THESIS

DYNAMIC EMISSIONS MODELING FOR SUSTAINABLE ALGAL CARBON NANOFIBER PRODUCTION

Submitted by

Katelyn Whiting

Department of Systems Engineering

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Spring 2025

Master’s Committee:

Advisor: Steve Conrad

Jason Quinn
Elizabeth Toman

ABSTRACT

DYNAMIC EMISSIONS MODELING FOR SUSTAINABLE CARBON NANOFIBER PRODUCTION

The demand for sustainable materials continues to grow, along with the need for accurate environmental impact assessments. Dynamic life cycle assessments (DLCA) provide a more comprehensive sustainability evaluation by incorporating temporal and spatial variability into traditional impact assessments.

This thesis uses a dynamic life cycle assessment (DLCA) to evaluate the environmental impact of algal carbon nanofibers (ACNF), including CO_2 emissions, material use, and water consumption. A process-based model estimated industrial-scale energy use, which was converted into emissions using a dynamic normalization factor (DNF). The approach assessed four future energy mix scenarios within the RMPA sub-grid. Results suggest strong system resilience for algal-based products, particularly with advanced cultivation methods like photobioreactors.

ACNF production is highly resource-intensive, with significant CO_2 emissions and upstream water use driven by the large quantities of solvent required. Mitigation strategies were explored and offer a foundation for future research. Incorporating dynamic LCA elements provided clear improvements by more accurately capturing evolving energy system impacts.

This study reinforces the importance of adaptive environmental assessments when evaluating novel materials with sustainability potential. Future research should further validate this framework with industrial-scale data, expand regional applicability, and explore additional life cycle impact categories to improve the accuracy and relevance of sustainability assessments.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my mentor and advisor, Dr. Steve Conrad, for his patience, guidance, and unwavering support throughout my research journey. His invaluable perspectives and steadfast mentorship have been instrumental in shaping both this thesis and my academic growth.

I am profoundly grateful to Dr. Jason Quinn and Dr. Elizabeth Toman for serving on my thesis committee. Their insightful feedback and diverse expertise have significantly enriched the quality of this work. This thesis would not have been possible without their thoughtful contributions.

My heartfelt appreciation goes to my research colleagues in the Blue-Green Decisions Lab, whose support, thought-provoking discussions, and friendship have propelled me throughout this process. Your collaboration and encouragement made this journey all the more enjoyable and rewarding.

I owe an immeasurable debt of gratitude to my partner and family for their unwavering support, understanding, and encouragement. Their belief in me has been a constant source of motivation, and I am deeply thankful for their presence throughout my academic endeavors.

I would also like to acknowledge Colorado State University for fostering an enriching environment of education, collaboration, and community. The opportunities and resources provided by the university were invaluable in completing this research.

To all those mentioned above—and to many others who have contributed in ways both big and small—thank you for your support and for being part of this meaningful chapter in my academic journey.

"If you want to go fast, go alone. If you want to go far, go together."

-African Proverb

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRYNOYMS

ACNF – Algal carbon nanofiber

AWARE – Available Water Remaining

CNF - Carbon nanofibers

DLCA – Dynamic life cycle assessment

DMF - Dimethylformamide

DNF – Dynamic normalization factor

EPA – Environmental protection agency

GHG – Greenhouse gas

GWP – Global warming potential

LCA – Life cycle assessment

PAN - Polyacrylonitrile

RMPA – Rocky Mountain Power Administration

WECC – Western Electricity Coordinating Council

WSCC – Western Systems Coordinating Council

KEYWORDS

Carbon Nanofiber Production, Dynamic Life Cycle Assessment, Energy Mix, Carbon Dioxide Emissions

CHAPTER 1 - INTRODUCTION

There is an ever-growing need for innovative, inexpensive, and sustainable materials to feed into commercial manufacturing schemes across the globe. Industries from pharmaceuticals to construction and packaging to animal feed production are seeking more sustainable and cost-effective alternatives to their traditional means. Current materials lack the long-term environmental feasibility to comply with world sustainable development goals. Opportunity exists in bio-based materials for their potential renewability and reduction of potential impacts and harm to humans and the environment that traditional materials cause. In this thesis I examine the life cycle impact of a novel biomaterial – algal based carbon nanofibers - while implementing a dynamic normalization factor (DNF) to examine the sustainability of this product during the production phase.

The objective of this research is to model the production of algal based carbon nanofibers on an industrial scale. The output from this industrial manufacturing system will then be used in a life cycle analysis. The DNF will account for a temporally changing energy resource mix for four different future scenarios. This thesis provides context on the challenges of producing algal based carbon nanofibers and their given CO_2 emissions, water and material consumption on an industrial scale as well as applying a novel approach in the assessment itself.

1.1 Algae Integrated Products

Algal infused or derived materials used in bio-based products have garnered the attention of researchers and industries as a sustainable alternative to petroleum-based products. A diverse array of products and co-products, including renewable diesel, bioplastics, animal feedstock, nutrition supplements, cosmetic compounds, and cooking oil have demonstrated considerable potential when compared to their non-algal counterparts (Parsons et al., 2020). A particular emphasis in research has been placed on algae derived fuels like renewable diesel or biofuel, giving popularity to the world of algae-based products (Beckstrom et al., 2020; Dębowski et al., 2022; Nogueira Junior et al., 2018; Osman et al., 2021; Parsons et al., 2020; Quiroz et al., 2022, 2023). Likewise, algae applications spanning water treatment, carbon capture/utilization and the overall promise of reducing the reliance on petroleum-based products have driven the need to assess the impact of algae during the various phases of its lifecycle(Dębowski et al., 2022; Kumar & Singh, 2019; Mehariya et al., 2021). In this study, I examine the production of algae-based carbon nanofibers (ACNF).

ACNF are a bio-based alternative to conventional, composite or polymer-based Nanofibers (NFS) or microfibers. NFS are used in a variety of industries with applications such as water filters, storage devices, dye-sensitized solar cells, lithium/sodium-ion batteries, sensors, and adsorbent materials, drug delivery, textiles, and supercapacitor electrodes (Malara, 2024). Both materials are produced using electrospinning, a process in which fluid is drawn through a needle into a high-voltage electromagnetic field, forming nanoscopic fibers as the solution elongates and solidifies. Algae oil has shown promise as a primary ingredient in the development of these materials, improving key properties such as capacitance, flexibility, porosity, and overall mechanical performance (Karaduman et al., 2022; T. Wang et al., 2022). Additionally, the use of a renewable product such as algae-derived oil has potential to improve the overall lifecycle impacts.

ACNF show promise in delivering the properties of traditional nanofibers while offering reduced lifecycle impacts due to the renewable nature of the algae base. Further supporting the investigation of ACNFs is their connection to other bio-based products, such as algae-based fuels. Biomass sources are viewed favorably given the shift in raw materials required, going from fossil derived oils to biomass from ponds and oceans (Carneiro et al., 2017). Unlike traditional fuels that rely on environmentally disruptive practices such as mining and fracking, algae-based fuels eliminate the need for resource extraction and can be produced on non-arable land, significantly reducing land-use impacts. (Osman et al., 2021).

However, limited evaluations have been conducted on the production of bio-based materials aimed at providing more sustainable alternatives to traditional materials. For example, nanofiber sheets are a product used for a variety of applications in the medical, water filtration, and electronics industries (Borah et al., 2024). Carbon nanofiber sheets are similar in their production methods and overlap some application areas, with the main difference being the lack of algae oil infusion (Khanna et al., 2008). Many of the assessments on carbon nanofiber focus on their effectiveness in different application areas or the ‘use’ phase of the products life rather than focus on the production phase (Borah et al., 2024). Or studies on algal nanofibers shed light on how the bio-based material contributes to health related properties, rather than an quantitative assessment of impacts (Karaduman et al., 2022). One study on bio-based plastics reflects the opportunity found in infusing conventional materials with sustainable or renewable sources at the resource stages (Beckstrom et al., 2020). Another study on ACNF focused on the carbonization (through annealing which is an additional process that improves the properties for specific electronic applications) of algal nanofibers, but lacks the specificity of the full production process (T. Wang et al., 2022). This thesis addresses the current gap in assessments of algae-infused carbon nanofiber production—a critical stage in the life cycle of any material.

1.2 Sustainability Assessments

For algal-based products, some form of impact assessment is required to show the sustainability of the generated products in comparison to their predecessors. A common impact assessed on non-renewable, fossil-based materials are the environmental impacts at the end of a product's useful life, when they are thrown away or decommissioned (Rossi et al., 2015). Other assessments address the impact through the whole of its lifecycle, from the extraction of raw material to manufacturing to the actual use of the product.

To manage the scope of investigation, this thesis focuses on the GHG emissions and water consumption of ACNF production, or the environmental element of sustainability, while recognizing that sustainability frameworks also emphasize the social and economic impacts of products and process. To assess this environmental sustainability, impact methods such as urban metabolisms, cost-benefit analysis, triple bottom line (TBL), and life cycle analysis (LCA) were considered. These methods take different approaches at quantifying the total required resources and effects that assorted products and processes have. LCA was selected to explore the impact of global energy mixes on the production portion of the life cycle of a material and analyze the opportunities to reduce emissions from the production phase of a product. Through life cycle assessment, the actual difference in GHG emissions with different energy mix scenarios can be investigated.

LCA is a systematic method for evaluating products, services, or processes environmental impact making it a useful tool to holistically examine how production differences will contribute to environmental impact categories such as water consumption and CO_2. Multiple life cycle assessments have compared algal products with petroleum-based alternatives, providing static impact assessments of water consumption, emissions to the air (GHG), pesticide/fertilizer consumption, emissions to the water, and other forms of waste generated(Clarens et al., 2010;

Osman et al., 2021; Quiroz et al., 2023). These studies have shown the many opportunities for algae to become a key component in many traditional products. LCAs have shown how different cultivation methods effect overall water and energy consumption and that challenges exist for specifically regarding evaporation in open raceway pond systems (Chen & Quinn, 2021; Nogueira Junior et al., 2018) and how the total energy generated by algal-based fuel is greater than other bio-based energy forms(Clarens et al., 2010). The results of these studies show the need for high value products to provide financial incentive to optimize and offset the necessary resources.

1.3 Dynamic Life Cycle Assessment and Its Application to Algal Systems

A critical observation from literature reviews of algal LCA studies notes the importance of representing changes in the input, outputs, and processes to provide more accurate cumulative impact over the life of algal systems(Cruce et al., 2021; Quinn & Davis, 2015). Notably, these reviews reveal a considerable variance in reported algal growth rates, a metric that influences the implementation of large scale technology systems and product applications(Cruce et al., 2021; Osman et al., 2021; Quinn & Davis, 2015). Other literature reviews summarize LCA studies of the conversion of biomass to biofuels emphasizing the difference in overall impacts in the various processing methods such as pyrolysis and hydrothermal liquefaction, also highlighting the variation in data sources and software systems used to conduct the studies (Osman et al., 2021). These variations are the result of system differences and the limitations of conventional LCA methods, suggesting the need for a standardized methods that accounts for the dynamic nature of these systems.

This thesis explores the application of Dynamic Life Cycle Assessment (DLCA) methodologies to represent the dynamic nature of ACNF production. DLCA is an approach to modeling real world system variances to capture the impacts of non-linear, changing, or variable elements within a life cycle assessment (Su et al., 2021). Dynamic elements can manifest in the form of dynamic processes, characterization, scope, and weighting(Sohn et al., 2020; Su et al., 2021). DLCA has been utilized to calculate outputs such as GHG emissions in commercial buildings, land use conversion impact in forestry applications, and global warming potential (GWP) in a time-based context to of warming potential (Boulay et al., 2018; Collinge et al., 2013; Kendall, 2012; Levasseur et al., 2010). DLCA has been applied to forestry, building assessment, green infrastructure, packaging and construction material assessment, carbon sequestration, renewable energy, and biodegradable plastics (Bixler et al., 2019; Chong et al., 2023; Levasseur et al., 2012; Rosse Caldas et al., 2020; Rossi et al., 2015; Su et al., 2017). Although scarce, LCA exists that assesses the water scarcity impacts of the cultivation of algal biomass using the Available Watering Remaining (AWARE) technique, a dynamic method that accounts for changing water scarcity over time (Boulay et al., 2018; Quiroz et al., 2021). These early DLCAs offer direction for enhancing the robustness of life cycle assessments for algal-based products and the associated systems.

To address the inherent temporal changes in bio-based product systems, many algal-based product LCAs have been conducted with varying assumptions, inputs such as growth rates, and minimum fuel selling prices (Cruce et al., 2021; Quinn & Davis, 2015). There also exists a related dynamic assessment to DLCA called Prospective LCA, which maps impacts to a future system state and calculates impacts accordingly (Sacchi et al., 2022). Prospective LCAs also focus on estimating the effects of improved technology readiness levels (TRL)(Arvidsson et al., 2018; Thomassen et al., 2019).

Dynamic assessments can be used for a variety of applications such as informing investor decisions, better understanding of the systems being modeled and optimizing of integration into larger systems. However, despite these efforts, there remains a notable gap in the application of dynamic processes and sufficient data to inform engineering and investment decisions with algal systems(Cruce et al., 2021; Dębowski et al., 2022). Furthermore, current LCA findings exhibit inconsistencies and lack the consideration of temporal variables and their potential impact on critical outputs(Cruce et al., 2021; Lueddeckens et al., 2020).

The exploration of temporally variable assessments within algal systems remains limited, despite the promise of DLCA. This thesis contributes to this deficiency by presenting a process model for the integration of dynamic elements into a partial LCA that examines the novel ACNF material. This will be accomplished through the exploration of DLCA and its value for algal systems. Armed with this knowledge, a dynamic characterization factor will be applied to a ANCF process model, resulting in dynamic predictive GHG emission values. This work represents both the exploration of the manufacturing of a novel product on an industrial scale as well as the reflected carbon dioxide (CO_2) emissions based on predicted future grid resource mixes.

CHAPTER 2 – LITERATURE REVIEW

A portion of this chapter contributed to a publication regarding the development of DLCAs for algae systems

A comprehensive review of multiple literature categories was conducted to establish the underpinnings of developing the ACNF process models and its corresponding assessment. This review was organized to 1) give context to algal systems and existing algal system assessments, including DLCA and 2) provide background on the development of the dynamic characterization applied in this study including future predictive resource mixes and the history of RMPA grid system. Objective 1 is reported on in four sections: 2.1.1) Algal Systems & Production, 2.1.2) LCA of Algal-Based Bio-Composites, 2.1.3) Carbon Nanofiber (Non-Algal) Production, and 2.1.4) ACNF Production Overview. Part 2 is reported on in four additional sections: 2.2.1) DLCA of Biomaterials, 2.2.2) Dynamics of Temporary Carbon Sequestration, 2.2.3) DLCA of Energy Consumption of Buildings, and 2.2.4) Predictive Resource Mix Scenarios. This breakdown is illustrated in Figure 1, which highlights the interconnected relationships among the categories.

