Life cycle assessment of electricity delivery systems: Attributional and Consequential approaches

by

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Abstract

The transition towards low carbon electricity generation can be guided by investigating the economic and environmental consequences of policy decisions. However, there is limited information on greenhouse gas (GHG) emissions, energy footprints, and changes in production cost under different policy constraints for emerging sustainable energy generation systems. This thesis, therefore, explores the environmental and economic implications of transitioning to a low carbon electricity generation system through a life cycle approach.

Large-scale solar power plants have captured the attention of energy policymakers and industrial stakeholders globally because they can contribute to the long-term plan to reduce the impacts of climate change related to conventional fossil fuel power plants. In this study, we developed a comprehensive bottom-up life cycle assessment model to evaluate the emissions and energy profiles of large-scale solar photovoltaic systems. A case study for a fossil fuel-based energy jurisdiction, Alberta, a western province in Canada, was conducted. We also investigated the potential to use such an energy system to provide consistent electricity supply to the grid compared to peak load options. The results show life cycle GHG emissions of 60.21-79.61 g CO_{2eq}/kWh, a net energy ratio (total energy output divided by total fossil fuel consumed over the lifecycle) of 7.48-10.04, and an energy payback time (time required to regain the invested energy) of 2.73-3.00 years. The system was integrated with lithium-ion energy storage for a consistent electricity supply over a period. The corresponding results are 155.25-220.61 g CO_{2eq}/kWh, an NER of 2.63-3.61, and a payback time of 7.01-9.45 years. More than 60% of the energy consumed is in upstream manufacturing processes.

We also developed a novel framework to evaluate the long-term environmental consequences of marginal changes in electricity generation that result from policy decisions in fossil fuel-dominant jurisdictions. The framework integrates market penetration, long-term energy demand and supply modeling, and marginal cost and emissions analyses. A case study for Alberta was conducted. Based on the province's specific energy generation resources and its policy initiatives, we created 9 scenarios investigate the effects of renewable energy penetration under competitive market conditions (no renewable targets), regulations to ensure minimum production from renewables, improved storage capabilities, and GHG emission targets. With the Long-range Energy Alternatives Planning (LEAP) framework, we developed an energy generation model to calculate probable future electricity mixes, generation costs, and the resulting GHG emissions. The marginal changes in energy generation and GHG emissions were quantified for each scenario to incorporate different policy decisions and market effects. We determined that in Alberta combined cycle power plants and wind energy are the key marginal suppliers of electricity in the transition to a cleaner grid. The effects of adding energy storage to the grid along with renewable energy systems, replacing natural gas with renewable energy, and setting more aggressive GHG emission reduction targets than current policies require were also investigated.

The information provided in this thesis would help concerned entities in formulating policies and making investments in the electricity sector.

Preface

This thesis is an original work by Tanveer Hassan Mehedi under the supervision of Dr. Amit Kumar. Chapter 2 is a version of a paper prepared for submission to a peer-reviewed journal as "Life cycle greenhouse gas emissions and energy footprints of utility-scale solar energy systems." Chapter 3 is a version of a paper prepared for submission to a peer-reviewed journal as "Transition to cleaner electricity generation for fossil fuel-dominant jurisdictions: a consequential life cycle assessment approach." I was responsible for the concept formulation, data collection, model development and validation, and manuscript composition. E. Gemechu, A.O. Oni and Matthew Davis contributed by assisting in model development, reviewing the results, and formatting the papers. A. Kumar was the supervisory author and was involved with concept formation, evaluation, assessment of results, and composition.

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My mother deserves a separate paragraph in this acknowledgment. She has made an untold number of sacrifices for me and my family. She has taught me to be patient and brave amidst great difficulties and uncertainty. Hence, great appreciation and enormous thanks to her.

My wife, Faizah Zahin, has been a constant source energy for the last eight years and her contribution not only to finish my graduate degree but in all aspects of life cannot be told in a few words. She was kind enough to go through all the difficulties that I have faced in life and helped me stay strong. I thank her for all the love, care, and memories.

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Chapter 1

Introduction

1.1 Background

Global primary energy consumption is projected to increase 10.17% between 2019 and 2050 in the Organization for Economic Co-operation and Development (OECD) countries and nearly 50% worldwide, which would increase energy-related CO_2 emissions by 18.6% [1]. Anthropogenic greenhouse gas (GHG) emissions from fossil-based energy are acknowledged as a major cause of global warming [2]. Unprecedented and rapid human intervention is a must to reduce GHG emissions and limit the global surface temperature below 1.5 °C [3]. The Paris Agreement is an ambitious collective effort to reduce climate change impacts by transitioning to low-carbon energy sources while maintaining a reliable energy supply [4]. While recent GHG emissions' reduction strategies in key global economic sectors have been discussed broadly, and several sets of procedures, rules, and mechanisms have been implemented [5-7], there have been aggressive enforcement of GHG mitigation policies in the electricity generation sector [8, 9]. The electricity sector provides an important share of energy services as demand is increasing with the rising electrification of transportation, heating, and cooling devices. One-third of global GHG emissions are from this sector because of its heavy reliance on fossil fuels [1]. Hence, the major avenue for energy policymakers to ensure climate change goals can be met by decarbonizing the electricity sector through increasing renewable energy resources resource shares and the electrification of the transportation and full electrification of building sectors [10, 11]. Globally, renewable capacity additions accounted for 75% of all net power capacity growth in 2018 [12]. The declining costs of renewables such as solar and wind have also gained considerable interest among policymakers. Solar, wind, and hydro technologies have proven to be reliable sources of electricity because of improved efficiencies and their capacities to provide bulk electricity. As a result of improvements in solar, wind and hydro energy technologies, these resources can help decarbonize the electricity sector.

The electricity sector in Canada was responsible for 78 Mt of CO_2 emissions in 2014, or about 11% of national emissions [13]. The sector is the fourth largest emitter, even though Canada has one of the cleanest electricity systems in the world (almost 80% of electricity is produced from non-emitting sources). As part of the Pan-Canadian Framework on Clean Growth and Climate Change, which aims to reduce the overall GHG emissions from 730 Mt CO_2 eq to 513 Mt CO_2 eq, the Canadian government has laid out many measures that it plans on implementing [13]. Alberta, one of the highest GHG-emitting provinces, has been considering renewable energy alternatives as a viable means to reduce electricity sector emissions. The electricity generation sector accounted for 17% of the GHG emissions in Alberta, of which 45% are from coal-based power plants in 2017 [14]. Currently, there is a plan to phase out coal by the end of 2030, which means a large portion of future electricity demand will need to be met by other clean sources. Solar energy has been gaining considerable interest among stakeholders in Alberta as the province has the highest annual sunlight of all the provinces in Canada (around 319 days) [15]. Alberta has an installed capacity of 17 MW of utility-scale solar power and more than 582 MW of planned capacity additions [16]. This huge addition of large-scale solar energy is an attempt to lower Alberta's electricity grid GHG intensity, which is the highest in Canada. Since utility-scale solar energy systems have significantly higher capacities, they have relatively larger economies of scale, which makes them great alternatives to some fossil fuel-based energy generation systems.

Although solar photovoltaic (PV) panels are considered a safe and reliable source of electricity with low GHG emissions, consideration of the full life cycle stages such as resource extraction, manufacturing, and the transportation of main components could provide information about their overall GHG footprint from a life cycle perspective. Around 60% of the solar PV panels used in Alberta are manufactured in China, where carbon-intensive fuels are used. The shipping of these materials over long distances also significantly contributes to overall life cycle GHG emissions. With these factors in mind, there is a pressing need to understand the economy-wide environmental consequences of implementing solar PV-based electricity generation projects in Alberta. That is one of the focus of this research.

1.2 Life cycle assessment

Life cycle assessment (LCA) is a system-based approach used to evaluate the environmental, economic, and social impacts of a product system that takes into account its entire life cycle starting from raw material acquisition through to production and use phases as well as end of life [17]. LCA identifies the most GHG-intensive processes in the life cycle of a product or service and provides insights to appropriate policymakers and stakeholders to help them make better decisions based on data-driven research. LCA is an internationally standardized and harmonized tool. The International Organization for Standardization (ISO) provides guidelines and frameworks for conducting LCA [18, 19]. LCA, according to the ISO, has four phases: goal and scope definition, inventory analysis, impact assessment, and interpretation [18, 19]. The goal of an LCA sets the context of the study. It should clearly state the main purpose, the intended audience, and how the key findings are communicated to the intended audience. The scope defines the system boundary of the product system, its functional unit, time and location, modeling approach, and other methodological procedures.

The life cycle inventory analysis compiles and evaluates material and energy inputs and the associated emissions at each stage of the product system. It is the most time-intensive part of an LCA. In the impact assessment, the results are translated to several environmental problems such as acidification, climate change, eutrophication, human health, resource depletion, etc. The last stage of an LCA is interpretation, which deals with how to communicate the LCA results.

There are two modeling choices in LCA: attributional and consequential. Attributional life cycle assessment (ALCA) links or/and partitions the unit processes of the system where the inputs and outputs are attributed to the functional unit according to a normative rule [20]. Consequential life cycle assessment (CLCA) is a system modeling approach in which activities within a product system are linked in such a way that they would change because of a change in demand of the functional unit. The questions that both approaches attempt to answer differ considerably. While the purpose of the attributional approach is to identify certain aspects of a product system and link them to the contributing unit processes, the consequential approach provides decision support, implying that consequences are traced forward in time. The main difference between these two approaches starts with the allocation methods in the life cycle inventory analysis phase. Attributional models use normative cut-off rules and allocation to isolate the investigated product system from the rest of the world [21]. In contrast, consequential models expand the system boundary to incorporate the changes that occur in multifunctional product systems. CLCAs also have the capabilities of reflecting economic and physical causalities. More details are discussed in subsequent chapters.

In a solar power system, for example, an ALCA provides information on the global share of its environmental impact as a snapshot. The results from a solar power system ALCA can be compared with technologies that have the same functionalities such as renewable- or fossil-based power generation systems. An attributional LCA of a utility-scale solar electricity generation system does not take into consideration the net change in environmental impacts as a response to change in demand for electricity or the penetration of renewable energy technologies that result from policy measures. However, most renewable technologies available today face economic and technological barriers [22]. Their ability to provide electricity to the grid on a large scale, to provide constant power, and to compete economically with existing power-providing sources are some of the major factors that determine the policies related to their penetration into the electricity grid, and these can be addressed through CLCA. Understanding the long-term environmental consequences of the penetration of renewable energy resources into the electricity generation sector would help determine the most beneficial GHG mitigation policies to implement while maintaining a reliable supply of electricity at the cheapest price possible. CLCA provides information about the long-term consequences of changes at the level of product output (plant capacity and energy production), which includes the effects of change both inside and outside the life cycle of the product. Creating a robust CLCA framework that can systematically answer the questions related to long-term economy-wide environmental effects of increased renewable penetration and marginal suppliers of electricity requires the development of market penetration and energy models capable of assessing electricity mixes under different policy scenarios.

1.3 Literature review

The environmental sustainability of solar-based energy technologies has been assessed widely through LCA [18, 19]. LCAs of solar photovoltaic (PV) panels have focussed largely on measuring the energy performance in terms of energy payback time (EPBT) [23, 24], net energy ratio (NER) [25, 26], and GHG emissions [24, 25]. Other factors such as heavy metal emissions [27], land-use intensity [27-29], human health and well-being [30], and impacts on biodiversity [31] have also been assessed as they influence the decisions of energy policymakers [26, 32, 33]. Most of the LCA studies on energy systems followed the ALCA approach.

Although ALCAs related to electricity generation are available in the literature, because of recent technological advancements [34], the life cycle environmental impact and techno-economic performance have changed considerably. Moreover, the recent wider application of utility-scale solar electricity systems presents the need for up-to-date, bottom-up estimates of energy and environmental profiles that incorporate the solar panels and their balance-of-system (BOS) requirements. A few research articles are available on grid-connected utility-scale solar farms [35, 36], mainly focusing on the production supply chain and associated GHG emissions and energy yield estimates. The impacts from the BOS equipment, end-of-life stages, and regionalized aspects have received little attention. In the case of utility-scale solar energy systems, BOS equipment such as inverters, mountings, and, in some cases, energy storage systems, is often required in large quantities. The integration of this equipment on a large scale would have significant life cycle implications. There are few Canadian studies on this topic. For example, Barrington-Leigh and Ouliaris performed a spatial analysis of Canada's renewable energy landscape at a provincial level [37]. The study provides information about installation and optimal site selection for solar energy systems. Vandelight et al. also carried out an environmental performance assessment of solar PV technologies for rooftops and façades in Ontario and British Columbia [38]. However, there is very limited information on ground-mounted utility-scale solar farms for Canada, let alone the province of Alberta, which plans to add significant solar capacity to its grid. Grid-connected systems have received less attention because of the difficulties in sizing system configurations, which could affect energy yield estimates over the entire life cycle. Similarly, ensuring a consistent supply of electricity using PV technology by adding energy storage options on a large scale is also missing from the LCAs, whose focus is mostly on off-grid systems [39, 40]. In addition, since LCAs are data intensive and LCA practitioners rely on publicly available data often, the uncertainties associated with the results need to be acknowledged. This thesis addresses these gaps and questions in chapter 2.

This thesis also extends the environmental assessment to include the long-term consequences of large-scale renewable penetration in fossil-dominant jurisdictions through a CLCA framework. Previous research in the domain of CLCA for the electricity sector has used publicly available projection datasets, which often do not consider policy alternatives [21]. Moreover, since CLCA modeling approaches are dictated by specific questions that have been set in line with the research objective, more often than not research articles related to CLCAs for the electricity sector are unable to provide universal answers. Since electricity is a strategic product, the conventional market mechanisms are often superseded by regional policy implementations and therefore often difficult to model. A few research articles demonstrate the application of this change-oriented LCA approach by modeling the effects of increased offshore wind power in the electricity grid [41], cycling of thermal power plants during electricity transition periods [42], and changes that may occur in the transmission and distribution lines due to the addition of newer technologies [32, 43]. But a holistic assessment of the long-term competitive technologies in the electricity sector is unavailable in the current literature, and a gradational method of conducting such assessment is also missing. As a result, even though a few research articles are available in this research domain, they are not directly applicable to Alberta, where the key question is: What are the implications of increased renewable energy generation and phase-out of fossil fuel-based power plants? Therefore, there is a need to develop proper scenarios that are in line with current and probable policy initiatives and to use the information from these scenarios for a robust market penetration estimation. Complex energy generation models have recently been developed for each province and territory aimed at identifying GHG emissions mitigation pathways from the electricity sector [44-46]. This research extends the scope of those energy models by developing scenarios based on policy alternatives and incorporating updated cost and technical information to conduct a CLCA aimed at identifying marginal suppliers and quantifying changes in the electricity marginal mix as consequence of demand change.

1.4 Research objectives

This thesis aims to address the following research and knowledge gaps:

- There is little research done on LCA of utility-scale solar power plants, especially for Western Canada, and we set out to conduct a comprehensive and independent LCA study on the energy and environmental viability of such systems by calculating overall energy consumption by primary sources as well as EPBT and NER.
- Implementing solar power systems at a large scale requires taking into consideration the intermittent nature of solar power systems. Hence, understanding energy storage requirements and consequent energy and environmental impacts is necessary from an LCA perspective. This issue has not been properly addressed in the existing literature. Thus, we performed an analytical simulation to estimate the optimum number of batteries and panels required to supply constant electricity, based on price and physical performance parameters.
- It is important to quantify the GHG emissions associated with every stage of the life cycle of utility-scale solar power plants (system components, the balance of system, end of life management, etc.) in order to implement policy decisions, and we developed a bottom up LCA model to incorporate all the lifecycle stages.
- In the electricity sector, ALCAs of standalone power systems have received more attention, but these do not take into consideration the long-term changes associated with shifts in market phenomena, which makes it difficult to make policy decisions based on LCA results. CLCAs for long-term electricity grid mixes have not received wide attention in the existing literature. We addressed this gap by conducting a CLCA to assess the long-term environmental consequences of the transition to cleaner electricity generation in Alberta,

- Accurate assessment frameworks that can aid in modeling the sector-wide energy and emission changes, which are essential to understand the consequences of policy decisions, have not been developed. We developed a market penetration and electricity grid model to estimate the optimal long-term electricity mixes in different policy scenarios and identify the technologies that would be the marginal suppliers**.**

1.6 Scope and limitations of the thesis

This research uses two life cycle assessment approaches, ALCA and CLCA. The ALCA quantitatively assesses the life cycle GHG emissions and energy use of utility-scale solar energy systems in Alberta. The results of this assessment help us understand the environmental impacts of implementing such systems on a large scale. The scope of the ALCA is extended in the CLCA approach, in which a framework is proposed and implemented for Alberta's electricity sector. It provides long-term analysis of energy mixes and marginal technologies to help policymakers understand the consequences of their decisions. Life cycle information, technical parameters, and cost data of existing technologies and emerging energy generating systems were considered to perform this assessment.

The research has the following limitations:

- With respect to solar panel production, only the multi-silicon solar PV modules were considered for the assessment as they are currently the most widely used PV technology.
- With respect to energy storage systems, only lithium-ion battery systems were considered, as reliable life cycle inventory data for other energy storage systems such as nickel-cadmium, nickel-metal hydride, sodium-sulfur, etc., were not available when this research was conducted. However, the method established to size the energy storage capacity

requirements for utility-scale solar energy systems can be used for other battery technologies.

- The ALCA model developed in this research assumes linearity in scaling up the production capacity of power plants; this may result in an overestimation of GHG emissions.
- The CLCA study is focused on the electricity generation system and does not incorporate interactions with other sectors, as they were deemed outside the scope of this study. Including the interactions between different sectors may require complex economic modeling efforts.

1.7 Organization of the thesis

The thesis is in paper format and organized in four chapters. It is written in such a way that each chapter can be read independently. Hence some of the introductory content might be repeated.

Chapter 1 discuss the background on overall global energy use, associated GHG emissions, and the role of renewable energy in decarbonizing the electricity sector. The chapter outlines the research gaps, key research objectives, and the scope and limitations of the study.

Chapter 2 discusses the development of a bottom-up ALCA framework to evaluate the energy and GHG footprints of a utility-scale solar energy system. The technology-specific description of the life cycle stages including raw material extraction, silicon upgrading, solar PV panel manufacturing processes, system integration, operation, and end-of-life management phases is presented. The chapter also includes an analysis of system sizing of utility-scale solar energy systems with energy storage to estimate the energy use and GHG footprint in the case of adding consistent electricity supply capabilities. The chapter provides key insights on GHG emissions and a net energy use profile of the systems, which would be beneficial to estimate site-specific regional aspects.

Chapter 3 provides a framework for evaluating the long-term environmental consequences of the transition to clean electricity generation in fossil-fuel dominant jurisdictions. This chapter extends the ALCA approach discussed in chapter 2 to incorporate a change oriented LCA model. The framework integrates market penetration modeling, energy modeling, and marginal supplier identification to answer key policy questions related to energy system transition and the long-term environmental consequences of marginal changes in electricity generation. Alberta was used as a case study in this chapter, and the research contributions include the development of cost-driven market penetration curves and electricity mixes in nine scenarios. The scenarios were meticulously developed based on policy drivers and technology advancements, current and future cost of electricity production, GHG emissions, and the impacts of substitutional effects. Key results include the environmental and economic consequences of increased renewable penetration in varying market conditions and marginally affected technologies.

Chapter 4 presents the key findings and notable observations from the research. It also includes recommendations for further improvements for the attributional and consequential models.

Chapter 2

Life cycle greenhouse gas emissions and energy footprints of utility-scale solar energy systems

2.1 Introduction

The electricity generation sector accounts for more than one-third of global greenhouse gas (GHG) emissions because of the fossil fuels consumed to generate electricity [47]. Using renewable energy sources in the electricity capacity market is of interest globally. Solar photovoltaic (PV) panels are among the many options. They are a reliable source of electricity and thus are expected to play an important role in future energy markets. Notable technological advancements in the manufacturing and operation of solar PV on a large scale can been seen in China, India, and Europe [48-50]. Projects there have proven the usefulness of solar PV panels as a means to generate electricity on a large scale.

Asia has seen remarkable growth in the market penetration of solar PV technology. China is the leader in its use, and India has surpassed European countries in generation capacity. The United States (US) is the second-fastest growing solar PV market. Unlike the US, Canada contributed less than 5% to global solar-based electricity generation [51] as of 2017. Canada has an installed capacity of 2911 MW and around 138 solar PV farms with a capacity over 1.0 MW [17, 52]. Alberta, a western province in Canada, has the country's highest solar electricity generation potential [53] and yet has less than 1% [34, 54] of the national generation capacity. Alberta is considered one of the most suitable provinces to install solar farms on a large scale. At large scales, the electricity generated can be incorporated into the market. According to the Government of Alberta's Climate Leadership Plan [55], 30% of the electricity generation must come from renewable energy sources, i.e., wind, solar, hydroelectricity, etc., by the end of 2030. Currently, about 89% of Alberta's electricity is produced from fossil fuels (50% from coal and 39% from natural gas) and the rest from sources like biomass, hydro, wind, etc. [56]. Alberta is committed to phasing out coal-based power plants by 2030 to ensure a transition to a clean and reliable electricity system. As of 2018, three major utility-scale solar farms in Brooks, Bassano, and Calgary, Alberta, with a combined capacity of 20 MW, are underway to supply electricity to the grid by 2020 [57, 58].

Ensuring the sustainability of electricity generation technologies is a crucial aspect of the transition to a low-carbon economy. Life cycle assessment (LCA) is a comprehensive framework for evaluating the environmental performance, economic viability, and social acceptance of a product along its life cycle starting from raw material acquisition through to production and use phases and end of life [17]. An LCA framework allows us to identify the key environmental hotspots through life cycle impact categories [18, 19]. The technology behind solar PV modules has changed rapidly in the last three decades [34], and its environmental impact have been evaluated through LCA. However, using generic results from the literature and making decisions for a specific situation has been challenging mainly because of differences in individual study's system boundaries and life cycle inventory models, as pointed out by Xu et al. [59] and in the assumptions about technology levels and installation sites [60].

The energy and environmental performances of solar PV applications have been assessed widely through LCA [18, 19]. The focus in most of the studies have been on energy payback time (EPBT) [23, 24], net energy ratio (NER) [25, 26], and GHG emissions [24, 25], as these indicators influence the decisions of energy policymakers [26, 32, 33]. Other indicators such as heavy metal emissions [27], land use intensity [27-29], human health and well-being [30], and impacts on biodiversity [31] have also been assessed. Although these studies conduct a detailed comparison of different solar PV technologies (i.e., crystalline silicon modules, CdTe modules, amorphous silicon modules, and many other laboratory-scale technologies), none consider the material and energy flows throughout the supply chain. This creates difficulty for concerned stakeholders as EPBT, NER, and GHG emissions are directly affected by the manufacturing technology of a specific product system and its energy-generating location [61]. Grid-connected systems have received less attention because of the difficulties in sizing system configurations, which could affect the estimation of energy yield over the entire life cycle. Hou et al. and Yu et al [35, 36] performed comparative LCAs of grid-connected systems (conventional and metallurgical solar PV panel productions), mainly focusing on production and with limited emphasis on the balance of system (BOS). For grid-connected systems, characterizing and accurately sizing BOS equipment is essential as it has environmental impacts. The methods used in most studies is to model the highly complex utility-scale solar components ("PV plus BOS") are ambiguous, making it difficult for others to use LCA results in user-specific situations [34, 62, 63].

Advances in battery systems (in terms of cost, efficiency, and improved cycle life [64, 65]), especially lithium-ion, nickel-cadmium, nickel metal hydride, and sodium sulfur batteries, have also helped address the intermittency of solar power generation technologies. Several authors have studied the integration of battery-based energy storage technologies in off-grid solar PV applications [39, 40, 66]. The studies focused on low-cost options of generating electricity through conventional lead-acid batteries. Several location-based LCA studies have been conducted in Asia [26, 59, 67] and Africa [61]. These places have high solar insolation; that is, there is an abundance of solar irradiation. Hence, the results of these studies are not helpful in countries like Canada. Until recently, including modern battery systems in LCAs of solar PVs was difficult, as there was no dependable life cycle inventory of new and modern battery technologies. Such inventories are now available for both stationary [64] and mobile operations [65, 68], yet the studies do not include an accurate prediction of environmental performances of on-grid electricity generation systems using solar PV and battery storage.

As solar electricity use is still in the early stages in Canada, the environmental consequences need to be investigated and compared to conventional sources of electricity. There are few detailed LCA studies on the energy and GHG performances of utility-scale solar PVs in Canada. Barrington-Leigh and Ouliaris performed a spatial analysis of Canada's renewable energy landscape at a provincial level to determine installation optimal sites [37]. Vandeligt et al. summarized the EPBT for crystalline solar PV for rooftops and façades [38]. To the best of the authors' knowledge, there is no information on ground-mounted utility-scale solar farms for Canada. One critical aspect of implementing solar panels in northern regions like Canada is the snowy conditions much of the year. Anis Haque [69] conducted experiments to evaluate the energy loss from snowy conditions in Alberta. Snow accumulation could reduce annual energy yield by 9%, a high marginal loss compared to the other system losses, so it needs to be considered in enviromental performance assessment studies.

Our review of the relevant research shows both a lack of robust LCA results for utility-scale solar power systems and ambiguities resulting from the regional aspects; different atmospheric conditions, system boundaries, and technological levels considered in the LCA studies; and improper sizing of utility-scale solar power systems (based on technical parameters). This study, therefore, aims to address these identified research gaps. The specific objectives of this study are:

- Developing a spreadsheet-based, bottom-up LCA model for cradle-to-grave utility-scale solar power plant analyses.
- Estimating energy payback time (EPBT) and net energy ratio (NER).

- Performing a simulation to estimate the optimum number of batteries and panels to supply constant electricity, based on price and physical performance parameters.
- Performing sensitivity and uncertainty analyses with the physical performance characteristics of the equipment and technological requirements in upstream processes.

2.2 Method

The LCA was conducted following the principles and framework and requirements and guidelines of the International Organization for Standardization [18, 19] and the guidelines provided by the International Energy Agency Photovoltaic Power System Programme [70, 71]. Each stage of the LCA is discussed in the sections that follow.

2.2.1 Goal and scope definition

The goal of this study is to quantitatively assess the life cycle GHG emissions and energy use footprint of utility-scale solar power systems. The findings of this study are intended to help energy stakeholders in government and private entities make informed energy policy decisions. The results can also be used to compare the environmental impacts of solar power plants with other large-scale electricity-generating technologies using both renewable and non-renewable sources. The defined product system is a 5 MW_p utility-scale grid-connected solar power plant assumed to be located in the province of Alberta in Canada. The functional unit is set as “1 kWh of electric energy generated” from solar PV.

Figure 2.1 depicts the cradle-to-grave system boundary considered in the study. The boundary includes the upstream processes of extracting the silicon ore from mines and several material processing steps. In the intermediate processes the high purity silicon feedstock is melted and turned into blocks. Subsequently they are sliced into thin wafers which are then etched and coated with screen printing materials. Energy and material requirements as well as raw material transportation in each step are considered in creating the life cycle inventory. In terms of transportation, both domestic ground and international maritime transportation are considered. For the "balance of system," the following major equipment types were considered: inverters, mounting structures, transformers, and physical infrastructures required for operation and maintenance. To account for the GHG emissions from recycling certain equipment, several end-of-life scenarios were considered. The total land requirement for module assembly, line transmission and distribution, and the associated land use change emissions are also evaluated.

2.2.2 Solar PV production

The silica (SiO_2) used in solar PV production is extracted using an established technology well described by Hou et al. [35]. We calculated GHG emissions by estimating the amount of explosive material and gasoline/diesel required to extract one kg of silica sand. The amount of explosive material required was estimated through the following equation:

$$4TNT + 21O_2 = 28CO_2 \uparrow + 10H_2O + 6N_2 \uparrow \quad (1)$$

The energy requirement in the form of electricity and fossil fuel was taken from literature [51]. The silica extracted from the mines is reduced to industrial-grade silicon, resulting in silicon of 99.6% purity. The typical process yield is 80% [23]. The byproduct of this process is silicon slag, which is sold separately. The silica is reduced according to the following carbothermic chemical reaction:

$$SiO_2 + 2C = Si + 2CO \quad (2)$$

Industrial-grade silicon for electronic or solar panel applications needs to have high purities and is produced through the Siemens process, wherein fractional distillation takes place to convert the silica sand into volatile compounds. This process is costly and has low yields [33, 72]. In this study, we consider a modified Siemens process, one that is more advanced, less energy-consuming, and offers 99.999% purity [33]. The solar-grade silicon is converted into large blocks of multi-crystalline silicon. In this process, silicon feedstock is melted under an inert atmosphere (Argon gas) and poured into a graphite crucible where the blocks solidify under controlled thermal conditions [23].

