.

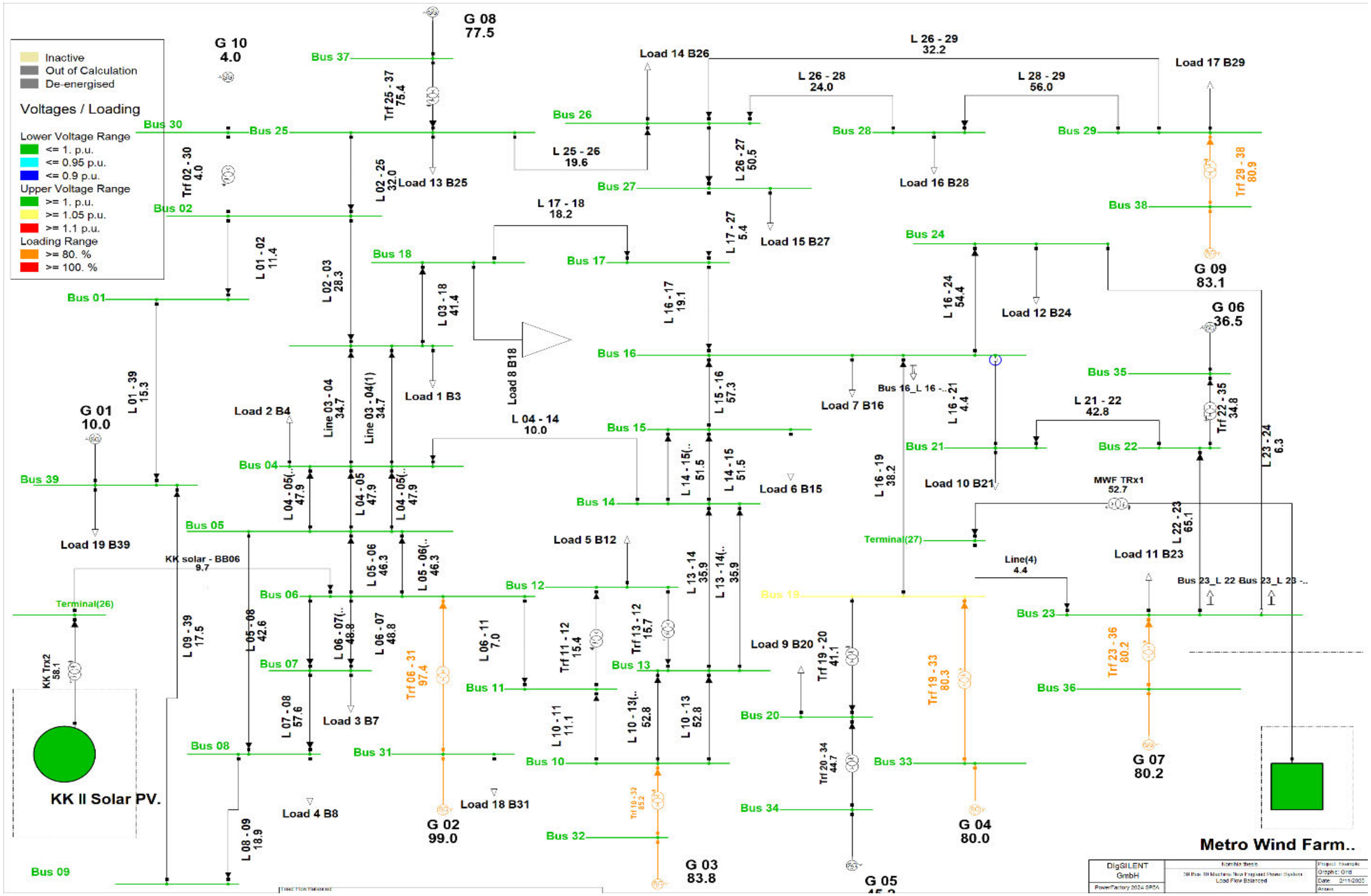


Figure 6. 38Load flow analysis after expansion

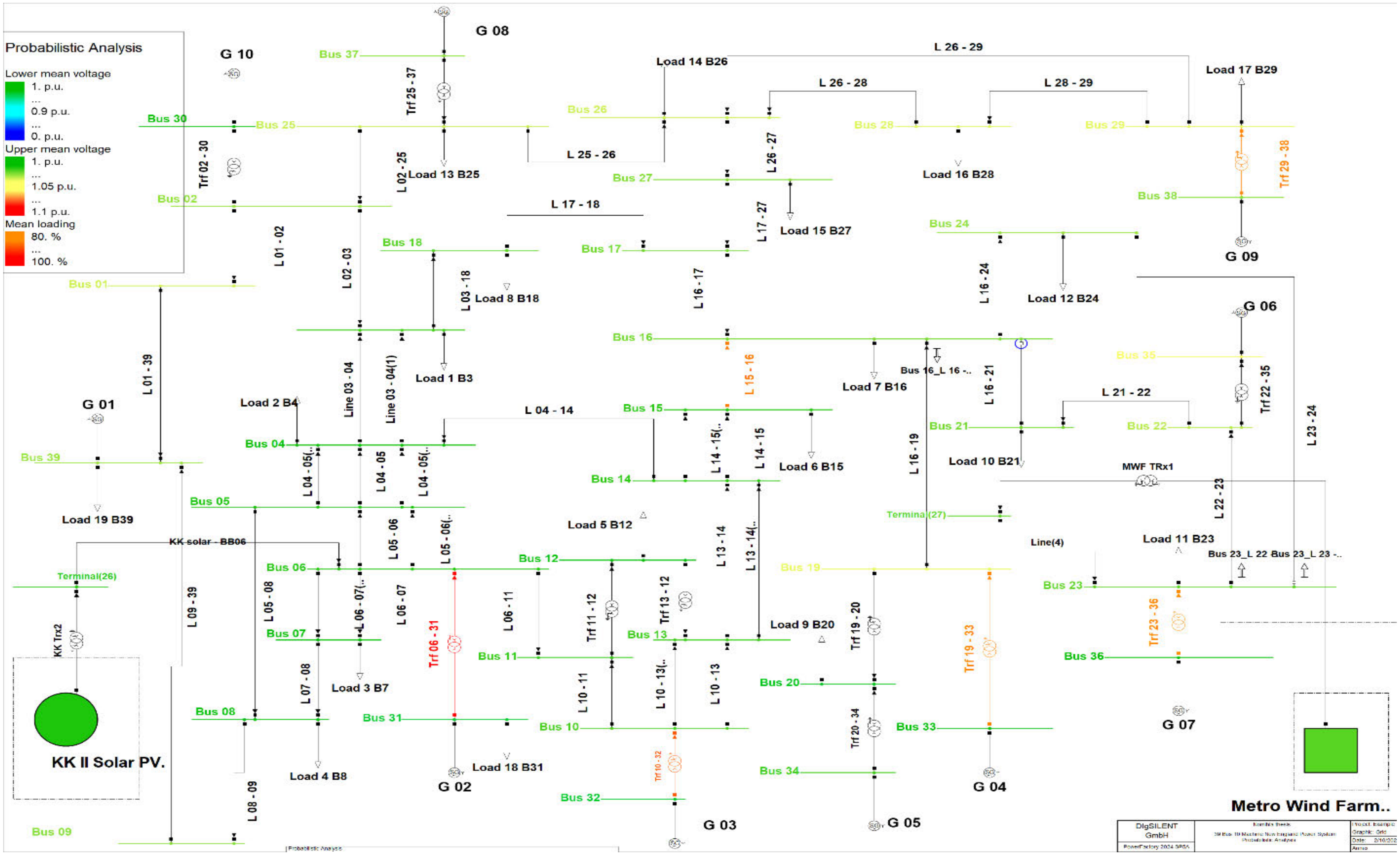


Figure 6. 3915 years probabilistic analysis after expansion

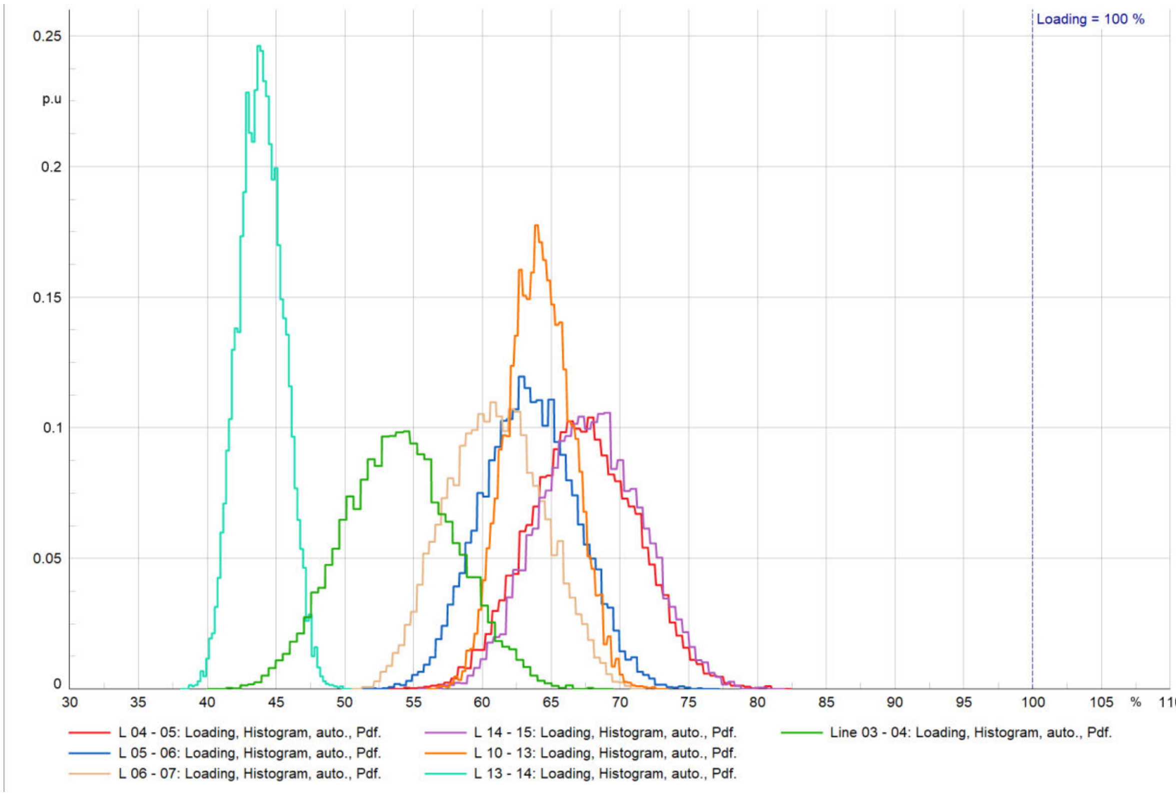
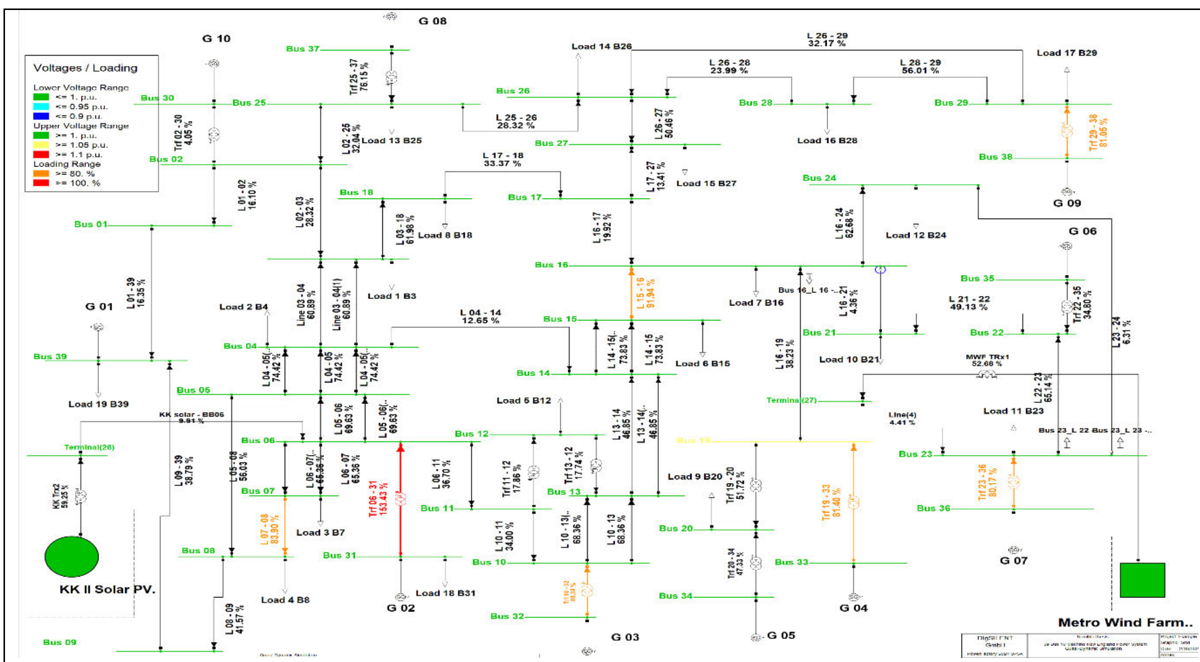
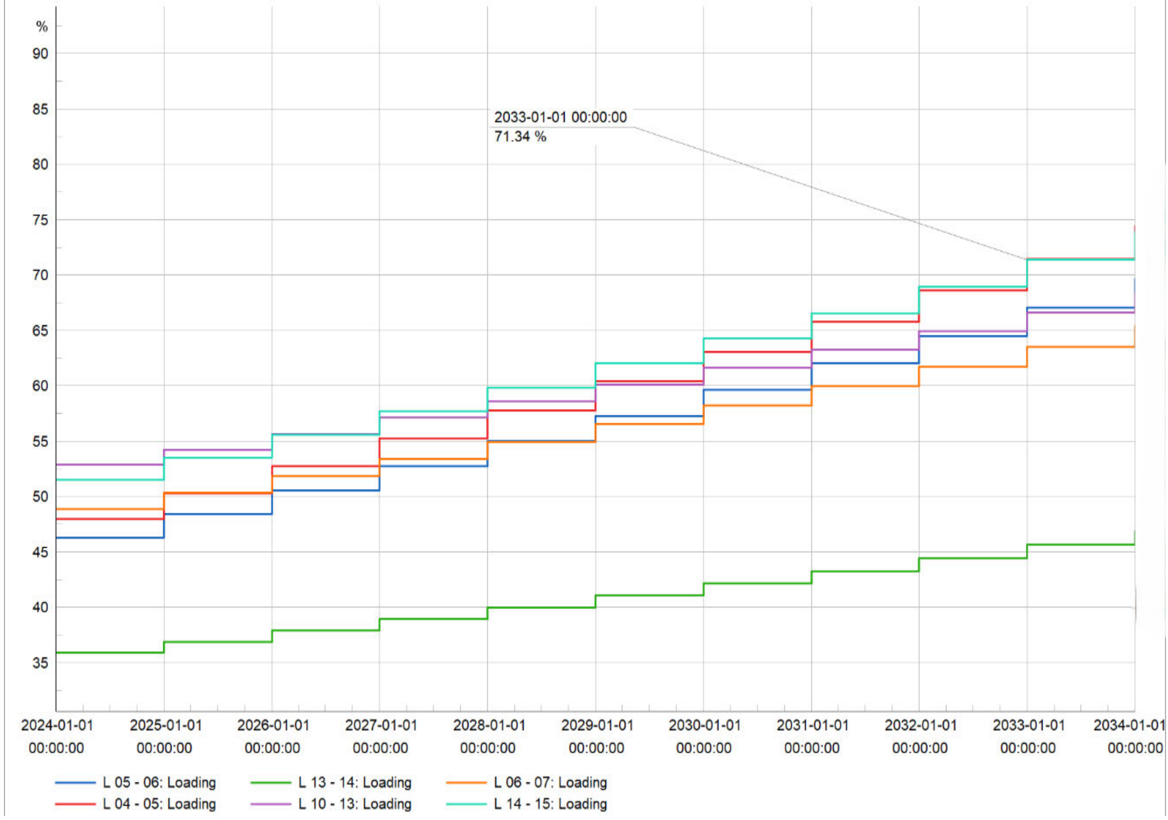


Figure 6. 4015 years of distribution estimation after expansion



(a) Quasi-dynamic simulation after expansion for 10 years

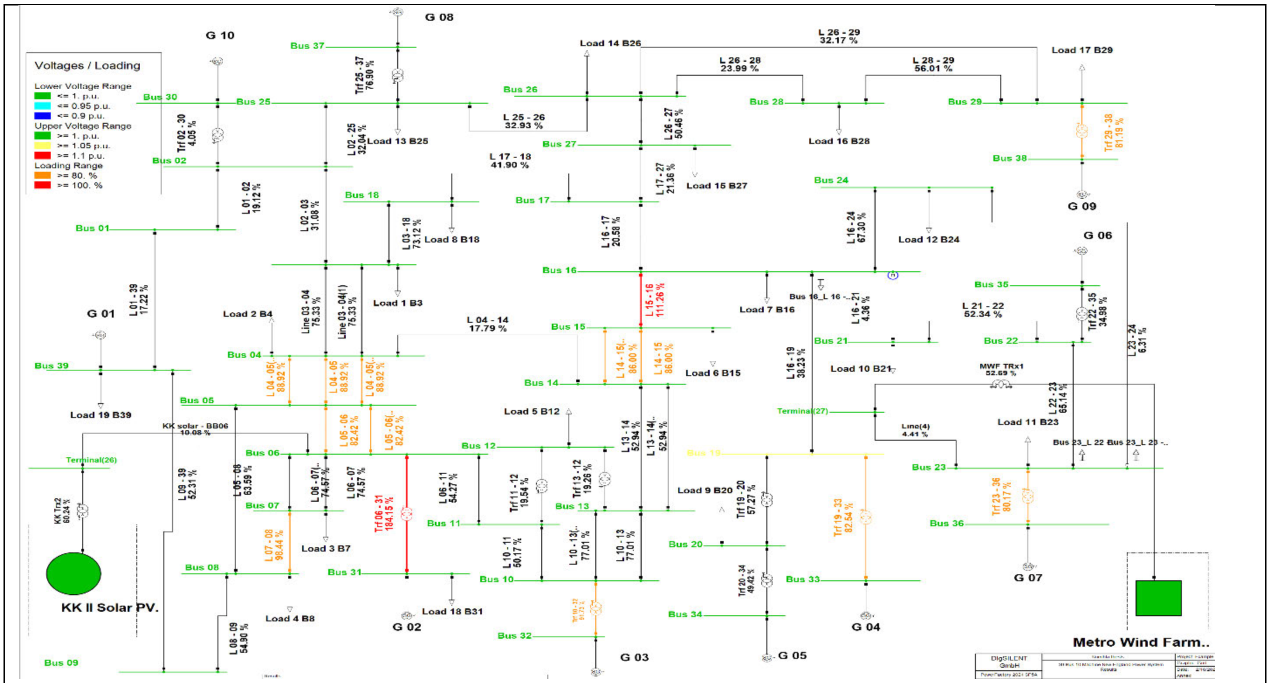


(b) Line loading after expansion for 10 years

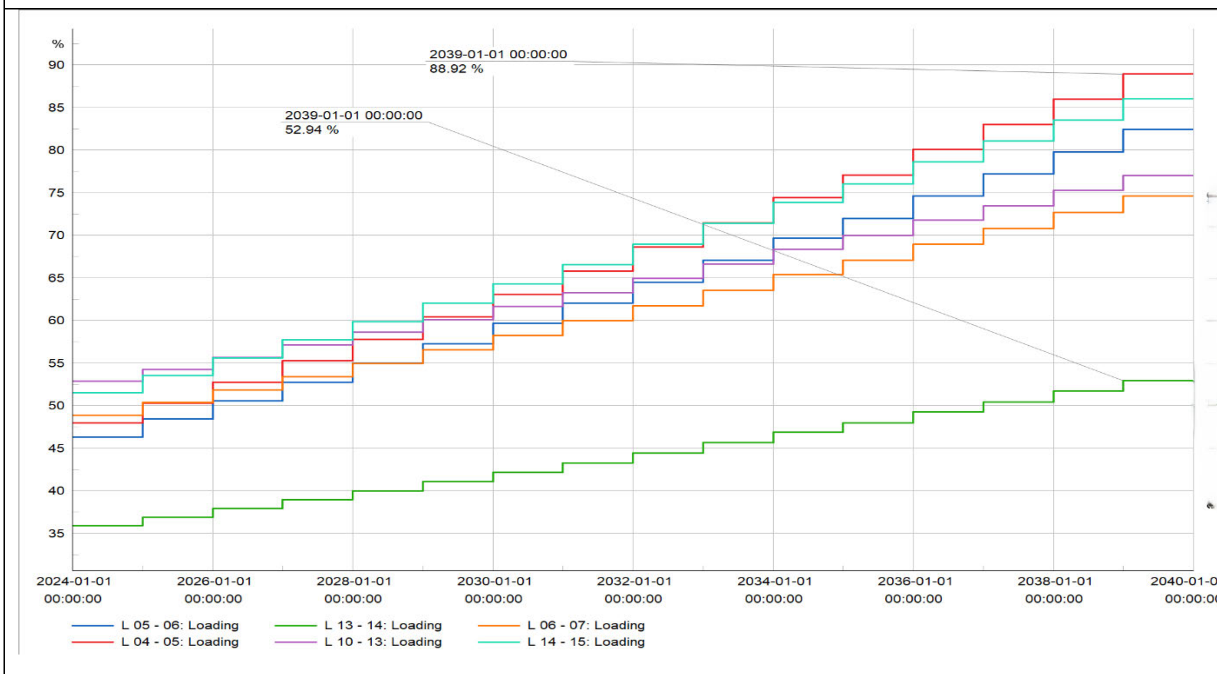
Figure 6. 41Quasi-dynamic simulation after expansion for 10 years

The quasi-dynamic simulation was conducted over 10 years to verify that none of the lines would encounter overloading. This is plainly seen in Figures 6.41(a) and 6.41(b), which demonstrate that none of the lines surpass 100%.