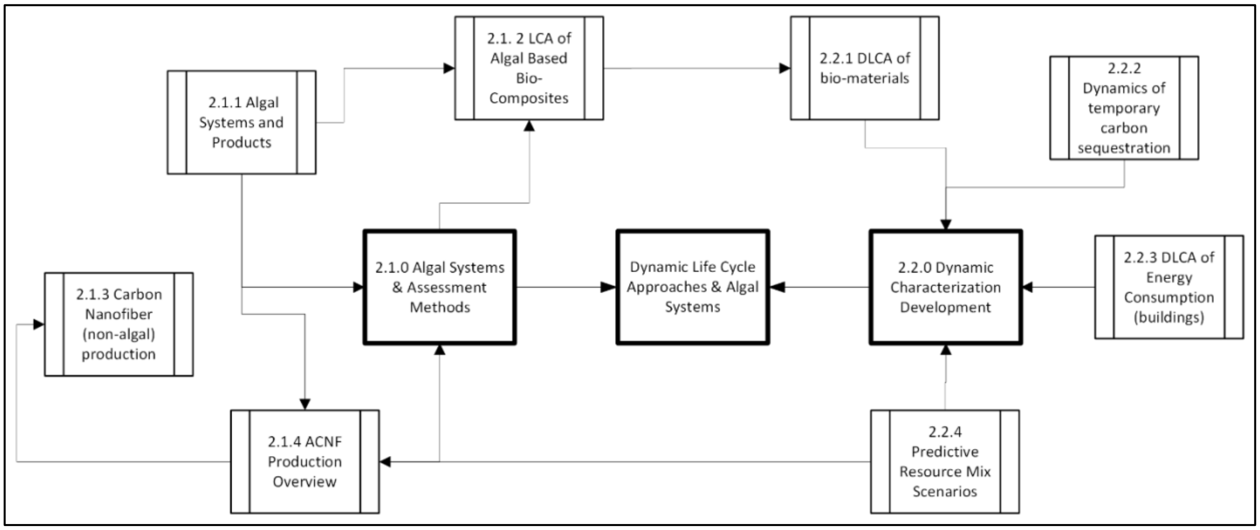


Figure 1 – Organization of literature sources informing the review framework

2.1 Algal Systems & Assessment Methods

For this review algae systems are defined as an interconnected networks of biological, technological, and chemical processes designed to cultivate, convert, and transform algal biomass into valuable products. These systems include the entire lifecycle of algae, including cultivation, harvesting, processing, and transformation into outputs such as biofuels, bio-composites, pharmaceuticals, food additives, and other materials with high economic value. Sometimes referred to as an algal biorefinery (Blanchard, 2014; Parsons et al., 2020), algal systems aim to optimize resource efficiency, promote sustainability, and integrate into broader environmental and industrial systems. This literature review found that extensive research exists about algae products from a biological perspective. And although this knowledge is quite useful to development of cultivation models, this thesis focuses on manufacturing of an algal-based product rather than the organism level perspectives of algae.

In summary this literature review found that research in algal systems has focused on optimizing scale and evaluating the effects of algal subsystem combinations to achieve the smallest environmental footprint and largest output. Environmental footprints are then evaluated through models and simulations that estimate the resources consumed by the plant and its operations, with these resources typically including land use change, energy, and water consumption. Outputs are typically measured in terms of biomass growth rate or gallons of biofuel produced. In the subsequent section this thesis reports on the findings across the two objective areas.

2.1.1 Algal Systems & Products

Existing algal systems and products research has focused on the combination of subsystems that will lower the footprint of interest, while maximizing growth rates. One study analyzed different combinations of cultivation and conversion methods, ultimately striving to make commercial scale biorefineries more feasible(Dębowski et al., 2022). Studies have also shown the potential for a beneficial relationship between water treatment methods and algal systems, emphasizing the reduction in blue or fresh water consumption as well as supplemental nutrients to improve growth rates(Mehariya et al., 2021; Quiroz et al., 2022; L. Wang et al., 2016). These studies suggest that synergistic environments and approaches can contribute to algal production while minimizing resource requirements.

Other research has focused on comparing algal products and their co-products, such as biochar, oils, and nutritional additives for animal feedstock. The literature indicates that co-products can affect economic viability, however there is still limited research being committed to individual co-products due to low selling prices relative to the cost of production. Research emphases the importance of finding an optimal ratio of main product with co products for profit and market stability(Kumar & Singh, 2019; Parsons et al., 2020; Subhadra & Edwards, 2011).

Research emphasizing co-product analysis has limited results related to the improvement of manufacturing sustainability with incorporated co-products. One study discusses the optimized water usages with the inclusion of coproducts in manufacturing (Subhadra & Edwards, 2011). Overarching themes across algal system publications emphasize the need to account for the environmental impacts across the life cycle of algal products and its manufacturing processes.

Several publications exist focused on various algal-inclusive products providing context on the different useful applications and manufacturing methods required for production. A particular area of interest revolves around the process of hydrothermal liquefaction, a conversion technologies that utilizes high temperature conditions that convert proteins, carbohydrates, and lipids into bio-crude oil, which in turn is used for bio fuel production (Chen & Quinn, 2021). Several studies judge the resources and effectiveness of the HTL, some even leverage comparative studies to boast the effectiveness of technologies against each other(Dębowski et al., 2022; Nogueira Junior et al., 2018; Osman et al., 2021). These studies assess conversion pathways that turn raw algae biomass into a precursor or constituent to then be further processed into a useful product such as biofuel or ACNF.

2.1.2 LCA of Algal Based Bio-Composites

To establish the boundary and scope of the ACNF LCA assessment this thesis examined the scope and framing of existing LCA studies of agal based bio-composites. Many studies focus on quantifying the impacts of algal based fuels to compare their feasibility compared to other bio-based fuels or conventional petroleum-based fuel. For instance Osman (2021) examines a series of thermochemical and biochemical conversion methodologies along with the LCA approaches taken to examine these methods (Osman et al., 2021). Several publications emphasize the importance of selecting co-products for overall system feasibility (Beckstrom et al., 2020; Parsons et al., 2020; Subhadra & Edwards, 2011). Product and co-product selection are critical to the choice of functional unit for an LCA study or similar sustainability assessments. Parsons et al. suggest that aggregating results facilitates comparison with other studies and note that the functional unit should ultimately reflect the study's objective (Parsons et al., 2020). In Life Cycle Assessment (LCA), aggregation involves grouping elements into clusters, resulting in outputs such as "per year of production" or "per biorefinery." These outputs are often translated into economic metrics, a common practice in LCA.

Another approach to modeling algal systems with co-products is to limit the output metrics being assessed. For instance, a water foot printing study modeled various co-product scenarios to evaluate water consumption and forecast economic potential(Subhadra & Edwards, 2011). Another assessment proposes a dual-product system, focusing on two main products (biofuel and bioplastic feedstock) and treating other products as waste management outlets rather than relying on them for financial stability (Beckstrom et al., 2020).

A commonality among studies emphasizing co-products is the use of sensitivity analysis. Sensitivity analysis allows researchers to examine the impact of varying resource allocation to co-products. These studies use sensitivity analysis to examine how different ratios of co-products to main products can be optimized either to improve the economic and environmental feasibility. Incorporating this perspective is crucial for accurately modeling and simulating a commercial-scale algal system. Because this study focuses on the production of ACNF and does not include co-products, no sensitivity analysis of this nature was conducted.

The increment improvements of subsystems within an algal biorefinery are another area of LCA studies. Major subsystems of note are cultivation, harvesting, dewatering, and biomass valorization (Dębowski et al., 2022). Depending on the impact areas of interest, different subsystems are put under the microscope to improve the current modeling practices or assess changes in pilot scale systems.

Many studies examine alterations to cultivation systems to reduce overall energy use and water consumption. Over the span of 3 years, Quiroz et al published a literature series that builds on itself, exploring the processes in the cultivation system, most notable the effect of geographical variation on open raceway ponds. These nested studies begin with an assessment of evaporation and growth rates on 400 hectare farms in 198 geographical locations (Quiroz et al., 2021). Results show a need to emphasize the need to reduce water consumption, while also presenting a suggested region (US Gulf Coast and Southwest) for optimal biomass production and water consumption (Quiroz et al., 2021). The latest publication expands this research beyond the United States to encompass the entire globe. By incorporating weather and economic data from 6685 different locations they build out the results of the previous study by incorporating elements of economic viability for potential algal biorefinery locations (Quiroz et al., 2023). This series emphasizes the modeling efforts aimed at improving a critical impact category to improve the overall environmental feasibility of an algae system.

LCAs have also investigated the the utilization of wastewater or grey water as a nutritional supplement for the biomass but also to reduce overall freshwater consumption. Assessment of impact categories such as water consumption provides valuable insight into the means of reducing critical impact categories. Water consumption has been found to be a large impact factor driving research to develop alternative approaches to not only predictive consumption modeling, but also cultivation sub-system optimization (Quiroz et al., 2022). The development of water footprints notes the large consumption requirements of open raceway ponds (Nogueira Junior et al., 2018). Attempts to remedy this come in the form of water treatment integration, offering an alternative source of water or water credits (Mehariya et al., 2021). Research builds upon these concepts by analyzing a micro-algae pond that is paired with activated sludge to produce the optimal results for the algae and outflowing water (L. Wang et al., 2016).

The coupling of techno-economic analysis with LCA is a common practice that allows for economic evaluation alongside the impact analysis in systems that generate products. As with LCA, the goal of these studies is to understand the potential of a product from an economic standpoint rather than an environmental one. For instance, the coupling of TEA and LCA into a single platform is one developing methodology (Mahmud et al., 2021). While outside the main interests of this thesis, the understanding of TEA is relevant to development of novel LCA methods including those involving dynamic assessment. Especially considering the relevance of operations costs associated with high energy production systems such as those of ACNF infrastructure. With the usual pairing of TEA studies with LCA's it's this author's prediction that future dynamic assessment methods will also include said costs.

The trend of LCA for biomaterials and algal systems appears to be a fixation on assessing impacts based on improvements of sub-systems such as cultivation, or valorization (Nogueira Junior et al., 2018). Studies often compare the impacts of multiple combinations of products, cultivation methods, and processing methods (Nogueira Junior et al., 2018; Parsons et al., 2020; Subhadra & Edwards, 2011). These studies allow for baseline comparisons of one or two impact metrics, future studies may aim to establish best practices for algal LCA to make comparison between systems and development of novel techniques and materials more uniform. Gaps also exist in the realm of assessing secondary manufacturing required to turn algal biproducts such as oil and biochar into high value products such as ACNF.

2.1.3 Carbon Nanofibers (non-algal) production

To build a foundational understanding of nanofiber production, this study reviewed research on traditional petroleum-based nanofibers. Literature on ACNF remains limited, whereas conventional nanofiber sheets (NFS) and carbon nanofibers (CNF) have been more extensively studied (Teymouri et al., 2024). Several sources focus on CNF manufacturing without algae, providing valuable insights into production feasibility (Cimini et al., 2023; Persano et al., 2013). While some studies explore the biodegradability of NFS, they do not specifically examine algae as a primary feedstock. However, due to the shared production methods between CNF and ACNF, these sources help inform modeling efforts, particularly given the lack of industrial-scale examples for algal-based CNFs.

A substantial body of research assesses conventional petroleum-based NFS, investigating ingredient ratios and electrospinning process variables (Malara, 2024). These studies primarily examine laboratory-scale production, analyzing how electrospinning parameter adjustments influence global warming potential (GWP) (Malara, 2024). While these findings are insightful, the materials used—polyvinyl acetate and ethanol solutions—do not provide direct guidance for evaluating commercial-scale NFS production using algae as a primary ingredient.

One study on CNF production and applications offers insight into non-bio-based CNF manufacturing processes. As previously discussed, these materials share key production steps, particularly electrospinning for nanofiber sheet fabrication across various applications. Khanna et al. (2008) analyze the life cycle impacts of CNF production, emphasizing high energy consumption associated with both electrospinning and annealing processes. Interestingly, the study suggests that the use phase of CNF materials may offset some negative environmental impacts, citing reinforced polymers with enhanced mechanical properties and longer lifespans. However, no empirical data is provided to support this claim. Future research should assess whether improved efficiency during the use phase compensates for the energy-intensive production methods of CNFs (Khanna et al., 2008).

2.1.4 ACNF Production & Overview

Publications surrounding bio-based, biodegradable or algae-based NFS provided insight into the perspectives researchers are taking on these materials. While interest is piqued around the potential sustainability, not many studies follow a standardized format like an LCA or triple bottom line assessment. This section explores publications on NFS claiming some degree of bio-friendliness. These include production, including the upscaling of processes to industrial or commercial levels. Sources exploring hyper-specifics in ingredient ratios, production time and temperatures are also included.

One review of electro spun biodegradable materials does mention the use of algae to create cellulose, a frequently cited biodegradable polymer (Borah et al., 2024). This source, a literature review, gives a vast overview of the process of developing bio-based NFS, exploring the numerous applications of these materials, specifically in regard to the medical and water treatment applications(Borah et al., 2024). While this review emphasizes the sustainability potential of the material, it falls short of thoroughly exploring its environmental impacts during its lifecycle. While discussing the electrospinning process in some detail, there is no mention of the large energy requirements or the resultant GHG emissions. Like traditional CNF, these materials suggest potential improvements in energy efficiency during their use phase. However, this thesis found no specific studies to substantiate this claim.

One publication focuses on algal NFS, highlighting the current state of knowledge, potential applications and challenges. Karaduman et al. discusses how an algal derived polymer can be applied using electrospinning to generate a variety of products, most notably potential applications in biomedical engineering (Karaduman et al., 2022). The strengths and weaknesses of the mechanical properties of algal NFS are analyzed from a few different publications giving perspective to the recent research focuses. Details are provided on different solution combinations, including the use of different strains and micro and macro algae. Little is mentioned about manufacturing energy consumption in the process, but the authors do note that little information is known in terms of commercial scale production, cautioning that there are several uncertainties that may arise.

A few sources address the concern of upscaling from laboratory to industrial production of nanofibers. One review focuses on the pairing of specific electrospinning methodologies, including melt spinning, solution spinning, and emulsion spinning, with various fiber sheet collection methods, such as roller drums. This combination aims to optimize production output and ensure feasibility at an industrial scale (Persano et al., 2013). Ultimately it was found that the major driving factors to industrial scaling are 1. Overall machinery production rates 2. Process monitoring 3. Quality control measures 4. Multidisciplinary manufacturing know-how (Persano et al., 2013). One study was found applying these upscaling suggestions to the industrial manufacturing of electro spun nanofibers for hybrid material facemasks (Cimini et al., 2023). The result of this was an examination of the complications associated with manufacturing of electro spun filter materials capable of advanced filtration and antibacterial performance. It was found that through the use of multi-nozzle electro spinners there is potential for feasibility of large-scale manufacturing of this hyper specific material. What is learned from this publication is that there is interest in upscaling of electro spinning nanofibers and there exists methods for examining that upscaling for unique applications like algal carbon nanofibers.

2.2 Dynamic Characterization Development

A novel methodology being applied in this thesis is a dynamic characterization factor utilized for carbon accounting of algal carbon nanofiber production. In order to develop this assessment, methods from LCA and DLCA studies inform on the methods and applications of studies with similar objectives. This being the goal of capturing the temporally or spatially changing elements that exist in the real world but fail to be represented in sustainability assessments. The literature examined below is broken down into 4 sections to inform on different perspectives/approaches to embracing this challenge.