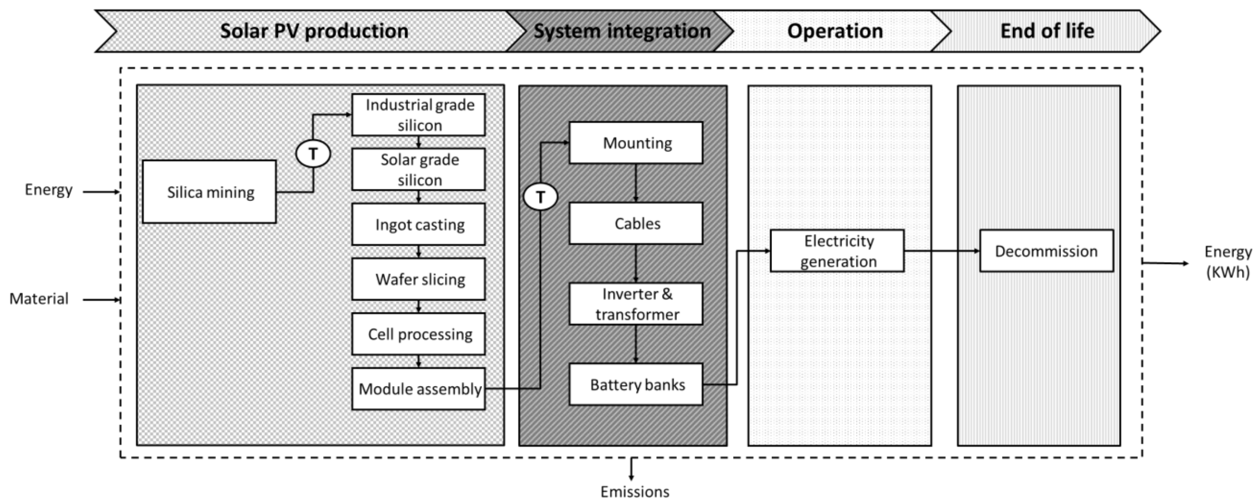


Figure 2.1: System boundary for a utility-scale solar farm

Following casting, the silicon blocks are cut into thin slices using a multi-wire saw combined with a slurry of cooling liquid and abrasive particles, typically silicon carbide (SiC) [73]. The damages occurred in this process is removed by subsequent etching with sodium hydroxide (NaOH) and washing with water and sulfuric acid (H_2SO_4). The solar cells are then processed by adding n-type emitter layers and treated with fluoric acid. Finally, the front and back of the solar cells are screen printed to prevent recombination of holes [23]. In this study, square shaped solar cells have been considered while modeling as they provide the highest packing density. Aluminum frame was considered for module assembly. Detailed description of the solar PV panel production process can be found in Appendix A1.

2.2.3 System integration

In this phase of the life cycle, energy and emissions from raw material production and manufacturing the BOS equipment (mounting structures, cables, inverters, transformers, and battery banks, for the case of consistent electricity supply) are considered.

2.2.4 Operation

For the electricity generation base case model, the energy yield was calculated using the following formula:

$$E = A \times H \times PR \times \eta \tag{3}$$

where E is energy output per year (kWh), A is the effective area of the panel, H is solar insolation (kWh/m^2), PR is the performance ratio, and η *is e*fficiency of the Solar panel. The procedure used to calculate the energy yield over the lifetime is provided in Appendix A2.

The solar insolation data is from the Natural Resources Canada dataset [53], which provides monthly electricity data for every municipality in Canada. Alberta's average insolation was used. The monthly average insolation in Alberta is 186.3 kWh/m^2; December and June have the lowest (65.7 kWh/m^2) and highest (297.6 kWh/m^2) [53]. Spring and summer have the highest electricity generation potential. The electricity generation potential from September to March is lower, but the yield from the panels should be higher, given the colder temperatures during this period, as the current flowing through the panels would be reduced and the voltage would increase. Table 1 shows the input parameters used to model the system.

Table 2.1: Input parameters for the electricity generation model

	Parameters	Value	Unit	Comments/Reference
Solar PV panel	Maximum peak power (W)	325	W_p	Values are taken from a Canadian solar panel supplier (manufacturers specification sheet) [74]. Peak power of panels ranges from 290-400W and efficiency from 12% to 23.81%. Those ranges were considered in sensitivity and uncertainty analyses.
	Efficiency (η_{pv})	16.72%		
	Dimension (A)	1.95	m^2	
	Weight (m)	22.4	kg	
	Performance ratio (PR)	0.8		Geographic specific PR value is according to the guidelines provided by the International Energy Agency (IEA) [70].
	Lifetime (L)	25	years	The solar PV panel lifetime can range from 20 to 30 years as reported in IEA. An average value was considered for the base case, while the maximum and minimum years were reflected in the sensitivity and uncertainty analyses [70].
Inverter	Input DC power	1	MW	Inverter specification data were obtained from the manufacturer's specification sheet according to the IEA's guidelines [75].
	Efficiency	96.50%		
	Lifetime	10	years	

For simplicity, we assumed that the degradation of the solar PV panels is the same every year. A linear degradation is often assumed [25, 71, 76]. Figure 2.2 shows the relationship between the lifetime of solar PV panels and the energy yield for different mounting orientations. The graph was developed using Equation 6.

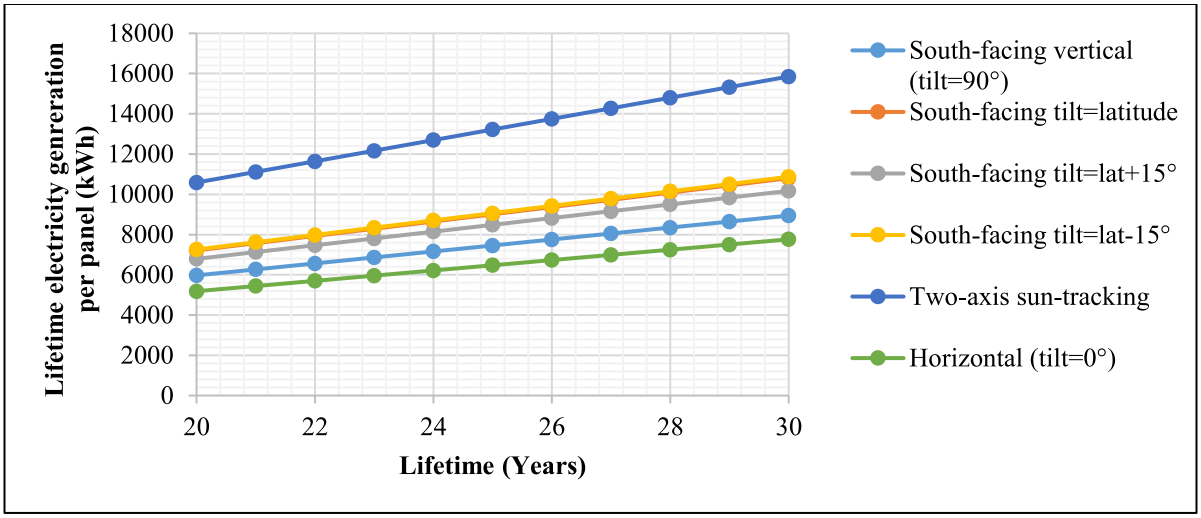


Figure 2.2: Annual electricity generation by a utility-scale solar farm for different orientations and lifetimes

Utility-scale solar power plant with energy storage

The intermittency of power generation has always been the biggest challenge in using solar energy. As the power generation industry moves toward smart grid technologies [77-79], rapid change in a distributed resource like solar power can result in voltage, frequency, and ramp rate issues [80]. The daytime-only nature of solar power has limited the growth of solar power globally [81]. In practice, solar and other intermittent renewable energy assets rely on conventional diesel generators or natural gas-based auxiliary power generators. Low-cost, deep-cycle, highly efficient batteries offer an opportunity to mitigate the intermittency issues and provide more reliability. At the same time, if fossil fuel-based power plants are phased out in the near future, it is essential to understand the potential of renewable energy technologies to provide base load consistently. Therefore, incorporating energy storage technologies and their environmental footprint would also be of interest to concerned stakeholders. The battery technologies currently used in various stationary and mobile applications are lead-acid, lithium-ion, sodium sulfur, nickel cadmium, and nickel metal hydride batteries [64, 65, 68]. Commercially, lead-acid and lithium-ion batteries have the widest applications in off- and on-grid solar PV installations. For this study, lithium-ion batteries were considered. Compared to lead-acid batteries, they have fewer environmental impacts [64, 82] and better electrical performance [83]. The depth of discharge (DOD) is another key performance metric used to compare battery technologies. While most lead-acid battery manufacturers suggest that the DOD should not be more than 50% in most cases [76, 84], lithium-ion batteries can achieve a discharge depth of 100% [85]. Lithium-ion batteries also have higher lifetime cycles of about 700-800 compared to lead-acid batteries with lifetime cycles of about 300.

Electricity generation model for a system with energy storage

A numerical algorithm was created to determine the optimal size at which solar power plants can provide consistent electricity to the grid. In the scenario with energy storage, the electricity generation system is the source of consistent electricity throughout the day, while the system without the energy storage provides intermittent energy. For a system with energy storage, the optimum number of solar panels and energy storage equipment (batteries) needs to be determined. The method developed by Borowi and Salameh [86] was used. This method applies the concept of loss of power supply probability and economics of the system. This method allows us to characterize a system that can provide a base load and to evaluate the energy and environmental consequences. Loss of power supply probability (LPSP) can be described as the long-term average fraction of the load that is not dispatched from the energy storage-enabled solar farm. The LPSP values range from 0 to 1, where 0 means no load dispatch and 1 refers full load dispatch [86] .

In the energy storage system model, it is assumed that energy will be stored in batteries when the power generated through the PV array is greater than the specified load, and energy will be discharged when the generated energy is below the load. If the power generated by the PV array is not enough to meet the demand and the batteries are also depleted to their maximum depth of discharge, the load will not be satisfied. To prevent the shortening of the battery life, the control system intervenes and stops the charging process should overcharging occur. The corresponding equations to the charging and discharging of the batteries to a specific condition can be found in the SI section. The input parameters for the simulation model are provided in Table 2. The algorithm used to determine the optimum number of solar PV panels and batteries is shown in Figure 2.3.

Table 2.2: Input parameters for the electricity generation model for the system with energy storage

Parameter	Value	Unit	Comments/reference
Capacity	13.5	kWh	The largest battery unit size at the time of this research work was considered [80].
Efficiency	90.00%		Based on the manufacturer's specification sheet [80]
Initial charge	11	kWh	Assumed 80% of capacity for increased performance.
Depth of discharge	75.00%		Ranges of 50%-75% have been considered
Lifetime	5	years	5 years lifetime was assumed based on charge cycles. Range of 3-7 years were considered in the sensitivity and uncertainty analyses.

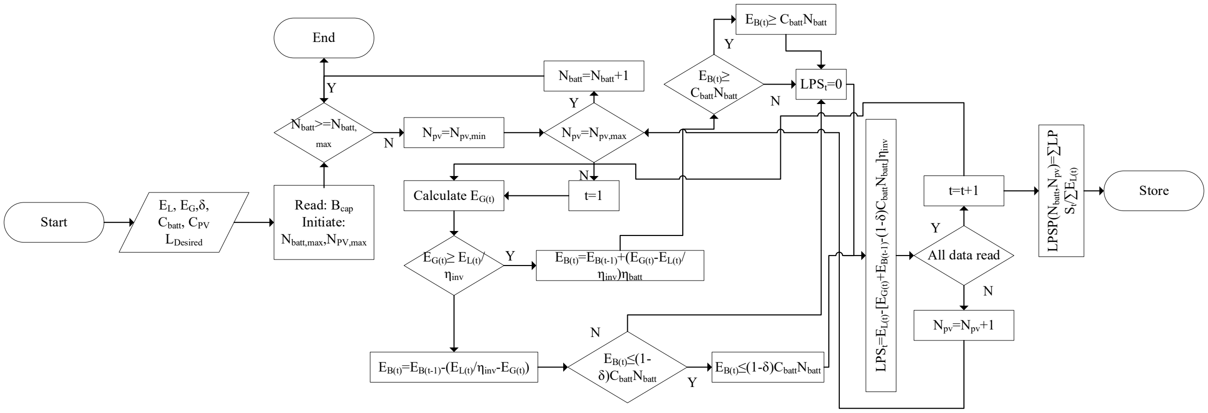


Figure key:

$E_{B(t)}$ Energy stored in batteries in hour t
E_{Bmin} depth of discharge
$E_{G(t)}$ total energy generated by PV panels in hour t
$E_{L(t)}$ load demand in hour t
$E_{PV(t)}$ energy generated by a PV panel in hour t
$LPS_{(t)}$ loss of power supply in hour t
LPSP Loss of power supply probability
N_{batt} number of batteries
N_{PV} number of PV panels
η_{batt} efficiency of battery
η_{inv} efficiency of inverter

Figure 2.3: Algorithm used to size the system with energy storage

The GHG emissions during the operation phase are mainly due to energy use in site preparation and maintenance. Site preparation includes leveling, constructing drainage and ditches, and pad area soil removal. The GHG emissions and energy use during the transportation of raw materials and equipment were considered separately as part of the transportation phase.

2.2.5 Decommissioning and recycling

There is no recycling policy in place in Canada or anywhere else in North America for solar PVs. Most solar projects are a long way from their end of life phase. Europe, on the other hand, has implemented a policy of "take back and recycle," wherein the PV panels are collected from solar farms and individual users and recycled [63]. Therefore, in this study, the recycling phase emissions are estimated based on the European Life Cycle Inventory Data [87]. Data from five solar PV recycling facilities in Europe were considered. The GHG emissions were estimated with energy consumption values and emissions factors specific to Alberta. A sensitivity analysis was conducted to estimate the impact of variation in GHG emissions factors.

Large-scale use of lithium-ion batteries in stationary and mobile applications began only a decade ago and has not reached the scale at which reliable data on energy use and GHG emissions from recycling can be forecasted accurately. Therefore, the energy use and GHG emissions from recycling the batteries were left out of this study.

2.2.6 Transportation

The transportation details of the raw materials in each life cycle stage were taken from industry data and the literature. Asia-pacific domestic transportation data was assumed for the raw materials for solar panels. The energy use and emissions from maritime transportation were calculated by creating a transportation model that uses the distance between ports in Asia and Vancouver, Canada. According to market research [88, 89], inverters are assumed to be produced in Quebec, Canada, and the batteries in Nevada, USA.

2.3 Life cycle inventory

A life cycle inventory was developed through relevant empirical models. Energy and mass balance were considered for equipment sizing. Data from literature and industrial sources were also used. Tables 3 and 4 summarize the characteristics of the solar panel and the inverter considered in the study. The physical characteristics are based on manufacturers' specification sheets and were used as inputs in the inventory calculation for the life cycle inventory.

The study developed a flow sheet to analyze the life cycle stages in the system boundary. The energy and raw materials required to generate 1 kWh of electricity by a utility-scale solar PV power plant were determined and converted to GHG emissions. Table 5 lists the inventory data in the production of the solar PV panels, inverter, mounting structure, and lithium-ion battery. The manufacturing energy for battery assembly was considered to be 8.34 kWh of electrical energy per kg of battery material based on earlier studies [90, 91].

Table 2.3: Physical characteristics of the solar panel under standard test conditions (STC) with an irradiance of 1000 W/m^2, AM spectrum of 1.5, and cell temperature of 25^{o}C based on manufacturer specification [74]

Parameter	Value	Unit
Nominal maximum power (P_{max})	325	W
Optimum operating voltage (v_{mp})	37	V
Optimum operating current (i_{mp})	8.78	A
Open Circuit voltage (V_{OC})	45.50	V
Short circuit current (i_{sc})	9.34	A
Efficiency	16.72	%
Operating temperature	-40 ≈ +85	ºC
Cell type	Multi-crystalline	
Cell arrangement	72 (6×12)	
Dimensions	1960×992×40	mm
Weight	22.4	Kg

Table 2.4: Specifications of the inverter considered for the LCA based on manufacturer specification sheet [75]

Input parameters	Value	Unit
Max PV power	2 × 600	kW
Nominal DC power	2 × 515	kW
DC voltage range, mpp	450 to 750	V
Maximum DC Voltage	900	V
Maximum DC Current	2 × 1145	A
Output parameters		
Nominal AC output power	1000	kW
Nominal AC current	28.9	A
Nominal output voltage	20	kV
Output frequency	50/60	
Efficiency	97.4	%
Own power consumption	1310	W
Physical parameters		
Dimensions	6930 × 2970 × 2430	Mm
Weight	20	Tons
Temperature range	-20 - +40	^{0}C

Table 2.5: Life cycle inventory for a multi-crystalline solar panel as determined in the study

Life cycle stage	Item	Amount	Unit	Comment/reference
Ore extraction	Explosives	0.056	kg	Estimated using equation 1. Electricity requirement was based on [35] . Ranges of ±10% were considered for the electricity requirement.
	Gasoline	0	kg	
	Electricity	0.038	kWh	
Product	**Silicon ore**	1	kg	
Industrial grade silicon upgradation	Wood chip	0.003	kg	Carbothermic reduction of silicon ore. Inventory data averaged from the most up to date IEA photovoltaic power systems program and literature representing recent PV technologies [36, 59, 71] .
	Hard coal	23.1	kg	
	Graphite	0.1	kg	
	Charcoal	0.17	kg	
	Petroleum coke	0.5	kg	
	Silicon ore	2.7	kg	
	Liquid oxygen	2	kg	
	Electricity	11	kWh	
Product	**Industrial grade silicon**	1	kg	
Solar grade silicon upgradation	Industrial grade silicon	1.3	kg	Modified Siemens process. Data obtained from literature representing the most recent PV technologies [36, 59]. The heat energy required in this process is disputed in the literature and a range of 148-225 MJ have been considered for the uncertainty analysis.
	HCl	1.6	kg	
	NaOH	0.348	kg	
	H_2	0.05	kg	
	Electricity	110	kWh	
	Heat	185	MJ	
Product	**Solar grade silicon**	1	kg	
Ingot Casting	Solar grade silicon	1.009	kg	This is a fairly well-established process with less uncertainties regarding the material and energy requirements. Data obtained from literature representing the most recent PV technologies [23, 27].
	Ar	1.92	kg	
	HF	0.046	kg	
	NaOH	0.009	kg	
	Electricity	9.917	kWh	
Product	**Ingot**	1	kg	
Wafer Slicing	Ingot	1.638	kg	The material and energy requirement in this unit process is low when considering the overall lifecycle. Data have obtained from the references which have provided full description of the process and the equipment involved [23].
	SiC	0.053	kg	
	Steel Wire	5.185	kg	
	Detergent	0.668	kg	
	Electricity	2	kWh	
Product	**Wafer**	1	kg	
Cell Processing	Wafer	3.242	kg	

Life cycle stage	Item	Amount	Unit	Comment/reference
	Ag	0.089	kg	The amount of POCl3 estimated using equation A1 in Appendix A1. Silver and aluminum requirements were varied by ±20% as different values are reported in literature [23, 36, 61, 92]. Average Similar numbers are reported for other chemical reagents, hence average values were considered [23, 36, 61, 92]
	Aluminum	0.405	kg	
	HCl	0.501	kg	
	HF	0.815	kg	
	HNO_3	1.083	kg	
	NH_3	0.2	kg	
	NaOH	0.222	kg	
	$POCl_3$	0.018	kg	
	N_2	6.99	kg	
	Electricity	162.5	kWh	
Product	**Cell**	1	kW_p	
Module Assembly	Cell	1.055	kW_p	Data obtained from literature representing the most recent PV technologies [23, 36, 61, 93]. Electricity requirement has been varied ±20% as the mentioned references provide different estimations. Rest of the values have been averaged from the sources.
	Glass	68.087	kg	
	Aluminum	15.023	kg	
	EVA	7.573	kg	
	PET	2.9	kg	
	Electricity	22.5	kWh	
Product	**Solar Module**	1	kW_p	
Inverter	Steel	9792	kg	Data obtained from International Energy Agency's guidelines and life cycle inventory estimation [71]. Transformer oil has been considered as vegetable oil instead of mineral oil to lower GHG emissions.
	Aluminum	894	kg	
	Copper	2277	kg	
	Polyamide injection molded	485	kg	
	Polyester	300	kg	
	Polyethylene	150	kg	
	Transformer oil	6001	kg	
Product	**Inverter**	1	p	
Mounting Structure	Aluminum	3.98	kg	Material inventory based on literature representing most recent technologies [71]. Base case considered as the 2-axis mounting system.
	Corrugated board	0.086	kg	
	Polyethylene	0.001	kg	
	Polystyrene	0.005	kg	
	Alloyed steel	7.2	kg	
	Stainless steel	0.247	kg	
	Concrete	0.001	kg	
Product	**Open ground**	1	p	

Life cycle stage	Item	Amount	Unit	Comment/reference
	mounting structure			
Energy Storage	Cathode	45	kg	Data for the energy storage was taken from [64, 82, 94]. Based on the mentioned references, a triangular distribution of the energy requirement has been considered, as they provided wide range of data. Other material composition has been considered from the GREET lifecycle model as they provide the most recent inventory and emission factors.
	Anode	38.75	kg	
	Electrolytes	13.75	kg	
	Separator	2.5	kg	
	Case	25	kg	
	Electricity equivalent	20.85	kWh/kg of battery material	

2.4 Environmental impact assessment

An LCA of a utility-scale solar PV power plant was conducted by developing a spreadsheet-based bottom-up data-intensive model. The study analyzed the energy and environmental performance of the system using NER, EPBT, and GHG emissions as metrics.

2.4.1 Net energy ratio

NER is an energy performance metric that measures the total amount of energy the solar power plant can generate throughout its lifetime relative to the total energy being consumed [95, 96]. It is estimated using Equation 4. An NER greater than one indicates that the system is a net energy generator meaning it produces more energy than consumed.

$$NER = \frac{Lifetime\ electricity\ generation}{Total\ energy\ consumed\ from\ fossil\ fuel\ sources\ during\ the\ entire\ lifecycle} \quad (4)$$

2.4.2 Energy payback time

The EPBT quantifies the years required to generate the same amount of energy that has been invested into the system over the entire lifecycle as primary energy. It is estimated using Equation 5:

$$EPBT = \frac{E_{mat} + E_{man} + E_{tran} + E_{ins} + E_{EOL}}{\frac{E_{annual}}{\eta_G} - E_{O\&M}} \tag{5}$$

where E_{mat}, E_{man}, E_{tran}, E_{ins}, and E_{EOL} are the energy consumption during raw material production, manufacturing, transportation, installation, and end-of-life phases of the system equipment in kWh, respectively. E_{annual} is the average annual electricity generation and $E_{O\&M}$ is the energy demand for operation and maintenance. η_G is the average energy-to-electricity conversion efficiency at the demand side. The average η_G values for North American countries are 0.30 to 0.31 [97].

2.4.3 Greenhouse gas emissions and land footprint

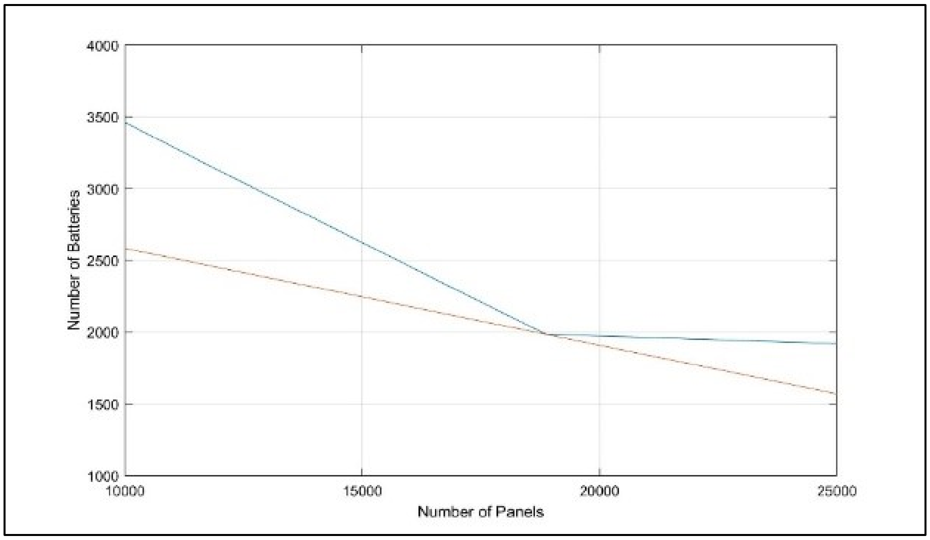
The life cycle GHG emissions of all the components in the system boundary were calculated with the most recent emission factors published by the IPCC [98] as grams of carbon dioxide equivalent.. The main GHG emissions included are carbon dioxide (CO_2), methane (CH_4), dinitrogen monoxide (N_2O), and chlorofluorocarbons (CFC) with global warming potential of 1, 34, 265, and 4750-14400, respectively. In addition to the GHG emissions from material and energy use, GHG emissions due to land use change are also included. Direct land use GHG emissions are taken from Yeh et al. [99] and, Turney and Fthenakis [30], where the carbon stock values for semi arid grassland, forest areas and mixed areas are provided. Land use change GHG emissions due to respiration of unsupported soil that occurs in the first 10-20 years after deforestation, removal of vegetation, and the loss of natural carbon sequestration has been incorporated in the study. GHG emissions are calculated through the following equation:

$$GHG\ Footprint = \frac{\sum(GHG_{energy\ and\ material\ use} + GHG_{direct\ land\ use\ change})}{\sum Electricity\ generated\ in\ each\ year} \quad (6)$$

Land use footprint has been calculated using the information about array area requirements, packing factors [100], transmission and distribution line requirements [101] and total lifecycle energy generation. Calculation methods related to land use footprint and direct land use change GHG emissions are provided in Appendix A7.

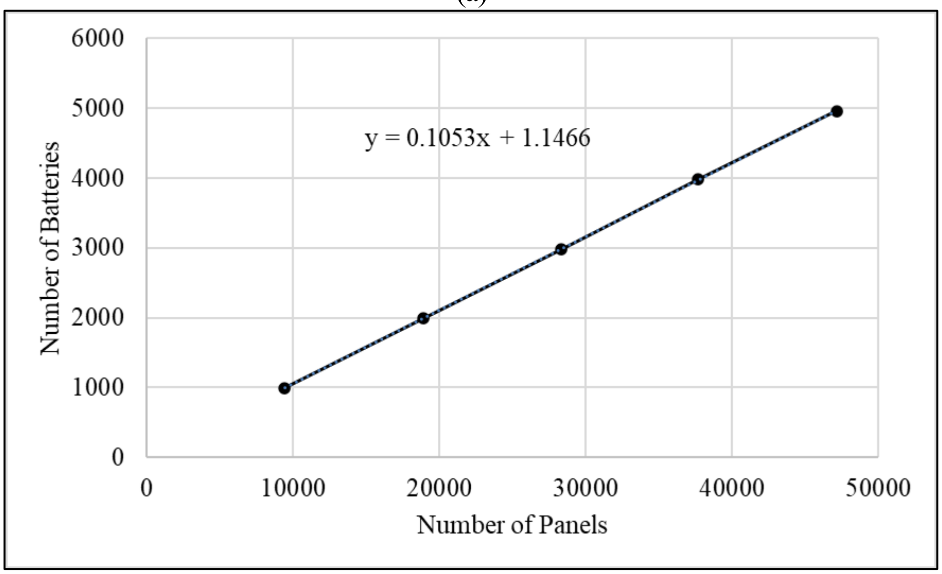
2.5 Results and discussion

A sample simulation model result for utility scale solar energy farms with energy storage under different hourly load requirements is illustrated in Figure 2.4(a). Based on the method described in section 2.1.3, 5 simulations were run to obtain the relationship between the solar PV capacity and energy storage capacity. It was found that they follow a linear trend as shown in Figure 2.4(b) and 2.4(c). The system has been designed in a way to ensure 8 hours of consistent electricity supply. The simulation model developed to size a system capable of supplying electricity consistently shows that with an assumed DOD of 75%, the ratio of panel-to-batteries requirements would be 9.49:1, or for every 10 panels there must be 1 battery as shown in Figure 2.4(b). For the case where 50% DOD was considered, it can be seen that the ratio changes to 6.17:1. This can be attributed to the fact that, due to the increased DOD, the amount of storage capacity required would be reduced by a significant amount.



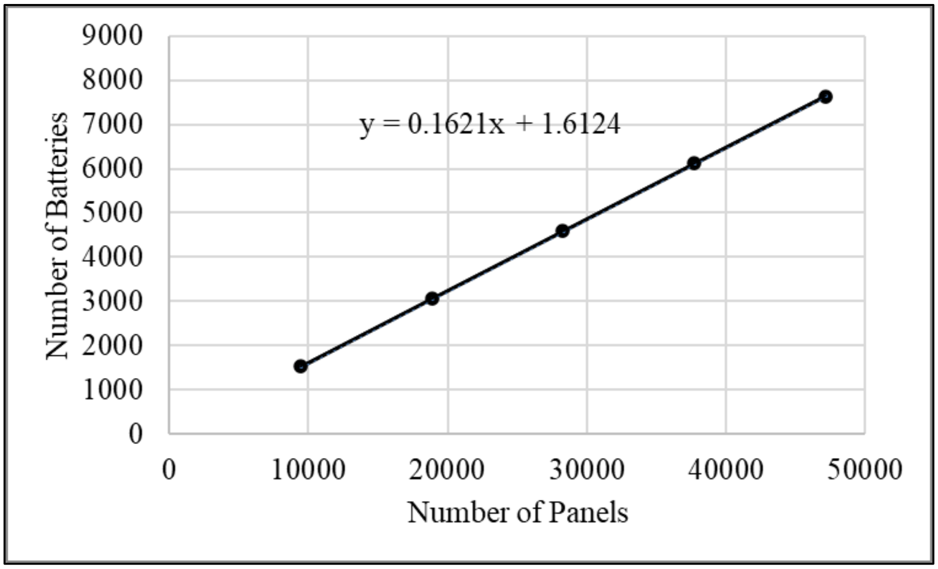
4000
3500
3000
2500
2000
1500
1000
10000
15000
20000
25000
Number of Batteries
Number of Panels

(a)



6000
5000
4000
3000
2000
1000
0
0
10000
20000
30000
40000
50000
y = 0.1053x + 1.1466
Number of Batteries
Number of Panels

(b)



(c)

Figure 2.4: (a) Sample simulation results for an optimal system configuration incorporating energy storage, (b) relationship between optimum number of panels and batteries for 75% DOD and (c) 50% DOD

2.5.1 Energy use profile and net energy ratio

Figure 2.5 shows the energy consumption in various stages of the life cycle of a utility-scale solar power plant with a rated capacity of 5 MW_p. The energy consumed during the life cycle is estimated to be 2.33×10^7 kWh_e. Upstream processes related to raw material production and solar PV panel assembly are the most energy intensive of all the processes and account for 76.56% of the energy use. The energy required to produce a single panel was calculated as 1157.5 kWh_e. Upgrading silicon ore into a usable form for solar cells consumes 65.29% of this energy. Process energy in the form of heat and electricity were found to be responsible for most of this energy use. This value is considerably lower than the values reported by others [59, 60, 71, 102] because the assumption in this study is that module assembly will take place in Canada and use a large share of recycled raw materials. The module assembly stage is the third highest energy-consuming process in the production process and accounts for 22.48% of the energy. Upstream energy consumed to produce the aluminum frames is responsible for a large share. According to the life cycle inventory analysis, each panel requires around 67.4 kWh_e to produce the aluminum frames needed. The mounting structures account for 68.79% of the energy consumption in the system integration stage, followed by the inverters at about 31.06%. The key challenge in providing more accurate results for this stage is that process energy data for the two processes is scarce, and so there is a high amount of uncertainty. Maritime and ground transportation are responsible for just over 1% of the energy consumption. As discussed above, the end-of-life scenarios were modelled with data from European recycling plants; this stage of the life cycle makes up less than 3% of energy consumption.

