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A Comprehensive Capacity Expansion Planning Model for Highly Renewable Integrated Power Systems

by

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Abstract

Due to the depletion of conventional energy and environmental concerns, the trend toward increasing integration of renewable energy resources brings new challenges to power system planning and operation. The fluctuation of renewable energy resources is the main concern of system planners for their efficient deployment. Incorporating a more precise and detailed model of system constraints is inevitable to deal with these resources' intermittent and volatile nature. However, due to the various aspects and computation complexity of the capacity expansion problem, it is vital to have a thorough understanding of the most affecting constraints on the system planning. The unique characteristics of power systems, along with the integration of renewable energy resources and modern technologies such as energy storage, require developing a profound model for planning future infrastructure based on the available data.

The primary objective of this research is to investigate and evaluate various aspects of power systems and develop a comprehensive capacity expansion model utilizing linear optimization techniques. The thesis includes the development of a data set for long-term planning purposes, a co-optimization expansion planning (CEP) model for identifying optimal transmission and generation expansion, modeling of storage technology and reserves, and reducing the network size to ensure model tractability. The framework was designed to facilitate the seamless integration of renewable energy sources and improve the performance of the whole power system, ensuring a smooth transition towards a high-renewable energy future.

This tool intends to provide system planners and stakeholders in the generation and transmission sectors insights into future realizations of high-renewable power systems. The model can also be used as a benchmark for future planning studies and adjusted for any possible future assumptions.

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List of Symbols and Abbreviations

Symbol	Definition
GHG	Green-House Gas
CEP	Co-optimization Expansion Planning
GEP	Generation Expansion Planning
TEP	Transmission Expansion Planning
LTP	Long-term Transmission Plan
LTO	Long-Term Outlook
ISO	Independent System Operator
RTO	Regional Transmission Operator
AESO	Alberta Electric System Operator
RE	Renewable Energy
ESS	Energy Storage System
STO	Storage
Res	Reserve
RegUp	Regulation Up Reserve
RegDn	Regulation Down Reserve
GasCC	Gas Combined Cycle
GasCT	Gas Combustion Turbine
OilCT	Oil Combustion Turbine
OilST	Oil Steam Turbine
RTS-GMLC	Reliability Test System-Grid Modernization Laboratory Consortium

Nomenclature

Indices / Sets

b/B	Buses
g/N_g	Generators
k/K	Seasons
l/L	Lines
p/N_p	Load blocks
s/S	Future scenarios
y/Y	Years

Parameters

τ	Load shed cost (\$/MWhr)
η_C	Energy storage charge efficiency
η_D	Energy storage discharge efficiency
η_{RT}	Energy storage round-trip efficiency
λ^{Max}	Maximum SOC level
λ^{Min}	Minimum SOC level
ζ	Annual discount factor
CC	Capacity credit
CF	Generation capacity factor

CV Renewable generation capacity value

D' Peak real power demand (MW)

D Real power demand (MW)

FOM Fixed operation & maintenance cost (\$/MW)

FP Fuel price (\$/MMBTU)

G^0 Existing generation capacity (MW)

G^{min} Generation minimum stable level

HR Average heat rate (MMBTU/MWhr)

I_G Generation investment cost (\$/MW)

I_T Transmission investment cost (\$/MW)

L^0 Existing transmission capacity (MW)

M Carbon emission rate (tons/MMBTU)

PRM Planning reserve margin for region

RPS Renewable Portfolio Standard (%)

T Hours in load block p

T^{ES} Energy storage duration (hours)

TL Transmission thermal limit rating (MW)

VOM Variable operation & maintenance cost (\$/MW)

X_l Transmission line reactance (pu)

Subsets

$N_g^{Ren} \subset N_g$ Renewable generators

$N_g^{Ret} \subset N_g$ Retirement-eligible generators

$N_g^{Therm} \subset N_g$ Thermal generators

$N_l^{Ex} \subset N_l$ Existing transmission lines

Variables

θ Bus angle (radian)

ϑ_{LS} Load shedding cost ($)

C Cost totals ($)

G Generation investments (MW)

IC_{Gen} Investment cost in generation($)

IC_{Trans} Transmission investments cost ($)

L_C Transmission investments (MW)

LS Load shed (MW)

OC_{FOM} Fixed operation and maintenance cost ($)

OC_{Fuel} Fuel cost ($)

OC_{VOM} Variable operation and maintenance cost ($)

P Generator dispatch (MW)

P^C Energy storage charging (MW)

P^D Energy storage discharging (MW)

P^{Curt} Generation curtailment (MW)

PF Power flow of line with sending and receiving buses $[b, b']$ (MW)

R Retired capacity (MW)

R^+ Regulation up reserve (MW)

R^- Regulation down reserve (MW)

SOC Energy storage state-of-charge (MWhr)

Chapter 1

Introduction

1.1 Motivation

Climate change affects the daily lives of millions of people around the globe and is considered the most serious threat to humanity. Canada has pledged to cut its greenhouse gas (GHG) emissions by 40-45 percent by 2030 compared to 2005 levels (739 Mt CO_2 eq.) and attain net-zero emissions by 2050 [1]. However, Canada's GHG emissions in 2019 (730 Mt CO_2 eq.) were just 1% lower than that of 2005, indicating Canada's GHG emissions have only stabilized, not reduced. Therefore, as Canada embarks on the revolutionary path of achieving net-zero GHG emissions across the economy by 2050, the milestone of obtaining a net-zero electricity grid by 2035 is also required [1]. Consequently, this effort will require a tremendous boost from wind, solar, and new technologies such as energy storage within the power systems.

Although 80% of Canada's electricity generation is currently non-GHG emitting (mostly hydro generation), a fully decarbonized power system will help minimize GHG emissions in many other applications such as transportation, buildings, and industry. Alberta's electricity network is one of Canada's most carbon-emitting power systems, generating 72% of its electricity from coal and gas facilities and 28% from renewable resources [2]. Minimizing the costs involved with decarbonizing and expanding Canada's power system will be vital to maintaining affordable consumer electricity and a competitive industrial sector.

Wind and solar generation can play a critical role on the road to a net-zero power system; however, the push towards more renewable electricity generation is hindered by these resources' intermittent and uncontrollable nature. Therefore, it is crucial to partner other technologies with renewable energies while planning for reliable and economic integration of significant renewable generation into the electricity grid. Energy storage systems (ESSs) have been introduced as a solution to address the negative effects of integrating large-scale renewable energies into power systems [3]. While the coordination of renewable energies and ESSs have been widely considered in power system studies, some aspects, such as the time dependency of these resources and their contribution as reserves, have not been addressed properly, especially in power system planning.

In this dissertation, a CEP is developed to explore possible futures for a test system, considering the inclusion of ESSs in the system planning. Moreover, the proposed CEP accounts for reserve requirements in the operation of power systems as more integration of intermittent renewable resources need a higher reserve for the system's secure operation. The effects of ESSs as a reserve are also studied.

1.2 Background

Power systems are capital-intensive; therefore, as the integration of renewable resources and new technologies increases, the decision on *when*, *where*, and *what* to invest becomes more prominent. Long-term capacity planning (CEP) of power systems answers these questions while considering the system's operational and investment constraints. CEP is the identification of transmission and generation investments necessary to satisfy future demand requirements in the most economic fashion, subject to constraints associated with network reliability, environmental considerations, and policy objectives. This problem has traditionally been solved deterministically through identifying a set of assumptions regarding future attributes, e.g., technology costs, fuel prices, demand growth, and policy impacts; identifying or predicting generation investments and retirements; and determining the transmission investments necessary to reliably deliver energy from resources to load centers.

To ensure that the decisions made by CEP do not violate the network operation constraints, the CEP investment decisions are checked against the operational constraints. This is done by adding the operational constraints to the CEP. However, the network's conditions change hourly and subhourly. Therefore, it is imperative to model all the operational conditions within CEP. Nonetheless, the CEP can be computationally demanding, taking days, weeks, or months to run on powerful computer servers due to long-term planning horizon, typical network size, uncertainty, and other features [4]. In order to reduce the computation time, it is usual to study tens of hours instead of all hours of a year (8760 hours per year) and evaluate each hour independently of the other hours. These selected hours must be representative of all operational conditions of the system over the planning horizon. The planning horizon can be several years, and selecting such representative hours is not trivial.

As newer technologies are integrated into power systems, it is essential to consider these new technologies and associated requirements in the planning models. Moreover, the new emission requirements change the generation mix to satisfy the electric load while reducing the emissions. These changes necessitate the use of high-fidelity CEP. A high-fidelity CEP can model many operational conditions and scenarios while accounting for new technologies and their requirements. Although reduced time resolution assessment significantly reduces compute time, it does so at a significant loss of modeling fidelity since only a small number of hours (and corresponding conditions) are studied; importantly, inter-temporal dependencies are not modeled. These modeling issues are of increased concern today because they directly impact the ability to plan and assess operational flexibility (i.e., the ability to adequately respond to changes in operating conditions). Operational flexibility is increasingly needed as wind and solar generation resources grow.

Exploring possible futures of power system generation and transmission scenarios under different assumptions while ensuring operational reliability would significantly enhance the flexibility and adaptability of transmission investment plans. Such flexible and adaptive planning potentially results in large investment cost reductions, more efficient operations, and more robust and adaptable infrastructure.

1.3 Objectives

The objective of this thesis is to develop, implement, test, and evaluate a computational method for identifying long-term power system expansion planning solutions. The key contribution of the proposed model is its ability to co-optimize both generation and transmission options, enabling the identification of minimum-cost solutions among all combinations of transmission and generation. This approach allows for transmission planning that predicts how generation and storage siting would respond to network expansion. This tool provides the system operator, generation, and transmission developers insights into future realizations of high-renewable power systems and helps such stakeholders adjust their positions accordingly.

To achieve this objective, the thesis involves the development of a dataset for long-term planning purposes based on the Reliability Test System Grid Modernization Lab Consortium (RTS-GMLC). This dataset will be made public, allowing other researchers to use it as a benchmark for their planning studies. Furthermore, the dataset can be adjusted for any future assumptions that researchers may have.

The thesis also includes the development of a coordinated generation and transmission planning model, enabling the identification of optimal network expansion by solving a single optimization problem. The model considers storage technology as an emerging technology and models it as time-dependent, allowing for its potential roles in energy and reserve markets to be analyzed. Additionally, the developed CEP considers and analyzes the effects of reserves on future investment plans, taking into account the operational risks that arise when integrating intermittent renewable resources.

In order to make the comprehensive planning model applicable to real-world large networks, this thesis implements a reasonable reduction method to minimize the size of the network. This approach makes long-term planning feasible by ensuring that the model remains tractable.

Overall, the thesis aims to provide a powerful tool for decision-makers in the energy industry to make informed decisions about how to best integrate renewable energy sources into the grid. By considering a range of factors, such as transmission and generation options, storage technology, and operational risks, the thesis provides valuable insights into the development of sustainable energy systems.

1.4 Contributions and Significance

In this thesis, a co-optimization expansion planning (CEP) is developed for a test system that is inspired by a real network. The developed CEP includes many features that a modern CEP must include to account for recent trends and changes in power systems. The contributions of this thesis are as follows:

- Development of a data set for long-term planning purposes based on the Reliability Test System Grid Modernization Lab Consortium (RTS-GMLC). This dataset will be made public for other researchers to use as a benchmark for the planning studies. The dataset can be adjusted for any possible future assumptions by other researchers.

- Development of a CEP model that simultaneously considers generation and transmission systems to identify the optimal network expansion. This approach solves a single linear optimization problem to determine the optimal timing and capacity of generation and transmission investments.

- Modeling storage technology as an emerging technology, recognizing its potential role in both energy and reserve markets. By doing so, the thesis provides a framework that captures the potential benefits of storage technology in both of these markets. The energy model represents the use of energy storage systems to balance energy supply and demand, while the reserve model the use of storage to provide fast-responding reserve capacity to ensure the stability and reliability of the grid. Both of these roles are important to enable the large-scale integration of renewable energy sources into the grid and ensure the continued reliable operation of the power system. Moreover, the storage system is modeled as time-dependent, taking into account its charging and capacity limitations over time. By incorporating this time dependence in the storage system model, the thesis can provide valuable insights into the optimal siting and capacity of storage systems under different scenarios.

- Considering reserves in CEP. Integrating intermittent renewable resources introduces operational risks to safe and secure network operation. Therefore, it is imperative to know how much reserve must be available when large amounts of renewable resources are integrated. The planning models ignore this aspect of system operation; however, the developed CEP in this thesis, considers and analyses the effects of reserves on future investment plans.

- Reducing the size of the network using the Kron reduction method. In this approach, long-term planning is performed on a smaller network to ensure the model is tractable.

The significance of the proposed model is that it accounts for various aspects of the modern power system, such as physical, environmental, and policy constraints, without making the CEP problem intractable. Therefore, it provides system planners with a comprehensive planning tool to identify the most efficient network plans.

1.5 Organization

This thesis is organized in five chapters as follows. In Chapter 2, the literature on power system planning is reviewed. The generation planning, transmission planning, and co-expansion planning are discussed. Moreover, the current power system practice in Canada and specifically in Alberta is discussed.

Chapter 3 provides the mathematical formulation of the co-expansion planning model. It includes the description of all parameters and variables, the investment and operation cost of generation resources and transmission lines, constraints on generation and transmission facilities, and energy storage model, in addition to reserve and policy constraints.

In Chapter 4, the test case is presented and the results for different scenarios of carbon reduction, reserve requirements, and energy storage is presented and analyzed. Chapter 5 concludes and suggests future works and new research directions.

Chapter 2

Power System Planning in the Literature

Power system expansion planning consists of generation expansion planning (GEP) and transmission expansion planning (TEP) with the goal of proposing an optimal path to a future power system that can operate securely while satisfying technical, economic, and policy constraints. Therefore, the expansion planning tools must answer questions related to the technology, capacity, timing, and location of generation and transmission investments. The objective can be to minimize the system's operation and planning costs while meeting other objectives and constraints such as boosting the system's resiliency, reducing environmental impacts, and meeting physical constraints.

Traditionally, transmission planning was carried out after the generation expansion plan was determined. The reasons for planning generation and transmission networks separately were twofold. First, generation accounted for the vast majority of investment cost, often between 80 and 90 % [5]. Second, the commonly used generation technologies like coal, hydro, and nuclear had significant location restrictions, limiting the options for transmission siting.

However, the recent changes in modern power systems have increased the tendency towards considering transmission siting and cost simultaneously in the generation planning process. One reason is the increased use of less capital-intensive resources, such as gas-fired generators, which have more flexibility in siting. Second, it takes a longer time to construct transmission lines than wind and solar generation plants [6], and the transmission siting decisions for grid expansion may affect the generation expansion plans. Moreover, the most potential renewable resource sites are usually located far from load centers, necessitating optimizing trade-offs between the amount of harvested energy and its transmission cost. The other reason is to benefit from the geodiversity of renewable resources and improve the total energy availability by dispersing their development over a large area.

These developments incentivize co-optimization of GEP and TEP to achieve minimum power system planning and operation cost. The importance of co-optimization is not only acknowledged in research but also in real-life resource planning by independent system operators (ISOs) and regional transmission operators (RTOs).

This chapter reviews the trending co-optimization of power system planning in literature and the current planning practices in real-world power systems.

2.1 Co-Expansion Planning

Although GEP and TEP have typically been developed by separate or sequential optimization problems, recent research highlights the advantages of simultaneous co-optimization of generation and transmission resources [7]–[9]. In addition to helping vertically integrated power utilities find more affordable solutions by taking into account how generation and transmission interact, co-optimization also benefits today's restructured power systems by analyzing how transmission configuration, congestion, and capacity could affect generation dispatch and incentivize generation developments [4]. Co-optimization in this context may be referred to as ”anticipatory” or ”proactive” transmission planning, where the the transmission planners anticipate how various network configurations will impact generation mix and siting, as well as the expenses, prices, and emissions of the electric system [10].

The objective of co-optimization of generation and transmission systems is usually to identify the least expensive system configuration over a specific time period. The review in [4] shows that planning transmission and generation separately results in sub-optimal solutions compared to the co-optimized expansion planning. Other transmission and generation planning studies, [10]–[12], also emphasize the cost-saving benefits of co-optimized approaches. The economic advantages of simultaneous CEP have been addressed in [8] by comparing its results to those of a sequential CEP approach, where the generation system is optimized first and then the transmission network is planned.

The generation and transmission co-optimization model for a large-scale power system of the US Eastern Connection is provided in [13]. The authors apply a scenario generation technique to consider wind and load uncertainty and present a MIP formulation for a 15-year expansion planning. An hourly resolution co-optimization model was applied to evaluate the effect of RES integration on transmission expansion planning of the IEEE 24-bus test system over a 10-year horizon [14]. To mitigate the high computational burden of hourly resolution operation modeling, an interpolation method has been applied to estimate operational costs to reduce the compute time [14]. For coordinated expansion planning in [15], a Bender's decomposition method is used to transform the initial mixed integer nonlinear programming (MINLP) model into a mixed integer linear programming (MILP) master problem, and a linear programming (LP) sub-problem. The proposed dynamic CEP model is evaluated by implementing it on a 6-bus and the IEEE 30-bus test systems [15]. A linear cost optimization problem is presented in [16] to model a yearly co-expansion planning of a power system with energy storage systems and a high-voltage direct-current (HVDC) transmission system. LP modeling is considered to tackle the computational difficulties and it is demonstrated that LP methods can accurately represent an electrical power system at a high level without adding unnecessary complexity by switching to MIP or NLP problems [16].

In [11], an MILP formulation for CEP is applied to a 24-bus representation of the US eastern interconnection considering renewable energy resources. An LP formulation is used in [17] to investigate expansion costs of a Chinese power system with high renewable penetration levels under ambitious CO_2 emission reduction targets. The network under study is resized to 31 buses and solved based on an hourly resolution. The study shows that applying a co-optimization technique is vital to obtaining the most economic plan due to the distance between the load centers and potential wind and solar sites [17]. The optimal expansion plan for the European power system for the years 2030 and 2050 has been obtained in [18]. The CEP is modeled by a 4-week hourly LP problem containing energy storage and CO_2 constraints [18].

2.2 Power System Planning in Canada and Alberta

2.2.1 Planning in Canada

Despite having large amounts of wind resources, Canada uses only a small percentage of its wind energy to generate electricity. The lack of research-based studies on the actual amounts of wind energy that could be safely and affordably added to Canada's electricity grid has been one of the main obstacles preventing wind from playing a more significant role.

In response to the need for a national wind integration study, the Canadian Wind Energy Association (CanWEA) proposed the Pan-Canadian Wind Integration Study (PCWIS) project collaborating with General Electric (GE) consulting group [19]. This study assessed whether it was technically feasible to incorporate significant amounts of wind generation into the country's electrical grid. Canada's power grid is modelled for reliability analysis under four scenarios of wind integration. To evaluate wind energy's effects on the power grid, the authors conducted hourly dispatch simulation and sensitivity analysis for one year (2025) for each scenario. They also considered adequate transmission capacity to transfer the generated power to the load centers, as well as sufficient firm generation capacity to meet reserve margin requirements. According to this study, Canada's power system should be able to handle 35% wind penetration, as long as there are sufficient marginal reserve and transmission reinforcement [20]. In order to accommodate this penetration level of wind, approximately 4.7 GW of additional transmission is estimated to be required. The 35% wind scenario could prevent up to 32 Mt CO_2 emissions each year and save $47/MWh in production costs compared to the business as usual 5% wind scenario [19]. This research also indicated that the wind sites around Canada have capacity factors of 36% or above, which means it is more sensible to build wind farms locally rather than concentrating on high-quality wind sites.

This study analyzed the feasibility of integrating high wind penetration into Canada's grid and has been greatly helpful in having a national view of Canadian wind integration capacity. However, the vast size of the country and its large power grid system make it difficult to find the optimal scenario for wind integration considering the physical constraints of the grid. Therefore, this study only has focused on the feasibility study of wind integration rather than optimizing it. It does not analyze the financial aspect of this plan and does not account for other options such as solar energy and energy storage systems to be used along with the wind resources to improve system reliability and identify which options are the most economical or reliable in integrating renewable resources. An optimization-based planning tool can help system planners and policymakers to have also an economic insight when making decisions.

2.2.2 Planning in Alberta

As a non-profit organization, the Alberta Electric System Operator (AESO) is responsible for the operation of the provincial power grid without holding an interest in any generation, transmission, or distribution properties. In order to support Alberta's economy, the AESO is responsible for operating the transmission system in a safe, reliable, and cost-effective manner and planning a transmission network that meets present and future electricity needs [21]. One of the AESO's duties is to forecast what the provincial grid will need in the future, and decide what transmission system improvements are necessary to meet those needs. AESO has to make timely and efficient plans to implement the required improvements in the system.

To account for future load growth, generation developments, and retirements, AESO prepares and updates a 20-year transmission system plan according to the forecasted system status and requirements. This plan is referred to as AESO's long term transmission plan (LTP) and relies on forecasts, assumptions, and expert inputs [21]. Since it is not possible to predict exactly when and where new generations will be developed or new loads be added to the system, the AESO uses scenarios described in the 2021 Long-term Outlook (LTO) [22] to make sure the LPT is made to take a variety of potential future circumstances into account.

LTP is designed to use Alberta's transmission system more efficiently to postpone transmission developments and concentrates on improving the efficiency of the current grid while reducing costs. It also provides useful insight into the required transmission infrastructure to fulfill future demands and maintain reliable power delivery in long term. The impacts of retiring and replacing coal-fired generation on the reliability of transmission system are also taken into account.

Increased integration of solar facilities, electric vehicles (EV), and energy storage facilities, as well as the development of DER in urban areas, are examples of new technological breakthroughs that their impacts must be considered in modern CEPs.

Although AESO uses the most updated data to provide its LTP, it does not apply a co-optimization process to achieve the most economic plan.

Alberta has the highest greenhouse gas emissions in Canada, and its emissions have been rising since 1990 [23]. As a result, it is inevitable that the province will move towards wind and solar as renewable resources. Therefore, developing and testing a CEP tool that enables system operators to explore various high-renewable futures is essential. The intermittent nature of wind and solar resources calls for new technologies such as storage to ensure power balance. Moreover, a major concern of system operators in conditions where high amounts of intermittent resources are connected is the availability of reserves, in case there are changes in the generated power. Therefore, a comprehensive CEP tool needs to account for modeling storage and accounting for reserve requirements. However, in the current CEP tools, reserve requirements are not considered. Moreover, not only reserve requirements must be considered, they must be functions of investments in wind and solar. In this thesis, the developed CEP considers both of these requirements and ensures that any proposed high-renewable future is operationally feasible. These features give the system operators confidence in the investment decisions and envision a path to a zero-carbon electricity network while ensuring a secure system operation.

2.3 Energy Storage Systems in Co-expansion Planning

Operational flexibility is becoming increasingly important with the high integration of wind and solar energy resources into modern power systems. Energy storage systems can reduce the effects of variable renewable production, improve system reliability, defer addition of generating capacity, and delay the expansion of transmission networks [24]. A wide range of research has investigated the ESSs' benefits on various operational aspects of power systems, including improving supply availability [25], minimizing operational costs [26], [27], alleviating congestion in transmission network [28], [29], improving operational reliability [30], [31], voltage stability and load management in distribution systems [32]–[34], and lowering the power demand profile's peaks at the end users' side [35], [36].

This study proposes a novel generation, storage, and transmission expansion planning (GSTEP) model to analyze the long-term effects of energy storage systems (ESS) on system costs as well as CO2 emissions. The model takes into account flexibility-related constraints that are typically ignored in long-term growth assessments (such as limits in investments and energy outputs, reserve requirements, and ramp requirements). By using a GSTEP model with flexibility-related restrictions, the research intends to evaluate the long-term effects of ESS on both the overall system costs and CO2 emissions.

The necessity of preserving chronology in modeling energy storage systems imposes challenges to the decoupled planning models. Some models allow for the "decoupling" of distinct operating periods, which permits natural decomposition and makes the models reasonably tractable in terms of computing. Such a modeling strategy is complicated by energy storage. Enhancing the system's balance representation can significantly impact the costs and advantages of energy storage.

Cost projections of energy storage vary widely and are available from various sources. Despite the availability of public cost data, more robust estimates of long-run performance and component-replacement costs of energy storage are important, particularly for planning modeling.

This work seeks to better understand how energy storage technologies and their modeling fidelity might increase modern power systems' reliability and efficiency. The focus is on enhancing energy storage models and applications for planning purposes.

2.4 Required Data for planning

Updating the test systems traditionally used in power system studies is important in light of the changing nature of power systems. IEEE's Reliability Test System (RTS), [37], was first developed in 1979 as a standard model and since then has been used and updated for testing and comparing results of various power system studies. The latest update of this system is provided in [37], where it presents a modern mix of generation resources, including natural gas, wind, solar panels, and energy storage. It also applies some modifications to the transmission system to account for line congestion and defines reserve requirements in the system. This work emphasizes on the importance of updating the benchmark system for the modern power systems [37].

Aside from the generation mix and topology of the network, investment and operation costs associated with these technologies also play a crucial role in power system planning as decision-makers evaluate the costs of different options for meeting a region's energy needs.

In addition to updating the generation mix by including renewable resources, using temporal and spatial variable wind, solar, and load data is required to properly model these resources' intermittent and uncertain behavior and plan the system accordingly.

The data provided in standard test systems in literature are often focused on the operation of the power system, including generators' capacities, operation cost, ramp rate, start time, etc.

Benchmark test systems provide data on the various parts of the power system, such as generators, loads, transmission lines, transformers, etc. Typically, the data is focused on power system operation and is used for optimal scheduling, power flow calculation, loss minimization, and reducing operating costs. They might contain details on the system load, network structure, voltage and power limits, and other significant factors that affect the power system's operation, including generator capacity, operating costs, ramp rates, and start times.

Since planning is becoming essential to modern power systems, providing a benchmark test system for planning studies is crucial. Aside from the operational characteristics of test systems, additional data is required regarding the investment costs of generators and transmission lines, reserve costs, fuel prices, and projections of all the costs to the future for planning purposes. However, the current test systems do not provide publicly-available data for planning studies. Researchers typically employ arbitrary parameters or confidential data that cannot be publicly available.

To obtain real-time load, wind, and solar generation data, AESO website is scraped, and the data is collected to account for their spatial and temporal variability. Moreover, investment, maintenance, and operation costs of generators and transmission lines are obtained from NREL Annual Technology Baseline (ATB) [38] and projected to the future for a long-term planning test case.

2.5 Optimization Techniques for Solving CEP

The formulated optimization problem may be solved by different optimization techniques, generally divided into two categories: mathematical and heuristic methods. Variety of these techniques have been implemented in the literature on power systems. We review different methods in each category in the following.

2.5.1 Mathematical Optimization Methods

In a mathematical optimization approach, the problem is represented in a mathematical formulation. Depending on the nature of variables, objective, and constraints, the problem is formulated in different models such as linear programming (LP), non-linear programming (NLP), integer programming (IP), and mixed integer linear programming (M ILP). In order to solve these types of optimization problems, there have been some algorithms and commercial software developed. The convergence of these methods may be guaranteed in most cases, however, obtaining the global optimum solution may be guaranteed only for LP types. It is also important to note that mathematical algorithms may become complicated in implementing and facing numerical problems. There are many different types of mathematical methods, but here we focus on methods that are of more interest for power system planning rather than the operation or market analysis.

Linear programming

The technique to solve an optimization problem with a linear objective function, subject to linear equality and inequality constraints is called linear programming (LP). It is a method to achieve the optimal (minimum or maximum) outcome value for the objective function in the feasible region, which is a convex set [39]. Economists first discovered this type of problem in the 1930s when developing models for optimal resource allocation [40]. Many of the fundamental principles of optimization theory, including convexity, duality, and decomposition have their origins in linear programming.

LP problems can be presented in both standard and augmented forms. In the augmented form, non-negative surplus/slack variables are utilized to convert inequality constraints into equality constraints. When formulated in augmented form, the simplex algorithm can be applied to solve the LP problem. This algorithm finds the optimal solution by traversing the polytope edges to vertices providing non-decreasing values of the objective function. The simplex algorithm is practically efficient and guarantees finding the global optimum if certain conditions are met. Another algorithm used for solving LP problems is the interior point, in which the interior part of the feasible region is traversed. Both simplex-based and interior-point methods perform similarly efficiently in general applications of LP problems. It is also possible to find a dual problem to the primal LP problem which might be easier to solve. Applying the decomposition principle to the LP problem might help with finding a solution more efficiently with a lower computational burden. With these advances linear programming is suitable for power system planning, allowing for very large problems such as combined planning of transmission and generation investments [41]. Linear programming is widely used in practical problems as the main model and also used in other optimization algorithms as a sub-problem. Many optimization tasks in power systems can be classified as LP problems. Planning of capital investments [16], [42], [43], optimal power flow [44]–[46], reactive power planning [47], and loss minimization are some of the areas where linear programming is applied in power systems.

Non Linear Programming

An optimization problem where the objective function or any constraints have a non-linear relationship with the decision variables is called non-linear programming (NLP). A special type of NLP is Quadratic programming (QP) in which quadratic functions are involved. Generally, a QP problem is a multivariate quadratic objective function with linear constraints on the decision variables.

The algorithms for solving NLP can be categorized into gradient and non-gradient methods. Gradient methods start from an initial point and continue to find the direction to the optimal solution by using the derivatives of the objective function. Depending on the definition and step length, there is a variety of gradient methods. Newton method works well when the coefficients of the Hessian matrix can be analytically calculated [48]. If an approximation of the Hessian matrix is available, the Quasi-Newton method provides a strong convergence [49]. QP can also be applied to solve non-linear problems by approximating the problem locally. QP and NLP problems can also be solved by interior point methods [50].

Non-gradient methods are applicable to straightforward problems with a few variables. Constraint approximation is a non-gradient method that linearizes the objective function and constraints around a point and applies LP methods to solve the problem [51].

There are many problems in power systems that are modeled as a NLP problem, from state estimation [52] and steady-state stability optimization [53] to optimal planning and operation of the power systems [54], [55].

Integer Programming

A mathematical optimization model with integer decision variables is considered an integer programming (IP) problem. Depending on the nature of the original problem and the type of other decision variables, a variety of IP problems can be defined. When the objective function and the constraints other than the integer ones are linear, the developed model is integer linear programming (ILP). A non-linear problem with integer variables is called integer non-linear programming (INLP). If some decision variables are not discrete and can take any real value, the problem would be mixed-integer programming (MIP).

In power systems, there are many problems that deal with integer variables and are formulated as IP models. These problems can range from the number of generators or transmission lines to be invested in, to the on and off state of units [56]–[58].

Stochastic Programming

In contrast to the previously discussed optimization models where all the parameters in the problem were precisely known and deterministic, stochastic programming is a mathematical framework for optimization problems with uncertain parameters. The purpose of stochastic programming is to develop a solution that optimizes certain criteria set while also accounting for the uncertainty of the parameters. In order to address the uncertainty of the parameters, various methods including confidence intervals, fuzzy numbers, interval analysis, and probability distribution functions (PDFs) can be used [59]. A common method to model stochastic problems is two-stage programming where the first stage is optimized based on the available data, not the future observations and the second stage is after the realization of uncertain data [60]. The two-stage programming can be extended to multi-stage problems in which decisions are partitioned into different stages based on the information flow. The realizations of the uncertain parameter are considered as a finite number of scenarios with defined probabilities [59]. This converts the stochastic problem into a large-scale deterministic programming problem which could involve linear, non-linear, or mixed-integer subproblems [61]. There are generally two solution techniques for stochastic programming namely primal and dual decomposition. The former decomposes the problem based on stages while the latter decomposes based on scenarios [62]. Benders' decomposition and LP-based branch and bond are examples of primal decomposition, and variable splitting and Lagrangian relaxation are the bases of dual decomposition [62].