2.2.1 DLCA of Biomaterials

The following section provides discussion on DLCA applications as well as outlines a series of literature that differentiates the use of Dynamic, prospective, or “time-dependent” life cycle assessments. A wide breadth of examples were sought to extend the literature search for opportunities to fit dynamic elements into a biomaterial or algal-based products. While the production systems of algal carbon nanofibers differ from these examples, the application of dynamic elements may not always translate directly or logically. However, examining all relevant studies provides valuable context for understanding existing dynamic assessment methodologies and contributes to a more comprehensive foundation for DLCA.

A consensus of literature aims for DLCA to build upon the existing LCA standards to accurately model elements that differ temporally and spatially. Key impact elements and resource consumption within LCA's such as carbon footprint and water consumption flow non-linearly in and out of a system meaning static analysis fails to capture the true nature of the flow of media (Bixler et al., 2019; Levasseur et al., 2012). Studies modeling these flows dynamically explored the effects of changes such as a broader understanding of the emission trends (Dyckhoff & Kasah, 2014; Levasseur et al., 2010).

This thesis found that studies identifying themselves as dynamic life cycle assessments contained time-dependent or space-dependent variations to establish spatiotemporal dynamic LCA models (Su et al., 2022). Whereas a traditional LCA lacks these time dependent variables, exposing a number of gaps, limitations, and assumptions (Lueddeckens et al., 2020). Sohn et al. (2020) identify three distinct methods for incorporating dynamic variations in life cycle assessments: dynamic process inventory, dynamic systems, and dynamic characterization. To model real-time global warming impacts one study suggests the generation of a dynamic life cycle inventory and then utilizing dynamic characterization factors (Levasseur et al., 2010). Another review source agrees that with these elements also suggesting the incorporation of dynamic weighting factors to better represent factors such as fluctuating pollution damage costs, temporal environmental policy targets and discount rates (Su et al., 2021).

One of the earliest studies to identify limitations in sustainability assessments was published in 2006, arguing that traditional LCA does not fully capture emissions from renewable energy sources (Pehnt, 2006). Like many DLCA examples, this study noted that conventional methods fail to capture the full picture of a system's emissions. Pehnt (2006) augured that the inputs of raw materials into renewable energy systems is not accurately modelled, giving the impression that larger impacts are created by these renewable energy technologies when this study found that results reduced impacts by 55%. The results of their study showed that by modeling the raw material inputs as finite, that the resulting impacts over time were more accurate. It was mentioned in the study that further research and understanding of said technologies would be required to understand other categories providing limited results. Renewable energy technologies and biomaterials share a common objective: to minimize environmental harm and enhance sustainability. Therefore, developing an appropriate assessment methodology for algal carbon nanofibers may require a new, more comprehensive approach that aligns with these sustainability goals.

2.2.2 Dynamics of temporary carbon sequestration

Another common trend in DLCA studies is the reassessment of previous work that fails to accurately capture non-linear impacts or one-time inputs that do not follow predictable patterns. For instance, pulse emissions are a common topic of discussion in DLCA, affecting how the global warming impact or GHG emissions are viewed over different time horizons. One study looked at the effects of modeling afforestation carbon sequestration projects using pulse emissions that consider time of occurrence (Levasseur et al., 2012). This approach demonstrates the effects of chosen time horizons at distinct stages in the project, specifically when it comes to the radiative forcing. Additionally, this publication examines the concept of land use change in LCA as a physical alteration of land, usually for new purposes such as agriculture, forestry, or urban development.

Similarly, a study on end-of-life options for single use packaging explored the dynamic release of greenhouse gases (Rossi et al., 2015). This publication chose varied materials as well as different methods of recycling, to assess the pattern GHG release over a 100-year time horizon. The software used was IMPACT 2002+, which utilizes the methods employed by Levasseur et al. for forestry applications. Results show that the selection of the 100-year time horizon did have differing results when including the dynamics. This study noted the importance in the selection of time horizon, implying that choosing a longer horizon may yield different results.

Although not explicitly identified as a DLCA, Van Vuuren et al. employ the IMAGE 3.0 integrated assessment model to dynamically simulate land use, energy, and GHG emissions (Van Vuuren et al., 2017). The main difference from LCA methods is this model integrates socio-economic, and human factors to represent potential real-world scenarios for the purpose of creating climate policy, a practice that aligns with the methods of triple bottom line assessment rather than LCA. The dynamic elements of this study are within IMAGE 3.0 in the TIMER system that addresses carbon cycle and vegetation dynamics. The results reflected the impacts of three separate shared socio-economic pathways or scenarios. This provides a valuable insight into how dynamic assessment can be used in the context of human systems for the advising of potential climate policy. Although this is not the direct intention of this thesis it provides insights for future works to build upon the efforts here.

2.2.3 Dynamic systems and energy consumption

A different trend that dynamic assessments follow is accountancy for a dynamic system rather than a dynamic release of a specific impacts category. For example, systems involving change due to human interaction and material degradation, such as buildings and infrastructure. While this does generate non-linear impact rates it takes the approach of modeling the change in the system rather than adjusting after the fact. Chong et al. (2023) examined system changes (preventative vs regular maintenance) over time in a study of asphalt pavement showing the effect on Global Warming Impact (Chong et al., 2023). The dynamic elements incorporated in this study included traffic volume, vehicle type, pavement roughness, maintenance timing, material recycling rate, electricity mix, and characterization factors. Through the incorporation of many dynamic factors, they demonstrated a more systematic view of the life cycle of the pavement, a practice that could be applied to a variety of systems.

DLCA's of buildings follow a similar approach, incorporating dynamic properties such as technological progress, variation in occupancy behavior, dynamic characterization factors, and dynamic weighting factors (Su et al., 2017). These elements are unique and relevant to the life span of buildings being selected from a variety of dynamic assessment elements (DAE's) (Su et al., 2019). One selection process followed by Su et al. was that of assessing the most common DAE's (dynamic consumption, dynamic basic inventory datasets, dynamic characterization factors, and dynamic weighting factors) and seeing which apply within the goal and scope of the assessment. This study provides valuable information on the understanding and selection of DAE based on data transformation path.

Another approach for incorporating time-dependent elements into an LCA is prospective LCA (PLCA). PLCA is the incorporation of inventory databases that encompasses the expected improvements in technologies and the changes in the environment at a defined future state. PLCA is applied to study early-stage technologies at a larger commercial scale (Arvidsson et al., 2018). The primary approach to PLCA is the incorporations of prospective life cycle inventories (PLCI) that are incorporated into a traditional LCA tool such as a python model or OpenLCA. One example of PLCA uses a tool that builds on specifically designated socio-techno-economic pathways by using a software tool called *Premise* that integrates various scenarios using Integrated Assessment Models (IAM) (Sacchi et al., 2022). This differs from DLCA were the calculations such as characterization factors are changed to alter the inputs affecting outputs. Literature noted the limitations of PLCA in that there exists difficulty ensuring the technologies in the IAM corresponds with the correct inventories. Another challenge is differentiating between foreground and background systems. A background system refers to parts of the product system that cannot be directly influenced by stakeholders or decision-makers. Arvidsson et al. (2018) suggest that reporting results for foreground and background systems separately yields more accurate assessments.

2.2.4 Predictive Resource Mix Scenarios

This thesis examined literature on the development of future resource mix scenarios to inform the approach for developing the dynamic emission profiles. The first publication examined was the *World Energy Outlook 2023*, a comprehensive 355-page report by the International Energy Agency (*World Energy Outlook 2023*, n.d.). This work was a collaboration between 44 countries to provide a global view of the trends in energy needs, fossil fuel demands, renewable energy growth and investment in clean energy. Summarized results were as followed 1) The future of clean energy looks bright due to solar photovoltaic systems and electric vehicles 2) The peak of fossil fuels will occur before 2030 3) Global powers are responsible for guiding the clean energy landscape including through investment and new technology development. These global perspectives provided insight into rates of renewable energy adoption but lack the geographic specificity to give direct inputs to a predictive resource mix model in individual locations in the United States.

A second report examined was The National Renewable Energy Laboratory (NREL) publication on future resource mix scenarios and their subsequent emissions (Gagnon et al., 2023). This 2022 Standard Scenario Report Proposes several potential scenarios that depict the future of the U.S. Energy system, including rates of adoption of clean energy, emphasize the need for innovative technology including energy storage and meeting grid demands. The 4 major findings of this reports are similar to those found in the World energy outlook; 1) Wind and Solar are trending upward 2)Still-nascent technologies will be upgraded to contribute more positively to total emissions 3)U.S. electricity emissions will decrease significantly through 2030 4)Phase outs of certain tax credits (Inflation reduction act [IRA] of 2022) will reveal rebounding emissions in the coming years. The inflation Reduction Act is a federal legislation that in part, aims at providing investment into clean energy and carbon management through electrification, improved efficiency, reduced emissions, and other proactive means (J. Bistline et al., 2023; J. E. T. Bistline et al., 2024). These findings are then translated into several scenarios, the primary of these being the ‘Mid-case’. The mid case is a scenario that depicts central estimates of driving factors such as technology costs, fuel prices, and demand growth. The set of standard scenarios use this mid case on two different timelines (2035 & 2050) with various decarbonization targets (95%, 100%) and inclusion/exclusion of nascent technologies. Nascent technologies are defined as early or emerging technologies that have the potential to greatly impact the energy scene. Another NREL publication focuses strictly on scenarios that represent 100% decarbonization (Denholm et al., 2022). The emphasis made in this report is that 4 major things would have to occur in order for this decarbonization goal to be achievable: 1) No restrictions to clean energy implication 2) no new fossil fuel infrastructure 3) Limits fossil fuel use (using carbon capture) 4) High electrification (through adoption of electric vehicles etc.). This situation assumes that demand will increase and technology for energy storage will improve to meet these demands. What is learned from the NREL scenarios is there are many paths to many destinations when examining the future energy mix, and that the ‘mid-case’ is a way to represent the averages of all these variables.

Other publications have developed predictive modeling tools for examining future scenarios but mainly through the lens of energy demand, and the capacity of the grid (Gagnon & Cole, 2022). One study critiques the futuristic scenarios by saying they lack emphasis into growing energy demand on the grid (Gagnon & Cole, 2022). This study then suggests the use of a new metric that factors in operations and structural changes that will occur due to growing demand. The long-run marginal emission rate (LRMR) is a metric applied in modeling efforts to better depict the growing role of renewable energy sources alongside a developing power sector (Gagnon & Cole, 2022). The LRMR metric is useful when analyzing energy consumption during daylight hours. The authors validate the use of developing renewable energy sources over time but cautions those who fail to incorporate the effects of growing demand of the U.S. grid system. The LRMR approach was not suitable for this thesis as it aims to assess the energy consumption of the manufacturing holistically, and that diurnal power sources such as photovoltaics only make up a small portion of the total energy provided.

The scenarios researched guided the scenarios used to represent the future trends of energy mix in an area that may house a ACNF production facility, mapping the emissions based on the resource mix in that specific sub-grid through a dynamic emission factor.

CHAPTER 3 – METHODS & MODEL DEVELOPMENT

This chapter describes the application of an LCA to identify the emissions from the energy required during the production of industrial algal ACNF production. This LCA developed a process model of industrial scale manufacturing process model of carbon nanofibers that use an algal bio-oil. Then to assess the longer-term sustainability effects of this production scheme, a dynamic emissions factor for carbon dioxide was introduced to provide a view of greenhouse gas emissions from energy consumption in a manufacturing infrastructure. Furthermore, chemical consumption was accounted for and a water footprint developed. Mapping water consumption from upstream chemical manufacturing.

3.1 Development of Carbon Nanofiber Production Model

To build a model depicting the production of carbon nanofiber sheets from algae I first examined the system boundary and processes. This examination included input materials and chemical and energy resources. This section discusses the formation of the process and system boundaries that drive the rates of production required to process a pre-determined volume of algae oil.

3.1.1 Carbon Nanofiber Production Process Overview

The series of subprocesses that are required to transform algae oil into the fibrous nanostructure is depicted in

Figure **2**. Prior to these processes, algal biomass is cultivated in open raceway ponds utilizing wastewater and carbon flue gas as nutrient sources. One of the main driving research interests is the opportunity for carbon capture and utilization through the use of flue gas and waste water as a nutrient source during cultivation (Quiroz et al., 2023; L. Wang et al., 2016). The allure of recycling waste emissions into a useful product such as ACNF is one of the primary drivers of research in this field. Once biomass is harvested, it is dried and then processed using pyrolysis or hydrothermal liquefaction to produce algae oil and other co-products such as bio-char (Dębowski et al., 2022). This micro algae-based oil is then used a main ingredient to produce ACNF as well as other products such as biofuels and cooking oils. The ACNF subprocesses were modelled after the following processes in place at the University of Wyoming’s College of Engineering and Physical Science led by Dr. Maohong Fan. Initially, algae oil is heated and combined with specific chemicals to prepare a dope solution, following a recipe that incorporates polyacrylonitrile (PAN) and dimethylformamide (DMF) as the solvent. The process of electrospinning is depicted by Figure 3. in which the dope solution is introduced into a device that feeds the solution through a syringe or capillary. At the tip of the needle, a high-voltage power source generates a strong electromagnetic field. The electrostatic forces overcome the liquid's surface tension, causing the solution at the needle tip to elongate into a structure known as a Taylor cone (Malara, 2024). As the solution is slowly extruded, the electrostatic forces stretch the liquid jet rapidly. During this process, the solvent evaporates, thinning the jet and forming nanoscale fibers. These nanofibers are then deposited onto a grounded collector, such as a rotating drum or moving belt, forming a fibrous mat or aligned structures (Karaduman et al., 2022).