Energy use during the production of lithium-ion batteries was calculated to be 5283.74 kWh_e per battery. The upstream energy requirements to produce the raw materials for batteries were calculated as 2606.25 kWh_e. The production lithium-ion batteries has six major steps; these are discussed in an earlier study [64]. The energy required for raw material production ranges from 8.33 to 27.78 kWh_e/kg [39]. The process energy required for battery manufacturing was estimated based on the life cycle inventories of lithium-ion batteries used in electric vehicles [90]. Although the energy requirement for that use can be much lower than for solar PV panels, their GHG emissions are significantly higher, as section 3.3 shows.

Figure 2.6 presents the NER results for a utility-scale solar power plant with several orientations. The NER values show a similar trend as EPBTs. The values range from 4.28-8.74, which indicates that the systems are net energy producers. The NER decreases by 34.76% when the plant is integrated with an energy storage system, because of the addition of batteries. The net energy ratio is highly dependent upon the efficiency and lifetime of the solar PV panels as they are the only energy-generating equipment in the assumed system boundary and these two parameters dictate how much energy will be generated throughout the entire life cycle. Continuous improvement in the solar PV industry to achieve higher efficiency and lifetime for solar PV panels should increase NERs in future.

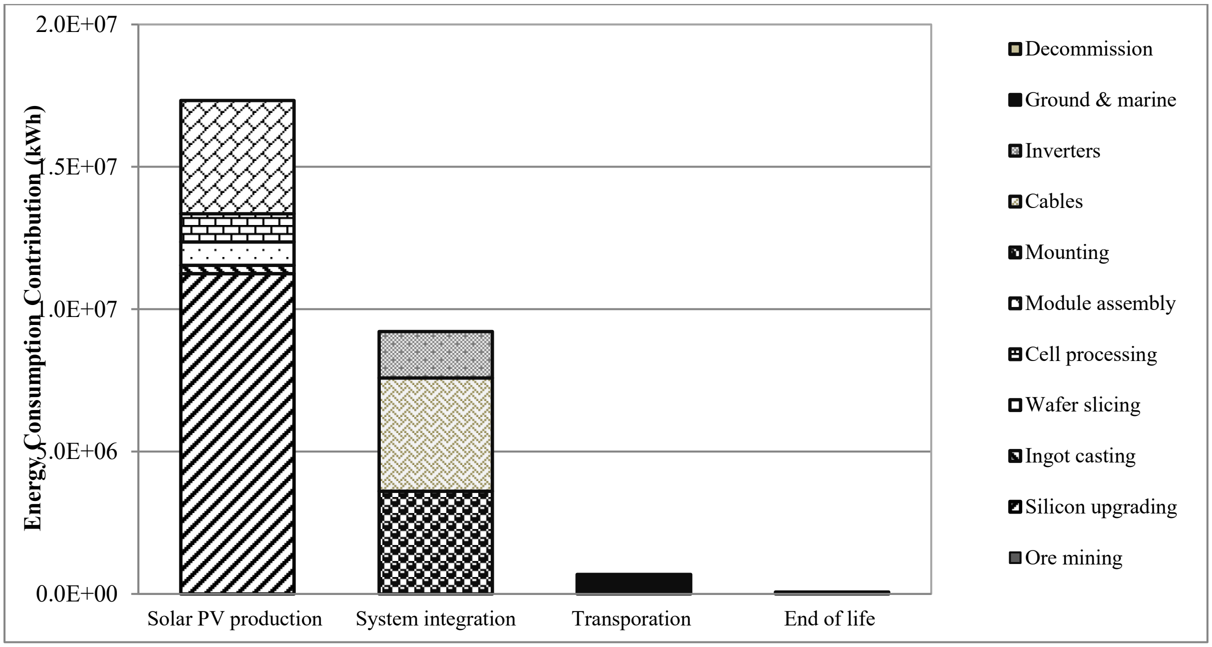


Figure 2.5: Energy consumption profile of a 5MWp utility scale solar farm

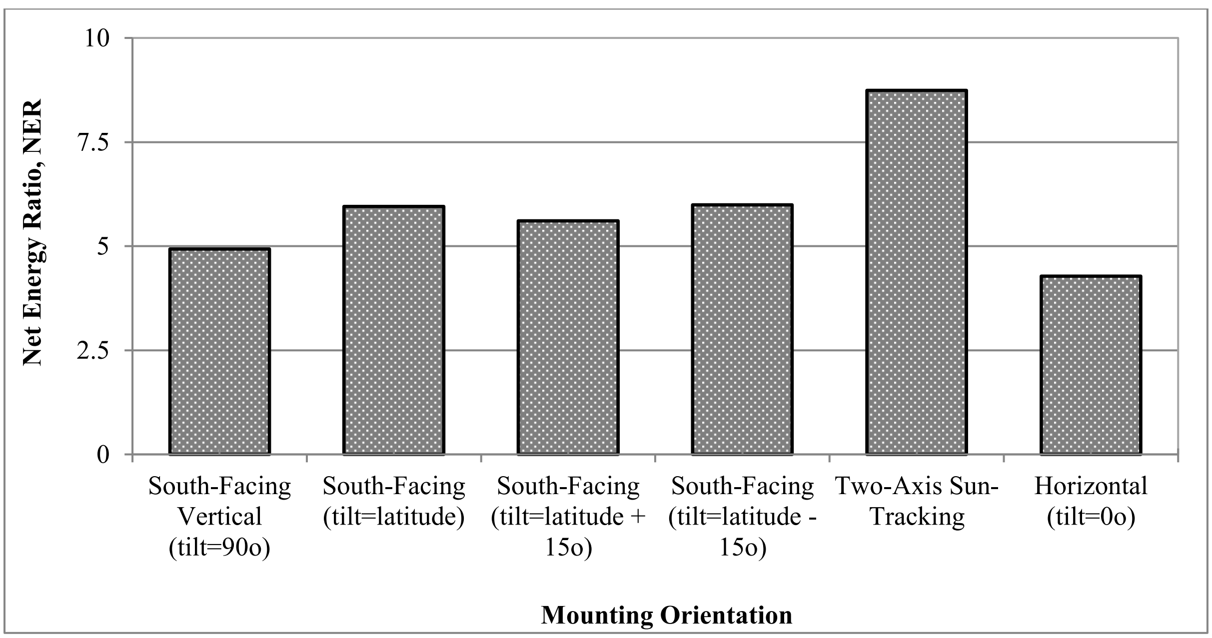


Figure 2.6: Net energy ratio for different orientations

2.5.2 Energy payback time

Figure 2.7 shows the EPBTs of utility-scale solar PV plants at different mounting orientations. Mounting orientations have a significant effect on overall energy yield of large-scale solar farms. It determines how much solar energy will fall on the panels and thus how much energy can be converted to usable electricity. As EPBT is a measure of how long it takes a system to return the amount of energy that has been invested during its material formation, production, transportation, installation, and estimated energy use at the end of life, a lower EPBT is always desired. The lowest EPBT of 2.86 years is estimated when dual-axis trackers are considered as mounting structures. On average, using a dual-axis tracking system would reduce the EPBT of large-scale solar farms by 1.7. Solar panels having the same or a $\pm 15^0$ tilt angle as the latitude of the location are the next best options with an EPBT of around 4.3 years. For a utility-scale system with energy storage, the EPBT values obtained are significantly higher, at a factor of 2.87. This is mainly due the consumption of high amounts upstream energy in the life cycle of the batteries.

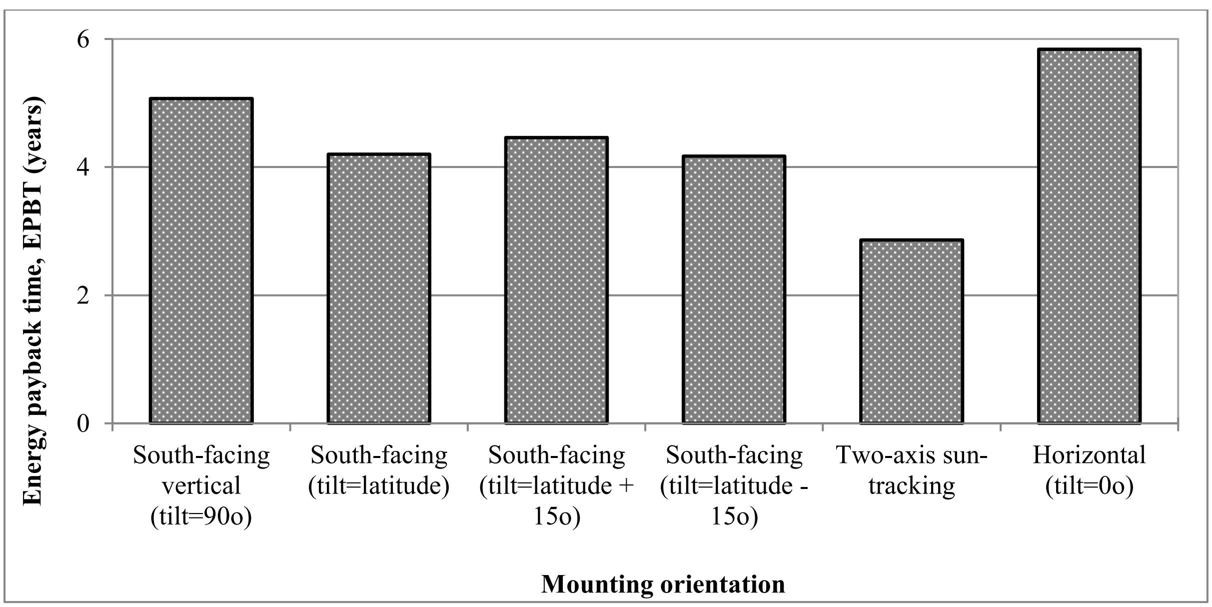


Figure 2.7: Energy payback time for different orientations

2.5.3 Life cycle GHG emissions and land use

For the base case, the total life cycle GHG emissions were 69.14 g CO_2 eq /kWh of generated electricity. This result is on par with regions of similar global solar irradiance values. Figure 2.8 shows the breakdown of system GHG emissions by life cycle stage. Understandably, the production phase of the solar PV panels contributes the highest amount of emissions, 48.68 g CO_2 eq /kWh. The most GHG-intensive processes in the production phase are associated with upgrading the quartz sand to a usable form, namely industrial grade (14.40 g CO_2 eq /kWh) and solar grade silicon (15.99 g CO_2 eq /kWh). During the assembly processing stage, the aluminum frames are another major source of GHG emissions, 10.90 g CO_2 eq /kWh. If the aluminum frames are not considered, then the module assembly stage constitutes only 3.47 g CO_2 eq /kWh. Aluminum frames are not required in snowy conditions like Alberta's as snow would easily slide off the panels. The contribution GHG emissions from direct land use is very marginal. The values range from 0.80-2.76 g CO_{2eq}/kWh, for arid grasslands and mixed type areas, which is minimal compared to overall lifecycle GHG emissions. Direct land use change GHG emissions have been calculated by discarding the transmission and distribution line area requirements as they do not directly affect the lifecycle emissions.

To supply the same amount of energy with energy storage options, the environmental cost of continuous electricity supply is 118.80 g CO_2 eq /kWh. The GHG footprints of batteries themselves is significantly higher than the system without the energy storage option.

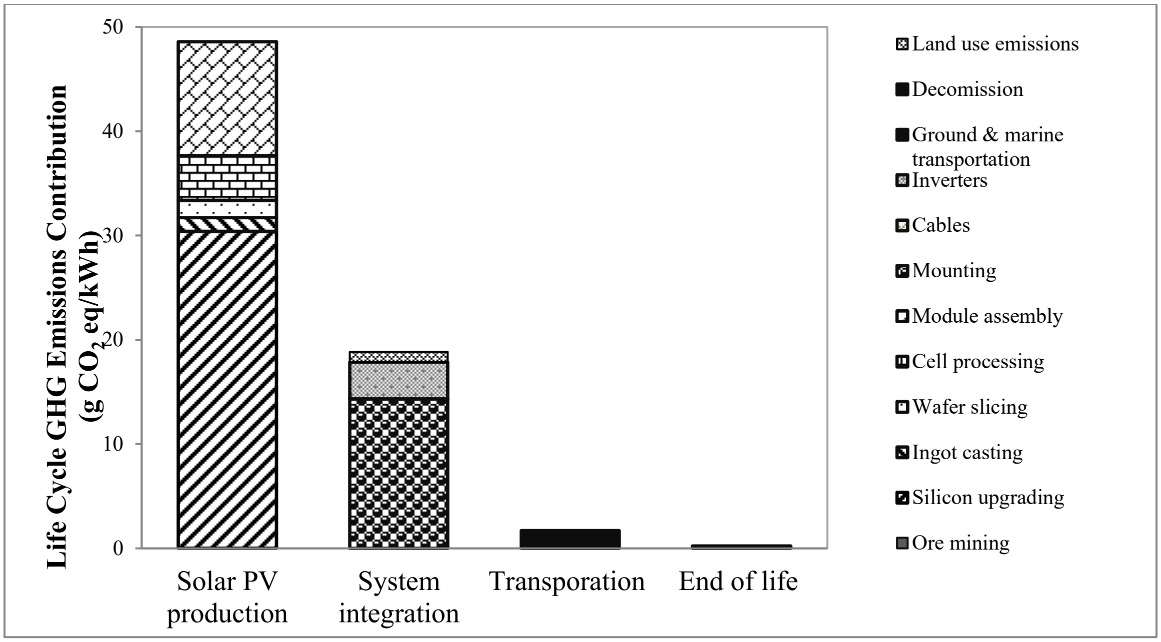


Figure 2.8: Life cycle GHG emissions by phase

To provide a contextual understanding of the results of this study, Table 6 lists some established electricity-generating technologies and impact assessment indicator figures extracted from studies that used a similar system boundary. The table makes clear that coal-based power plants have the biggest impact on the environment based on GHG emissions, but they also have a very high NER. The ranges shown for domestic natural gas-based power plants are averaged values for simple and combined cycles; these have significantly fewer GHG emissions than coal. They also provide high energy yield during their life cycle. These two fossil fuels are currently the major electricity sources in Alberta. However, renewable energy wind and hydroelectricity are the most relevant as they account for more than 61% of the renewable energy-based electricity produced in Alberta [52]. Relevant LCA results based on regional characteristics for these two technologies were not found in the literature. According to the results obtained in this study, the energy and environmental performance of utility-scale solar farms would be most comparable with wind energy. Economic lifetime assumptions for hydropower reservoirs are 70-100 years, which is one of the main reasons for their low GHG emissions and high life cycle energy yield predictions.

Bearing in mind Alberta's long-term plan to phase out coal power plants, the feasibility of using renewable energy sources as the base load has to be considered, as earlier discussed. The results from the LCA model with energy storage show that adding batteries to ensure consistent electricity supply would significantly increase GHG emissions compared to the scenario without an energy storage system. That said, electricity from such sources would still be at least 76% cleaner than coal power. When LCA studies are compared, it was found that a major parameter affecting the overall life cycle performance of different utility-scale electricity-generating facilities is their lifetime. Tradeoffs between GHG emissions and energy yield must be considered by concerned policymakers, as coal power plants generally serve well beyond 50 years.

Table 2.6: GHG emission and energy performances of conventional and renewable energy sources

System Type	GHG (gCO_2/kWh)	EPBT (years)	NER (kWh/kWh)	Reference
Coal-fired	780-1029.65	1.73	29-31	[103-105]
Natural gas	400-725.75	9-12	28	[103, 104]
Nuclear	22.2-24.2	0.8	74.92	[104, 106]
Hydropower (run of river/non-tropical)	0.5-152	0.37-8.92	3.27-112.7	[104, 107]
Wind (onshore)	3-45	0.58-1.4	3.9-16	[104]

The land use footprint from utility-scale solar farms largely depends on the transmission and distribution line length which is defined as the distance from the powerplant to the end user. In this study a range of value from 0.25-1.23 m^2/kWh were found for twin axis systems for transmission and distribution line lengths of 100-500 km, and 0.23-1.15 m^2/kWh for fixed width systems. The land footprint attributed only from the PV and balance of system installation is very insignificant.

2.5.4 Sensitivity and uncertainty analysis

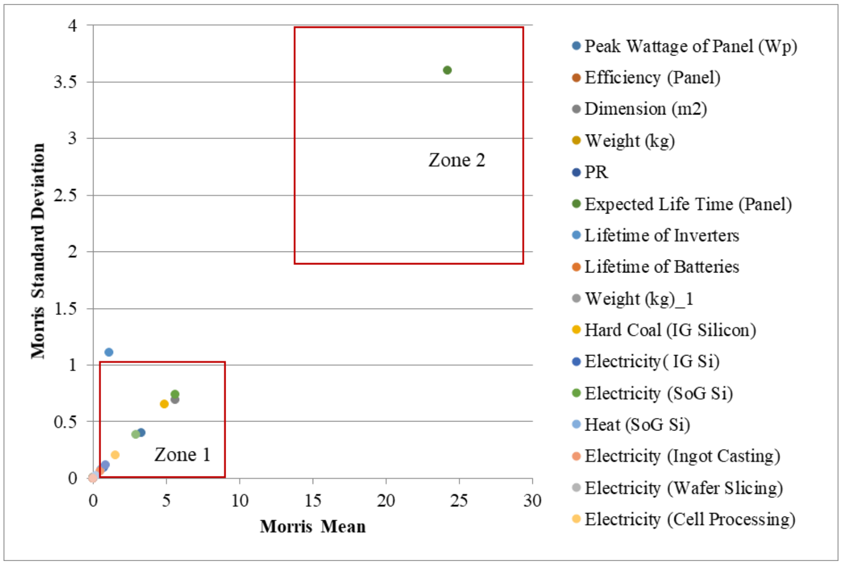
Sensitivity and uncertainty analysis were performed to capture the effects of changes in the input parameters on the NER, EPBT, and GHG emissions of a utility-scale solar power plant. The effects of changes in lifetime, efficiency, electricity and other forms of unit operation energy, and physical parameters such as dimension and weight were investigated through the sensitivity analysis. The Morris statistical method was used to perform this analysis. A detailed description of the methodology is given in [108]. The results are given in Figure 2.9.

Higher Morris mean and standard deviation values indicate higher sensitivity of the input parameter in changing the results of the LCA model. One hundred partial derivatives were considered across the parameter space (model inputs). A large standard deviation (y-axis) indicates that the model is either non-linear or there is interaction effect between the inputs. Since all the input variations and the relationships in the formulas have been identified as linear relations, it can be interpreted that for all the three outputs (as shown in Figure 2.9(a), 2.9(b) and 2.9(c)), are driven by the interaction effect. Each of the points that are depicted in the zone 1 can be neglected as the have negligible effect on the output. The parameters in the zone 2, shown in the upper right quartile of the graph are the critical ones and influence the output most.

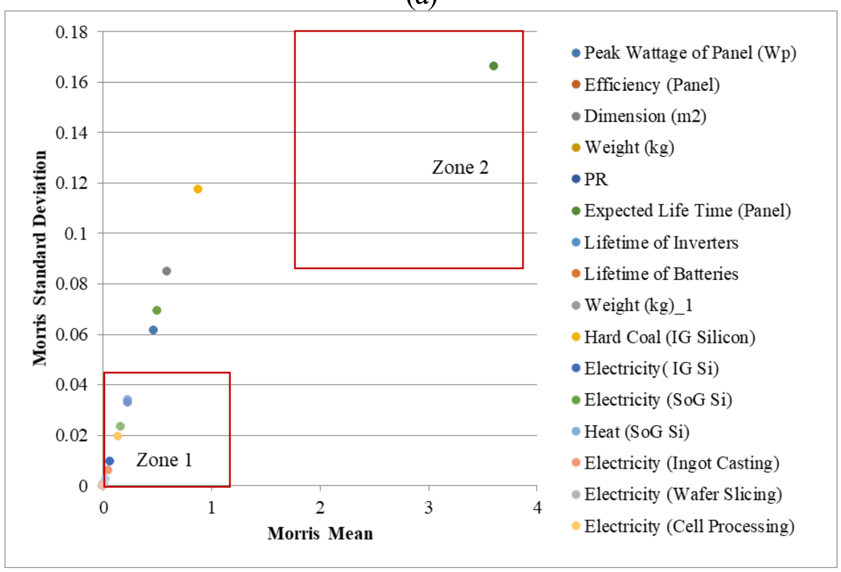
GHG emissions are most sensitive to the expected lifetime of the system as shown in Figure 2.9(a). As the lifetime of the solar PV modules increases, allowing the system to produce more electricity during the life cycle, the overall GHG emissions of the system is expected to decrease. The lifetime sensitivity can vary up to 24.22 gCO_2 eq/kWh. The electricity for solar-grade silicon upgradation and hard coal for industrial-grade silicon demand are also important parameters. As both energy sources account for a significant portion of GHG emissions during these processes, increasing the efficiency of energy conversion would drastically reduce the GHG emissions. For the system with the energy storage option, the process energy requirement for battery production, the material requirements, and expected lifetime are the most sensitive parameters, in addition to those mentioned in the base case. As discussed in section 2.3, it is difficult to estimate the process energy requirements during battery production due to lack of reliable data.

The EPBT is most sensitive to the peak wattage of panels, the hard coal for industrial-grade silicon, and the electricity for solar-grade silicon production as shown in Figure 2.9(b). The peak wattage of PV panels and their dimensions dictate the energy per effective area, and the higher the peak wattage from the same panel dimensions, the lower the EPBT will be. For the system with energy storage, process energy and material percentages add to the parameters.

The NER, like the EPBT, is sensitive to the same parameters, as both depend on upstream energy consumption and energy yield during the operational phase. It can be seen from Figure 2.9(c), the sensitivity for electricity consumption during the upgrading of silicon cells can account for a change in NER of 5.65 for the base case. All three life cycle impact indicators are sensitive to the weight of the panels, and this is related to the upstream energy requirements and emissions during raw material production. The parameters in between zone 1 and zone 2 can be identified as semi-sensitive parameters and the choice of including them in the uncertainty analysis is a subjective matter. In this study, all the semi-sensitive parameters have been included in the uncertainty analysis.


Morris Standard Deviation
Morris Mean
Zone 1
Zone 2
Peak Wattage of Panel (Wp)
Efficiency (Panel)
Dimension (m2)
Weight (kg)
PR
Expected Life Time (Panel)
Lifetime of Inverters
Lifetime of Batteries
Weight (kg)_1
Hard Coal (IG Silicon)
Electricity(IG Si)
Electricity (SoG Si)
Heat (SoG Si)
Electricity (Ingot Casting)
Electricity (Wafer Slicing)
Electricity (Cell Processing)

(a)


Morris Standard Deviation
Morris Mean
Zone 1
Zone 2
Peak Wattage of Panel (Wp)
Efficiency (Panel)
Dimension (m2)
Weight (kg)
PR
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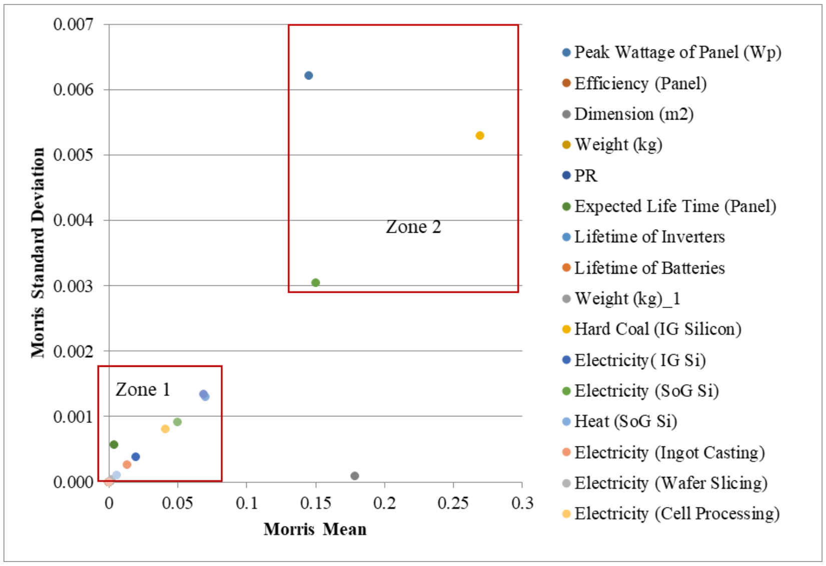
Lifetime of Inverters
Lifetime of Batteries
Weight (kg)_1
Hard Coal (IG Silicon)
Electricity(IG Si)
Electricity (SoG Si)
Heat (SoG Si)
Electricity (Ingot Casting)
Electricity (Wafer Slicing)
Electricity (Cell Processing)

(b)

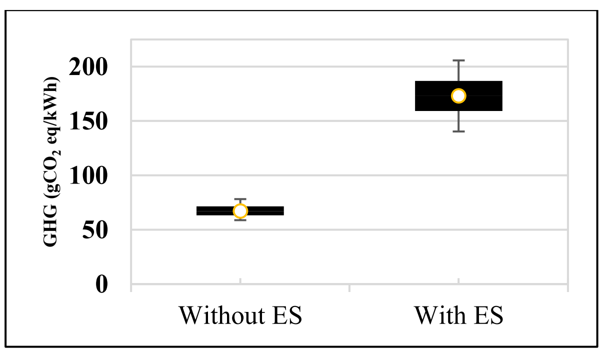


(c)

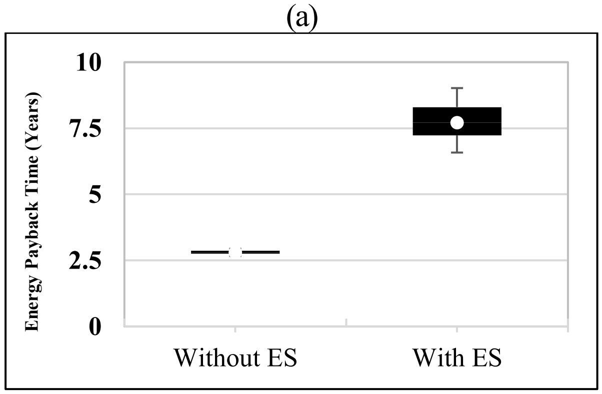
Figure 2.9: Sensitivity analysis of the LCA model outputs using Morris method (a) GHG emissions, (b) EPBT, (c) NER

Uncertainty analysis was performed to evaluate the effects of a simultaneous change in multiple input parameters on the NER, EPBT, and GHG emissions. A Monte Carlo simulation was conducted using the RUST model developed by Di Lullo et al. [108]. In order to perform the simulations, the statistical distributions of the input parameters are required. Because data is limited, a triangular distribution was generated for every parameter except peak wattage, weight, lifetime, and solar PV panel efficiency (detailed information is provided in the SI). A triangular distribution gives conservative results for predictable values as well as a lower standard deviation. For the energy requirements in different unit processes, especially silicon upgrading, it is hard to predict values reliably as these parameters can differ significantly from site to site. This difference is accounted for by choosing a uniform distribution as it gives the most conservative distribution and treats all the inputs equally. A random sample was selected from the range of input variables and iterated 10,000 times to obtain final output distributions. The formulas used to calculate the sampling error are provided in the SI. To reduce the computational time a total of 20 parameters were selected for the uncertainty analysis based on the identified sensitive parameters in the Morris sensitivity test.

The results of the uncertainty analysis are shown in Figure 2.10(a), 2.10(b) and 2.10(c). The mean GHG emissions for a system with and without energy storage options are 69.14 and 187.89 g CO_2 $_{eq}$ /kWh, respectively as shown in Figure 10(a). It can be seen that there is high uncertainty in the estimation of GHG emissions for the system with the energy storage option, which can be attributed to the unreliable data related to energy requirements during the production of lithium ion batteries as discussed in section 2.2. The EPBT mean values are 2.80 and 7.71 years, respectively, for the two scenarios. Their ranges are 2.67-2.94 years and 6.58-9.02 years, respectively as shown in Figure 2.10(b). The NER mean values are 8.92 and 3.22. Their ranges are 7.66-10.22 and 2.78-3.76 for systems without and with energy storage options, respectively as shown in Figure 2.10(c).