Similar to many other real-world problems, there is a wide range of problems in power systems that involve uncertain parameters and requires decision-making under uncertainty. Generator forced outages and intermittent output of renewable resources in unit commitment problems, stochastic regulation signals for energy storage systems, uncertain prices in the electricity market, sudden failure of generation or transmission equipment, uncertain future load and generation in planning are examples of stochastic problems in power systems [63]–[65].

2.5.2 Heuristic Optimization Methods

When the optimization problem is too complicated to be formulated as a mathematical model or finding the optimal solution is not guaranteed, heuristic algorithms can be helpful in finding a near-optimal solution to the problem. The reason for this is that formulating the problem for heuristic algorithms does not require any assumptions and is flexible. Heuristic methods use an iterative process to improve an initial solution based on a given quality [66]. The main advantage of heuristic algorithms is their reasonable computational cost, which is usually taking less time and memory to find a solution. However, there is no guarantee that the solution will be optimal, and in some cases finding a solution might take longer than expected. Heuristic methods can be applied directly to the problem or be used in combination with other mathematical methods to provide a good baseline for the solution.

Most of the heuristic algorithms are inspired by biological patterns, such as genetic algorithm (GA), particle swarm (PS), ant colony (AC), tabu search (TS) [67], [68]. These methods have been used in different problems in power systems from long-term planning [69]–[71], operation [72]–[74] and analysis [75], [76].

2.6 Discussion on challenges in co-optimization

Reviewing the literature indicates the power system planning is a critical process that involves developing strategies for ensuring reliable, efficient, and cost-effective energy supply to meet current and future demand. However, power system planning faces several challenges, including:

- Lack of standard dataset for planning purposes: Power system planning requires access to reliable and comprehensive data on power generation, transmission, and distribution. However, the lack of standard dataset makes it difficult to compare and analyze data from different sources, hindering the decision-making process.

- Complexity of the planning models: Power system planning models need to consider various factors, such as network size, investment years, conditions per year, and candidate investments. The complexity of these models increases with the scale of the power system, making it challenging to be implemented in real-world complex power systems.

- Integrating energy storage systems: Energy storage systems, such as batteries, are becoming increasingly popular as a source of energy and reserve. However, integrating these systems into the power system requires careful modeling to ensure their optimal coordination with other generation sources.

- Considering reserve requirements: With high shares of renewable energies, power systems need to maintain sufficient reserve capacity to ensure grid stability and reliability. However, determining the appropriate reserve requirements can be challenging due to the intermittent nature of renewable energy sources.

- Reducing the power system size: Power systems can span large geographic areas and involve complex interactions between various components. This makes it challenging to collect and analyze operational data and plan for future developments.

It is important to address these challenges to ensure that power systems can meet the growing demand for energy while minimizing costs and reducing the environmental impact. Effective power system planning can also contribute to energy security, economic development, and social welfare. Addressing these challenges can help ensure that power systems remain reliable, resilient, and sustainable for generations to come.

2.7 Summary

To address the aforementioned challenges, this thesis proposes a co-optimization expansion planning (CEP) model for a test system that mimics a real network. The CEP model includes several features to account for recent trends and changes in power systems. The thesis makes the following contributions: first, it develops a dataset based on the Reliability Test System Grid Modernization Lab Consortium (RTS-GMLC) for long-term planning purposes, which can be adjusted for other researchers. Second, it simultaneously models generation and transmission to identify the optimal network expansion, including storage technology and reserves. Third, it reduces the network size using the Kron reduction method to ensure the model is tractable. The proposed model provides a comprehensive planning tool for system planners to identify the most efficient network plans while accounting for physical, environmental, and policy constraints.

Chapter 3

CEP Tool: Mathematical Formulation and Main Modeling Features

3.1 Introduction

The main objective of this thesis is to present a co-optimized generation and transmission expansion formulation for electric networks to meet the electric demand while minimizing costs. CEP formulations provide insight for necessary investments to integrate high penetrations of renewable energies and meet goals for greenhouse gas emission reductions while supplying the future electric load. The objective of CEP is to minimize the investment and operational costs of the network, subject to operational and physical constraints.

For a smooth transition to energy and environmental goals of future power grids, it is vital to have a comprehensive understanding of the network operation and future challenges and plan for required changes in advance. The planning horizon is generally long because it takes a long time to build generation and transmission facilities, requiring getting permissions and providing finances, coordinating multiple organizations, preparing the infrastructure, account for environmental impacts, energy costs, and reliability concerns. Therefore, decisions on which technologies to build, where, and when, along with maintenance of existing equipment and retirement of old facilities, should be made precedently. Being equipped with an exploratory tool to study different scenarios enables decision-makers to choose an appropriate course of action for the future of the network.

Although generation facilities are the main resource to supply future energy needs, reinforcing the transmission network to deliver the generated electric power to load centers is an inevitable part of this process. Recently, there has been more emphasis on the importance of co-optimization of generation and transmission as these facilities are not operated by one single organization anymore. It is vital to make sure that their effects on each other's performance and operation are taken into consideration. To this end, unlike the traditional sequential planning of generation and transmission systems, we model an optimization problem for the co-expansion of generation and transmission networks to find the most economic combination possible.

The model includes both generation and transmission expansion planning simultaneously and helps identify the most economic investments in generation and transmission networks to support renewable energy requirements, develop reliable infrastructures, enable a competitive electricity market, analyze various scenarios, provide information to stakeholders, and coordinate planning processes. However, co-optimizing generation and transmission systems is a complex problem with various challenges. A power system is generally a massive network with thousands of buses, which makes the model's dimension an issue. Another challenge in network planning is the number of operating hours that needs clustering the data to reduce time resolution. Not having the exact data and information from the generation side is another challenge in analysis. Due to various conditions and the complexity of the problem, the infeasibility of solving it can also happen. Numerical problems are another challenge because of the large difference between high investment costs and other expenses, which are much lower.

In this chapter, a mathematical model for the CEP problem is presented. In the first section, the variables and parameters of the problem are defined. Different system costs are discussed, constituting the objective function as a cost-minimizing problem. Then, various constraints are formulated, including generation and transmission, storage, power balance, reserve requirement, and policies. In the second section, we discuss: *how the provided CEP model helps solve the problem and fills the gap in the literature and industry*; what were the challenges and how they were addressed; and what expectations are met by solving this problem. The chapter is concluded with a summary of the proposed models.

3.2 CEP Model

CEP should be formulated as a multi-objective problem (MOP). However, MOPs are usually more complicated than single-objective problems. Therefore, CEP is often modeled as a single objective problem where one objective function is considered the main objective and other objective functions are considered constraints [43]. The main objective is usually the cost minimization or to minimize the net present value of all generation and transmission networks, including their investment, operation, and maintenance costs over a long-term planning horizon. Other vital objectives in planning, such as reliability, flexibility, and environmental sustainability, are considered constraints in the model. CEP defines the most effective and economical combination of generation and transmission resources required to supply future electric load by minimizing the system's total cost subject to physical, environmental, and economical constraints.

Depending on the study framework, required granularity, and organization objectives, various models are used for the CEP problems, including linear, mixed-integer linear, Dynamic, and stochastic programming. Traditionally, the optimization is run for the generation sector first to determine new required technologies and their capacity and location. Then, the transmission network is considered and optimized for operation. Recently, with developments in optimization algorithms, co-optimization models have been used to simultaneously optimize generation and transmission networks.

In this work, the CEP problem is formulated as a linear programming (LP) model, where the costs of co-expanding generation and transmission networks are simultaneously minimized. Using a linear programming model is common in power systems planning when the model becomes complex and computationally intense [4]. The following sections provide the sets, parameters, variables, and mathematical formulations for the objective function and its constraints.

Table 3.1: Indices and Sets

Index	**Sets**
b/B	Buses
g/N_g	Generators
k/K	Seasons
l/L	Lines
p/N_p	Load blocks
s/S	Future scenarios
y/y	Years

3.2.1 Sets

There are various sets of buses, bus parameters, generation technologies, lines, time blocks, seasons, years, investment years, future scenarios, fuel types, reserve types, line and generation parameters, and scalars. Table 3.1 presents all the defined sets and their indices for the planning model.

3.2.2 Parameters

Parameters present different characteristics of the system and are defined based on combinations of sets. There are 28 parameters defined for this model that include generator characteristics, Transmission lines reactance and flow limits, base and peak demand, capacity factors and capacity credit of generating units, energy storage power, capacity, and efficiency, existing generation and transmission capacity, various operation and investment costs, and annual discount factor. A list of the parameters describing various aspects of the model is provided in Table 3.2.

3.2.3 Variables

The decision variables in the CEP problem consist of generation, transmission, load, and bus variables. Each variable is defined based on different sets and parameters. These decision variables are shown in Table 3.3 and are explained in more detail in the following.

Table 3.2: Parameters

Parameter	Description
τ	Load shed cost ($/MWhr)
I_G	Generation investment cost ($/MW)
I_T	Transmission investment cost ($/MW)
FOM	Fixed operation & maintenance cost
VOM	Variable operation & maintenance cost ($/MW)
FP	Fuel price ($/MMBTU)
HR	Average heat rate (MMBTU/MWhr)
T	Hours in load block p
D	Real power demand (MW)
D'	Peak real power demand (MW)
X_L	Transmission line reactance (pu)
ζ	Annual discount factor
CC	Capacity credit
CF	Generation capacity factor
CV	Renewable generation capacity value
G^0	Existing generation capacity (MW)
L^0	Existing transmission capacity (MW)
PRM	Planning reserve margin for region
TL	Transmission thermal limit rating (MW)
G^{min}	Generation minimum stable level
M	Carbon emission rate (tons/MMBTU)
η_C	Energy storage charge efficiency
η_D	Energy storage discharge efficiency
η_{RT}	Energy storage round-trip efficiency
T^{ES}	Energy storage duration (hours)
λ^{Max}	Maximum SOC level
λ^{Min}	Minimum SOC level
RPS	Renewable Portfolio Standard (%)

Table 3.3: Variables

IC_{Gen}	Investments cost in generation ($)
$G(b,g,y,s)$	Generation investments (MW)
$R(b,g,y,s)$	Retired capacity (MW)
OC_{FOM}	Fixed operation and maintenance cost ($)
OC_{VOM}	Variable operation and maintenance cost ($)
$P(b,g,y,k,p,s)$	Generator dispatch (MW)
$P^{Curt}(b,g,y,k,p,s)$	Generation curtailment (MW)
$P^{C}(b,g,y,k,p,s)$	Energy storage charging (MW)
$P^{D}(b,g,y,k,p,s)$	Energy storage discharging (MW)
$SOC(b,g,y,k,p,s)$	Energy storage state-of-charge (MWhr)
$R^{+}(b,g,y,k,p,s)$	Regulation up reserve (MW)
$R^{-}(b,g,y,k,p,s)$	Regulation down reserve (MW)
OC_{Fuel}	Fuel cost ($)
IC_{Trans}	Investments cost in transmission ($)
$L_C(b,g,y,s)$	Transmission investments (MW)
$PF(l,b,b',y,k,p,s)$	Power flow of line with sending and receiving buses $[b,b']$ (MW)
$\theta(b,y,k,p,s)$	Bus angle (radian)
$LS(b,y,k,p,s)$	Load shed (MW)
ϑ_{LS}	Load shedding cost ($)
C	Cost totals ($)

Generator Variables

Generation variables are generation investment capacity, $G(b,g,y,s)$, generation investment cost, IC_{Gen}, and retirement capacity, $R(b,g,y,s)$. The generation variables on the operation side include fixed operation and maintenance cost, OC_{FOM}, variable operation and maintenance cost, OC_{VOM}, fuel cost, OC_{Fuel}, generator power dispatch, $P(b,g,y,k,s)$, generator power curtailment, $P^{Curt}(b,g,y,k,s)$, energy storage charge $P^{C}(b,g,y,k,s)$, energy storage discharge, $P^{D}(b,g,y,k,s)$, and energy storage state-of-charge, $SOC(b,g,y,k,s)$.

Transmission Line Variables

Transmission variable include transmission investment capacity, $L_C(b,g,y,s)$, transmission investment cost, IC_{Trans}, and power flow of transmission lines, $PF(l,b,b',y,k,p,s)$.

Bus and Load Variables

Other variables of the problem are the bus angles, $\theta_{b,y,k,p,s}$, the amount of load shed, $LS(b,y,k,p,s)$, load shedding cost, ϑ_{LS}, and cost totals, C.

All the problem variables of CEP model are displayed in Table 3.3.

3.2.4 Total Cost of the System

The objective function is to minimize the total cost of the system, C, during the planning horizon, which includes generation investment cost, IC_{Gen}, transmission investment cost, IC_{Trans}, fixed operation and maintenance cost, OC_{FOM}, variable operation and maintenance cost, OC_{VOM}, fuel cost, OC_{Fuel}, and load shedding cost, ϑ_{LS}. This section discusses each contributing cost to the total system cost.

Generation investment cost

In order to account for the future load growth, the retirement of old facilities, and the reduction in greenhouse gases, new generation capacity must be planned and built into the power system. The generation investment cost is the expense of building these new generation facilities at different locations of the system to help supply the load. The candidate generation technologies considered in this model are natural gas combined cycle (CC), natural gas combustion turbine (CT), utility-scale wind, distributed solar (DPV), and battery storage (STO).

The investment cost of generation is a function of the added generation capacity of each technology in MW, presented by $G^{new}(b,g,y,s)$ at the bus and year of investment [43]. This cost is calculated by the multiplication of generation capacity and its investment cost $I_G(g,y,s)$ in ($/MW) considering the time value of the money $\zeta(y)$ for each year, which is also called discount factor

[77]. The total generation investment cost is the summation of the cost of all technologies built on each bus over the planning horizon as the following:

$$IC_{Gen}(G) = \sum_{B,N_g,Y,S} \zeta(y) * I_G(g,y,s) * G^{new}(b,g,y,s) \tag{3.1}$$

The amount of capacity added for each technology, $G(b,g,y,s)$, is a decision variable in this equation. $\zeta(y)$ and $I_G(g,y,s)$ are parameters.

Transmission investment cost

Sufficient transmission capacity is required to transfer the generated electricity by the new generation capacity to the growing load. Therefore, there is a need to invest on the transmission network along with the generation sector. As the network topology is known and the goal is to expand the existing transmission network, the length of new lines is included as a parameter rather than a decision variable. The investment cost of transmission $IC(L)$ is considered a linear function of the line capacity L_C. This cost is calculated for each bus, scenario, and year by multiplying the transmission investment cost $I_L(l,y,s)$ to the line capacity $L_C(b,l,y,s)$ and line length $L_l(b,l,y,s)$. The total cost of transmission investment is the summation of the cost of all new lines over the planning horizon as the following:

$$IC_{Trans}(L) = \sum_{B,N_l,Y,S} \zeta(y) * I_L(l,y,s) * L_C(b,l,y,s) * L_l(b,l,y,s) \tag{3.2}$$

In this equation of transmission investment cost, capacity of new lines, $L_C(b,l,y,s)$, is the decision variable and $I_L(l,y,s)$ and $L_l(b,l,y,s)$ are parameters.

FOM cost

The production costs of generation units are given by fixed operation and maintenance (FOM), variable operation and maintenance (VOM), and fuel costs. As its name implies, $FOM(g)$ costs are the fixed costs of operating and maintaining generation units. These costs are incurred whether or not the unit is generating electricity. For instance, these can be costs of regular maintenance, monitoring, and inspection of the units [78]. This cost, $OC_{FOM}(G)$, is a function of the capacity of generation unit, $G(b,g,y,s)$.

$$OC_{FOM}(G) = \sum_{B,N_g,Y,S} \zeta(y) * FOM(g) * G(b,g,y,s) \tag{3.3}$$

VOM cost

VOM costs are the costs of generation units operations and maintenance which vary with the electricity production. Moreover, when operating, generation units are exposed to more degrade compared to their idle mode, which leads to increased need of repair or replacement of parts. This $VOM(g)$ cost is a parameter which is defined for each generating technology.

The system VOM cost, $OC(VOM)$, is a function of the dispatched power of each generation unit P, and the hours in load block p that unit is working, $T(k,p)$.

$$\begin{aligned} OC_{VOM}(P) = \sum_{B,N_g,Y,K,N_p,S} & \zeta(y) * VOM(g) \\ & * T(k,p) * P(b,g,y,k,p,s) \end{aligned} \tag{3.4}$$

The power generation level for each technology, $P(b,g,y,k,p,s)$, is a decision variable that has to be optimized on the operation side of the problem. While, $\zeta(y)$, $VOM(g)$, and T(k,p) are parameters.

Fuel cost

Fuel cost is one of the operational costs of the system that depends on the fuel price delivered to the generating unit and the efficiency at which it converts the fuel into electricity. Fuel price, $FP(g,y)$, is the cost per BTU of the energy, and heat rate, $HR(g)$, is the efficiency of converting fuel energy to electric energy.

$$\begin{aligned} OC_{Fuel}(P) = \sum_{B,N_g,Y,K,N_p,S} & \zeta(y) * FP(g,y) \\ & * T(k,p) * HR(g) * P(b,g,y,k,p,s) \end{aligned} \tag{3.5}$$

In this equation, $P(b,g,y,k,p,s)$ is the decision variable, while $FP(g,y)$ and $HR(g)$ are parameters.

Regulation reserve costs

Regulating helps to balance out minor imbalances between generation and load that could jeopardize the stability of the power grid. Regulation reserves are flexibility products that make adjustments for small fluctuations in electricity consumption or generation to maintain the power system stability. with the increased penetration of intermittent wind and solar resources, accounting for operational flexibility becomes more vital in power system planning.

The cost of regulation reserves is a function of the assigned reserve to each bus, R^{+} or R^{-}, the fuel price, FP, and the heat rate, HR.

$$\begin{aligned} OC_{RU} = \sum_{B,N_g,Y,K,N_p,S} & \zeta(y) * FP(g,y) * T(p) \\ & * HR(g) * R^{+}(b,g,y,k,p,s) \end{aligned} \tag{3.6}$$

$$\begin{aligned} OC_{RD} = \sum_{B,N_g,Y,K,N_p,S} & \zeta(y) * FP(g,y) * T(p) \\ & * HR(g) * R^{-}(b,g,y,k,p,s) \end{aligned} \tag{3.7}$$

Load shedding cost

Load shedding is considered a ”last resort” to balance generation and load, during an unexpected peak load or generation blackout [43]. This can be accomplished by assigning load shedding a cost, τ, which is the cost per MWhr of the curtailed load and is much higher than any generation dispatch. The system load shedding cost, $\vartheta(LS)$, depends on the MW of load that is shed, $LS(b,y,k,p,s)$, and the hours in that load block, $T(k,p)$.

$$\vartheta(LS) = \sum_{B,Y,K,N_p,S} \zeta(y) * T(k,p) * \tau * LS(b,y,k,p,s) \tag{3.8}$$

Here the amount of load shedding, $LS(b,y,k,p,s)$, is a decision variable, and τ is a parameter.

Cost totals

The total cost, C is composed of all the system's costs during the planning period, including generation investment cost, IC_{Gen}, transmission investment cost, IC_{Trans}, fixed operation and maintenance cost, OC_{FOM}, variable operation and maintenance cost, OC_{VOM}, fuel cost, OC_{Fuel}, regulation up cost, C, regulation down cost, OC_{RD}, load shedding cost, ϑ_{LS}. The objective is to minimize the summation of these costs as follows:

$$\min \quad C = IC_{Gen} + IC_{Trans} + OC_{FOM} + OC_{VOM} + OC_{Fuel} + OC_{RU} + OC_{RD} + \vartheta_{LS} \tag{3.9}$$

This optimization problem is subjected to several physical, operational, and policy constraints:

$$\text{s.t.} \begin{cases} Generation\ constraints \\ Transmission\ constraints \\ Storage\ constraints \\ Power\ balance \\ Reserve\ requirement \\ Policy\ constraints \end{cases}$$

These constraints are discussed in more detail in the following.

3.2.5 Generation Constraints

Generation investment is subject to several equality and inequality constraints related to cumulative generation capacity, thermal and renewable generation capacity, energy storage, and energy curtailment [79]. In the following, these constraints are described and formulated.

Cumulative generation capacity

The total cumulative generation capacity for each year, G, is included in the problem formulation as an equality constraint. It consists of the initial exiting capacity in the network, $G^0(g)$, summation of new generation capacity, G^{new}, minus the retired capacity, R.

$$G(b,g,y,s) = G^0(g) + \sum_{y \leq y'} [G^{new}(b,g,y) - R(b,g,y)] \qquad \forall b \in B, g \in N_g, s \in S \tag{3.10}$$

Thermal generation

The maximum power of thermal generations is limited by their capacity factor, CF_g. The capacity factor is a parameter that accounts for the tendency of a generating plant to produce a certain fraction of the energy it would produce if it continuously operated at its capacity over a defined time frame (e.g., a year) [43]. The output power of thermal generation technologies plus their regulation up, R^+, should be less than or equal to the amount of power they generally produce relative to their maximum capacity.

$$P(b,g,y,k,p,s) + R^+(b,g,y,k,p,s) \leq CF_g * G_{b,g,y,s} \qquad \forall b \in B, g \in N_g^{Therm}, k \in K, p \in N_p, s \in S \tag{3.11}$$

A thermal generator's output power is also limited to a stable amount at which the generator should work. When a thermal generating unit is turned on and working, its power generation cannot go lower than this minimum output power, G^{min}.

$$P(b,g,y,k,p,s) \geq G^{min}(g,y) \qquad \forall b \in B, g \in N_g^{Therm}, k \in K, p \in N_p, s \in S \tag{3.12}$$

Renewable generation

In order to account for renewable resources' intermittent nature and not being able to provide full power output at all time instances, capacity factor inequality constraint is considered for renewable resources. The output power of renewable resources is limited to a fraction of their nominal capacity.

$$P(b,g,y,k,p,s) \leq CF(g,k,p) * G(b,g,y,s) \qquad \forall b \in B, g \in N_g^{Ren}, k \in K, p \in N_p, s \in S \tag{3.13}$$

3.2.6 Energy storage

The energy storage state-of-charge, SOC, at a time step (t) is equal to its SOC at the previous step ($t-1$) plus the power charged, P^C, minus the power discharged ,P^D, considering charge, η_C, and discharge,η_D, efficiencies.

$$\begin{aligned} SOC(b,g,y,k',p',s) &= SOC(b,g,y,p,s) \\ +(\eta_C * P^C(b,g,y,k,p,s) &- 1/\eta_D * P^D(b,g,y,k,p,s)) \\ \forall b \in B, g \in N_g^{ES}, k' &= k, p' = p+1, \\ p &\neq |N_p|, s \in S \end{aligned} \tag{3.14}$$

The upper bound of the energy storage is limited to its maximum SOC level, λ^{max}, as a percentage of its generation capacity, G^{ES}, and the energy storage duration, T^{ES}.

$$\begin{aligned} SOC(b,g,y,k,p,s) \leq \lambda^{max} * T^{ES} * G^{ES}(b,g,y,k,p,s) \\ \forall b \in B, g \in N_g^{ES}, k \in K, p \in N_p, s \in S \end{aligned} \tag{3.15}$$

The lower bond is also enforced by the product of minimum SOC level, λ^{min}, energy storage duration, and generation capacity.

$$\begin{aligned} SOC(b,g,y,k,p,s) \geq \lambda^{min} * T^{ES} * G(b,g,y,k,p,s) \\ \forall b \in B, g \in N_g^{ES}, k \in K, p \in N_p, s \in S \end{aligned} \tag{3.16}$$

The SOC level of the energy storage at the end of each season should stay the same as its level at beginning of the season.

$$\begin{aligned} SOC(b,g,y,k',p',s) &= SOC(b,g,y,k,p,s) \\ \forall b \in B, g \in N_g^{ES}, k' &= k+1, \\ p' &= 0, p = |N_p|, s \in S \end{aligned} \tag{3.17}$$

$$\begin{aligned} \sum_{N_p}(P^C(b,g,y,k,p,s) - P^D(b,g,y,k,p,s)) = 0 \\ \forall b \in B, g \in N_g^{ES}, k \in K, s \in S \end{aligned} \tag{3.18}$$

The storage charge and discharge power is bounded to its generation capacity. The charging power minus the discharging power should remain less than or equal to the generation capacity of the energy storage system.

$$P^C(b,g,y,k,p,s) - P^D(b,g,y,k,p,s) \leq G(b,g,y,s)$$
$$\forall b \in B, g \in N_g^{ES}, k \in K, p \in P, s \in S \tag{3.19}$$

3.2.7 Transmission Constraints

Total transmission capacity

The total transmission capacity for each year, L, is an equality constraint consisting of the initial exiting capacity in the network, $L^0(l)$, plus summation of new transmission capacity, L^{new}.

$$L_{l,y,s} = L_l^0 + \sum_{y \leq y'} [L^{new}(l,y)] \tag{3.20}$$

DC power flow

The physical constraints of the transmission network are accounted for by the direct current (DC) power flow equation. DC power flow, as an estimation of lines power flow, only considers active power while neglecting reactive power flows. Although this method is less accurate than the original alternating current (AC) power flow, its non-iterative and convergent nature is incredibly useful in long-term planning where repetitive and fast power flow estimations are required [80].

Power flow across lines, PF, is determined by the difference in voltage phasor angles, θ, between the terminating buses $[b,b']$, divided by the line reactance, X_l.

$$PF(l,b,b',y,k,p,s) = (1/X_l) * (\theta(b) - \theta(b'))$$
$$\forall l \in N_l, [b,b'] \in B, y \in Y, k \in K, p \in N_p, s \in S \tag{3.21}$$

Transmission limits

The power flows in the transmission lines are constrained by their thermal limit rate, TL. This constraint is modeled as two inequalities, expressing that the power flow in both directions is bound to the thermal limit.

$$-TL(l,y,s) \leq PF(l,b,b',y,k,p,s) \leq TL(l,y,s)$$
$$\forall l \in N_l, [b,b'] \in B, y \in Y, k \in K, p \in N_p, s \in S \tag{3.22}$$

3.2.8 Reserve Constraints

Planning reserve margin

Planning reserve margin, PRM, is a metric used in long-term planning models to ensure the amount of available generation capacity meets the expected peak demand, D', in the planning horizon [81]. In this regard, the fraction of rated generation capacity which is available at peak load is indicated by capacity credit, CC, and it is used for reliability calculations. The cumulative available generation capacity should be equal to or greater than the peak load plus a reserve margin as a fraction of the peak load.

$$\sum_{B,G} CC(g * G_{b,g,y,s}) \geq PRM * \sum_{B} D'(b,y,s)$$
$$\forall y \in Y, s \in S \tag{3.23}$$

Regulation reserve

Regulation reserves are used to maintain the stability of the power system during deviations of load or generation. Regulation-up reserve, R^+, is used when the generated power is lower than the real-time load, and regulation-down reserve, R^-, is applied when there is excessive generation than required. The R^+ and R^- are constrained to the ramp up, RU_g, and ramp down, RD_g, rates of generation technologies.

$$R^+(b,g,y,k,p,s) \leq RU_g * G(b,g,y,s)$$
$$\forall b \in B, g \in N_g, y \in Y, k \in K, p \in P, s \in S \tag{3.24}$$

$$R^-(b,g,y,k,p,s) \leq RD_g * G(b,g,y,s)$$
$$\forall b \in B, g \in N_g, y \in Y, k \in K, p \in P, s \in S \tag{3.25}$$

The amount of R^+ and R^- assigned to each bus should be equal or greater than the required regulation reserves, RU^{Req} and RD^{Req}.

$$\sum_{B,N_g} R^+(b,g,y,k,p,s) \geq RU^{Req} * \sum_B D(b,k,p,s)$$
$$\forall y \in Y, k \in K, p \in P, s \in S \tag{3.26}$$

$$\sum_{B,N_g} R^-(b,g,y,k,p,s) \geq RD^{Req} * \sum_B D(b,k,p,s)$$
$$\forall y \in Y, k \in K, p \in P, s \in S \tag{3.27}$$

3.2.9 Policy Constraints

Renewable portfolio standard

The renewable portfolio standard, *RPS*, accounts for the government's policy regarding the integration of renewable energy resources into the electricity system by a target year. The cumulative power generated by renewable resources should be greater than a percentage of the total generated power.

$$\sum_{B,N_g^{Ren},K,N_p} P(b,g,y,k,p,s) \geq$$
$$RPS_{y,s} * \sum_{B,N_g,K,N_p} P(b,g,y,k,p,s) \tag{3.28}$$
$$\forall y \in Y, s \in S$$

Energy curtailment

Energy curtailment happens when system operators require to deliberately reduce the output power to blow what has been planned to produce, to respond to an imbalance between energy supply and demand or transmission lines congestion [82]. This power should be lower than the dispatched power of the targeted generator.

$$P^{Curt}(b,g,y,k,p,s) \leq P(b,g,y,k,p,s)$$
$$\forall b \in B, g \in N_g^{Curt}, k \in K, p \in N_p, s \in S \tag{3.29}$$

Generation retirement

With the emergence of the new natural gas, wind, and solar resources, conventional generation technologies such as fossil-fired and nuclear plants tend to retire. This transition is a result of various drivers, including environmental policies, cost of mitigating emissions, advances in new technologies, lower natural gas prices, market forces, and consumers preferences [83]. The total generation retirement, R, as a decision variable, should be greater than or equal to the specified forced retirement, RET.

$$\sum_{B,N_g^{Ret}} R(b,g,y) \geq RET(y,s) \;\; \forall y \in Y, s \in S \tag{3.30}$$

Carbon emission reduction

The trend toward sustainable and green economies, and environmental laws, have imposed carbon emission policies on electricity generation and continue to impact the economics of generating units and the future of demand and supply [84]. In the planning phase, the carbon emission reduction parameter, CE, limits the percentage of carbon dioxide emitted by the generating units. The cumulative amount of carbon emission during each year of the planning horizon is calculated by the specified generator's carbon emission rate, M_g, in tons/MMBTU, heat rate, HR_g, in MMBTU/MWhr, generated power, P, and hours in load block, T. This amount should be lower than a specific percentage of carbon emitted during the initial year of planning, y'.

$$\begin{aligned} &\sum_{B,N_g^{Therm},K,N_p} M(g) * HR(g) * T(k,p) * P(b,g,y,k,p,s) \leq \\ CE(y,s) * &\sum_{B,N_g^{Therm},K,N_p} M(g) * HR(g) * T(k,p) * P(b,g,y',k,p,s) \\ &\forall y \in Y, y' = 1, s \in S \end{aligned} \tag{3.31}$$

3.2.10 Power Balance Constraint

The power balance constraint is to ensure that the supply and demand match at each bus of the network in each time slice. The sum of the power output of generators, P, energy storage discharge power, P^D, and power flows to the bus, $PF_{b,b'}$, minus energy storage charging power, P^C, power flows from the bus, $PF_{b',b}$, and the curtailed power, P^{Curt}, should equal to the demand, D, minus the load shed, LS.

$$\begin{aligned} \sum_B P(b,g,y,k,p,s) + P^D(b,g,y,k,p,s) - P^C(b,g,y,k,p,s) + \\ \eta_l * PF(l,b,b',y,k,p,s) - \eta_l * PF(l,b',b,y,k,p,s) - P^{Curt}(b,g,y,k,p,s) \\ = D(b,k,p,s) - LS(b,y,k,p,s) \\ \forall g \in N_g, l \in N_l, y \in Y, k \in K, p \in N_p, s \in S \end{aligned} \tag{3.32}$$

3.3 Discussion of the CEP Model

The CEP problem is formulated as a cost minimization model to optimize two different networks simultaneously with continuous decision variables. The model is solved as a multi-period problem to study the impacts of different policies, adding new technologies, and integrating renewable energy resources into the long-term planning horizon. CEP is an exploration tool to identify the investments given the assumptions in each scenario.

In order to make the CEP problem tractable, representative operating hours are selected by applying clustering to the hourly data of the base year. Wind geodiversity effects on the generation supply are taken into account by considering Alberta's wind profiles. Reserve constraints are also included in the problem to account for system flexibility in the high presence of renewable resources.