Figure 6.42 illustrates the network under quasi-dynamic simulation for 15 years post-expansion. It is observed that line L15-16 experiences overloading, as depicted in Figure 6.42(a). Conversely, Figure 6.42(b) indicates that all lines requiring reinforcement prior to expansion are now operating within permissible limits.



(a) Quasi-dynamic simulation after expansion for 15 years



(b) Line loading after expansion for 15 years

Figure 6. 42Quasi-dynamic simulation after expansion for 15 years

Figure 6.43 illustrates the distribution estimation for line L15-16. To determine the necessity of reinforcement for this line, the figure indicates a minimal quantity exceeding 100%, approaching

0, which suggests that reinforcement is unnecessary; the network can sustain 15 years of load growth without requiring any enhancements.

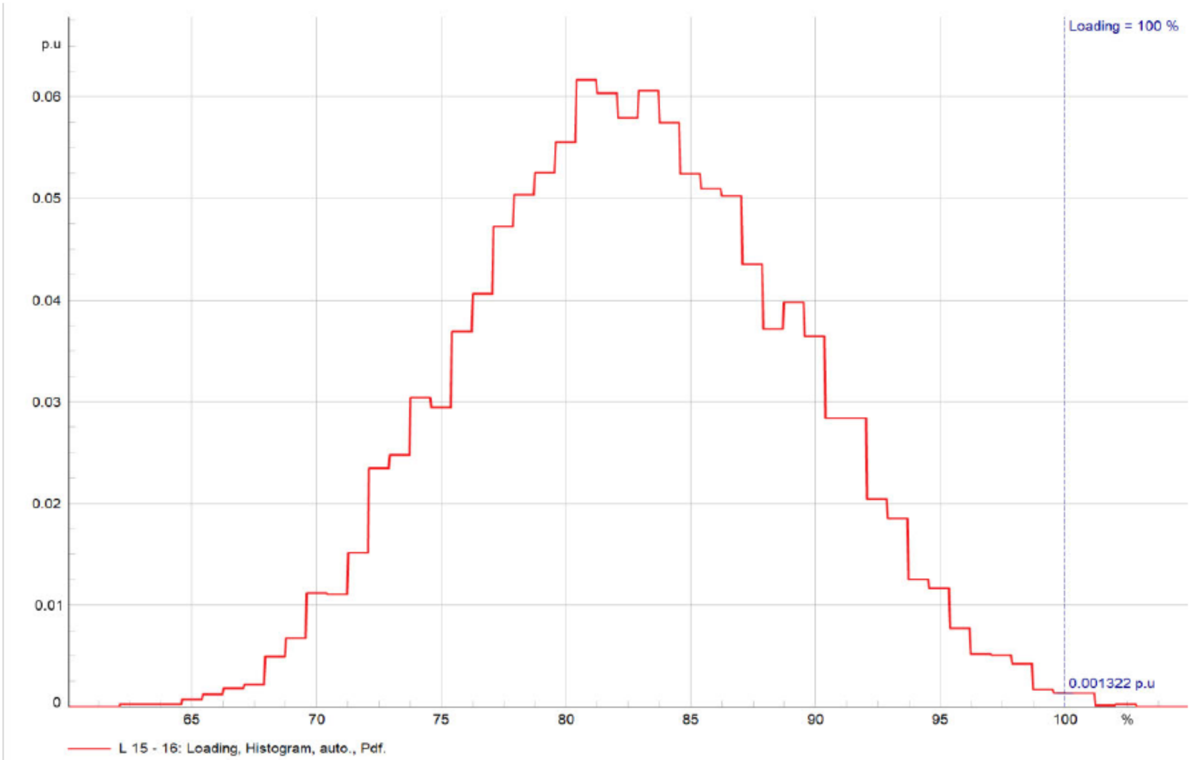


Figure 6. 43Distribution estimation of line L15 -16

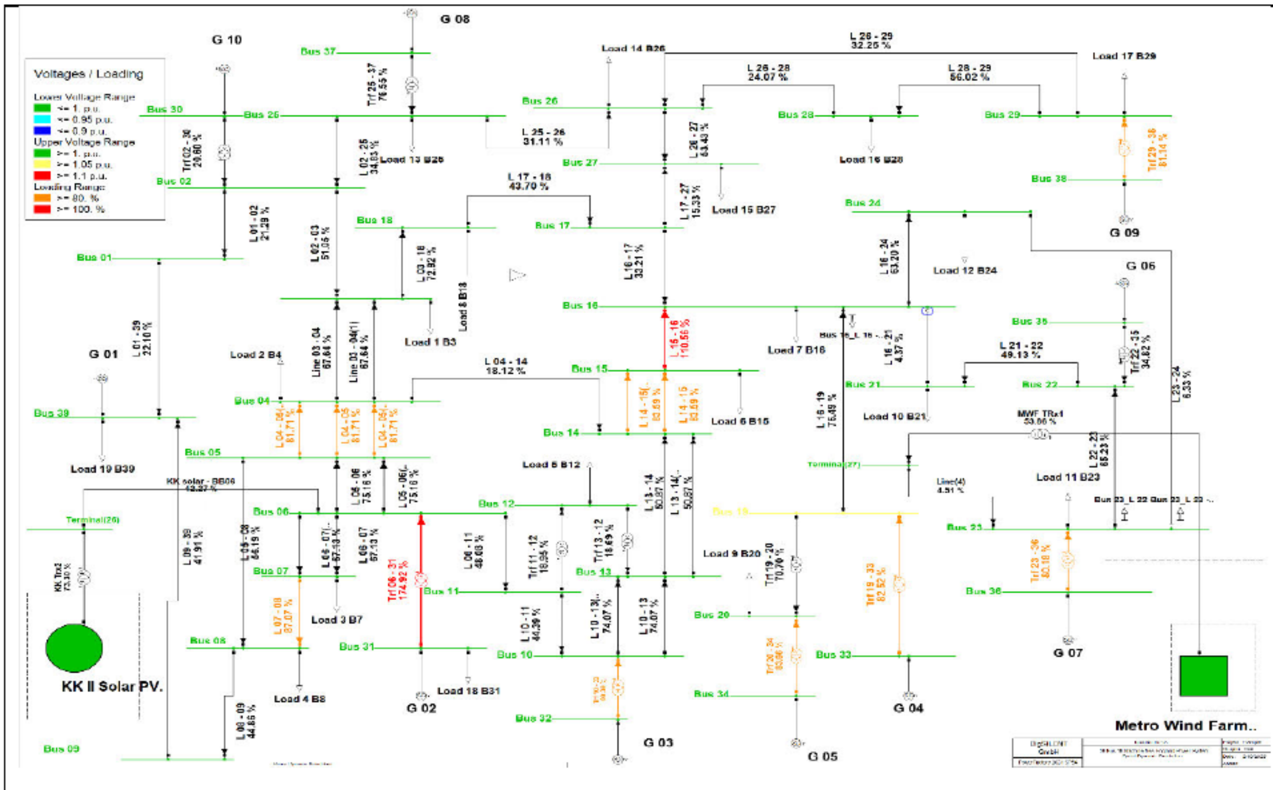
Table 6.10 presents the power summary of the network post-expansion, indicating that while the load demand remains unchanged, losses have reduced from 45.4 MW in Table 6.5 to 40.6 MW.

Table 6. 10Power summary after 15 years of expansion

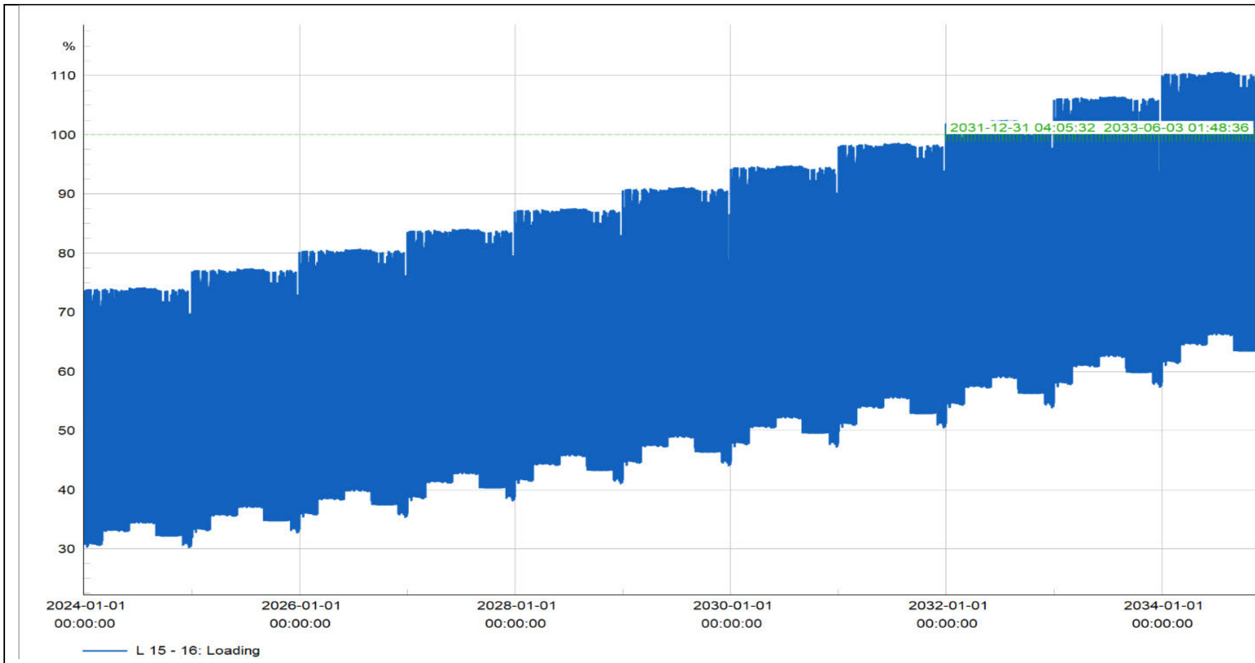
Power Summary		
Generators, Active Power	Generators, Reactive Power	Generators, Apparent Power
6137.7MW	1230.8MVAr	6259.9MVA
Generators, Nominal Active Power	Generators, Nominal Reactive Power	Generators, Nominal Apparent Power
15549.5MW	9620.2MVAr	18248.8MVA
Generators, the difference between the maximum and actual active power	Generators, the difference between the maximum and actual reactive power	
9389.6MW	10619.6MVAr	
Loads, Active power	Loads, Reactive power	Loads, Apparent power

6097.1 MW	1408.9MVAr	6257.8MVA
Loads, Nominal Active Power	Loads, Nominal Reactive Power	Loads, Nominal Apparent Power
6097.1 MW	1408.9MVAr	6257.8MVA
Losses, Active Power	Losses, Reactive Power	
40.6MW	-178.1MVAr	

Furthermore, Figure 6.44 illustrates the quasi-simulation concentrating on RE integration into the network, demonstrating their impact as they fluctuate bi-hourly throughout the year. Additionally, considering the load growth, a quasi-dynamic simulation is conducted over a decade, indicating that L15-16 is prone to experiencing overload. Figure 6.44(b) clearly illustrates the uncertainty of RE as demand escalates, indicating that the significant uncertainty may lead to overloading by the year 2032.

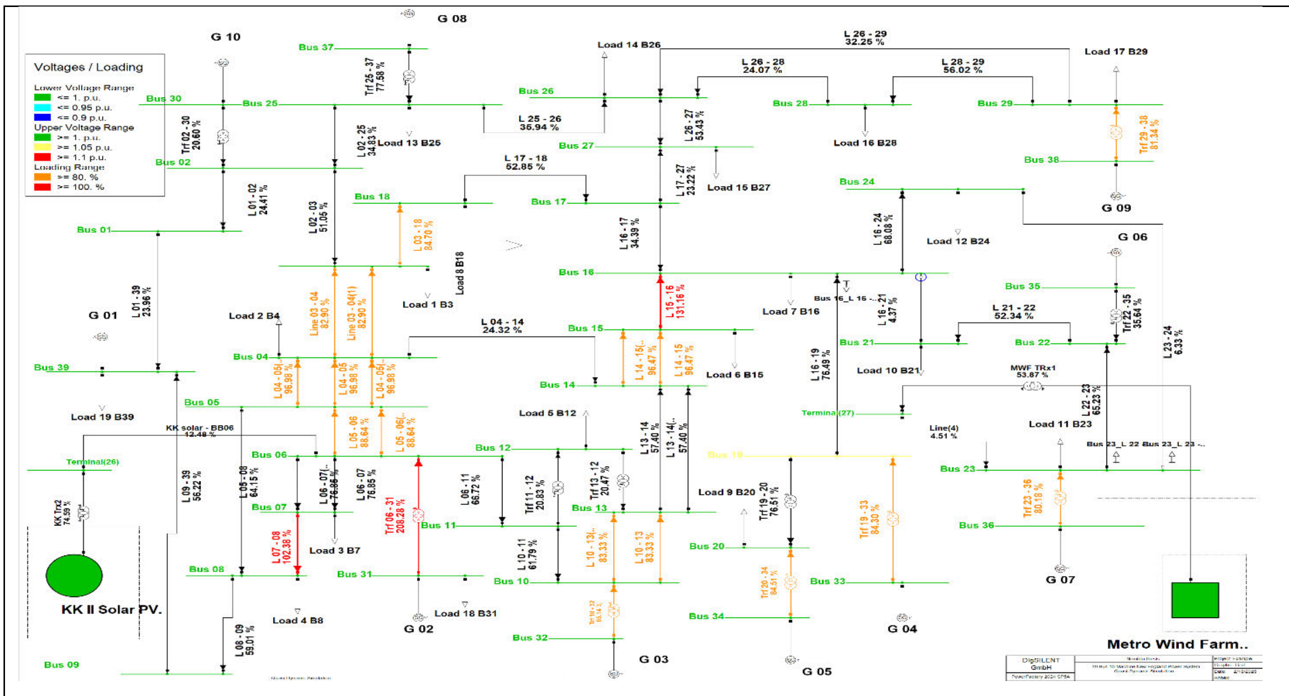


(a) Quasi-dynamic simulation after expansion for 10 years with RE focus

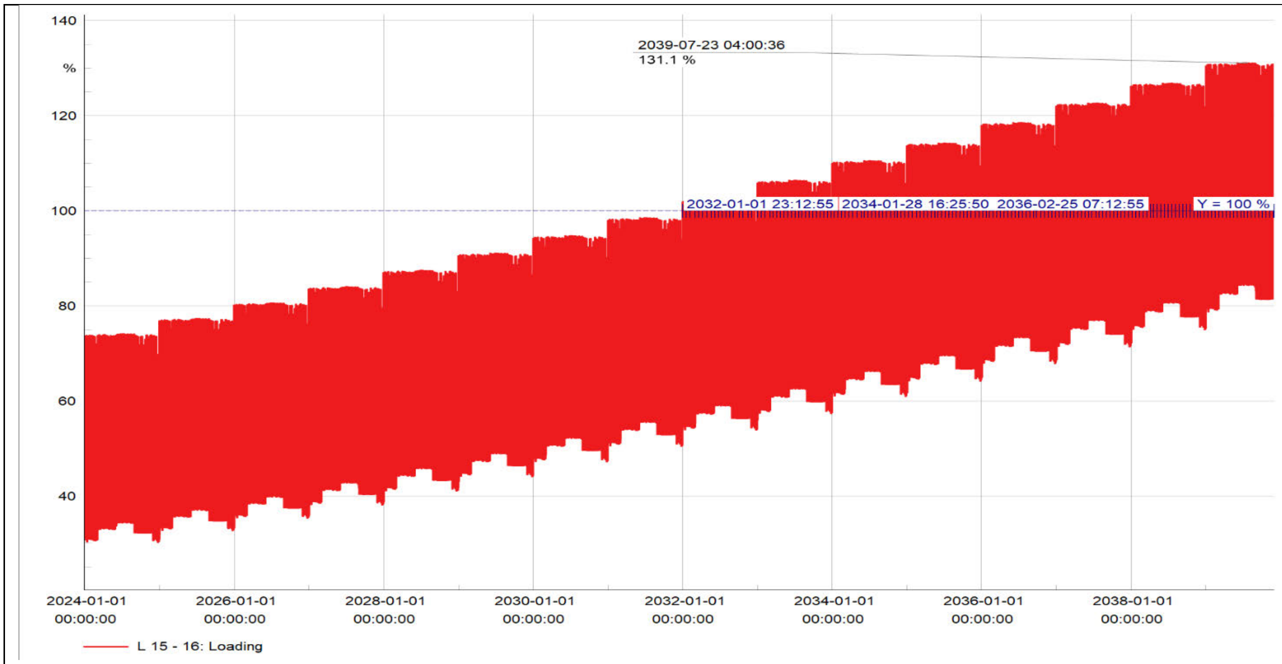


(b) Line loading after expansion for 10 years with RE focus

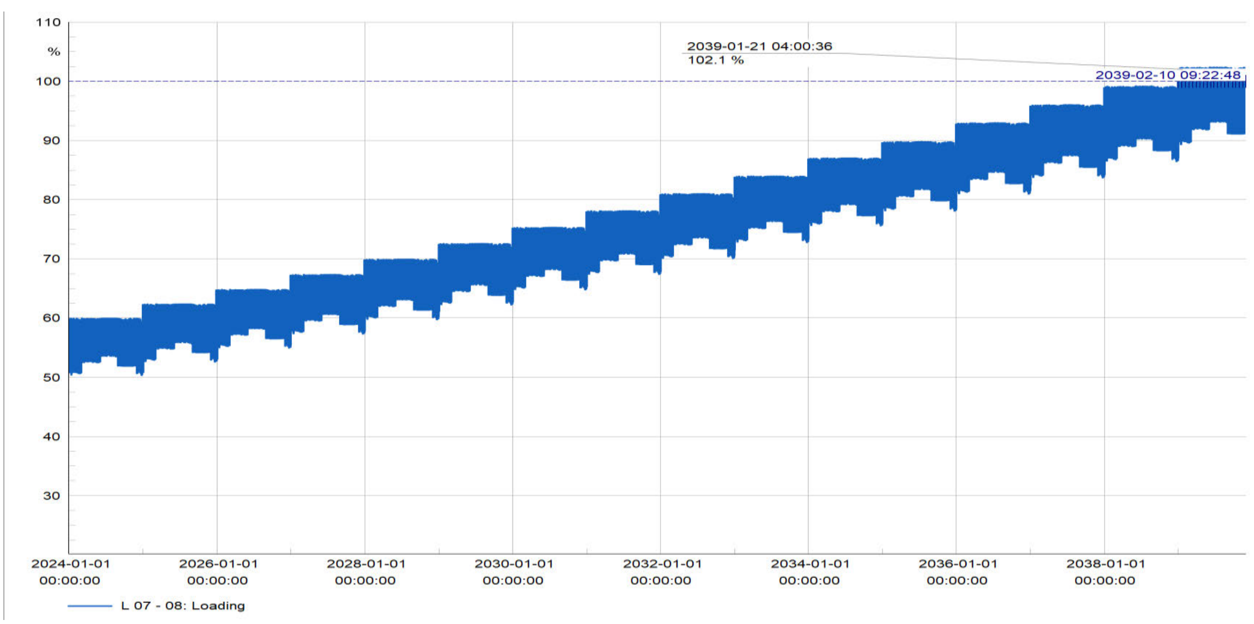
Figure 6. 44Quasi-Dynamic with RE after 10 years after expansion