(a)



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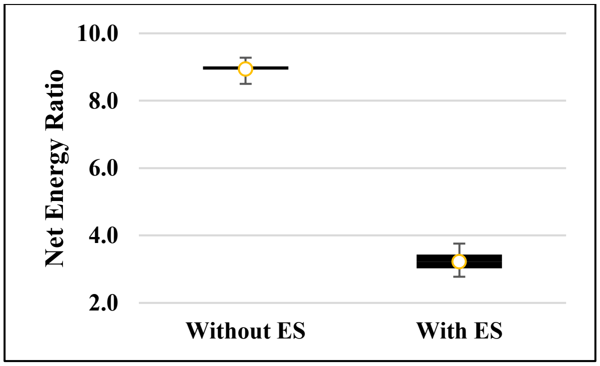

(c)

Figure 2.10: Uncertainty analysis results for the systems with and without energy storage (a) GHG emissions, (b) EPBT, (c) NER

2.6 Conclusions

The objective of this study was to evaluate the GHG emissions and energy use profile of utility-scale solar farms. A case for a North American jurisdiction was conducted. The key results for the base case were found to be in the range of $69.14^{+10.47}_{-8.93}\, gCO_{2\,eq}/kWh$ for GHG emissions, $2.86^{+0.14}_{-0.13}$ years for energy payback time and $8.74^{+1.30}_{-1.26}$ for net energy ratio. In order to fill the identified research gaps, this study provides a robust model with life cycle inventory data based on the most recent commercially available technologies and maps the entire value chain. Simulation models were used to develop a utility-scale solar power plant and determine the required equipment sizes, thereby improving the reliability of the results. The electricity generation models developed used location-specific solar insolation data and considered changes in performance from snowy conditions. The results provide a good estimate of energy yield. The complimentary model, where an optimal system configuration was sized using the LPSP concept and prices of panels and batteries, provides a robust platform to calculate the energy and GHG emissions profile for a system that incorporates energy storage.

The life cycle energy profile for a utility-scale solar power plant shows that most of the energy is consumed during the production of solar panels and BOS equipment accounting for more than

76% of the total energy demand. The energy mix of the manufacturing site plays a crucial role. For example, the fossil fuel-dependent electricity mix in China contributes more than 36% of the GHG emissions. China is the largest manufacturer of solar panels, and yet its GHG footprint is imposed on the end user, in this case Alberta. It was also found that the land use change emissions are minimal in terms of lifecycle GHG emissions (less than 1%) and would not be a key hotspot in case of power plants in Alberta landscape.

The principal findings of this work are the determination of the optimum size requirements for utility-scale solar farms with and without ES options and the resulting environmental and energy implications. The study found that the GHG emissions from prospective solar farms in Alberta would be well below those from conventional power plants currently in use. This information would be relevant during the phase-out of coal-based power plants and provide a better understanding of environmental implications. The trade-off between energy efficiency and GHG reduction can also be understood through the sensitivity and uncertainty analyses of the life cycle GHG and energy performance results.

Chapter 3

Transition to cleaner electricity generation for fossil fuel-dominant jurisdictions: a consequential life cycle assessment approach

3.1 Introduction

Global energy-related CO_2 emissions increased by 1.7% in 2018 from the previous year (almost double the average growth in 2010) due to increased energy consumption [1]. Natural gas is the main contributor, accounting for nearly 45% of the change in energy demand. The contribution from coal has substantially decreased over the last decade, but they still account for almost 26% of the total global energy consumption [1].While renewable energy sources accounted for 25% of global energy demand growth, these are far from meeting the fast-growing global demand for electricity [1]. The electricity generation sector accounted for more than 30% of the global greenhouse gas (GHG) emissions in 2019 [1, 47]. In an attempt to reduce global temperature increases and the adverse effects of global warming, there is a growing focus on mitigating GHG emissions from the electricity generation sector in regions that rely heavily on fossil fuel energy sources [109].

The transition to a lower carbon electricity generation system has put considerable emphasis on increasing the penetration of renewable resources into electricity generation systems. Many jurisdictions have recognized the need to address global warming caused by energy generation systems and started to set energy policies to reach emission reduction targets [110-113] through the transition towards low-carbon electricity [114]. However, understanding the pathways to achieving a reliable electricity supply is a challenge. Although a decline in fossil fuel-based energy generation has been predicted throughout the last century [115], conventional fossil fuel industries have proven to be very resilient. The integration of renewable energy sources poses technological and economic challenges [116], [117]. Incorporating renewable energy into existing electricity generation systems has challenges related to renewable energy ramp-up, production, and the added cost of power generation [81]. Understanding the long-term environmental and economic consequences of different policy alternatives on renewable energy is not straightforward. It requires a robust framework that can systematically answer questions such as: What would be the optimal long-term electricity mix in different policy scenarios for a jurisdiction? Which of the technologies would be the marginal supplier of electricity? How would the emissions change from an increase in demand in each policy scenario? How would these change from a substitution? How does the cost of generating electricity change in each situation?

Resolving these questions requires determining the optimal electricity generation mix for each policy decision. It can be expected that changes in the electricity mix, especially from the penetration of renewable energy technologies, would result in drastic GHG emissions mitigation in a fossil fuel-dominant jurisdiction. However, due to technical constraints such as lower efficiencies and intermittent delivery of power for technologies such as solar and wind, any change from the forecasted demand may be detrimental to overall grid performance. Here the question is whether marginal environmental benefits outweigh the technical drawbacks incurred along a product value chain. These key issues raise further questions about incorporating market information into environmental assessments of renewable energy technologies and the electricity market. In addition to these issues, deviating from the status quo would have a substitutional effect on GHG emissions. Understanding the substantial effect requires thorough investigation to measure the perceived benefits of increased penetration from renewable energy technologies. This paper, therefore, conducts a consequential life cycle assessment (LCA) of the available technical and economic characteristics of power generation systems currently in use as well as potential new technologies.

LCA is a tool widely used to integrate the environmental, economic, and social aspects of decision-making processes [118]. LCA has two approaches, attributional and consequential [119], [120]. Attributional LCA uses the normative rule to account for inputs and outputs and associated environmental impacts of a product system. Attributional LCA determines the allocated shares of activities that make up the life cycle of a product using market average data. Consequential LCA (CLCA) is a modeling approach that determines the potential change in a product system [121]. The long-term consequences of modifying electricity generation systems to decarbonize the sector need to be studied in the context of optimal electricity mixes for specific jurisdictions, which vary. The CLCA approach has been widely used to quantify the environmental implications of policy alternatives in different sectors such as agriculture [122-124], animal husbandry, bioenergy [125-127], livestock production [128-130], etc. The multi-functionality of these product systems creates the need to avoid allocating co-products and quantifying the changes happening outside the system boundary. There is limited CLCA research on electricity generation. Published research related to the electricity sector, considered a "uni-functional" system, receives less attention from LCA practitioners, and there are relatively very few assessments of the long-term consequences of policy decisions in this sector. Moreover, the few research articles in the electricity domain have different concerns, mainly because they focus on different aspects of the electricity sector [131-133]. As long-term electricity policies are often dictated by jurisdictional preferences and government initiatives, directly applying the CLCA approach in the electricity sector from different regions often becomes difficult. This study addresses these gaps and uses the CLCA approach to quantitatively assess changes in the electricity sector.

A few studies have demonstrated the CLCA approach in the electricity sector. But the researchers followed their own methods to reach the answers which were sought. Turconi et al., for example, evaluated the emissions from the expansion of electricity distribution infrastructure in Denmark's electricity transmission and distribution system [43]. The authors argued that the impacts of electricity distribution would significantly increase in the future, because of the forecasted increase in the penetration of renewables and decentralized electricity generation. Their main contribution was the life cycle inventory datasets for electricity distribution systems (power lines, transformer substations and other equipment) that can be added to LCAs of energy systems. But their work does not analyze the penetration of renewable electricity in terms of capacity addition or projected market share. A more focused of a specific technology penetrating the electricity grid was done by Pehnt et al., who performed a consequential environmental system analysis of expected offshore wind electricity production in Germany [41]. Their work analyzed in depth the substitutive and structural effects of wind power on the supply of power and the subsequent altered operation of conventional power plants. The authors did this by coupling the life cycle assessment of offshore wind use with a stochastic model of the German electricity market. Their work demonstrates that the construction and operation of offshore wind parks have lower CO_2 emissions than substitutions in the electricity mix and offshore wind mainly replaces medium-load technologies. Turconi et al. investigated the effect of wind power penetration on the cycling of thermal power plants [42]. They used the attributional approach and then expanded the system boundary to account for the effects outside the system boundary. They argued that increased cycling emissions did not negate the benefits of higher wind penetration. They also found that energy storage combined with baseload coal did not reduce system emissions. Although there are many studies on the effects of increased renewables on conventional thermal power plants, there is scarcity of studies focusing on market dynamics or the effects of policy decisions on net GHG emissions due to increased electricity demand and the replacement of energy sources over a long time period, which are the focus of this research.

To the best of the authors' knowledge, Canada-specific research related to the long-term consequences of policy decisions in the electricity sector from a CLCA point of view has not been developed yet. Davis et al. conducted long-term energy modeling for Canada, including an integrated energy systems model of the national energy system [45]. They used the Long-range Energy Alternative Planning (LEAP) system to model the energy system in each region in Canada, and their modeling approach can be used to perform CLCA [134]. The electricity mix of Alberta, a western province in Canada and the area of investigation in this study, comprises 35.53% coal-based power plants, with a little over 15% from renewable sources (hydroelectric, wind, and other) [135]. The optimal way of transitioning to a lower carbon electricity generation for this region is to consider the technical, economic, and environmental parameters from the life cycle perspective. This study aims to address the research gaps by developing a framework to quantitatively assess the changes in the electricity sector through the CLCA approach. The framework incorporates market penetration information and energy modeling systems with environmental impact assessment methods. The specific objectives are to:

1. Develop a general electricity sector - CLCA framework integrating bottom-up energy modeling,
2. Develop scenarios based on policy initiatives and future available electricity generation technologies,
3. Identify the technologies that would be the marginal supplier in each scenario,
4. Quantify the change in GHG emissions due to an increase in demand in each policy scenario,

5. Determine the effect of technology substitution on GHG emissions in each scenario,
6. Estimate the change in the cost of electricity generation in each scenario.

3.2 Methodology

3.2.1 General framework

A generalized CLCA framework was developed to provide insights into long-term marginal changes in a product system and economy-wide environmental consequences resulting from policy decisions. Figure 3.1 presents the conceptual framework, which includes scenario development, market penetration, energy modeling, and marginal supplier identification methods. Scenario development refers to the creation of pathways using qualitative and quantitative parameters in order to understand critical issues related to long-term consequences of a change in demand from a product system. The scenarios are used as input in the market penetration model, which provides information on the current and probable future outputs of a product system. The long-term consequences are quantified based on changes in the system and thus the penetration potential of emerging suppliers over the timeframe of the study helps assess changes in environmental impacts. While the market penetration model estimates of the probable capacity of each technology in the future, the technology mix depends on the amount of the output and the technology cost. Hence, in order to understand the competitiveness of each technology and to evaluate economic and environmental performances from different policy scenarios, an energy model was developed capable of handling different technical and economic aspects through the Long-range Energy Alternatives Planning (LEAP) model platform. LEAP is a data-intensive framework and primarily used for energy-environment investigations of different sectors in an economy. The LEAP framework consists of technological and environmental datasets, which include the technical features, costs, and environmental impacts of energy-generating resources. The framework uses a bottom-up approach allowing the characteristics of each individual resource or technology to be modeled accurately. The framework has been used widely to conduct GHG mitigation studies in Alberta related to regional energy systems [44, 45], in the mining industry [135, 136] and in renewable electricity generation pathways [46]. For example, Davis et al. assessed various renewable electricity generation pathways for coal-dominant jurisdictions by developing a number of scenarios based on different policies and technology mixes with a focus on the GHG abatement cost of each scenario [46]. The energy modeling in LEAP provides information on technology mix, cost, and GHG emissions of each technology. That information is fed to the marginal supplier identification model. The objective of identifying the marginal supplier is to determine which technologies would be used as a consequence of additional demand in a given year. Identifying the marginal supplier through a robust consequential assessment is challenging, but as the environmental characteristics can be examined by identifying affected activities (changes in the technology mix), it can add significant value in making informed policy and investment decisions. Unlike the conventional attributional approach, any change within the system boundary as a result of a change in output levels needs be identified. This allows market information to be included in the product's system boundary and provides realistic and detailed results of environmental consequences [137].

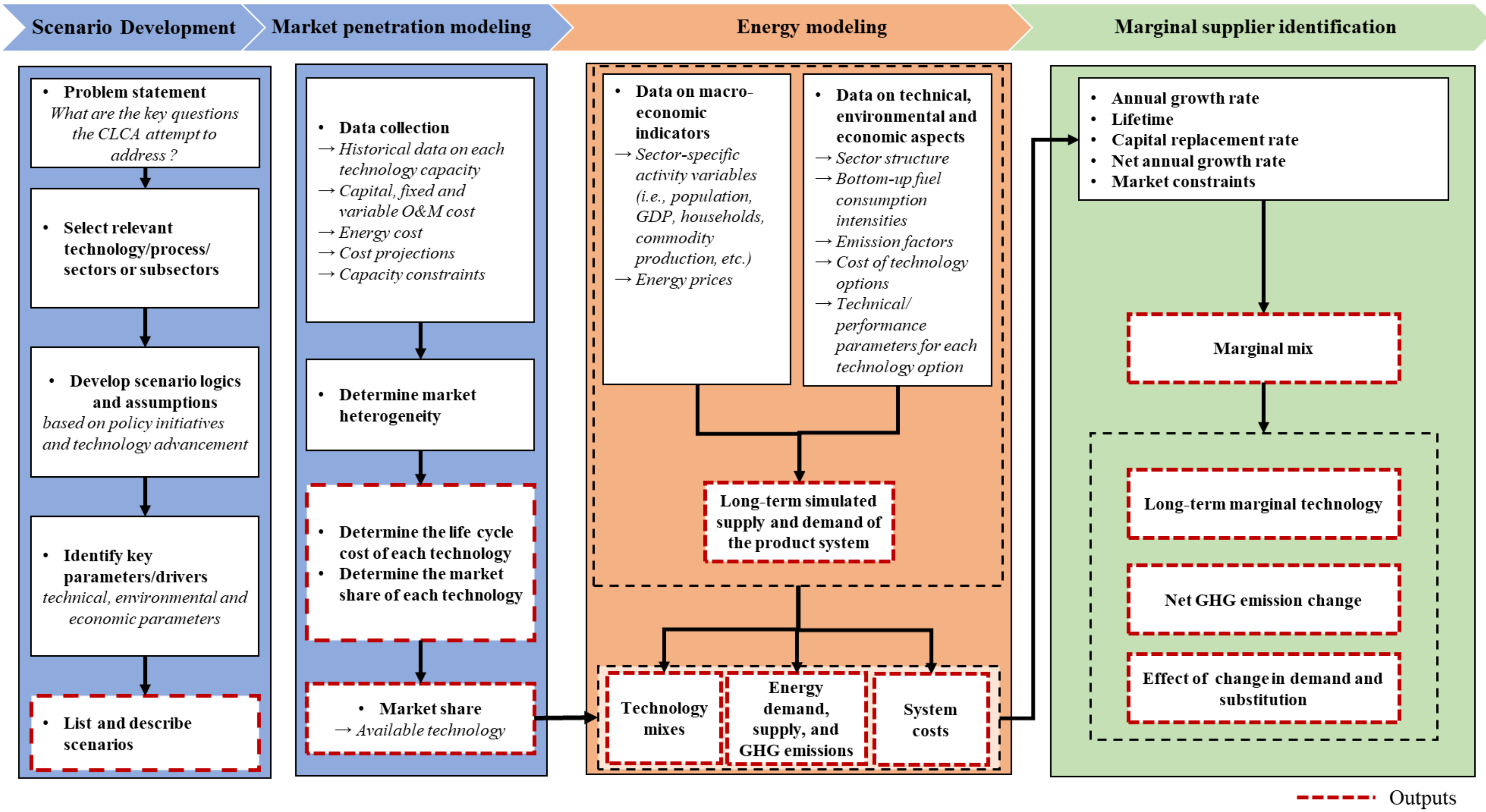

Figure 3.1: Proposed framework for consequential life cycle assessment

3.2.2 Case study for Alberta's (a western province in Canada) electricity generation sector using the proposed framework

Alberta is a western Canadian province and has a fossil fuel-based electricity system. The developed framework was applied to Alberta's electricity generation sector to provide insights into long-term marginal changes in electricity generation from different sources and potential environmental consequences due to policy decisions in a fossil-fuel dominant jurisdiction. The application includes the energy use and emissions in the processes required to get the final energy product. Energy demand was calculated based on end-use categories ranging from industrial to residential energy use; this was done in prior work by the authors [44]. These bottom-up projections take into account the economic, energy efficiency, and industry production expectations for the study period. The assessment is focused on the net GHG emissions change that due to the variation in electricity mixes, thus net changes in the upstream processes were not taken into consideration. Such upstream analysis demands further research and modeling of wider economic consequences and might require the coupling of economic models that are outside the scope of this work. Energy use and GHG emissions at the end of life of the infrastructure in each electricity-generating technology (such as decommissioning) and the recycling of solar and wind components were not included due to the lack of reliable data. Land reclamation from coal mines and natural gas infrastructure were also excluded from this study due to the unavailability of reliable data. Each component of the framework is discussed in the following sections.

3.2.3 Scenario development

We developed 9 scenarios for Alberta's electricity sector based on policy initiatives, available resources, and key technical parameters. Electricity systems are multifaceted and influenced by social, political, economic, technical, and environmental drivers. The overarching emphasis on GHG mitigation, diversifying technology, and ensuring low-cost electricity generation presents critical uncertainty for the future and hence was the rationale in developing the scenarios. Table 1 lists and describes the scenarios.

The base case scenario is the only one in which the results of the market penetration model are used. In all the other scenarios, where changes in market penetration depend on the policy decisions or the changes in technological advancements, the future capacities are derived from the energy modeling exercise based on the lowest cost of electricity generation. Since LEAP's built-in functions perform market penetration of electricity generation facilities only, market penetration modeling was not used for any of these scenarios. This assessment focuses on the policy decisions of the aggressive phase-out of coal power plants and the deployment of power generation systems with lower GHG intensities.

Table 3.1: Detailed descriptions of the scenarios developed for energy modeling

Scenario	Symbol	Main Features	Description
Base case	BASE	• Historical and future capacities from the market penetration model • 30% renewable target by 2030	The exogenous capacity of the power mix specified from the logistic curves is obtained from the market penetration model. Policies of phasing out coal power plants and a target of 30% renewable energy by 2030 are implemented by constraining the total fossil fuel capacity. No optimization features are used, and the dispatch order is generated based on the specified merit order.
Optimized base case scenario	O-BASE	• Only historical capacity information is provided. Future capacity is determined using the OSYMOSYS optimization feature.	Exogenous capacities of different technologies are specified only based on historical electricity generation capacities. The planned decommissioning and estimated end of operational lifetime for existing power plants (natural gas and renewables) are specified so that the optimization framework can replace outgoing power plants with incoming "new" technologies based on the lowest net present value (NPV) at the system level, subject to constraints.
No renewable targets	NO-R-TAR	• Optimized capacities without any renewable targets • No emissions target • Objective is to minimize the cost of production.	The only difference from O-BASE in this optimized scenario is that there are no renewable energy electricity generation targets set in the foreseeable future, and no emissions targets are set. The planned decommissioning of the coal power plants remains. This scenario was developed to understand the consequences of no policy actions towards greening the electricity generation system with the penetration of renewables.
Solar farms with storage	SOL-B	• Capacity credits increased for solar farms. • Increased capital cost for sized systems • 30% renewable target, as before	Utility-scale solar farms are added with energy storage options by modeling the effect of energy storage by increasing capacity credits. The capital cost of utility-scale solar farms was increased based on the system-sizing method using the concept of loss of power supply probability (LPSP) and economics of panels and batteries [138]. The cost declination projection for panels and batteries were also considered. The method used to size such systems can be seen in Appendix A4. The emissions factors for such systems were also adjusted based on the system sizing principles.
Wind farms with storage	WND-B	• Capacity credits increased for wind farms. • Increased capital cost for sized systems • 30% renewable target, as before	The same method applied for utility-scale solar farms was applied to the base optimization model with wind instead of solar farms.

Scenario	Symbol	Main Features	Description
Solar and wind farms with storage	SOL-WND-B	• Capacity credits increased for solar and wind farms. • Increased capital cost for sized systems • 30% renewable target, as before	In this scenario, both solar and wind power systems are given energy storage options. The use of storage in both renewable options allows us to understand the comparative performance characteristics in terms of cost of electricity generation, GHG emissions, and change in the marginal mix over a long period of time for renewable systems.
Energy storage instead of natural gas	NO-NG	• Historical natural gas capacities and their decommissioning time specified • No new natural gas addition	In this scenario, natural gas power systems (both simple cycle and combined cycle) are removed from the supply system and solar and wind systems are equipped with storage systems. The existing natural gas power systems are not rendered inactive from 2019, but their assumed end of operational life is specified. This is an extreme scenario, as a full omission of natural gas power plants may not be completely realistic in real life, but the this scenario was developed to understand the economic and environmental consequences of replacing all coal and natural gas power systems with solar and wind power plants.
GHG emissions reduction by 50% by 2050	50×50	• Emissions reduction target instead of renewable addition targets	Instead of aiming for a 30% electricity generation commitment from renewables by 2030, the GHG emissions target was changed to a reduction of GHG emission to 50% of 2019 levels by 2050. This scenario was created to understand the differences in policy implementations of setting GHG emission targets versus simply specifying renewable penetration targets.
GHG emissions reduction by 50% by 2030	30×30	• Emissions reduction target instead of renewable addition targets	This scenario sets a more aggressive target of reducing GHG emissions to 50% of 2019 levels by 2030 instead of by 2050.

3.2.4 Market penetration modeling

The market penetration of current and potential future electricity-providing technologies was estimated by developing an energy-economic model. Several market penetration modeling studies of renewable energies were found in the literature. Many studies use experience curves to estimate the cost of GHG emissions' reduction; the studies assume improved market penetration related to economies of scale for renewable energy technologies [139-141]. However, the market penetration of many emerging technologies such as solar, wind, and biomass relies on techno-economic factors, which may depend on system infrastructure characteristics, cost of energy resources, and jurisdictional protocols [142]. In most of these studies, a specific renewable energy system was examined, but the studies did not compare the market penetration potential of the renewable system to the established and commercially more viable technologies. This study develops a market penetration model that focuses on the techno-economic factors of emerging and established electricity generation systems to estimate the available capacities of different electricity generation technologies.

In Alberta, there is an ongoing phase-out of coal-fired power plants with the goal of reducing the GHG intensity of electricity generation. This goal presents the question: which technologies are best equipped technically and economically to reduce the GHG intensity of electricity generation? The economies of scale for many emerging renewable technologies and the resulting decline in the projected cost of electricity production need to be considered when developing a market share model. The main factors taken into consideration are the phase-out of specific technologies, capacity constraints, capital cost, operation and maintenance costs, and the discount rate, which affects the market adoption rate. The specific technologies considered are subcritical coal, supercritical coal, simple cycle natural gas, combined-cycle natural gas, cogeneration, solar, wind, and hydro in line with AESO's projection about future emerging technologies capacity addition and based on data availability.

Equations 1 and 2 were used to analyze the market adoption rate of individual electricity generation technologies; their application in projecting the market share of competing technologies have been demonstrated by Mau et al. and Nyober [143, 144]. $MS_{i,j}$ is the market share of technology i in year j. LCC_i is the life cycle cost of technology i. m is the number of technologies in the competition node. r is the discount rate and n is the cost variance (power function) parameter which is a measure of market heterogeneity, which is an indication of market structure, consumer segmentation, and consumer type. Cost variance was derived from historical capacities and used for future predictions [145, 146]. The results from Equations 1 and 2 provide the market share of individual technologies in a specific time period.

$$MS_{i,j} = \frac{LCC_i^{-n}}{\sum_{i=1}^{m} LCC_{i,j}^{-n}} \tag{1}$$

$$LCC_i = \left(CC \times \left(\frac{(1+i)^r}{(1+i)^r - 1} \right) \right) + O\&M_t + \sum E_{j,k} \tag{2}$$

3.2.5 Energy modeling

The most critical parameters in accurate analysis of electricity sector modeling are demand trends and load shapes, available resources, and their associated economic and environmental costs. Relevant technical characteristics such as electricity generation process efficiencies, capacity factors, and energy resource requirements are also key parameters that need to be considered for reliable regional energy modeling. Given the accuracy required, an electricity generation model was developed using the Long-range Energy Alternatives Planning (LEAP) framework, which is a data-intensive framework and primarily used for energy-environment investigations of different sectors in each economy.

This LEAP modeling work extends the modeling completed in an earlier study in which electricity demands in Alberta were modeled to the year 2050 [45, 46]. The calculations in the LEAP model start from the end-user demand by determining annual electricity requirements from the different demand sectors in Alberta. The electricity demand and peak load requirements prompt the electricity supply system to respond. Then the total required capacity is determined, and technology-specific expansion is determined. The expansion of specific technologies is governed by technical and economic characteristics and the constraints that have been set up in each scenario. To account for the upstream emissions, primary resource extraction modules were added; these calculate the amount of feedstock fuel required and their associated emissions. GHG emissions can be quantified by applying Intergovernmental Panel on Climate Change (IPCC) emission factors from the Fifth Assessment Report within the model at any point of fuel combustion in the energy system being analyzed (electricity generation, upstream fossil fuel production, etc.). For a detailed description of this model, the reader is referred to earlier studies [45, 46].

Key differences between the LEAP modeling done in the present study and the modeling done by Davis et al. [46] include the addition of life cycle GHG emissions, battery storage, an alternative capacity building method, and a different set of scenario assumptions and evaluation criteria. Furthermore, in this research, LEAP was integrated into CLCA methods in order to quantify electricity mixes, the cost of electricity generation, and the resulting GHG emissions to identify the marginal supplier of electricity following policy decisions. The framework used for energy modeling in LEAP is demonstrated in Figure 3.2.

Modeling the scenarios defined in Section 2.2.1. involved two capacity-building approaches in LEAP, one in which the electricity transformation module was not optimized, meaning future capacity additions are specified by the user based on the results derived from market penetration modeling, and one in which the electricity transformation module was optimized, meaning that instead of user-defined future capacities, LEAP would add required capacities based on sets of constraints. For the unoptimized case, the required input data for the electricity generation module (exogenous capacity) was obtained from the market share model (mentioned in the previous section), which was validated against the Alberta Electricity System Operator's (AESO) historical electricity generation data [145]. Comprehensive industry-specific data on load curves, capacity factors, transmission and losses, reserve margin, etc., were incorporated into this module to assess the electricity generation dispatch of each process in the electricity mix. The key modeling considerations for the LEAP framework are provided in Table 2 with references.

For the optimized scenarios, only the existing electricity generating capacities were defined along with their planned decommissioning year. One of the main objectives of this CLCA was to find out which technologies penetrate the market when the demand for electricity increases or a planned decommissioning happens. The LEAP optimization feature uses the Open Source Energy Modeling System (OSeMOSYS), which provides energy generation outputs based on the least-cost method [147].

Energy storage has a key role in the grid integration of intermittent renewable energy sources like solar and wind, hence energy storage systems are added to electricity generation systems worldwide. Energy storage modules help balance fluctuations in supply and demand by storing electricity during periods of high production and low demand and dispatching electricity during periods of low production and high demand. These technologies are even more crucial with increased penetration of solar and wind power [148]. Since the application considered in this research for energy storage systems is for peak load delivery, the approach to model the effect of storing energy was to increase the capacity credit of the processes taking on energy storage (i.e., solar and wind electricity generation systems). The capacity credit variable in LEAP represents the fraction of a plant's installed capacity that is used to calculate capacity addition requirements to satisfy reserve margin requirements. Solar and wind plants have a lower capacity credit than fossil-fuel-based plants because solar and wind have variable output generation whereas a fossil-fuel plant's output can be highly controlled. Capacity credit is a function of storage duration for variable output generators [149, 150]. The AESO has not developed any regulations on capacity credit for utility-scale energy storage systems, but the California Public Utilities Commission (CPUC) has developed a resource adequacy rule ("CPUC 4-hour rule") for investor-owned utilities [151]. The regulation mentions that for any energy storage system to be eligible, it must be able to operate for at a minimum of four consecutive hours at its maximum output, which in turn results in a 100% capacity constraint. A similar "4-hour-rule" is used by the New York Independent System Operator [152]. For this research, based on previous work by the authors, solar and wind energy systems were designed to provide electricity for four hours at 50% of their nameplate capacity [138].