While solving the defined problem, there were some challenges that needed to be addressed. The power system is an AC network which makes the problem non-linear and complex; therefore, to make the model tractable, a DC power flow was used in modeling the system. Obtaining the future prices of generation technologies is a challenge. This information was obtained from NREL ATB website [85]. In the objective function, the problem has different orders of magnitude; therefore, the solver settings had to be modified to numeric emphasis to get the optimal solutions.

The result of this work is a tool developed to explore various future scenarios of power generation and transmission networks and study the impacts of carbon emission and renewable integration policies on the generation portfolio. Being able to conduct such an analysis paves the path to achieving a more sustainable and cleaner power system. By studying different network scenarios, system planners and stockholders will be able to make informed decisions for the system's future. Even though the developed model considers most of the important features and constraints in modeling power systems, there are still constraints that can affect the validity of provided results for the network under study. This can range from affecting the reliability metrics of the system by integrating a high level of renewable resources to causing infeasibility in the system operation scheduling, because the current model does not include reliability analysis or secured operation of the power system. Therefore, it is vital for users to consider the limitations of the model and conduct further analysis and studies depending on the nature of the system or study constraints that they are focusing on.

3.4 Developed CEP Tool

The model developed for co-optimization of generation and transmission expansion planning is coded using the General Algebraic Modeling Language (GAMS) [86]. The model is developed in separate and independent modules for easier modifications and applications for system planners. By having various modules, this tool enables system planners to use their desired constraints and policies for their study of networks. In the following, the tool's features and structure are described.

3.4.1 Inputs of CEP Tool

The input of the model is a single Excel data file, and all the parameters, sets, and data are read from that file. This is done using the GAMS data exchange (GDX) tools available in GAMS to avoid the tedious work of manually inserting the data in the model and making interaction with the CEP model easier for users.

First, sets and parameters of the model are defined in separate GAMS files with their descriptions as Table 3.4 and Table 3.4.1 show. The elements of these sets and parameters are all defined in the Excel file. As Table 3.4 shows, sixteen sets have been defined in the model. There are 25 parameters in the model that have the sets as indices.

In order to facilitate data exchange, an index chart is developed to link GAMS to different data records in the data set and enable it to read the data automatically. These indices are provided as Table 3.6 in the data set. The rows and columns defined here are for interaction with GAMS to define the table row and column indices. With the help of GDX functions the whole Excel file is uploaded to the model. Then the required data is extracted from it where needed.

By defining the sets and parameters, and reading the data file to the GAMS, data should now be converted to the format that the model can read. A function is defined for reading all the required data from the Excel file and loading it to the model. Table 3.8 summarizes the inputs of the model that the defined function loads into the model.

Then a function is defined to extract the dynamic sets from the sets that not all combinations are desired. An example of a dynamic set is lines connected between a pair of buses. However, there is not necessarily a connection between all bus pairs in the system, and only a subset of those pairs are connected through lines. Therefore, lines are defined as a dynamic set.

Table 3.4: List of Sets and Their Description

Set	**Description**
Bus	Buses
Bus_p	Bus parameters
SN	Seasons
BK	Time blocks
Year	Years
Year_p	Year parameters
Tech	Technologies
Tech_p	Technology parameters
Lid	Line ids
Line	Lines dynamic set (fr_bus, to_bus, id)
Line_p	Line parameters
Gid	Generation ids
Gen	Generation dynamic set (Bus, Tech, id)
Gen_p	Generators parameters
Param	Scalars
Scen	Scenarios
Scen_p	Scenario parameters
Fuel	Fuel types
ResType	Reserve types
TechFuelMap	Mapping of technologies with fuels
Res_p	Reserve parameters
Dfac_p	Discount factors

Table 3.5: List of Parameters with Their Descriptions.

Parameter	Description
Time(SN, BK)	Time period represented by *SN* and *BK*.
Load(Year, SN, BK, Bus, Scen)	Load at *Year*, *SN*, *BK*, *Bus*, and *Scen*.
Peak(Year, Bus, Scen)	Peak load at *Year*, *Bus*, and *Scen*.
Years(Year, Year_p)	Year of *Year* with *Year_p*.
DFac(Year, Dfac_p)	Demand factor of *Year* and with *Dfac_p*.
Techs(Tech, Tech_p)	Technology parameters based *Tech* and *Tech_p*.
Lines(Bus, Busi, Lid, Line_p)	Line between *Bus* and *Busi* with *Lid* and *Line_p*.
Gens(Bus, Tech, Gid, Gen_p)	Generation unit located at *Bus* with *Tech*, *Gid*, and *Gen_p*.
Scens(Scen, Scen_p)	Scenarios parameters of *Scen* and *Scen_p*.
RPS(Year, Scen)	Renewable portfolio standard (RPS) at *Year* and *Scen*.
GenExpC(Tech, Year, Scen)	Generation expected cost for *Tech*, *Year*, and *Scen*.
FuelPrices(Fuel, Year, Bus, Scen)	Price of fuel *Fuel* at *Year*, *Bus*, and *Scen*.
Params(Param)	Parameters of the model.
CF(Tech, SN, BK, Bus)	Capacity factor of *Tech* in *SN*, *BK*, and *Bus*.
Buses(Bus, Bus_p)	Set of buses between *Bus* and *Bus_p*.
ResReq(SN, BK, ResType)	Reserve requirement for *ResType* in *SN* and *BK*.
Reserves(Tech, ResType, SN, BK)	Reserve capacity of *Tech* for *ResType*.
CarbonEmRed(Year, Scen)	Carbon emissions reduction target at *Year* and *Scen*.
ResCost(Tech, ResType)	Reserve cost *Tech* and *ResType*.
ResDir(ResType, Res_p)	Reserve direction for *ResType* and *Res_p*.
GapFac(Year)	The gap factor for year *Year*.
Blocks(SN, BK)	Blocks of *SN* and *BK*.
Hours(SN)	Hours for *SN*.

Table 3.6: Indices for Reading Input Data

Type	Name	Description	Rows	Cols
SET	Bus	Buses	1	0
SET	Bus_p	Bus parameters	0	1
PAR	Buses	Buses(Bus, Bus_p)	1	1
SET	SN	Seasons	1	0
SET	BK	Time blocks	0	7
PAR	Time	Time(SN, BK)	1	1
PAR	Load	Load(Year, SN, BK, Bus, Scen)	3	2
PAR	Peak	Peak(Year, Bus, Scen)	1	2
SET	Year	Years	1	0
SET	Year_p	Year parameters	0	1
PAR	Years	Years(Year, Year p)	1	1
SET	Dfac_p	Dfac	0	1
PAR	DFac	DFac(Year, Dfac p)	1	1
SET	Tech	Technologies	1	0
SET	Tech_p	Technology parameters	0	1
PAR	Techs	Tech(Tech, Tech p)	1	1
SET	Lid	Line ids	1	0
DSET	Line	Lines dynamic set	3	0
SET	Line_p	Line parameters	0	1
PAR	Lines	Lines(Bus, Busi, Lid, Line p)	3	1
SET	Gid	Generation ids	1	0
SET	Gen	Generation dynamic set (Bus, Tech, id)	3	0
SET	Gen_p	Generators parameters	0	1
PAR	Gens	Gens(Bus, Tech, Gid, Gen_p)	3	1
SET	Scen	Scenarios	1	0
SET	Scen_p	Scenario parameters	0	1
PAR	Scens	Scens(Scen, Scen p)	1	1
PAR	GenExpC	GenExpC(Tech, Year, Scen)	1	2
DSET	Fuel	Fuel types	1	0
PAR	FuelPrices	FuelPrices(Fuel, Year, Bus, Scen)	2	2
SET	TechFuelMap	Mapping of technologies with fuels	2	0
SET	Param	Scalars	1	0
PAR	Params	Params(Param)	1	0
PAR	CF	CF(Tech, SN, BK, Bus)	3	1
PAR	CarbonEmRed	CarbonEmRed(Year, Scen)	1	1
PAR	GapFac	GapFac(Year)	1	0

Table 3.7: Indices for Reading Input Data (Cont)

Type	**Name**	**Description**	**Rows**	**Cols**
Set	ResType	Reserve types	0	1
PAR	ResReq	ResReq(ResType, ResReq p)	2	1
PAR	Reserves	Reserves(Tech, ResType, SN, BK)	2	2
PAR	ResCost	ResCost(Tech, ResType)	1	1
PAR	ResDir	ResDirRes(Type, Res_p)	1	1
SET	Res_p	Reserve parameters	0	1
PAR	Blocks	Blocks(SN, BK)	1	1
PAR	Hours	Hours(SN)	1	0

Table 3.8: Inputs of the CEP model

Input Data	**Model Representation**
Buses	Bus
Bus parameters	Bus_p
Time blocks	BK
Seasons	SN
Years	Year
Years parameters	Year_p
Discount factors	Dfac_p
Technologies	Tech
Technology parameters	Tech_p
Lines	Line
Line IDs	Lid
Line parameters	Line_p
Generators	Gen
Generator parameters	Gen_P
Investment years	{2025, 2030, 2035, 2040}
Future scenarios	{1, 2, ...,6, 7}
Scenario	Scen
Scenario parameters	Scen_p
Fuel types	Fuel
Reserve types	{RegUp, RegDwn}
Scalars	

3.4.2 Variables & Equations

The model has 26 variables, three of which are free variables, and the rest are positive. These variables include objective function, investment costs, investment values, generator variables, transmission line variables, operation costs, and operating conditions. Table 3.4.2 summarizes the variables defined in the model and their descriptions.

Table 3.9: List of Variables with Their Description and Type.

Variable	**Description**	**Type**
OBJ_CEP	Objective function cost	free
GenCapTot	Total generation capacity	positive
GenInvYear	Yearly generation investments	positive
GenRetYear	Yearly generation retirement	positive
CarbonEmission	Carbon emission	positive
GenRetYear	Yearly generation retirement	positive
LineInv	Transmission investments	positive
PG	Power production of each generator	positive
LineFlow	Transmission line flows	free
Theta	Bus angle	free
LoadShed	Load shed	positive
SOCSTO	Storage systems state of charge	positive
STOCh	Storage systems charge	positive
STODCh	Storage systems discharge	positive
C_GenInvper	Generation investment cost per generator	positive
C_GenRes	Cost of reserve provided by generators	positive
C_GenResCost	Total cost of reserve	positive
C_GenVOM	Total cost of VOM	positive
C_GenVOM	VOM cost per generator	positive
C_GenInv	Total generation investments cost	positive
C_LineInv	Transmission investments cost	positive
C_LineInvper	Transmission investments cost	positive
C_STOCost	Total storage cost	positive
C_FuelCost	Total fuel cost	positive
C_GenFuelCostpergen	Fuel cost per generation	positive
C_GenFOM	Total cost of FOM	positive
C_GenFOMper	FOM cost per generator	positive

The cost functions described in section 3.2.4 are modeled as equations in the CEP tool. These costs functions include generation investments, transmission investments, FOM, VOM, fuel, regulation reserve, load shedding, and the total cost of the system which serves as the objective of the optimization problem. The list of cost function equations that are used in the objective function, are provided in Table 3.4.2.

Table 3.10: List of Cost Function Equations with Their Description.

Cost Equation	**Description**
Eq_C_GenFuelCostpergen	Fuel cost equation of generators
Eq_C_FuelCost	Total fuel cost equation
Eq_C_GenFOMper	FOM cost equation of generators
Eq_C_GenFOM	Total FOM cost equation
Eq_C_GenInvper	Generation investment cost equation of generators
Eq_C_GenInv	Total generation investment cost equation
Eq_C_GenRes	Cost equation of generators' reserve
Eq_C_GenResCost	Total cost equation for reserves
Eq_C_GenVOM	VOM cost equation of generators
Eq_C_GenVOM	Total VOM cost equation
Eq_C_LineInvper	Transmission investments cost equation of lines
Eq_C_LineInv	Total transmission investments cost equation
Eq_C_STOCost	Storage system cost equation
Eq_OBJ_CEP	Objective function equation

The optimization problem is subjected to several physical, operational, and policy constraints that were defined earlier in this chapter. These constraints are linearized equality and inequality constraints that are divided into six major categories including generation constraints, transmission constraints, storage constraints, power balance, reserve requirement, and policy constraints.

Table 3.11: List of Constraint Equations with Their Description and Type.

Constraint Equation	**Description**	**Type**
Eq_GenInv	Cumulative generation capacity	equality
Eq_InvCap	Generation investment cap	inequality
Eq_DispCapFac	Thermal generators dispatch limits	inequality
Eq_GenUpLim	Thermal generators upper limit	inequality
Eq_GenDnLim	Thermal generators lower limit	inequality
Eq_HydroDisp	Hydro generators dispatch limits	inequality
Eq_ESDisp	Energy storage dispatch limits	inequality
Eq_ESSOC	Energy storage state of charge	equality
Eq_ESSOCWS	Spring energy storage SOC level tacking	equality
Eq_ESSOCSS	Summer energy storage SOC level tacking	equality
Eq_ESSOCSF	Fall energy storage SOC level tacking	equality
Eq_ESSOCYEARLY	winter energy storage SOC level tacking	equality
Eq_ESSOCYEARLY	Energy storage	inequality
Eq_ESMinSOC	Energy storage SOC lower limit	inequality
Eq_ESMaxSOC	Energy storage SOC upper limit	inequality
Eq_DCLineFlow	DC power flow equation	equality
Eq_LineLimUp	Transmission line positive limit	inequality
Eq_LineLimDn	Transmission line negative limit	inequality
Eq_GenPlanRes	Planning reserve margin equation	inequality
Eq_GenRes	Regulation reserve equation	inequality
Eq_ResReq	Reserve balance equations	inequality
Eq_RetMax	Generation retirement	inequality
Eq_CarbonEmRed	Carbon emission reduction equation	inequality
Eq_CarbonGen	Generators carbon emission equation	equality
Eq_PowerBalance	Power balance equation	equality

3.4.3 Model Statement

In order to make interactions with the model easier, variables and equations associated with each constraint or consideration are developed independently in separate GAMS files and then included in the final model. The model is divided into fifteen different sections which include:

- Sets
- Parameters
- Reading inputs
- Data extraction
- Display options
- Generation constraints
- Generation capacity investments
- Transmission line constraints
- Physical constraints
- Generation costs
- Transmission costs
- Flexibility requirements
- Energy storage constraints
- Carbon reduction policies
- Objective function

Dividing the model into independent sections helps the tool to be user-friendly and make desired changes in the model. Depending on the study and planning goals, the CEP tool can be readily modified to consider various equations, constraints, and objective function combinations. Users can include or remove different sections in the model and run the planning based on their study objective.

Developing different parts of the model as separate packages also makes it possible and easier to expand the tool for further considerations such as scenario-based and stochastic planning.

3.4.4 Solution of CEP

After defining the desired constraints and equations for the study, the selected model is passed to the solution section of the CEP tool. In this section, various solvers such as CPLEX, GUROBI, XPRESS, MINOS, SNOP, CONOPT, and LINDO can be selected for the optimization problem depending on the available computational resources. In the developed tool, CPLEX is used as the solver because it can also provide all the equation terms, making it possible for the user to check the model and see the active constraints.

Based on the type of optimization problem, the programming method can be defined for the solver. The developed CEP model in this work is based on linearized objective function and constraints; therefore, linear programming is used to solve the model. However, if the model is further extended and integer variables or non-linear constraints are added to it, other algorithms such as MILP, QP, or NLP can be used from any of the above-mentioned solvers.

3.4.5 CEP Outputs & Results

Once the optimization problem is solved, it is vital to read the outputs of the model, analyze the decision variables and interpret the results before taking any actions based on the obtained plan. To facilitate this procedure, it is essential to save and present the results in an effective manner. For this purpose, an option file is defined for the CPLEX solver to save all the relevant data on the level, marginal, upper, and lower values for variables and equations in GDX format. These data can be easily imported into GAMS software and analyzed by the CEP tool user.

Due to the large number of variables involved in CEP problems, it is useful to export the results into an Excel file, which can then be analyzed and post-processed using Python. A Python program is also developed to post-process the output data and then provide customized tables and plots highlighting important features and values from the output data. The output of the Python code is plots of generation and transmission investments, capacity distributions, energy and reserve providers, breakdown of the objective function costs, and so on.

Figures 4.15 and 4.16 and the cost function breakdown in Table 4.5 are illustrative examples of the types of graphs and summary tables provided by the Python program. Despite some imperfections, these visuals are highly useful for summarizing the CEP results and enabling the creation of detailed reports on the expansion plan.

Figure 3.1 presents a high-level structure of the developed CEP tool. This CEP tool has two user-friendly components that make it possible for users to interact with the tool, even if they do not completely understand the underlying model. The first component is the input data section, which can be readily updated to reflect the system under study. The second component is the model statements section, where users can choose which constraints to include in the model. These two components provide an intuitive interface for users to include the information of the system being studied and consider their preferred model based on the objective of their study without needing to have an in-depth understanding of the model to interact with or modify it.

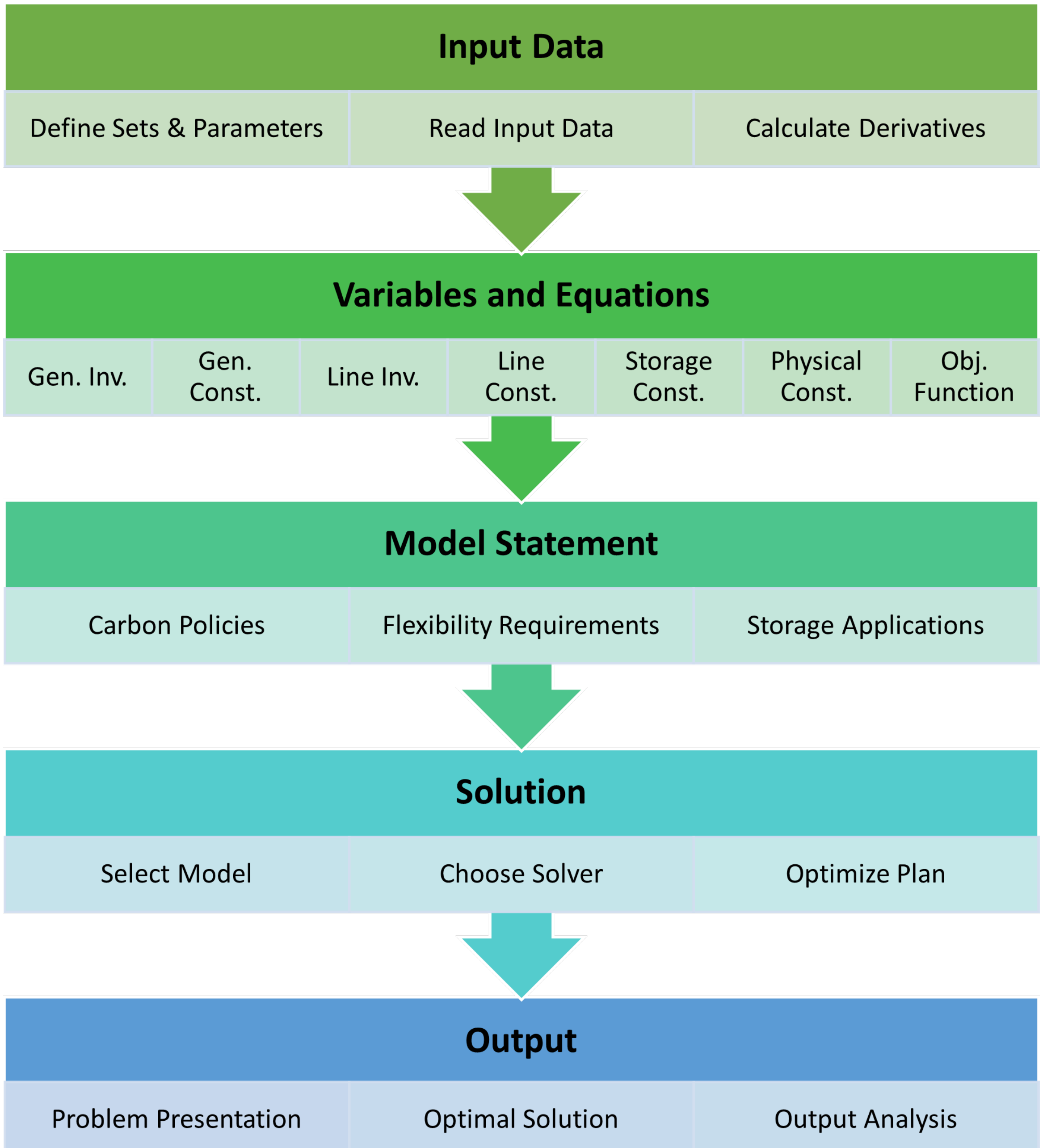

Figure 3.1: Structure of the Developed CEP Tool

3.5 Summary of the Chapter

In this chapter, an introduction to generation and transmission system planning was provided, and the proposed CEP model was discussed in detail. The problem parameters and decision variables were explained, and the generation and transmission systems were modeled. Then the components of the objective function and various constraints of the problem were illustrated in mathematical formulations. A final discussion of the model, its importance, and how it will help in the industry was also provided. Finally, the CEP tool developed based on the optimization model, its inputs, variables, equations, solver, and output were explained.

Chapter 4

Test Case, CEP Results, and Discussion

4.1 Introduction

In this chapter, the details of the developed data set are provided and the test cases are upgraded for planning studies. The proposed model is run on the two test systems for several scenarios on Carbon reduction policy, reserve requirements, and employing energy storage systems as energy and reserve providers. The results and discussions of the results are presented in this chapter.

4.2 Test System

In recent years, power systems have substantially evolved with the retirement of traditional energy resources and the integration of renewable sources. In order to account for these changes in the modern power system, an updated test system with a modernized generation mix is used in this study.

The network is a modified version of the IEEE Reliability Test System (RTS), which has traditionally been used for power systems analysis [87]. The updated network is called RTS-Grid Modernization Laboratory Consortium (RTS-GMLC) which enables power system modeling and analysis with a mixed generation fleet and a spatially and chronologically consistent time series data-set [37].

This is a 73-bus network inspired by a real network and includes a variety of generation technologies ranging from renewable to thermal generators. The system consists of coal, hydro, wind, solar, concentrating solar power, nuclear, gas combined cycle, gas steam turbine, oil steam turbine, oil combustion turbine, synchronous condenser generators, and energy storage systems. The total generation capacity of the system is 14.55 GW. Considering the capacity credit of technologies, the effective capacity available is 10.79 GW. The average load of the system is 4164 MW, while the peak load is 8550 MW.

The size of the network is sufficiently large to highlight the complexity of power systems while simple enough to apply expansion optimization and analyze the results. There are 120 transmission lines in total in this network. Some of the lines have been removed, or their capacity has been reduced, in RTS-GMLC in order to account for binding transmission constraints in operational studies and analysis [37].

The topology of the test system is shown in Figure 4.1. This network is projected to a location in the southwestern United States, which also provides a reference for load, wind, solar, and hydro geospatial data [37]. The generation portfolio of renewable energy resources has been drawn from the dataset used in the Western Wind and Solar Integration Study Phase 2 (WWSIS-2) [88].

Table 4.1 illustrates the generation type mix of the RTS-GMLC network, which includes both conventional and renewable resources. Natural gas is the dominant fuel in the generation fleet with a 35% share. Solar generation forms 20%, and wind power constitutes 17% of the whole generation profile.

Type	Capacity-MW	Share(%)
Coal	2317	16
Oil	324	2
Natural Gas	5035	35
Nuclear	400	3
Hydro	1000	7
Wind	2508	17
Solar	2916	20
Total	14500	100

Table 4.1: Initial RTS-GMLC Generation Mix.

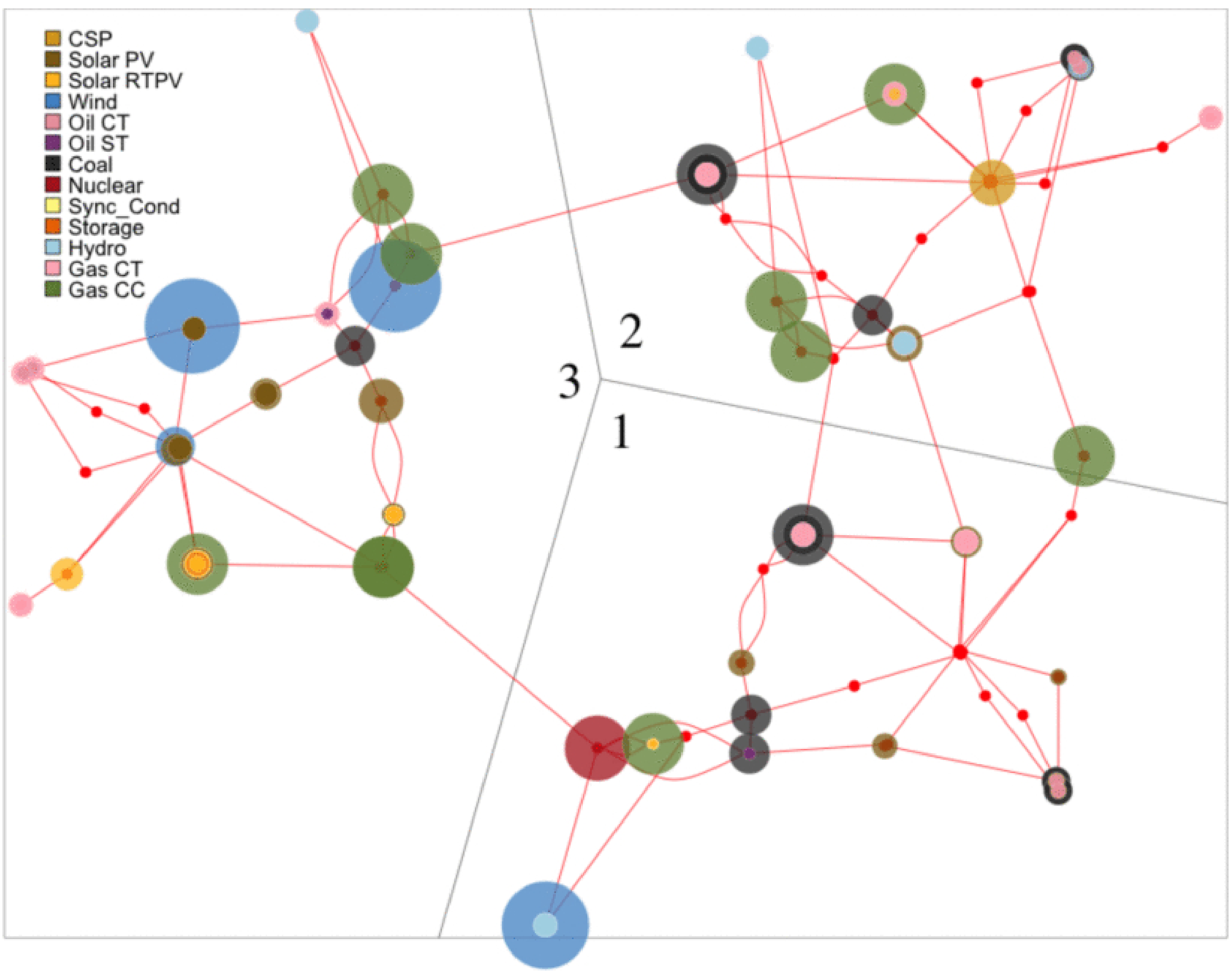

Figure 4.1: RTS-GMLD Test System [37]

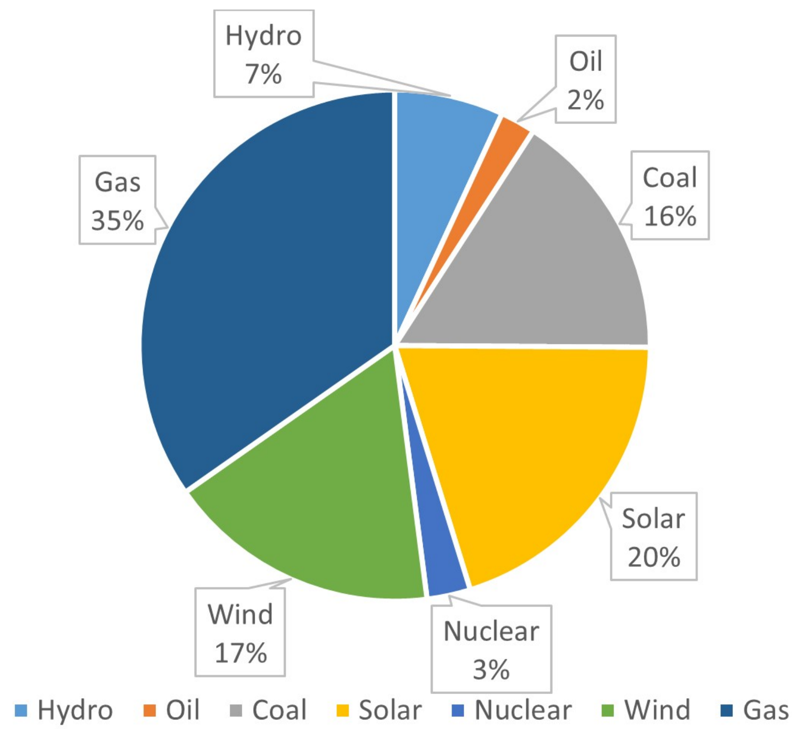

Figure 4.2: Initial RTS-GMLC Generation Mix

4.3 Database Development

Test systems act as a benchmark for the development of new algorithms and approaches in power systems. These test systems allow the researchers to test their ideas on a smaller scale to identify possible shortcomings and strengths of their ideas. Moreover, these test systems must be updated as the needs of the power systems change and as the power systems evolve to be modernized. An example of a test system in power systems is the IEEE Reliability Test System [87], which is widely used for a range of studies. Initially proposed in 1979, it has since been updated a few times and continues to evolve. One of the most updated versions of IEEE RTS is RTS-GMLC version [37].

With planning becoming more important in modern power systems, developing a test system for planning studies is vital. However, there are currently no test systems for planning studies using publicly available data. The papers usually use modified versions of the existing networks or proprietary data that cannot be shared publicly. In this thesis, the RTS-GMLC network is adopted for the development of the data for long-term planning.

In a long-term planning problem, two sets of data are needed: power flow data and economic data. The power flow data consists of the electrical aspects of the network. These aspects include load, generation, transmission line characteristics, and network topology. However, the objective of long-term planning models is to minimize the cost of network expansion over a planning horizon. Therefore, the power flow and economic data of the present network and their projections into the future are needed. The required economic data range from variable and fixed operation and maintenance costs of generators to the expansion costs of generation for different technologies and transmission lines. There are several uncertainties associated with projections of power flow and economic data. The growth of electrical demand, the climate conditions affecting the output of wind and solar, costs of expansion of different generation technologies and transmission lines are a few of such uncertainties.

The capacity factors of wind/solar are obtained from the annual time series of measurements. Working with planning models requires the projection of all aspects of the model into 20 to 40 years in the future. In this model and other models in the literature, the capacity factors of wind/solar are coming from today's measurements. However, with global warming, it is important to consider the changes in wind/solar capacity factors in certain areas of Canada.

All the required data for expansion planning is gathered in a single Excel file for easier access and modification. The first sheet is defined as an index and includes the sets and parameters of the model linked to the other network data. This means that the sets and parameters do not need to be updated separately for the model, and if some parameters or features of the system change, the model sets and parameters get updated automatically. This feature contributes to the simplification of the CEP tool by making the input data flexible for the user.

4.3.1 Sets and Parameters

The model includes sets of buses, bus parameters, generation technologies, lines, time blocks, seasons, years, investment years, future scenarios, fuel types, reserve types, line and generation parameters, and scalars. The summary of all these sets for the modified RTS-GMLC test system is provided in Table 4.2.