(a) Quasi-dynamic simulation after expansion for 15 years



(b) Line loading after expansion for 15 years with RE focus



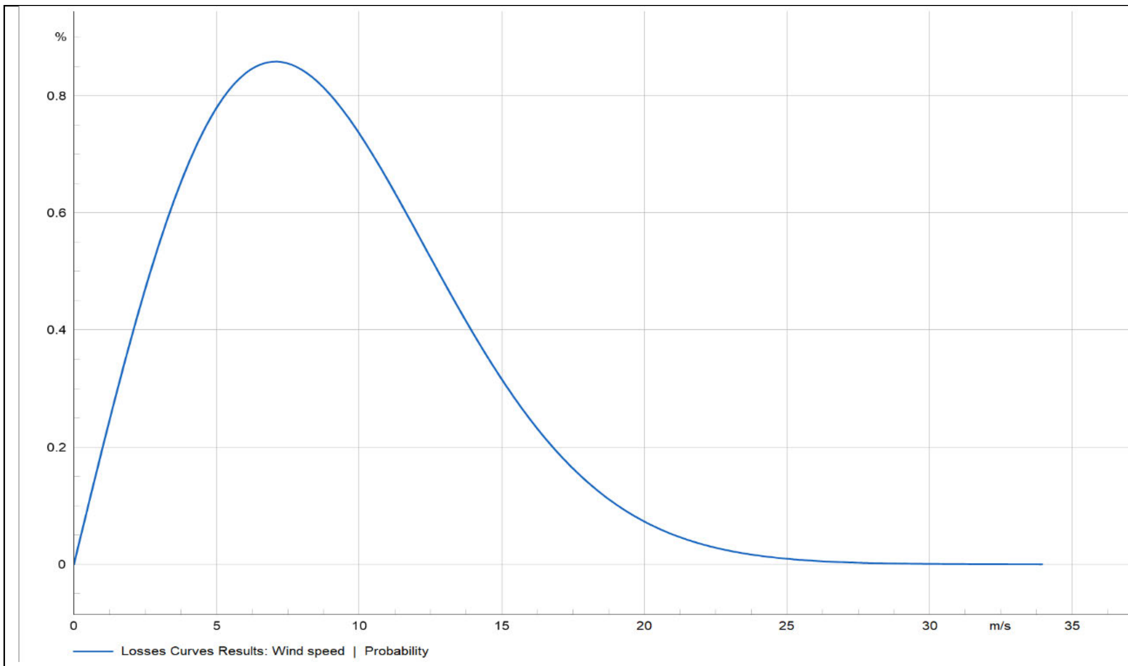
(c) Line loading after expansion for 15 years with RE focus

Figure 6. 45Quasi-dynamic with RE after expansion for 15 years

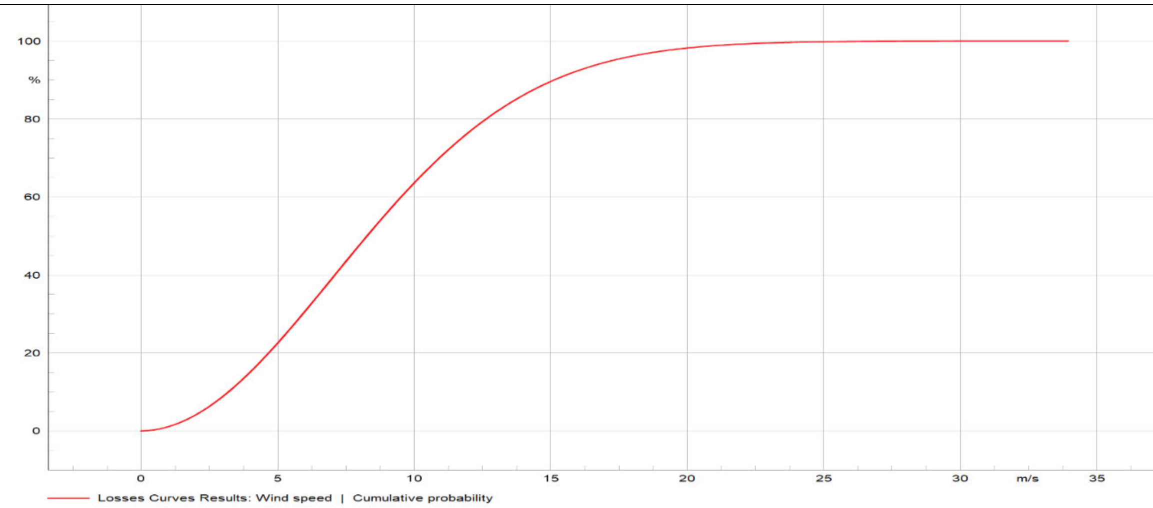
The quasi-dynamic simulation was ultimately conducted over a 15-year period, emphasizing the uncertainties associated with renewable energy, as seen in Figure 6.44. Figure 6.45(a) indicates that after a duration of 15 years, two lines, specifically Line L07-08 and Line L15-16, are expected to undergo overloading. Figure 6.45 (b) clearly illustrates the overloading of line L15-16, which reaches 100% by the year 2032, whereas Figure 6.45 (c) indicates that line L07-08 becomes overloaded in 2039, the final year of the TEP in this research.

6.10 Power park analysis

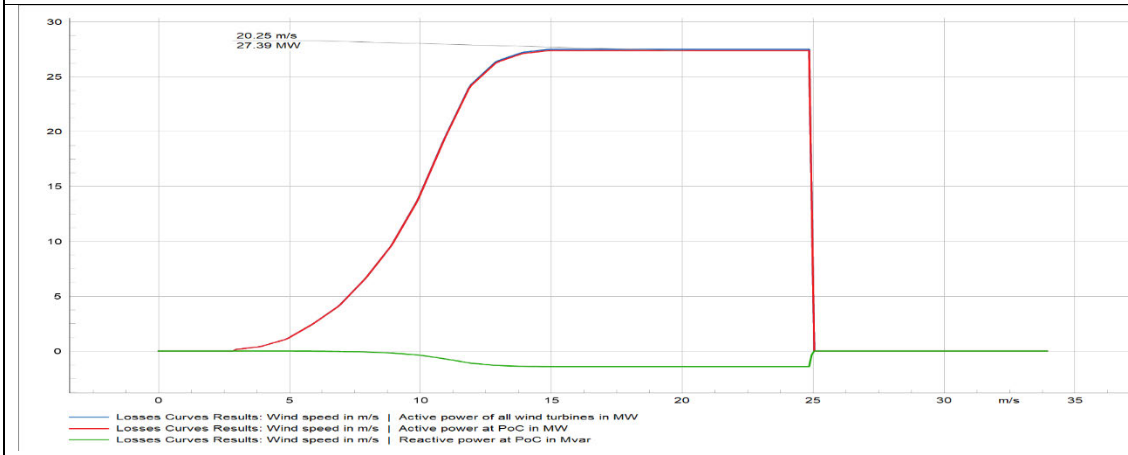
The wind farm's energy analysis is conducted using the basic calculation technique, which performs a series of load flow calculations throughout the range of wind speeds from zero to the maximum speed under consideration. The wind farm is made up of 11 wind turbines with identical configurations. During the wind speed assessment, electrical losses in the network at each wind speed are computed through load flow analysis, considering the operational limits of active and reactive power of the turbine. Subsequently, annual energy losses are determined using a Weibull distribution of the provided wind speed. This tool, based in load flow calculations, enables the determination of critical metrics such as losses, energy, and profit.



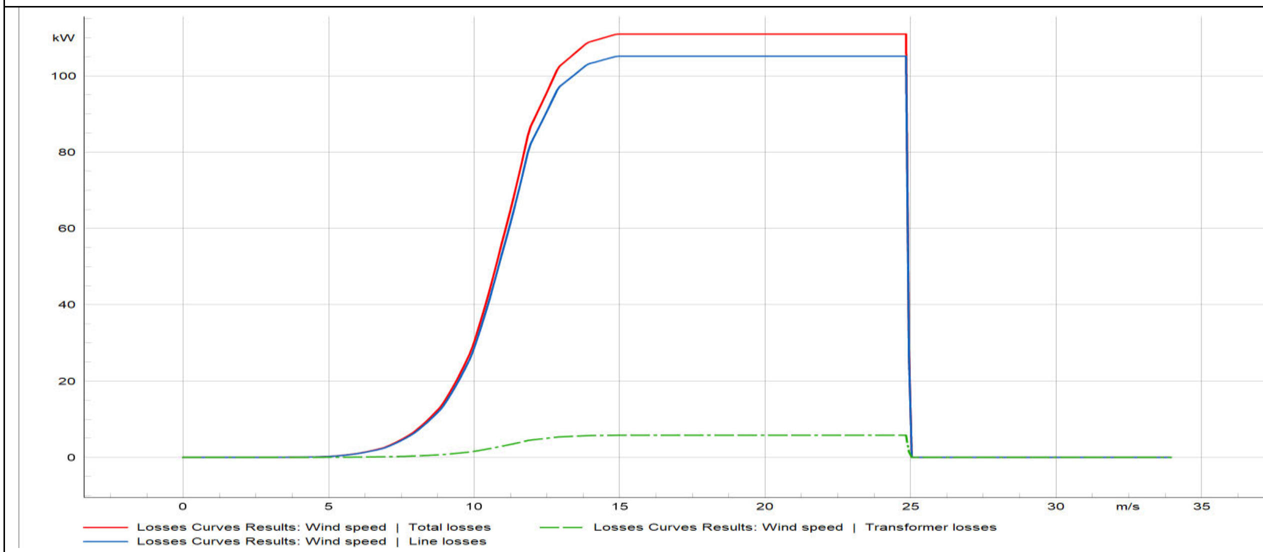
(a) Wind speed probability density



(b) Wind speed cumulative probability



(c) System losses over active power



(d) Total losses, lines losses, and transformer losses.

Figure 6. 46Basic energy analysis results

Figure 6.46 illustrates the variation in wind speed, with electrical losses in the network computed by load flow analysis for each wind speed. Figure 6.46 (a) illustrates the probability density function for wind speed, while Figure 6.46 (b) depicts the cumulative probability for wind speed. Figure 6.46 (c) presents the top part, displaying the active power losses and active power of all wind turbines at the point of common coupling in relation to wind speed, and the lower part exhibits the reactive power at the point of common coupling. Finally, Figure 6.46 (d) indicates the transformer losses within the wind farm, including total losses and line losses.

In the second part, a probabilistic analysis employing the QMCS technique is utilized, applying the previously mentioned tariff for evaluation over a one-year period. This analysis processes probabilistic data inputs and produces stochastic results, from which statistical quantities such as mean values and standard deviations can be derived.

Figure 6.47 illustrates the wind farm subjected to probabilistic analysis, indicating the average power output for each wind turbine. For instance, MWT 7 exhibits an average power of 1.03 MW and a full load hour (FLH) of 3601.71 hours per annum.

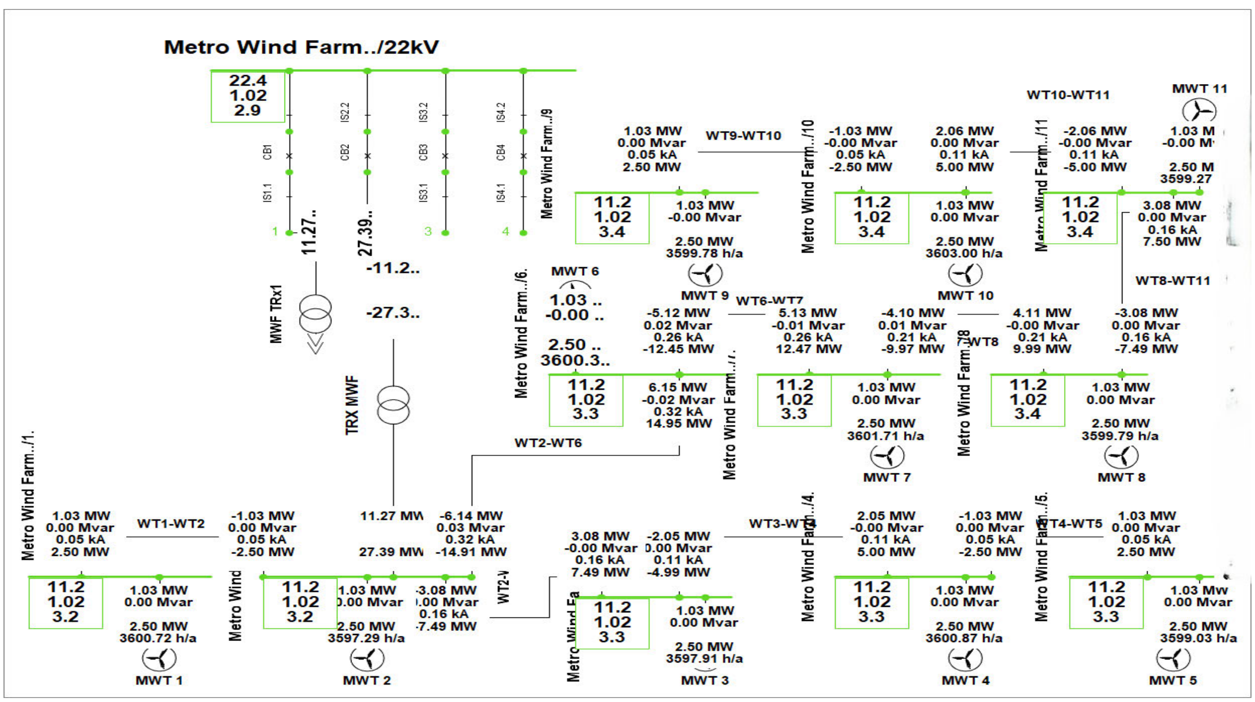


Figure 6. 47Metro WF under probabilistic analysis

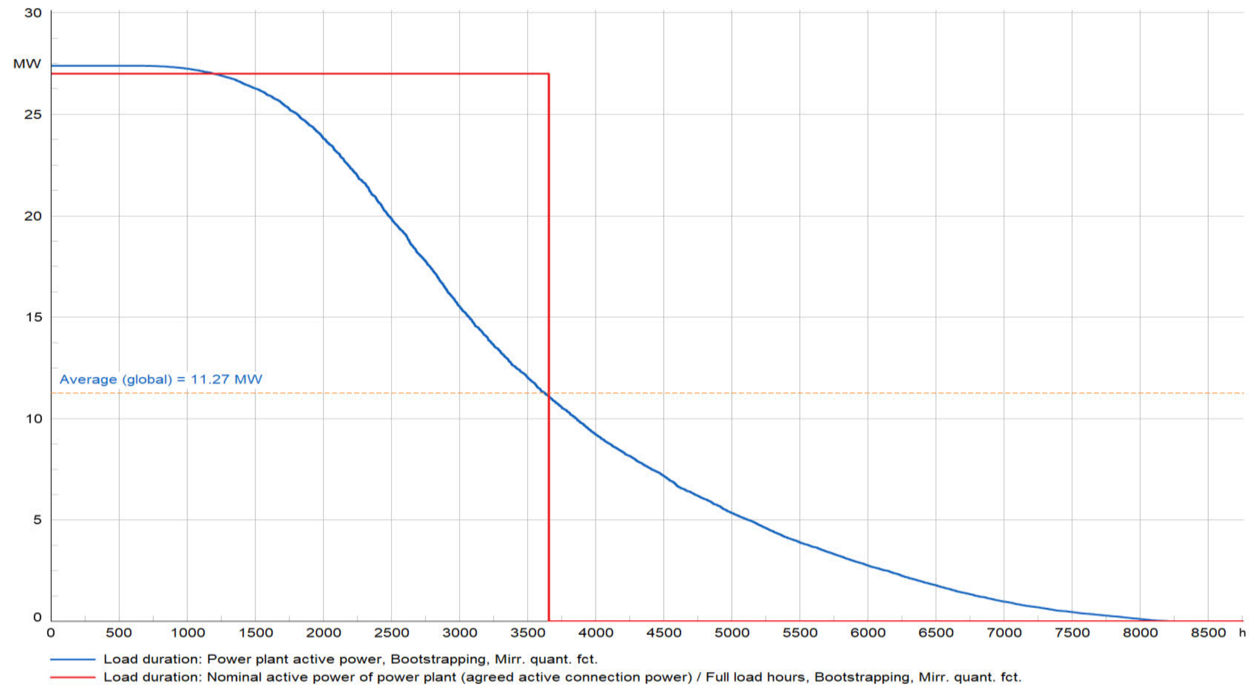


Figure 6. 48Metro wind farm annual load duration curve

Figure 6.48 illustrates the yearly load duration curve, with the blue line representing the active power of the power plant at the connection point throughout the year, the red line indicating the energy equivalent at full load output, and the orange dotted line depicting the average power derived from confidence intervals.

Tables 6.11 and 6.12 present the methodologies employed to analyze the wind farm, namely basic analysis and probabilistic analysis, for assessing losses, profits, and energy production. Initially, a technique known as the boundary tool was employed to segregate the wind farm from the remainder of the network, to assess the potential power transfer from the wind farm to the entire network. A comparison can be drawn from both tables, indicating that the average power during the year is nearly the same. Basic analysis yields greater profits than probabilistic analysis; however, it also incurs more losses. Furthermore, the probabilistic analysis demonstrates that the average power of each turbine guarantees network stability and electricity capacity.

Table 6. 11Basic analysis of a wind farm

Basic Analysis	
Average power of power park over a year	11.3MW
Total annual net energy output at PoC	98745MWh

Total Average electrical energy losses per year	305.2MWh
Number of hours of power park full load operation	3668.5267 h
Loss of profit due to losses in the feed-in operation	15261.84 USD
profit	4937249.24

Table 6. 12Probabilistic analysis of a wind farm

Probabilistic Analysis	
Average power over a year	11.27MW
Annual generation	99007.2 MWh
Annual energy yield	98703.9 MWh
Total Average Electrical energy losses per year	303.3 MWh
Number of hours of power park full load operation	3655.7001 h
Electrical losses (Price)	15163.29 USD
Profit	4935195.16 USD

6.11 Summary

This research proposes a technique that identifies the optimal locations for expanding transmission lines to accommodate additional renewable energy, considering their inherent unpredictability, as well as to manage load growth over time and fluctuations in power supply. TOPO, in conjunction with GA, is proposed to minimize transmission losses. Hosting Capacity is proposed to integrate RE into the network effectively, thus integrating the wind farm and Solar PV plant. Reliability assessment with contingency, which examines the network response to possible faults, is configured in the network components to analyze the network response to any possible faults. Load forecast - 2 cases have been demonstrated, which are short-term and long-term transmission expansion planning. Quasi-dynamic strategies encompass fluctuating wind turbines, solar photovoltaic systems, and generators. Probabilistic analysis in conjunction with QMCS to expand the transmission line. A power park analysis tool is proposed to provide an evaluation of the profitability of the wind farm. Two methods are used, which are basic energy analysis and probabilistic analysis in conjunction with the QMCS

CHAPTER 7 CONCLUSIONS AND FUTURE RECOMMENDATION

The incorporation of renewable energy into transmission networks offers both advantages and obstacles. Transmission Expansion Planning (TEP) is essential for maintaining a stable, efficient, and cost-effective power infrastructure that addresses the unpredictability and decentralization of renewable energy sources. Effective planning reduces congestion, enhances grid resilience, and enables the smooth incorporation of renewable energy sources while preserving grid stability and security. The following part presents conclusions and future recommendations for the study.