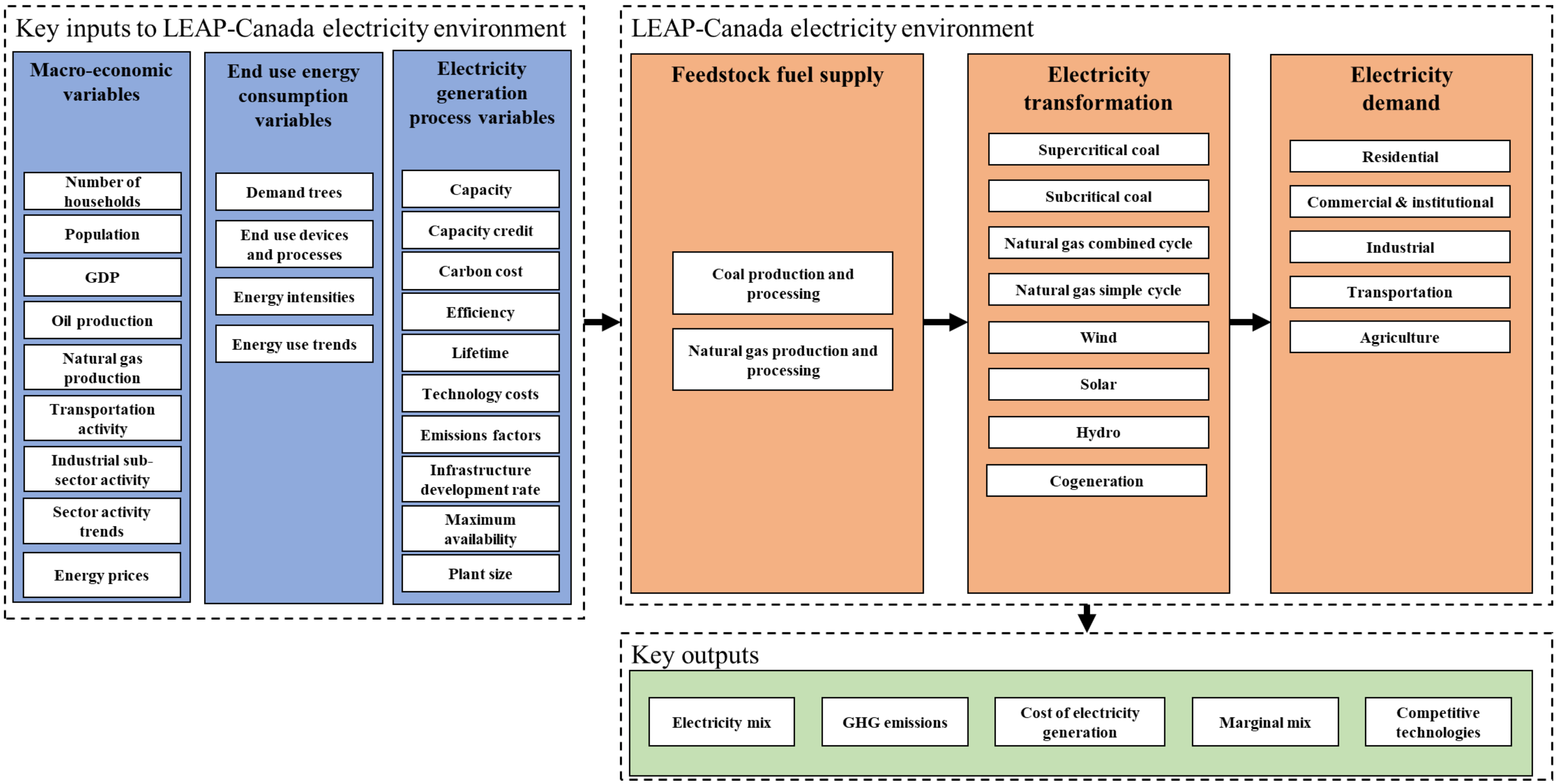

Figure 3.2: Energy modeling framework

Table 3.2: Key parameters considered while developing scenarios in the LEAP framework

Process	Efficiency (%)[a]	Maximum availability (%)[b]	Capacity credit	Merit order[i]	Maximum capacity addition (MW)[c]	Overnight capital cost ($2017 CAD/kW)	Fixed O&M ($2017 CAD/kW)	Variable O&M ($2017 CAD/MWh)	Lifetime (years)	References
Subcritical coal	33.6	72	100	1	n/a	n/a	35.1	7	n/a	[146, 153]
Supercritical coal	39.5	72	100	1	n/a	n/a	36	7	n/a	[146]
Combined cycle	52.4-60[e]	71	100	2	455	1259	50	3	30	[88]
Simple cycle	35.2	84	100	3	240	1359	53	1	30	[88]
Wind	35	33	0, 50[f]	1	1000	1,091-1,928[e,g]	37	0	25	[89, 154]
Solar	16-21	16.7	0, 50	1	1000	958-1,333[f,g]	46	0	25	[154, 155]
Hydro	95	50	50	1	100	4,106	18	4	40	[153]
Cogeneration	59-65[d]	70	100	1	300	1,290.6	15	4	30	[146, 153]

a. Assumed based on published literature values [88, 155-158]. Efficiencies have been adjusted by accounting for plant use of electricity.
b. Based on historical ranges and expected changes in maximum availability and capacity factors.
c. Assumed or based on Canada's historical ranges and penetration requirements to meet renewable electricity generation targets from the market penetration model.
d. Effective efficiency refers to the electricity output, a portion of input fuel used to produce electricity, and fuel savings due to the cogeneration of electricity and steam compared to using a stand-alone boiler for steam generation.
e. Ranges represent 2017-2050 values.
f. Capacity credit of 50% given for 4 hours of storage in scenarios where energy storage functions have been added [159].
g. For wind energy systems with energy storage, an overnight capital cost range of 1301.9 - 2,426.7 $CAD/kW was considered [89, 91, 154]
h. For solar energy systems with energy storage, an overnight capital cost range of 1616.8 - 2,675 $CAD/kW was considered [91, 154, 155].
i. The merit order of a process indicates the order in which it will be dispatched. Processes with the lowest value merit order are dispatched first (baseload) and those with the highest merit order are dispatched last (peak load). Processes with equal merit orders are dispatched together in proportion to their available capacity (Capacity * Availability). The merit order is only used for dispatching for the base case scenario.
j. A conservative value of 10% for T&D losses was considered and is in line with reports from the AESO [160].

3.2.6 Marginal supplier identification

Implementing the consequential approach for electricity generation is difficult because identifying the marginal electricity technology, an energy resource affected by a small change in demand, is a contentious issue [161-163]. Since electricity is a strategic product, generation sources and capacities are often influenced by regional and national policies instead of technological competitiveness and historical trends. At the same time, the electricity market is temporally segmented due to short-term changes in demand that lead to a mix of suppliers for peak and off-peak hours [164]. The co-production of electricity from industrial or district heating processes creates difficulty in discerning the main product. Lastly, capital costs, the "environmental cleanliness" of producing electricity from certain sources, and the subsequent monetary credit given to cleaner technologies also need to be taken into consideration. Thus, electricity is different from other industrial products, wherein a new and improved technology replaces an older technology in a predictable manner. This uniqueness in the sector demands that probable policy measures be taken into consideration while modeling. Consequently, the changes that might occur in the electricity generation sector due to changes in technical parameters and environmental policy initiatives also need to be understood. That said, valuable insights can be found by identifying the marginal suppliers of electricity, as these provide information on the most competitive technologies under certain market conditions and the resulting changes in GHG emissions caused by a decision.

In this assessment, a five-step process, first proposed by Weidema et al., was adopted to identify the marginal technology in each scenario [163]. This step-wise approach provides a specific and easy-to-implement framework for identifying marginal suppliers from a CLCA perspective. The approach has been widely used in a number of recent studies for application in various industries

[129, 165-167]. Several authors modeled the potential changes in a system boundary due to output variability by identifying marginal technologies following different approaches. Rehl et al. showed the difference between attributional and consequential LCA of energy generation from biogas [168]. They used system expansion to deal with the multi-functionality of the biogas system, whose alternative products include manure, digestate, and heat. Marginal systems were identified based on past trends using data from national statistics. Lund et al. identified the long-term yearly average marginal technology of the Danish electricity system using the EnergyPLAN system analysis model to include the processes that are most likely to respond to a change [169].

Figure 3.3 shows the main steps involved in our study. In the first step, the time frame is defined. For a long-term assessment, the time frame needs to be set so that the technologies considered can finish their useful life and be replaced. In the second step, the projected demand is analyzed and the subsequent effect observed, i.e., it is observed whether the changes affect a market or different processes. The constrained technologies are also identified based on planned decommissioning, phase-out, insufficient primary resources, political constraints, etc. The last three steps are quantitative; the marginal mix is based on the classification of newer and older technologies. The marginal technology is the one with the lowest cost.

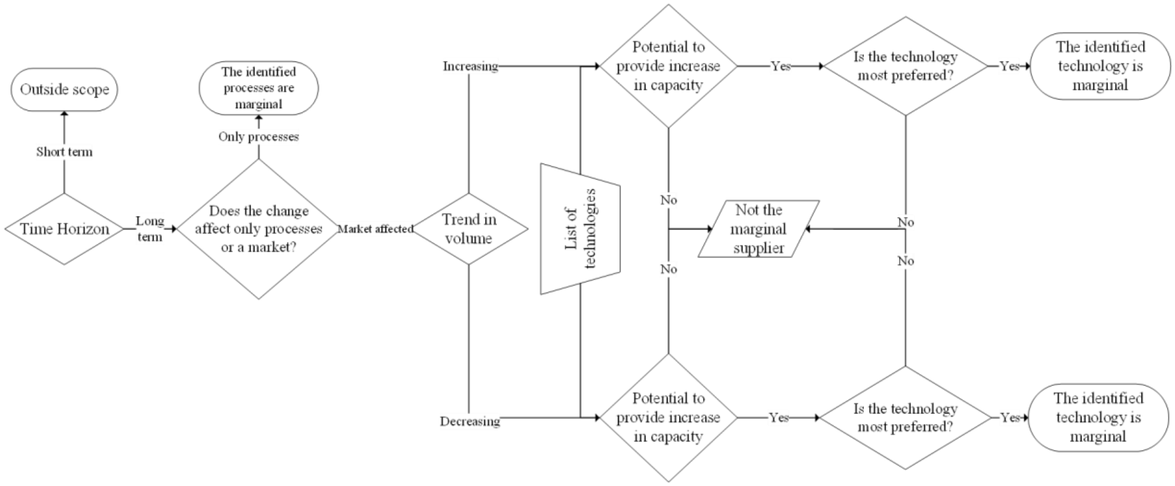

Figure 3.3: The identification of the marginal mix of technologies through the process adopted from Weidema et al. [163]

With respect to defining the qualitative steps, the long-term time horizon was considered, from 2019 to 2050. This was done to identify the effects of technologies' replacement of electricity generation plants as a result of policy implementation as well as technical and environmental constraints. This timeframe was used to determine which technology is competitive in the long term. As this study focuses on the overall electricity generation mix instead of changes in the upstream stages, the effects of demand changes in the manufacturing processes are outside the study scope.

The details of the quantitative aspects are provided in Appendix B2 information section. Using the energy mixes obtained from the LEAP framework, the trends in the volume of energy provided by each technology for each scenario were analyzed. The technologies projected to be decommissioned or phased out are identified as constrained technologies. In addition, technologies that might have insufficient primary resources or be dependent on other processes to generate electricity are also identified as constrained technologies. This step allows us to discard the technologies that may not be able to react to an increase in demand and add capacity to the electricity generation system. The remaining technologies are classified as "new" or "old" based on their capital replacement rates and annual growth rates. Technologies that have higher annual growth rates than capital replacement rates are classified as new technologies and they constitute the marginal mix. This process was followed for each scenario. The lowest economic cost option is identified as the marginal supplier that would supply any increase in demand.

In addition to identifying the marginal suppliers, the current policies were compared with the effects of different policy decisions in terms of change in electricity mix to find out which technology is more competitive in the electricity market in each scenario. This analysis shows that the long-term effectiveness and investment requirements shift from one policy to the other.

Hourly marginal supplier

The approach described here to identify marginal technology focuses on the long-term marginal mix and marginal technology. When intermittent renewable resources such as wind and solar are considered, the mixture of marginal production is complex [169]. In addition to assessing the long-term marginal suppliers of electricity in a regional electricity generation system, it is important to understand a specific technology's adaptability with short-term load changes. While a number of studies discuss the long-term implications of the transition of electricity generation systems from fossil fuel dominance to newer renewable options, none of them include hourly marginal analysis. Hence, this study augments the analysis provided in the previous sections by providing an hourly simulation model of the electricity generation using hourly demand and supply data. Figure 3.4 shows the developed linear programming framework that models the hourly mix of electricity supply based on real-time hourly demand data [89]. Equations 3 through 10 present the objectives and constraints considered. Equations 4 through 7 are the constraints for hourly demand and supply, and Equations 8 through 10 are the capacity, GHG emissions, and cost constraints. The levelized cost of electricity is calculated using the same dataset that was used for the LEAP model as shown in Table 2. The model calculates the electricity demand at a particular hour and then dispatches electricity from the lowest cost and lowest GHG-intensive processes. After modeling the supply and demand equilibrium, the changes in the electricity mix were identified. Two scenarios were developed, one in which the only objective was to minimize production costs and one in which economic and environmental costs were minimized. The AESO considers two seasons to define Alberta's internal load, winter (November 1-April 31) and summer (May 1-October 31) [170]. One of the drawbacks of our model is that it was created using Alberta's historical electricity demand for one year, as future projections of hourly electricity demand are not available [171]. Hence this model cannot identify marginal suppliers in future conditions where the hourly trends of demand might vary significantly. The model takes into consideration the following factors: seasonal hourly electricity demand (average load during each season), hourly availability of each technology (hourly global solar irradiance data for Alberta [63]), real-time data from Blackspring Ridge Wind Farm [172], cost parameters, GHG emission intensities, and seasonal variation in demand and supply capacities.

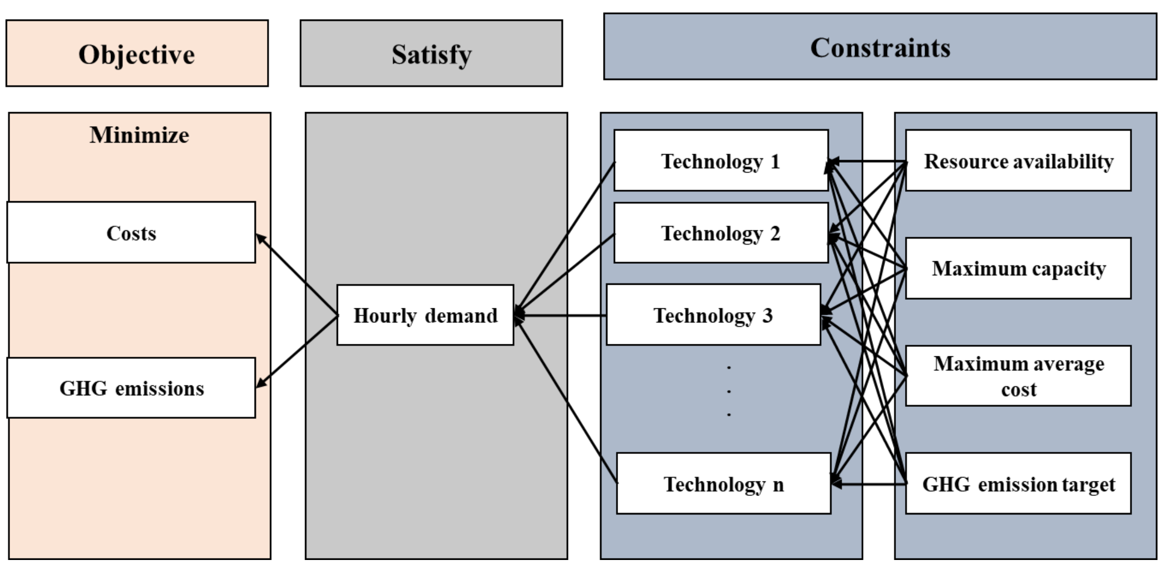

Figure 3.4: Framework for hourly analysis of marginal technologies

The equations for the linear programming model are given below:

$$\min z = \sum c_j x_{i,j+} \, c_{GHG,j} \sum GHG_j x_{i,j} \quad (3)$$

Subject to:

$$\sum x_{1,j} \geq d_1 \quad (4)$$

$$\sum x_{2,j} \geq d_2 \quad (5)$$

$$\sum x_{3,j} \geq d_3 \quad (6)$$

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$$\sum x_{24,j} \geq d_{24} \quad (7)$$

$$x_{i,j} \leq h(a_{i,j}) \quad (8)$$

$$\sum E_j \leq E_{j,\, base\ year} \quad (9)$$

$$\frac{\sum c_j x_{i,j}}{\sum x_{i,j}} \leq C \quad (10)$$

where c_j is the cost of electricity production by technology j, \$/kWh; $x_{i,j}$ is electricity supplied by technology j at hour i,kWh; $c_{GHG,j}$ is the cost assigned to a unit mass of GHG emissions, \$/metric ton CO_2 eq; d_i is electricity demand at hour i, kW; h is the percentage of available capacity, $a_{i,j}$ is the available capacity of technology j at hour i, kW; and E is emission, g CO_2 eq/kWh.

3.3 Results and Discussion

3.3.1 Development of market penetration curves

Figure 3.5 shows the market penetration curves for seven technologies considered: coal-subcritical, coal-supercritical, hydro, natural gas-combined cycle, natural gas-simple cycle, solar, and wind. To comply with the status quo in Alberta as of 2019, market share curves for several commercially available electricity generating technologies were also developed through a cost-driven modeling approach. The penetration model results were validated using the AESO's long-term predictions [145]. This was done by determining the cost variance for the base year of calculation based on the existing capacities of each technology and then keeping a constant value for this parameter throughout the timeframe. The more narrowly defined the cost of a technology becomes, the less likely it will overlap the costs of a competitive technology. The steeper the curve, the greater the share of the market the less-expensive technology assumes. As shown in Figure 3.6, the results from all the renewable sources appear to accurately match the AESO's future projections. After the anticipated coal phase-out by 2030, most of the electricity supply mix will be dominated by the penetration of natural gas-based combined cycle power systems, due to its higher capacity factor (maximum availability), leading to a lower levelized cost of electricity. The market penetration rate of combined cycle power generation will jump from 10.7% in 2019 to more than 28.7% in 2050. Among the renewable energy options, wind energy penetrates the electricity mix at the highest rate of around 9.7% in 2019 and 27.6% in 2050. The main reason behind this massive growth in wind power compared to solar is due to its higher efficiency and capacity. The higher energy generation potential of wind power plants with the same nameplate capacity as solar power results in a more cost-effective and efficient energy resource [173, 174]. Since there is no feedstock cost, other than coal and natural gas, the variable cost of such energy is also lower for this technology. Although the market penetration rate of solar power is high, reaching 4.4% in 2050 from 0.1% in 2019, the overall growth is not as high as wind or combined cycle power plants. This is because the efficiency of solar PV panels (15-17%) is projected to increase by only a fractional level from 2019 values. The lower efficiency of solar panels results in lower power output over the nameplate capacity and, as a result, the investment cost of this technology is higher than its counterparts. Electricity from hydro is dependent on the usable resources in the jurisdiction and therefore an additional constraint on its capacity increase was imposed. The production of electricity from cogeneration facilities depends largely on industrial heating and electricity demands. Hence, the market penetration curve for this technology was not used and the projection from the AESO was used in the succeeding steps of the analysis.

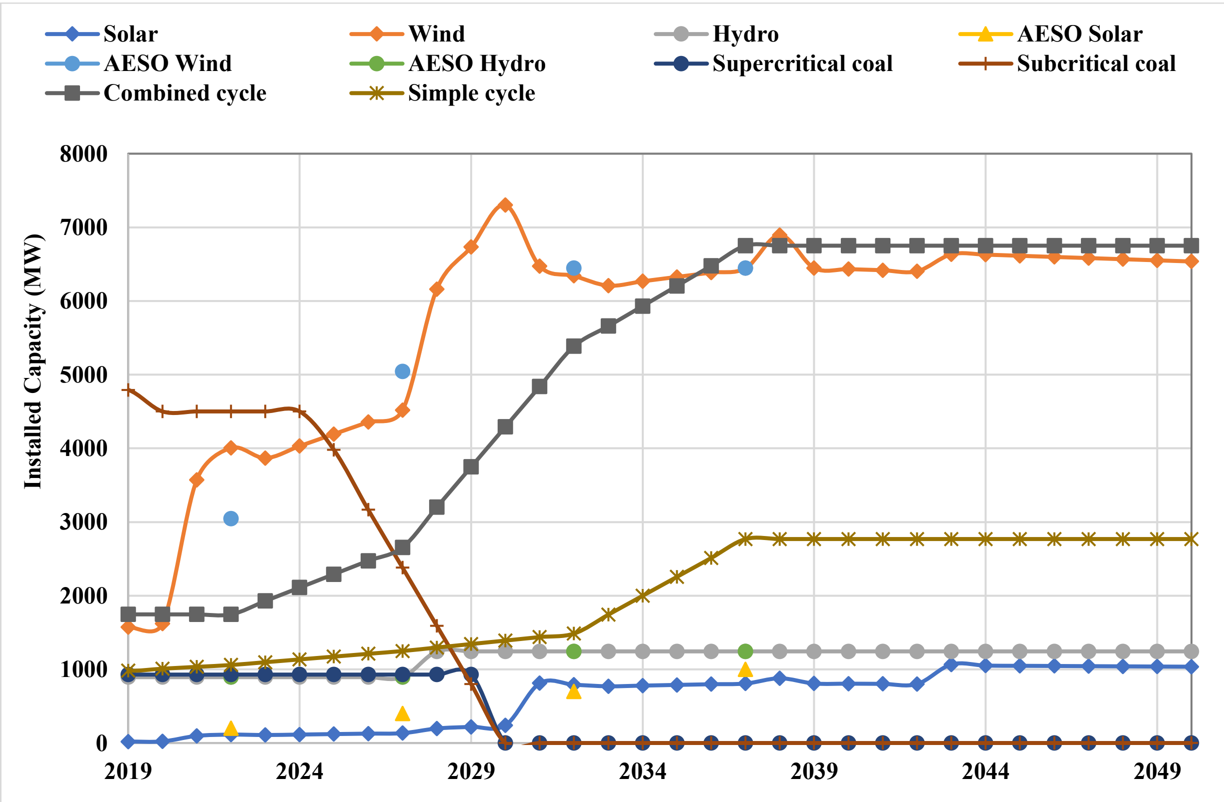


Figure 3.5: Projected market share for different technologies

3.3.2 Electricity mix in different scenarios

Figures 3.6, 3.7, and 3.8 show the electricity mix in the nine scenarios: status quo (with and without optimized capacities) with no targets for renewables, solar with storage, wind with storage, solar and wind with storage, solar and wind with storage to replace natural gas power systems, and 50% GHG emissions' reduction by 2030 and 2050. The base case scenario (BASE) is based on the assumption that capacities would be added to the generation system according to the AESO's projections [145]. In this case, the LEAP framework dispatches power systems from the supply module based on their merit order. Since natural gas power plants would become baseload suppliers (merit order=1) after the phase-out of coal resources, combined cycle and simple cycle power plants would supply most of the energy demand. The results from this scenario, as shown in Figure 3.6-A, highlight the fact that the electricity mix is heavily dependent on natural gas-based power systems, especially combined-cycle power plants. The mix is projected to generate 50.1 thousand GWh by 2030 and plateau at about 54.8 thousand GWh of electricity by 2040 from combined cycle power plants. In the modeling, wind and solar resources were selected to be dispatched at full capacity, meaning that whenever these resources produce electricity, they should be added to the electricity generation system. Electricity from renewable resources is mostly dominated by wind resources, starting at 4.4 thousand GWh and reaching 15.2 thousand GWh in 2050. Solar electricity dispatch is anticipated to be much lower (only 1.7 thousand GWh per year) due to the assumption that the capacity addition would not exceed 1000 MW during the considered timeframe, according to the AESO's long-term outlook [145].

In the succeeding scenarios, where the optimization feature of the LEAP framework was used (from O-BASE to 50×30), only the 2019 capacity of each technology and its decommissioning time were specified based on the assumed lifetime. For all the scenarios, LEAP presents the optimal electricity generation mix based on the lowest cost of production. In addition to the lowest cost of production, a 30% target of renewable electricity generation was added in accordance with current Alberta policies. Figure 3.6-B shows the electricity mix obtained from the O-BASE scenario. The results follow the same trend as the unoptimized (BASE) scenario. The only differences are the earlier retirement of coal capacities and significantly higher dispatch from wind energy (reaching 34.9 thousand GWh per year in 2036), which together reduce the overall share of electricity from combined cycle power plants, which are expected to peak at 31.1% of overall electricity generation in 2030. Electricity production from utility-scale solar power plants will decrease as their yield will be significantly lower than wind power and other natural gas-based power systems. The lower yield of solar power results in a higher levelized cost of electricity. Simple cycle power plants will dispatch a significantly lower amount of energy from combined cycle power plants because of their lower efficiency and higher costs. Even when there are no renewable targets set on the electricity generation system for the third scenario (NO-R-TAR), the optimal electricity generation mix does not change significantly. As the capital cost of the renewable energy options is projected to decrease in the later years of the timeframe, a case can be made that adopting renewable energy systems, especially wind power, might become a preselected phenomenon. The addition of storage to renewable energy resources (in scenarios SOL-B, WND-B, and SOL-WND-B) increases the overall capital cost of these technologies, which results in a lower generation share in the electricity generation mix. In sizing the optimal systems, we found that wind power systems would require less storage than the solar power systems as they tend to have a higher capacity factor (maximum availability) and, as a result, a much lower capital investment.

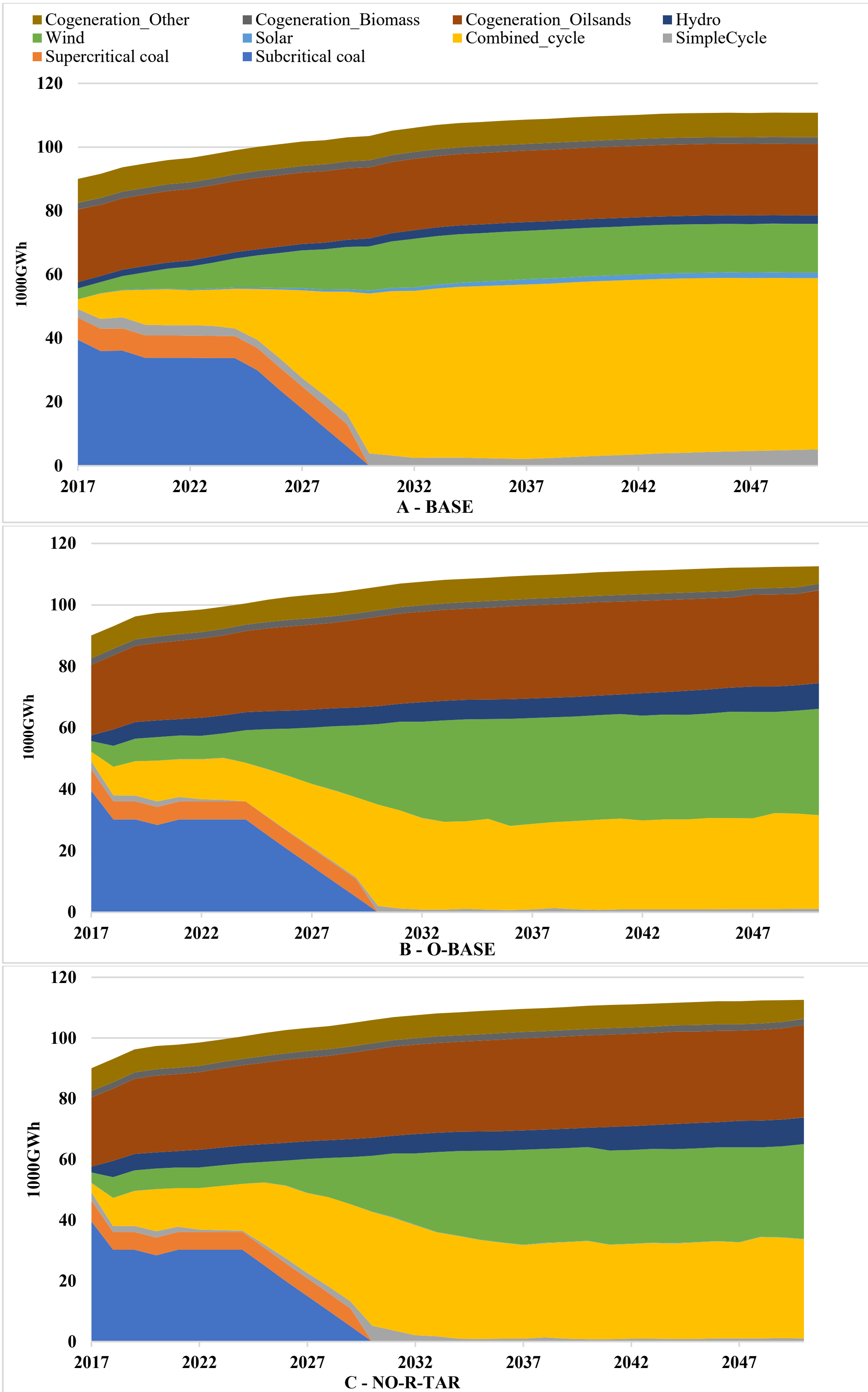
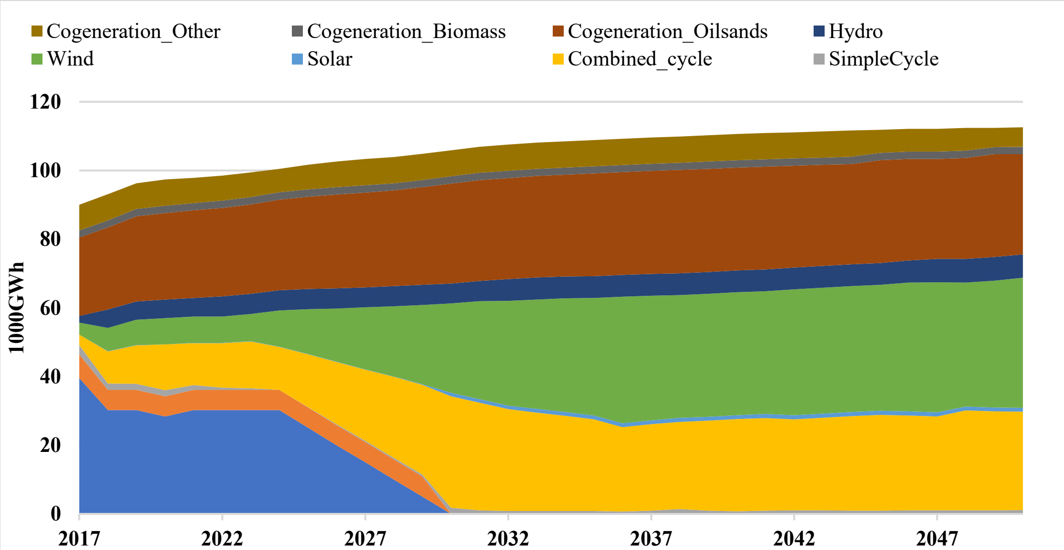
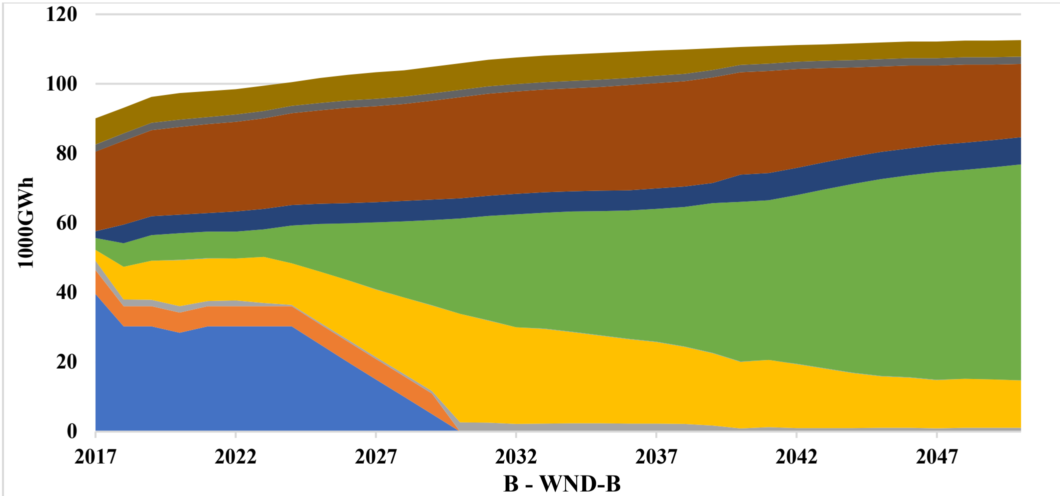


Figure 3.6: Electricity generation mix in the BASE (A), O-BASE (B), and NO-R-TAR (C) scenarios

The share of electricity generation from wind with storage is projected to peak at 25.9% in 2030 and 55.2% in 2050 (Figure 3.7-B). The significant increase in wind power generation can be attributed to the capital cost reduction in the later stages of the timeframe. Solar with storage is projected to reach 1.08% (1.2 thousand GWh) of the total electricity mix by 2050 (Figure 3.7-A). As mentioned earlier, the effect of storage was mimicked by increasing the capacity credits of these renewable energy resources. Solar with storage (SOL-B) is projected to have the lowest amount of penetration into the electricity mix as it would incur the highest capital cost with the lowest capacity factor. As shown in Figure 3.7-C, the scenario in which both solar and wind are added with storage does not show any significant change from the scenario in which only wind has added storage options.