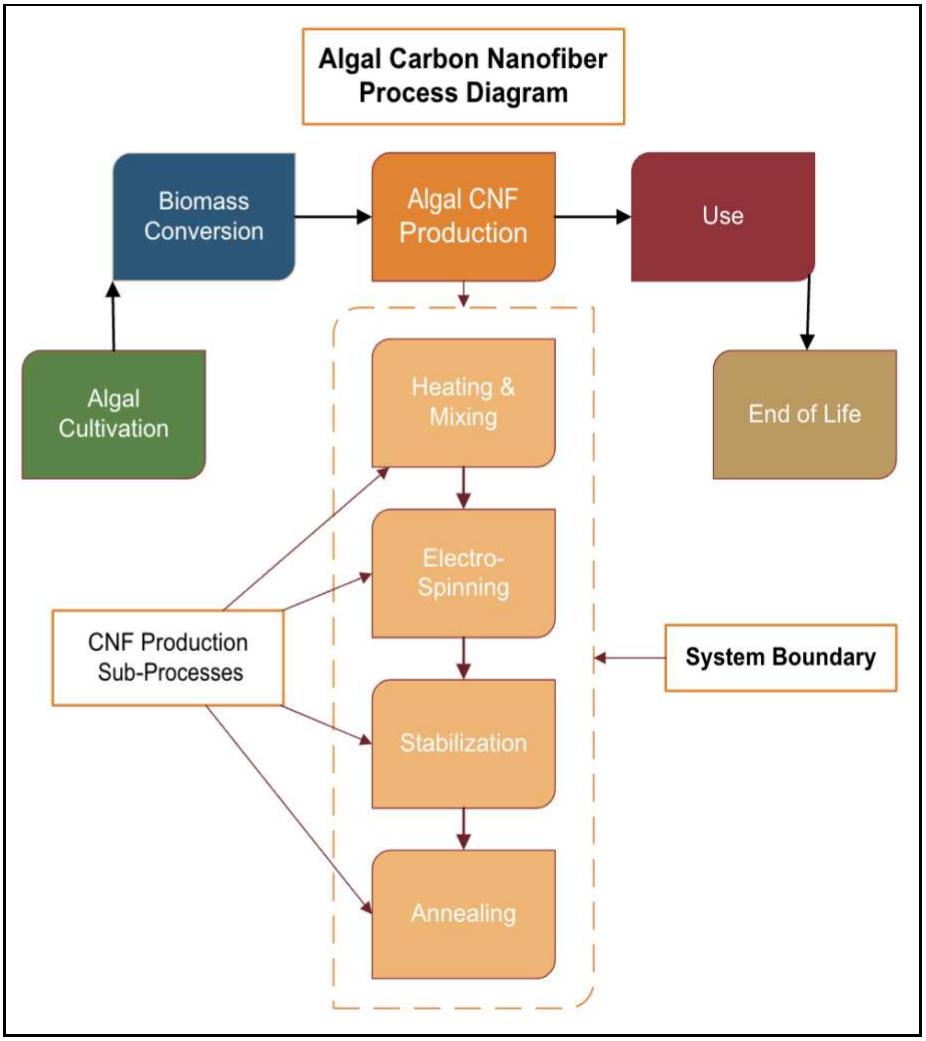


Figure 2 – Process diagram of the production of carbon nanofibers including the ACNF production subprocesses modeled for LCA

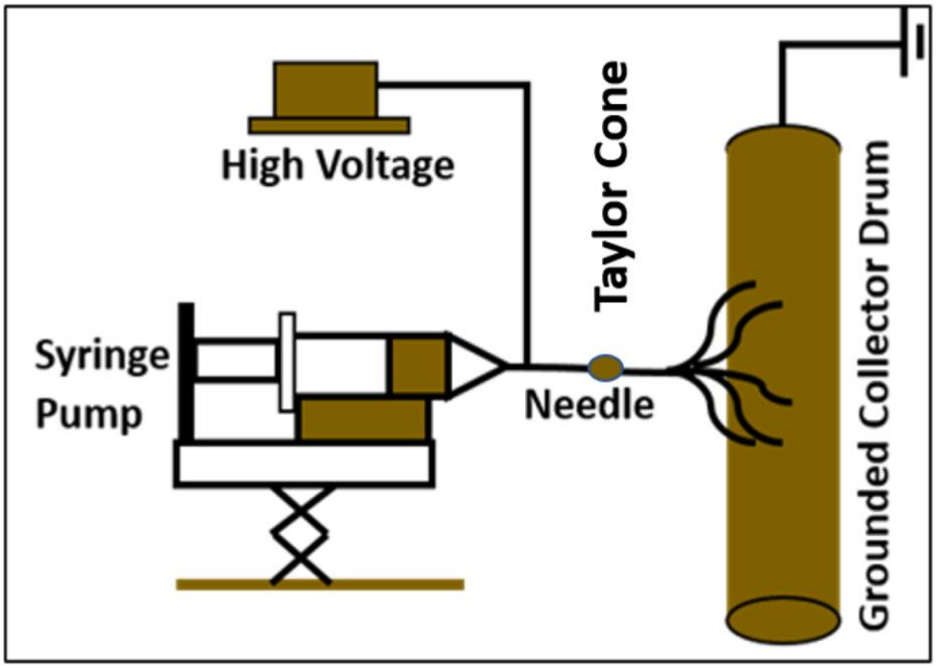


Figure 3 - Working principle of electrospinning (Isaac et al., 2021)

3.1.2 Laboratory Scale Process Data

The ACNF processes as described in

Figure 2 exist at laboratory scales (T. Wang et al., 2022). This thesis utilized data from research at the University of Wyoming's laboratory research to construct the development of an industrial scale model, which included a recipe for how to make ACNF. First, the ratio of oil to DMF to PAN used for this model was 1:29:2; an update from a recipe used in a laboratory scale publication (T. Wang et al., 2022). This ratio, as well as time spent in each process stage, are foundational to the developed industrial scale model. The ratio drives the total solution volume, which in turn affects the scaling requirements (e.g. necessary machinery) and energy that is consumed. Second, mixing and heating, stabilization, and annealing factors were derived from laboratory scale investigation and applied in the model. It is expected that some factors applied in this thesis will change with real world industrial scale data. Machinery specifications, processing time, and final output area were used to calculate energy consumption per unit (kWh/m^2), providing a basis for comparison with the industrial-scale model.

3.1.3 Primary Data for ACNF Model Development

Quantitative data describing the sub-processes within the ACNF production process were gathered from both literature and industry contacts. Accurately modeling large-scale production requires a clear understanding of how material flows interact with machine capacities. The primary flow driver is the quantity of algal oil, supplemented by necessary chemical components such as DMF solvent and PAN. The input of algal oil, set at 1 ton (approximately 950 liters), was based on a cultivation and conversion model simulating biomass production on a 16-ha (40-acre) wetted farm (Greene et al., 2021).

Additionally, machine capabilities and energy requirements for each sub-process were critical for modeling the system accurately. The key data requirement for this stage was quantitative information on industrial-scale machinery used in ACNF production. Large-scale versions of laboratory equipment were identified to handle the full volume of dope solution (approximately 250,000 liters), a complete list can be found in the appendix Figure 15. Industry professionals provided data sheets detailing processing rates, machine capacities (both storage and processing), power ratings, and efficiency values.

Since no direct data existed for the production of algae oil and PAN solution, I estimated electrospinning production rates using current machine designs. Electrospinning suppliers provided performance estimates based on their highest-capacity machine, which processes PAN solutions at 2,400 mL per hour per machine (Y. Hammadi, personal communication, October 9, 2024). Data for solvent recovery methods was also sourced from an industrial professional, providing context on machine capacities, processing rates, and energy consumption (R. Yearout, personal communication, February 1, 2025). Most critically the processing rate of 180 gallons per day per machine was used. Additionally, assumptions were made regarding the processing rates for stabilization and annealing furnaces. Industry consultants recommended custom furnaces that combine stabilization and annealing to optimize energy consumption. Since such furnaces are not yet commercially available, I estimated performance by comparing existing furnace models with similar functionalities. The selected design was a 24-zone belt furnace with a 138-kW power rating for heating and 15-kW for additional components.

The primary data regarding the production process and machinery requirements for manufacturing ACNF are outlined as follows. The production consists of four distinct processes, as illustrated in the graphic below (Figure 4).

1. Dope Solution Preparation: The precursor solution is heated and mixed in large storage tanks equipped with heaters capable of maintaining a temperature of 50°C. The solution is continuously agitated for a predetermined duration to ensure homogeneity.
2. Electrospinning: The prepared solution is then processed through electrospinning machinery, where it is extruded and spun into nanofibers under controlled conditions.
3. Stabilization: The electrospun fibers undergo thermal stabilization in a furnace capable of reaching 270°C, facilitating structural modification and precursor transformation.
4. Annealing: In the final phase, the stabilized fibers are subjected to annealing in a nitrogen gas atmosphere at 800°C for a minimum of one hour, enabling the development of the desired structural and physicochemical properties.

This systematic approach ensures precise thermal and mechanical processing, contributing to the controlled fabrication of ACNF with the requisite material characteristics.

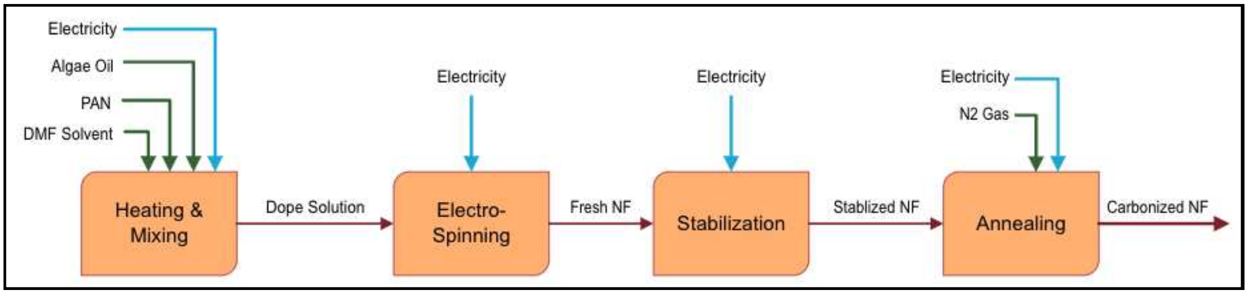


Figure 4 – Algal carbon nanofiber production process diagram

3.1.4 ACNF Model Development Methods

A model representing the ACNF production processes was built using Microsoft Excel with individual tabs for each subprocess as seen in Figure 5 and additionally in Figure 14 and Figure 15 in the appendix. Separate tabs of the model represented individual sub-processes and their respective calculations as well as cumulative findings, equipment lists, and meta data. Resulting material volume, and energy requirements would flow from one process to the next until the product was complete. Any upstream impacts from the production of the machinery are negated as it would be identical whether you were making the machines for ACNF or traditional CNF.

he heating and mixing sub-process utilized the previously described recipe ratio to calculate the total dope solution volume. Main equipment for this subprocess included large, heated vats to maintain the solution at a temperature of 50 degrees Celsius while mixing would occur. Machine data such as tank size and energy consumption from large scale brewing equipment was used as it performs similar functions on a similar scale. Another key element of the heating and mixing sub-process was the cyclic heating rate, this give a more accurate energy consumption as the dope solution would only need to be maintained at temperature and not constantly heated, assuming a good installation and even heat dispersion in the tanks. In this portion of the model tons of doping solution was converted into volume (liters) by applying the respective densities of each ingredient to align with the volumetric flow rates typically used in electrospinning processes (e.g., ml/hr.).

Once the processing volume was determined, the number of machines that would be required to process this volume of solution was calculated from the industry provided 2400 mL/hr./machine value. This derivation of number of machines occurred in the electrospinning sub-process tab along with several other contributing calculations. The total volume of dope solution was divided by the processing capacity of a single electrospinner to determine the number of units required. On an industrial scale, this calculation results in a relatively high number of machines, requiring 431 machines to process a 1-ton algae oil size batch of dope solution, a critical factor that largely impacts overall energy consumption and associated carbon dioxide emissions. Other energy consumption considerations that were explored during the electrospinning phase was the cyclic energy consumption for the main components of the electro spinner. This included the main processing unit, mostly consisting of the high-voltage power unit, a heater, and dehumidifier. Each component contained varying energy consumption rate and thus the amount of time used for each component would have to be included. As the ACNF is a PAN solution, usage calculations were based on the optimal electrospinning settings for a traditional PAN as recommended by industry professionals at Inovenso (Y. Hammadi, personal communication, October 9, 2024). It was assumed that with in a continuous productions scheme the main processing unit would be always running. The humidity recommendation for electrospinning a PAN solution is around 50-60% humidity, as this model was geographically based around energy consumption in northern Colorado / southern Wyoming, average humidity from this region was used (Fort Collins Weather Station Data Access, n.d.). Since the average humidity in this region aligns with the optimal condition for electrospinning PAN, it was assumed that the dehumidifier would only run about 5% of the total operation time. It was stated that no heating would be required for the spinning of PAN solution and thus it was assumed that that heater would not run (Y. Hammadi, personal communication, October 9, 2024). Although a space was left in the model for heater energy consumption for any future changes to be made. From electrospinning to stabilization, a similar process was followed to derive the number of stabilization and annealing furnaces required. Stabilization furnaces require a heating to 270 degrees Celsius for 1 hour and used a cyclic heating process to represent the maintenance of the temperature within a closed furnace space. The assumed cyclic heating rate for this was .25, meaning the heater only runs 25% of the time to hold an adequate temperature range. Subsequently, annealing require material to be held at 800 degrees C for an hour. Stabilizing and annealing a single layer of freshly spun nanofibers would require an enormous number of furnaces to process which is not representative of realistic industrial scale applications. Thus, an assumption about the effectiveness of stacking nanofiber sheets was made in this sub-process. It was assumed that although stacked, proper heating and gas penetration occurs to properly stabilize the freshly spun sheets. This greatly increased the processing volume of those machines and reduced the number of furnaces required. It was also recommended by an industry professional that a zone-system furnace be utilized to execute stabilization and annealing all using one furnace with different heated zones (D. Ma, personal communication, October 22, 2024). It was assumed that the ACNF sheets would not be affected by a gradual increase towards annealing temperature. With the selection of a zone-system furnace, number of zones would have to be chosen. This translated to energy consumption per zone calculations as well as total Nitrogen gas consumption based on utilization rates and specific atmospheric conditions required. For this thesis an average consumption was assumed at 30 L/min/gas inlet and 24 minutes of gas usage for every hour of annealing.

To calculate total area of ACNF produced, materials were translated into different forms from one subprocess to another. Material begins as a dope solution prior to electrospinning, once spun, the material becomes a fresh nanofiber sheet. Through stabilization and annealing processes, the nanofiber sheets become carbonized. Across the different translations, total material volume is reduced due to losses in the system such as solvent evaporation and shrinkage during stabilization. Yield of mass going from dope solution to electrospinning, was calculated using data from a laboratory scale test (Chen, Zhe, personal communication, November 11, 2024). A mass-based yield of 77.75% accounted for lost fibers and evaporated solvent within the electro spinner. With this yield the material could then be translated to an area (m^2) by using a standard PAN based CNF value of 0.5 g/m^2 which was given by an electrospinning industry professional (Y. Hammadi, personal communication, October 9, 2024). After electrospinning additional area losses occur due to shrinkage of the fibers at high temperatures, this included a 50% yield in mass post-annealing (Chen, Zhe, personal communication, November 11, 2024).

Additionally, the upstream impacts including CO_2 emissions and water consumption from the production of the chemicals was also included. These chemical impact values were sourced from Ecoinvent v3.4. These impacts were then combined with the emissions from the electricity consumption to give a cumulative emissions value from the production phase. These impacts were selected for their relevance to larger algal systems projects. CO_2 is a key consideration during the cultivation stage due to algae's ability to utilize emissions from coal power plants as a carbon source (Chen & Quinn, 2021).