Set	Elements	Cardinality
Buses	{101-124, 201-224, 301-325}	73
Lines	{From Bus, To Bus, ID}	121
Line parameters	{Adm, Imp, FW, BW, EC2, Length, IsDC, EC}	8
Generation parameters	{Cap, HR, CandCap}	8
Time blocks	{1, 2, 3, 4}	4
Seasons	{Spring, Summer, Fall, Winter, Peak}	5
Years	{2020, 2021, 2022, ..., 2039, 2040}	21
Investment years	{2025, 2030, 2035, 2040}	4
Fuel types	{Coal, Gas, Oil, Nuclear, Water, Sun, Wind}	7
Reserve types	{RegUp, RegDwn}	2
Future scenarios	{1, 2, ...,6, 7}	7
Scenario parameters	{Prob, EELim, DRLim, DERLim, CAGRDemand, CAGREnergy, RenPen, CoalRet, GasOilRet, NuclearRet}	10
Generation technologies	{Coal, GasCC, GasCT, OilCT, OilST, Nuclear, Hydro, Solar, Wind, STO}	11
Technology parameters	{Fuel, CC, CarbEm, VOM, FOM, FOR, IsInv, IsWind, IsSolar, IsDPV, IsSTO, IsGas, IsCoal, IsOil, IsHydro, IsNuclear, IsNoCurt, IsCF, IsRen, IsDR, IsRes}	21
Scalars	{VoLL, Beta, PRM, SOCmax, SOCmin, STOChEff, STODchEff, STODur, RUP%, RDWN%, TransLoss}	11

Table 4.2: Sets in the CEP model

There are parameters associated with each set or different subsets of them, including time, load, peak load, discount factor, technology parameters, line parameters, generation parameters and expenses, fuel prices, scenarios, capacity factor, carbon emission reduction, gap factor, reserve requirement, technologies reserves, reserves cost, blocks, hours, and scalar parameters. A summary of their size and dimensionality is provided in Table 4.3

Table 4.3: Sets in the CEP model

Parameter	**Index size**	**Indices**	**Records**
Time	$[1 * 1]$	[season, time block]	20
Load	$[3 * 2]$	[(year, season, time block), (bus, scenario)]	26061
Peak load	$[1 * 2]$	[year, (bus,scenario)]	1533
Discount factor	$[1 * 1]$	[year, Dfac]	21
Technology parameters	$[1 * 1]$	[technology, technology parameter]	231
Lines parameters	$[3 * 1]$	[lines, line parameters]	968
Generation parameters	$[3 * 1]$	[(bus, tech, id), generation parameters]	273
Generation expenses	$[1 * 2]$	[generation technologies, (year, scenario)]	189
Fuel prices	$[2 * 2]$	[(technology, year), (bus, scenario)]	79205
Scenarios	$[1 * 10]$	[scenarios, scenario parameters]	70
Capacity factors	$[3 * 1]$	[(Technology, season, time block), bus]	3723
CO_2 emission reduction	$[1 * 1]$	[year, scenario]	231
Gap factor	$[1 * 0]$	[investment year]	4
Reserve requirement	$[2 * 1]$	[(season, time block),reserve type]	32
Technologies reserves	$[2 * 2]$	[(technology, time block),]	1309
Reserves cost	$[1 * 1]$	[technology, reserve type]	143
Blocks	$[1 * 1]$	[season, time block]	16
hours	$[1 * 0]$	[season]	5

4.3.2 Planning Economic Data

For a long-term planning test case, economic and technical value projections for the period of the planning horizon are developed. The economic projection data are obtained from NREL Annual Technology Baseline (ATB) [38]. Moreover, different CO_2 reduction scenarios are developed to represent mild to aggressive greenhouse gas reduction efforts. These emission reduction scenarios are as follows:

- 90% carbon emission reduction
- 98% carbon emission reduction
- 100% carbon emission reduction

4.3.3 Energy Blocks

The number of operating hours during the planning horizon is very large and it is not possible to run the CEP model for the whole period. Therefore, it is essential to cluster the data to reduce time resolution. In this section, the representative energy and peak blocks for net load are defined.

In order to find representative hours for modeling the operation of the system, time series of load, wind, and solar are clustered into blocks. There is new research work in this area to improve the clustering accuracy [89]–[91]. These works show promising improvements in modeling highly renewable energy integrated power systems. However, in this work for simplicity, the frequently used K-means clustering algorithm is applied to find the periods with similar patterns in load, wind, and solar power [92]. Definitely, using the mentioned methods can help improve the planning results; however, the focus of this work is on the planning model; therefore, even though applying those methods and comparing the results with K-means clustering is highly recommended, it is out of the scope of this work.

To capture the annual variation of load, wind, and solar time series, four seasons were considered: winter (January, February, March), spring (April, May, June), summer (July, August, September), and fall (October, November, December). The clustering is done for each season and the optimal number of clusters is defined by considering both silhouette coefficients and elbow method [93]. This led to four representative periods for each season and sixteen periods in total for each year. Figure 4.3 shows a conceptual illustration of the energy blocks.

The developed test system is publicly available on a Github page at [94].

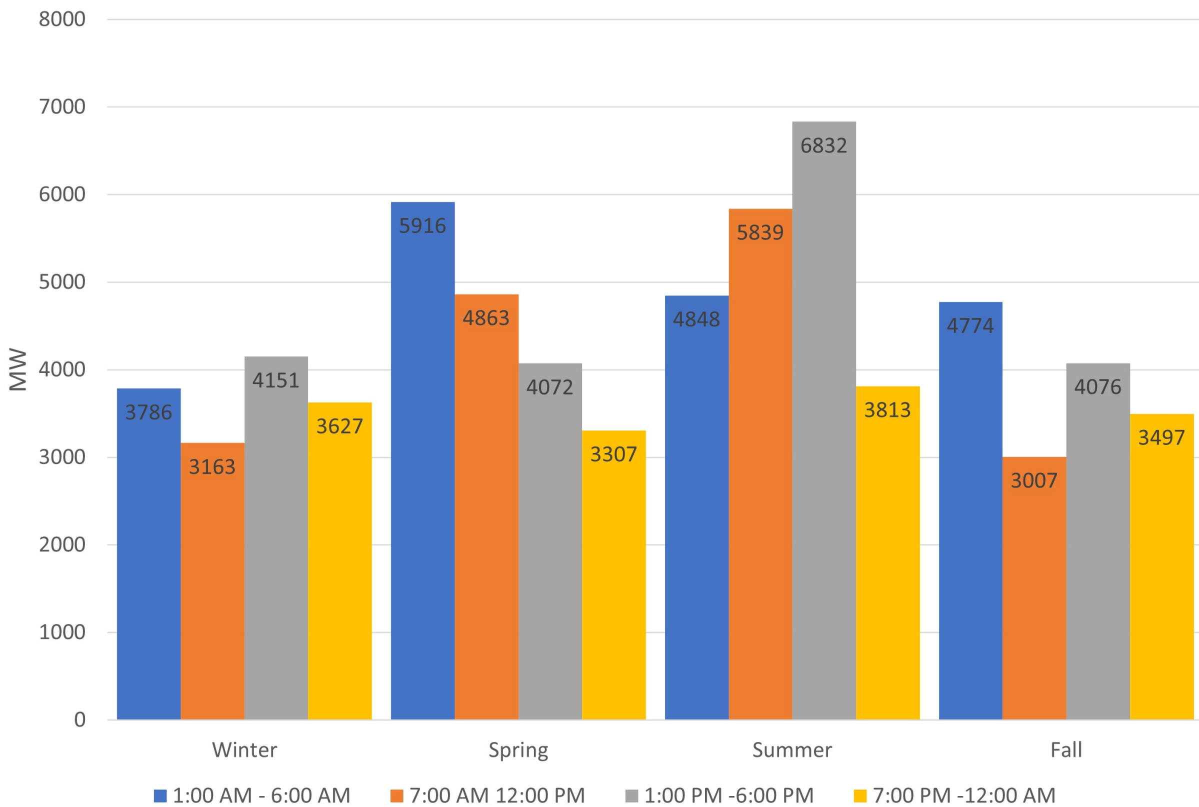

Figure 4.3: Representative Energy Blocks in 2020

4.4 Carbon Reduction Scenarios

One of the main goals of planning future electricity networks is to reduce electricity production from fossil-fueled technologies and achieve a net-zero carbon emission power system. In order to analyze the possible configurations and their associated costs, four different scenarios are considered. The base scenario is when there are no restrictions on carbon emissions. Studying this scenario helps to have an insight into the optimal generation and transmission portfolios and their costs and to show how adding CO_2 emission constraints change system configurations and costs.

When applying CO_2 reduction policies, different levels of carbon emission reduction percentages are considered, and the changes in the investments are studied. Three different CO_2 reduction scenarios, 90%, 98%, and 100%, are studied, and the change in generation portfolio compared to the base case scenario with no constraint on CO_2 emission is analyzed.

The 90% reduction in CO_2 emission scenario represents a power system that is not fully committed to cutting off CO_2 emissions and allows utilizing fossil fuel sources such as gas to about 10% usage due to their reliability and economic benefits. On the other hand, the 100% CO_2 reduction scenario is an ambitious case to reach a fully renewable power system without using any fossil-fueled technologies.

The %98 CO_2 reduction case is considered to investigate the effect of a small allowance of CO_2 emission on system costs compared to pushing net-zero CO_2 emission electricity generation. This scenario helps decision-makers investigate if it is worth the investment costs to force the net-zero target on the power system or if it is better to use fossil-fueled technologies for flexibility purposes.

4.4.1 Base case scenario

In the base case scenario, the generation and transmission networks are planned based on minimizing the total cost without considering any carbon emission and renewable energy integration constraints. The generation portfolio in this scenario does not differ significantly from the existing portfolio for the year 2020, except that there is more solar and gas and lower coal generation in the

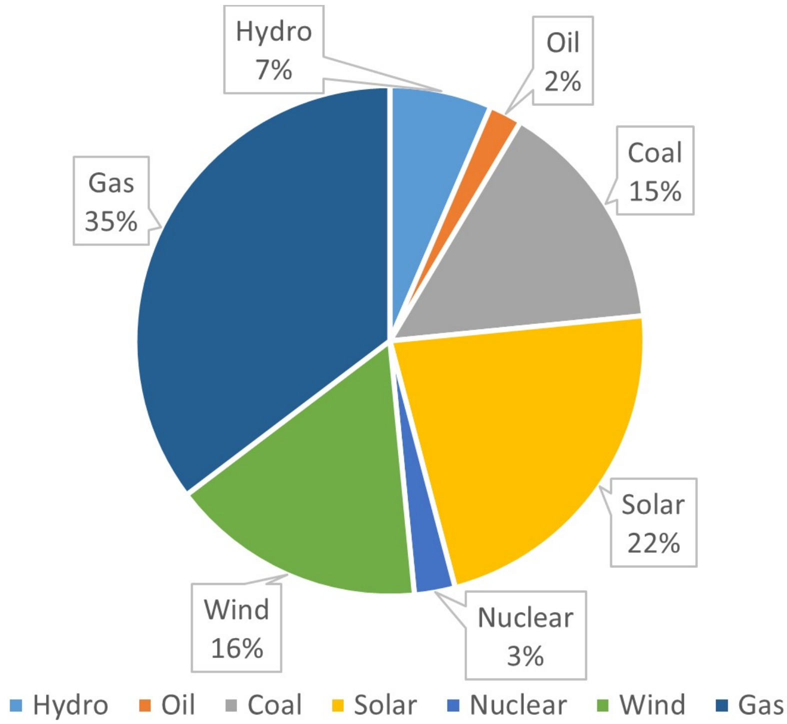

Figure 4.4: Generation Capacity Distribution with no CO_2 constraint

capacity distribution, Fig. 4.4. This is due to the retirement of coal generation in 2025, which is 21 MW in this case.

Generation investments occur in the year 2035, 342 MW in GasCC, and in the year 2040, including another 80 MW in GasCC and 554 MW in solar energy, Fig. 4.5. The cost of generation investment is 212 M$ and the total cost of the system during the planning period is 10490 M$. Table 4.4 shows the breakdown of the objective function for the base case planning.

Item	Cost (M$)	Share(%)
Generation Investment	212	2
Transmission Investment	0.0	0.0
Fuel Cost	5178.6	49.4
FOM Cost	4369.6	41.7
VOM Cost	729.7	7.0
Total	10489.9	100

Table 4.4: Cost Function Breakdown for Base Case Scenario

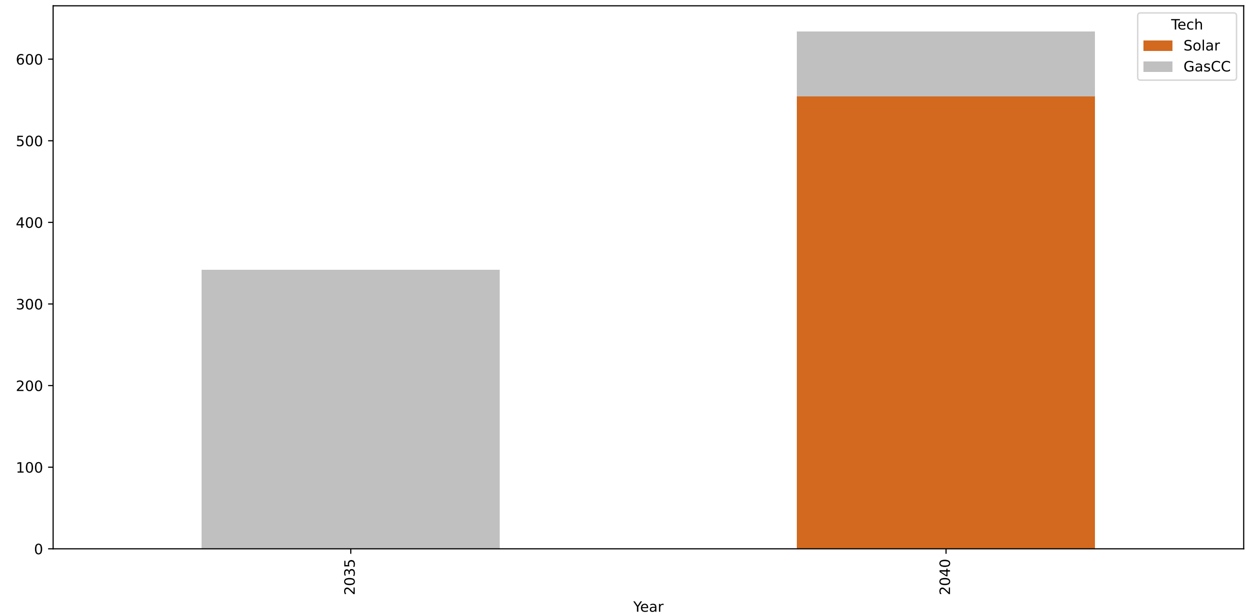

Figure 4.5: Generation Capacity Investment with no CO_2 constraint

Investing in 975 MW new generation and retiring 21 MW coal generation, there is a total of 954 MW increase in generation capacity by the end of the planning horizon. This investment in generation covers the growth in electricity demand, 557 MW, in the year 2040.

The reason for investing in more generation than the load growth is that the generators' capacity factor, CF, is considered in modeling their contribution to the system. Moreover, the reliability constraint of the planning reserve margin, PRM, is applied to make sure that the available generation capacity covers the expected peak demand, D', in the planning horizon.

In this case, the current capacity of the transmission network is enough to transfer the generated power to the load centers. Therefore, no enhancement is required in the transmission system.

4.4.2 90% Carbon Reduction

A 90 percent reduction in CO_2 emission by the end of the planning period is considered, and the optimization model is run with this constraint. Including this constraint in the model leads to more investment in renewable energy resources as it is shown in Fig. 4.6. There is a 5.6 GW investment in wind power and a 2.3 GW investment in solar power throughout the planning period, depicted

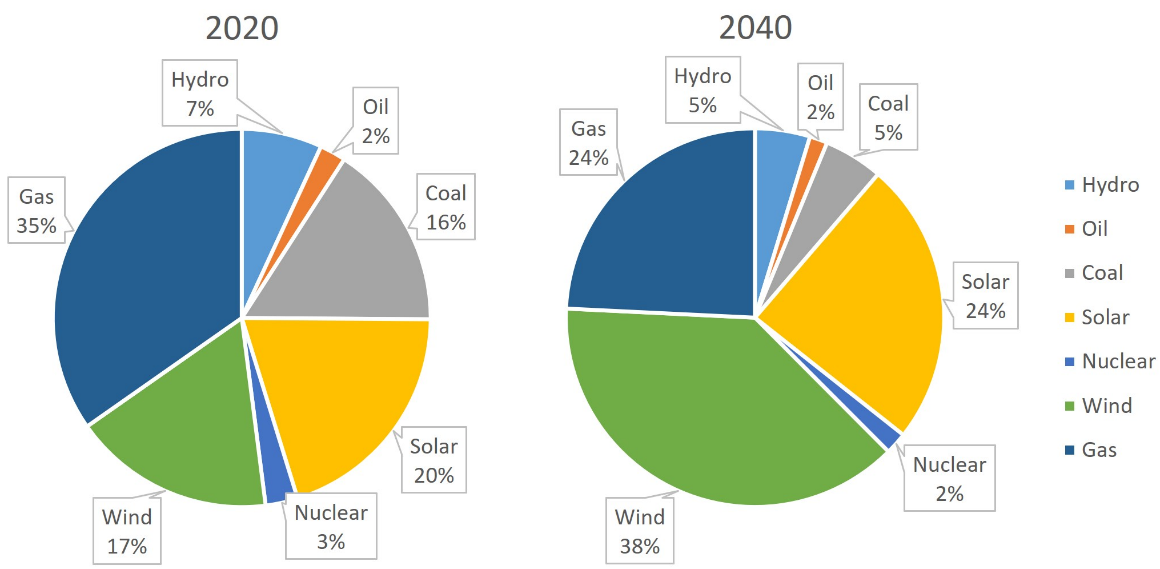

Figure 4.6: Capacity Distribution for 90% CO_2 reduction

in Fig. 4.7. There is also a small 90 MW investment in GasCC technology due to a 10% allowance of CO_2 emission. GasCC technology has low VOM and FOM costs, making it a preferable option for electricity generation.

Wind energy provides 38% of generation capacity, which is the highest share in the generation portfolio in this scenario. Solar and GasCC provide the same 24% of the generation capacity, while the share of coal has reduced from 16% to only 5% of the generation fleet. The capacity of other technologies has remained the same as they have not been retired or invested in.

This CO_2 reduction scenario leads to the retirement of 190 MW of coal power plants in 2030 and the retirement of another 1051 MW in the last planning year as shown in Fig. 4.8.

The investment in the generation sector costs 2514 M$, which is almost ten times higher than the investment cost for the basic scenario. However, the system's total cost at the end of the planning horizon is 12030 M$, which is 1540 M$ higher than the case with no constraints on carbon emission. This implies that investing in wind and solar resources with zero variable operation and maintenance (VOM) reduces operational costs and instead will compensate for the initial high investment cost. The extra cost can be considered as the cost of reducing carbon emissions, or in other words, the cost that would have been paid for the carbon emission policy.

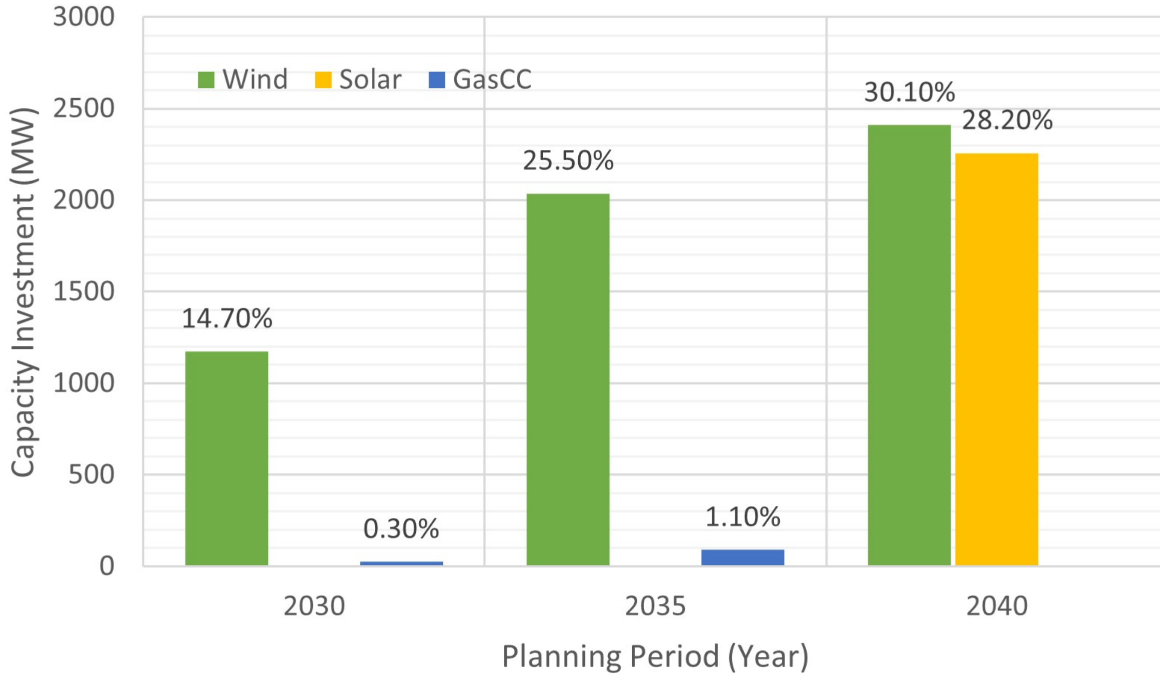

Figure 4.7: Generation Capacity Investments for 90% CO_2 Reduction Scenario

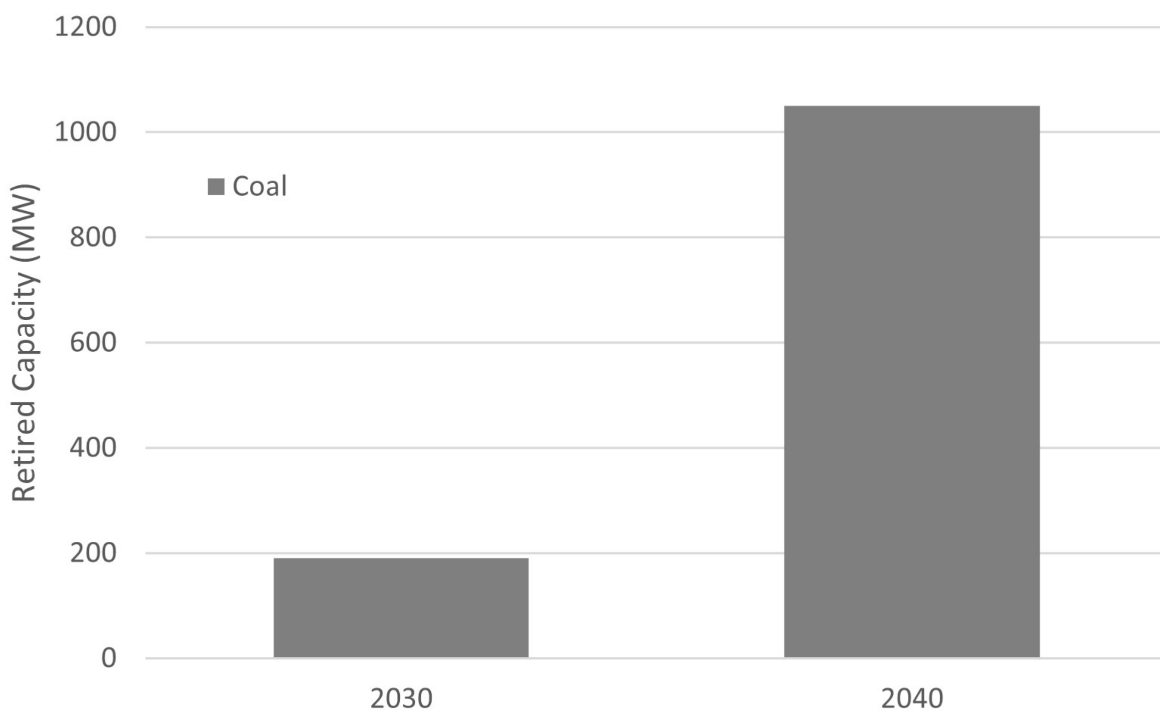

Figure 4.8: Generation Retirement for 90% CO_2 Reduction Scenario

Item	Cost (M$)	Share(%)
Generation Investment	2513.7	20.9
Transmission Investment	49.3	0.4
Fuel Cost	3574.8	29.7
FOM Cost	5357.7	44.5
VOM Cost	534.5	4.4
Total	12030	100

Table 4.5: Cost Function Breakdown for 90% CO_2 Reduction Scenario

There is an investment of 3.5 GW in transmission lines, which costs around 49.3 M$. These line improvements mainly occur on or near the sites where new wind, solar, and GasCC generations have been invested. In 2030, only a 88 MW line is added to the bus where the 1.2 GW wind generation is invested. In the years 2035 and 2040, 6 and 8 new lines are added to the transmission network, respectively. These additions also happen in response to the new generation investments.

4.4.3 98% Carbon Reduction

In this scenario, the optimization model is run for a 98 percent reduction in CO_2 emission. As expected, this constraint leads to more investment in wind and solar resources and the retirement of coal and gas technologies. The investment in wind reaches 10 GW and there is a 4.3 GW investment in solar generation during the years 2035 and 2040, as shown in Fig. 4.10. This costs 3452 M$ for wind turbines and 874 M$ for solar panels.

By the end of 2040, wind energy provides the highest share in the new generation portfolio, which is 48%, equal to 12.6 GW. Solar energy is the second largest energy provider in the system by a 28% share, equal to 7.3 GW of power. Fig 4.11 illustrates both the initial and the final generation fleet in 2020 and 2040.

Retiring carbon-emitting power plants is more serious under this constraint. The coal retirement in 2025 is 225 MW. Then another 625 MW retirement in the year 2035. Later in the year 2040, 368 MW of GasCC generation and 1467 MW more of coal generation is retired 4.12. This

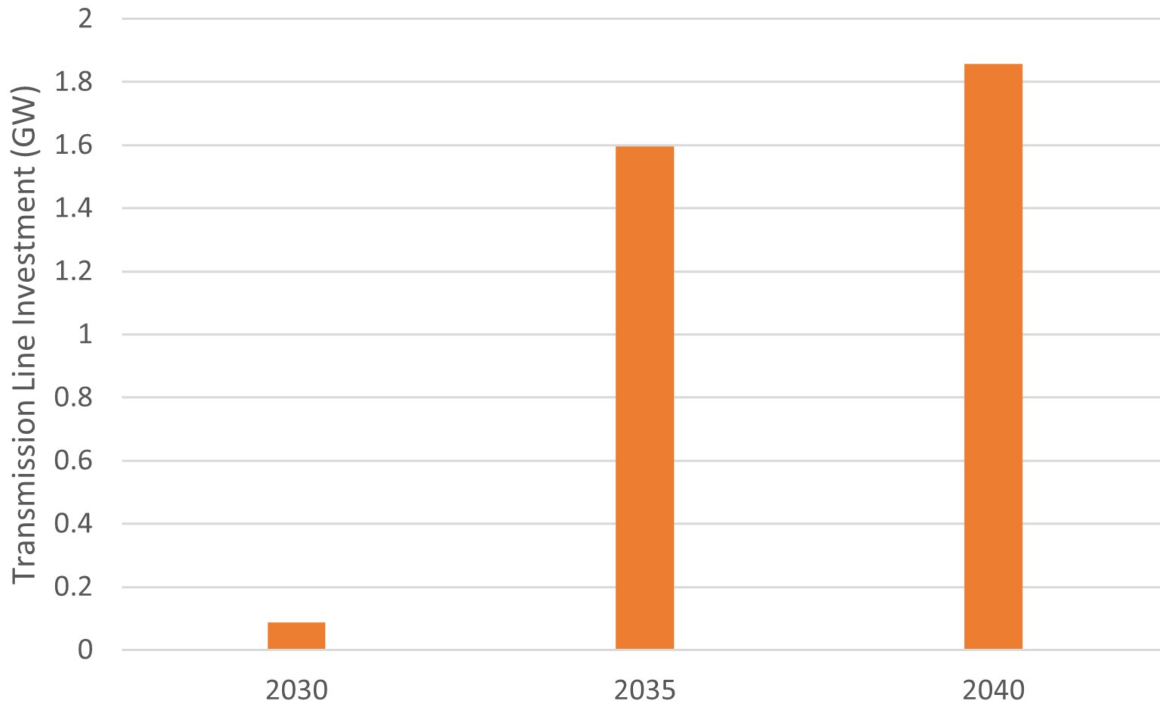

Figure 4.9: Transmission Capacity Investments for 90% CO_2 Reduction Scenario

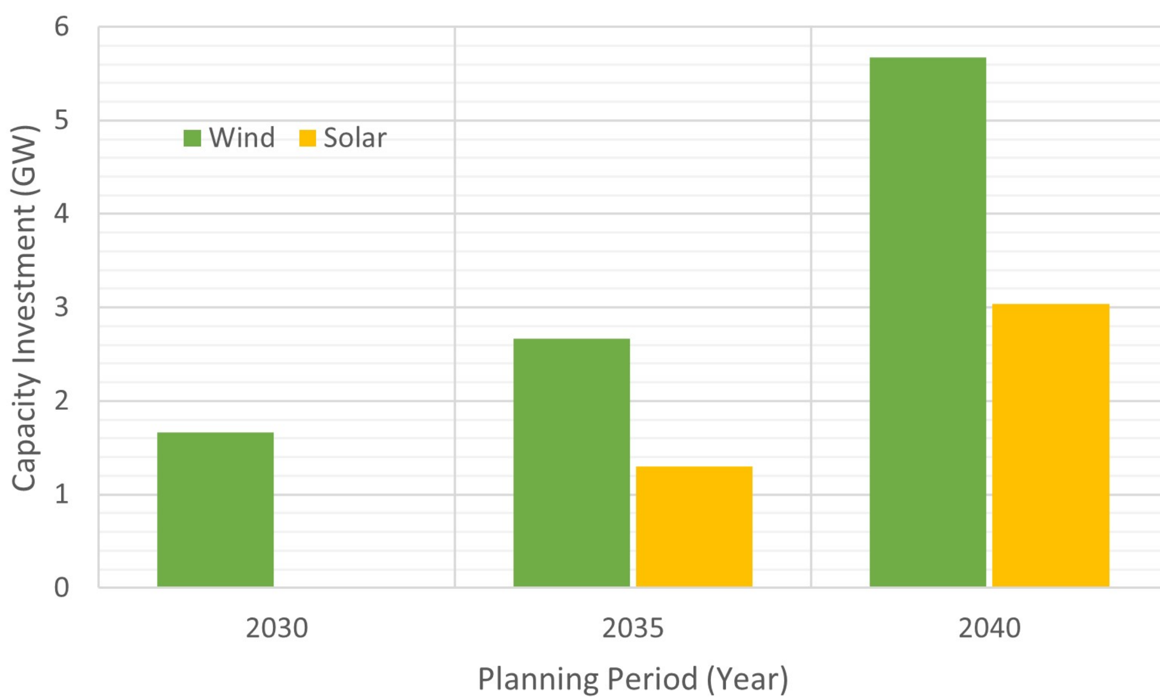

Figure 4.10: Generation Capacity Investments for 98% CO_2 Reduction Scenario

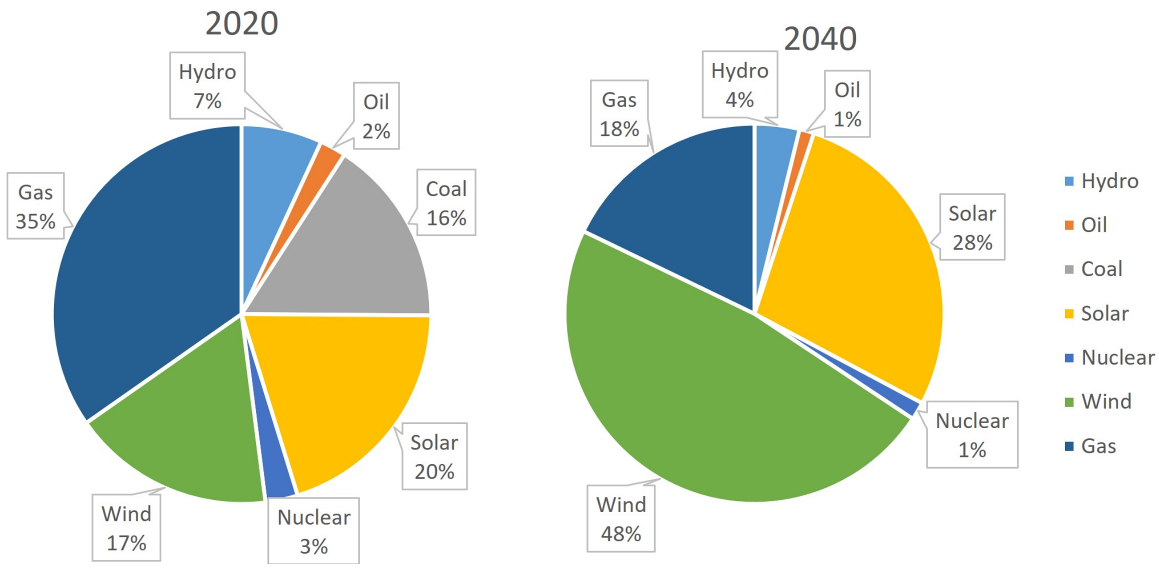

Figure 4.11: Capacity Distribution for 98% CO_2 reduction

is no load shed happening in this scenario which means the system can still work properly with more renewable energy integration.