7.1 Conclusions

Renewable energy integration would be inefficient, unreliable, and expensive without TEP. Transmission improvements will ease the shift to greener, more sustainable energy. Table 2.4 summarizes published research on classic TEP approaches, including control methods, contexts, network models, implementation year, contributions, and limitations. Traditional methods employ predictable inputs and struggle with ambiguity as systems grow. The integration of renewable energy sources, shifting demand patterns, and dynamic market processes create uncertainty in modern power networks. Complex, large systems may render typical approaches computationally impossible. Traditional methods are less accommodating to current power networks, particularly with the rise of renewable energy and distributed generation. Similar to Tables 2.5 and 2.4, Table 2.6 lists all TEP hybrid algorithms, including improvements, potential advances, gaps, and the justification for hybridizing the algorithm. It uses many optimization methodologies to maximize its benefits and minimize their drawbacks. Power systems need TEP to proactively design the transmission network for the future in a cost-efficient, reliable, and secure way to meet expanding needs, renewable energy inclusion, and uncertainties.

In conclusion, the network with hybrid renewable plant integration was successfully constructed through both short-term and long-term transmission planning amidst various uncertainties. The TOPO, in conjunction with GA, was employed to reduce losses, as seen in Table 6.3. Most studies on the expansion of transmission lines overlook strategies that can mitigate losses. The hosting capacity method is suggested to efficiently incorporate RE into the system without necessitating network reinforcement, as illustrated in Figure 6.6, where the wind farm and solar photovoltaic plant are seamlessly integrated. Furthermore, a review of prior studies indicates that renewable energy sources, primarily PV and wind turbines, are predominantly integrated into the network (busbars). Whereby it does not show the true image of what is happening in real life where RE are located far from the grid and have their losses, transmission lines, and energy infeed. This study uses two types of RE which are solar PV plant located 31km away from the grid, producing 73.26MW from 15 solar PV and wind farm producing 27.39MW. The losses, average power over a year, energy, and profits of these farms are analyzed using probabilistic analysis in conjunction with QMCS as shown in table 6.11 and table 6.12, moreover, a boundary tool is used to state the available power that can be transferred to the rest of the network, this power is not the same as RE output power changes due to them being intermittent.

The reliability assessment was conducted, in which the fault rate data was configured in the reliability section of equipment such as busbars, transformers, and lines to analyze any potential fault and the network's response to that fault, even in the future. This is crucial, as the objective of this study is to maximize the system's reliability while minimizing losses as Figure 6.10 illustrates this. This study expands transmission lines for both short and long-term scenarios, as detailed in Chapter 6. In both scenarios, losses were minimized, as shown in Table 6.9 for the short term and in Table 6.10 for the long term. The proposed tool is quasi-dynamic simulation combined with probabilistic analysis using QMCS, aimed at identifying the optimal locations for adding transmission lines to enhance system stability amid increasing or varying loads, including renewable energy integration, uncertainties, and generator fluctuations. The ideal methods utilized for transmission expansion planning successfully preserved system stability over a 15-year period with minimized losses during reliability evaluation. It also enhanced the system's reliability throughout several seasons throughout the year.

7.2 Future recommendations

For future work, utilizing big data analytics and machine learning (ML) for TNEP can substantially improve the planning, efficiency, and resilience of power networks [375]. Real-Time Data processing utilizes Distributed Data Processing Frameworks such as Apache Spark, planners can manage and analyze real-time data to guide both urgent and long-term decisions in transmission expansion planning. ML algorithms like as support vector machines (SVM), decision trees, and neural networks enhance load forecasting by examining historical consumption patterns, socioeconomic variables, meteorological data, and seasonal trends [376]. ML algorithms can forecast the failure probability of network components from historical maintenance and operational data, allowing planners to incorporate these insights into growth strategies. ML algorithms assist in estimating the likelihood of faults or overloads, enabling planners to incorporate potential hazards when assessing various expansion scenarios [377]. Moreover, advanced ML models, such as convolutional neural networks (CNNs), examine intricate data patterns and variations, facilitating the optimization of network extension strategies to fit the intermittent characteristics of renewable energy [378].

The utilization of big data and ML in TNEP enables energy providers to proactively address new difficulties while maximizing cost, reliability, and environmental sustainability, becoming a crucial component of contemporary grid management. The integration of big data analytics and ML in TNEP is promising yet presents considerable challenges. These can be classified into technical, organizational, regulatory, and data-related challenges. By overcoming these obstacles through a combination of technological advancement, organizational modification, regulatory cooperation, and strategic investment, TNEP can harness the capabilities of big data analytics and machine learning to augment decision-making and enhance grid resilience. Moreover, for future projects, the implementation of devices such as HVDC or FACTS is recommended to reduce losses during the expansion of transmission lines and to enhance the reliability of the system in long-term planning. Furthermore, strategizing for intelligent grids, energy storage solutions, and digital transformation

REFERENCES

[1] X. Zhang and A. J. Conejo, "Candidate line selection for transmission expansion planning considering long-and short-term uncertainty," *International Journal of Electrical Power & Energy Systems,* vol. 100, pp. 320-330, 2018.

[2] P. V. Gomes and J. T. Saraiva, "A two-stage strategy for security-constrained AC dynamic transmission expansion planning," *Electric Power Systems Research,* vol. 180, p. 106167, 2020.

[3] S. Lumbreras, H. Abdi, and A. Ramos, *Transmission Expansion Planning: The Network Challenges of the Energy Transition*. Switzerland: Springer, 2021.

[4] H. Shayeghi and M. Mahdavi, "Application of PSO and GA for transmission network expansion planning," *Analysis, Control and Optimal Operations in Hybrid Power Systems: Advanced Techniques and Applications for Linear and Nonlinear Systems,* pp. 187-226, 2013.

[5] D. Rajoria and A. Sharma, "Nature inspired algorithms for transmission network expansion planning problems: a review," *International Journal of Intelligent Engineering Informatics,* vol. 10, no. 6, pp. 435-463, 2022.

[6] N. G. Ude, H. Yskandar, and R. C. Graham, "A comprehensive state-of-the-art survey on the transmission network expansion planning optimization algorithms," *IEEE Access,* vol. 7, pp. 123158-123181, 2019.

[7] O. M. Babatunde, J. L. Munda, and Y. Hamam, "A comprehensive state-of-the-art survey on power generation expansion planning with intermittent renewable energy source and energy storage," *International Journal of Energy Research,* vol. 43, no. 12, pp. 6078-6107, 2019.

[8] E. Naderi, M. Pourakbari-Kasmaei, and M. Lehtonen, "Transmission expansion planning integrated with wind farms: A review, comparative study, and a novel profound search approach," *International Journal of Electrical Power & Energy Systems,* vol. 115, p. 105460, 2020.

[9] S. Cho, C. Li, and I. E. Grossmann, "Recent advances and challenges in optimization models for expansion planning of power systems and reliability optimization," *Computers & Chemical Engineering,* p. 107924, 2022.

[10] E. G. Morquecho *et al.*, "Comparison of an Improved Metaheuristic and Mathematical Optimization Based Methods to Solve the Static AC TNEP Problem," *IEEE Transactions on Power Systems,* 2024.

[11] Q. Hassan *et al.*, "Implications of a smart grid-integrated renewable distributed generation capacity expansion strategy: The case of Iraq," *Renewable Energy,* vol. 221, p. 119753, 2024.

[12] M. Zakariya and J. Teh, "A systematic review on cascading failures models in renewable power systems with dynamics perspective and protections modeling," *Electric Power Systems Research,* vol. 214, p. 108928, 2023.

[13] C. Li, A. J. Conejo, P. Liu, B. P. Omell, J. D. Siirola, and I. E. Grossmann, "Mixed-integer linear programming models and algorithms for generation and transmission expansion planning of power systems," *European Journal of Operational Research,* vol. 297, no. 3, pp. 1071-1082, 2022.

[14] H. Zhang, V. Vittal, G. T. Heydt, and J. Quintero, "A mixed-integer linear programming approach for multi-stage security-constrained transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 27, no. 2, pp. 1125-1133, 2011.

[15] A. S. Dagoumas and N. E. Koltsaklis, "Review of models for integrating renewable energy in the generation expansion planning," *Applied Energy,* vol. 242, pp. 1573-1587, 2019.

[16] M. Mahdavi, C. S. Antunez, M. Ajalli, and R. Romero, "Transmission expansion planning: Literature review and classification," *IEEE Systems Journal,* vol. 13, no. 3, pp. 3129-3140, 2018.

[17] P. F. Freitas, L. H. Macedo, and R. Romero, "A strategy for transmission network expansion planning considering multiple generation scenarios," *Electric Power Systems Research,* vol. 172, pp. 22-31, 2019.

[18] M. Meneses, E. Nascimento, L. H. Macedo, and R. Romero, "Transmission network expansion planning considering line switching," *Ieee Access,* vol. 8, pp. 115148-115158, 2020.

[19] C. J. Newlun, "Co-optimized expansion planning for power system resilience and adaptation," DOCTOR OF PHILOSOPHY, Electrical Engineering (Electric Power and Energy Systems), Iowa State University, Ames, Iowa, 2022.

[20] J. Li, Y. Zhang, L. Xu, L. Zhang, and Z. Yuan, "Modeling and planning a transmission network expansion system in a regulated electricity market by considering demand-side management via a developed fuzzy-salp optimization algorithm," *Advances in Engineering and Intelligence Systems,* vol. 1, no. 02, 2022.

[21] S. E. Uhunamure and K. Shale, "A SWOT Analysis approach for a sustainable transition to renewable energy in South Africa," *Sustainability,* vol. 13, no. 7, p. 3933, 2021.

[22] K. Wu, M. Tanneau, and P. Van Hentenryck, "Strong Mixed-Integer Formulations for Transmission Expansion Planning with FACTS Devices," *arXiv preprint arXiv:2310.02347,* 2023.

[23] S. Yin and J. Wang, "Generation and transmission expansion planning towards a 100% renewable future," *IEEE Transactions on Power Systems,* vol. 37, no. 4, pp. 3274-3285, 2020.

[24] M. R. Ansari, S. Pirouzi, M. Kazemi, A. Naderipour, and M. Benbouzid, "Renewable generation and transmission expansion planning coordination with energy storage system: a flexibility point of view," *Applied Sciences,* vol. 11, no. 8, p. 3303, 2021.

[25] P. Vilaça, A. Street, and J. M. Colmenar, "A MILP-based heuristic algorithm for transmission expansion planning problems," *Electric Power Systems Research,* vol. 208, p. 107882, 2022.

[26] M. C. Da Rocha and J. T. Saraiva, "A discrete evolutionary PSO based approach to the multiyear transmission expansion planning problem considering demand uncertainties," *International Journal of Electrical Power & Energy Systems,* vol. 45, no. 1, pp. 427-442, 2013.

[27] Eskom, "Transmission Development Plan 2020-2029," Eskom, South Africa, 2021.

[28] T. Keokhoungning *et al.*, "Transmission Network Expansion Planning with High-Penetration Solar Energy Using Particle Swarm Optimization in Lao PDR toward 2030," *Energies,* vol. 15, no. 22, p. 8359, 2022.

[29] B. Alamri, M. A. Hossain, and M. J. Asghar, "Electric power network interconnection: A review on current status, future prospects and research direction," *Electronics,* vol. 10, no. 17, p. 2179, 2021.

[30] Y. Wang, C. Xu, and P. Yuan, "Is there a grid-connected effect of grid infrastructure on renewable energy generation? Evidence from China's upgrading transmission lines," *Energy & Environment,* vol. 33, no. 5, pp. 975-995, 2022.

[31] N. W. Ndlela, I. E. Davidson, and K. Moloi, "Power Planning for a Reliable Southern African Regional Grid," *Energies,* vol. 16, no. 3, p. 1028, 2023.

[32] C. D. Justo, J. E. Tafula, and P. Moura, "Planning sustainable energy systems in the Southern African Development Community: A review of power systems planning approaches," *Energies,* vol. 15, no. 21, p. 7860, 2022.

[33] T. Moyo, N. Madushele, O. Olajide, S. Faboye, Z. Rasmeni, and O. Ogunkunle, "Forging a new generation of African leaders in the Energy sector," Open Afrfica Power, Itally, 2023.

[34] R. Bertoni and H. Willebald, "Electricity and the role of the state: New Zealand and Uruguay before state-led development (1870-1930)," *Revista de Historia Industrial—Industrial History Review,* vol. 32, no. 87, pp. 11-44, 2023.

[35] P. V. Gomes and J. T. Saraiva, "State-of-the-art of transmission expansion planning: A survey from restructuring to renewable and distributed electricity markets," *International Journal of Electrical Power & Energy Systems,* vol. 111, pp. 411-424, 2019.

[36] G. U. Nnachi, Y. Hamam, and C. G. Richards, "The Efficacy of Multi-Period Long-Term Power Transmission Network Expansion Model with Penetration of Renewable Sources," *Computation,* vol. 11, no. 9, p. 179, 2023.

[37] E. M. Carlini, R. Schroeder, J. M. Birkebæk, and F. Massaro, "EU transition in power sector: How RES affects the design and operations of transmission power systems," *Electric Power Systems Research,* vol. 169, pp. 74-91, 2019.

[38] A. Davoodi, A. R. Abbasi, and S. Nejatian, "Multi-objective dynamic generation and transmission expansion planning considering capacitor bank allocation and demand response program constrained to flexible-securable clean energy," *Sustainable Energy Technologies and Assessments,* vol. 47, p. 101469, 2021.

[39] S. B. Pandya, S. Ravichandran, P. Manoharan, P. Jangir, and H. H. Alhelou, "Multi-objective optimization framework for optimal power flow problem of hybrid power systems considering security constraints," *IEEE Access,* vol. 10, pp. 103509-103528, 2022.

[40] R. Heydari and T. Barforoushi, "HVDC/HVAC transmission network expansion planning in electricity markets in the presence of wind resources," *Electric Power Systems Research,* vol. 229, p. 110182, 2024.

[41] V. Telukunta, J. Pradhan, A. Agrawal, M. Singh, and S. G. Srivani, "Protection challenges under bulk penetration of renewable energy resources in power systems: A review," *CSEE journal of power and energy systems,* vol. 3, no. 4, pp. 365-379, 2017.

[42] R. Alvarez, C. Rahmann, R. Palma-Behnke, and P. Estévez, "A novel meta-heuristic model for the multi-year transmission network expansion planning," *International Journal of Electrical Power & Energy Systems,* vol. 107, pp. 523-537, 2019.

[43] G. Muñoz-Delgado, J. Contreras, J. M. Arroyo, A. S. de la Nieta, and M. Gibescu, "Integrated transmission and distribution system expansion planning under uncertainty," *IEEE Transactions on Smart Grid,* vol. 12, no. 5, pp. 4113-4125, 2021.

[44] L. Gacitua *et al.*, "A comprehensive review on expansion planning: Models and tools for energy policy analysis," *Renewable and Sustainable Energy Reviews,* vol. 98, pp. 346-360, 2018.

[45] S. Singh and S. Singh, "Advancements and challenges in integrating renewable energy sources into distribution grid systems: A comprehensive review," *Journal of Energy Resources Technology,* vol. 146, no. 9, 2024.

[46] I. Alotaibi, M. A. Abido, M. Khalid, and A. V. Savkin, "A comprehensive review of recent advances in smart grids: A sustainable future with renewable energy resources," *Energies,* vol. 13, no. 23, p. 6269, 2020.

[47] S. Gómez and L. Olmos, "Coordination of generation and transmission expansion planning in a liberalized electricity context—coordination schemes, risk management, and modelling strategies: A review," *Sustainable Energy Technologies and Assessments,* vol. 64, p. 103731, 2024.

[48] W. Zheng, H. Lu, M. Zhang, Q. Wu, Y. Hou, and J. Zhu, "Distributed energy management of multi-entity integrated electricity and heat systems: A review of architectures, optimization algorithms, and prospects," *IEEE Transactions on Smart Grid,* 2023.

[49] M. S. Javadi, M. Saniei, and H. Rajabi Mashhadi, "An augmented NSGA-II technique with virtual database to solve the composite generation and transmission expansion planning

problem," *Journal of Experimental & Theoretical Artificial Intelligence,* vol. 26, no. 2, pp. 211-234, 2014.

[50] J. P. Bukenberger and M. D. Webster, "Approximate latent factor algorithm for scenario selection and weighting in transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 35, no. 2, pp. 1099-1108, 2019.

[51] P. M. Anderson, C. F. Henville, R. Rifaat, B. Johnson, and S. Meliopoulos, *Power system protection*, 2nd ed. Canada: John Wiley & Sons, 2022.

[52] Q. Wang, C. Zhang, Y. Ding, and J. Østergaard, "MOPSO-based multi-objective TSO planning considering uncertainties," in *IEEE PES Innovative Smart Grid Technologies, Europe*, Istanbul, Turkey, 12-15 October 2014: IEEE, pp. 1-5.

[53] M. Khalid, "Smart grids and renewable energy systems: Perspectives and grid integration challenges," *Energy Strategy Reviews,* vol. 51, p. 101299, 2024.

[54] M. J. B. Kabeyi and O. A. Olanrewaju, "Geothermal wellhead technology power plants in grid electricity generation: A review," *Energy Strategy Reviews,* vol. 39, p. 100735, 2022.

[55] L. A. Zadeh, "Fuzzy logic," in *Granular, Fuzzy, and Soft Computing*. New York: Springer, 2023, pp. 19-49.

[56] G. Grimmett and D. Stirzaker, *Probability and random processes*, fourth edition ed. United Kingdom: Oxford university press, 2020.

[57] C. Zhang, Q. Wang, Y. Ding, and J. Østergaard, "A multi-objective model for transmission planning under uncertainties," in *2014 IEEE Electrical Power and Energy Conference*, 2014: IEEE, pp. 42-47.

[58] J. Zheng, F. Wen, G. Ledwich, and J. Huang, "Risk control in transmission system expansion planning with wind generators," *International Transactions on Electrical Energy Systems,* vol. 24, no. 2, pp. 227-245, 2014.

[59] R. Hemmati, R. A. Hooshmand, and A. Khodabakhshian, "Comprehensive review of generation and transmission expansion planning," *IET Generation, Transmission & Distribution,* vol. 7, no. 9, pp. 955-964, 2013.

[60] K. Li *et al.*, "Enhancing reliability assessment in distributed generation networks: Incorporating dynamic correlation of wind-solar power output uncertainty," *Sustainable Energy, Grids and Networks,* vol. 39, p. 101505, 2024.

[61] B. Saka, A. M. Aibinu, Y. S. Mohammed, and D. E. Olatunji, "Voltage Stability of the Power System using Genetic Algorithm: A Review," in *2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS)*, 2021: IEEE, pp. 1-6.

[62] R. Arghandeh, A. Von Meier, L. Mehrmanesh, and L. Mili, "On the definition of cyber-physical resilience in power systems," *Renewable and Sustainable Energy Reviews,* vol. 58, pp. 1060-1069, 2016.

[63] S. Garip, M. Bilgen, N. Altin, S. Ozdemir, and I. Sefa, "Reliability Analysis of Microgrids: Evaluation of Centralized and Decentralized Control Approaches," *Electric Power Components and Systems,* vol. 51, no. 19, pp. 2319-2338, 2023.

[64] P. P. Verma, "Computational Optimization in Operational and Expansion Planning," MASTER OF SCIENCE, Department of Electrical, National University of Singapore (Singapore), India, 2022.

[65] N. W. Ndlela and I. E. Davidson, "A load flow analysis of the southern African power pool interconnections using high voltage AC, high voltage DC, and flexible AC transmission system," in *2022 IEEE PES/IAS PowerAfrica*, Kigali, Rwanda, 22-26 August 2022, pp. 1-5.

[66] H. Haes Alhelou, M. E. Hamedani-Golshan, T. C. Njenda, and P. Siano, "A survey on power system blackout and cascading events: Research motivations and challenges," *Energies,* vol. 12, no. 4, p. 682, 2019.

[67] M. Roustaei, A. Letafat, M. Sheikh, R. Sadoughi, and M. Ardeshiri, "A cost-effective voltage security constrained congestion management approach for transmission system operation improvement," *Electric Power Systems Research,* vol. 203, p. 107674, 2022.

[68] N. I. Yusoff, A. A. M. Zin, and A. B. Khairuddin, "Congestion management in power system: A review," in *2017 3rd international conference on power generation systems and renewable energy technologies (PGSRET)*, Johor Bahru, Malaysia, 04-06 April 2017: IEEE, pp. 22-27.

[69] R. P. Pungaliya, "Assessing Transmission Bottlenecks for Renewable Energy Development in North Carolina," Masters degree, Environmental Management degree, Duke University Durham, NC, USA, 2021.