A - SOL-B



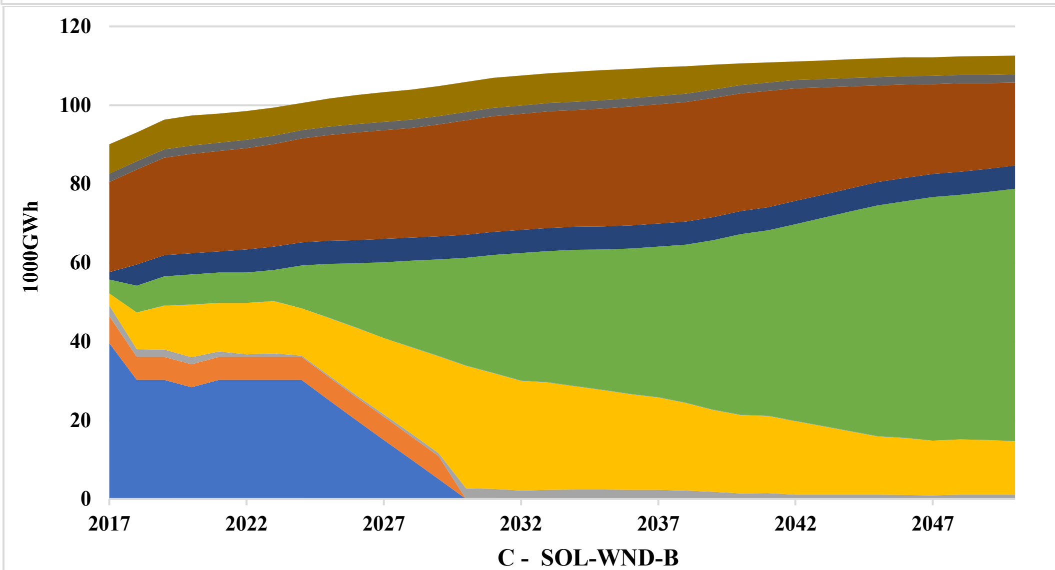
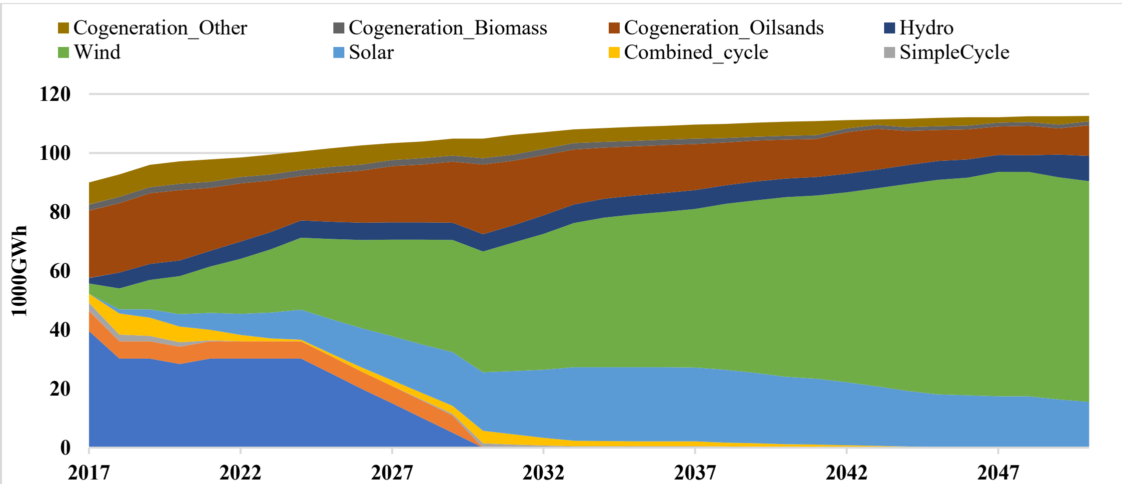
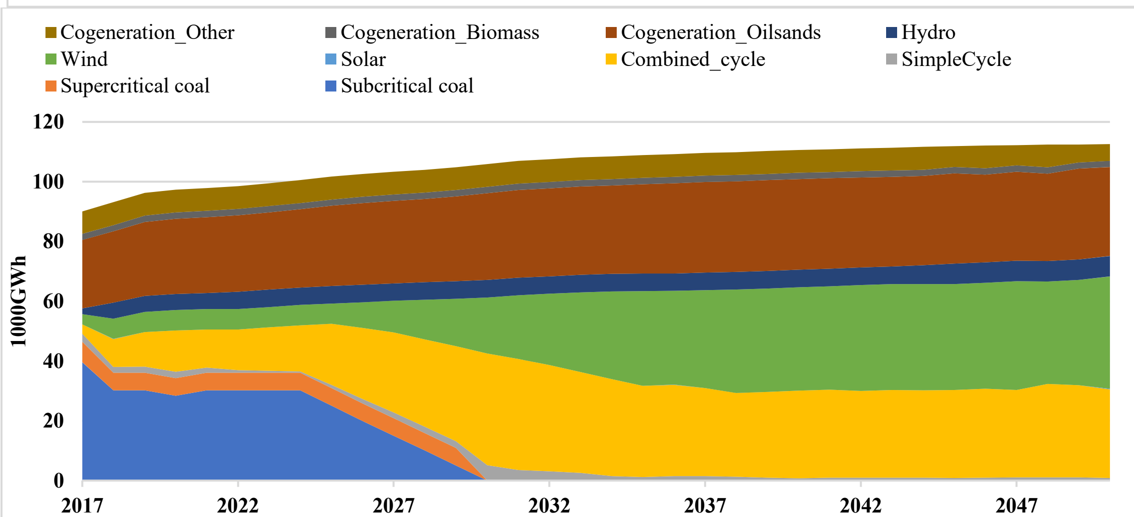


Figure 3.7 Electricity generation mix in the SOL-B (A), WND-B (B), and SOL-WND-B (C) scenarios

Figure 3.8 A-C show the electricity mix results for storage instead of natural gas (NO-NG), and 50% GHG emission reductions by 2050 (50×50) and 2030 (50×30). The data related to each of the scenarios can be found in section S2 of the SI. In the NO-NG scenario, in which renewable energy resources (solar and wind) were considered as replacements for natural gas power plants, almost the entire replacement is seen from wind resources, which are projected to reach a peak of 67.9% in the total electricity generation mix by 2050. The electricity mixes are projected to change more significantly in terms of renewable energy penetration as the 30% renewable energy target is replaced with GHG emission reductions. In both 50% GHG emission reduction scenarios (50×50 and 50×30), wind energy penetration is significantly higher than the optimized base scenario. The electricity generation share reaches peaks of 33.3% and 33.8% when a 50% reduction in GHG emissions in 2050 and 2030, respectively, is considered. Fossil fuel-based systems, both natural gas-based combined cycle and simple cycle systems, and cogeneration dispatch fall significantly as they have much higher emission factors.



A - NO-NG



B - 50×50

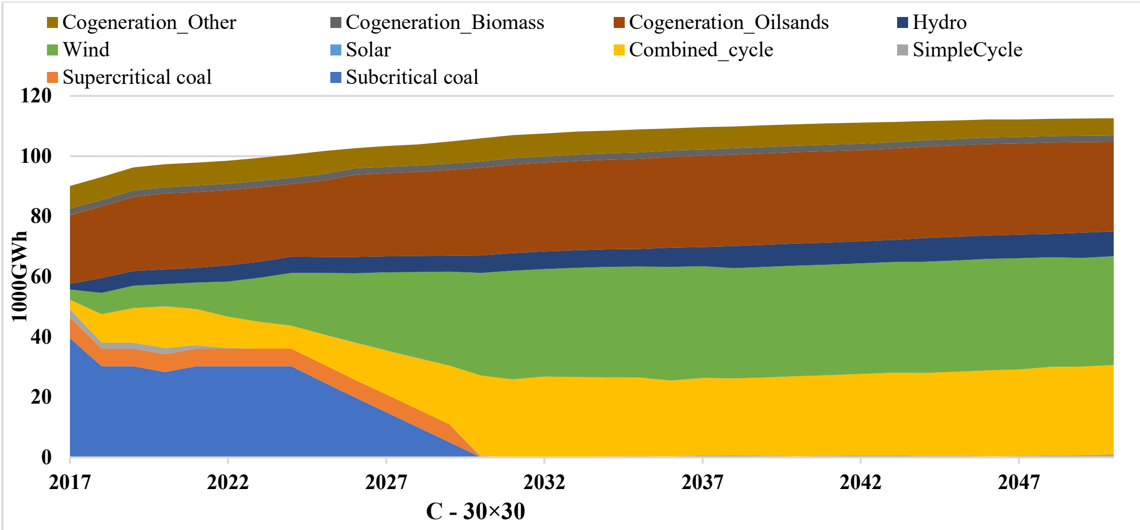


Figure 3.8: Electricity generation mix in the NO-NG (A), 50×50 (B), and 50×30 (C) scenarios

The optimization with the LEAP framework is based on the lowest cost of generation of electricity. However, the cost of electricity generation is also one of the most important parameters to understand the long-term consequences of different policy decisions in the overall electricity generation mix. Figure 3.9 shows the cost results obtained from all the scenarios developed in the LEAP framework. The NO-NG scenario appears to be the most expensive pathway as it requires more new investment and capacities of renewable energy resources than the others. In this scenario, the cost of electricity production reaches the peak cost of $ 63.2/MWh, a 16.9% increase from the base case assumptions. The BASE has the second highest production cost, $54.5/MWh at its peak. The analysis shows that the cost trends are similar in the earlier part of the time period (2019-2030). As the projected cost of renewable power generation systems decline and become more competitive in the later years, the overall electricity generation costs can be projected to rise unless renewable options are not adopted. The O-BASE scenario in which the capacities are optimized shows the second lowest cost trend with production costs ranging from $16.8/MWh to $50.2/MWh. The cost estimates, especially for the renewable electricity generation systems (solar and wind), are significantly lower in this scenario as the additional energy storage systems were not accounted for. However, the lower capacity credits attributed to solar and wind energy systems make them less competitive. The SOL-WND-B scenario with energy storage added both to solar and wind shows the lowest cost of electricity production in the later stages of the timeframe as costs decline rapidly. The remaining scenarios show a similar cost trend as the GHG emissions reduction targets and renewable energy penetration result in similar energy mixes. A key aspect is that, in all the scenarios, a significant share of the energy demand is satisfied by cogeneration power systems, the most cost-competitive technology among the systems.

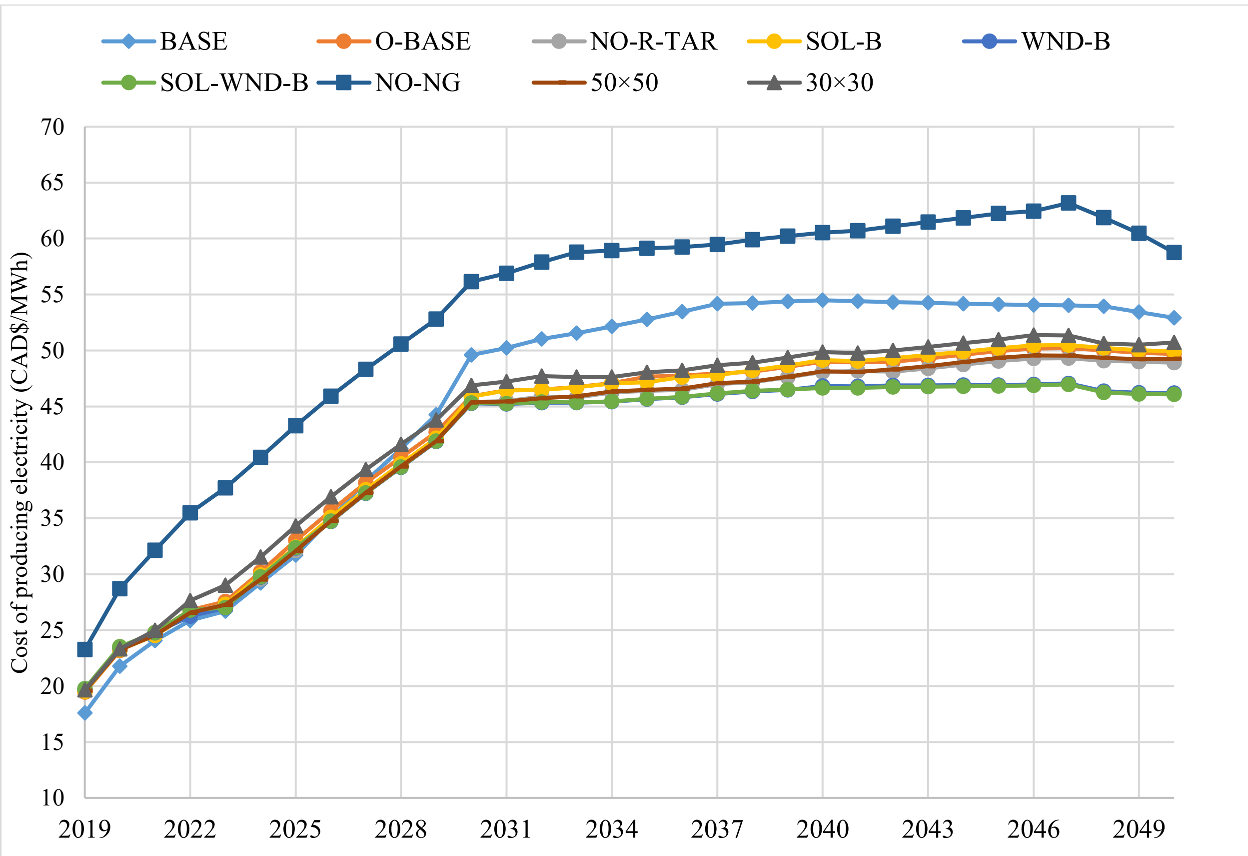


Figure 3.9: Cost of producing electricity from the grid in each of the modeled scenarios

3.3.3 Greenhouse gas emissions for different scenarios

In this section, the GHG emissions' footprint in kg CO_2 eq per MWh of electricity generation mix from all scenarios is discussed (Figure 3.10). The BASE scenario, based on current policies without any optimization, results in the highest GHG emissions per MWh of electricity production. The GHG footprint ranges from 661.7 kg CO_2 eq/MWh down to 278.2 kg CO_2 eq/MWh in the later years of the timeframe. The O-BASE scenario provides a GHG emissions' reduction opportunity, 50.4 kg CO_2 eq/MWh on average. The NO-R-TAR scenario with no renewable target also shows low GHG emissions from the electricity generation system (from 661.7 to 218.9 kg CO_2 eq/MWh), because it has a similar electricity generation mix to the BASE scenario. The lowest GHG emissions, 74.6 kg CO_2 eq/MWh, are seen in the scenarios where energy storage along with renewable energy is used instead of natural gas power plants. Adding energy storage with wind and solar power systems also shows promising GHG emissions' reduction potential in the long term, taking the total GHG emissions to less than 150 kg CO_2 eq/MWh in the later stages of the assessment period. GHG emissions' reduction of 50% by 2050 and 2030 also provide similar results as the optimized base case. In both the 50×50 and the 30×30 scenarios, wind and combined cycle power systems are the dominant producers of electricity.

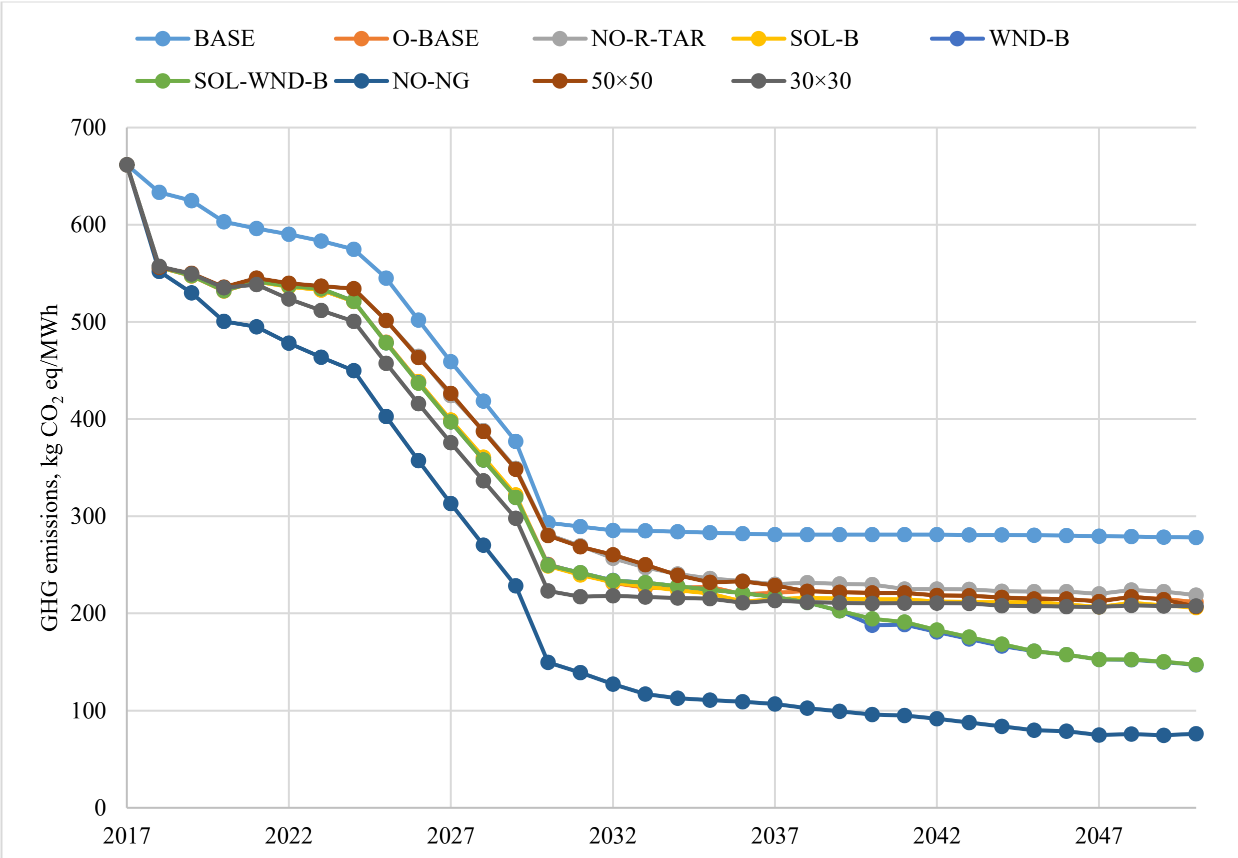


Figure 3.10: GHG emissions in each of the modeled scenarios

3.3.4 Marginal technologies and GHG emissions

As discussed in section 2.2.4, one of the most important aspects of consequential LCA is to identify the marginal energy supplying technology that offers the lowest cost option to meet the demand increase. Figure 3.11 presents the results obtained from the marginal technology identification process. The percentages in the figure are the contributions of electricity supplied by the respective technologies in the case of demand increase in each scenario. In every scenario, natural gas-based simple and combined cycle power systems, solar, and wind were identified as the constituents of the long-term marginal mix. The phasing-out of coal-based power plants, the limited hydro capacity development opportunities due to resource constraints, and the dependence of cogeneration-based power systems on oil sands projects in Alberta are main constraints in the long term. In the BASE scenario, combined cycle power plants can meet the marginal demand increase most competitively with an incremental cost of $57.5/MWh. The incremental cost of wind power is less than $54.4/MWh, although wind technology provides the largest share of energy supply, 21.1%. Except for the NO-R-TAR scenario, the wind power generation system appears to be the most competitive technology to provide increased supply at higher percentage shares (up to 82.5% in the NO-NG scenario) and the lowest marginal cost (38.6 to 54.4 $/MWh). As peak load power plants, natural gas based simple cycle power plants are the least cost-competitive technology; the cost of providing additional energy ranges from $108.3/MWh in the BASE scenario to $608.5/MWh in the 50×30 scenario.

Figure 3.11: Marginal mix of technologies in each scenario

Table 3 presents the marginal change in GHG emissions per MWh from an increase in demand by one thousand GWh. Almost every scenario shows very little change in marginal emissions as the marginal mix is dominated by two technologies, combined cycle power plants and wind power plants. In most of the scenarios, these plants have a large share in the electricity mix, thus an increase in production from either shows minute changes.

Table 3.3: Marginal change in emissions due to demand increase

Scenario	2020	2025	2030	2035	2040	2045	2050
BASE	-2.9	-2.1	0.5	0.6	0.5	0.5	0.5
O-BASE	-1.3	-0.7	1.1	-1.1	-2.0	-1.4	-3.0
NO-R-TAR	-6.0	-6.4	-3.5	9.5	17.1	20.3	29.7
SOL-B	-5.5	0.1	0.8	-1.0	-0.9	-3.5	-1.8
WND-B	-1.6	0.3	3.3	-0.9	10.4	3.3	3.6
SOL-WND-B	-1.0	-2.1	2.1	0.8	2.5	1.8	1.7
NO-NG	-0.6	-0.7	1.7	-4.2	-0.8	-0.9	-0.4
50×50	-6.1	-7.4	-7.5	22.3	31.8	28.4	0.4
50×30	-9.7	-8.4	-5.3	-4.8	-4.2	-5.0	-2.0

3.3.5 Substitution effect

This section discusses the environmental consequences of a change in policy measures displacing a technology. Each scenario is compared with the status quo or reference scenario to find out which technologies will be substituted and what the change in GHG emissions is. Figure 3.12 shows the results for the O-BASE scenario only. Almost all the other scenarios show a similar trend; they are presented in section S4. All the scenarios show that the transition pathways towards cleaner electricity in the long term are mostly dominated by those adding capacities of wind power generation systems. This is an interesting phenomenon observed in Alberta given that we identified natural gas-based combined cycle power plants as one of the major marginally competitive technologies in both the long-term and in the short-term (hourly) analyses. The substitutional effect in terms of GHG emissions follows the same pattern as that of the electricity mixes. Figure 3.14 shows the substitution of GHG emissions from four scenarios compared with the BASE scenario.

The results from the other scenarios can be found in section S5. In every scenario, the increase in GHG emissions is from the expansion of cogeneration facilities. The O-BASE scenario considers that a large portion of coal-based power plants would be replaced by natural gas-based combined cycle power plants. While the replacement of older coal-based power plants is dominated by natural gas-based power plants, the GHG emissions' reduction from the overall grid system is seen from the additional expansion of wind power systems. Since it is projected that the cost of energy generation from wind would become competitive with combined cycle power plants, its addition would be beneficial both economically and environmentally.