On the transmission side, there are 32 new lines added to the system, which equals 8.3 GW of capacity. These lines provide the required transmission capacity for the new 14.3 GW generation investments. This implies that for each new 1 GW of generation capacity, 0.58 GW of new transmission capacity is required.

In the year 2025, even though there is no investment in the generation section, there are two new lines added to the transmission system as Fig. 4.13 shows. This is because of the retirement of coal generation that happens in the year 2025. This shifts the electricity generation to other resources in different parts of the network which require upgrades to be able to supply the shifted load. The line investments increase in the following years in response to the new generation capacities and the larger retirement of fossil-fueled technologies.

In this scenario, the generation investment cost increases by 72% in comparison to the 90 percent CO_2 reduction. The cost of upgrading the transmission system to keep up with changes in the generation system is 117.6 M$. Fuel cost is 2946 M$, generation FOM costs 5985 M$, and generation VOM costs 452.7 M$.

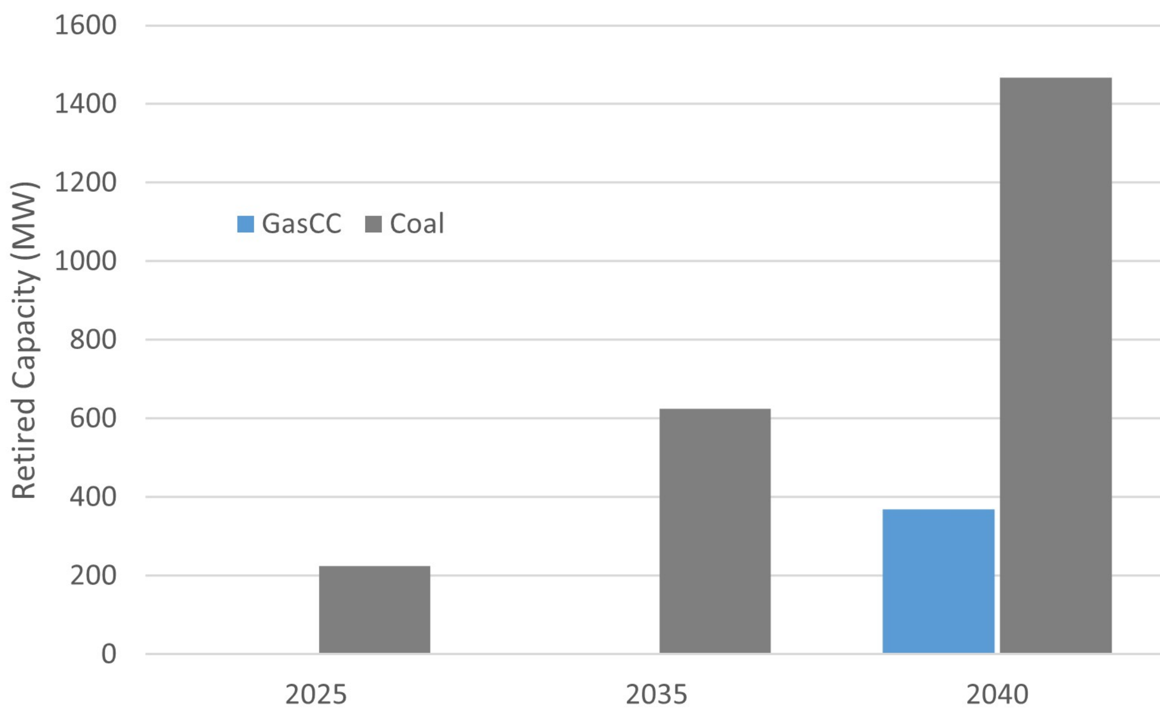

Figure 4.12: Generation Retirement for 98% CO_2 Reduction Scenario

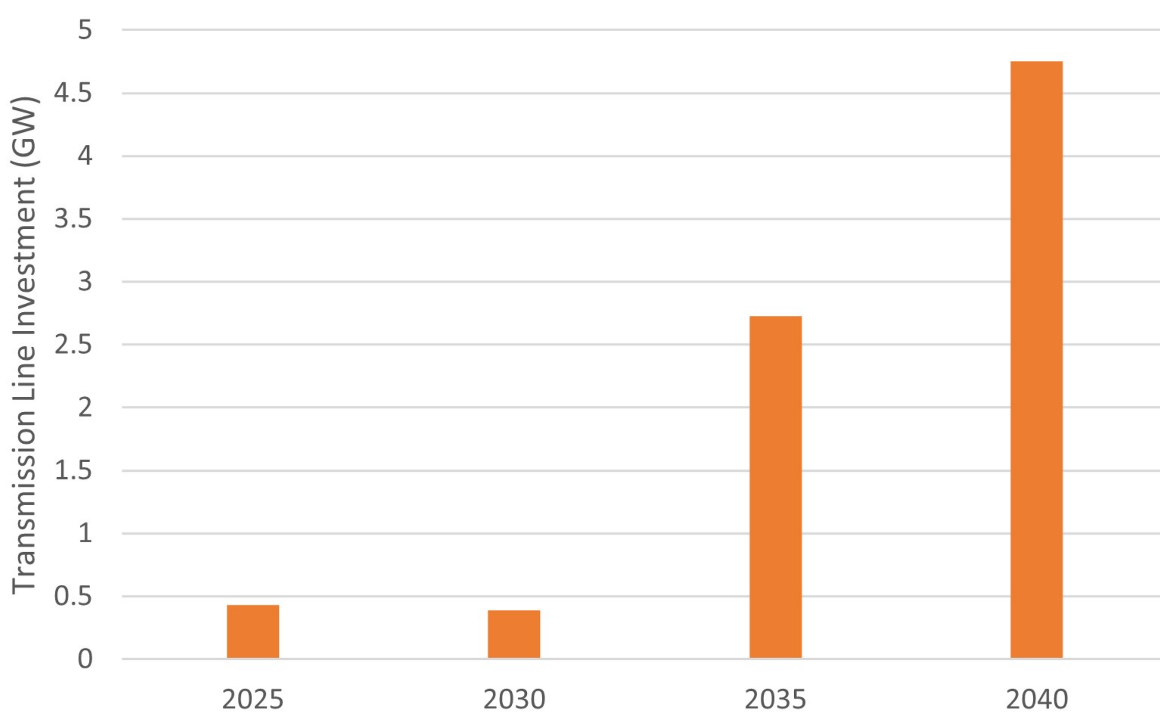

Figure 4.13: Transmission Capacity Investments for 98% CO_2 Reduction Scenario

The total planning cost for this scenario adds up to 13828 M$, where the FOM cost has the largest share of 43.3 %. Although the investment cost changes drastically in this scenario, the total investment cost only increases by 15% compared to the previous case.

Item	Cost (M$)	Share(%)
Generation Investment	4325.9	31.3
Transmission Investment	117.6	0.9
Fuel Cost	2946.3	21.3
FOM Cost	5985.1	43.3
VOM Cost	452.7	3.3
Total	13827.6	100

Table 4.6: Cost Function Breakdown for 98% CO_2 Reduction Scenario

4.4.4 100% Carbon Reduction

The goal in this case is to reach zero emissions by the end of the planning horizon in the year 2040. This scenario results in enormous investment in wind and solar generation, and the retirement of coal and gas generating plants.

The new investments in wind and solar technologies for 5 each year of the planning period are shown in Fig. 4.14. Because of the constraint to have zero CO_2 emission by the year 2040, the main investments happen closer to the final year. There is a total of 12 GW capacity investment in solar generation, which makes it the largest share of the generation mix. In 2040, solar generation forms 44.7% of the generation portfolio. Wind generation has the next largest contribution to the generation section with a total 10.8 GW investment in capacity accounting for 43.3% of generation. The changes to the generation mix during the four stages of the planning period are shown in Fig. 4.15.

Although wind and solar technologies provide the main share of the generation fleet, other technologies including 1000 MW hydro, 400 MW nuclear, 842 MW GasCT, 240 MW OilCT, and 84 MW OilST are also contributing to the system. The changes in power generation share of each

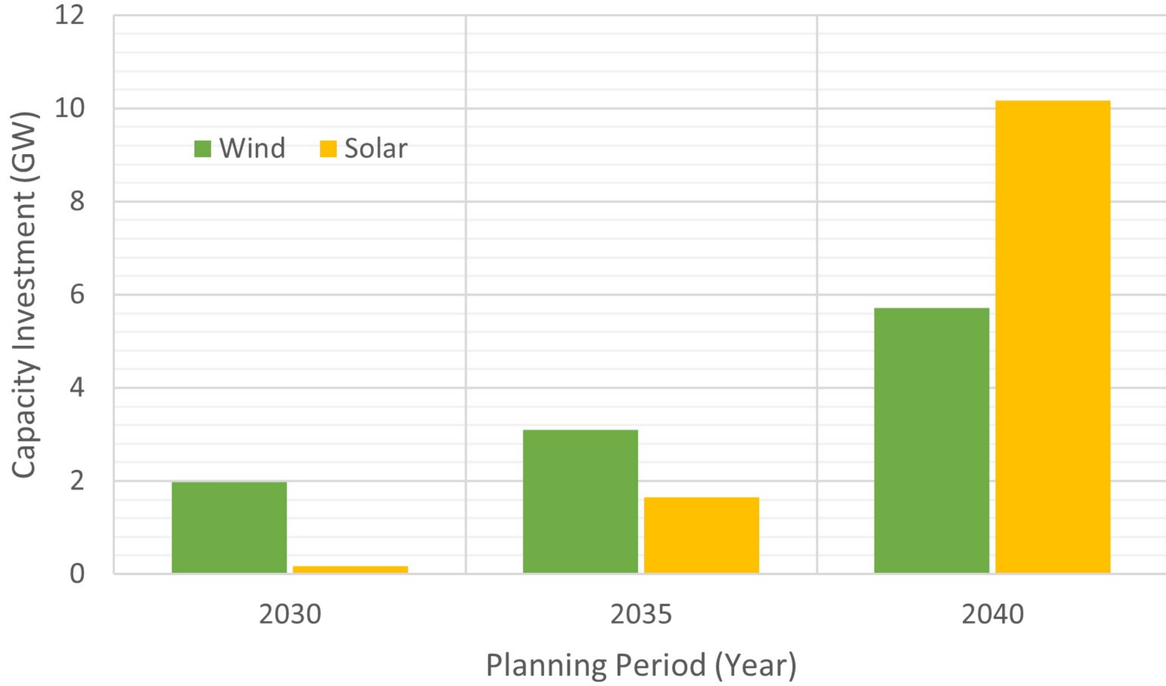

Figure 4.14: Generation Investment for 100% CO_2 Reduction

technology are depicted in Fig 4.16 for each year.

The reason for having fossil fuel generators in the generation mix is the constraint to providing the planning reserve margin considered in Eq. 3.23.

There is a large retirement of coal and gas technologies under this scenario to achieve net-zero electricity production. By the end of the planning horizon, the whole 2.3 GW coal units are retired. There is also a 3.5 GW retirement of GasCC units and 692 MW retirement of GasCT units as presented in Fig. 4.17.

The total 20-year planning costs 15782 M\$ which is about 50% more than that of the base case scenario with no limits on CO_2 emission. The breakdown of planning costs of the system is provided in Table 4.7. The largest costs in this scenario are from FOM and generation investment costs. Generation investment costs about 6100 M\$ which composes 38.6% of the total costs. This cost is due to the large investments in new wind and solar generations to achieve the scenario's goal. The FOM cost of wind turbines is higher than that of coal generators, and FOM for solar

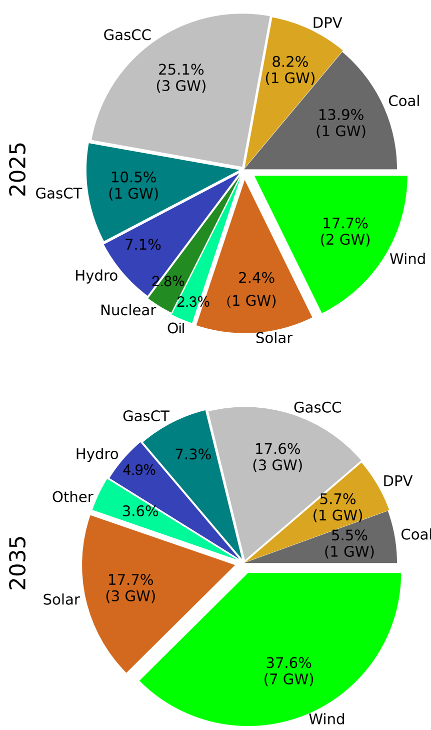

Figure 4.15: Capacity Distribution for 100% CO_2 Reduction

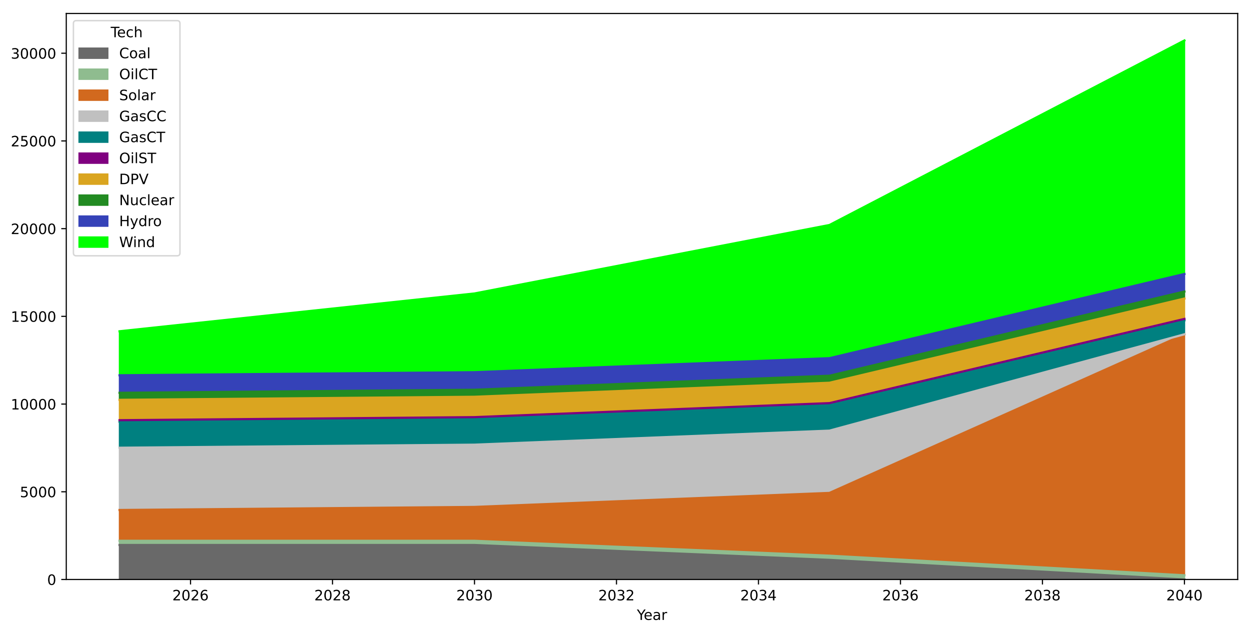

Figure 4.16: Yearly Capacity of Technologies for 100% CO_2 Reduction Scenario

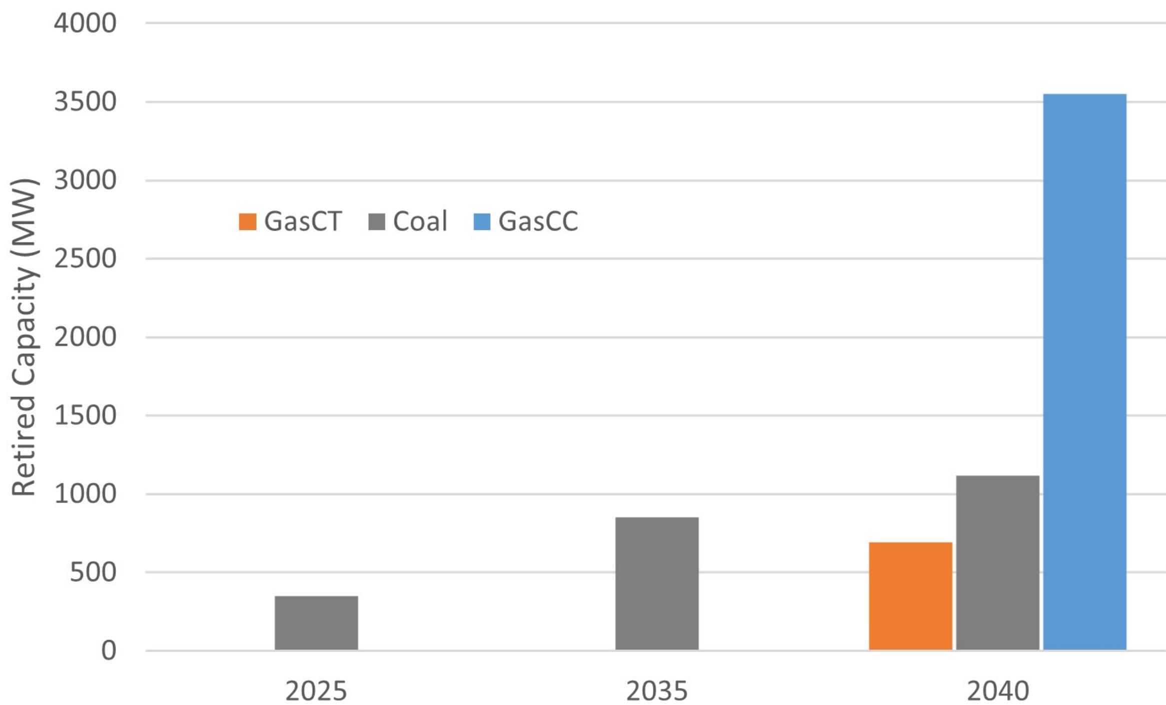

Figure 4.17: Generation Retirement for 100% CO_2 Reduction Scenario

panels costs more than the FOM for gas generators. However, coal and gas generators are mostly retired in this scenario, and wind and solar technologies are substituted for them. This results in an increase in FOM cost which is 6433 M$ in this case.

Item	Cost (M$)	Share(%)
Generation Investment	6094.8	38.6
Transmission Investment	181.2	1.1
Fuel Cost	2663.3	16.9
FOM Cost	6432.6	40.8
VOM Cost	410.9	2.6
Total	15782.8	100

Table 4.7: Cost Function Breakdown for 100% CO_2 Reduction Scenario

There is also a total investment of 181 M$ in the transmission network. The investment in new transmission lines helps to transfer the power generated from the newly added renewable resources to the load centers. The co-optimization of generation and transmission systems in this scenario

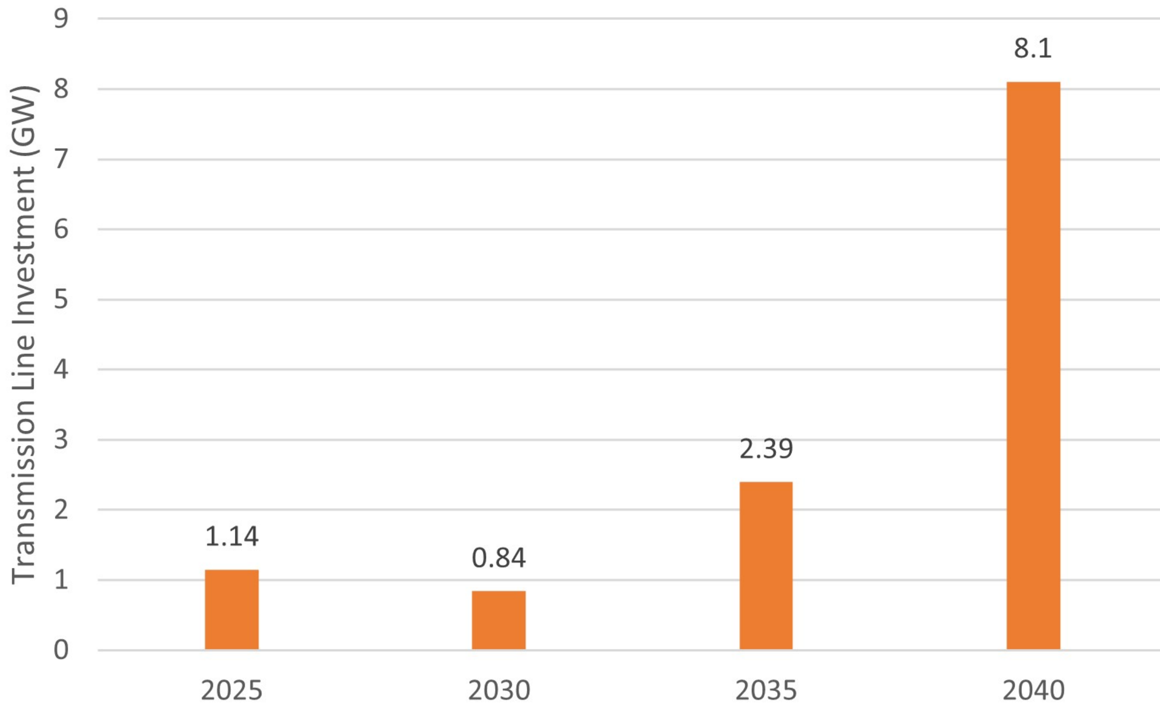

Figure 4.18: Transmission Capacity Investments for 100% CO_2 Reduction Scenario

helps to find the optimal trade-off between the amount of harvested energy from potential wind and solar sites and their transmission cost. A total of 12.5 GW of transmission lines are added to the network in this scenario. Fig. 4.18 shows the transmission capacity investments throughout the planning period.

4.4.5 Comparison of Carbon Reduction Scenarios

In this section, the CEP results of the four cases are compared. First, the shares of different technologies are compared for the final year of the planning horizon in Figure 4.19. This shows that with more restrictions on carbon emission, more fossil-based resources are retired and more renewable resources are added to the system to compensate for the retirement of carbon-emitting sources. On the other hand, due to the lower capacity factor of renewable resources, more capacity has to be added to the system to account for this issue. Figure 4.20 clearly shows that the total generation capacity of cases increases with more integration of renewable resources.

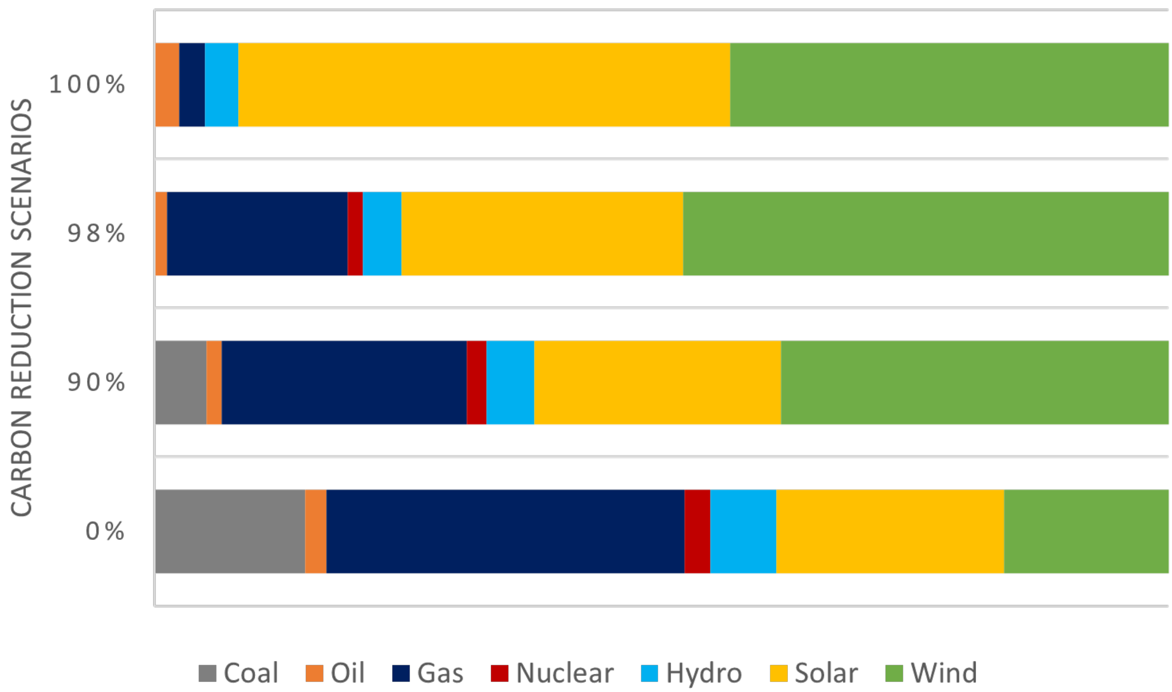

Figure 4.19: Technology Shares for Carbon Reduction Scenarios in 2040

By analyzing the CEP results of different cases for CO_2 reduction, a comparison between these cases shows the importance of incorporating co-optimization planning for future power systems that are highly renewable integrated.

In Table 4.8, the breakdown of costs for four different scenarios is included. For carbon reduction cases, the largest cost is for generation investment, with the cost increasing as the level of CO2 reduction becomes more ambitious. The reason for this is the retirement of fossil-fueled generators and also the lower capacity factor of renewable resources. However, the sum of fuel, FOM, and VOM costs decreases compared to the base case due to the low cost of operating renewable resources.

Even though the transmission cost is not significant compared to other costs, the results show that adding more renewable resources to the system requires investment in new transmission lines. This is because the sites with a high potential for renewable energy are usually located far from load centers. This shows the importance of co-optimization of generation and transmission systems

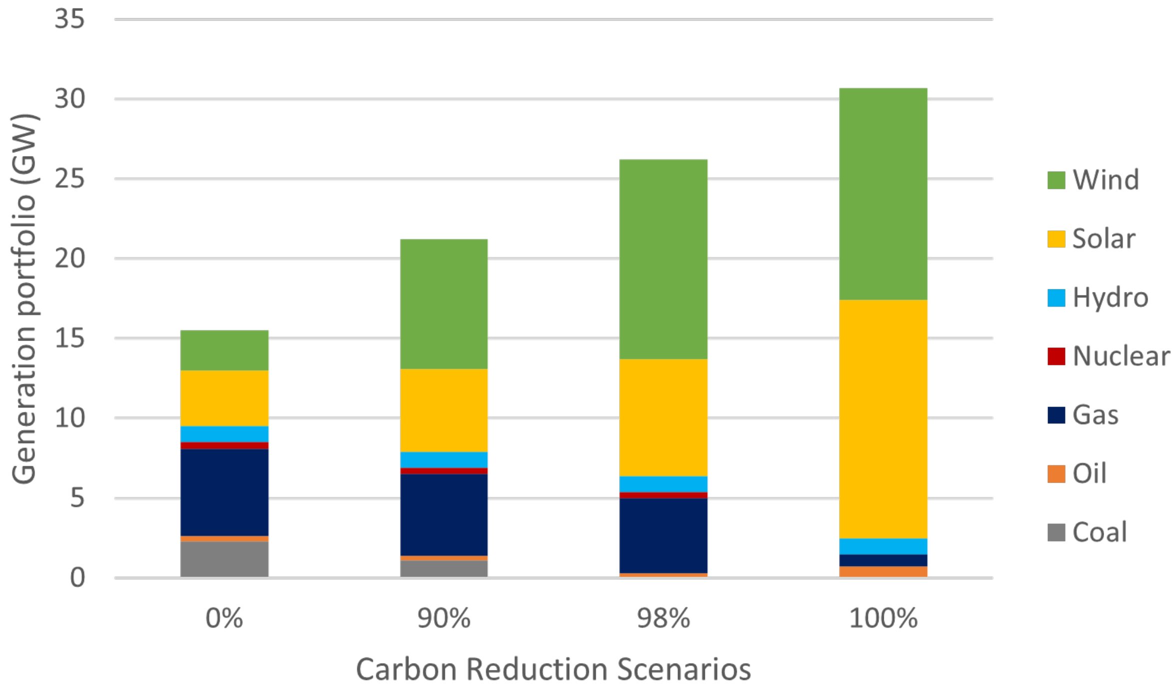

Figure 4.20: Generation Portfolio of Carbon Reduction Scenarios in 2040

in modern power systems compared to the traditional systems with fossil-fueled generations. Co-optimization helps determine the optimal trade-off between the quantity of energy harvested from potential wind and solar sites and the transmission cost.

Overall, it is evident that attaining higher levels of CO_2 reduction is expensive, with costs rising dramatically as reduction levels become more ambitious. However, it is important to note that these costs are part of transitioning to a more environmentally friendly and sustainable energy system, which could have long-term benefits for society and the environment.

	Base Case		90% CO_2 Reduction		98% CO_2 Reduction		100% CO_2 Reduction	
Item	Cost (M$)	Share(%)	Cost (M$)	Share(%)	Cost (M$)	Share(%)	Cost (M$)	Share(%)
Gen. Inv.	212	2	2513.7	20.9	4325.9	31.3	6094.8	38.6
Trans. Inv.	0.0	0.0	49.3	0.4	117.6	0.9	181.2	1.1
Fuel Cost	5178.6	49.4	3574.8	29.7	2946.3	21.3	2663.3	16.9
FOM Cost	4369.6	41.7	5357.7	44.5	5985.1	43.3	6432.6	40.8
VOM Cost	729.7	7.0	534.5	4.4	452.7	3.3	410.9	2.6
Total	10489.9	100	12030	100	13827.6	100	15782.8	100

Table 4.8: Cost Function Breakdown for All Scenarios

4.5 Flexibility Requirements

In conventional power systems mostly including dispatchable generators, such as coal and gas, there has been sufficient flexibility in the generation sector to compensate for changes in load or unexpected outages. However, renewable resources like wind and solar, are not dispatchable, which means we cannot control their power output and their power generation depends on uncontrollable factors such as the speed of blowing wind or the radiance of the sun. Therefore, with these resources the flexibility in responding to changes in the system by controlling the power output of generators is limited. With the high integration of intermittent renewable energy resources into the power system, flexibility becomes a concern because not only are these resources not controllable but also they increase the variation in power balance by their natural volatile and unpredictable power output.