[70] J. Zhao, "Transmission congestion management and security cost optimization in deregulated electricity markets," 2020.

[71] C. Medina, C. R. M. Ana, and G. González, "Transmission grids to foster high penetration of large-scale variable renewable energy sources–A review of challenges, problems, and solutions," *International Journal of Renewable Energy Research (IJRER),* vol. 12, no. 1, pp. 146-169, 2022.

[72] M. Numan, A. Z. Khan, M. Asif, S. M. Malik, and K. Imran, "Exploiting the inherent flexibility in transmission network for optimal scheduling, wind power utilization, and network congestion management," *IEEE Access,* vol. 9, pp. 88746-88758, 2021.

[73] F. Chen, J. Liu, M. Zhao, and H. Liu, "Congestion identification and expansion planning methods of transmission system considering wind power and TCSC," *IEEE Access,* vol. 10, pp. 89915-89923, 2022.

[74] M. J. B. Kabeyi and O. A. Olanrewaju, "Decentralized and Distributed Power Generation," in *Proc. 5th African Int. Conf. Ind. Eng. Oper. Manag. Decentralized, no*, Lusaka, Zambia, April 4-6, 2023: IEOM Society International.

[75] C. D. Iweh, S. Gyamfi, E. Tanyi, and E. Effah-Donyina, "Distributed generation and renewable energy integration into the grid: Prerequisites, push factors, practical options, issues and merits," *Energies,* vol. 14, no. 17, p. 5375, 2021.

[76] B. Adebanji, A. Ojo, T. Fasina, S. Adeleye, and J. Abere, "Integration of renewable energy with smart grid application into the Nigeria's power network: Issues, challenges and Opportunities," *European Journal of Engineering and Technology Research,* vol. 7, no. 3, pp. 18-24, 2022.

[77] Z. Chen *et al.*, "Overview of transmission expansion planning in the market environment," *Energy Reports,* vol. 8, pp. 662-670, 2022.

[78] Y. Wang, J. Qiu, Y. Tao, and J. Zhao, "Carbon-oriented operational planning in coupled electricity and emission trading markets," *IEEE Transactions on Power Systems,* vol. 35, no. 4, pp. 3145-3157, 2020.

[79] A. S. Siddiqui, M. Tanaka, and Y. Chen, "Sustainable transmission planning in imperfectly competitive electricity industries: Balancing economic and environmental outcomes," *European Journal of Operational Research,* vol. 275, no. 1, pp. 208-223, 2019.

[80] R. R. Kumar and P. J. Stauvermann, "Environmental Injustice: The Effects of Environmental Taxes on Income Distribution in an Oligopolistic General Equilibrium Model," *Sustainability,* vol. 16, no. 10, p. 4142, 2024.

[81] S. N. Hashemian, M. A. Latify, and G. R. Yousefi, "PEV fast-charging station sizing and placement in coupled transportation-distribution networks considering power line conditioning capability," *IEEE Transactions on Smart Grid,* vol. 11, no. 6, pp. 4773-4783, 2020.

[82] S. Verma and V. Mukherjee, "Transmission expansion planning: A review," in *2016 International Conference on Energy Efficient Technologies for Sustainability (ICEETS)*, Nagercoil, India 07-08 April 2016 2016: IEEE, pp. 350-355.

[83] S. Haffner, A. Monticelli, A. Garcia, J. Mantovani, and R. Romero, "Branch and bound algorithm for transmission system expansion planning using a transportation model," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 147, no. 3, pp. 149-156, 2000.

[84] R. Romero, A. Monticelli, A. Garcia, and S. Haffner, "Test systems and mathematical models for transmission network expansion planning," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 149, no. 1, pp. 27-36, 2002.

[85] M. D. Khardenvis, P. P. Bedekar, and V. N. Pande, "Transmission Network Expansion Planning–A Critical Review," *Power Research-A Journal of CPRI,* pp. 7-15, 2019.

[86] U. Shahzad, "A review of challenges for security-constrained transmission expansion planning," *Journal of Electrical Engineering, Electronics, Control and Computer Science,* vol. 7, no. 2, pp. 21-30, 2021.

[87] D. H. Huanca, D. M. Falcão, and M. E. Bento, "Transmission Expansion Planning Considering Storage, Flexible AC Transmission System, Losses, and Contingencies to Integrate Wind Power," *Energies,* vol. 17, no. 7, p. 1777, 2024.

[88] J. Zhou *et al.*, "Security-constrained Transmission Expansion Planning with Nk Security Criterion and Transient Stability," *Electric Power Systems Research,* vol. 222, p. 109505, 2023.

[89] A. Almalaq, K. Alqunun, R. Abbassi, Z. M. Ali, M. M. Refaat, and S. H. Abdel Aleem, "Integrated transmission expansion planning incorporating fault current limiting devices and thyristor-controlled series compensation using meta-heuristic optimization techniques," *Scientific Reports,* vol. 14, no. 1, p. 13046, 2024.

[90] J. Choi and K. Y. Lee, *Probabilistic power system expansion planning with renewable energy resources and energy storage systems*, 1st ed. Canada: John Wiley & Sons, 2021.

[91] M. N. I. Sarkar, L. G. Meegahapola, and M. Datta, "Reactive power management in renewable rich power grids: A review of grid-codes, renewable generators, support devices, control strategies and optimization algorithms," *Ieee Access,* vol. 6, pp. 41458-41489, 2018.

[92] B. H. Alajrash, M. Salem, M. Swadi, T. Senjyu, M. Kamarol, and S. Motahhir, "A comprehensive review of FACTS devices in modern power systems: Addressing power quality, optimal placement, and stability with renewable energy penetration," *Energy Reports,* vol. 11, pp. 5350-5371, 2024.

[93] V. Kuchanskyy, D. Malakhatka, and B. Ihor, "Application of reactive power compensation devices for increasing efficiency of bulk electrical power systems," in *2020 IEEE 7th international conference on energy smart systems (ESS)*, Kyiv, Ukraine, 12-14 May 2020: IEEE, pp. 83-86, doi: 10.1109/ESS50319.2020.9160072.

[94] S. M. Kaplan, *Smart Grid: Modernizing electric power transmission and distribution; Energy independence, Storage and security; Energy independence and security act of 2007 (EISA); Improving electrical grid efficiency, communication, reliability, and resiliency; integrating new and renewable energy sources*, 1st ed. United states of America: The Capitol Net Inc, 2009.

[95] B. Ismail, N. I. A. Wahab, M. L. Othman, M. A. M. Radzi, K. N. Vijyakumar, and M. N. M. Naain, "A comprehensive review on optimal location and sizing of reactive power compensation using hybrid-based approaches for power loss reduction, voltage stability improvement, voltage profile enhancement and loadability enhancement," *IEEE access,* vol. 8, pp. 222733-222765, 2020.

[96] E. I. Ogunwole and S. Krishnamurthy, "Transmission congestion management using generator sensitivity factors for active and reactive power rescheduling using particle swarm optimization algorithm," *IEEE Access,* vol. 10, pp. 122882-122900, 2022.

[97] T. Ahmad, H. Zhang, and B. Yan, "A review on renewable energy and electricity requirement forecasting models for smart grid and buildings," *Sustainable Cities and Society,* vol. 55, p. 102052, 2020.

[98] A. Airoboman, P. James, I. Araga, C. Wamdeo, and I. Okakwu, "Contingency analysis on the Nigerian power systems network," in *2019 IEEE PES/IAS PowerAfrica*, 2019: IEEE, pp. 70-75.

[99] A. Marot *et al.*, "Perspectives on future power system control centers for energy transition," *Journal of Modern Power Systems and Clean Energy,* vol. 10, no. 2, pp. 328-344, 2022.

[100] B. O. Adewolu and A. K. Saha, "Contingency control capability of an optimized HVDC-based VSC transmission system," *IEEE Access,* vol. 9, pp. 4112-4128, 2020.

[101] Y. Zhang, Y. Hu, J. Ma, and Z. Bie, "A mixed-integer linear programming approach to security-constrained co-optimization expansion planning of natural gas and electricity transmission systems," *IEEE Transactions on Power Systems,* vol. 33, no. 6, pp. 6368-6378, 2018.

[102] M. Qorbani and T. Amraee, "Long term transmission expansion planning to improve power system resilience against cascading outages," *Electric Power Systems Research,* vol. 192, p. 106972, 2021.

[103] M. Z. Jahromi, M. Tajdinian, and M. H. M. Jahromi, "A Novel Optimal Planning Between Generation and Transmission Expansion Planning Considering Security Constraint," in *2019 International Power System Conference (PSC)*, Tehran, Iran 09-11 December 2019 2019: IEEE, pp. 241-249.

[104] S. Sewchurran and I. Davidson, "Guiding Principles for Grid Code Compliance of Medium-High Voltage Renewable Power Plant Distributed Generation Integration onto South Africa's Transmission and Distribution Networks," in *Proceedings of the 24th South African Universities Power Engineering Conference*, Vereeniging, South Africa, 26 - 28 January 2016, pp. 26-28.

[105] A. Ameur, A. Berrada, K. Loudiyi, and M. Aggour, "Analysis of renewable energy integration into the transmission network," *The Electricity Journal,* vol. 32, no. 10, p. 106676, 2019.

[106] M. S. Javadi and A. Esmaeel Nezhad, "Multi-objective, multi-year dynamic generation and transmission expansion planning-renewable energy sources integration for Iran's National Power Grid," *International Transactions on Electrical Energy Systems,* vol. 29, no. 4, p. e2810, 2019.

[107] R. Hemmati, R.-A. Hooshmand, and A. Khodabakhshian, "State-of-the-art of transmission expansion planning: Comprehensive review," *Renewable and Sustainable Energy Reviews,* vol. 23, pp. 312-319, 2013.

[108] E. B. Tirkolaee, N. S. Aydin, and I. Mahdavi, "A bi-level decision-making system to optimize a robust-resilient-sustainable aggregate production planning problem," *Expert Systems with Applications,* vol. 228, p. 120476, 2023.

[109] C. Vrionis, V. Tsalavoutis, and A. Tolis, "A Generation Expansion Planning model for integrating high shares of renewable energy: A Meta-Model Assisted Evolutionary Algorithm approach," *Applied energy,* vol. 259, p. 114085, 2020.

[110] A. Mohammadi and F. Sheikholeslam, "Intelligent optimization: Literature review and state-of-the-art algorithms (1965–2022)," *Engineering Applications of Artificial Intelligence,* vol. 126, p. 106959, 2023.

[111] S. Claeys, M. Vanin, F. Geth, and G. Deconinck, "Applications of optimization models for electricity distribution networks," *Wiley Interdisciplinary Reviews: Energy and Environment,* vol. 10, no. 5, p. e401, 2021.

[112] F. Neumann and T. Brown, "Transmission expansion planning using cycle flows," in *Proceedings of the Eleventh ACM International Conference on Future Energy Systems*, 2020, pp. 253-263.

[113] S. L. Gbadamosi and N. I. Nwulu, "A multi-period composite generation and transmission expansion planning model incorporating renewable energy sources and demand response," *Sustainable Energy Technologies and Assessments,* vol. 39, p. 100726, 2020.

[114] C. Li, A. J. Conejo, P. Liu, B. P. Omell, J. D. Siirola, and I. E. Grossmann, "Power Systems Infrastructure Planning with High Renewables Penetration," *Computer Aided Chemical Engineering,* vol. 49, pp. 703-708, 2022.

[115] Z. Huang, Q. P. Zheng, and A. L. Liu, "A nested cross decomposition algorithm for power system capacity expansion with multiscale uncertainties," *INFORMS Journal on Computing,* vol. 34, no. 4, pp. 1919-1939, 2022.

[116] R. T. Zoppei, M. A. Delgado, L. H. Macedo, M. J. Rider, and R. Romero, "A branch and bound algorithm for transmission network expansion planning using nonconvex mixed-integer nonlinear programming models," *IEEE Access,* vol. 10, pp. 39875-39888, 2022.

[117] M. J. Rider and A. V. Garcia, "A constructive heuristic algorithm to short term transmission network expansion planning," in *IEEE Power Engineering Society General Meeting, 2004.*, Denver, CO, USA, 06-10 June 2004: IEEE, pp. 2107-2113.

[118] Z. Wu, P. Zeng, and X.-P. Zhang, "Two-stage stochastic dual dynamic programming for transmission expansion planning with significant renewable generation and Nk criterion," *CSEE Journal of power and energy systems,* vol. 2, no. 1, pp. 3-10, 2016.

[119] S. Goodarzi, M. Gitizadeh, and A. Reza Abbasi, "Efficient linear network model for TEP based on piecewise McCormick relaxation," *IET Generation, Transmission & Distribution,* vol. 13, no. 23, p. 10, 2019.

[120] V. Bayram, "Optimization models for large scale network evacuation planning and management: A literature review," *Surveys in Operations Research and Management Science,* vol. 21, no. 2, pp. 63-84, 2016.

[121] M. M. Hussain *et al.*, "SONG: A multi-objective evolutionary algorithm for delay and energy aware facility location in vehicular fog networks," *Sensors,* vol. 23, no. 2, p. 667, 2023.

[122] J. M. Ramirez, A. Hernandez-Tolentino, and J. A. Marmolejo-Saucedo, "A stochastic robust approach to deal with the generation and transmission expansion planning problem embedding renewable sources," in *Uncertainties in Modern Power Systems*: Elsevier, 2021, pp. 57-91.

[123] G. Chicco and A. Mazza, "Metaheuristics for Transmission Network Expansion Planning," in *Transmission Expansion Planning: The Network Challenges of the Energy Transition*. Torino, Italy: Springer, 2021, pp. 13-38.

[124] C. L. B. Silveira, A. Tabares, L. T. Faria, and J. F. Franco, "Mathematical optimization versus Metaheuristic techniques: A performance comparison for reconfiguration of distribution systems," *Electric Power Systems Research,* vol. 196, p. 107272, 2021.

[125] V. K. Yadav, K. Singh, and S. Gupta, "Market-oriented transmission expansion planning using non-linear programming and multi-criteria data envelopment analysis," *Sustainable Energy, Grids and Networks,* vol. 19, p. 100234, 2019.

[126] Z. Al-Hamouz and A. Al-Faraj, "Transmission expansion planning using nonlinear programming," in *IEEE/PES transmission and distribution conference and exhibition*, Yokohama, Japan, 06-10 October 2002 2002, vol. 1: IEEE, pp. 50-55.

[127] B. Ghaddar and R. A. Jabr, "Power transmission network expansion planning: A semidefinite programming branch-and-bound approach," *European Journal of Operational Research,* vol. 274, no. 3, pp. 837-844, 2019.

[128] M. E. Cebeci, S. Eren, O. B. Tor, and N. Güven, "Transmission and substation expansion planning using mixed integer programming," in *2011 North American Power Symposium*, Boston, MA, USA, 04-06 August 2011 IEEE, pp. 1-5.

[129] B. Alizadeh and S. Jadid, "Reliability constrained coordination of generation and transmission expansion planning in power systems using mixed integer programming," *IET generation, transmission & distribution,* vol. 5, no. 9, pp. 948-960, 2011.

[130] R. Chaturvedi, K. Bhattachary, J. Parikh, and K. Bhattacharya, "Transmission planning for Indian power grid: a mixed integer programming approach," *International Transactions in Operational Research,* vol. 6, no. 5, pp. 465-482, 1999.

[131] S. Han, H.-J. Kim, and D. Lee, "A long-term evaluation on transmission line expansion planning with multistage stochastic programming," *Energies,* vol. 13, no. 8, p. 1899, 2020.

[132] H. Samarakoon, R. Shrestha, and O. Fujiwara, "A mixed integer linear programming model for transmission expansion planning with generation location selection," *International journal of electrical power & energy systems,* vol. 23, no. 4, pp. 285-293, 2001.

[133] M. Jalali, K. Zare, and M. T. Hagh, "A multi-stage MINLP-based model for sub-transmission system expansion planning considering the placement of DG units," *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 8-16, 2014.

[134] I. G. Sanchez, R. Romero, J. R. Mantovani, and M. J. Rider, "Transmission-expansion planning using the DC model and nonlinear-programming technique," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 152, no. 6, pp. 763-769, 2005.

[135] M. A. El-Meligy and A. M. El-Sherbeeny, "Hybrid robust/stochastic transmission expansion planning considering uncertainties in generators' offer prices: A second-order cone program approach," *Electric Power Systems Research,* vol. 203, p. 107631, 2022.

[136] Y. Xie and Y. Xu, "Transmission Expansion Planning Considering Wind Power and Load Uncertainties," *Energies,* vol. 15, no. 19, p. 7140, 2022.

[137] A. Bagheri, J. Wang, and C. Zhao, "Data-driven stochastic transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 32, no. 5, pp. 3461-3470, 2017.

[138] M. Pantoš, "Stochastic generation-expansion planning and diversification of energy transmission paths," *Electric power systems research,* vol. 98, pp. 1-10, 2013.

[139] Z. Zhuo, E. Du, N. Zhang, C. Kang, Q. Xia, and Z. Wang, "Incorporating massive scenarios in transmission expansion planning with high renewable energy penetration," *IEEE Transactions on Power Systems,* vol. 35, no. 2, pp. 1061-1074, 2020.

[140] M. Navidi, S. M. M. Tafreshi, and A. Anvari-Moghaddam, "A game theoretical approach for sub-transmission and generation expansion planning utilizing multi-regional energy systems," *International Journal of Electrical Power & Energy Systems,* vol. 118, p. 105758, 2020.

[141] M. Jenabi, S. M. T. F. Ghomi, and Y. Smeers, "Bi-level game approaches for coordination of generation and transmission expansion planning within a market environment," *IEEE Transactions on Power systems,* vol. 28, no. 3, pp. 2639-2650, 2013.

[142] S. K. Ng, J. Zhong, and C. W. Lee, "A game-theoretic study of the strategic interaction between generation and transmission expansion planning," in *2009 IEEE/PES Power Systems Conference and Exposition*, Seattle, WA, USA, 15-18 March 2009 IEEE, pp. 1-10.

[143] J. Contreras, "A cooperative game theory approach to transmission planning in power systems," Doctor of philosophy, Engineering-Electrical Engineering and Computer Sciences, University of California, Berkeley, USA, 24, 1997.

[144] A. B. Rodrigues and M. G. Da Silva, "Probabilistic assessment of available transfer capability based on Monte Carlo method with sequential simulation," *IEEE Transactions on Power Systems,* vol. 22, no. 1, pp. 484-492, 2007.

[145] N. Yang and F. Wen, "A chance constrained programming approach to transmission system expansion planning," *Electric Power Systems Research,* vol. 75, no. 2-3, pp. 171-177, 2005.

[146] H. A. Mahmoud, M. Sharaf, and M. A. El-Meligy, "An adaptive robust optimization model for transmission expansion planning considering uncertain intervals," *International Journal of Electrical Power & Energy Systems,* vol. 157, p. 109821, 2024.

[147] L. Baringo and A. Baringo, "A stochastic adaptive robust optimization approach for the generation and transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 33, no. 1, pp. 792-802, 2017.

[148] Á. García-Cerezo, R. García-Bertrand, and L. Baringo, "Acceleration techniques for adaptive robust optimization transmission network expansion planning problems," *International Journal of Electrical Power & Energy Systems,* vol. 148, p. 108985, 2023.

[149] R. Mínguez, R. García-Bertrand, and J. M. Arroyo, "Adaptive robust transmission network expansion planning using structural reliability and decomposition techniques," *Computational Engineering, Finance, and Science,* p. 32, 2015.

[150] H. Khorasani, M. Pourakbari-Kasmaei, and R. Romero, "Transmission expansion planning via a constructive heuristic algorithm in restructured electricity industry," in *2013 3rd International Conference on Electric Power and Energy Conversion Systems*, Istanbul, Turkey 02-04 October 2013 2013: IEEE, pp. 1-6.

[151] I. M. Mendonça, C. Ivo, B. H. Dias, A. L. Marcato, and E. J. de Oliveira, "Static expansion planning of electric power transmission systems using sensitivity indice," in *2017 IEEE Manchester PowerTech*, Manchester, UK 18-22 June 2017: IEEE, pp. 1-5.

[152] H. Khorasani, M. Pourakbari-Kasmaei, and R. Romero, "A heuristic method for transmission network expansion planning under security constraints," *Innovations in Energy, Power and Electrical Machines (IEPEM),* pp. 1-6, 2013.