	A	B	C	D	E	F	G	H	I	J	K
1	TONS OF ALGAL OIL	10									
2						FLOW					
3	INPUTS	UNITS	Specs		QUANTITY				OUTPUTS	UNITS	QUANTITY
4	Algae Oil	liters	0.34	3.83%	9,500.00	Mixing is minimal, holding time / temperature was up for debate. Overall the aim is to minimize any holding/heating time. Mixing and Heating done with industrial brewing equipment. Heated to 50 C, mixed for 2 hours.			Dope Solution	liters	248,132.75
5	DMF Solvent	liters	10	90.08%	223,529.41						
6	PAN input	liters	0.8	6.09%	15,103.34						
7					248,132.75						
8	RESOURCES								CONSUMPTIVE USE		
9	Heating and Mixing Energy	kWh/batch			2484				Energy	kwh	2,484.00
10	Number of Machines			62,033.19	4				CO2e	kg	963.79
11									Man hours?		
12									Materials?		
13						INPUTS / INFORMATION					
14	NAME	UNITS	VALUE								
15	Mixing and Heating time	hr	24								
16	Co2e converstion	kg/kWh	0.388								
17	Heating temp	degrees C	50								
18	Heating and Mixing Tank	kW	90	Estimate GPT, based on energy required to heat that quantity of water							
19	Efficiency	%	0.85	Estimate							
20	Max Batch size	L / Machine	65	Inovenso SS-1600	Ratio of ingredients			Weight of ingredients (kg)			
21	Algae Oil Density	g/mL	0.8	0.425	0.038285958	0.038285958	Peter Chen R	7600			
22	DMF Density	g/mL	0.945	10	0.900846065	0.900846065	https://pubcl	211235.294			
23	PAN Density	g/mL	1.184	0.675675676	0.060867977	0.060867977	https://www.	17882.3529			
24	Total Solution Volume	mL	11.1	11.10067568	1						
25	Assumed cyclic heating		0.25	Similar to furnace, only requires active heating 25% of time							
26	Oil weight to volume	liters/ton	950	Based on calculation using solution densities. .							
27	Solution Density	g/ml	0.954								
28											
29		LAB SCALE				CHEMICAL IMPACT INFO					
30	Ideal mixture temp	C	50	Zhe	Acrylonitirle	kg/kg acrylonitirle	Source	Impacts	Unit		Unit
31	Mixing Time	hours	2	Zhe	CO2	2.6416	Ecoinvent v3.4: cutoff, U- GLO				
32	Total Time	min	135	Zhe	CH4	0.01236	Ecoinvent v3.4: cutoff, U- GLO				
33	Heating Time	min	15	Zhe	Methly Acrylate						
34	Holding Time	min	120	Zhe	CO2	2.37669	Ecoinvent v3.4: cutoff, U- GLO				
35					CH4	0.0115	Ecoinvent v3.4: cutoff, U- GLO				
36					PAN						
37					CO2	2.615109	0.9	46764.3021	kg	1E+05	lbs
38					CH4	0.012274	0.1	219.488	kg	483.9	lbs

Dope Solution | Electro-Spinning | Stabilization | Annealing | Totals | Other | Equipment

Figure 5 – Spreadsheet workbook showing the process model for dope solution of ACNF

3.2 Material Consumption and Water Footprint

It is important to account for water consumption during the production phase, as many studies highlight the use of wastewater as a nutrient source for algal biomass (Carneiro et al., 2017). Including water consumption at this stage enables a more comprehensive calculation of total lifecycle impacts when integrated with data from subsequent phases.

To comprehensively capture both water and material consumption, the scope of this assessment includes upstream impacts associated with the production of input materials. This involved first calculating the total quantity of materials required throughout the ACNF production process. Specifically, the model accounted for the consumption of DMF solvent and

PAN used in the dope solution for electrospinning, as well as nitrogen gas used to maintain an inert environment during the annealing phase.

Total material consumptions were calculated using referenced conversations with researchers and industry professional. First the driving ratio in the heating and mixing scenario was sourced from laboratory scale research and publications (Chen, Zhe, personal communication, November 11, 2024; T. Wang et al., 2022) . This approach enabled all quantities to be scaled relative to an input of 1 ton of algae oil. The required amounts of DMF and PAN were then determined based on established weight ratios. Finally, these material inputs were converted to volume using their respective densities: PAN at 1.18 g/mL, DMF at 0.95 g/mL, and algae oil at an estimated 0.8 g/mL, approximating the density to be similar to that of crude oil. Similarly the total consumption of nitrogen gas was calculated based on a consumption rate of 30 liters/minute/gas inlet valve as provided by the industry professional providing data for the stabilization and annealing furnaces (D. Ma, personal communication, October 22, 2024). It was assumed that there would be one gas inlet valve per furnace zone (12 zones) and that the gas would flow for 1 minute for every hour of operation. This assumption was suggested by the machine supplier as curtain systems within the furnaces are designed to maintain the inert environment as to minimize total nitrogen gas consumption.

To obtain the upstream water consumption and CO_2 impacts from the production of these chemicals, Ecoinvent version 3.4 was utilized within OpenLCA version 2.1.1. Data for finished PAN was not available for this so impacts for the primary ingredients (acrylonitrile and methyl acrylate) were used as supplements. The ratio of these primary ingredients used was 9:1 acrylonitrile to methyl acrylate. Similarly, data on direct nitrogen gas production was unavailable, so liquid nitrogen production data was used instead. The liquid nitrogen values were then converted to gaseous nitrogen using an expansion ratio of approximately 694 liters of gas per gallon of liquid nitrogen.

Impacts from these processes accounted for were the total water consumption and the CO_2 emissions. However, energy consumption for the generation of these chemicals was not included as it was already converted into emissions within the established product system in OpenLCA. Furthermore, as generation of these chemicals was not specific to the region being examined for the dynamic predicted resource mix, the energy sources are not aligned with that region and thus would not share the emission rates reflected in the future scenarios. Thus, consumptive totals for CO_2 emissions from material generation were added to the final total emissions after accounting for the dynamic emissions form the process energy consumption.

Water consumption values were totaled for production of all the chemicals and compared with data from a separate study mapping the water footprint of algae biomass cultivation(Greene et al., 2021). Additionally, water consumption associated with electricity generation was incorporated into the total water impact of ACNF production. A value of 2.11 kilograms of H_2O per kilowatt-hour (kg H_2O/kWh) was applied to represent the water use linked to energy production. The water consumption data was categorized by source, specifically river, well, and lake. Accordingly, each consumption category was further broken down based on these three water sources. This breakdown can be seen as cultivation phase and then PAN production and ACNF production. PAN production was separated out as it requires steam during manufacturing whereas DMF solvent did not. This separation is visualized in Figure 11. Holistic consumption quantities tallied the water consumption from material manufacturing and water associated with energy use during ACNF production.

3.3 Dynamic Carbon Emission Factor Development

To develop the dynamic carbon emission factor, I considered several perspectives on sustainability and how quantifying GHG emissions fits into those assessments. First, carbon foot printing is defined as a tool for indicating corporate environmental performance in physical terms i.e. Greenhouse gases produced over a period, typically presented in units of tons of CO2e (Kaur et al., 2023). Typical life cycle assessments include GHG emissions in a way that fails to account for changes in systems and technologies over time (Kendall, 2012). For this thesis the system boundary is focused on the production phase of the carbon nano fiber life cycle, and the key media flows being mapped is the energy requirement and subsequent CO2e emissions in the coming years. The carbon emission factors were also developed considering the envisioning of an industrial scale production scheme for a novel biomaterial – the importance of assessing the future impacts of this process can't be understated. To convert the energy consumed during the ACNF production process into these emissions a dynamic characterization factor in the form of an emissions value was developed to represent how emissions will vary in the coming future as the resource mix of a particular grid system moves towards renewable energy sources this framework can be depicted in Figure 12 in the appendix.

3.3.1 Scenario Development

This thesis required data to assess how the adoption of renewable energy sources impacts emissions in an ACNF production system. To build a dynamic life cycle inventory, the grid-specific forecasted energy mix data was incorporated. The energy mix directly influences the relationship between energy consumption and resultant CO_2 emissions. While other environmental impacts exist, such as the raw silicon required for solar panels, they are excluded from this analysis since changes in the energy mix occur regardless of whether this system is implemented. Similarly, end-of-life challenges, such as the disposal of wind turbine blades, are not considered. This study focuses specifically on CO_2 emissions, a key impact category for evaluating this novel material.

For the static assessment, which represents GHG impacts within a traditional LCA, a static emission factor is applied to convert energy consumption into CO_2 emissions. This factor is based on 2022 Rocky Mountain Power Area – Western Electricity Coordinating Council (RMPA-WECC) grid data, ensuring alignment with current regional energy conditions. This grid region can be seen in Figure 17 in the appendix. The static assessment represents a control scenario to be used in comparison with the predicted future resource mix scenarios.

Before sourcing energy mix data, it is essential to consider data quality factors, particularly geographical relevance. Energy mixes vary across U.S. grid systems, making regional specificity critical. This study focuses on the RMPA sub-grid within WECC using datasets that reflect resource adoption trends and future adoption goals (Western Electricity Coordinating Council, n.d.). The RMPA sub-grid was selected due to its proximity to the authors and its potential relevance to a future project site in Gillette, Wyoming.

Historical resource mix data was obtained from the U.S. Environmental Protection Agency's (EPA) eGrid database, a comprehensive public resource detailing energy production and environmental impacts across U.S. sub-grids. From these datasets, RMPA-specific data was extracted, focusing on generation resource mix (%) from the WECC Rockies eGrid subregion. An analysis of the historical resource mix revealed changes in grid system naming conventions and structural divisions over time. The WECC was previously known as the Western Systems Coordinating Council before merging with the southwestern U.S. grid. While eGrid data spans

1996–2022, the RMPA sub-region did not exist before 2012. This subdivision improved grid management, stability, and reliability by segmenting the WECC into smaller sub-regions. This division segments the WECC into smaller sub-regions to improve grid load management, stability, and reliability. As a result, pre-2012 data included resource mixes from coastal states, skewing the percentages of individual energy sources. To ensure accuracy, this study focuses on historical resource mix data from 2012 to 2022, with a few exceptions. The eGrid summary data was unavailable for 2013, 2015, and 2017. To fill these gaps, a linear interpolation method was applied, averaging values from the preceding and following years for each resource type.

With a complete historical dataset, trends in resource adoption within the RMPA sub-grid became apparent. These trends provide insight into investment patterns and the technological development of energy sources over time. Understanding where these trends lead is crucial for building accurate future resource mix scenarios.

Researchers have developed various future resource mix scenarios to predict how the energy landscape may evolve. These scenarios account for policy changes, technological advancements, and economic factors, providing a comprehensive outlook on potential developments. As discussed in the literature review, the National Renewable Energy Laboratory (NREL), the U.S. Department of Energy, and the International Energy Agency each present unique perspectives on future energy mix projections, both globally and within the United States. This project leverages NREL's insights, focusing on key drivers such as investment in emerging technologies (Denholm et al., 2022). Specifically, the 'mid-case' scenario serves as the baseline for establishing goal values and projecting trend trajectories. To explore different potential futures, this study developed four distinct scenarios based on NREL's framework:

1. Two time horizons: projections to 2035 and 2050, aligning with commonly used benchmarks in energy forecasting studies (Denholm et al., 2022; Donohoo-Vallett et al., 2023; U.S. Department of State, 2021; *World Energy Outlook 2023*, n.d.).
2. Two levels of investment and technological development:
   a. Moderate Investment ('Mid-Case' RMPA Scenario) – Represents gradual adoption of clean energy technologies.
   b. Low Investment ('Pessimistic' RMPA Scenario) – Represents limited technological advancements and slow adoption of renewable energy.

These scenarios establish a 'business-as-usual' control case alongside a pessimistic outlook, offering future researchers a comparative framework to evaluate how low investment in renewables affects the environmental feasibility of energy-intensive systems, such as ACNF production.

Table 1 - presents the goal resource share values developed from these scenarios, with each energy source expressed as a percentage of the total RMPA energy mix. To project the future energy mix, historical data was analyzed using linear regression modeling. This approach identified trend rates for each energy source based on past changes in historical shares.

Following established energy forecasting practices, a best-fit regression model was applied to each energy source (Gagnon et al., 2023). The slope of each regression equation represents the annual rate of change in total energy share, enabling extrapolation to 2035 and 2050. To maintain accuracy, common-sense checks ensured that the total future values summed to 100%. Some iteration was required, and adjustments were made to maintain this balance, with uncertainty accounted for in value adjustments.

Once the goal values were established, additional processes were applied to populate preceding years, ensuring a consistent and realistic trend progression.

To assess the accuracy of these predictions, coefficients of determination (R^2 values) were calculated, measuring how well the regression model fits historical data. The R^2 values ranged from 0.91 to 0.98, indicating strong predictive reliability. These values provide an initial assessment of the method's accuracy in generating goal values. The process was then repeated once the predictive trend equations were established. Additionally, a ±5% confidence interval was applied around the forecasted values to estimate uncertainty, following standard statistical practices in energy system modeling (Hong et al., 2020).

All energy production categories in this region were sourced from eGrid and remained within the eight defined categories. To clarify ambiguous classifications, inquiries were made into the 'Biomass' and 'Other' sections. eGrid correspondents confirmed that plant-level exploration reveals specific biomass fuel sources, including agricultural byproducts, landfill gas, municipal solid waste, sludge waste, and wood-based waste. The 'Other' category encompasses marginal energy sources that do not fit into existing classifications, such as hydrogen, process gases, purchased fuel, and waste heat recovery. The emission rates for each of these energy sources can be seen in Table 6 within the appendix.

Table 1 - Projected resource mix percentages for each future energy scenario

	Coal	Solar	Wind	Hydro	N. Gas	Biomass	Oil	Other	Total
2035 – Mid-Case	0.05	0.2	0.3	0.08	0.3	0.02	0.005	0.045	1
2035 – Low Investment	0.15	0.12	0.3	0.05	0.35	0.02	0.01	0	1
2050 – Mid-Case	0	0.35	0.35	0.07	0.1	0.01	0	0.12	1

2050-Low Investment	0.05	0.15	0.35	0.07	0.3	0.03	0	0.05	1

3.4 Dynamic Emissions Factor Generation

Traditionally life cycle inventories are used to quantify various environmental impacts over the entire life cycle of a product. These inventories are often represented as flows that build up as elements from processes and subprocesses are tallied. The associated flows such as energy consumption are translated into environmental impacts using emissions/impact factors. This method lacks the ability to assess the effects of a product as these emission factors change over time due to environmentally focused policy. The key emission factor being assessed in this study is the translation from energy consumption to pounds of CO2 emissions. As greener energy sources are put into play the total CO2 emissions from energy production are expected to change (*World Energy Outlook 2023*, n.d.).

In this thesis a static emission factor was generated using data from the US EPA eGrid that represents the quantity of CO2 emitted per kilowatt hour in the RMPA sub grid region in the WECC (*Emissions & Generation Resource Integrated Database (eGRID)*, 2024). This emission factor uses a weighting system that uses percentage of the total resource mix and the individual sources emission factors. The equation below represents this weighting, E= individual resource emission factor, S=percentage of total resource mix.

$$\text{Cumulative Weighted Emission Factor} = \sum_{r=1}^{n} (E_r \times S_r)$$

Equation 1-Equation for cumulative CO2e/kWh weighted by total resource mix

The static emission factor represents that unchanging number that would typically be present in a life cycle inventory or a carbon footprint, meaning the same cumulative emission factor is used every year in a production plan that stretches 10 years into the future for example. In this study the value calculated was 0.9665 kg CO_2/kWh. This value is slightly below the US EPA report's value of 0.5102 kg CO_2/kWh. The possible source of the difference is the accounting for emissions in the ambiguous 'other' category as provided in the data as individual emissions factors for each energy source in the other category were neglected, with an average being used that considers petroleum (1.533 kg/kWh) and battery storage (0.0328 kg/kWh). This decision may have a larger effect as that category is predicted to grow under NREL's mid-case prediction, demanding reassignment of those portions of emissions as novel energy sources are introduced at scale (Gagnon & Cole, 2022).

With the emission factor generated simple multiplication with the total kWh required by the industrial scale ACNF production gives the static emission value that would be used in traditional LCA or carbon foot printing. Building of the dynamic aspect of this assessment follows a similar methodology that utilizes a dynamic normalization factor (DNF). DNF is a way of accounting for temporal changes in background environmental conditions and environmental profiles (Su et al., 2021). For this assessment the background condition of interest is the various energy sources providing power to the simulated ACNF production facility. The normalization value in question is represented at the changing emission factor based on a predicted resource mix.