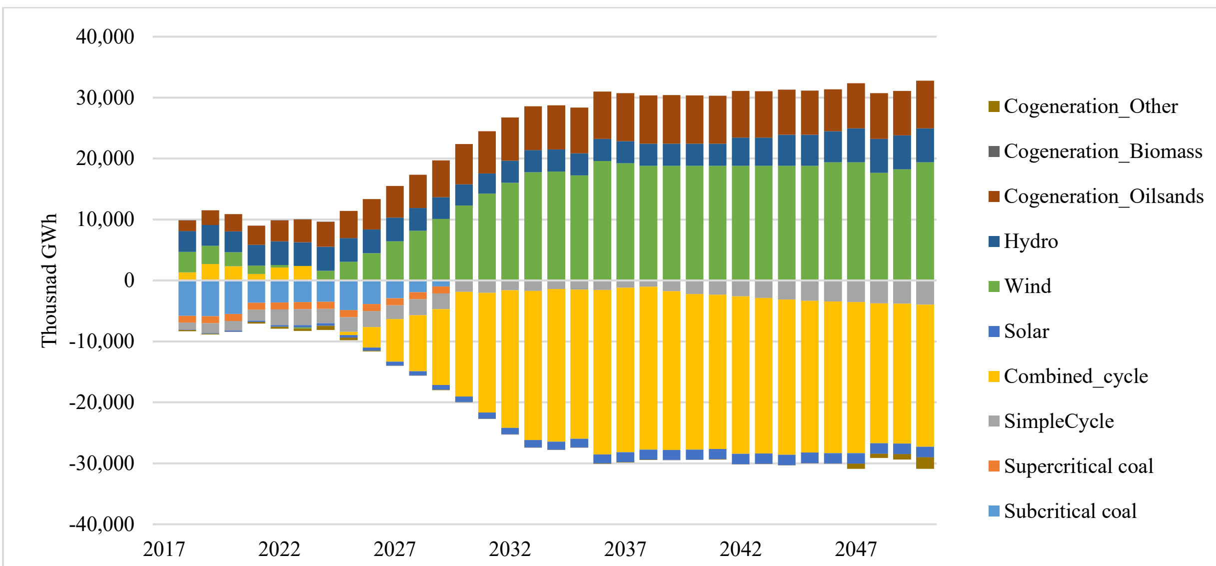


Figure 3.12: Substitution of energy generation sources in the BASE scenario

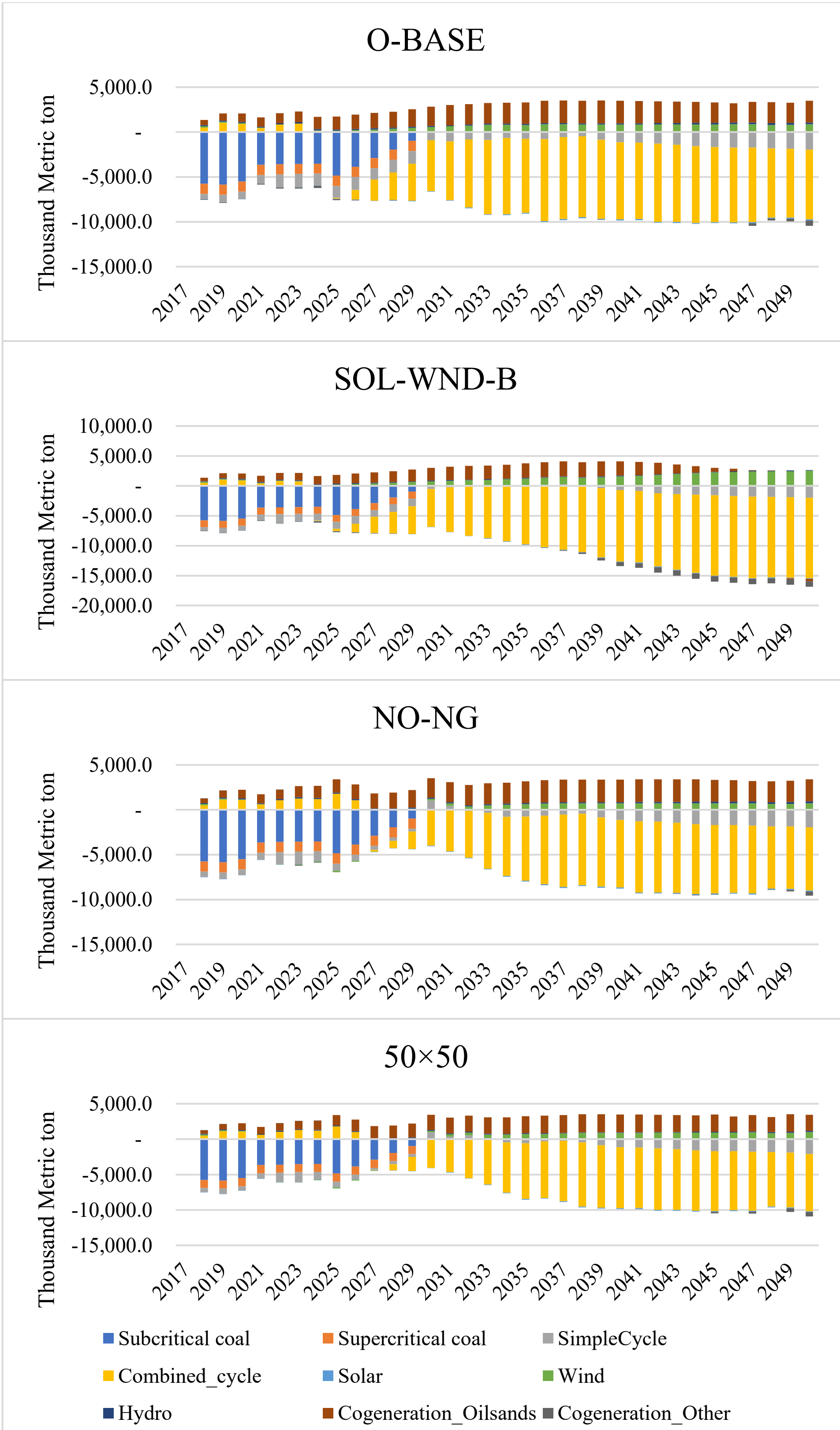


Figure 3.13: Changes in GHG emissions due to the substitution of energy sources

Hourly marginal supplier

The approach taken in this study to identify the marginal supplier was based on the analysis of the electricity generation mix over the long term. Since one of the main objectives of this study is to understand the performance of solar and wind energy in the mix, the intermittency of these sources must be considered. Thus, the marginal technologies were identified on an hourly basis and the results are shown in Figure 3.14. The hourly analysis shows that in addition to high initial capital cost, the daily availability of solar power is relatively low compared to every other technology; therefore, increasing production from this source is difficult. Wind power availability is higher than solar in Alberta and as a result this source's ability to respond to demand growth is greater. Compared to wind and solar energy generation, natural gas-fired power plants have a lower electricity production cost; ramping up production is easier, although these plants are the most GHG intensive of all the options. The results from this analysis confirm the findings of the long-term analysis; that is, natural gas-based power plants are the lowest cost marginal technology when the objective is to minimize the cost of electricity production. However, if the goal is to minimize GHG emissions as well as cost, regardless of the time of year, wind energy reduces both GHG emissions and costs more than the other options.

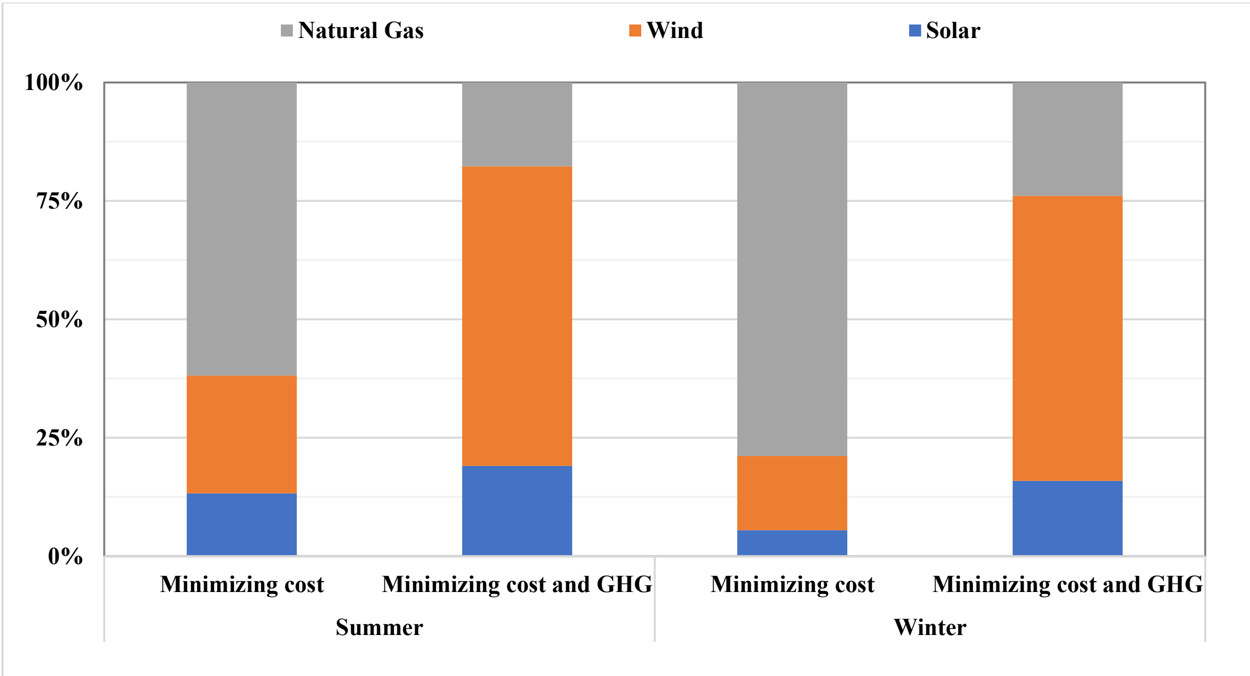


Figure 3.14: Hourly marginal analysis of competing technologies based on an increase in demand

3.4 Conclusion

The applications of life cycle assessment methods continue to evolve as demands from policymaker's change. This research proposed a generalized framework to understand the cause and effect relationship between technologies in a product system and successfully demonstrated its application to Alberta's electricity sector. The penetration of renewable energy resources into the electricity mix will have a significant effect on cost and GHG emissions. Both electricity production costs and the GHG emissions can be reduced significantly in the long run by increasing the capacity of renewable technologies, thus proving that the marginal benefits from higher renewable penetration outweigh the current technical drawbacks. Incorporating energy storage with wind energy is more feasible than with solar in Alberta, thus wind energy is more competitive over the long term. Wind power generation systems, in addition to natural gas-based power plants, offer the most cost-competitive way to transition to cleaner electricity generation from coal-based power. A 30% renewable energy generation target could result in a similar electricity mix as 50%

GHG emission reduction targets in Alberta, as the declining cost of renewables would automatically make their adoption a natural choice in the long term.

By integrating the CLCA and long-term energy modeling, this research demonstrates how cause and effect relationships within an energy generation system can be modeled and how the resulting changes in environmental impacts can be incorporated in long-term decision making.

There are many additional interactions within the entire value chain of an electricity generation system that have not been investigated using this study's approach, and that is a major limitation of this work. These interactions include the effects of carbon pricing in the electricity generation mix, the effects on the distribution network due to the addition of large amounts of renewable resources, and the emissions from fossil fuel-based thermal power plant cycling during the transition period. Despite the shortcomings, the results obtained in this research would have significant benefit to the LCA community and policymakers in general. Applying this framework may alleviate some of the ambiguities in the current literature related to CLCA and enable the LCA community to examine various energy policy issues more thoroughly.

Chapter 4

Conclusions and recommendations

4.1 Conclusion

The economic and infrastructure growth of any jurisdiction is heavily dependent on the electricity sector. At the same time, there is an overarching need to reduce the negative environmental impacts from this sector to achieve sustainable development. Alberta is the third largest electricity producer in Canada and contributes the highest amount of GHG emissions per capita from this sector. This research aims to provide relevant, up-to-date, and actionable information for concerned policymakers on the environmental impacts of changes in the electricity generation system.

The ALCA conducted in this research work comprehensively provides the results of detailed bottom-up estimates to determine the energy and environmental impacts of utility-scale solar energy systems implemented in Alberta. A bottom-up LCA model was developed to conduct this assessment and incorporates life cycle inventory data associated with all the life cycle stages of a utility-scale solar energy system. The upstream processes, i.e., raw material extraction, manufacturing/assembly of major components, and transportation, account for 75% of the energy use and are the most energy-intensive processes. Upgrading the silicon ore to a usable form of solar cell accounts for 65% of the total life cycle energy consumption. The contribution of transportation is less than 1%.

A complimentary analytical model was created to estimate the amount of energy storage required to supply consistent electricity from utility-scale solar energy systems. The results indicate that the addition of energy storage systems to solar farms significantly increases the GHG emissions from such systems, yet environmentally they are still better than their fossil fuel-based counterparts, as shown in Figure 4.1.

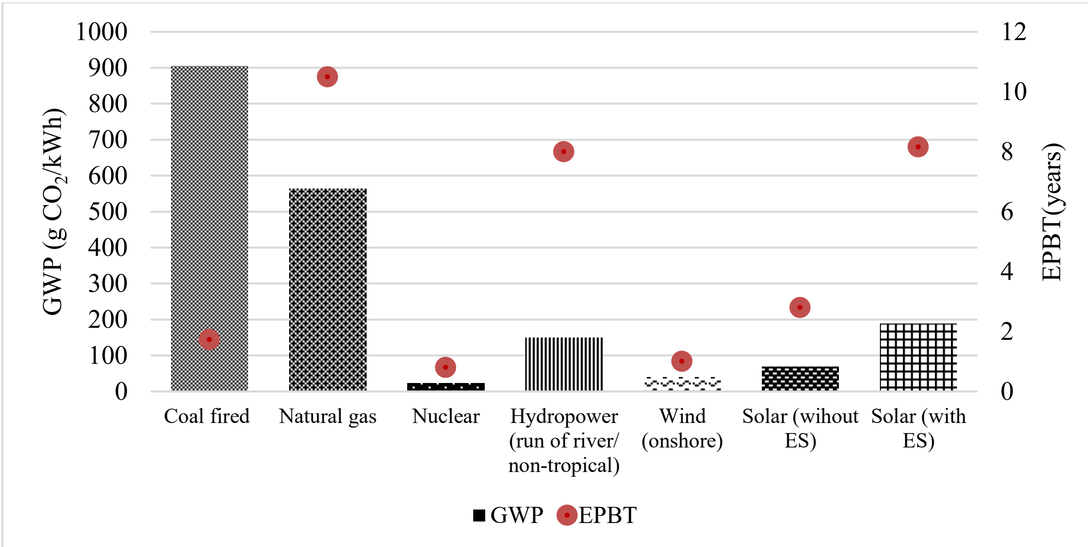


Figure 4.1: Energy and environmental performance parameters for different systems

Extensive sensitivity and uncertainty analyses were performed to provide key information on sensitive parameters over the life cycle stages and capture uncertainties in life cycle inventory data. We found that the overall life cycle GHG emissions were mostly sensitive to the efficiency and lifetime of solar panels, as they dictate the amount of energy generated. Energy requirements during the upgrading of silicon solar cells and the peak power of solar panels during the operational phase affected NER and EPBT the most.

The research also extends the scope of ALCA to include the long-term, economy-wide environmental consequences of marginal changes in the electricity sector to help policymakers in formulating energy policies and their potential environmental significance. We developed a generalized CLCA framework that provides a clear workflow to identify long-term marginal changes in a product system and its economy-wide implications in policy decisions. This framework was applied to assess the long-term changes in the Alberta electricity sector. Nine policy scenarios were strategically developed based on qualitative and quantitative parameters. This enabled us to address critical issues related to the long-term consequences of decarbonizing electricity grids.

We found that although replacing coal and natural gas-based power plants with solar and wind energy provides the highest opportunity to mitigate GHG emissions among the nine scenarios, it also results in the highest cost of generation (as shown in Figure 4.2 and 4.3), which may deem it infeasible in a real context.

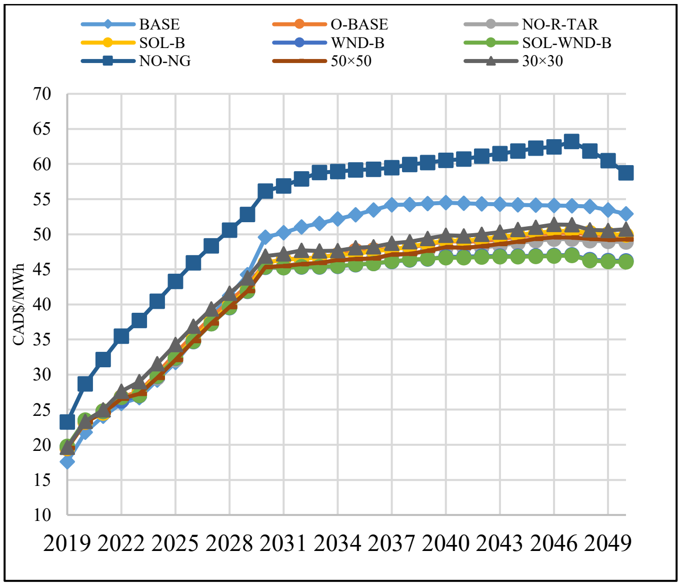


Figure 4.2 Cost of electricity production in the scenarios developed in the CLCA

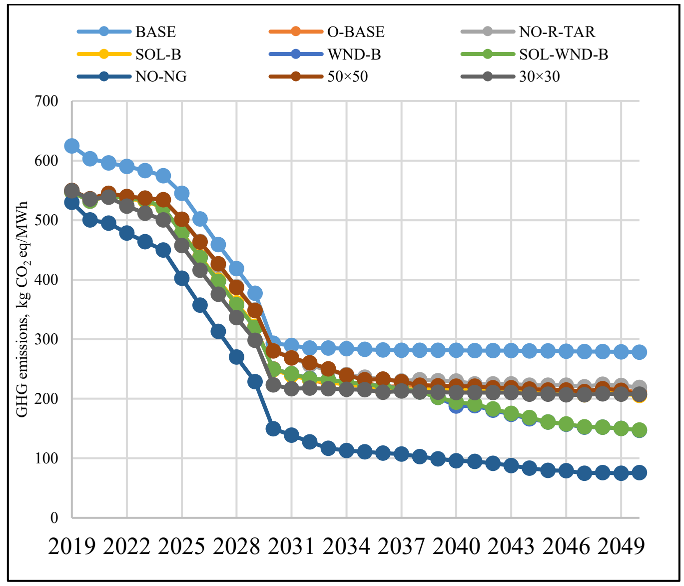


Figure 4.3 GHG emissions per MWh of electricity production in the scenarios developed in the CLCA

We also found that the capital cost predictions for renewable energy resources compete with the combined cycle and simple cycle power plants. This makes a bigger case for the penetration of renewable resources, especially for wind energy in Alberta as it has higher energy yield and lower environmental impacts than solar resources.

While identifying the marginal suppliers of electricity, we found that natural gas-based power plants (simple cycle and combined cycle) were the most cost-competitive options in any change in demand, but wind energy systems constituted the major portion of the marginal supplier mix in almost every scenario. As the marginal mix is dominated by wind energy systems, the CLCA demonstrates that the expansion of wind power systems would be beneficial both in terms of environmental effects and economic feasibility.

This research can make a significant contribution to policy formulation for government agencies and investment decision making for industry. As this research includes an ALCA model for a utility-scale solar energy system that can be replicated for other renewables, it will help the renewable energy industry pinpoint areas to further reduce GHG intensity. Incorporating a framework for CLCA will provide insights into the consequences of long-term policy decisions, and the framework can be replicated in other sectors as well.

4.2 Recommendations for future work

Further research is recommended in the following areas:

- The ALCA modeling of utility-scale solar was done based on current best practices and the most commercially available technological resources used in the industry. Several new methods of solar PV production and different types of solar cells with new materials are being developed globally. An investigation into their life cycle environmental performances can be incorporated into the model to capture a wide array of solar technologies.
- In this research project, emissions from land use and infrastructure construction were not included for either attributional or consequential LCA. Although land-use and infrastructure emissions are assumed to be minor (unlike other life cycle emissions), incorporating them in the system boundary would result in a more robust analysis.
- When incorporating energy storage systems in the utility-scale solar and other technologies in the ALCA and CLCA approaches, only lithium-ion battery technology was considered due to a lack of reliable life cycle inventory data for other emerging storage technologies for these applications. Analyzing the effects of other mechanical and chemical storage systems would broaden this study.

- The research can also be extended to evaluate the cost feasibility of utility-scale solar energy in Alberta and compare it with other large-scale renewable and non-renewable energy technologies through a techno-economic assessment framework.
- In the consequential analysis, the focus was mainly on the electricity grid and resulting marginal changes in the production of electricity, costs, and environmental emissions. By using partial/general equilibrium models or economic input-output tables, we can capture the interaction between sectors that are interlinked with the electricity sector to provide policymakers even more in-depth information on global consequences of policy decisions as they relate to the economy and the environment.
- A major drawback in the LEAP framework was the incorporation of storage systems as a separate transformation module. As a result, there is still room for improvement in estimating the effects on the electricity grid from the large-scale implementation of storage systems.

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Appendix

Appendix A

A1. Solar PV material processing steps

The n-type emitter layer forms in the wafers through a $POCl_3$ process in which nitrogen gas passes over the wafers with oxygen in an 800-900°C oven.

$$4POCl_3 + 3O_2 \rightarrow 2P_2O_5 + 6Cl_2 \quad \text{(A1)}$$

The phosphorus silica glass layer that remains after the chemical process is treated with fluoric acid.

$$SiO_2 + 6HF \rightarrow H_2SiF_6 + 2H_2O \quad \text{(A2)}$$

To prevent short circuiting, the edges formed during fluoric acid treatment are etched off through a plasma etching process. In this process, the wafers are placed in a plasma reactor where fluorine atoms are freed from CF_4 and react with silicon [23].

$$Si + 4F \rightarrow SiF_4 \quad \text{(A3)}$$

The final stage in solar cell processing is screen printing the front (aluminum) and back (silver) of the cells. This prevents the generated electrons and holes from recombining. After that is done, the wafers are fired into a belt oven where they go through heat treatment at temperatures of 120-150°C, evaporating the solvents, and then at 300-400°C where the resins are burned to sintered frit at a temperature of 600°C.

The individual cells produced in screen printing are laid out in a 6×12 formation (6 columns and 12 rows). They are interconnected in series and parallel patterns. Square-shaped cells were considered here as they provide the highest packing density, thereby increasing the effective area. In this study, the material and energy balances of the aluminum frame were considered in the module assembly process. The process yield for this unit operation is considered to be 99% [23].

A2. Electricity generation model for the system without the energy storage

The following procedure was followed to configure the size of the power generation system:

- The peak capacity of the system was specified in MW.
- The number of panels required to achieve the peak wattage of power was determined by the following formula:

$$Total\ number\ of\ panels = \frac{Peak\ wattage\ of\ the\ system\ (MW)}{Peak\ wattage\ of\ solar\ PV\ panel\ (W) \times 10^{-6}} \quad \text{(A4)}$$

- The number of inverters was calculated through the following:

$$Total\ Number\ of\ Inverters = \frac{Peak\ Wattage\ of\ the\ system\ (MW)}{Input\ DC\ Wattage\ of\ the\ inverter\ (MW)} \quad \text{(A5)}$$

- The electricity generation on year i was calculated as follows:

$$Electricity\ generated\ at\ year\ (i) = (A \times H \times PR \times \eta)_{i-1} \times (1 - \frac{PR}{Lifetime}) \quad \text{(A6)}$$

- The life cycle electricity generation was calculated using the following:

$$Life\ cycle\ electricity\ output = \sum Electricity\ generated\ at\ year\ (i) \quad \text{(A7)}$$

A3. Electricity generation model for the system with energy storage

The loss of power supply probability (LPSP) value is calculated using Equation 5:

$$LPSP = \Pr\{E_B(t) \leq E_{B_{min}}: for\ t \leq T\} \quad \text{(A11)}$$

where $E_B(t)$ is energy stored in batteries at any time, t, E_{Bmin} is the battery's minimum allowable energy level (depth of discharge).

Energy generated by the PV array for hour t, $E_{G(t)}$, can be expressed as follows:

$$E_{G(t)} = N_{PV} \,.\, E_{PV(t)} \quad \text{(A12)}$$

where $E_{PV(t)}$ is energy generated by a PV module and N_{PV} is the number of PV modules in a PV array.

If the energy generated by the PV array exceeds the load demand, the batteries will be charged according to the following equation:

$$E_{B(t)} = E_{B(t-1)} + \frac{(E_{G(t)} - E_{L(t)}}{\eta_{inv}} \quad \text{(A13)}$$

where η_{inv} is the efficiency of the inverter, $E_{B(t)}$ is energy stored in batteries in hour t, $E_{B(t-1)}$, is energy stored in batteries in the previous hour, and $E_{L(t)}$ is load demand in hour t.

When the load demand is greater than the available energy generated, the batteries will discharge the amount of energy needed to cover the deficit. This discharge can be expressed as follows:

$$E_{B(t)} = E_{B(t-1)} - (\frac{E_{L(t)}}{\eta_{inv}} - E_{G(t)}) \quad \text{(A14)}$$

The energy stored in the batteries is subject to the following constraint, which ensures that the batteries would not be overcharged or over discharged at any time:

$$E_{B\,min} \leq E_{B(t)} \leq E_{B\,max} \quad \text{(A15)}$$

When the available energy generated and stored in the batteries is insufficient to satisfy the load demand for hour *t,* that deficit, called Loss of power supply, for hour *t*, can be expressed as

$$LPS_{(t)} = E_{L(t)} - \left(E_{G(t)} + E_{B(t-1)} - E_{B\,min}\right).\eta_{inv} \tag{A16}$$

The LPSP for a considered period *t* is the ratio of all LPS_t values for that period to the sum of the load demand. This can be defined as:

$$LPSP = \frac{\sum_{t=1}^{T} LPS_t}{\sum_{t=1}^{T} E_{L(t)}} \tag{A17}$$

Once we had determined the available energy generated from the PV module for every hour of a typical day each month, we were able to calculate different combinations of the number of PV modules and batteries for the desired LPSP.

Once the total electricity generation potential is determined, the optimum number of panels and batteries are calculated based on an economic approach. To estimate the most economical PV and battery combination at the lowest cost, the following was developed:

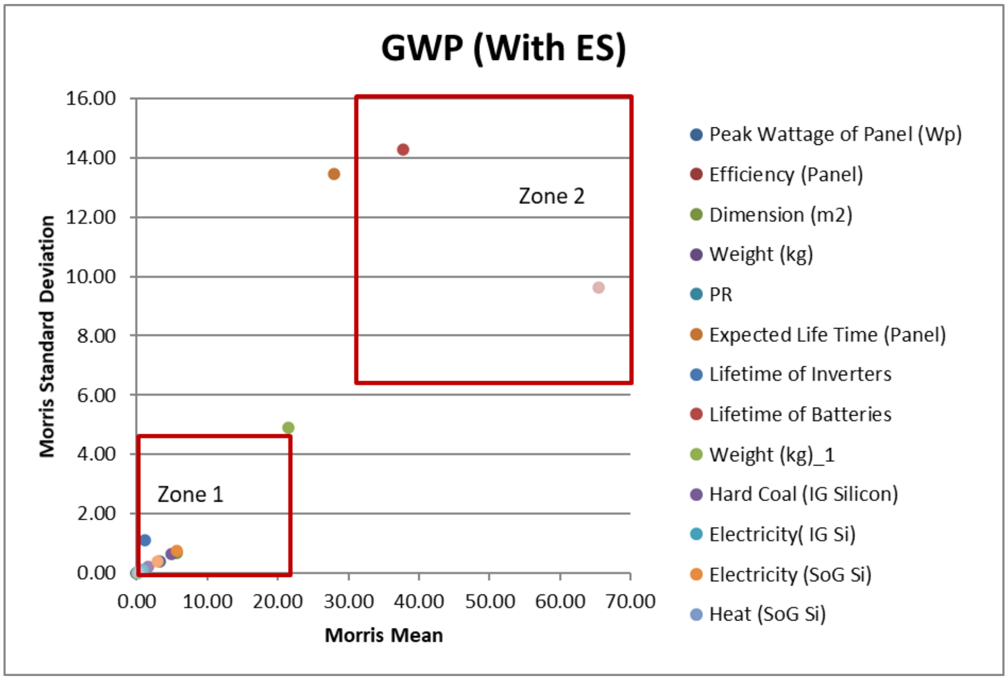
$$C = \alpha\,.N_{PV} + \beta\,.N_{batt} + C_0 \tag{A18}$$

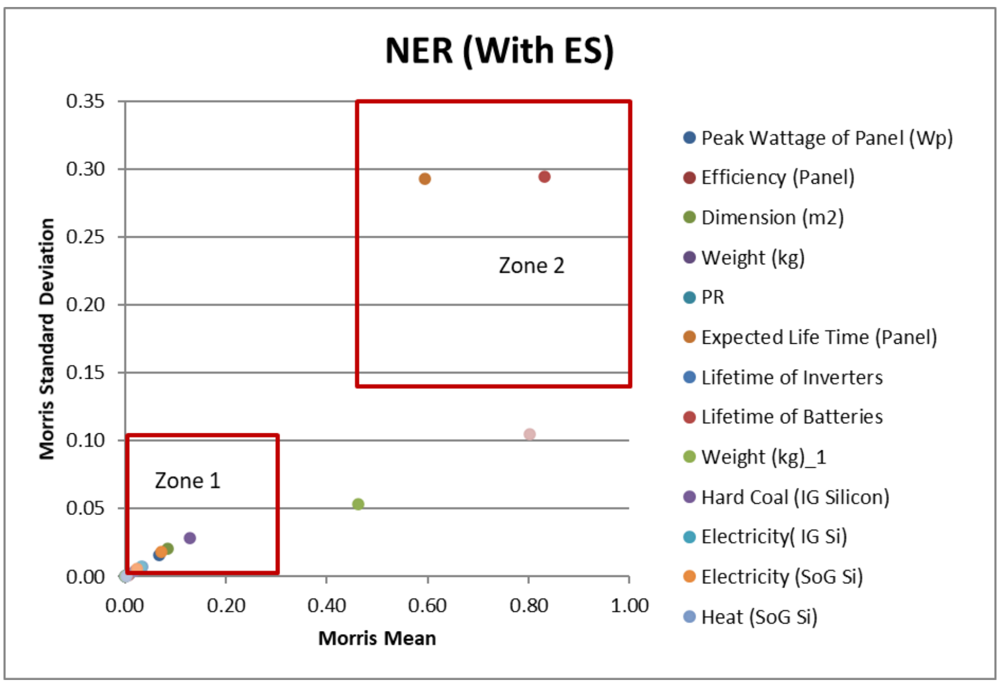
where *C* is the capital cost of the system, α is the cost of a PV module, β is the cost of the battery, and C_0 represents the fixed costs, including the cost of design and installation.