[153] R. Romero and A. Monticelli, "A hierarchical decomposition approach for transmission network expansion planning," *IEEE transactions on power systems,* vol. 9, no. 1, pp. 373-380, 1994.

[154] H. Zhong, G. Zhang, Z. Tan, G. Ruan, and X. Wang, "Hierarchical collaborative expansion planning for transmission and distribution networks considering transmission cost allocation," *Applied Energy,* vol. 307, p. 118147, 2022.

[155] M. d. L. Latorre, G. C. Oliveira, R. C. Perez, L. Okamura, and S. Binato, "A stochastic-robust approach to hierarchical generation-transmission expansion planning," *arXiv preprint arXiv:1910.01616,* 2019.

[156] Q. Sun, Z. Wu, W. Gu, T. Zhu, L. Zhong, and T. Gao, "Flexible expansion planning of distribution system integrating multiple renewable energy sources: An approximate dynamic programming approach," *Energy,* vol. 226, p. 120367, 2021.

[157] J. Contreras and F. F. Wu, "A kernel-oriented algorithm for transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 15, no. 4, pp. 1434-1440, 2000.

[158] F. Evans, J. M. Zolezzi, and H. Rudnick, "Cost assignment model for electrical transmission system expansion: An approach through the kernel theory," *IEEE Transactions on Power Systems,* vol. 18, no. 2, pp. 625-632, 2003.

[159] K. A. Alnowibet and M. A. El-Meligy, "A stochastic programming approach using multiple uncertainty sets for AC robust transmission expansion planning," *Sustainable Energy, Grids and Networks,* vol. 30, p. 100648, 2022.

[160] I. Sánchez, R. Romero, J. Mantovani, and A. Garcia, "Interior point algorithm for linear programming used in transmission network synthesis," *Electric power systems research,* vol. 76, no. 1-3, pp. 9-16, 2005.

[161] M. Ahmadigorji, N. Amjady, and S. Dehghan, "A novel two-stage evolutionary optimization method for multiyear expansion planning of distribution systems in presence of distributed generation," *Applied soft computing,* vol. 52, pp. 1098-1115, 2017.

[162] H. Mazaheri, H. Ranjbar, H. Saber, and M. Moeini-Aghtaie, "Expansion planning of transmission networks," in *Uncertainties in modern power systems*: Elsevier, 2021, pp. 35-56.

[163] E. Osaba *et al.*, "A tutorial on the design, experimentation and application of metaheuristic algorithms to real-world optimization problems," *Swarm and Evolutionary Computation,* vol. 64, p. 100888, 2021.

[164] V. C. SS and A. HS, "Nature inspired meta heuristic algorithms for optimization problems," *Computing,* vol. 104, no. 2, pp. 251-269, 2022.

[165] R. Alvarez, C. Rahmann, R. Palma-Behnke, P. A. Estévez, and F. Valencia, "Ant Colony Optimization Algorithm for the Multiyear Transmission Network Expansion Planning," in *2018 IEEE Congress on Evolutionary Computation (CEC)*, Rio de Janeiro, Brazil 08-13 July 2018: IEEE, pp. 1-8.

[166] M. Dewantara, L. M. Putranto, and R. Irnawan, "Minimization of Power Losses through Optimal Placement and Sizing from Solar Power and Battery Energy Storage System in Distribution System," in *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, Yogyakarta, Indonesia 10-11 December 2020 2020: IEEE, pp. 400-405, doi: 10.1109/ISRITI51436.2020.9315446.

[167] M. A. El-Shorbagy and A. M. El-Refaey, "Hybridization of grasshopper optimization algorithm with genetic algorithm for solving system of non-linear equations," *IEEE Access,* vol. 8, pp. 220944-220961, 2020.

[168] L. A. Gallego, M. J. Rider, M. Lavorato, and A. Paldilha-Feltrin, "An enhanced genetic algorithm to solve the static and multistage transmission network expansion planning," *Journal of Electrical and Computer Engineering,* vol. 2012, pp. 5-5, 2012.

[169] K. Mansuwan, P. Jirapong, and P. Thararak, "Optimal battery energy storage planning and control strategy for grid modernization using improved genetic algorithm," *Energy Reports,* vol. 9, pp. 236-241, 2023.

[170] T. Papi Naidu, G. Balasubramanian, and B. Venkateswararao, "Optimal power flow control optimisation problem incorporating conventional and renewable generation sources: a review," *International Journal of Ambient Energy,* vol. 44, no. 1, pp. 1119-1150, 2023.

[171] A. A. Abou El-Ela, R. A. El-Seheimy, A. M. Shaheen, W. A. Wahbi, and M. T. Mouwafi, "PV and battery energy storage integration in distribution networks using equilibrium algorithm," *Journal of Energy Storage,* vol. 42, p. 103041, 2021.

[172] O. G. Carmona, K. M. Silva, V. M. V. Marín, D. A. G. Neira, and C. C. M. Cano, "A Novel Approach for Reconfiguring Large-Scale Power Distribution Systems Using Genetic Algorithms and DIgSILENT Power Factory," in *2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 2023: IEEE, pp. 1-6.

[173] M. Mahdavi, H. H. Alhelou, A. Bagheri, S. Z. Djokic, and R. A. V. Ramos, "A comprehensive review of metaheuristic methods for the reconfiguration of electric power distribution systems and comparison with a novel approach based on efficient genetic algorithm," *IEEE Access,* vol. 9, pp. 122872-122906, 2021.

[174] L. A. Gallego, L. P. Garcés, M. Rahmani, and R. A. Romero, "High-performance hybrid genetic algorithm to solve transmission network expansion planning," *IET Generation, Transmission & Distribution,* vol. 11, no. 5, pp. 1111-1118, 2017.

[175] M. Mahdavi, A. R. Kheirkhah, L. H. Macedo, and R. Romero, "A genetic algorithm for transmission network expansion planning considering line maintenance," in *2020 IEEE Congress on Evolutionary Computation (CEC)*, Glasgow, UK, 19-24 July 2020, pp. 1-6, doi: 10.1109/CEC48606.2020.9185821.

[176] F. S. Kebede, "Improving the Reliability of the Electrical Supply by the Development of a Multi-source Solution on a Weak Electrical Network," ECOLE DOCTORALE, Electric Power, Nantes Université, Nantes, France, 154, 2023. [Online]. Available: https://theses.hal.science/tel-04090776v1

[177] M. Ahanch, M. S. Asasi, M. S. Amiri, and H.-A. Shayanfar, "Considering shunt and fixed series compensations in dynamic transmission network expansion planning using Real Codded Genetic Algorithm," in *2017 IEEE 4th International Conference on Knowledge-Based Engineering and Innovation (KBEI)*, Tehran, Iran 22-22 December 2017: IEEE, pp. 0646-0658.

[178] D. H. Huanca and L. A. G. Pareja, "Chu and Beasley genetic algorithm to solve the transmission network expansion planning problem considering active power losses," *IEEE Latin America Transactions,* vol. 19, no. 11, pp. 1967-1975, 2021.

[179] C. A. Correa, R. Bolaños, and A. Escobar, "Transmission expansion planning considering multiple generation scenarios and demand uncertainty," *Ingeniare. Revista chilena de ingeniería,* vol. 22, no. 2, pp. 177-188, 2014.

[180] C. Correa, A. Sanchez, and G. Marulanda, "Expansion of transmission networks considering large wind power penetration and demand uncertainty," *IEEE Latin America Transactions,* vol. 14, no. 3, pp. 1235-1244, 2016.

[181] I. d. J. Silva, M. J. Rider, R. Romero, and C. A. Murari, "Transmission network expansion planning considering uncertainty in demand," *IEEE transactions on Power Systems,* vol. 21, no. 4, pp. 1565-1573, 2006.

[182] Y. Hu, Z. Bie, T. Ding, and Y. Lin, "An NSGA-II based multi-objective optimization for combined gas and electricity network expansion planning," *Applied energy,* vol. 167, pp. 280-293, 2016.

[183] M. A. Kamarposhti, E. Kabalci, and R. Alayi, "Optimal Transmission Expansion Planning considering Distributed Generations by using Non-dominated sorting genetic algorithm-II (NSGAII)," *Authorea Preprints,* vol. 101, no. 01, p. 8, 2020, doi: 10.22541/au.160807087.74478199/v1.

[184] A. E. Nezhad, M. S. Javadi, A. Borghetti, M. Taherkhani, A. Heidari, and J. P. Catalão, "A VDS-NSGA-II algorithm for multiyear multiobjective dynamic generation and

transmission expansion planning," in *Multi-Objective Combinatorial Optimization Problems and Solution Methods*: Academic Press, 2022, pp. 157-177.

[185] X. Chen, H. Tianfield, and W. Du, "Bee-foraging learning particle swarm optimization," *Applied Soft Computing,* vol. 102, p. 107134, 2021.

[186] K. Rameshkumar, C. Rajendran, and K. Mohanasundaram, "A novel particle swarm optimisation algorithm for continuous function optimisation," *International Journal of Operational Research,* vol. 13, no. 1, pp. 1-21, 2012.

[187] M. Jain, V. Saihjpal, N. Singh, and S. B. Singh, "An overview of variants and advancements of PSO algorithm," *Applied Sciences,* vol. 12, no. 17, p. 8392, 2022.

[188] A. G. Gad, "Particle swarm optimization algorithm and its applications: a systematic review," *Archives of computational methods in engineering,* vol. 29, no. 5, pp. 2531-2561, 2022.

[189] E. H. Houssein, A. G. Gad, K. Hussain, and P. N. Suganthan, "Major advances in particle swarm optimization: theory, analysis, and application," *Swarm and Evolutionary Computation,* vol. 63, p. 100868, 2021.

[190] M. Li, L. Huang, G. Xu, and K. Biao, "A parallel particle swarm optimization framework based on a fork-join thread pool using a work-stealing mechanism," *Applied Soft Computing,* p. 110537, 2023.

[191] C. Yang *et al.*, "Optimal power flow in distribution network: A review on problem formulation and optimization methods," *Energies,* vol. 16, no. 16, p. 5974, 2023.

[192] H. Arasteh, M. S. Sepasian, V. Vahidinasab, and P. Siano, "SoS-based multiobjective distribution system expansion planning," *Electric Power Systems Research,* vol. 141, pp. 392-406, 2016.

[193] A.-D. Li, B. Xue, and M. Zhang, "Improved binary particle swarm optimization for feature selection with new initialization and search space reduction strategies," *Applied Soft Computing,* vol. 106, p. 107302, 2021.

[194] H. R. R. Zaman and F. S. Gharehchopogh, "An improved particle swarm optimization with backtracking search optimization algorithm for solving continuous optimization problems," *Engineering with Computers,* vol. 38, no. Suppl 4, pp. 2797-2831, 2022.

[195] C. Karaaom, P. Jirapong, and P. Thararak, "Optimal distribution network reconfiguration implemented with tie line and capacitor using improved particle swarm optimization," in

2020 International Conference on Power, Energy and Innovations (ICPEI), 2020: IEEE, pp. 61-64.

[196] P. Thongbouasy and R. Chatthaworn, "Transmission expansion planning considering solar photovoltaic using novel binary particle swarm optimization," *Energy Reports,* vol. 9, pp. 1145-1153, 2023.

[197] T. Haryono, "Novel binary PSO algorithm based optimization of transmission expansion planning considering power losses," in *IOP Conference Series: Materials Science and Engineering*, 2016, vol. 128, no. 1: IOP Publishing, p. 012023.

[198] M. C. da Rocha and J. ToméSaraiva, "Multiyear transmission expansion planning using discrete evolutionary particle swarm optimization," in *2011 8th International Conference on the European Energy Market (EEM)*, Zagreb, Croatia 25-27 May 2011 IEEE, pp. 802-807.

[199] P. V. Gomes and J. T. Saraiva, "Hybrid discrete evolutionary pso for ac dynamic transmission expansion planning," in *2016 IEEE International Energy Conference (ENERGYCON)*, Leuven, Belgium 04-08 April 2016 IEEE, pp. 1-6.

[200] S. Shandilya, I. Izonin, S. K. Shandilya, and K. K. Singh, "Mathematical modelling of bio-inspired frog leap optimization algorithm for transmission expansion planning," *Math. Biosci. Eng,* vol. 19, no. 7, pp. 7232-7247, 2022.

[201] Z. Hu, M. Ivashchenko, L. Lyushenko, and D. Klyushnyk, "Artificial neural network training criterion formulation using error continuous domain," *Int. j. mod. educ. comput. sci,* vol. 13, pp. 13-22, 2021.

[202] F. Wen and C. Chang, "Transmission network optimal planning using the tabu search method," *Electric power systems research,* vol. 42, no. 2, pp. 153-163, 1997.

[203] A. M. L. da Silva, L. A. da Fonseca Manso, L. C. de Resende, and L. S. Rezende, "Tabu search applied to transmission expansion planning considering losses and interruption costs," in *Proceedings of the 10th International Conference on Probablistic Methods Applied to Power Systems*, Rincon, PR, USA 25-29 May 2008: IEEE, pp. 1-7.

[204] B. R. Pereira Junior, A. M. Cossi, J. Contreras, and J. R. S. Mantovani, "Multiobjective multistage distribution system planning using tabu search," *IET Generation, Transmission & Distribution,* vol. 8, no. 1, pp. 35-45, 2014.

[205] B. C. Mohan and R. Baskaran, "A survey: Ant Colony Optimization based recent research and implementation on several engineering domain," *Expert Systems with Applications,* vol. 39, no. 4, pp. 4618-4627, 2012.

[206] P. Limsakul, S. Pothiya, and N. Leeprechanon, "Application of ant colony optimization to transmission network expansion planning with security constraint," in *8th International conference on advances in power system control, operation and management (APSCOM 2009)*, Hong Kong, China 08-11 November 2009: IET, pp. 1-6.

[207] E. Şenyiğit, S. Mutlu, and B. Babayiğit, "Transmission expansion planning based on a hybrid genetic algorithm approachunder uncertainty," *Turkish Journal of Electrical Engineering and Computer Sciences,* vol. 27, no. 4, pp. 2922-2937, 2019.

[208] M. Malakoti-Moghadam, A. Askarzadeh, and M. Rashidinejad, "Transmission and generation expansion planning of energy hub by an improved genetic algorithm," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects,* vol. 41, no. 24, pp. 3112-3126, 2019.

[209] K. Tantrapon, P. Jirapong, and P. Thararak, "Mitigating microgrid voltage fluctuation using battery energy storage system with improved particle swarm optimization," *Energy Reports,* vol. 6, pp. 724-730, 2020.

[210] Y. Liu, "A Reliable Approach for Solving Transmission Network Expansion Planning with Objective of Planning Cost Reduction," *Advances in Engineering and Intelligence Systems,* vol. 1, no. 01, pp. 21-30, 2022.

[211] L. S. Rezende, A. M. Leite da Silva, and L. de Mello Honório, "Artificial immune system applied to the multi-stage transmission expansion planning," in *Artificial Immune Systems: 8th International Conference, ICARIS 2009, York, UK, August 9-12, 2009. Proceedings 8*, Berlin Heidelberg, 9-12 August 2009: Springer, pp. 178-191.

[212] S. Prakash and J. Henry, "Transmission expansion planning for 133 bus Tamil Nadu test system using artificial immune system algorithm," in *Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018, Volume 1*, Singapore, 30 December 2019: Springer, pp. 143-153.

[213] L. S. Rezende, A. M. L. da Silva, and L. M. Honório, "Artificial immune systems and differential evolution based approaches applied to multi-stage transmission expansion

planning," in *2009 15th International Conference on Intelligent System Applications to Power Systems*, Curitiba, Brazil, 08-12 November 2009: IEEE, pp. 1-6.

[214] S. Amakali, "Development of models for short-term load forecasting using artificial neural networks," Master of Technology, Electrical Engineering, Cape Peninsula University of Technology, Capetown, South Africa, 2008.

[215] C. Rathore, R. Roy, U. Sharma, and J. Patel, "Artificial Bee Colony Algorithm based static transmission expansion planning," in *2013 International Conference on Energy Efficient Technologies for Sustainability*, Nagercoil, India 10-12 April 2013: IEEE, pp. 1126-1131.

[216] M. Mahdavi, A. Kimiyaghalam, H. H. Alhelou, M. S. Javadi, A. Ashouri, and J. P. Catalão, "Transmission expansion planning considering power losses, expansion of substations and uncertainty in fuel price using discrete artificial bee colony algorithm," *IEEE Access,* vol. 9, pp. 135983-135995, 2021.

[217] M. D. Khardenvis, S. B. Tembhare, and V. Pande, "Artificial Bee Colony (ABC) Algorithm based Transmission Expansion Planning with Security Constraints," *Power Research-A Journal of CPRI,* pp. 27-36, 2018.

[218] M. Rahim, I. Musirin, I. Abidin, M. Othman, and D. Joshi, "Congestion management based optimization technique using bee colony," in *2010 4th International Power Engineering and Optimization Conference (PEOCO)*, Shah Alam, Malaysia 23-24 June 2010 IEEE, pp. 184-188.

[219] G. Qu *et al.*, "Transmission surplus capacity based power transmission expansion planning using Chaos optimization Algorithm," in *2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, Nanjing, 06-09 April 2008: IEEE, pp. 1446-1452.

[220] I. Alhamrouni, A. Khairuddin, A. K. Ferdavani, and M. Salem, "Transmission expansion planning using AC-based differential evolution algorithm," *IET Generation, Transmission & Distribution,* vol. 8, no. 10, pp. 1637-1644, 2014.

[221] P. S. Georgilakis, "Market-based transmission expansion planning by improved differential evolution," *International Journal of Electrical Power & Energy Systems,* vol. 32, no. 5, pp. 450-456, 2010.

[222] T. Sum-Im, G. Taylor, M. Irving, and Y. Song, "A comparative study of state-of-the-art transmission expansion planning tools," in *Proceedings of the 41st International*

Universities Power Engineering Conference, Newcastle upon Tyne, UK 06-08 September 2006, vol. 1: IEEE, pp. 267-271.

[223] J.-R. Shin and Y.-M. Park, "Optimal long-term transmission planning by expert system approach," in *Proceedings of TENCON'93. IEEE Region 10 International Conference on Computers, Communications and Automation*, Beijing, China 19-21 October 1993, vol. 2: IEEE, pp. 713-717.

[224] R. K. Gajbhiye, D. Naik, S. Dambhare, and S. Soman, "An expert system approach for multi-year short-term transmission system expansion planning: An Indian experience," *IEEE Transactions on Power Systems,* vol. 23, no. 1, pp. 226-237, 2008.

[225] H. Sun, "Planning and Expansion of the Transmission Network in the Presence of Wind Power Plants," *Planning,* vol. 14, no. 12, p. p884, 2023, doi: 10.14569/ijacsa.2023.0141289.

[226] B. B. Maaroof *et al.*, "Current studies and applications of shuffled frog leaping algorithm: a review," *Archives of Computational Methods in Engineering,* vol. 29, no. 5, pp. 3459-3474, 2022.

[227] M. Eghbal, T. K. Saha, and K. N. Hasan, "Transmission expansion planning by meta-heuristic techniques: a comparison of shuffled frog leaping algorithm, PSO and GA.," in *2011 IEEE power and energy society general meeting*, Detroit, MI, USA 24-28 July 2011: IEEE, pp. 1-8.

[228] S. Jaganathan, S. Palaniswami, C. Sasikumar, and R. Muthukumaran, "Multi-objective optimization for transmission network expansion planning using modified bacterial foraging technique," *International Journal of Computer Applications,* vol. 9, no. 3, pp. 28-34, 2010.

[229] I. Alhamrouni, M. Salem, M. K. Rahmat, and P. Siano, "Bacterial foraging algorithm & demand response programs for a probabilistic transmission expansion planning with the consideration of uncertainties and voltage stability index," *IEEE Canadian Journal of Electrical and Computer Engineering,* vol. 44, no. 2, pp. 179-188, 2021.

[230] H. Kiani Rad and Z. Moravej, "Sub-transmission sub-station expansion planning based on bacterial foraging optimization algorithm," *Journal of AI and Data Mining,* vol. 5, no. 1, pp. 11-20, 2017.

[231] G. Srinivasulu, B. Subramanyam, and M. S. Kalavathi, "Multi-objective transmission expansion planning for IEEE 24 bus RTS," in *2015 Conference on Power, Control, Communication and Computational Technologies for Sustainable Growth (PCCCTSG)*, Kurnool, India, 11-12 December 2015: IEEE, pp. 144-149.