Using historical data as a foundational trend for each energy source, relationships between the scenario goal values and these trends were established through the utilization of many different tools. OpenAI was leveraged to perform polynomial fitting, least squares regression, symbolic equation solving, and linear regression to derive equations that connect historical trends with predictive objectives (OpenAI, 2024). These methodologies were systematically applied to ensure that the resulting trendline accurately captured past data points while aligning with predefined target values this process is displayed visually in Figure 13 in the appendix. Polynomial fitting was used to generate an initial best-fit trendline based on historical data. Least squares regression was then employed to refine the equation, minimizing errors and optimizing the fit. Symbolic equation solving allowed for precise adjustments, ensuring that the trendline passed through critical data points, such as specified years with known values. Finally, linear regression techniques were utilized to develop a functional predictive model that maintains mathematical consistency while extrapolating future values.

Adjustments to each year's resources were made following the development of historical trends and goal points so they sum to a cumulative 1 or 100%. The equations generated individually for each resource type were not adjusted initially to meet this summation, rather the emphasis was placed on reflecting the adoption rates and direction of each resource type. This led to some years being over or under the total summation of 100%, especially in scenarios extending to 2050 where trends had more time to develop. This was remedied by utilizing the predicted resource share values (percentages) by dividing then redistributing or removing any remaining energy shares. In other words, the percentage either over or under the year total 100% was divided based on the share percentages for each resource type derived from the historic trends. Any remaining difference after this process was then applied to the multifaceted 'other' category. All yearly totals were ensured developed to be within +/- 0.01 of a total sum of 1 as to not represent the full capacity of the RMPA gird while not overfitting the data.

With the equations derived from these methods, predictive values were systematically calculated for each year leading up to the specified goal value, ensuring that the trendline provided both historical accuracy and forward-looking reliability as seen in Figure 13 in the appendix. Subsequently, for each equation R-squared values were calculated to analyze the fit of the developed equations with the historic values and the goal point as seen in Table 2. R-squared values of 1 were due to the use of linear equations representing resource adoption. Once a matrix of predictive resource share values was calculated, the cumulative emissions factor for the future years in all scenarios was calculated using equation 1.

Table 2 - R-squared values for each resource type, across scenarios.

	Coal	Solar	Wind	Hydro	Natural Gas	Biomass	Oil	Other
2035 Mid-Case	0.934	0.968	0.788	1	0.614	1	1	0.9998
2035 Low Investment	0.9681	0.9982	0.9063	0.9064	0.8436	0.9696	0.9964	1
2050 Mid-Case	0.933	0.94	0.782	1	0.9314	1	1	1
2050 Low Investment	0.9766	0.9994	0.7892	0.485	0.529	0.897	1	0.66

3.5 Verification and Validation Practices

3.5.1 Verification of ACNF Model

Due to the absence of publicly available datasets on commercial-scale ACNF manufacturing, direct validation of the production model using primary industry data was not feasible. Thus, an alternative validation approach was utilized comparing model outputs with qualitative data derived from related nanofiber and carbon nanofiber publications. This included a publication on the upscaling of electrospinning, lab-scale experimental data, and energy consumption data of alternative manufacturing schemes of similar scale.

For example, validation in the choice to use multi-nozzle electro spinners was found in a publication about the large scale manufacturing of hybrid nanofiber materials for masks (Cimini et al., 2023). While the materials themselves differ in composition and use-case applications, they share a key process similarity, providing confidence towards the feasibility of this system if built into a physical system. To improve the validation of this model, future work should incorporate pilot-scale data from laboratories or pre-commercial ACNF production facilities. This data would allow for direct measurement of energy consumption and efficiencies both cumulatively and within individual sub-processes. Utilization of primary data would also be helpful for identifying scaling factors that are not captured in theoretical models. Additionally, future collaboration with industry partners would provide accessibility to any proprietary datasets that may strengthen model accuracy. While the industry partners who assisted with this model were helpful, they could not provide insight into component level data that may have altered energy consumption values.

To mitigate uncertainties in machine energy consumption data a few approaches could be taken. First a sensitivity analysis can be conducted to determine how variations in energy estimates affect overall model predictions. Additionally, refining machine-specific parameters through direct experimentation would yield improvements accuracy of future model versions.

3.5.2 Discussion of Model Sensitivities

During model development it was discovered that several factors had noticeable impact on the resulting cumulative energy requirements. The algae oil input variable is the driving variable in which other metrics like total number of machines required is derived from. When this input is changed the number of machines adjusts to meet the needs to process that quantity of algae oil, in- turn the energy consumption increases drastically when the oil input is increased. Additionally, assumptions about the efficiencies of several machines were made due to the lack of data. These variables have the potential to affect final energy consumption values substantially as well. Future iteration on this model would include a sensitivity analysis into these factors.

3.6 Computational and Analytical Tools

The computation tool used to conduct this experiment was Microsoft Excel. Some python scripts were also utilized for deriving equations for inputs into the spreadsheet. Both the ACNF process model and the dynamic emission factor were conducted using these spreadsheets. The regression modeling used for derivation of equations and goal values was done using python. Specific regression techniques were selected by identifying trendlines that represented the data well. This was achieved by visually mapping historical and target data points, then iteratively testing various trendline slopes to ensure an optimal goodness of fit using R-squared values. While this approach provided a practical solution within the scope of this project, future model development could enhance precision by incorporating advanced statistical validation methods or automated curve-fitting algorithms. However, given the project's objectives, the chosen methodology was both appropriate and effective.

3.7 Gaps and Assumptions

3.7.1 Data Gaps and Future Refinements

Data gaps did exist in this project due to the nature of upscaling from a known laboratory process to a novel industrial scale manufacturing system. For example, no data currently exists on the economies of scale for electrospinning machinery—an omission that could significantly affect the estimated resource requirements for large-scale production. One potential method for addressing this gap is the 'energy of scale' approach, which accounts for how energy consumption scales with production volume. While not applied in this study, this concept could meaningfully contribute to future iterations of this foundational model. Other assumptions were made about the efficiency of these machines. Not only this but also the energy consumption cycling within these machines. For furnaces, energy cycling data from household ovens was used, as it reflects the dynamics of heating within an enclosed space, similar to the operational conditions of industrial furnaces. Since the electrospinning machinery is assumed to run continuously throughout the day, assumptions were made about the frequency of usage within subcomponents of the system such as heaters and dehumidifiers. Future data collection efforts may aim to collaborate with commercial partners to collect primary data regarding the energy consumption of these systems and subsequent effects caused by using algae oil in production.

3.7.2 Evaluating Predictive Accuracy

Coefficients of determination were used twice in the development of the future resource mix. First, they were used alongside a linear regression model to determine the trend rates. To ensure the trends towards future goal values were a strong fit with the historical data. Next, they were used again when novel trend lines were created to fit both the historical data and the predicted goal values. This methodology was chosen because following trendlines of historical data alone would not accurately represent the future distribution of the different resource types. Thus, the goal values had to be generated to represent both world energy objectives and the geographic specific trends in the RMPA sub-grid. The calculation of R-squared values represents this method's ability to meet these goals.

CHAPTER 4 - RESULTS

This section presents the results of developing the ACNF production process model, LCA results and the application of the DNF for future GHG emissions to assess the projected CO_2 impacts of the manufacturing of ACNF. The findings are organized by the following 1) ACNF Production Model Outputs 2) Life Cycle Analysis Results 2.1) Material Consumptions and Water Footprint 2.2) Carbon Emissions Results 3) Scenario Analysis 4) Uncertainty in Energy Estimation 5) Model Validation and Reliability.

4.1 ACNF Production Model Outputs

All outputs from the ACNF process model are derived through calculations originating from the input of quantity of algae oil being processed. For the scope of this thesis, all results are based on an input of 1 ton (approximately 950 liters) of algae oil—a value established by leadership within the larger project to which this work contributes. Additional input quantities were also charted to assess the relationship between input oil and total energy consumption as shown in Figure 18 in the appendix. This quantity of oil is processed with a working recipe requiring 22,352 liters of DMF solvent, and 1,510 liters of PAN. This total volume of this combination equates to 24,813 liters of dope solution. Based on the processing rates of a single industrial electro spinner, a total of 431 electrospinning units (Inovenso SS1600) are necessary to spin this much fluid in 24 hours. Given the number of machines required, it is important to note that the environmental impacts associated with their manufacturing were not included in this assessment. This exclusion is justified by the fact that a similar quantity of equipment would be necessary regardless of whether the production involves algal carbon nanofibers or conventional polymer nanofibers. The driving factor for these low processing rates is the concept of pushing large quantities of fluid through very small needle heads, translating to a processing rate of 2400 mL/hr. Volume based calculations were made to calculate the number of stabilization and annealing furnaces needed, including the number of zones that each furnace would contain. The calculated number of machines was then used to find the total energy consumption for each sub process which was fed into a cumulative energy consumption.

Energy consumption for each sub process is show in Table 3 with electrospinning being the largest consumer of electricity. Additionally, the flow and transformation of the material itself was mapped to calculate a total final volume of ANCF. During each phase reductions in volumetric yield occur, ending with a final area of 1,363,070.62 m^2 ACNF (0.5 g/m^2). The industrial scale model resulted in a consumption of 28.808 kWh/kg ACNF, showing improvement in efficiency when compared to the laboratory scale processes. For reference, another publication researching the production of CO_2 fixation on carbon nanofibers, found that at laboratory scale, consumption of energy during production was around 162 kWh/kg CNF (Xie et al., 2024). This main source of this difference most likely comes from the incorporation of stacking within the stabilization and annealing furnaces, so that more material is processed using less machine units.

Table 3 - Energy consumption breakdown by sub-process based on a processing volume of 1,363,071 m^2 ACNF (0.5 grams/m^2) – 681.5 kg of ACNF.

Sub-Process	**Electricity Consumed (kWh)**
Mixing and Heating (dope solution)	248
Electrospinning	13,800
Solvent Recapture	4,900
Stabilization	156

Annealing	542
Total	19,600
Per kg ACNF	28.80

4.2 Life Cycle Analysis Results

To address the environmental impacts of CO_2 emissions, material and water consumption this portion of the results will be broken down by 4.2.1) Material Consumption and Water Footprint Impacts and 4.2.2) Carbon Emissions Results. These results will provide comparison with laboratory scale production and then comparison between the dynamic and static assessment methodologies. Comparison with similar products is done qualitatively.

4.2.1 Material Consumption and Water Footprint Impacts

Total consumptive quantities for each material type can be seen in Figure 6. Due to the industrial batch size, a large amount of solvent is required (approximately 22,532.94 liters) this accounts for 56% of the total CO_2 emissions in the system. The cause of this is primarily due to the carbon intensity of dimethylamine production, which contributes 44.69% of DMF's overall life cycle emissions. It's also important to note that a three-time reuse assumption was applied to the solvent. If fresh solvent were used in every batch instead, total emissions associated with DMF would triple, while emissions from process energy consumption would decrease due to the elimination of recovery operations. The next highest contributor is the process energy consumption is seen in Table 3, contributing 30 % of total CO_2 emissions in the static scenario. Without solvent recapture machinery this value would drop to around 24% which equates to approximately 14,738 kg CO_2 for 24 hours of continuous use.

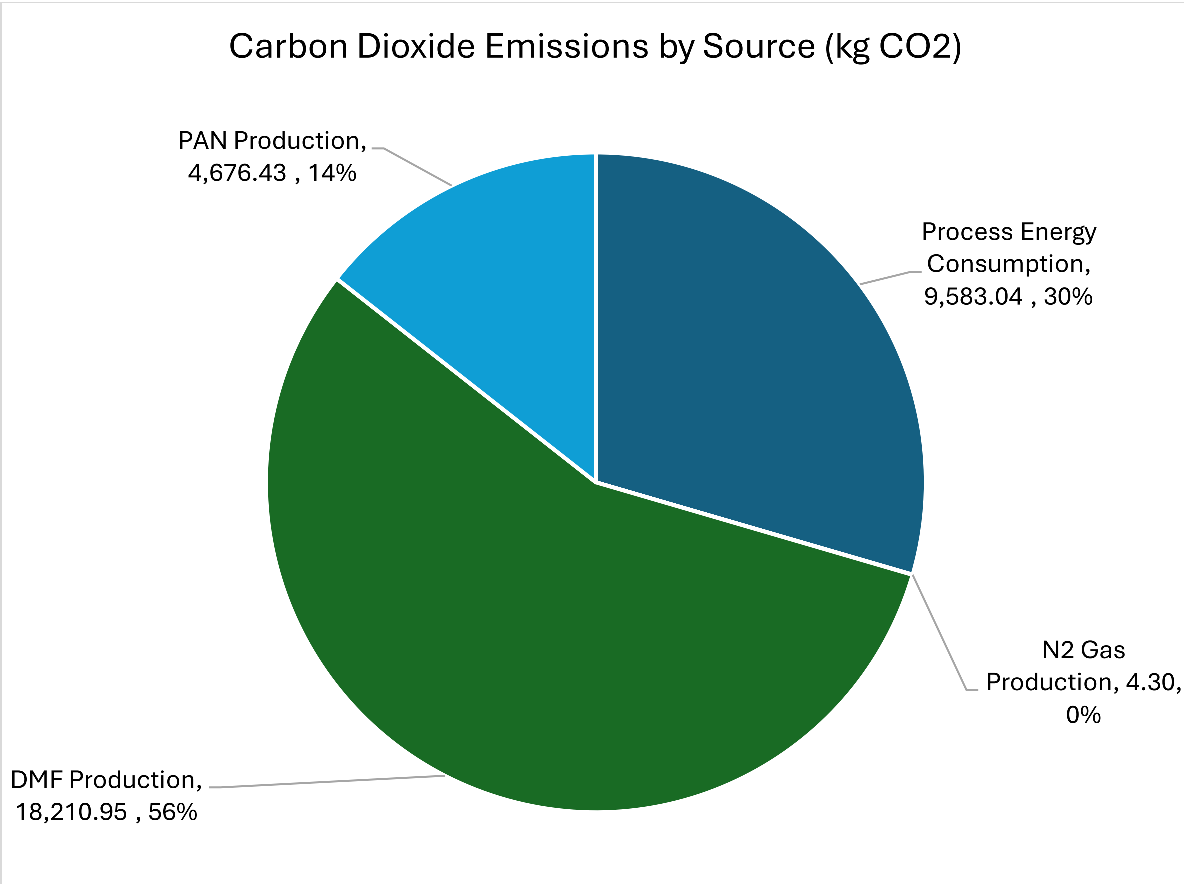


Figure 6 - Distribution of CO2 Emissions by Project Component

4.2.2 Carbon Emissions Results

A baseline emissions rate was established using 2022 resource mix and carbon emissions data for the RMPA sub-grid from the US EPA (U.S. Environmental Protection Agency, 2024). This data represents the static value assignment given by traditional sustainability assessments representing one stagnate point in time. The resulting stagnate emissions factor for the year 2022 was 0.9665 kg/kWh (2.131 lbs./kWh). The difference between the dynamic emissions factors and the static value is depicted in Figure 7. The straight dotted line represents the unchanging nature that is typically utilized in LCA type assessments and does not account for upgrades and improvements to the source material. The scenarios depicted visualize the development of renewable energy sources and how that reflects greenhouse gas emissions per kilowatt hour of energy used.