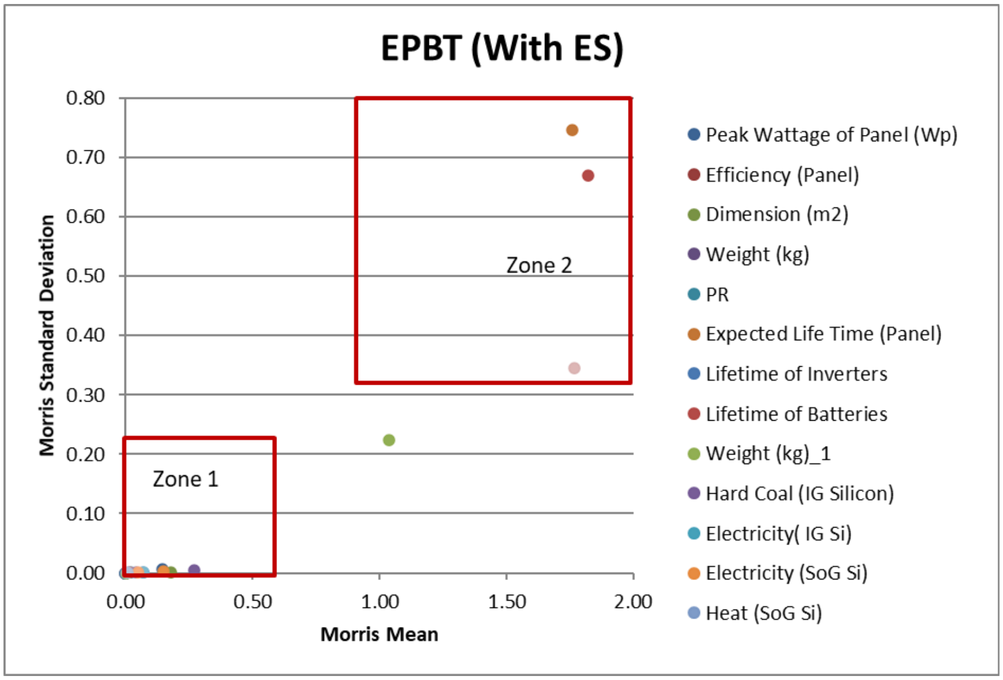
The condition to obtain the optimum solution from Equation A12 yields:

$$\frac{\partial N_{PV}}{\partial N_{batt}} = -\frac{\beta}{\alpha} \tag{A19}$$

A4. Results of the sensitivity analysis for the ES option







A5. Inputs for the uncertainty analysis

Parameter	Minimum	Most Likely	Maximum
Peak wattage of panel (Wp)	310	325	330
Efficiency (Panel)	0.12	0.17	0.18
Dimension (m^2)	1.56	1.95	2.33
PV panel weight (kg)	17.9	22.4	26.9
PR	0.7	0.8	0.9
Expected lifetime (panel) (years)	20	25	30
Lifetime of inverters (years)	8	10	12

Lifetime of batteries (years)	4	5	6
Battery weight (kg)	100	125	125
Hard coal (IG Silicon) (kg)	18.5	23.1	27.72
Electricity (IG Si)	8.8	11	13.2
Electricity (SoG Si) (kWh)	88	110	132
Heat (SoG Si)	148	185	222
Electricity (ingot casting) (kWh)	7.9	9.92	11.9
Electricity (wafer slicing) (kWh)	1.6	2	2.4
Electricity (cell processing) (kWh)	130	162.5	195
Glass (module assembly)	54.5	68.09	81.8
Aluminum (module assembly)	12.02	15.02	18.02
Electricity (module assembly) (kWh)	18	22.5	27
Energy (kWh/kg) (battery)	8.34	20.85	22.24

A6. Equation for calculating the sampling error in the Monte Carlo simulation

The Monte Carlo sampling error determines the error that occurs between simulations and can be calculated using the following equation:

Sampling error, $X = \frac{z \times \sigma}{\sqrt{n}}$

where σ is the standard deviation of the mean and n is the number of samples. The Z value is determined based on the confidence interval of the standard normal distribution.

Confidence Interval (%)	**Z value**
90	1.645
95	1.96
98	2.33
99	2.58

A7. Calculation method for land use footprint

The following equations were used to evaluate the land use footprint:

$$LUF\left(\frac{m^2}{kWh}\right) = \frac{Land_{PV\ installation} + Land_{T\&D}}{Total\ energy\ delivered\ (lifecycle)} \tag{A20}$$

$$\begin{aligned} Land_{PV\ installation}(m^2) & \\ &= (area\ per\ module \times number\ of\ modules) \\ &/array\ packing\ factor \end{aligned} \tag{A21}$$

$$Land_{T\&D}(m^2) = line\ length \times right\ of\ way\ width \tag{A22}$$

$$Array\ packing\ factor = \frac{array\ area}{actual\ land\ area} \tag{A23}$$

A8. Emission factors for land use change emissions

Emission source	Low carbon stock (Semi arid grassland)	Medium carbon stock (mixed)	High carbon stock (forest)	Unit
Soil Carbon	400	1200	2000	kg/ha
Biomass	1900	8950	16000	kg/ha
sequestration	2200	2650	3100	kg/ha

Appendix B

B1. Marginal supplier identification process

1. The generation in target years is derived from LEAP outputs for each scenario.
2. The capital replacement rate is calculated as the inverse of plant lifetime, with a minus sign.
3. The net annual growth rate is calculated as the annual growth rate minus the capital replacement rate.
4. If the annual growth is lower than the capital replacement rate, the technology is considered old.
5. Net annual growth is calculated as the generation in base year times the net annual growth rate.

Table B4: Quantitative calculation for marginal mix identification in the base case scenario (BASE)

BASE												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (thousand GWh/year)**	**Long-term marginal mix**	**Aggregated cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	36096	0	-3.2%	40	-2.50%	-0.73%	OLD	-261.99	0.00%	$3,477,261,627	$11,784	$12
Supercritical coal	6995	0	-3.2%	40	-2.50%	-0.73%	OLD	-50.77	0.00%	$896,090,624	$11,650	$12
Simple cycle	3480	5111	1.5%	30	-3.33%	4.84%	NEW	168.62	2.02%	$11,492,989,008	$108,298	$108
Combined cycle	8516	53770	17.1%	30	-3.33%	20.48%	NEW	1743.69	20.86%	$76,691,670,372	$57,500	$58
Solar	127	1752	41.4%	25	-4.00%	45.40%	NEW	57.50	0.69%	$2,918,012,867	$79,619	$80
Wind	4364	15244	8.0%	25	-4.00%	12.04%	NEW	525.52	6.29%	$22,711,548,339	$54,423	$54
Hydro	1958	2724	1.3%	50	-2.00%	3.26%	NEW	63.88	0.76%	$2,300,356,578	$29,212	$29
Cogeneration oil sands	22399	22411	0.0%	30	-3.33%	3.34%	NEW	747.03	8.93%	$25,380,195,269	$35,401	$35
Cogeneration biomass	2112	2114	0.0%	30	-3.33%	3.34%	NEW	2495.32	29.85%	$681,123,825	$10,074	$10
Cogeneration other	7618	7623	0.0%	30	-3.33%	3.34%	NEW	2559.20	30.61%	$8,632,516,345	$35,401	$35
								8360.75	100.00%			

Table B5: Quantitative calculation for marginal mix identification in the optimized base case scenario (O-BASE)

O-BASE												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual Growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (Thousand GWh/year)**	**Long term Marginal mix**	**Aggregated Cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	1844	1112	-1.3%	30	-3.33%	2.05%	NEW	37.86	0.47%	$10,955,058,477	$365,069	$365
Combined cycle	11204	30499	5.6%	30	-3.33%	8.89%	NEW	995.89	12.40%	$52,598,967,151	$65,701	$66
Solar	20	0	-3.2%	25	-4.00%	0.77%	NEW	0.15	0.00%	$7,617,600	$30,652	$31
Wind	7357	34632	12.0%	25	-4.00%	15.96%	NEW	1174.10	14.62%	$34,619,718,308	$41,371	$41
Hydro	5367	8310	1.8%	50	-2.00%	3.77%	NEW	202.28	2.52%	$3,934,395,538	$18,779	$19
Cogeneration oilsands	24803	30207	0.7%	30	-3.33%	4.04%	NEW	1001.08	12.47%	$32,528,792,986	$35,383	$35
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2208.01	27.50%	$478,167,284	$7,075	$7
Cogeneration other	7479	5712	-0.8%	30	-3.33%	2.57%	NEW	2410.29	30.02%	$7,700,026,089	$32,472	$32
								8029.66	100.00%			

Table B6: Quantitative calculation for marginal mix identification in the (no renewable targets) scenario (NO-R-TAR)

NO-R-TAR												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (thousand GWh/year)**	**Long term marginal mix**	**Aggregated cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	2049	1093	-1.5%	30	-3.33%	1.83%	NEW	37.45	0.47%	$10,493,726,639	$228,245	$228
Combined cycle	11486	32691	6.0%	30	-3.33%	9.29%	NEW	1066.91	13.44%	$57,236,200,197	$63,348	$63
Solar	41	79	3.0%	25	-4.00%	6.98%	NEW	2.86	0.04%	$167,624,822	$67,389	$67
Wind	6779	31163	11.6%	25	-4.00%	15.60%	NEW	1057.73	13.32%	$27,161,938,219	$38,639	$39
Hydro	5367	8801	2.1%	50	-2.00%	4.06%	NEW	218.11	2.75%	$4,224,679,525	$19,614	$20
Cogeneration oil sands	24730	30396	0.7%	30	-3.33%	4.07%	NEW	1007.12	12.69%	$32,616,189,016	$35,376	$35
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2164.95	27.27%	$478,167,284	$7,075	$7
Cogeneration other	7623	6249	-0.6%	30	-3.33%	2.75%	NEW	2383.05	30.02%	$7,822,336,727	$32,418	$32
								7938.17	100.00%			

Table B7: Quantitative calculation for marginal mix identification in the solar farms with storage scenario (SOL-B)

SOL-B												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (thousand GWh/year)**	**Long term marginal mix**	**Aggregated cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	1828	1134	-1.2%	30	-3.33%	2.11%	NEW	38.54	0.47%	$10,321,995,405	$347,226	$347
Combined cycle	11183	28598	5.0%	30	-3.33%	8.36%	NEW	934.54	11.48%	$50,329,858,006	$66,087	$66
Solar	62	1183	58.0%	25	-4.00%	61.99%	NEW	38.63	0.47%	$2,330,357,101	$93,877	$94
Wind	7357	37811	13.4%	25	-4.00%	17.35%	NEW	1276.68	15.68%	$35,890,878,279	$41,155	$41
Hydro	5367	6838	0.9%	50	-2.00%	2.88%	NEW	154.81	1.90%	$3,329,979,682	$16,883	$17
Cogeneration oil sands	24803	29195	0.6%	30	-3.33%	3.90%	NEW	968.46	11.89%	$32,372,476,696	$35,404	$35
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2288.39	28.10%	$478,167,284	$7,075	$7
Cogeneration other	7473	5712	-0.8%	30	-3.33%	2.57%	NEW	2443.20	30.00%	$7,595,447,629	$32,487	$32
								8143.24	100.00%			

Table B8: Quantitative calculation for marginal mix identification in the wind farms with storage scenario (WND-B)

WND-B												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (thousand GWh/year)**	**Long term marginal mix**	**Aggregated cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	1836	1064	-1.4%	30	-3.33%	1.98%	NEW	36.28	0.42%	$7,158,267,487	$157,229	$157
Combined cycle	11194	13626	0.7%	30	-3.33%	4.03%	NEW	451.58	5.17%	$39,294,125,468	$65,010	$65
Solar	41	53	0.9%	25	-4.00%	4.91%	NEW	2.01	0.02%	$117,256,360	$67,688	$68
Wind	7357	62094	24.0%	25	-4.00%	28.00%	NEW	2059.99	23.60%	$48,487,757,888	$44,085	$44
Hydro	5367	7820	1.5%	50	-2.00%	3.47%	NEW	186.46	2.14%	$3,837,373,759	$18,489	$18
Cogeneration oil sands	24803	21065	-0.5%	30	-3.33%	2.85%	NEW	706.17	8.09%	$30,869,031,417	$35,622	$36
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2549.87	29.21%	$478,167,284	$7,075	$7
Cogeneration other	7476	4751	-1.2%	30	-3.33%	2.16%	NEW	2736.33	31.35%	$6,777,868,746	$32,595	$33
								8728.69	100.00%			

Table B9: Quantitative calculation for marginal mix identification in the solar and wind farms with storage scenario (SOL-WND-B)

SOL-WND-B												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (thousand GWh/year)**	**Long term marginal mix**	**Aggregated cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	1828	1059	-1.4%	30	-3.33%	1.98%	NEW	36.14	0.41%	$7,165,986,653	$157,718	$158
Combined cycle	11183	13608	0.7%	30	-3.33%	4.03%	NEW	451.00	5.13%	$39,424,664,593	$64,989	$65
Solar	62	26	-1.9%	25	-4.00%	2.13%	NEW	1.33	0.02%	$236,137,068	$113,103	$113
Wind	7357	64118	24.9%	25	-4.00%	28.89%	NEW	2125.27	24.17%	$49,230,069,714	$44,053	$44
Hydro	5367	5857	0.3%	50	-2.00%	2.29%	NEW	123.16	1.40%	$2,773,097,589	$14,912	$15
Cogeneration oil sands	24803	21051	-0.5%	30	-3.33%	2.85%	NEW	705.75	8.03%	$30,902,257,445	$35,617	$36
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2613.74	29.72%	$478,167,284	$7,075	$7
Cogeneration other	7473	4751	-1.2%	30	-3.33%	2.16%	NEW	2736.90	31.12%	$6,792,093,220	$32,594	$33
								8793.28	100.00%			

Table B10: Quantitative calculation for marginal mix identification in the energy storage instead of natural gas scenario (NO-NG)

NO-NG												
Feedstock	**Generation in 2019(GWh)**	**Generation in 2050 (GWh)**	**Annual growth (%)**	**Lifetime (years)**	**Capital replacement rate (%)**	**Net annual growth**	**Classification**	**Net annual growth (thousand GWh/year)**	**Long term marginal mix**	**Aggregated cost (CAD)**	**Per GWh**	**Per MWh**
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	2223	1	-3.2%	30	-3.33%	0.11%	NEW	2.42	0.02%	$1,410,773,587	$122,362	$122
Combined cycle	7209	239	-3.1%	30	-3.33%	0.21%	NEW	15.47	0.16%	$3,561,816,323	$66,241	$66
Solar	1418	15315	31.6%	25	-4.00%	35.60%	NEW	505.02	5.17%	$71,008,000,954	$126,864	$127
Wind	7068	74878	30.9%	25	-4.00%	34.95%	NEW	2470.14	25.31%	$74,042,550,985	$47,937	$48
Hydro	5367	8562	1.9%	50	-2.00%	3.92%	NEW	210.42	2.16%	$3,523,117,603	$17,854	$18
Cogeneration oil sands	23617	10412	-1.8%	30	-3.33%	1.53%	NEW	361.27	3.70%	$20,107,142,984	$38,716	$39
Cogeneration biomass	2112	1316	-1.2%	30	-3.33%	2.12%	NEW	2993.06	30.66%	$433,577,486	$7,682	$8
Cogeneration other	7623	1859	-2.4%	30	-3.33%	0.89%	NEW	3203.48	32.82%	$5,139,367,572	$33,005	$33
								9761.28	100.00%			

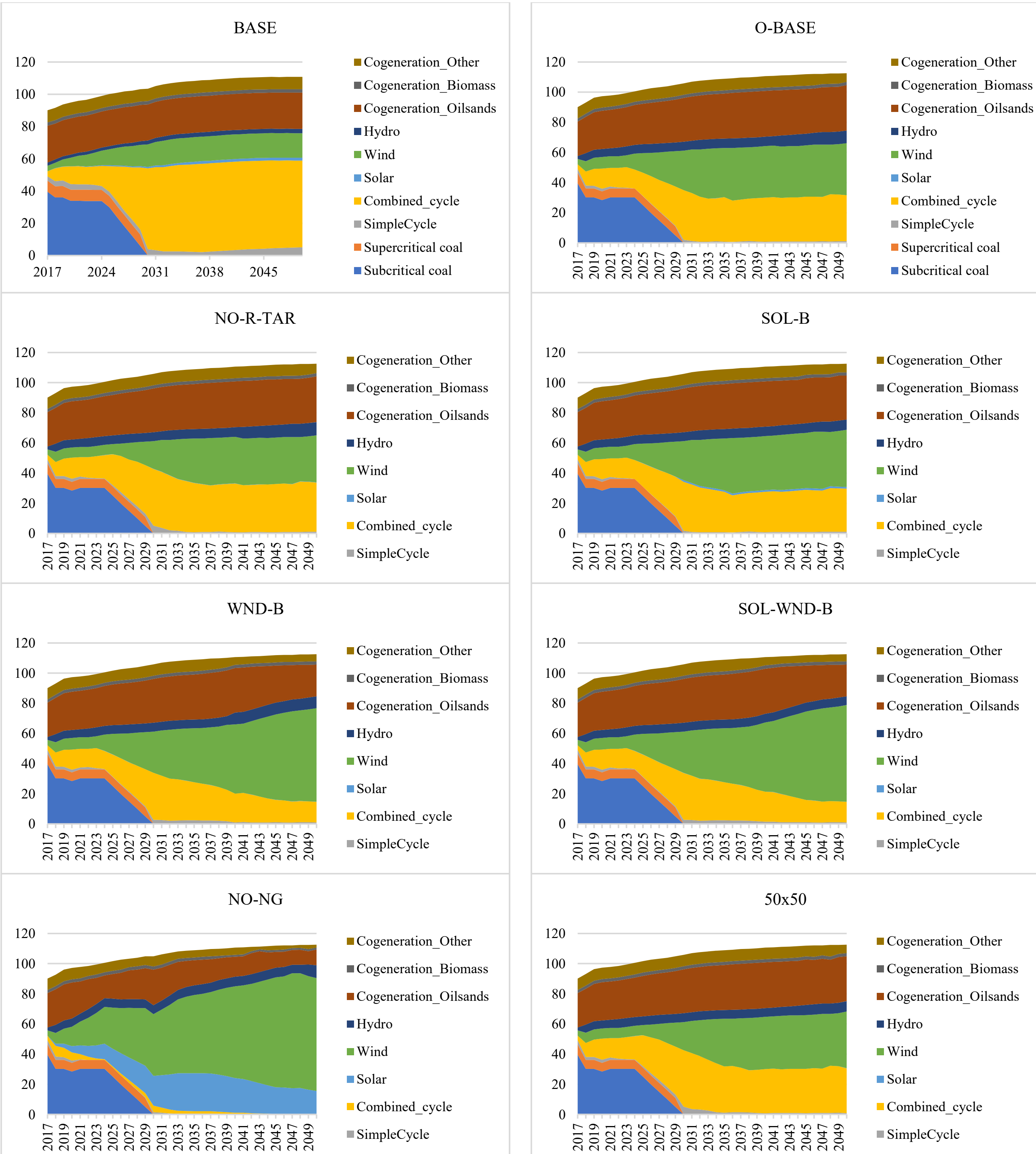
Table B11: Quantitative calculation for marginal mix identification in the GHG emissions reduction by 50% by 2050 scenario (50×50)

50×50												
Feedstock	Generation in 2019(GWh)	Generation in 2050 (GWh)	Annual growth (%)	Lifetime (years)	Capital replacement rate (%)	Net annual growth	Classification	Net annual growth (thousand GWh/year)	Long term marginal mix	Aggregated cost (CAD)	Per GWh	Per MWh
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	2057	881	-1.8%	30	-3.33%	1.49%	NEW	30.63	0.38%	$12,182,936,361	$245,890	$246
Combined cycle	11497	29588	5.1%	30	-3.33%	8.41%	NEW	966.80	11.93%	$54,749,157,190	$63,406	$63
Solar	20	289	44.3%	25	-4.00%	48.27%	NEW	9.48	0.12%	$25,490,280	$47,415	$47
Wind	6779	37522	14.6%	25	-4.00%	18.63%	NEW	1262.88	15.58%	$29,702,544,661	$38,544	$39
Hydro	5367	6838	0.9%	50	-2.00%	2.88%	NEW	154.81	1.91%	$3,087,283,211	$16,051	$16
Cogeneration oil sands	24732	29778	0.7%	30	-3.33%	3.99%	NEW	987.19	12.18%	$32,505,894,574	$35,393	$35
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2269.79	28.00%	$478,167,284	$7,075	$7
Cogeneration other	7623	5574	-0.9%	30	-3.33%	2.47%	NEW	2424.60	29.91%	$7,738,900,227	$32,422	$32
								8106.19	100.00%			

Table B12: Quantitative calculation for marginal mix identification in the GHG emissions reduction by 50% by 2030 scenario (30×30)

30×30												
Feedstock	Generation in 2019(GWh)	Generation in 2050 (GWh)	Annual growth (%)	Lifetime (years)	Capital replacement rate (%)	Net annual growth	Classification	Net annual growth (thousand GWh/year)	Long term marginal mix	Aggregated cost (CAD)	Per GWh	Per MWh
Subcritical coal	30237	0	-3.2%	40	-2.50%	-0.73%	OLD	-219.46	0.00%	$3,236,873,478	$12,708	$13
Supercritical coal	5859	0	-3.2%	40	-2.50%	-0.73%	OLD	-42.53	0.00%	$808,837,944	$12,549	$13
Simple cycle	2017	913	-1.8%	30	-3.33%	1.57%	NEW	31.63	0.39%	$9,611,718,139	$608,511	$609
Combined cycle	11442	29719	5.2%	30	-3.33%	8.49%	NEW	970.99	12.03%	$49,801,057,369	$70,441	$70
Solar	41	0	-3.2%	25	-4.00%	0.77%	NEW	0.32	0.00%	$65,263,108	$70,016	$70
Wind	7357	36077	12.6%	25	-4.00%	16.59%	NEW	1220.73	15.12%	$42,387,210,930	$44,036	$44
Hydro	4876	8310	2.3%	50	-2.00%	4.27%	NEW	208.29	2.58%	$3,714,510,944	$18,111	$18
Cogeneration oil sands	24719	29740	0.7%	30	-3.33%	3.99%	NEW	985.93	12.21%	$32,470,243,419	$35,418	$35
Cogeneration biomass	2112	2112	0.0%	30	-3.33%	3.33%	NEW	2223.67	27.54%	$478,167,284	$7,075	$7
Cogeneration other	7623	5712	-0.8%	30	-3.33%	2.52%	NEW	2431.96	30.12%	$7,322,644,485	$32,476	$32
								8073.52	100.00%			

B2. Electricity generation mixes in different scenarios



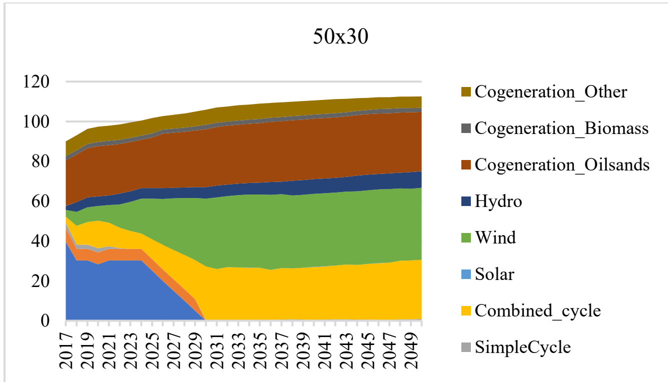


Figure B1: Electricity mixes in different scenario

B3. Substitution of technologies due to changes in policy decisions

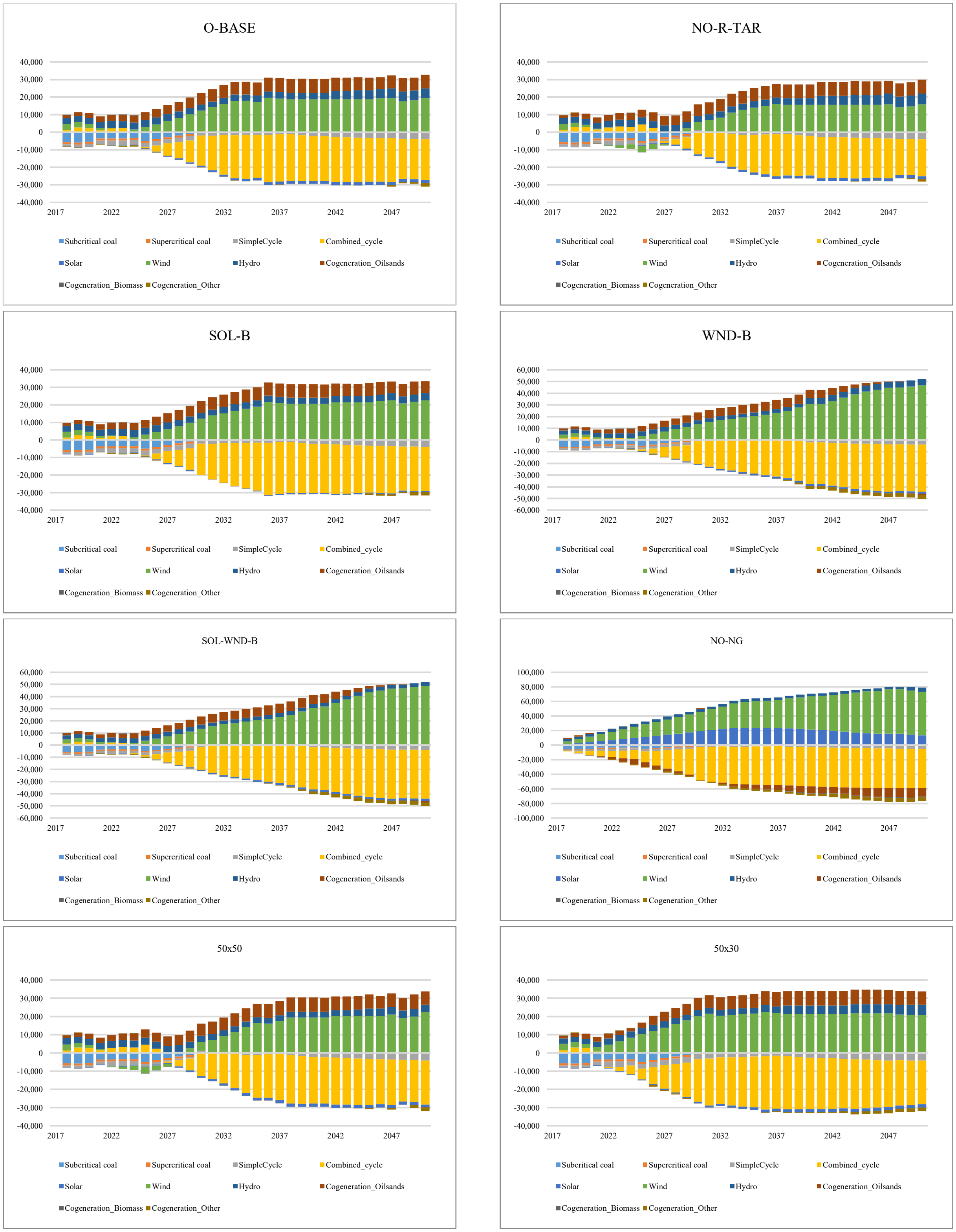


Figure B2: Substitution of technologies due to changes in policy decisions

B4. The effect of technology substitution on GHG emissions

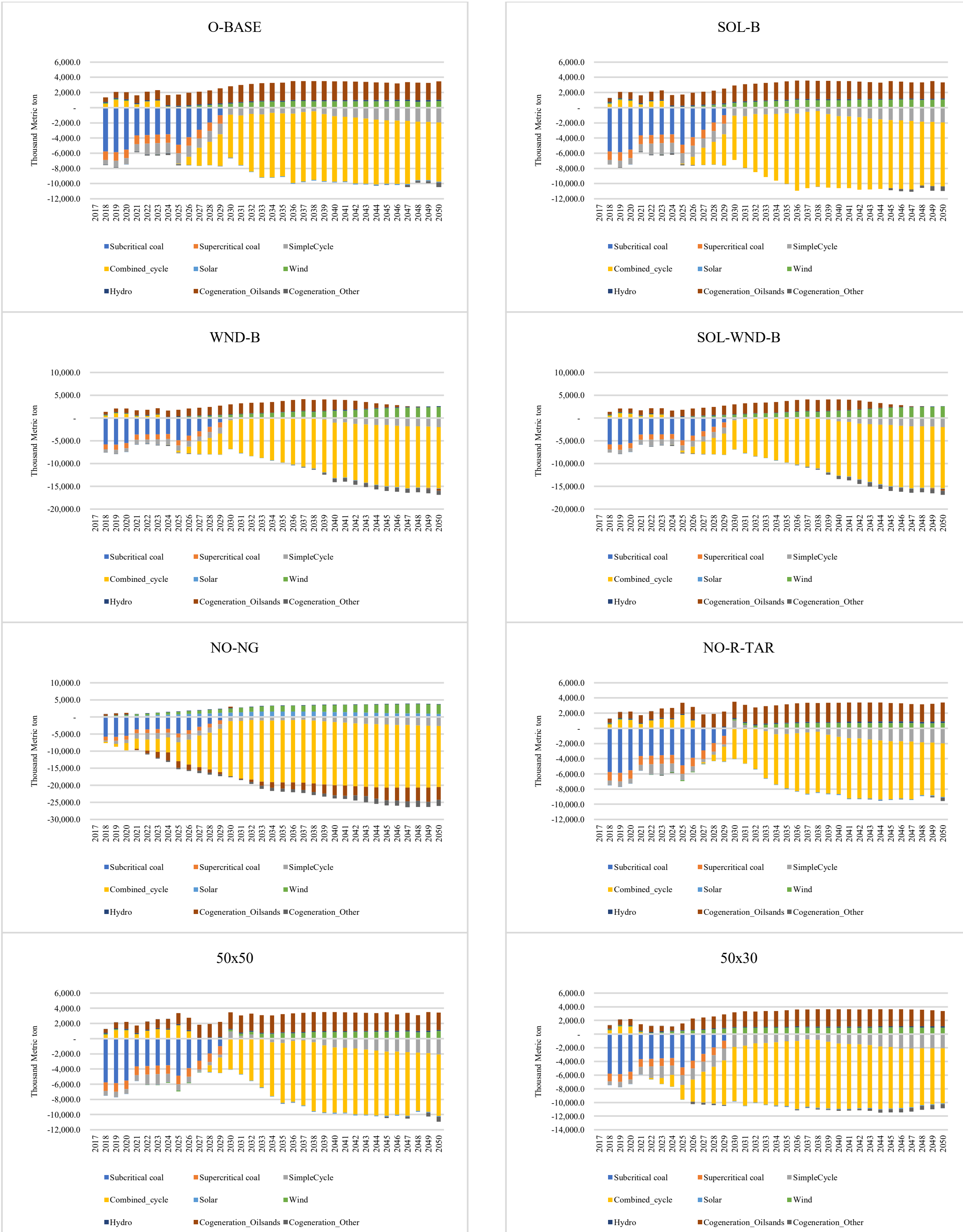


Figure B3: The effect technology substitution on GHG emissions