[232] R. Chanda and P. Bhattacharjee, "A reliability approach to transmission expansion planning using fuzzy fault-tree model," *Electric Power Systems Research,* vol. 45, no. 2, pp. 101-108, 1998.

[233] A. MAHMOUDABAD, M. Rashidinejad, M. Zeinaddini-Meymand, and M. Rahmani, "Implementation of an AC model for transmission expansion planning considering reliability constraints," *Turkish Journal of Electrical Engineering and Computer Sciences,* vol. 21, no. 4, pp. 1120-1133, 2013.

[234] M. Al-Dhaifallah, M. M. Refaat, Z. Alaas, S. H. A. Aleem, E. E. El-kholy, and Z. M. Ali, "Multi-objectives transmission expansion planning considering energy storage systems and high penetration of renewables and electric vehicles under uncertain conditions," *Energy Reports,* vol. 11, pp. 4143-4164, 2024.

[235] M. Rahmani, R. Romero, and M. J. Rider, "Strategies to reduce the number of variables and the combinatorial search space of the multistage transmission expansion planning problem," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2164-2173, 2012.

[236] S. Binato, G. C. De Oliveira, and J. L. De Araújo, "A greedy randomized adaptive search procedure for transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 16, no. 2, pp. 247-253, 2001.

[237] R. Figueiredo, P. G. Silva, and M. Poss, "Transmission expansion planning with re-design- a greedy randomized adaptive search procedure," in *ICORES*, Algarve, Portugal. , 25 Jan 2013, pp. 380-385.

[238] M. Ameli, M. Shivaie, and S. Moslehpour, "Transmission network expansion planning based on hybridization model of neural networks and harmony search algorithm," *International Journal of Industrial Engineering Computations,* vol. 3, no. 1, pp. 71-80, 2012.

[239] A. Verma, B. Panigrahi, and P. Bijwe, "Harmony search algorithm for transmission network expansion planning," *IET generation, transmission & distribution,* vol. 4, no. 6, pp. 663-673, 2010.

[240] L. E. de Oliveira, F. D. Freitas, I. C. da Silva, and P. V. Gomes, "Dynamic and static transmission network expansion planning via harmony search and branch & bound on a hybrid algorithm," in *Progress in Artificial Intelligence: 18th EPIA Conference on Artificial Intelligence, EPIA 2017, Porto, Portugal, September 5-8, 2017, Proceedings 18*, Porto, Portugal, 09 August 2017: Springer, pp. 271-282.

[241] R. Romero, R. Gallego, and A. Monticelli, "Transmission system expansion planning by simulated annealing," in *Proceedings of Power Industry Computer Applications Conference*, Salt Lake City, UT, USA 07-12 May 1995 IEEE, pp. 278-283.

[242] P. Gomes, "Simulated Annealing with Gaussian Probability Density Function for Transmission Expansion Planning," *U. Porto Journal of Engineering,* vol. 1, no. 1, pp. 104-113, 2015.

[243] M. Cortes-Carmona, R. Palma-Behnke, and O. Moya, "Transmission network expansion planning by a hybrid simulated annealing algorithm," in *2009 15th International Conference on Intelligent System Applications to Power Systems*, Curitiba, Brazil 08-12 November 2009: IEEE, pp. 1-7.

[244] H. Tran, N. Vo, and H. Quyen, "A cuckoo search algorithm for transmission expansion planning," in *2023 International Conference on System Science and Engineering (ICSSE)*, 2023: IEEE, pp. 55-60.

[245] P. Suriya, S. Subramanian, S. Ganesan, and M. Abirami, "Generation and transmission expansion management using grasshopper optimization algorithm," *International Journal of Engineering Business Management,* vol. 11, p. 1847979018818320, 2019.

[246] J. Jangid, A. Saxena, R. Kumar, and V. Gupta, "Transmission expansion planning using composite teaching learning based optimisation algorithm," *Evolutionary Intelligence,* vol. 15, no. 4, pp. 2691-2713, 2022.

[247] J. Jangid, A. Mehta, A. Saxena, S. Surana, and S. Shekhawat, "Comparative Analysis of Different Optimization Algorithms on Transmission Expansion Planning Problem," 2021.

[248] A. Toopshekan, A. Abedian, A. Azizi, E. Ahmadi, and M. A. V. Rad, "Optimization of a CHP system using a forecasting dispatch and teaching-learning-based optimization algorithm," *Energy,* vol. 285, p. 128671, 2023.

[249] M. Basu, "Teaching–learning-based optimization algorithm for multi-area economic dispatch," *Energy,* vol. 68, pp. 21-28, 2014.

[250] S. Yin, "Electricity Market Operations With Massive Renewable Integration: New Designs," Doctor of Philosophy, School of Engineering, Southern Methodist University, Texas, United States, 154, 2021.

[251] I. C. Gonzalez-Romero, S. Wogrin, and T. Gómez, "Review on generation and transmission expansion co-planning models under a market environment," *IET Generation, Transmission & Distribution,* vol. 14, no. 6, pp. 931-944, 2020.

[252] M. Shivaie, M. S. Sepasian, and M. K. Sheikh-El-Eslami, "Multi-objective transmission expansion planning based on reliability and market considering phase shifter transformers by fuzzy-genetic algorithm," *International Transactions on Electrical Energy Systems,* vol. 23, no. 8, pp. 1468-1489, 2013.

[253] M. Khakpoor, M. Jafari-Nokandi, and A. Akbar Abdoos, "A new hybrid GA-fuzzy optimization algorithm for security-constrained based generation and transmission expansion planning in the deregulated environment," *Journal of Intelligent & Fuzzy Systems,* vol. 33, no. 6, pp. 3789-3803, 2017.

[254] A. Mahmoudabadi and M. Rashidinejad, "An application of hybrid heuristic method to solve concurrent transmission network expansion and reactive power planning," *International Journal of Electrical Power & Energy Systems,* vol. 45, no. 1, pp. 71-77, 2013.

[255] R.-C. Leou, "A multi-year transmission planning under a deregulated market," *International Journal of Electrical Power & Energy Systems,* vol. 33, no. 3, pp. 708-714, 2011.

[256] B.-H. F. Flores, J. H. M. Salonga, and A. C. Nerves, "Multi-objective transmission expansion planning using an elitist non-dominated sorting genetic algorithm with fuzzy decision analysis," in *2011 Fifth Asia Modelling Symposium*, Manila, Philippines 2011: IEEE, pp. 168-173.

[257] M. Karimi and M. R. Haghifam, "Risk based multi-objective dynamic expansion planning of sub-transmission network in order to have eco-reliability, environmental friendly network with higher power quality," *IET Generation, Transmission & Distribution,* vol. 11, no. 1, pp. 261-271, 2017.

[258] S. Abbasi and H. Abdi, "Multiobjective transmission expansion planning problem based on ACOPF considering load and wind power generation uncertainties," *International Transactions on Electrical Energy Systems,* vol. 27, no. 6, p. e2312, 2017.

[259] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and M. Moeini-Aghtaie, "A multi-objective transmission expansion planning framework in deregulated power systems with wind generation," *IEEE Transactions on Power Systems,* vol. 29, no. 6, pp. 3003-3011, 2014.

[260] Y. Hu, Z. Bie, G. Li, and T. Ding, "Application of improved point estimate method on multi-objective transmission network expansion planning," in *2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, Xi'an 25-28 October 2016: IEEE, pp. 1038-1042.

[261] L. Zhang, Q. Zhou, Q. Gao, H. Cheng, and S. Zhang, "Multistage fuzzy-robust transmission network expansion planning under uncertainties," *International Transactions on Electrical Energy Systems,* vol. 29, no. 7, p. e12054, 2019.

[262] S. Sisodia, Y. Kumar, and A. K. Wadhwani, "Hybrid ga and pso approach for transmission expansion planning," in *Proceedings of the Second International Conference on Computer and Communication Technologies: IC3T 2015, Volume 3*, India, 01 January 2016: Springer, pp. 311-322.

[263] S. Mehroliya, S. Tomar, A. Arya, and A. Verma, "A Novel Hybrid GA-PSO Algorithm-Based Optimization of Transmission and Expansion Planning," *SN Computer Science,* vol. 4, no. 5, p. 690, 2023.

[264] T. Al-Saba and I. El-Amin, "The application of artificial intelligent tools to the transmission expansion problem," *Electric Power Systems Research,* vol. 62, no. 2, pp. 117-126, 2002.

[265] D. Sun, X. Xie, J. Wang, Q. Li, and C. Wei, "Integrated generation-transmission expansion planning for offshore oilfield power systems based on genetic Tabu hybrid algorithm," *Journal of Modern Power Systems and Clean Energy,* vol. 5, no. 1, pp. 117-125, 2017.

[266] N. E. Koltsaklis and A. S. Dagoumas, "State-of-the-art generation expansion planning: A review," *Applied energy,* vol. 230, pp. 563-589, 2018.

[267] B. Alizadeh and S. Jadid, "A dynamic model for coordination of generation and transmission expansion planning in power systems," *International Journal of Electrical Power & Energy Systems,* vol. 65, pp. 408-418, 2015.

[268] B. S. Palmintier, "Incorporating operational flexibility into electric generation planning: Impacts and methods for system design and policy analysis," Doctor of Philosophy, Engineering systems, Massachusetts Institute of Technology, United States, Cambridge, 273, 2013. [Online]. Available: http://hdl.handle.net/1721.1/79147

[269] Y. Wang *et al.*, "Flexible transmission network expansion planning based on DQN algorithm," *Energies,* vol. 14, no. 7, p. 1944, 2021.

[270] C. MacRae, "Energy storage optimisation for transmission network expansion planning," Doctor of Philosophy, School of Science, RMIT University, Australia, 137, 2017.

[271] A. Sajadi, L. Strezoski, V. Strezoski, M. Prica, and K. A. Loparo, "Integration of renewable energy systems and challenges for dynamics, control, and automation of electrical power systems," *Wiley Interdisciplinary Reviews: Energy and Environment,* vol. 8, no. 1, p. 14, 2019.

[272] B. Rashedi and A. Askarzadeh, "A multi-objective approach for solving transmission expansion planning problem considering wind power uncertainty," *Evolutionary Intelligence,* vol. 15, no. 1, pp. 497-511, 2022.

[273] A. M. Alshamrani, M. A. El-Meligy, M. A. F. Sharaf, W. A. M. Saif, and E. M. Awwad, "Transmission Expansion Planning Considering a High Share of Wind Power to Maximize Available Transfer Capability," *IEEE Access,* vol. 11, pp. 23136-23145, 2023.

[274] S. Abeysinghe, M. Abeysekera, J. Wu, and M. Sooriyabandara, "Electrical properties of medium voltage electricity distribution networks," *CSEE Journal of Power and Energy Systems,* vol. 7, no. 3, pp. 497-509, 2020.

[275] A. M. Amani and M. Jalili, "Power grids as complex networks: Resilience and reliability analysis," *IEEE Access,* vol. 9, pp. 119010-119031, 2021.

[276] T. F. Agajie, B. Khan, H. H. Alhelou, and O. P. Mahela, "Optimal expansion planning of distribution system using grid-based multi-objective harmony search algorithm," *Computers & Electrical Engineering,* vol. 87, p. 106823, 2020.

[277] M. J. B. Kabeyi and O. A. Olanrewaju, "Sustainable energy transition for renewable and low carbon grid electricity generation and supply," *Frontiers in Energy Research,* vol. 9, 2022.

[278] N. Voropai, S. Podkovalnikov, and L. Chudinova, "The evolution of interstate power grid formation," *Global Energy Interconnection,* vol. 4, no. 4, pp. 335-353, 2021.

[279] H. Hamidpour *et al.*, "Coordinated expansion planning problem considering wind farms, energy storage systems and demand response," *Energy,* vol. 239, p. 122321, 2022.

[280] M. L. Di Silvestre, M. G. Ippolito, E. R. Sanseverino, G. Sciumè, and A. Vasile, "Energy self-consumers and renewable energy communities in Italy: New actors of the electric power systems," *Renewable and Sustainable Energy Reviews,* vol. 151, p. 111565, 2021.

[281] K. Kotilainen, *Perspectives on the Prosumer Role in the Sustainable Energy System*. Tampere University, 2020.

[282] PowerFactory DIgSILENT, "TechRef_SynchronousMachine," Germany, 2021.

[283] Eskom, "TRANSMISSION AND DISTRIBUTION OF ELECTRICITY," Eskom Generation Communication, South Africa, 2023.

[284] H. Saadat, *Power system analysis*. NewYork: McGraw-hill, 1999.

[285] X. Ma, H. Zhou, and Z. Li, "On the resilience of modern power systems: A complex network perspective," *Renewable and Sustainable Energy Reviews,* vol. 152, p. 111646, 2021.

[286] C.-C. Sun, A. Hahn, and C.-C. Liu, "Cyber security of a power grid: State-of-the-art," *International Journal of Electrical Power & Energy Systems,* vol. 99, pp. 45-56, 2018.

[287] N. Y. Puvvada, A. Mohapatra, and S. C. Srivastava, "Robust AC transmission expansion planning using a novel dual-based bi-level approach," *IEEE Transactions on Power Systems,* vol. 37, no. 4, pp. 2881-2893, 2022.

[288] T. Klatzer, U. Bachhiesl, and S. Wogrin, "State-of-the-art expansion planning of integrated power, natural gas, and hydrogen systems," *International Journal of Hydrogen Energy,* vol. 47, no. 47, pp. 20585-20603, 2022.

[289] J. Xu, T. Lv, X. Hou, X. Deng, and F. Liu, "A bibliometric analysis of power system planning research during 1971–2020," *IEEE Transactions on Power Systems,* vol. 37, no. 3, pp. 2283-2296, 2021.

[290] S. Sreekumar, S. Yamujala, K. C. Sharma, R. Bhakar, S. P. Simon, and A. S. Rana, "Flexible Ramp Products: A solution to enhance power system flexibility," *Renewable and Sustainable Energy Reviews,* vol. 162, p. 112429, 2022.

[291] M. Ahmed *et al.*, "Mitigating Uncertainty Problems of Renewable Energy Resources Through Efficient Integration of Hybrid Solar PV/Wind Systems Into Power Networks," *IEEE Access,* vol. 12, pp. 30311-30328, 2024.

[292] X. Deng and T. Lv, "Power system planning with increasing variable renewable energy: A review of optimization models," *Journal of Cleaner Production,* vol. 246, p. 118962, 2020.

[293] S. Makhloufi, S. Khennas, S. Bouchaib, and A. H. Arab, "Multi-objective cuckoo search algorithm for optimized pathways for 75% renewable electricity mix by 2050 in Algeria," *Renewable Energy,* vol. 185, pp. 1410-1424, 2022.

[294] Z. Wei, L. Yang, S. Chen, Z. Ma, H. Zang, and Y. Fei, "A multi-stage planning model for transitioning to low-carbon integrated electric power and natural gas systems," *Energy,* vol. 254, p. 124361, 2022.

[295] H. B. Yamchi, A. Safari, and J. M. Guerrero, "A multi-objective mixed integer linear programming model for integrated electricity-gas network expansion planning considering the impact of photovoltaic generation," *Energy,* vol. 222, p. 119933, 2021.

[296] J. Gea-Bermúdez, R. Bramstoft, M. Koivisto, L. Kitzing, and A. Ramos, "Going offshore or not: Where to generate hydrogen in future integrated energy systems?," *Energy Policy,* vol. 174, p. 113382, 2023.

[297] F. Neumann, E. Zeyen, M. Victoria, and T. Brown, "The potential role of a hydrogen network in Europe," *Joule,* vol. 7, no. 8, pp. 1793-1817, 2023.

[298] D. Yang *et al.*, "A review of solar forecasting, its dependence on atmospheric sciences and implications for grid integration: Towards carbon neutrality," *Renewable and Sustainable Energy Reviews,* vol. 161, p. 112348, 2022.

[299] P. V. Gomes, J. T. Saraiva, L. Carvalho, B. Dias, and L. W. Oliveira, "Impact of decision-making models in Transmission Expansion Planning considering large shares of renewable energy sources," *Electric Power Systems Research,* vol. 174, p. 105852, 2019.

[300] M. Hämmerling, N. Walczak, and T. Kałuża, "Analysis of the Influence of Hydraulic and Hydrological Factors on the Operating Conditions of a Small Hydropower Station on the Example of the Stary Młyn Barrage on the Głomia River in Poland," *Energies,* vol. 16, no. 19, p. 6905, 2023.

[301] S. Das and S. P. Jena, "THE BENEFITS AND DRAWBACKS OF HYDROELECTRIC POWER PLANTS," *UGC Care Group I Listed Journal,* vol. 10, no. 01, 2020.

[302] B. Ashtari, M. Yeganeh, M. Bemanian, and B. Vojdani Fakhr, "A conceptual review of the potential of cool roofs as an effective passive solar technique: elaboration of benefits and drawbacks," *Frontiers in Energy Research,* vol. 9, p. 738182, 2021.

[303] A.-R. Nadia, N. A. M. Isa, and M. K. M. Desa, "Advances in solar photovoltaic tracking systems: A review," *Renewable and sustainable energy reviews,* vol. 82, pp. 2548-2569, 2018.

[304] M. J. B. Kabeyi and O. A. Olanrewaju, "Sustainable energy transition for renewable and low carbon grid electricity generation and supply," *Frontiers in Energy research,* vol. 9, p. 1032, 2022.

[305] M. T. Sarker, M. H. S. M. Haram, G. Ramasamy, F. Al Farid, and S. Mansor, "Solar Photovoltaic Home Systems in Malaysia: A Comprehensive Review and Analysis," *Energies,* vol. 16, no. 23, p. 7718, 2023.

[306] M. S. Nazir, A. J. Mahdi, M. Bilal, H. M. Sohail, N. Ali, and H. M. Iqbal, "Environmental impact and pollution-related challenges of renewable wind energy paradigm–a review," *Science of the Total Environment,* vol. 683, pp. 436-444, 2019.

[307] R. Reja *et al.*, "A review of the evaluation of urban wind resources: Challenges and perspectives," *Energy and Buildings,* vol. 257, p. 111781, 2022.

[308] D. Raffat, "Renewable Energy (Alternative to fossil fuel energy)," degree of (BSc.)

in chemistry, Department of chemistry, University of Salahaddin -Erbil, Erbil, Iraq, 34, 2021.

[309] R. Rohit, D. C. Kiplangat, R. Veena, R. Jose, A. Pradeepkumar, and K. S. Kumar, "Tracing the evolution and charting the future of geothermal energy research and development," *Renewable and Sustainable Energy Reviews,* vol. 184, p. 113531, 2023.

[310] M. Jayachandran *et al.*, "Challenges in achieving sustainable development goal 7: Affordable and clean energy in light of nascent technologies," *Sustainable Energy Technologies and Assessments,* vol. 53, p. 102692, 2022.

[311] K. Moloi, J. Jordaan, and Y. Hamam, "Optimal power grid integration with distributed generation using genetic algorithm," in *2021 Southern African Universities Power Engineering Conference/Robotics and Mechatronics/Pattern Recognition Association of South Africa (SAUPEC/RobMech/PRASA)*, Potchefstroom, South Africa 27-29 January 2021: IEEE, pp. 1-5.

[312] R. Hemmati, R.-A. Hooshmand, and A. Khodabakhshian, "Coordinated generation and transmission expansion planning in deregulated electricity market considering wind farms," *Renewable Energy,* vol. 85, pp. 620-630, 2016.

[313] Tumiran *et al.*, "Transmission expansion planning for the optimization of renewable energy integration in the sulawesi electricity system," *Sustainability,* vol. 13, no. 18, p. 10477, 2021.

[314] E. S. Chatzistylianos, G. N. Psarros, and S. A. Papathanassiou, "Insights from a Comprehensive Capacity Expansion Planning Modeling on the Operation and Value of Hydropower Plants under High Renewable Penetrations," *Energies,* vol. 17, no. 7, p. 1723, 2024.

[315] F. Prinsloo, P. Schmitz, and A. Lombard, "Sustainability assessment framework and methodology with trans-disciplinary numerical simulation model for analytical floatovoltaic energy system planning assessments," *Sustainable Energy Technologies and Assessments,* vol. 47, p. 101515, 2021.

[316] T.-T. Ku and C.-S. Li, "Implementation of battery energy storage system for an island microgrid with high PV penetration," *IEEE Transactions on Industry Applications,* vol. 57, no. 4, pp. 3416-3424, 2021.