Emissions rates for each year across scenarios can be found in Table 5 in the appendix. Using the static emissions value, a comparison was made between the greenhouse gas intensities of laboratory-scale and industrial-scale production. The laboratory-scale process produced 0.086 kg CO_2 per square meter, whereas the industrial-scale process reduced this to just 0.001 kg CO_2 per square meter, highlighting a substantial decrease in emissions intensity at scale.

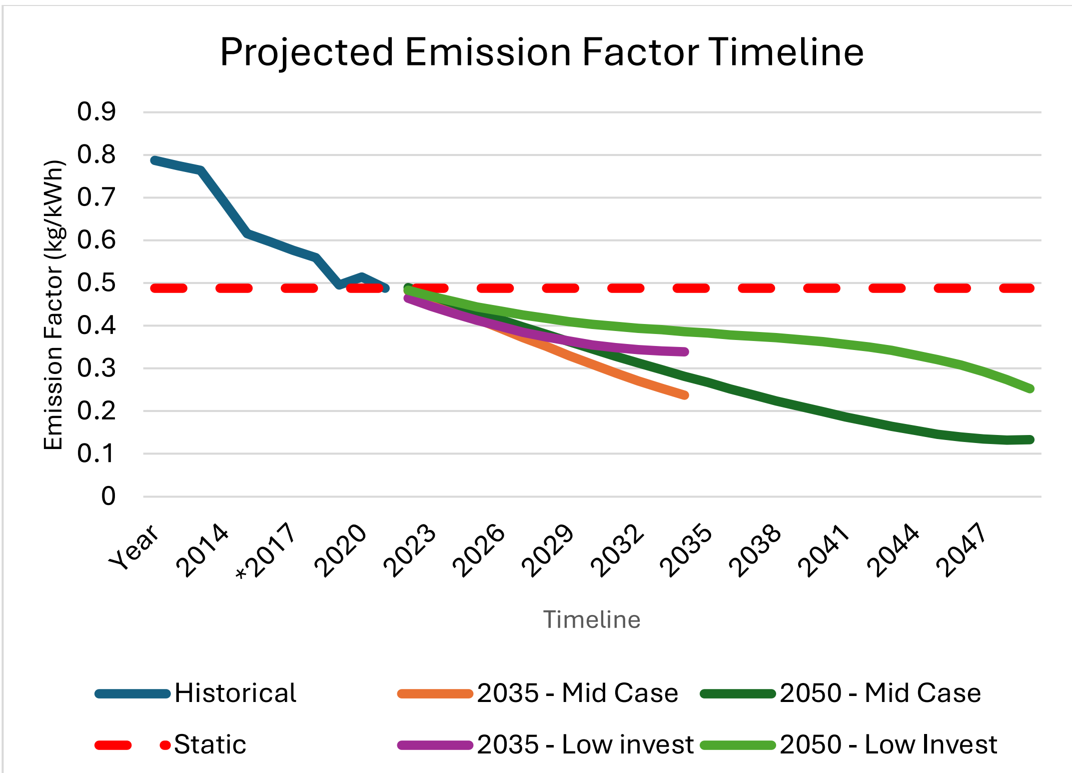


Figure 7 - Projected emissions factors over time as compared to traditional static LCA profiles

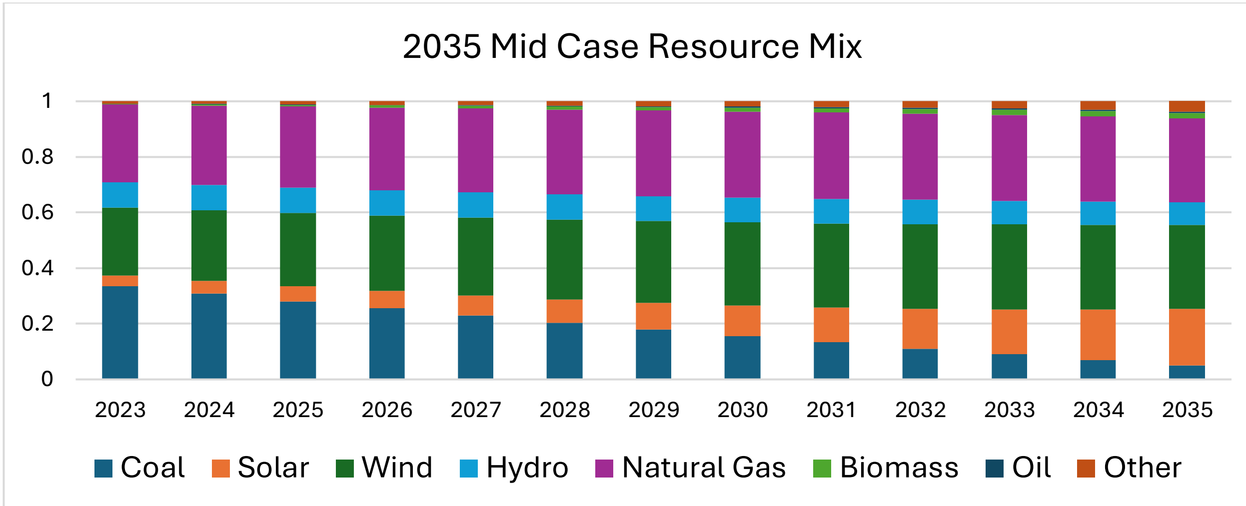
2035 and 2050 timelines illustrate how extending renewable energy investment goals over a longer period, results in increased cumulative emissions. For instance, the 2050 Mid-Case scenario exhibits an average emissions factor that is 0.0211 kg CO_2/kWh higher than the 2035 Mid-Case, indicating greater CO2 emissions during the first 13 years. Pressing to meet these renewable energy goals by 2035 will require substantial growth for both wind and solar to account for coals retired share of the total energy generation. Total increase in wind and solar shares are 2.5% and 16.5% by 2035 and 7.5% and 31.5% by 2050. This reflects that investments will mainly be put towards solar energy as a supplement for lost coal energy. The small increases to wind energy may be due to that resource already making up a considerable share of the total resource mix (27.5 % in 2022) (U.S. Environmental Protection Agency, 2024). The mid-case scenarios reflect consistent downward trend for total emissions generated, leaning on solar generation to substitute for the lost energy sourced from coal power plants.

The low investment scenarios reflect contrasting results and depict a much more fluid nature of renewable energy adoption. When comparing with the 2035 mid-case scenario, the first 13 years the low investment scenario improves by 0.1247 kg CO_2/kWh while the Mid-case nearly doubles this with an improvement of 0.2540 kg CO_2/kWh. Through 2050 this difference widens slightly to a 0.2426 kg CO_2/kWh net change for low investment and a reduction in 0.3873 kg CO_2/kWh in the mid case scenario. From an end point perspective, the difference in the resulting emission factor is less drastic than anticipated.

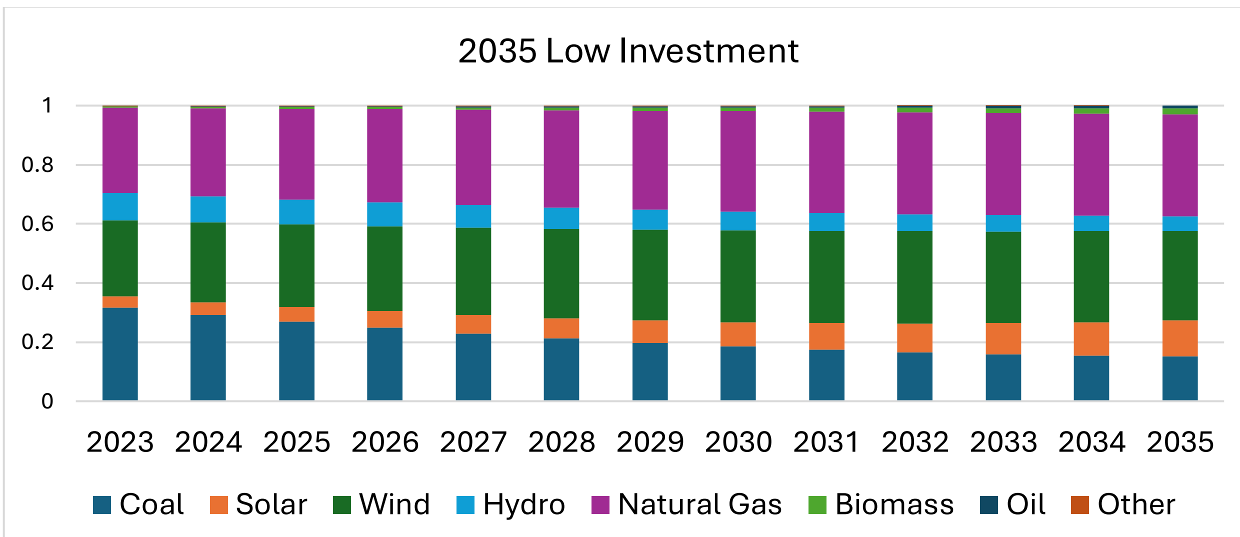
These factors suggest that a static LCA over the span of several years will create a notable overestimation of GHG impacts from ACNF production, even with low investment in renewable energy transition. Given the extended timelines needed to transition technologies from laboratory settings to industry, these variances may influence stakeholders looking to invest in ACNF manufacturing. To improve on static assessments the life cycle inventories that capture a snapshot of a products impacts with data from one point in time could be updated yearly to account for reductions in emission factors. However, even with updated data, results can only be extrapolated so far into the future.

The dynamic emission factor is a derivative of the predictive scenarios representing the development of less carbon intensive energy sources in a particular grid region, this can be visualized over time in Figure 7. Longer timelines such as those in the 2050 scenarios depict more volatility as resources such as solar are greatly expanded to account for the deficit in coal production. Outside of this case we see most resource types only adjust by less than 10%. Although there is a visible increase in the 'other' category which may be a result of the redistribution methods used during resource mix production but also may reflect the unknown aspect of new technologies. This could be explored further to ensure the emissions related to this category are accurately accounted for.

When comparing the dynamic emissions factors for the same region generated in this study to those reported in NREL's Long-Run Marginal Emissions Rates (LRMER) dataset, a slight discrepancy between predicted values is observed. This study estimated a 20-year average emissions factor of 0.289 kg CO_2/kWh under the mid-case scenario, while NREL's Cambium model reported a lower value of 0.199 kg CO_2/kWh for a similar scenario (Gagnon, 2024). This difference may be attributed to several factors, including the use of more recent data in the Cambium model, which is based on 2023 projections, whereas this study relied on 2022 assumptions about technologies, markets, and policies.

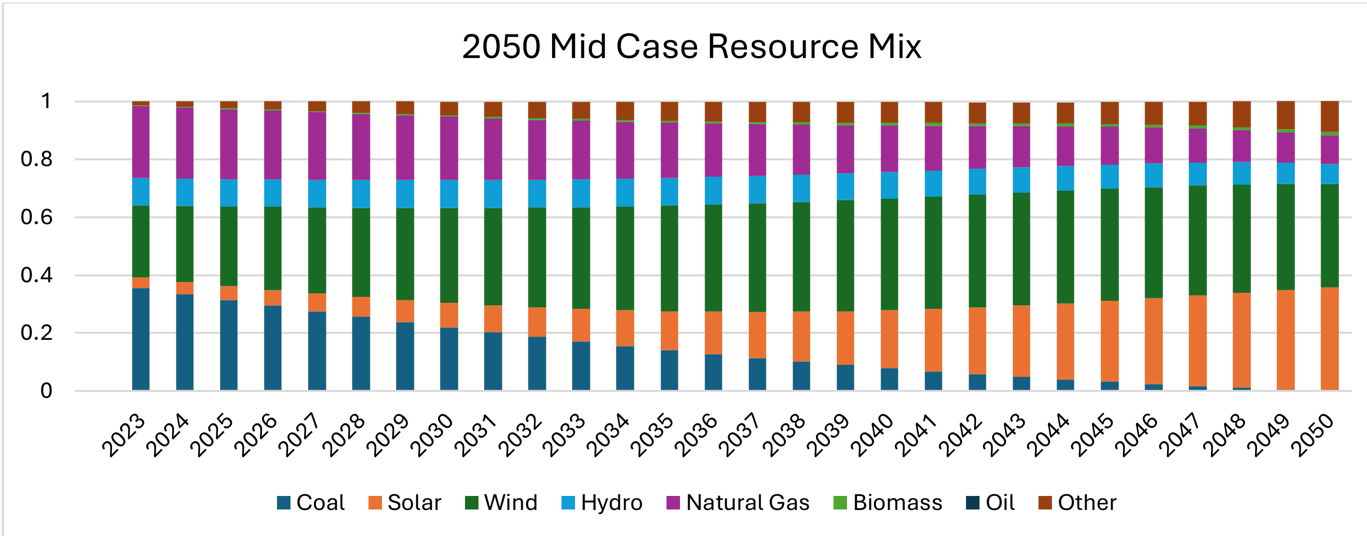


A)

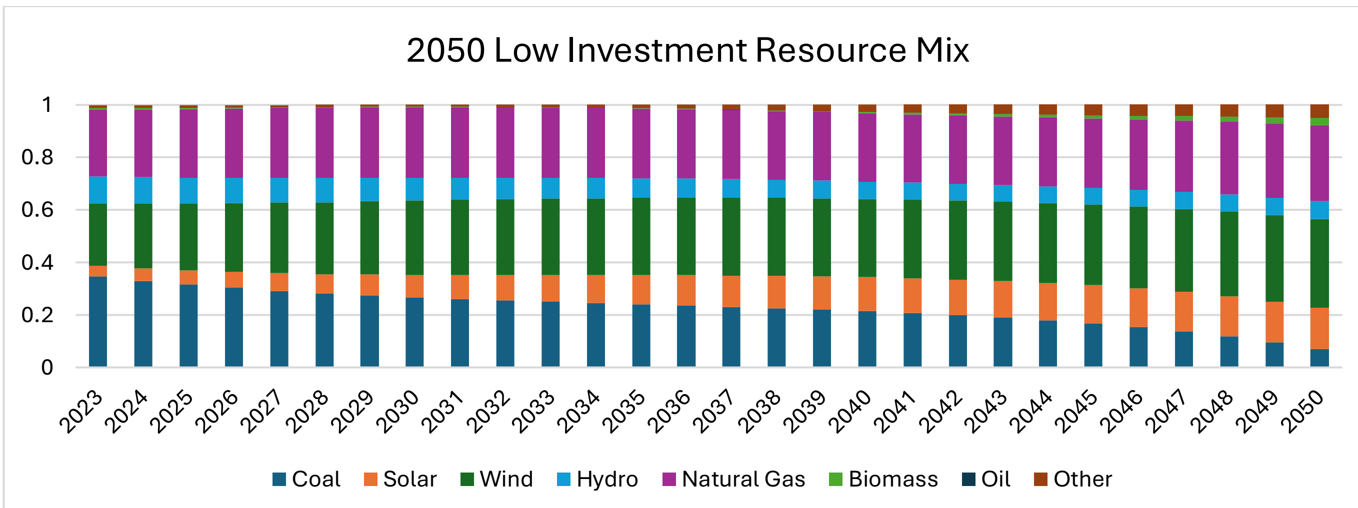


B)

Figure 8 - 2035 Predicted resource mixes. A) 2035 mid-case B) 2035 low investment



A)



B)

Figure 9 – 2050 Predicted resource mixes A) 2050 mid-case B) 2050 low investment

4.3 Scenario Analysis

Results from a scenario analysis of dynamic emission factors show how impactful energy investments are on the energy requirements and resulting GHG emissions of ACNF production. The profile of one day of production is shown using the total energy requirement and the dynamic emissions timelines from all four scenarios in Figure 10. These profiles show how the use of static emissions factors such as those in life cycle analysis are drastically different than those that factor in temporally dynamic resource mixes across a variety of futuristic scenarios. These differences also highlight the potential value of long-term investments in the development of such production facilities. As discussed later, changes in emissions-related credits or taxes could translate into significant cost savings or expenses depending on the future energy mix scenario. While this perspective aligns more closely with a financially focused assessment, such as a TEA, the dynamic modeling framework developed in this thesis could serve as a valuable foundation for incorporating those financial dimensions in future work.