In order to account for this issue, ramping up and ramping down regulation reserves in the planning model are considered. Ramp-up reserve is required when the load is higher than the available power. This can happen when the load is higher than the prediction or the generators are providing less power than expected. Ramp down, on the other hand, is needed when the load is lower than the generated power. In these situations, dispatchable generators which are supposed to provide ramp reserves, adjust their output to compensate for the aforementioned changes. Considering regulation reserve constraints help to make sure that there is enough dispatchable capacity to respond to imbalances in generation and load.

The following section provides analysis of the system under different carbon emission scenarios with reserve regulations imposed on the model.

4.5.1 Base Case with Reserve Requirement

In this base case, where no CO_2 constraints are considered in the planning, the reserve requirements are imposed to see how the investments change in the provided plan.

By applying reserve constraint, there is no change in the generation investment of this case

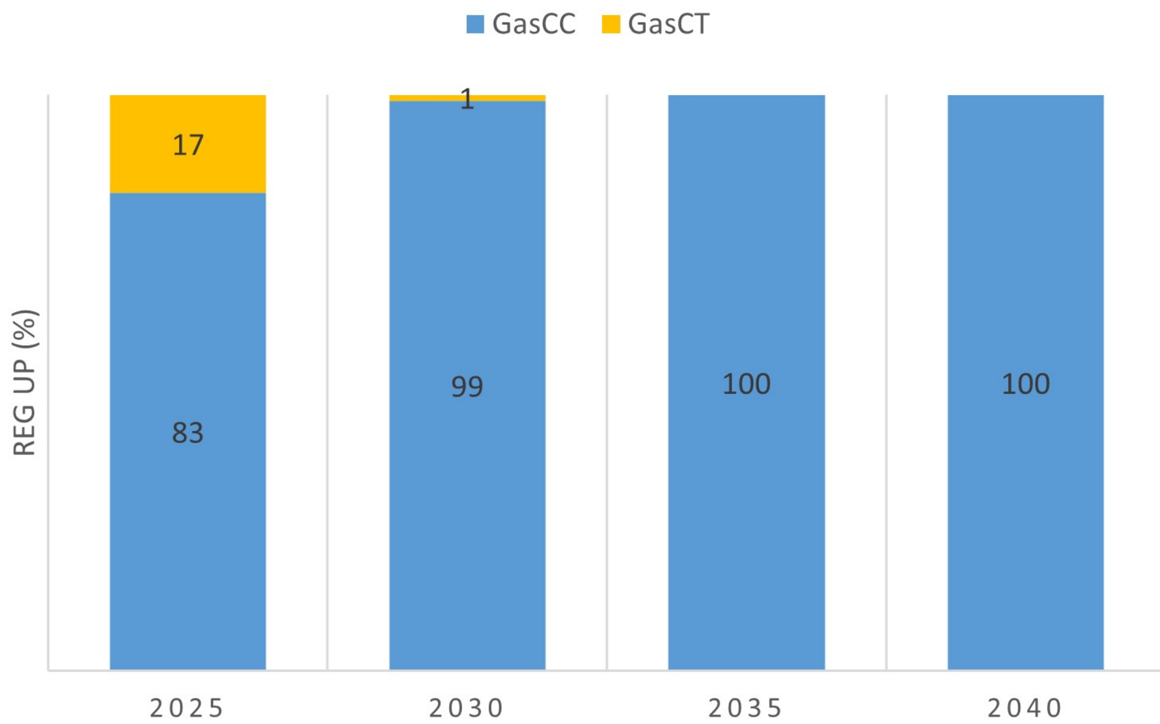

Figure 4.21: Regulation-up Reserve Providers for Base Case Scenario with Reserve Constraints

compared to the other base case with no reserve constraint. All the generation investments, fuel costs, FOM and VOM costs remain the same. There is only the cost of provided reserve added to the objective function, which is 96.5 M$.

The required regulation-up reserve for the whole planning period of this case is 4 GW, which costs 56.2 M$. This reserve is provided by gas technologies as depicted in Fig. 4.21. Among the available generation technologies, gas technologies are fast in response to power changes and they can rapidly ramp up or down their power output in order to keep the balance between electricity supply and demand.

Costs of regulation-up for GasCC and GasCT are 10 and 11 $ per MW, respectively, which are the lowest after the 7 $/MW regulation-up cost of hydro plants. Since hydro plants have zero VOM cost, their capacity is fully used to provide energy and is not kept idle for regulation-up reserve. Therefore, GasCC and GasCT are preferred to be used as regulation-up reserve resources.

For regulation down reserves, hydro-power plants are responsible for the whole planning period. Due to their zero VOM cost, the hydro-power plants are already running and providing energy. Therefore, when a regulation-down reserve is required, hydro is the best option to reduce its generated power because of its fast response time and low regulation-down cost. The total cost of the regulation-down reserve for this scenario is 40.3 M$.

4.5.2 90% Carbon Reduction with Reserve

With the goal to decrease the CO_2 emissions by 90%, electric energy provided by renewable resources is almost doubled as studied in section 4.4.2. Adding more renewable energy to the generation mix requires more reserve capacity as the volatility increases in the system. In this scenario, the total regulation-up reserve required is 6.7 GW, adding a 103.3 M$ cost to the plan. The required regulation-down for this planning period is 5.9 GW, which is again provided by hydro plants and costs 59 M$. The breakdown of investment and operation costs for this case is provided in Table 4.9. Reserve constraint with a total cost of 162.4 M$ secures the operation of the power system while integrating renewable resources.

Item	Cost (M$)	Share(%)
Generation Investment	2548.1	20.9
Transmission Investment	50.9	0.4
Fuel Cost	3545.6	29.1
FOM Cost	5380.9	44.1
VOM Cost	531.9	4.3
Reserve Cost	145.7	1.2
Total	12203.5	100

Table 4.9: Cost Function Breakdown for 90% Carbon Reduction with Reserve

Accounting for reserve requirements in the planning model, some changes occur in investments. There is a slight change in generation and transmission investment costs compared to the case in 4.4.2. The reserve consideration in this scenario justifies the increase in generation and transmission line investments. More generation capacity is required to provide the reserves and

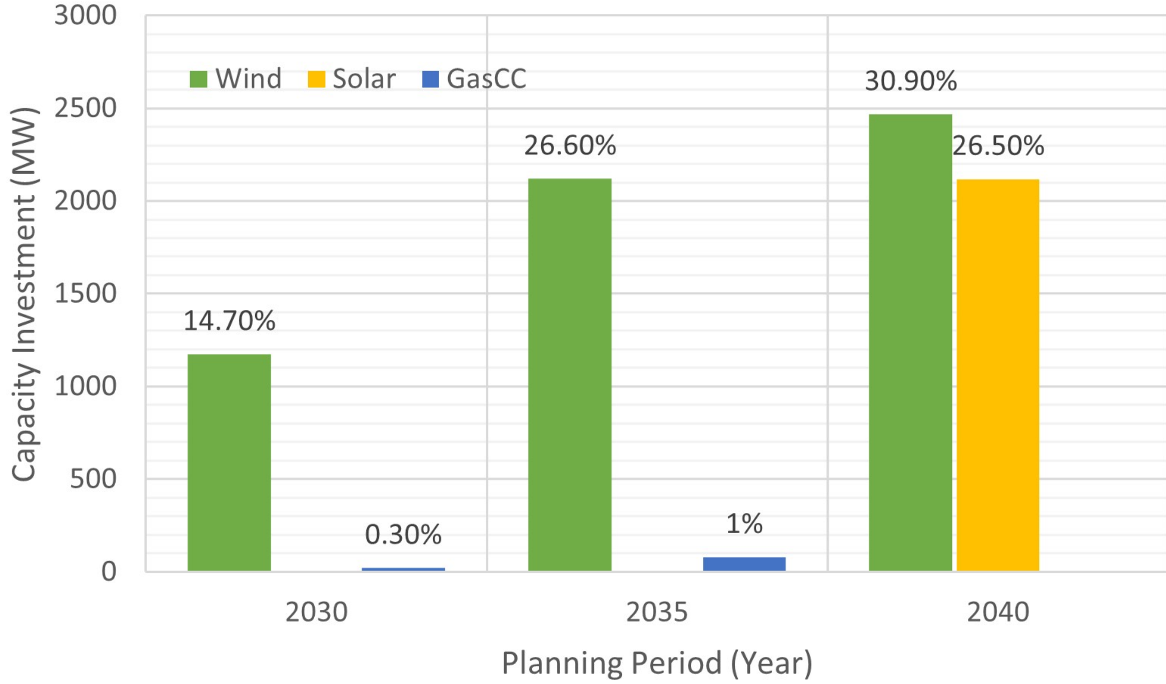

Figure 4.22: Generation Capacity Investments for 90% CO_2 Reduction Scenario with Reserve

more transmission capacity is needed to deliver these reserves.

As Fig. 4.22 shows, there are 14 and 200 MW more investments in GasCC and wind technologies, respectively. On the other hand, there is 212 MW less investment in solar energy. The reason for this change is that GasCC is a reliable power source and an affordable reserve provider. Wind generation also has a higher capacity factor than solar, which means wind power is more reliable in generating electricity and requires less reserve compared to solar. Therefore, considering reserve in the CEP leads to investing in more reliable resources to make sure that the new configuration is operationally viable.

The reserve providers are more diverse in this case as depicted by each technology's share in Fig. 4.23. GasCT and coal technologies provide the regulation-up reserves during the first 5 years of the planning period when still the CO_2 reduction is not fully forced. For the next two periods, GasCC technologies mostly supply the required reserve. In order to reduce the carbon footprint by the year 2040, hydro plants also contribute to regulation-up reserve.

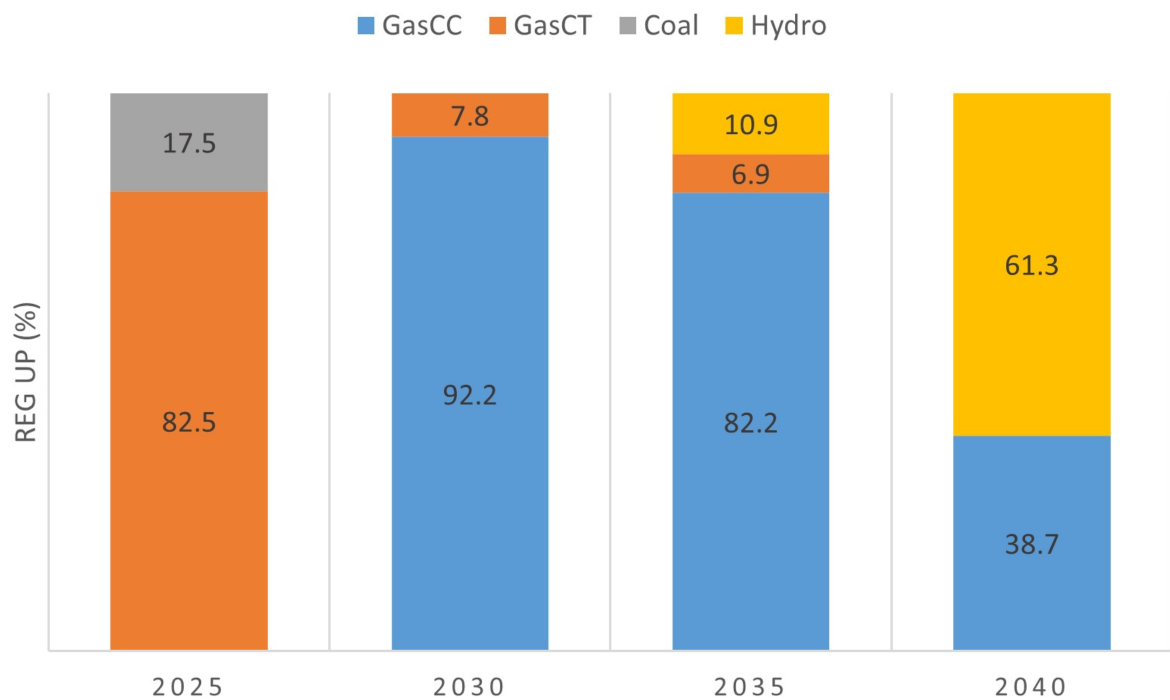

Figure 4.23: Regulation-up Reserve Providers for 90% CO_2 Reduction Scenario with Reserve

Retirement of coal technologies is reduced from 1241 MW in the case with no reserve constraint, to 1176 MW in this case. This is due to utilizing coal generators as a reserve provider.

4.5.3 98% Carbon Reduction with Reserve

In the case 4.4.3, the penetration level of wind and solar resources reaches 75% of the generation portfolio. The high share of renewable resources in the generation system necessitates considering reserve services to compensate for deviations in generated power by these resources.

A total of 6.6 GW regulation-up reserve is required in this case, which is provided by gas and hydro technologies. As Fig. 4.24 shows, GasCT is the main provider of the regulation-up reserve during the first years of the planning period. Then GasCC replaces it, and finally, hydro plants provide the major part of the required reserve. This change in the reserve providers is due to the more strict constraint on CO_2 reduction. Providing regulation-up reserve costs 88.1 M$, in this case.

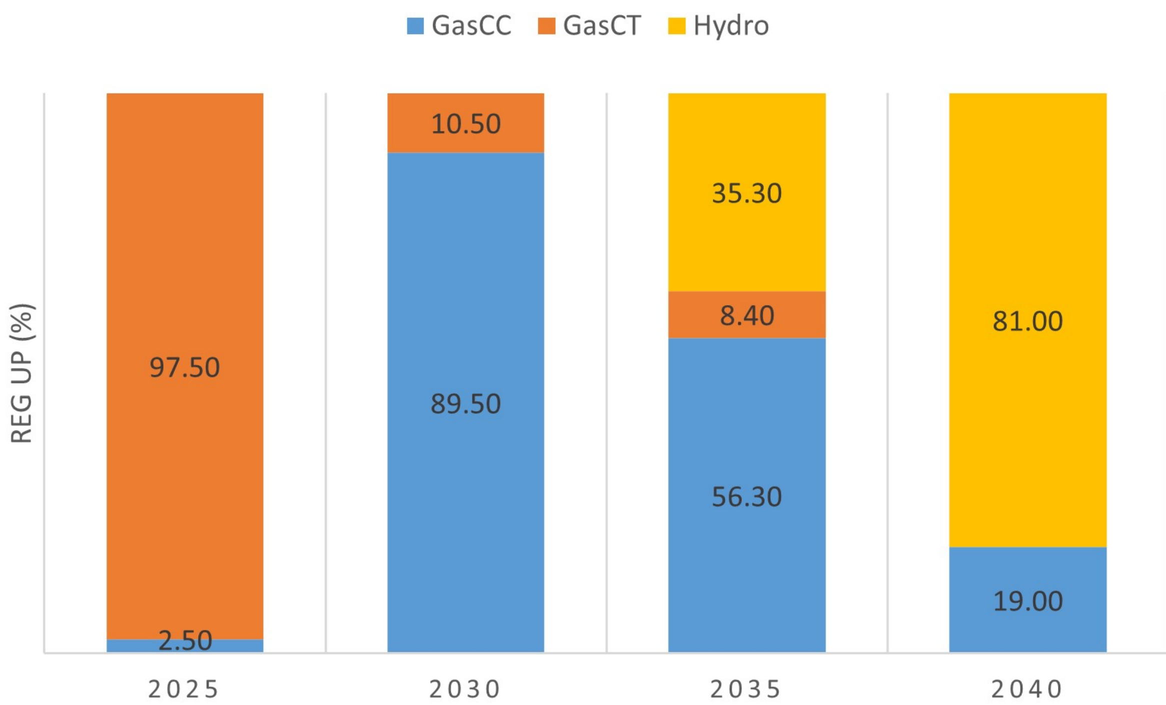

Figure 4.24: Regulation-up Reserve Providers for 98% Scenario with Reserve Constraints

The regulation-down requirement for this scenario is 6.7 GW, because of the higher penetration of renewable resources. Hydro power plants provide this service since they are already supplying energy to the system and are able to reduce their generation in a timely manner in response to an increase in the generation of other non-dispatchable resources. The cost of providing this reserve is 66.4 M$.

Considering reserve requirements in the model changes the investments in the generation system. There is 14.9 GW of new investment in wind and solar energy. Solar capacity has increased to 4.9 GW compared to that of 4.3 GW in the case 4.4.3. Investment in wind energy capacity is the same as that of case 4.4.3. Fig. 4.25 presents the generation investments during the planning horizon.

The breakdown of investment and operation costs for this case is shown in Table 4.10. Comparing these costs to the costs of 98% CO_2 reduction case without reserve consideration (Table 4.6), a 135.7 M$ increase in the generation investment cost is noticeable. This is due to adding more solar

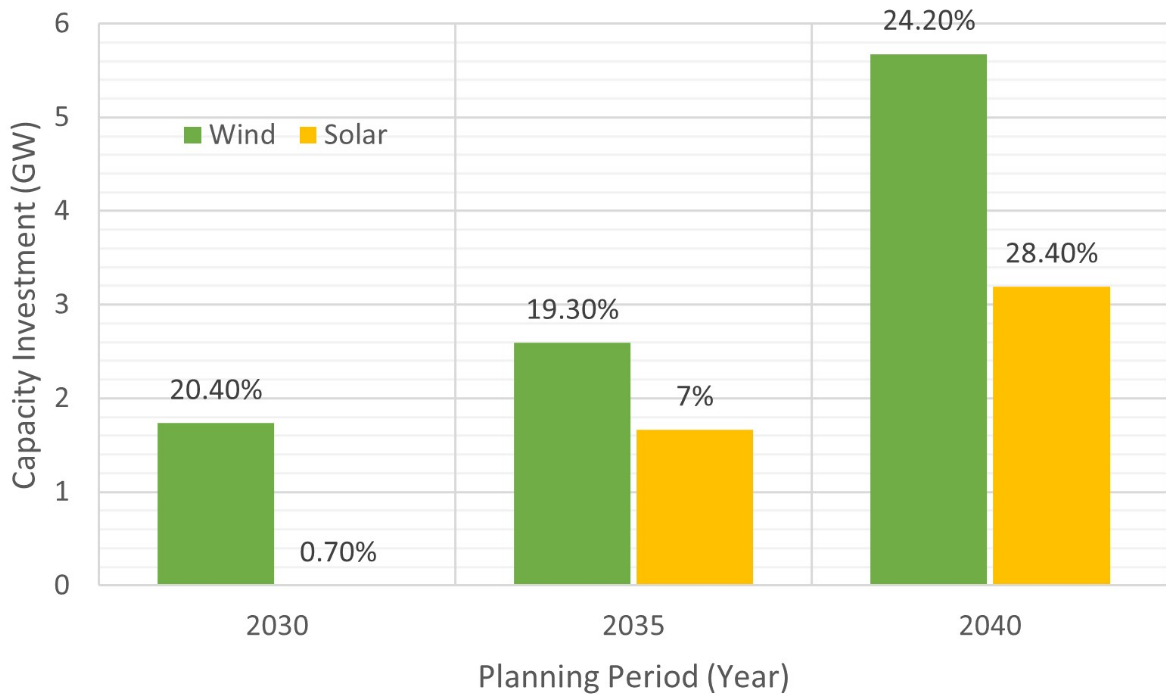

Figure 4.25: Generation Capacity Investments for 98% CO_2 Reduction Scenario with Reserve

energy to the generation mix. Fuel cost decreases in this case because fossil-fueled technologies are used more as a reserve than an energy provider. The FOM cost also rises by keeping some generators idle to be able to contribute to reserve needs. The total cost of supplying reserve is 154.5 M$. The total increase in investment cost, caused by the reserve constraint, is 279 M$.

4.5.4 100% Carbon Reduction with Reserve

In order to achieve 100% CO_2 reduction in electricity generation, a large share of renewable resources is added to the system. When the percentage of intermittent generation increases, having enough reserve available becomes more vital to keep the power system running without interruptions.

In this case, wind generation composes 44% of the generation (13.3 GW) and solar generation provides 49% (15 GW) of the generation as depicted in Fig. 4.26. Although 6.6 GW of coal and gas technologies are retired in this case, there is still a small percentage of fossil-fueled technologies

Item	Cost (M$)	Share(%)
Generation Investment	4461.6	31.6
Transmission Investment	117.5	0.8
Fuel Cost	2911.9	20.6
FOM Cost	6013.3	42.6
VOM Cost	449.8	3.2
Reserve Cost	154.5	1.1
Total	14108.6	100

Table 4.10: Cost Function Breakdown for 98% Carbon Reduction with Reserve

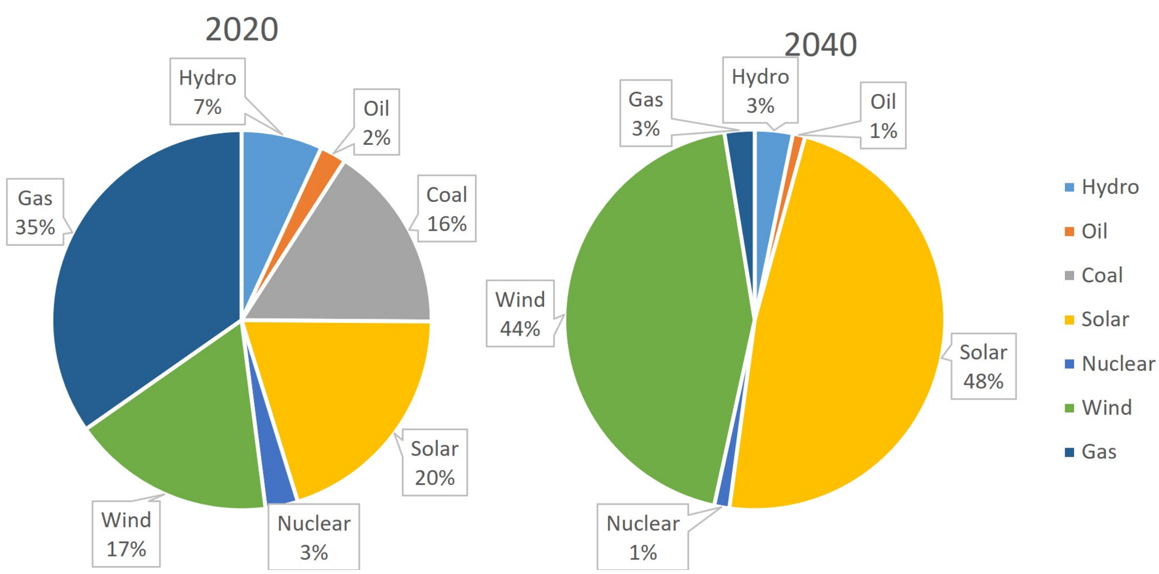

Figure 4.26: Capacity Distribution for 100% CO_2 Reduction with Reserve

in the generation mix. They are not fully retired and are kept in the generation mix to provide the planning reserve margin (PRM) and the regulating reserves. Since these technologies are not actively used for generating power, and their dispatched power in the power balance equation is zero, their CO_2 emission is not considered in the CO_2 emission constraint.

The total required reserve for this case is 7.5 GW, which is provided by gas and hydro plants. Fig. 4.27 shows that in the year 2020, the regulation-up comes almost from GasCT technology. This is because GasCT has the highest VOM cost among all the candidates for regulation reserve, which makes it suitable to be used as a reserve provider rather than an energy resource. The other

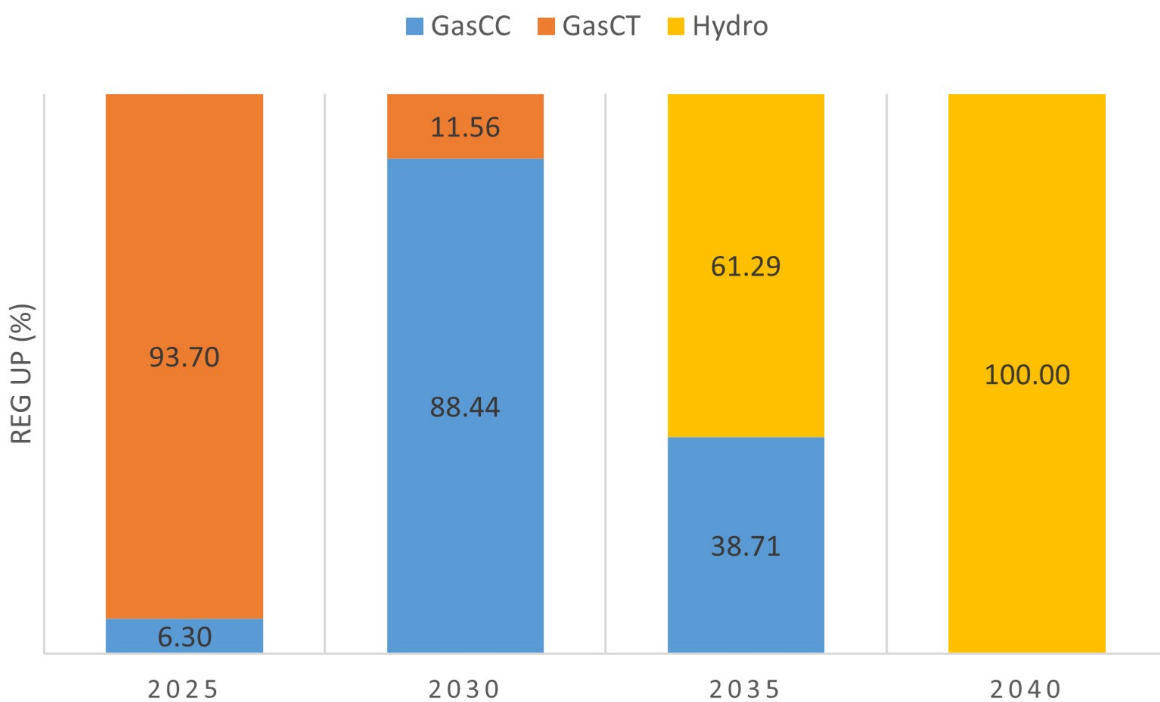

Figure 4.27: Regulation up reserve providers for 100% CO_2 Reduction Scenario with Reserve

options, like GasCC with 2.2 VOM and hydro with zero VOM, are used to supply energy at full capacity during this year.

However, in 2030 and 2035, GasCC becomes the main provider of the regulation-up reserve. The reason is that GasCT technologies are used as PRM and GasCC is preferred to provide the regulation-up reserve. In 2040, since fossil fuel generators are not supposed to generate power in normal conditions, hydro-power plants provide all the ramp-up reserves.

For regulation down reserves, hydro power plants are responsible for the whole planning period. It is because the hydro power plants are already running and providing energy due to their zero VOM cost, therefore they can easily reduce their power whenever required, and provide regulation-down reserves.

Item	Cost (M$)	Share(%)
Generation Investment	6227.8	38.7
Transmission Investment	190.1	1.2
Fuel Cost	2600.8	16.1
FOM Cost	6508.4	40.4
VOM Cost	404.3	2.5
Reserve Cost	172.6	1.1
Total	16104	100

Table 4.11: Cost Function Breakdown for 100% Carbon Reduction with Reserve

4.6 Energy Storage System Integration as an Energy Provider

The planning results in previous cases indicate that wind and solar energy will be the basis for expanding and decarbonizing power systems. Due to the production variability of wind and solar energy, it is necessary to consider enough reserve resources to compensate for the deviations in their power generation. Including energy storage systems in the system facilitates the integration of these resources into the grid and helps to achieve high penetration levels of volatile energy.

Energy storage systems can help the integration of renewable resources in two ways. They can store the excess generated energy from renewable resources to reduce power curtailment (arbitrage), and also compensate for their shortfall if they generate lower energy than anticipated to prevent load shedding (reserve). The energy generated by renewable resources depends on weather conditions and it is not dispatchable like conventional generators, which means system operators cannot fully control their output energy. Although improvements in forecasting methods allow for more precise predictions of wind and solar power output, the actual power generated by these sources may still differ from the forecast. Therefore, it is vital to employ energy storage systems to store excess energy or provide reserve services when needed.

This section examines the potential contribution of integrating energy storage into power system planning as an energy provider. The role of energy storage systems as a reserve provider is studied in the next section.

4.6.1 Base Case with Energy Storage as Energy Provider

In this case, energy storage is integrated into the power system and further investments in it are allowed. This way, the general benefits of adding energy storage to the system can be studied, even when there is no constraint on CO_2 emissions.

There is a change in generation investments when there is storage compared to the case in section 4.5.1 without investment in storage systems. Here the added capacity of GasCC is reduced to 178 MW, which is less than half of its amount for the case without storage. Instead of investing in solar energy, there is a 540 MW investment in energy storage technology. Fig. 4.28 presents the details of generation investment during the planning period. In this case, the total amount of invested capacity is 718 MW, which is 275 MW less than the case in 4.5.1.

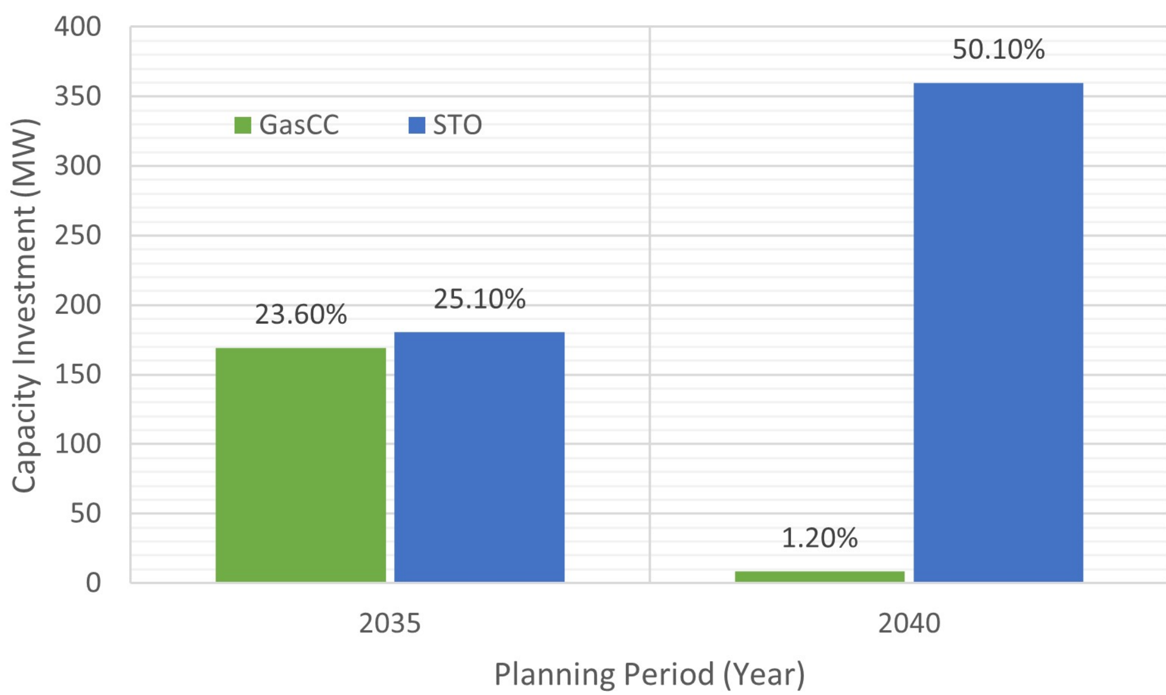

Figure 4.28: Generation Capacity Investments for Base Case with Energy Storage as Energy Provider

Even though this case has less investment in generation capacity, the presence of energy storage leads to 47 MW more retirement of coal generation. The total amount of capacity added to the power system is 650 MW, in this scenario.

The regulation reserve providers are similar to the 4.5.1 case. The GasCC technologies supply the majority of the regulation-up and hydro plants provide the regulation-down reserve. Therefore, the cost of the regulation reserve is the same as 96.5 MW in the previous case.

Investment and operation costs are slightly different due to the presence of energy storage in the model as Table 4.12 shows. Considering the energy storage system results in a 30 M$ saving in the total planning costs.