[317] H. Iranmehr *et al.*, "Modeling the price of emergency power transmission lines in the reserve market due to the influence of renewable energies," *Frontiers in Energy Research,* vol. 9, p. 792418, 2022.

[318] M. Peker, A. S. Kocaman, and B. Y. Kara, "Benefits of transmission switching and energy storage in power systems with high renewable energy penetration," *Applied Energy,* vol. 228, pp. 1182-1197, 2018.

[319] S. Allard, S. Mima, V. Debusschere, T. T. Quoc, P. Criqui, and N. Hadjsaid, "European transmission grid expansion as a flexibility option in a scenario of large scale variable renewable energies integration," *Energy Economics,* vol. 87, p. 104733, 2020.

[320] J. Liu, Z. Huang, M. Fan, J. Yang, J. Xiao, and Y. Wang, "Future energy infrastructure, energy platform and energy storage," *Nano Energy,* vol. 104, p. 107915, 2022.

[321] M. Sharafi and T. Y. ELMekkawy, "Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach," *Renewable energy,* vol. 68, pp. 67-79, 2014.

[322] D. C. Baruah and C. C. Enweremadu, "Prospects of decentralized renewable energy to improve energy access: A resource-inventory-based analysis of South Africa," *Renewable and Sustainable Energy Reviews,* vol. 103, pp. 328-341, 2019.

[323] O. J. Ayamolowo, P. Manditereza, and K. Kusakana, "South Africa power reforms: The Path to a dominant renewable energy-sourced grid," *Energy Reports,* vol. 8, pp. 1208-1215, 2022.

[324] H. Tazvinga, O. Dzobo, and M. Mapako, "Towards sustainable energy system options for improving energy access in Southern Africa," *Journal of Energy in Southern Africa,* vol. 31, no. 2, pp. 59-72, 2020.

[325] H. Wang and T. Jin, "Prevention and survivability for power distribution resilience: A multi-criteria renewables expansion model," *IEEE Access,* vol. 8, pp. 88422-88433, 2020.

[326] M. Adnan, Y. Ghadi, I. Ahmed, and M. Ali, "Transmission network planning in super smart grids: A survey," *IEEE Access,* 2023.

[327] Eskom. "Generation." https://www.eskom.co.za/eskom-divisions/gx/ (accessed 03-02-2023.

[328] U.S.A Government-Led Partnership, "POWER AFRICA FACT SHEET," United State Agency for International Development (USAID)

America, 2023. Accessed: 16/ 04/ 2020. [Online]. Available: https://www.usaid.gov/powerafrica/countries

[329] O. K. Overen and E. L. Meyer, "Solar energy resources and photovoltaic power potential of an underutilised region: a case of Alice, South Africa," *Energies,* vol. 15, no. 13, p. 4646, 2022.

[330] G. Mutezo and J. Mulopo, "A review of Africa's transition from fossil fuels to renewable energy using circular economy principles," *Renewable and Sustainable Energy Reviews,* vol. 137, p. 110609, 2021.

[331] M. M. Peta, "Exploring the efficacy of solar photovoltaic application as an alternative energy source for rural households in Atok, Limpopo," Master of Philosophy in Energy Studies, Geography, Environmental Management & Energy Studies, University of Johannesburg (South Africa), Johannesburg (South Africa), 2021.

[332] A. Muhtadi, D. Pandit, N. Nguyen, and J. Mitra, "Distributed energy resources based microgrid: Review of architecture, control, and reliability," *IEEE Transactions on Industry Applications,* vol. 57, no. 3, pp. 2223-2235, 2021.

[333] E. Merem *et al.*, "The Evaluation of Wind Energy Potentials in South Africa," *Energy and Power,* vol. 12, no. 1, pp. 9-25, 2022.

[334] A. Mostafaeipour *et al.*, "Statistical evaluation of using the new generation of wind turbines in South Africa," *Energy Reports,* vol. 6, pp. 2816-2827, 2020.

[335] S. C. Pryor and R. J. Barthelmie, "A global assessment of extreme wind speeds for wind energy applications," *Nature Energy,* vol. 6, no. 3, pp. 268-276, 2021.

[336] O. Siram, N. Sahoo, and U. K. Saha, "Changing landscape of india's renewable energy and the contribution of wind energy," *Cleaner Engineering and Technology,* vol. 8, p. 100506, 2022.

[337] C. Jung and D. Schindler, "The annual cycle and intra-annual variability of the global wind power distribution estimated by the system of wind speed distributions," *Sustainable Energy Technologies and Assessments,* vol. 42, p. 100852, 2020.

[338] M. D'ANGELO, "Onshore Wind Energy Market Analysis: Of Sweden, Poland, and Romania," Master of Science, KTH School of Industrial Engineering and Management, Poland, 2020.

[339] G. Rae and G. Erfort, "Offshore wind energy-South Africa's untapped resource," *Journal of Energy in Southern Africa,* vol. 31, no. 4, pp. 26-42, 2020.

[340] K. Umoh and M. Lemon, "Drivers for and barriers to the take up of floating offshore wind technology: A comparison of Scotland and South Africa," *Energies,* vol. 13, no. 21, p. 5618, 2020.

[341] P. Struisbult and H. Place, "CONSTRUCTION OF A 100MW PHOTOVOLTAIC SOLAR ENERGY FACILITY (PV2) ON THE FARM STRUISBULT (FARM NO. 104 PORTION 1) NEAR COPPERTON, NORTHERN CAPE PROVINCE," Holland & Associates Environmental Consultants, Capetown, 2020.

[342] South African Wind Energy Association (SAWEA), "South African Wind Farms," SAWEA, South Africa, Johannesburg, 2023.

[343] Enel Green Power, "driving the future of sustainable energy," Enel Green Power, South Africa, 2024.

[344] W. S. Tan, M. Shaaban, and M. Z. A. Ab Kadir, "Stochastic generation scheduling with variable renewable generation: methods, applications, and future trends," *IET Generation, Transmission & Distribution,* vol. 13, no. 9, pp. 1467-1480, 2019.

[345] H. Zsiborács, G. Pintér, A. Vincze, N. H. Baranyai, and M. J. Mayer, "The reliability of photovoltaic power generation scheduling in seventeen European countries," *Energy Conversion and Management,* vol. 260, p. 115641, 2022.

[346] A. D. Mills, T. Levin, R. Wiser, J. Seel, and A. Botterud, "Impacts of variable renewable energy on wholesale markets and generating assets in the United States: A review of expectations and evidence," *Renewable and Sustainable Energy Reviews,* vol. 120, p. 109670, 2020.

[347] A. NECIRA, "Power system performance improvement in the presence of renewable sources," Doctorat LMD, Génie Electrique, Faculté des Sciences et de la technologie, Biskra, Algeria, 137, 2022.

[348] M. Petrovic, "Quantifying the Value of Renewable Energy as a Hedge Against the Volatility of Natural Gas Prices in Wisconsin," Doctor of Business Administration, School of Business, Liberty University, Lynchburg, United States, 189, 2023.

[349] C. Breyer *et al.*, "On the history and future of 100% renewable energy systems research," *IEEE Access,* vol. 10, pp. 78176-78218, 2022.

[350] P. Glaum and F. Hofmann, "Leveraging the existing German transmission grid with dynamic line rating," *Applied Energy,* vol. 343, p. 121199, 2023.

[351] G. K. Sakki, I. Tsoukalas, P. Kossieris, C. Makropoulos, and A. Efstratiadis, "Stochastic simulation-optimization framework for the design and assessment of renewable energy systems under uncertainty," *Renewable and Sustainable Energy Reviews,* vol. 168, p. 112886, 2022.

[352] C. Li, N. Shah, Z. Li, and P. Liu, "Modelling of wind and solar power output uncertainty in power systems based on historical data: A characterisation through deterministic parameters," *Journal of Cleaner Production,* p. 144233, 2024.

[353] D.-A. Ciupageanu, L. Barelli, and G. Lazaroiu, "Real-time stochastic power management strategies in hybrid renewable energy systems: A review of key applications and perspectives," *Electric Power Systems Research,* vol. 187, p. 106497, 2020.

[354] A. Sau, A. Singh, and P. Mahalakshmi, "Forecasting Energy Consumption Patterns: Weather-Driven Insights from Time Series Analysis," in *2024 IEEE Students Conference on Engineering and Systems (SCES)*, Prayagraj, India, 21-23 June 2024 2024: IEEE, pp. 1-6.

[355] N. Mlilo, J. Brown, and T. Ahfock, "Impact of intermittent renewable energy generation penetration on the power system networks–A review," *Technology and Economics of Smart Grids and Sustainable Energy,* vol. 6, no. 1, p. 25, 2021.

[356] W. Velasquez, G. Z. Moreira-Moreira, and M. S. Alvarez-Alvarado, "Smart Grids Empowered by Software-Defined Network: A Comprehensive Review of Advancements and Challenges," *IEEE Access,* 2024.

[357] G. Wang, Q. Zhang, B. Su, B. Shen, Y. Li, and Z. Li, "Coordination of tradable carbon emission permits market and renewable electricity certificates market in China," *Energy Economics,* vol. 93, p. 105038, 2021.

[358] A. Z. Kenfack, M. K. Nematchoua, E. Simo, G. J. B. Ntegmi, and V. S. Chara-Dackou, "Transition towards net zero emissions: Integration of a PV/T system with a hydroelectric generator and the impact of demand-side management," *Heliyon,* vol. 10, no. 17, 2024.

[359] Y. Li and Y. Huang, "Enhancing resources efficiency: Studying economic development in resource-rich regions for long-term sustainability of China," *Resources Policy,* vol. 86, p. 104234, 2023.

[360] Q. Hassan *et al.*, "Enhancing smart grid integrated renewable distributed generation capacities: Implications for sustainable energy transformation," *Sustainable Energy Technologies and Assessments,* vol. 66, p. 103793, 2024.

[361] E. Hilmi, E. Yandri, U. Uhanto, R. Saiful, and N. Hamja, "Hybrid Energy Solutions for Sustainable Offshore Oil and Gas Operations: Leveraging Thermoelectric, Solar, and Wind Potential," *Leuser Journal of Environmental Studies,* vol. 2, no. 2, pp. 52-61, 2024.

[362] Y. Parag and M. Ainspan, "Sustainable microgrids: Economic, environmental and social costs and benefits of microgrid deployment," *Energy for Sustainable Development,* vol. 52, pp. 72-81, 2019.

[363] M. Fan and S. Lu, "Benefit analysis and preliminary decision-making of electrical and thermal energy storage in the regional integrated energy system," *Journal of Energy Storage,* vol. 55, p. 105816, 2022.

[364] M. Faizan, A. K. Alkaabi, B. Nie, and I. Afgan, "Thermal energy storage integration with nuclear power: A critical review," *Journal of Energy Storage,* vol. 96, p. 112577, 2024.

[365] D. PowerFactory, "39 Bus New England System," Germany, 2025.

[366] S. D. Ahmed, F. S. Al-Ismail, M. Shafiullah, F. A. Al-Sulaiman, and I. M. El-Amin, "Grid integration challenges of wind energy: A review," *IEEE Access,* vol. 8, pp. 10857-10878, 2020.

[367] M. Ntombela, K. Musasa, and K. Moloi, "A comprehensive review of the incorporation of electric vehicles and renewable energy distributed generation regarding smart grids," *World Electric Vehicle Journal,* vol. 14, no. 7, p. 176, 2023.

[368] K. N. Lawson, "Property Rights, Consequences of Electrical Blackouts, and Measures of Institutional Quality," Ph.D. in Economics, Department of Economics, West Virginia University, Morgantown, West Virginia, 2021.

[369] P. Staudt and S. S. Oren, "Merchant transmission in single-price electricity markets with cost-based redispatch," *Energy Economics,* vol. 104, p. 105610, 2021.

[370] K. R. Abbasi, M. Shahbaz, J. Zhang, M. Irfan, and R. Alvarado, "Analyze the environmental sustainability factors of China: The role of fossil fuel energy and renewable energy," *Renewable Energy,* vol. 187, pp. 390-402, 2022.

[371] A. A. Eladl, M. I. El-Afifi, M. A. Saeed, and M. M. El-Saadawi, "Optimal operation of energy hubs integrated with renewable energy sources and storage devices considering CO2 emissions," *International Journal of Electrical Power & Energy Systems,* vol. 117, p. 105719, 2020.

[372] S. W. Ali *et al.*, "Offshore wind farm-grid integration: A review on infrastructure, challenges, and grid solutions," *IEEE Access,* vol. 9, pp. 102811-102827, 2021.

[373] M. Powers, "Anticompetitive transmission development and the risks for decarbonization," *Environmental Law,* vol. 49, no. 4, pp. 885-929, 2019.

[374] J. Aghaei, N. Amjady, A. Baharvandi, and M.-A. Akbari, "Generation and transmission expansion planning: MILP–based probabilistic model," *IEEE Transactions on Power Systems,* vol. 29, no. 4, pp. 1592-1601, 2014.

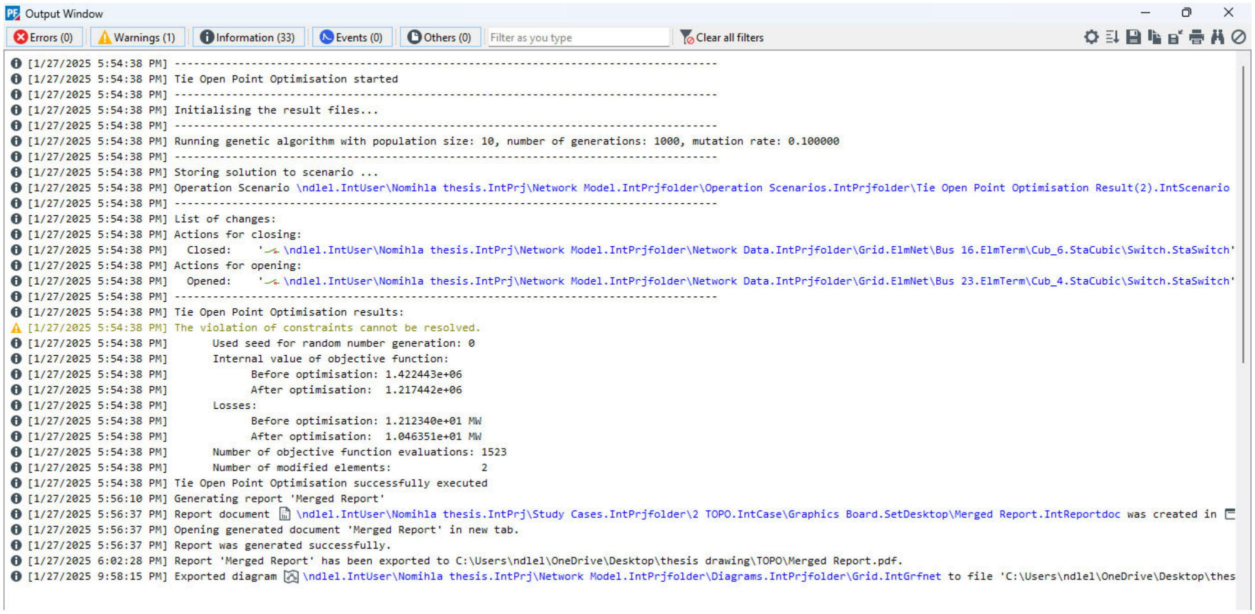
[375] G. Pesántez, W. Guamán, J. Córdova, M. Torres, and P. Benalcazar, "Reinforcement Learning for Efficient Power Systems Planning: A Review of Operational and Expansion Strategies," *Energies,* vol. 17, no. 9, p. 2167, 2024.

[376] D. Solyali, "A comparative analysis of machine learning approaches for short-/long-term electricity load forecasting in Cyprus," *Sustainability,* vol. 12, no. 9, p. 3612, 2020.

[377] M. S. Qureshi, S. Umar, and M. U. Nawaz, "Machine Learning for Predictive Maintenance in Solar Farms," *International Journal of Advanced Engineering Technologies and Innovations,* vol. 1, no. 3, pp. 27-49, 2024.

[378] J. Klaiber and C. Van Dinther, "Deep learning for variable renewable energy: a systematic review," *ACM Computing Surveys,* vol. 56, no. 1, pp. 1-37, 2023.

APPENDIX



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Output Window
Errors (0)  Warnings (1)  Information (33)  Events (0)  Others (0)  Filter as you type  Clear all filters
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[1/27/2025 5:54:38 PM] Tie Open Point Optimisation started
[1/27/2025 5:54:38 PM] --------------------------------------------------------------------------------
[1/27/2025 5:54:38 PM] Initialising the result files...
[1/27/2025 5:54:38 PM] --------------------------------------------------------------------------------
[1/27/2025 5:54:38 PM] Running genetic algorithm with population size: 10, number of generations: 1000, mutation rate: 0.100000
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[1/27/2025 5:54:38 PM] Storing solution to scenario ...
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[1/27/2025 5:54:38 PM] The violation of constraints cannot be resolved.
[1/27/2025 5:54:38 PM]      Used seed for random number generation: 0
[1/27/2025 5:54:38 PM]      Internal value of objective function:
[1/27/2025 5:54:38 PM]           Before optimisation: 1.422443e+06
[1/27/2025 5:54:38 PM]           After optimisation:  1.217442e+06
[1/27/2025 5:54:38 PM]      Losses:
[1/27/2025 5:54:38 PM]           Before optimisation: 1.212340e+01 MW
[1/27/2025 5:54:38 PM]           After optimisation:  1.046351e+01 MW
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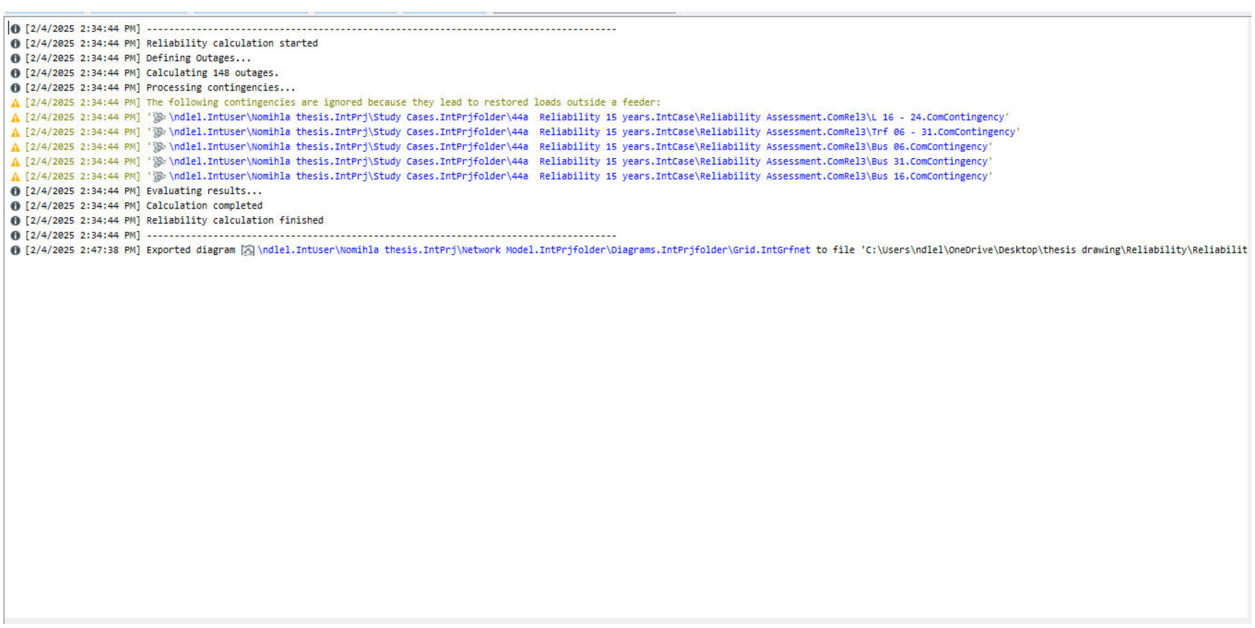
Appendix A: TOPO optimization



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[2/4/2025 2:34:44 PM] '\ndlel.IntUser\Nomihla thesis.IntPrj\Study Cases.IntPrjfolder\44a  Reliability 15 years.IntCase\Reliability Assessment.ComRel3\L 16 - 24.ComContingency'
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Appendix B: Reliability analysis