Item	Cost (M$)	Share(%)
Generation Investment	156.24	1.96
Transmission Investment	0.0	0.0
Fuel Cost	5218.26	48.99
FOM Cost	4335.09	41.26
VOM Cost	748.84	6.88
Reserve Cost	96.53	0.91
Total	10556.1	100

Table 4.12: Cost Function Breakdown for Base Case with Energy Storage as Energy Provider

4.6.2 90% Carbon Reduction with Energy Storage as Energy Provider

The potential benefits of integrating energy storage into a power system with higher penetration of renewable energies are examined in this case. The investment results of this case are compared with the case in 4.5.2, where storage systems are not considered.

Fig. 4.30 illustrates the generation investments for this scenario. There is no investment in GasCC technology and the 2.1 GW investment in solar is reduced to 1.6 GW. There is also a decrease in wind energy investment. The total added wind capacity is 5.4 GW, which is 800 MW less compared to the wind investment in case 4.5.2. The total investment in wind and solar generation is 7 GW, in this case. The capacity of the energy storage systems added in this case is 1.5 GW. A higher retirement of coal technology happens in this case as represented in Fig. 4.29.

All the 2.7 GW of coal generation retires, while in the case without storage 1.2 GW of coal capacity is retired.

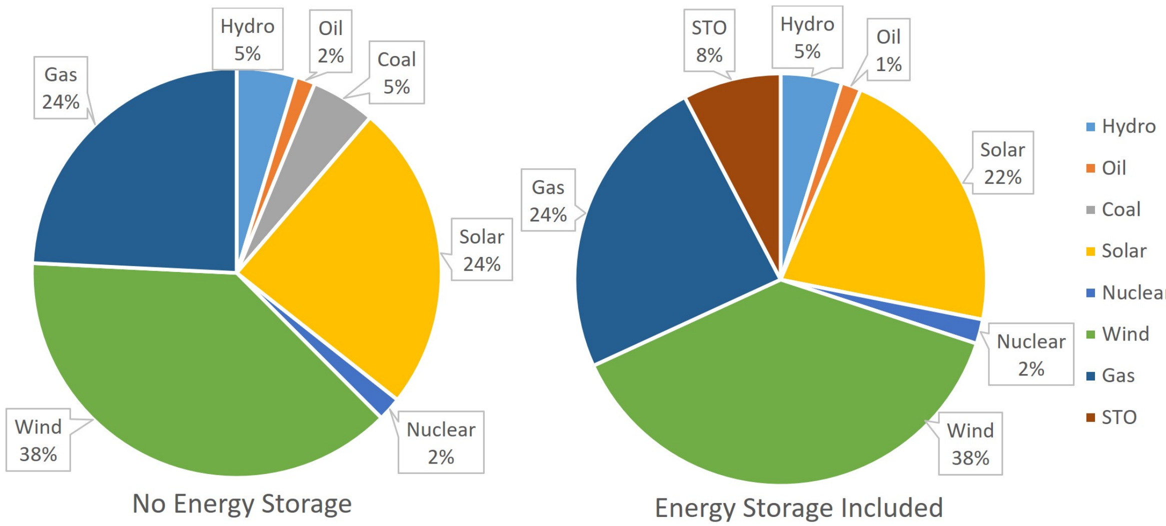

Figure 4.29: Comparison of Generation Mix with and without Energy Storage Systems for 90% CO_2 Reduction

There is a total reduction of 2.1 GW of generation capacity compared to the case without storage. This 2.1 GW reduction is compensated by 1.6 GW of energy storage as Fig. 4.30. Energy storage systems help store the excess produced energy from wind and solar resources, and discharge it to the power system when they generate less energy than expected. This way the generated power from intermittent renewable energies is harnessed more efficiently and the same electricity load is supplied by a lower generation capacity. This confirms the importance of integrating energy storage systems into a highly renewable power system.

By integrating energy storage, a lower amount of renewable energies is required for the same level of CO_2 emission reduction. Having less intermittent generation resources in the system also results in lower reserve requirements. Moreover, energy storage systems help with the reliability of the system, as they can couple with wind and solar generation and mitigate their fluctuations by storing their excess energy and compensate for their energy shortcomings. As a result, the reserve requirement for this scenario decreases 3 GW in comparison to the 4.5.2 case. The total amount of required reserve is 9.6 GW, which includes 4.7 GW regulation-up and 4.9 regulation-down

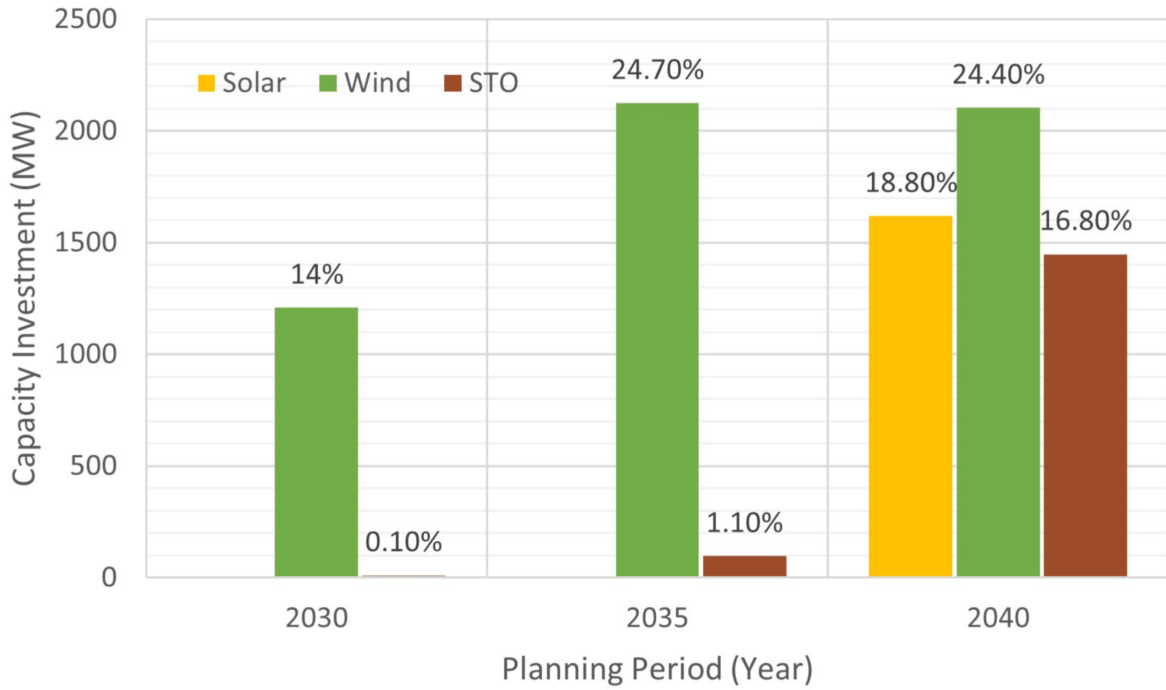

Figure 4.30: Generation Capacity Investments for 90% CO_2 Reduction with Energy Storage as Energy Provider

reserves.

The presence of energy storage in a highly renewable penetrated power system leads to cost saving in the investment and operation costs of the power system. Table 4.13 provides the details of these cost. FOM and reserve costs are reduced by 148 and 25 M$, respectively compared to the case without storage. The generation investment cost is increased by 63 M$, which is due to investments in energy storage to compensate for less capacity investments in wind and solar, as well as more retirement of coal technologies.

4.6.3 98% and 100% Carbon Reduction with Energy Storage as Energy Provider

Here the impacts of integrating energy storage systems on the two CO_2 emission scenarios are analyzed. The capacity investments for these scenarios are compared to those of the two other cases without energy storage. Fig. 4.31 presents the generation capacity investments for all four cases. By including storage technology in the investment model, it replaces some of the wind

Item	Cost (M$)	Share(%)
Generation Investment	2610.8	21.6
Transmission Investment	50.8	0.4
Fuel Cost	3559.2	29.4
FOM Cost	5232.8	43.2
VOM Cost	535.5	4.4
Reserve Cost	120.3	1.0
Total	12109.4	100

Table 4.13: Cost Function Breakdown for 90% Carbon Reduction with Energy Storage as Energy Provider

and solar invested capacities. In both cases with storage, there is more MW of invested capacity compared to the cases without storage. The reason for the additional investments in the generation is the retirement of more fossil-fueled technologies in these cases. In the 98% CO_2 reduction case, there is 1 GW of extra retirement, and for 100% CO_2 reduction case, 1.1 GW more is retired.

With the presence of energy storage, the reserve requirements decrease for both cases as shown in Fig. 4.32. For the 98% CO_2 reduction scenario, the total required reserve reduces by 2 GW, while for the 100% CO_2 reduction case, there is a 2.2 GW reduction in reserve requirement when energy storage is used. The difference between the reduction in reserve requirement in these two cases shows that the presence of energy storage becomes more important as the penetration of renewable resources increases.

The details of the investment and operation costs of these scenarios are provided in Table 4.14. There is an increase in generation investment cost due to retiring more fossil-fueled technologies and adding more generation capacity consequently. Other investment costs are decreased due to the integration of energy storage. Fig. 4.33 depicts the change in various costs of the planning for both 98% and 100% CO_2 reduction cases in comparison to the cases in which energy storage is not present.

The transmission investment costs decrease when energy storage contributes to the system. Energy storage systems are mostly located in the buses where wind and solar energy are invested.

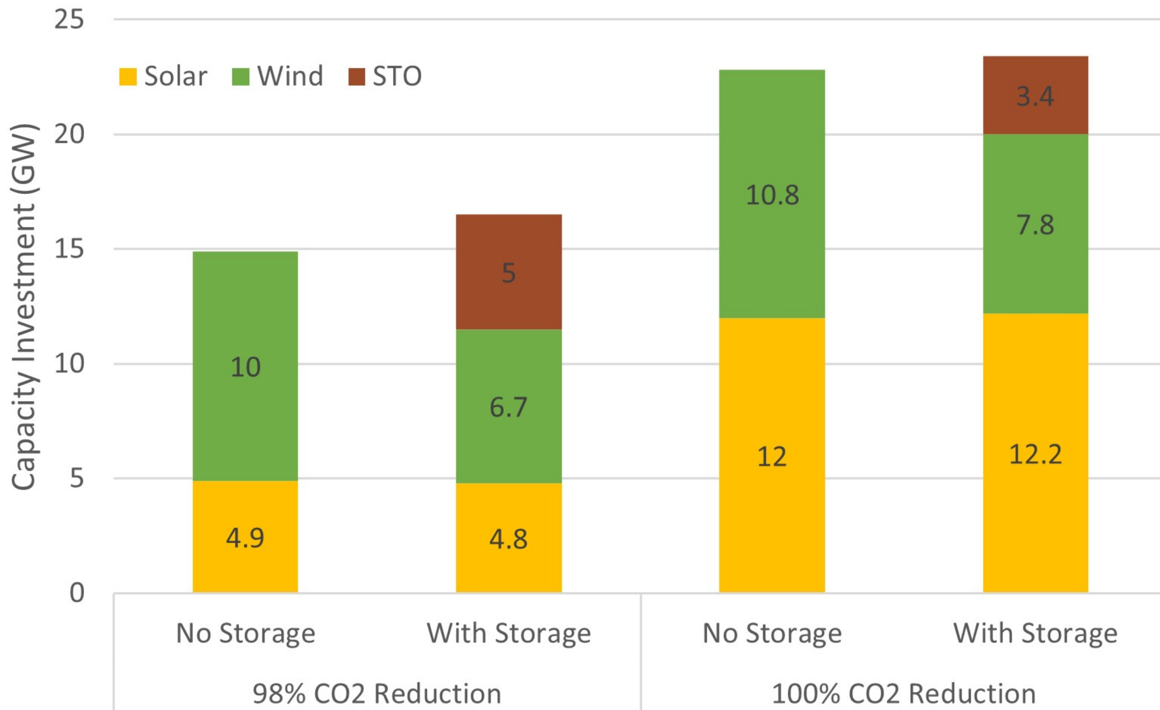

Figure 4.31: Generation Capacity Investments for 98% and 100% CO_2 Reduction with Energy Storage as Energy Provider

This helps manage the deviations in the generated power locally and reduces the need to invest in new transmission lines. There is a 4 GW investment in new transmission lines for the 98% CO_2 reduction case and 12 GW of new transmission lines in 100% CO_2 reduction scenario.

The total cost of the long-term plans in both CO_2 reduction cases decreases with the presence of energy storage. For the 98% CO_2 reduction case, there is 411 M$ saving in the total costs, and for the 100% CO_2 reduction case, 244 M$ is saved compared to the case with no energy storage.

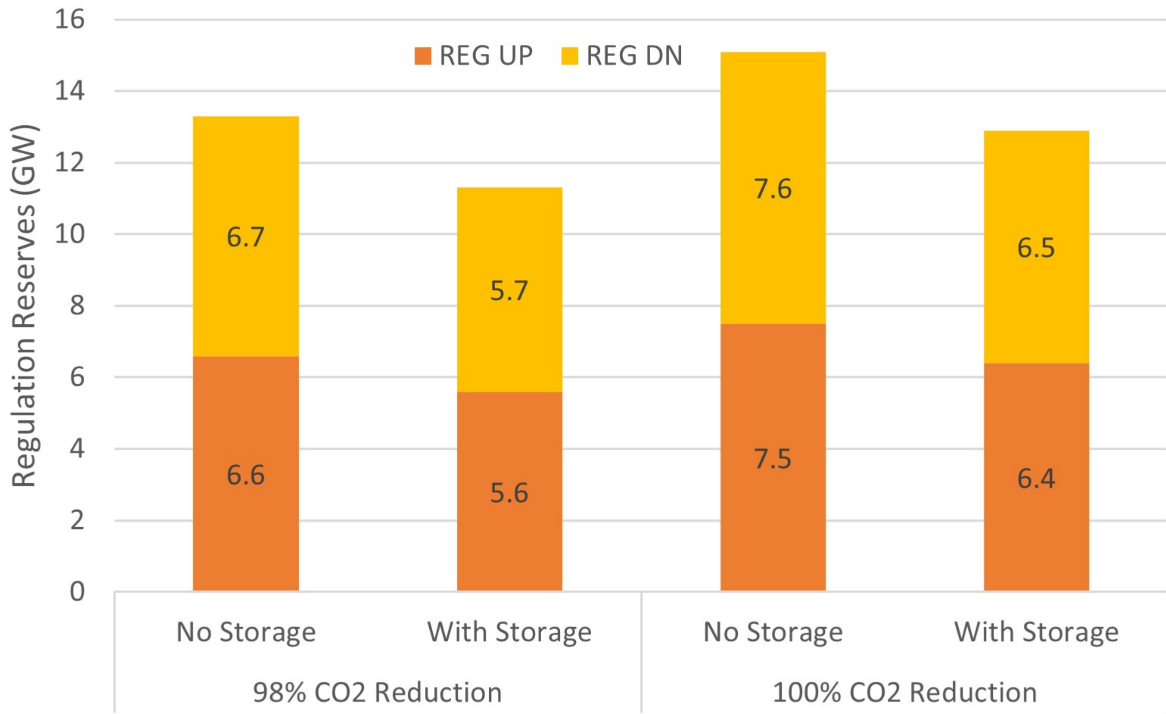

Figure 4.32: Regulation Reserve Requirements for 98% and 100% CO_2 Reduction with Energy Storage as Energy Provider

	Cost (M$)	
Item	98% CO_2 Reduction	100% CO_2 Reduction
Generation Investment	4535.38	6214.7
Transmission Investment	62.0	176.6
Fuel Cost	2850.7	2624.2
FOM Cost	5670.7	6289.3
VOM Cost	442.0	407.8
Reserve Cost	130.9	147.0
Total	13697.6	15859.6

Table 4.14: Cost Function Breakdown for 98% and 100% CO_2 Reduction with Energy Storage as Energy Provider

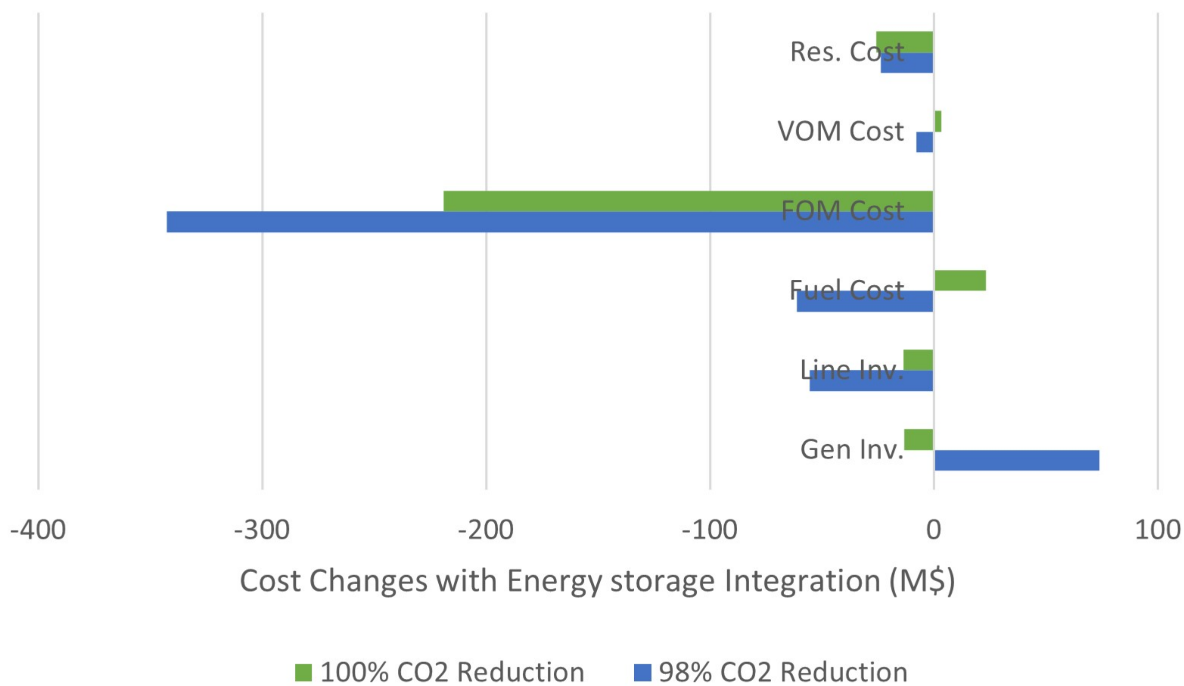

Figure 4.33: Changes in Investment and Operation Costs of the System for 98% and 100% CO_2 Reduction with Energy Storage as Energy Provider in Comparison to the Cases without Energy Storage

4.7 Energy Storage Integration as Energy and Reserve Provider

As discussed earlier, one of the energy storage contributions is providing regulation reserve to highly renewable penetrated power systems. This section evaluates the advantages of utilizing energy storage as a reserve provider. In this case, energy storage systems are allowed to contribute to the power system's reserve requirements. The breakdown of investment costs of the system is shown in Table 4.15.

Item	Cost (M$)	Share(%)
Generation Investment	6133.6	39.1
Transmission Investment	176	1.1
Fuel Cost	2639.1	16.8
FOM Cost	6254.1	39.8
VOM Cost	407.4	2.6
Reserve Cost	86.9	0.6
Total	15699	100

Table 4.15: Cost Function Breakdown for 100% Carbon Reduction with Energy Storage as Energy and Reserve Provider

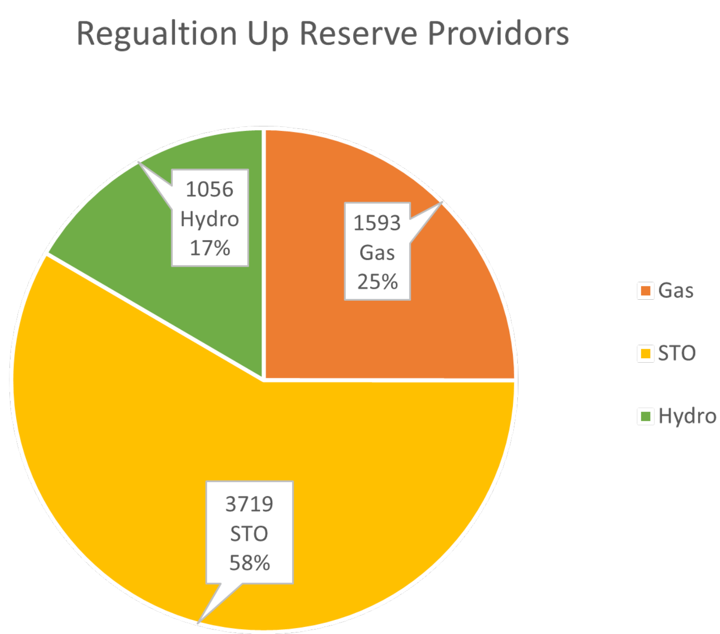

Figure 4.34: Regulation Up Reserve Providers for 100% CO_2 Reduction with Contribution from Energy Storage

The total required reserve for this case is 12.9 GW, which is provided by gas, hydro, and storage technologies. Fig. 4.34 shows that the energy storage system provides almost 60% of the required reserve in this case. This is because energy storage has the lowest VOM cost, which makes it a preferable candidate to provide reserve to the system.

Comparing the investment costs of this case with the previous case where storage was used only as an energy source, Table 4.16 shows a considerable decrease in reserve costs when energy storage provides reserve service as well. In fact, energy storage improves the efficiency of renewable energies' integration into the system by storing excess energy when demand is low and discharging its energy to the system when needed. In addition to that, if used as a reserve provider, it will reduce the need for adding more generation capacity to provide the required reserve. Therefore, the application of energy storage as both energy and reserve resources improves the system's overall performance and reduces the power system's investment costs compared to the other case.

	Cost (M$) with Storage as		Saving (M$)
Item	Energy & Reserve	Energy Only	
Generation Investment	6133.6	6214.7	81.1
Transmission Investment	176.0	176.6	0.6
Fuel Cost	2639.1	2624.2	-15
FOM Cost	6254.1	6289.3	35.2
VOM Cost	407.4	407.8	0.4
Reserve Cost	86.9	147.0	60.1
Total	15699.0	15859.6	**160.6**

Table 4.16: Investment Cost Comparison Between Different Applications of Energy Storage for 100% CO_2 Reduction

4.8 Network Size Reduction for Planning Purposes

As mentioned earlier in the thesis, CEP can be computationally intensive in real power systems with thousands of buses and transmission lines, taking months to run on high-end computer servers. One typical way to decrease the computation burden and tackle the intractability problem is to reduce the network size while maintaining power flow accuracy.

In this process, the key buses of the network should be identified based on the study focus, and maintained in the model, while the other buses get eliminated, and the lines connecting to them are represented by equivalent lines. An effective technique for decreasing the size of power systems and simplifying the analytical procedure is the Kron reduction technique [95]. This method has been used for many different studies in power systems, and it can be beneficial for the purpose of this study, which is planning future generation and transmission investments.

4.8.1 Kron Reduction

Kron reduction is a power system network modeling technique to simplify large interconnected networks by reducing them to a smaller equivalent network. The equivalent network is supposed to preserve the essential characteristics of the original network while making it simpler to analyze and simulate.

The Kron reduction method is based on the Gaussian elimination technique, which is used to solve linear equations. In this approach, a matrix is transformed into an upper triangular form through a series of row operations, such as multiplying a row by a constant and adding it to another row.

To apply Kron reduction to a power system network, the admittance matrix of the network is partitioned into four sub-matrices. The sub-matrix corresponding to the reduced network is then inverted, and the remaining sub-matrices are multiplied to obtain the residual network's admittance matrix.

The reduced network is obtained by eliminating the rows and columns of the admittance matrix corresponding to the buses and branches that belong to the residual network. This is done by multiplying the inverse of the reduced network sub-matrix with the rows and columns of the admittance matrix corresponding to the residual network.

In a power system with N buses, the admittance matrix Y is a square matrix with dimensions $N \times N$ that describes the admittance connection between all the buses in a network. This matrix simplifies numerous calculations and has been applied to power system optimization issues and studies of power flow. This matrix would be huge for large systems with thousands of buses, making the computations intense. In 1939, Gabriel Kron presented a mathematical method to obtain a reduced but electrically-equivalent network [96]. This method involves defining which buses are to be retained and which ones are to be removed from the old admittance matrix in order to calculate the admittance matrix of the new reduced network. Equations 4.1 and 4.2 present the Kron reduction formulation based on the Gaussian elimination on the admittance matrix Y.

$$Y^{red} = K - LM^{-1}L^{\top} \tag{4.1}$$

$$Y_{jk}^{red} = Y_{jk}^{full} - \frac{Y_{jn}Y_{nk}}{Y_{nn}} \tag{4.2}$$

After applying the reduction technique to the system, it is important to validate the accuracy of the reduced model against the original model to ensure the reduction process is valid. The power flows of the lines are compared in both full and reduced models to study how effective and accurate is the reduced model.

4.8.2 Model Reduction of IEEE 118-bus System

This section applies the proposed CEP model to the standard IEEE 118-bus system widely used in power system studies. This test system represents a simple approximation of the Midwest portion of the American Electric Power System in 1962 [97]. A single-line diagram of the system is

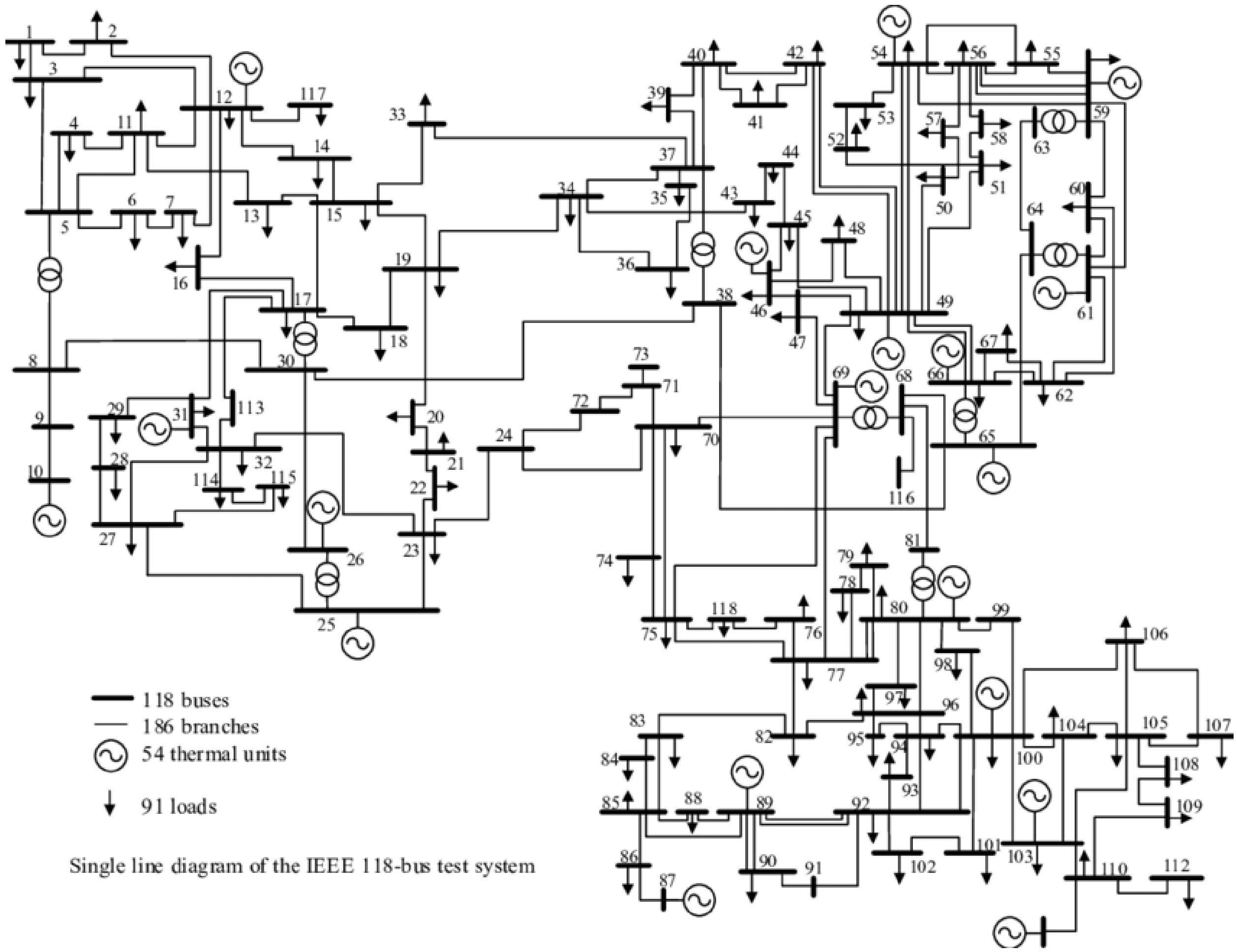

Figure 4.35: Single line diagram of the IEEE 118-bus test system [97]

provided in Fig. 4.35. This IEEE 118-bus system contains 186 transmission lines, 54 generating units, 35 synchronous condensers, nine transformers, and 91 load buses [97]. All the units in the original test system are thermal units. An extension of this system was provided in [98], which features ten modern generation technologies, including wind, solar, hydro, and gas technologies.

In this case, generation capacity is used as a criterion to select the remaining buses, and therefore, generation buses with more than 100 MW capacity are kept in the model, Fig. 4.36.

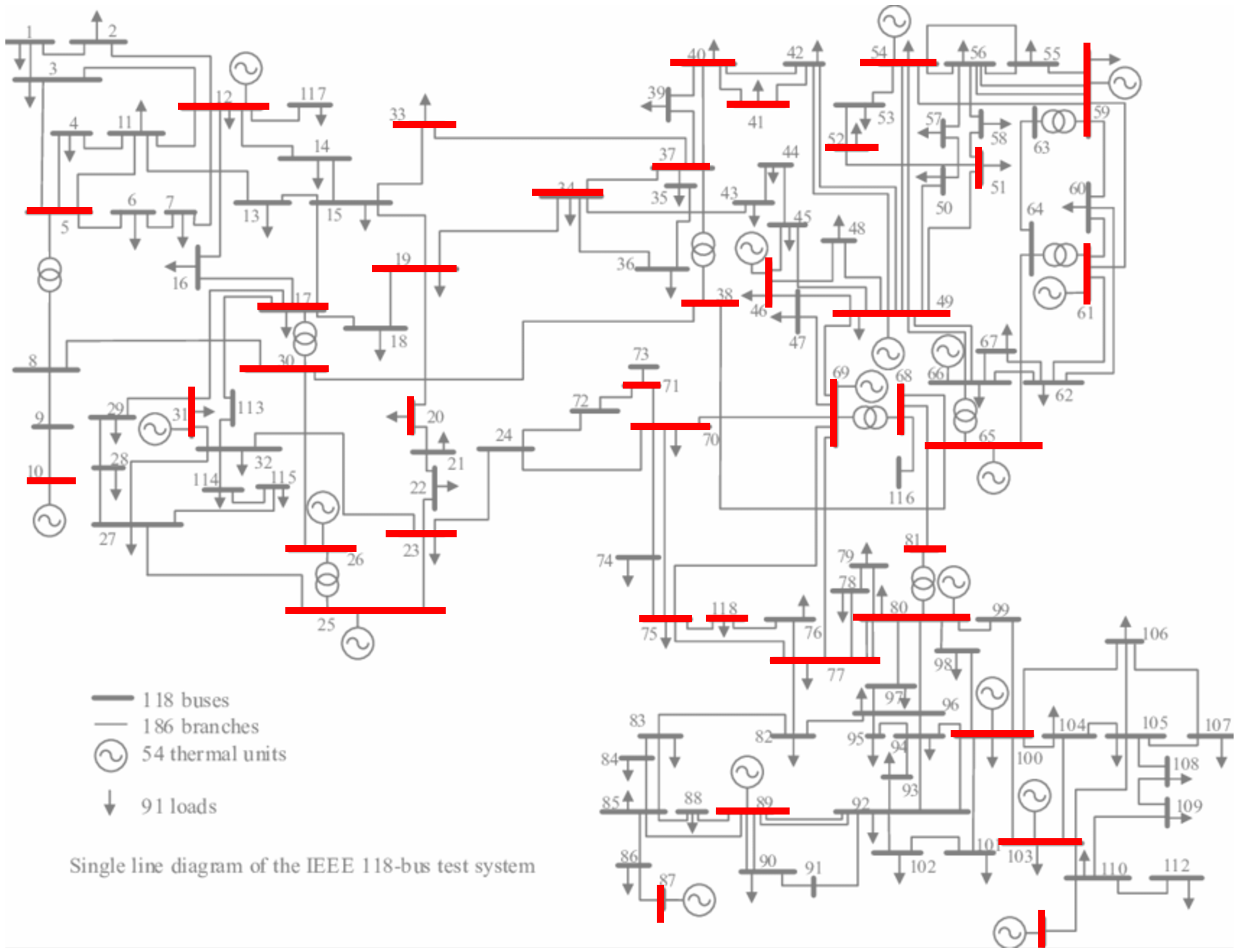

Figure 4.36: Reduced IEEE Test System with the Key Buses Retained

By doing this, some lines will stay the same because their buses are remained, while some lines are eliminated by removing their buses. Thus they should be represented by equivalent lines between the remained buses. In order to obtain the new equivalent lines, Kron reduction should be applied to find the new admittance between retained buses. By using Kron reduction and obtaining the new Y-bus matrix, equivalent lines can be extracted along with their impedance.

Elements of two networks are presented in Table 4.17 for comparison. This shows a significant decrease in the number of elements in the reduced model which helps with CEP application to large systems.

Power flow is run on both full and reduced networks. Generation dispatch, load quantity, and the flows of different sets of lines are compared in Table 4.18.

Elements	Full Model	Reduced Model	Reduction %	Features
Buses	118	40	66%	Voltage, Type, PQ quantities
Lines	186	79	57%	Impedance, Capacity, Length
Generators	54	30	48%	Maximum Capacity, gen power
Loads	99	36	64%	Demand Quantity
Shunts	14	0	100%	Neglected in DC power flow
Transformers	11	0	100%	Removed by reduction

Table 4.17: Characteristics of the reduced network

As the results show, the power flow of the reduced network is very close to the original full network, which shows that the reduction procedure is performing well in terms of maintaining similar flows in the model.

This reduction procedure can be applied to large power systems in order to reduce the network size while maintaining the physical characteristics of the system.

Parameter	Full Network	Reduced Network	Deviation	Relative Error (%)
Generation Dispatch	4242 MW	4250 MW	8 MW	0.18%
Load	4242 MW	4250 MW	8 MW	0.18%
PF all lines	Ave = 52 MW	Ave = 59 MW	7 MW	13.00%
PF existing Connections	Ave = 55 MW	Ave = 63 MW	8 MW	15.00%

Table 4.18: Performance Comparison

4.8.3 CEP on Full and Reduced IEEE 118-Bus System

In this section, CEP is applied to the full and reduced IEEE 118-bus systems while the CO_2 reduction is set to 95% and energy storage contributes to the system as an energy and reserve provider. The breakdowns of the investment costs in the two cases are provided in Table 4.19 and Table 4.20.

Item	Cost (M$)	Share(%)
Generation Investment	8530	43
Transmission Investment	632	3
Fuel Cost	4387	22
FOM Cost	5281	26
VOM Cost	1034	5
Reserve Cost	141	1
Total	20004	100

Table 4.19: Cost Function Breakdown for Full IEEE 118-Bus System

Item	Cost (M$)	Share(%)
Generation Investment	427	42
Transmission Investment	591	3
Fuel Cost	4417	23
FOM Cost	4998	26
VOM Cost	8102	5
Reserve Cost	145	1
Total	19312	100

Table 4.20: Cost Function Breakdown for Reduced IEEE 118-Bus System

Comparing the investments and costs of the two cases shows that the investments are less in the reduced network compared to the full case. The total cost in the reduced network is 3.5%, relatively lower than the full model. However, the investment percentages are quite similar in both cases, which provides a good insight into the various costs of the future network.

4.9 Discussion on CEP results

In power system planning, the pursuit of carbon reduction scenarios results in a greater investment in renewable energy sources such as wind and solar power. While these sources provide numerous benefits, they also pose certain challenges for the long-term planning of electrical systems. Renewable energy sources have a lower capacity factor than conventional fossil fuel generators, which leads to more investment in the generation section.

Despite higher initial investment costs, renewable energy sources have lower life-cycle operating and maintenance costs compared to fossil fuel generators. This indicates that the ultimate cost of electricity generated from renewable sources is less, despite the higher initial investment, which in some way compensates for the higher investment costs.

By analyzing the CEP results of different cases for CO_2 reduction, a comparison between these cases indicates that adding more renewable resources to the system necessitates the installation of new transmission lines. This demonstrates the importance of co-optimization of generation and transmission systems when planning future power systems that are highly renewable integrated. This is due to the fact that sites with high renewable energy potential are typically widespread and located far from load centers. Co-optimization assists in determining the optimal trade-off between the quantity of energy harvested from potential wind and solar sites and the cost of transmission.

Considering flexibility requirements in the CEP model changes the generation portfolios and investments in the considered cases. These changes are due to the different FOM, VOM, and carbon emission rates of technologies. When reserve requirements are imposed, the dispatchable generators are responsible for providing reserves; therefore fewer fossil fuel technologies are retired as they are required to provide reserves. In this case, generation technologies with the cheapest operating costs provide energy and regulation-down reserves, while the other dispatchable technologies are kept idle for regulation-up reserve services. The results indicate that with the increased share of renewable energy resources in the generation system, more regulation reserves are required, and this observation shows the importance of considering flexibility requirements in highly renewable energy integrated power systems.

Incorporating energy storage systems into the power system expansion planning provides various benefits to the system even when there are no limits on CO_2 emissions. In general, it leads to less investment in the generation sector even with higher retirement of coal generators and saving in the total planning costs. For the cases with renewable energy integration, in addition to these benefits, storage systems reduce the need for reserves as they can mitigate fluctuations of renewable resources. The benefits of integrating energy storage into the power system are highlighted by the increased penetration of renewable resources.

By allowing energy storage systems to provide regulation reserves, these systems provide most of the required regulation-up reserve. This is due to the fact that energy storage has the lowest VOM cost compared to other technologies, making it a preferable candidate for providing system regulation reserves. Deploying energy storage as an energy and reserve provider facilitates the integration of renewable energy resources into the power system. It enhances the efficiency of renewable resources by storing the excess generated energy when demand is low and releasing it when it is required. It also reduces the need for additional generation capacity to provide the necessary reserve. Consequently, the application of energy storage as both energy and reserve resource enhances the system's overall performance and reduces the investment costs of the power system. These results highlight the importance of incorporating energy storage systems into power systems and their high potential to contribute even more to future power systems.

The complexity of running CEP on large power systems can be diminished by reducing the network size while maintaining the power flow similar to the full network. Despite the difference in the CEP results for the full and reduced networks, the investment percentages are quite similar in both cases, which provides a good insight into the various costs of the future network and can provide a base plan for power system expansion.

Chapter 5

Conclusions and Future Work

5.1 CEP in Modern Power Systems

In this thesis, a co-optimized expansion planning (CEP) model is developed for future power systems. CEPs are tools that system operators and policymakers use to envision the future of power grids and devise a path to emission reduction goals. The current CEP models need to be upgraded to account for emerging new technologies and renewable resources in power systems operation and planning. Specifically, energy storage and wind/solar resources play an important role in future power grids.

Considering the intermittent nature of wind/solar in power systems, it is required to account for the reserve that is required to compensate for the changes in the output of wind/solar. The developed CEP models storage as a resource for energy shifting and a contributor to reserve requirements. Reserve requirements are considered to ensure that expansion planning decisions are indeed operationally viable. The developed tool enables us to explore possible futures given a set of assumptions on uncertain parameters. System operators and policymakers can use this tool to envision a path to a zero-carbon emission future power system, the required changes to the network's generation and transmission, and secure operational requirements.

The CEP model is designed to optimize the expansion of power systems while minimizing costs and emissions. It considers the intermittent nature of wind/solar in power systems by accounting for the reserve required to compensate for the changes in the output of wind/solar. The model also considers reserve requirements to ensure that expansion planning decisions are operationally viable. The developed tool enables us to explore possible futures given a set of assumptions on uncertain parameters such as fuel prices, technology costs, and carbon prices. This allows system operators and policymakers to make informed decisions about the future of power systems.

The results show that the incorporation of electric storage not only helps in providing energy (peak shaving and valley filling) but also contributes to reserve procurement, displacing investments in thermal resources. This is an important observation as it emphasizes the role of electric storage in emission-free future power grids. Moreover, enforcing carbon reduction policies renders the thermal plants, most notably coal power plants, uneconomical as the cost of carbon emission rises and the electricity producing sector cuts back on its carbon emissions. The results also show the role of transmission networks in enabling the system operators to move renewable power from remote but rich in wind/solar areas to load centers.

5.2 Future Work

One of the major obstacles to achieving carbon emission reduction in power systems is envisioning a path while ensuring a reliable and secure operation throughout the transition. Multi-period CEP lays out the path while modeling operational constraints to ensure secure operation throughout the transition to the last year of the planning horizon. However, the size of a typical power system and the number of operational conditions do not allow for modeling all operational requirements and conditions within CEP.

Therefore, CEPs cannot accurately model the operation of the power system internally. One future work is to ensure the security of the system operation by verifying the investment decisions against an *external* production simulation. This production simulation can be done with secure operational constraints, including temporal constraints such as the minimum up and down time of generating units and storage charging/discharging constraints. Once the external production simulation is run, the power network's conditions can be checked to ensure the system satisfies all the requirements. If some conditions are violated, the constraints in the CEP can be adjusted accordingly.

Since the operational time frame of power systems is enormous and cannot be fully considered in the planning model, it is essential to find representative hours for system operation modeling. This work implements the widely used K-means clustering algorithm for simplicity to identify periods with similar load, wind, and solar patterns. However, improving the selection of representative hours by using enhanced time aggregation techniques can improve the CEP fidelity.

The intensive size of the power systems requires reducing the network size before running CEP. In this work, Kron's reduction is used. However, other reduction methods offer different advantages. Therefore, exploring and investigating the effects of reduction methods on CEP results would be advantageous.

As is outlined in this thesis, reserves play a crucial role in ensuring the secure operation of power systems, and they must be considered in the long-term planning of power systems. As more renewable resources are integrated, the need for reserves will increase. However, the reserve is currently provided mainly by thermal units. As thermal units retire, the resources capable of providing reserves will become more scarce, increasing reserve prices. Therefore, accurate modeling of reserves is required. The reserve requirements are a function of the output of wind and solar power plants, which are a function of the weather data. It is important to obtain accurate weather predictions for different locations. Such meteorological predictions are key in reserve calculations of the future power grids.

References and Citations

[1] *Powering canada's journey to net-zero: Canrea's 2050 vision*, https://renewablesassociation.ca/2050-vision/, Accessed: 2022-03-29.

[2] *Alberta electricity system operator, (2022). current supply demand report*, http://ets.aeso.ca/ets_web/ip/Market/Reports/CSDReportServlet, Accessed: 2022-03-29.

[3] Z. Parvini, A. Abbaspour, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Operational reliability studies of power systems in the presence of energy storage systems," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 3691–3700, 2018. DOI: 10.1109/TPWRS.2017.2771521.

[4] V. Krishnan, J. Ho, B. F. Hobbs, A. L. Liu, J. D. McCalley, M. Shahidehpour, and Q. P. Zheng, "Co-optimization of electricity transmission and generation resources for planning and policy analysis: Review of concepts and modeling approaches," *Energy Systems*, vol. 7, no. 2, pp. 297–332, 2016.

[5] A. Liu, B. Hobbs, J. Ho, J. McCalley, V. Krishnan, M. Shahidehpour, and Q. Zheng, "Co-optimization of transmission and other supply resources," *Prepared for the Eastern Interconnection States' Planning Council, NARUC*, 2013.

[6] G. Cuello-Polo and E. O'Neill-Carrillo, *Power system modeling for the study of high penetration of distributed photovoltaic energy. designs 2021, 5, 62*, 2021.

[7] G. G. Dranka, P. Ferreira, and A. I. F. Vaz, "A review of co-optimization approaches for operational and planning problems in the energy sector," *Applied Energy*, vol. 304, p. 117 703, 2021.

[8] P. Maloney, P. Liu, Q. Xu, J. D. McCalley, B. F. Hobbs, S. Daubenberger, A. Johnson, and S. Williams, "Wind capacity growth in the northwest united states: Cooptimized versus

sequential generation and transmission planning," *Wind Engineering*, vol. 43, no. 6, pp. 573–595, 2019.

[9] 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.

[10] D. Pozo, E. Sauma, and J. Contreras, "When doing nothing may be the best investment action: Pessimistic anticipative power transmission planning," *Applied energy*, vol. 200, pp. 383–398, 2017.

[11] E. Spyrou, J. L. Ho, B. F. Hobbs, R. M. Johnson, and J. D. McCalley, "What are the benefits of co-optimizing transmission and generation investment? eastern interconnection case study," *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4265–4277, 2017. DOI: 10.1109/TPWRS.2017.2660249.

[12] A. H. Van Der Weijde and B. F. Hobbs, "The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty," *Energy Economics*, vol. 34, no. 6, pp. 2089–2101, 2012.

[13] S. You, S. W. Hadley, M. Shankar, and Y. Liu, "Co-optimizing generation and transmission expansion with wind power in large-scale power grids-implementation in the us eastern interconnection," *Electric Power Systems Research*, vol. 133, pp. 209–218, 2016.

[14] E. Mortaz and J. Valenzuela, "Evaluating the impact of renewable generation on transmission expansion planning," *Electric Power Systems Research*, vol. 169, pp. 35–44, 2019.

[15] 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.

[16] C. Clack, Y. Xie, and A. MacDonald, "Linear programming techniques for developing an optimal electrical system including high-voltage direct-current transmission and storage," *International Journal of Electrical Power & Energy Systems*, vol. 68, pp. 103–114, 2015.

[17] H. Liu, T. Brown, G. B. Andresen, D. P. Schlachtberger, and M. Greiner, "The role of hydro power, storage and transmission in the decarbonization of the chinese power system," *Applied Energy*, vol. 239, pp. 1308–1321, 2019.

[18] K. Siala, C. de la Rúa, Y. Lechón, and T. Hamacher, "Towards a sustainable european energy system: Linking optimization models with multi-regional input-output analysis," *Energy Strategy Reviews*, vol. 26, p. 100 391, 2019.

[19] *Canadian wind energy association, 2016. pan-canadian wind integration study*, `https://www.nrcan.gc.ca/energy/funding/current-funding-programs/eii/16634`, Accessed: 2022-03-29.

[20] *General electric consulting, 2016. pan-canadian wind integration study*, `https://www.nrcan.gc.ca/energy/funding/current-funding-programs/eii/16634`, Accessed: 2022-03-29.

[21] *Alberta electricity system operator, (2022). aeso 2022 long-term transmission planning*, `https://www.aeso.ca/grid/long-term-transmission-plan/`, Accessed: 2022-03-29.

[22] *Alberta electricity system operator, (2021). aeso 2021 long-term outlook*, `https://www.aeso.ca/assets/Uploads/grid/lto/2021-Long-term-Outlook.pdf`, Accessed: 2022-03-29.

[23] *Greenhouse gas emissions canadian environmental sustainability indidators*, `https://www.canada.ca/en/environment-climate-change/services/environmental-indicators/greenhouse-gas-emissions.html`, Access: 2022-08-09.

[24] J. Mitali, S. Dhinakaran, and A. Mohamad, "Energy storage systems: A review," *Energy Storage and Saving*, vol. 1, no. 3, pp. 166–216, 2022, ISSN: 2772-6835. DOI: https://doi.org/10.1016/j.enss.2022.07.002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S277268352200022X.

[25] S. Ghosh and S. Kamalasadan, "An energy function-based optimal control strategy for output stabilization of integrated dfig-flywheel energy storage system," *IEEE Transactions on Smart Grid*, vol. 8, no. 4, pp. 1922–1931, 2017. DOI: 10.1109/TSG.2015.2510866.

[26] H. Fan, Y. Xu, L. Zheng, and X. Liu, "Optimal planning of energy storage systems considering operational cost minimization and reliability enhancement in distribution networks," *Applied Energy*, vol. 309, 2022.

[27] A. Pasban-Gajan, M. Moeini-Aghtaie, Z. Parvini, and M. Fotuhi-Firuzabad, "Optimal scheduling of renewable-based energy hubs considering time-of-use pricing scheme," in *2017 Smart Grid Conference (SGC)*, IEEE, 2017, pp. 1–6.

[28] A. D. Del Rosso and S. W. Eckroad, "Energy storage for relief of transmission congestion," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 1138–1146, 2014. DOI: 10.1109/TSG.2013.2277411.

[29] S. Chen, Z. Li, and W. Li, "Integrating high share of renewable energy into power system using customer-sited energy storage," *Renewable and Sustainable Energy Reviews*, vol. 143, p. 110 893, 2021, ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2021.110893. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032121001878.

[30] Z. Parvini, A. Abbaspour, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Operational reliability studies of power systems in the presence of energy storage systems," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 3691–3700, 2017.

[31] ——, “An analytical framework for operational reliability studies of highly wind integrated power systems,” pp. 1–6, 2016.

[32] A. Kumar and S. Singh, “Battery energy storage system to stabilize transient voltage and frequency stability in interconnected power systems,” *IEEE Transactions on Power Systems*, 2018.

[33] M. Talal, S. S. Kaddah, and A. A. Eladl, “Impact of energy storage devices on the distribution system stability with distributed generation.,” *MEJ. Mansoura Engineering Journal*, vol. 45, no. 3, pp. 1–10, 2020.

[34] Y. Wang, Y. Li, and J. Wang, “Optimized energy storage system configuration for voltage regulation in distribution networks,” *Frontiers in Energy Research*, 2021.

[35] R. Liemthong, C. Srithapon, and R. Chatthaworn, “Home energy management strategy for electricity energy cost minimization considering tou tariff,” in *2021 International Conference on Power, Energy and Innovations (ICPEI)*, 2021, pp. 107–110. DOI: 10.1109/ICPEI52436.2021.9690694.

[36] Y. Sun, H. Yue, J. Zhang, and C. Booth, “Minimization of residential energy cost considering energy storage system and ev with driving usage probabilities,” *IEEE Transactions on Sustainable Energy*, vol. 10, no. 4, pp. 1752–1763, 2019. DOI: 10.1109/TSTE.2018.2870561.

[37] C. Barrows, A. Bloom, A. Ehlen, J. Ikaheimo, J. Jorgenson, D. Krishnamurthy, J. Lau, B. McBennett, M. O’Connell, E. Preston, A. Staid, G. Stephen, and J.-P. Watson, “The ieee reliability test system: A proposed 2019 update,” *IEEE Transactions on Power Systems*, vol. 35, no. 1, pp. 119–127, 2020. DOI: 10.1109/TPWRS.2019.2925557.

[38] *2022 electricity atb technologies and data overview*, https://atb.nrel.gov/electricity/2022/index, Accessed: 2021-10-29.

[39] G. B. Dantzig and M. N. Thapa, *Linear programming: Theory and extensions*. Springer, 2003, vol. 2.

[40] A. Schrijver, *Theory of linear and integer programming*. John Wiley & Sons, 1998.

[41] J. K. Delson and S. Shahidehpour, “Linear programming applications to power system economics, planning and operations,” *IEEE Transactions on Power Systems*, vol. 7, no. 3, pp. 1155–1163, 1992.

[42] M. A. MartıXXXX Here I am XXXnez-Quintana, C. MartıXXXX Here I am XXXn-del-Campo, and G. Cruz-Mendoza, “A power optimization model for the long-term planning scenarios: Case study of mexico’s power system decarbonization,” *The Canadian Journal of Chemical Engineering*, vol. 99, no. 4, pp. 884–897, 2021.

[43] *Energy system planning*, `http://home.engineering.iastate.edu/~jdm/ee552/GEP.pdf`, Accessed: 2021-10-29.

[44] E. Mohagheghi, M. Alramlawi, A. Gabash, and P. Li, “A survey of real-time optimal power flow,” *Energies*, vol. 11, no. 11, p. 3142, 2018.

[45] T. Gayibov, S. Latipov, and B. Uzakov, “Power system mode optimization by piecewise-linear approximation of energy characteristics of power plants,” in *E3S Web of Conferences*, EDP Sciences, vol. 139, 2019, p. 01 086.

[46] S. Mhanna and P. Mancarella, “An exact sequential linear programming algorithm for the optimal power flow problem,” *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 666–679, 2021.

[47] N. Karmakar and B. Bhattacharyya, “Techno-economic model for reactive power planning using series-shunt compensation devices under load demand in power transmission network,” *Energy Technology*, vol. 9, no. 7, p. 2 100 156, 2021.

[48] A. V. Pazderin and S. V. Yuferev, "Steady-state calculation of electrical power system by the newton's method in optimization," in *2009 IEEE Bucharest PowerTech*, IEEE, 2009, pp. 1–6.

[49] W. Zheng and W. Wu, "An adaptive distributed quasi-newton method for power system state estimation," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5114–5124, 2018.

[50] R. Bansal, "Optimization methods for electric power systems: An overview," *International Journal of Emerging Electric Power Systems*, vol. 2, no. 1, 2005.

[51] H. Seifi and M. S. Sepasian, *Electric power system planning: issues, algorithms and solutions*. Springer, 2011.

[52] H. A. Florez, D. Marujo, G. P. López, J. M. López-Lezama, and N. Muñoz-Galeano, "State estimation in electric power systems using an approach based on a weighted least squares non-linear programming modeling," *Electronics*, vol. 10, no. 20, p. 2560, 2021.

[53] B. I. Ayuev, V. V. Davydov, and P. M. Erokhin, "Nonlinear-programming-based model of power system marginal states: Theoretical substantiation," *arXiv preprint arXiv:1505.03991*, 2015.

[54] Y. Alhumaid, K. Khan, F. Alismail, and M. Khalid, "Multi-input nonlinear programming based deterministic optimization framework for evaluating microgrids with optimal renewable-storage energy mix," *Sustainability*, vol. 13, no. 11, p. 5878, 2021.

[55] H. H. Alhelou, M. E. Hamedani-Golshan, E. Heydarian-Forushani, A. S. Al-Sumaiti, and P. Siano, "Decentralized fractional order control scheme for lfc of deregulated nonlinear power systems in presence of evs and rer," in *2018 International Conference on Smart Energy Systems and Technologies (SEST)*, IEEE, 2018, pp. 1–6.

[56] 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, ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2021.06.024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0377221721005397.

[57] 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*, 2022.

[58] A. Abedi, M. R. Hesamzadeh, and F. Romerio, "Adaptive robust vulnerability analysis of power systems under uncertainty: A multilevel opf-based optimization approach," *International Journal of Electrical Power & Energy Systems*, vol. 134, p. 107 432, 2022.

[59] M. Moeini-Aghtaie, A. Safdarian, Z. Parvini, and F. Aramoun, "Optimal stochastic short-term scheduling of renewable energy hubs taking into account the uncertainties of the renewable sources," in *Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs*, B. Mohammadi-Ivatloo and F. Jabari, Eds. Cham: Springer International Publishing, 2018, pp. 189–220, ISBN: 978-3-319-75097-2. DOI: 10.1007/978-3-319-75097-2_9. [Online]. Available: https://doi.org/10.1007/978-3-319-75097-2_9.

[60] S. M. Robinson and R. J.-B. Wets, "Stability in two-stage stochastic programming," *SIAM Journal on Control and Optimization*, vol. 25, no. 6, pp. 1409–1416, 1987.

[61] J. R. Birge and F. Louveaux, *Introduction to stochastic programming*. Springer Science & Business Media, 2011.

[62] T. K. Kristoffersen, "Stochastic programming with applications to power systems," *Working Papers, Department of Mathematical Sciences, University of Aarhus*, vol. 2007, no. 1, 2007.

[63] B. Li, Y. Chen, W. Wei, Y. Hou, and S. Mei, "Enhancing resilience of emergency heat and power supply via deployment of lng tube trailers: A mean-risk optimization approach," *Applied Energy*, vol. 318, p. 119 204, 2022.

[64] H. Shuai, J. Fang, X. Ai, J. Wen, and H. He, “Optimal real-time operation strategy for microgrid: An adp-based stochastic nonlinear optimization approach,” *IEEE Transactions on Sustainable Energy*, vol. 10, no. 2, pp. 931–942, 2018.

[65] C. Li, “Algorithms for stochastic mixed-integer nonlinear programming and long term optimization of electric power systems,” Ph.D. dissertation, Carnegie Mellon University, 2021.

[66] F.-S. Wang and L.-H. Chen, “Heuristic optimization,” in *Encyclopedia of Systems Biology*, W. Dubitzky, O. Wolkenhauer, K.-H. Cho, and H. Yokota, Eds. New York, NY: Springer New York, 2013, pp. 885–885, ISBN: 978-1-4419-9863-7. DOI: 10.1007/978-1-4419-9863-7_411. [Online]. Available: https://doi.org/10.1007/978-1-4419-9863-7_411.

[67] E. A. Silver, “An overview of heuristic solution methods,” *Journal of the operational research society*, vol. 55, no. 9, pp. 936–956, 2004.

[68] K. Y. Lee and Z. A. Vale, *Applications of Modern Heuristic Optimization Methods in Power and Energy Systems*. John Wiley & Sons, 2020.

[69] E. d. S. Oliveira, I. C. S. Junior, L. W. de Oliveira, I. M. de Mendonça, P. Vilaça, and J. T. Saraiva, “A two-stage constructive heuristic algorithm to handle integer investment variables in transmission network expansion planning,” *Electric Power Systems Research*, vol. 192, p. 106 905, 2021.

[70] N. Hajibandeh, M. Shafie-Khah, G. J. Osório, J. Aghaei, and J. P. Catalão, “A heuristic multi-objective multi-criteria demand response planning in a system with high penetration of wind power generators,” *Applied energy*, vol. 212, pp. 721–732, 2018.

[71] A. M. Shaheen, S. R. Spea, S. M. Farrag, and M. A. Abido, “A review of meta-heuristic algorithms for reactive power planning problem,” *Ain Shams Engineering Journal*, vol. 9, no. 2, pp. 215–231, 2018.

[72] I.-I. Avramidis, F. Capitanescu, and G. Deconinck, “Practical approximations and heuristic approaches for managing shiftable loads in the multi-period optimal power flow framework,” *Electric Power Systems Research*, vol. 190, p. 106 864, 2021.

[73] I. U. Khan, N. Javaid, K. A. Gamage, C. J. Taylor, S. Baig, and X. Ma, “Heuristic algorithm based optimal power flow model incorporating stochastic renewable energy sources,” *IEEE Access*, vol. 8, pp. 148 622–148 643, 2020.

[74] Z. Wu, W. Xu, C. Li, and X. Meng, “A new approach for generator startup sequence online decision making with a heuristic search algorithm and graph theory,” *Energy Reports*, vol. 8, pp. 678–686, 2022.

[75] Y.-C. Tsao and V.-V. Thanh, “Toward sustainable microgrids with blockchain technology-based peer-to-peer energy trading mechanism: A fuzzy meta-heuristic approach,” *Renewable and Sustainable Energy Reviews*, vol. 136, p. 110 452, 2021.

[76] F. Lezama, J. Soares, Z. Vale, J. Rueda, S. Rivera, and I. Elrich, “2017 ieee competition on modern heuristic optimizers for smart grid operation: Testbeds and results,” *Swarm and evolutionary computation*, vol. 44, pp. 420–427, 2019.

[77] C. J. Newlun, J. D. McCalley, R. Amitava, A. J. Ardakani, A. Venkatraman, and A. L. Figueroa - Acevedo, “Adaptive expansion planning framework for miso transmission planning process,” in *2021 IEEE Kansas Power and Energy Conference (KPEC)*, 2021, pp. 1–6. DOI: `10.1109/KPEC51835.2021.9446221`.

[78] *The changing costs and values of electricity generation technologies: Measuring profitability and evaluating options for integrating renewables*, `https://media.rff.org/documents/RFF-IB-19-04_4.pdf`, Accessed: 2021-10-29.

[79] A. L. Figueroa-Acevedo, “Opportunities and benefits for increasing transmission capacity between the us eastern and western interconnections,” Ph.D. dissertation, Iowa State University, https://lib.dr.iastate.edu/etd/16128, 2017.

[80] *Dc load flow*, https://link.springer.com/content/pdf/bbm%3A978-3-642-17989-1%2F1.pdf, Accessed: 2021-11-24.

[81] *Reserve margin*, https://www.nerc.com/pa/RAPA/ri/Pages/PlanningReserveMargin.aspx, Accessed: 2021-11-24.

[82] *Wind and solar energy curtailment: Experience and practices in the united states*, https://www.nrel.gov/docs/fy14osti/60983.pdf, Accessed: 2021-11-17.

[83] *Generation retirement scenario*, https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/NERC_Retirements_Report_2018_Final.pdf, Accessed: 2021-11-24.

[84] *Aeso 2021 long-term outlook*, https://www.aeso.ca/assets/Uploads/grid/lto/2021-Long-term-Outlook.pdf, Accessed: 2021-11-24.

[85] *2021 electricity atb technologies and data overview*, https://atb.nrel.gov/electricity/2021/index, Accessed: 2021-10-05.

[86] GAMS Development Corporation, *General Algebraic Modeling System (GAMS) Release 36.1.0*, Fairfax, VA, USA, 2021.

[87] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, Q. Chen, C. Fong, S. Haddad, S. Kuruganty, W. Li, R. Mukerji, D. Patton, N. Rau, D. Reppen, A. Schneider, M. Shahidehpour, and C. Singh, "The ieee reliability test system-1996. a report prepared by the reliability test system task force of the application of probability methods subcommittee," *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 1010–1020, 1999. DOI: 10.1109/59.780914.

[88] D. Lew and G. Brinkman, "The western wind and solar integration study phase 2 (executive summary)," National Renewable Energy Lab.(NREL), Golden, CO (United States), Tech. Rep., 2013.

[89] N. Sarajpoor, "On time aggregation techniques for power system planning applications," 2023.

[90] N. Sarajpoor, L. Rakai, J. Arteaga, N. Amjady, and H. Zareipour, "Time aggregation in presence of multiple variable energy resources," *IEEE Transactions on Power Systems*, 2023.

[91] N. Sarajpoor, L. Rakai, J. Arteaga, and H. Zareipour, "A shape-based clustering framework for time aggregation in the presence of variable generation and energy storage," *IEEE Open Access Journal of Power and Energy*, vol. 8, pp. 448–459, 2021.

[92] M. Nick, R. Cherkaoui, and M. Paolone, "Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support," *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2300–2310, 2014.

[93] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[94] *Planning test system, (2022). development of a test system for power system long-term planning*, `https://github.com/parvinizohreh/PlanningTestSystem`.

[95] B. Souza, L. Araujo, and D. Penido, "An extended kron method for power system applications," *IEEE Latin America Transactions*, vol. 18, no. 08, pp. 1470–1477, 2020. DOI: `10.1109/TLA.2020.9111684`.

[96] G. Kron, *Tensor analysis of networks*. J. Wiley & Sons Chapman & Hall, 1939.

[97] P. Fernandez-Porras, M. Panteli, and J. Quiros-Tortos, "Intentional controlled islanding: When to island for power system blackout prevention," *IET Generation, Transmission & Distribution*, vol. 12, May 2018. DOI: `10.1049/iet-gtd.2017.1526`.

[98] I. Peña, C. B. Martinez-Anido, and B.-M. Hodge, "An extended ieee 118-bus test system with high renewable penetration," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 281–289, 2018. DOI: 10.1109/TPWRS.2017.2695963.