The significant differences observed across scenarios in this study are also reflected in the LRMR dataset, which predicts average emissions rates over various time horizons. Notably, the 2050 average emissions rate from this study's mid-case scenario closely aligns with NREL's '95% decarbonization by 2050' scenario (.222 kg CO_2/kWh) (Gagnon, 2024). This similarity suggests that the goal values defined in the mid-case scenario may implicitly target a comparable level of decarbonization. This is reasonable, given that the mid-case scenario is not based on specific emissions targets but instead emphasizes projected annual financial investments and technological advancements. That methodological alignment may help explain why this study's 20-year average emissions factor is higher than NRELs, as discussed earlier.

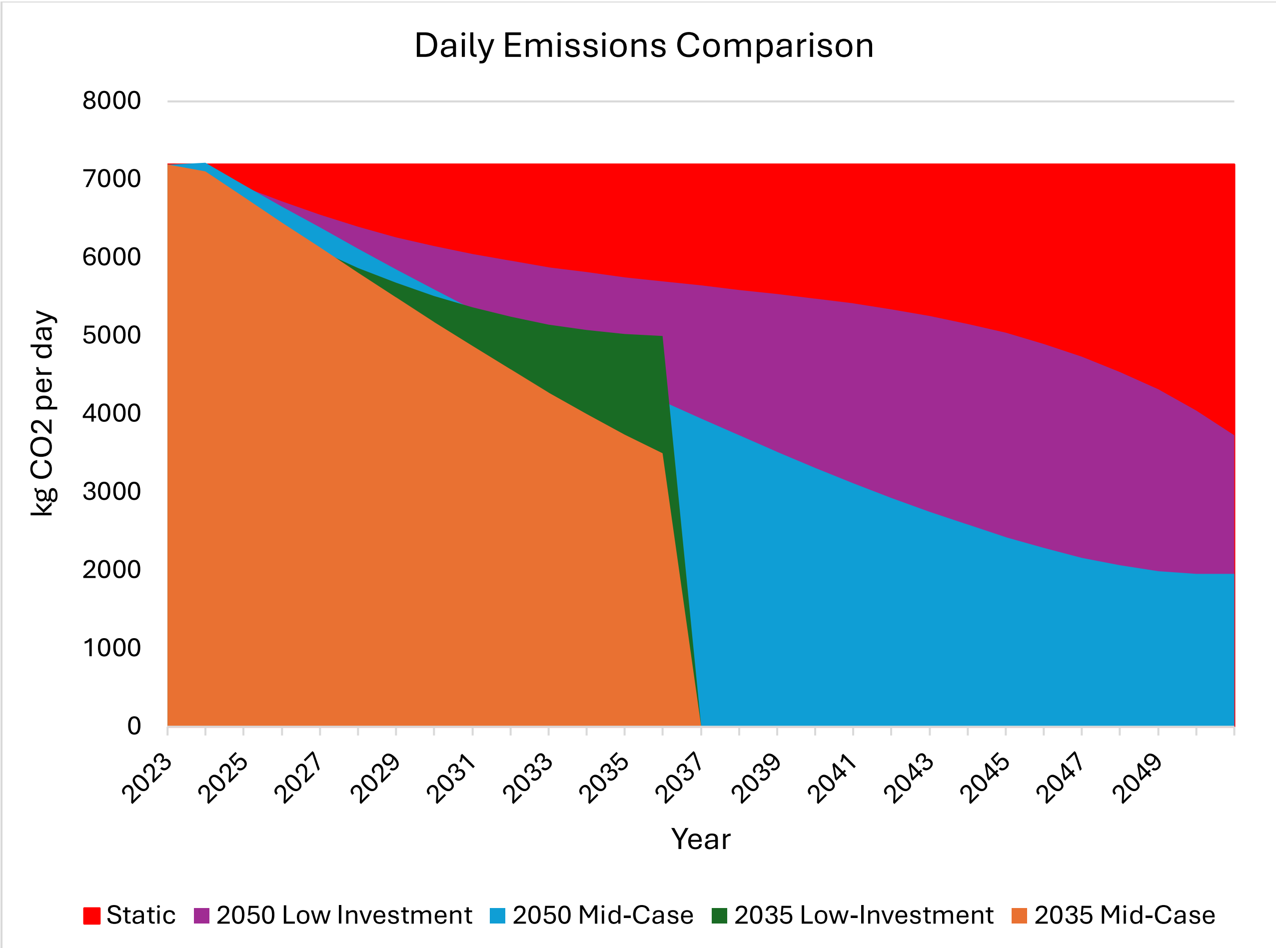


Figure 10 - Daily ACNF emissions across predictive scenarios for a 2035, and 2050 timeline forecast

4.4 Uncertainty in Energy Estimation

Energy efficiency assumptions were applied to each ACNF production subprocess to generate more realistic consumption estimates, given the limited availability of detailed machine data. A standard efficiency rate of 85% was used across all subprocesses. This value represents a reasonable average for well-maintained industrial machinery, capturing both mechanical and electrical losses without overstating real-world performance. On an industrial scale, even small deviations in efficiency can significantly impact the total energy consumption of an ACNF production facility. These assumptions aim to represent an industrial scale facility because final production models have a higher efficiency as reflected by industrial economies of scale. An example of this exists in the context of AI data centers, where improving the energy efficiency of machine learning models reduces the overall consumption and impacts (Xue, n.d.).

4.5 Model Validation and Reliability

One of the primary challenges in validating the model used in this thesis is the scarcity of publicly available industry data related to ACNF Modeling. To this author's knowledge there are no companies attempting to utilize algae oil in the production of ACNF as modelled in this thesis. Even if they did, this author assumes that many companies would treat operational data as proprietary. As a result, parameterization of the ACNF model relies on approximations and extrapolations from published sources and adjacent industry professionals, introducing potential sources of uncertainty. Additionally, several variables such as process configuration, machine technology improvements, specifics in algae species, and oil quality may lead to discrepancies between modeled and actual performance.

Given the lack of industry-scale data on the manufacturing of ACNF, alternative methods of model validation were employed. This involved comparing ACNF production trends with findings from similar products and processes. For example, the ACNF model resulted in a consumption-to-yield energy consumption ratio that was a multiple lower than those reported in in comparable laboratory-scale production models (Xie et al., 2024). The reduction of laboratory-scale findings suggest that the model's outputs represented a realistic extrapolation from laboratory-scale results. Further modeling results were compared to a secondary study that modeled a commercial-scale electrospinning process for nanofiber production in mask manufacturing. While this study primarily focused on the material properties of the electrospun fibers, it also demonstrated that a multi-nozzle electrospinning apparatus is capable of achieving production rates suitable for commercial-scale operations, thereby supporting the feasibility of the ACNF model's scaling assumptions (Cimini et al., 2023). Although a direct comparison with these studies was not conducted due to differences in materials and specific subprocesses, their findings support the conclusion that key components of this project—such as multi-nozzle electrospinning—are capable of scaling to commercial production.. While primary assessments were conducted to evaluate the robustness of the model more research is needed to further refine the model's predictive accuracy.

CHAPTER 5 – DISCUSSION

5.1 Summary of Key Findings

This thesis provides insights into both the challenges and opportunities of ACNF production, as well as the potential of dynamic sustainability assessment. One key discovery was the high energy consumption associated with the electrospinning process. This energy consumption translates into emissions affecting both static and dynamic emission models of the future. The dynamic assessment demonstrates how shifts in the energy resource mix over time led to reductions in expected emissions for ACNF manufacturing. This approach differs from traditional static assessments by offering a more robust perspective for stakeholders seeking accurate long-term emissions estimates for industrial-scale processes. For algae-related products in particular, dynamic assessment revealed system resilience, highlighting the ability of related processes to adapt and optimize based on the findings of this study.

5.2 ACFN Model

5.2.1 Industrial Scaling

When building an industrial scale model based on laboratory scale process there is some level of uncertainty to be expected during translation. This uncertainty came in the form of scaling factors and custom machinery that could improve the precision of energy consumption per unit of finished product. A decrease in energy consumption per unit is to be expected at some point with the increased level of production, similar to the concept of decreased price per unit as is shown from the financial perspective in economies of scale. One study introduces the concept of 'energy of scale,' which explores how energy consumption decreases as production capacity increases in industrial energy systems (Binderbauer et al., 2023). To represent this potential difference a comparison between laboratory production at the Wyoming Research Lab and production in the industrial ACNF model was made. By representing this production as a yield per unit of energy (m^2/kW) it can be seen as an example of the difference that exists and may be improved upon. When compared to the laboratory findings, this thesis found a substantial increase in production efficiency per kilowatt hour (see Table 4). While no adjustments were made to the results of this thesis to account for economies of scale, future iterations of the model should incorporate aspects of scale as data is found or comparing to industrial data of a similar product.

Table 4 - Industrial vs. laboratory yield per unit energy

Industrial (m^2/kW)	**Laboratory (m^2/kW)**
69.42	0.57

5.2.2 Custom Manufacturing Machinery

During the data collection for the ACNF model it became apparent that there a need for ACNF machinery built for various scales of production. In many instances professional communiques, vendors expressed that their machinery is built for pilot/small scale production schemes. This was reflected in the pricing for each unit by giving discounts if you bought machinery in quantities of 1,2 or 3 instead of several hundred machines that our system would require. Many companies also indicated they could custom-build machinery for each subprocess to maximize production and reduce total energy consumption. This would be achieved by eliminating unnecessary components and optimizing individual parts to meet the specific requirements of the application (Y. Hammadi, personal communication, October 9, 2024; D. Ma, personal communication, October 22, 2024). Furthermore, the inclusion of custom-built machinery would be able to apply assembly line type of connections to maximize production per unit time.

There remains uncertainty associated with novel machinery particularly when it comes to operation and maintenance costs. It's worth mentioning that there may exist challenges in interactions between machines. It is reasonable to assume that a substantial amount of automation and assembly machinery would be required to take ACNF from one production phase to the next. Industry professionals were not willing to provide data on any custom designed systems due to the lack of financial compensation for their design efforts.

5.2.3 Solvent Recovery Systems

During the formulation of the ACNF production model it was revealed that dimethylformamide (DMF Solvent) had substantial upstream resource consumption and emissions. Life cycle assessment data to produce DMF indicated a major water consumption and CO^2 emissions associated with the large quantity of solvent required. During the development of the water footprint, it was revealed that DMF accounted for approximately 70% of water consumption of direct processes and downstream manufacturing of chemicals (see Figure 11). The potential solution explored in this project was a solvent recovery system. Solvent recovery systems are setups that collect, clean, and reuse solvents from industrial processes. They often use methods like distillation or filtration to reduce waste, lower emissions, and limit the need for new solvent inputs. While the selection of DMF as a solvent has be shown to reduce overall evaporative losses during electrospinning, the substantial consumption of this material drives the investigation of potential solutions (Shen et al., 2022). Operationally this translates to solvent being captured through vents and filtered/recycled to be incorporated once again into the dope solution. There are many forms of solvent recapture and recycling that offer a range of solvent qualities and require different inputs. While lowering the total consumption of DMF did lower operational and upstream impacts of water consumption and GHG emissions, there are associated costs with incorporating new machinery. This study utilized an already existing design that conducts the main recycling efforts, additional equipment such as fans, pumps and condensers was not included as it would likely be smaller contribution to the total solvent recovery energy consumption and would likely be built into custom machine designs as is discussed later in this thesis. A future iteration of this production model could incorporate a custom designed, industrial scale solvent recapture system to assess the overall feasibility and sustainability from both economic and environmental perspectives.

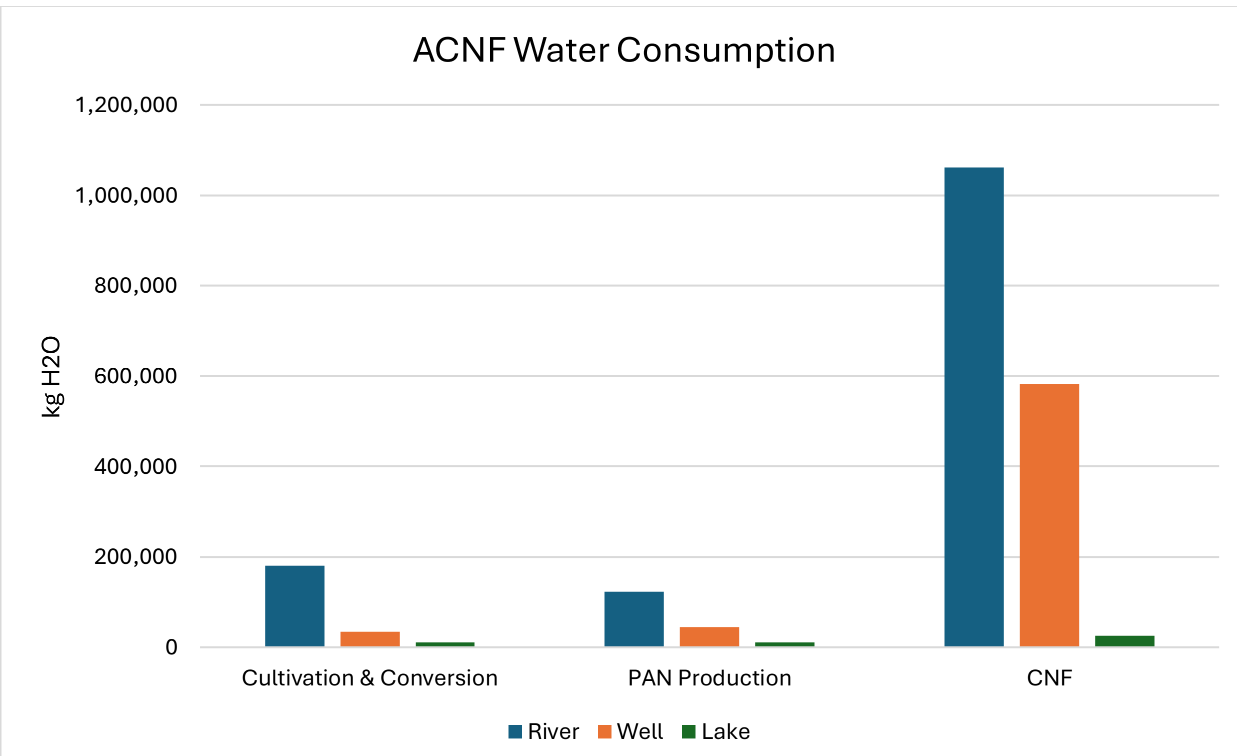


Figure 11 - ACNF water footprint organized by subprocesses and water source

5.3 Dynamic Resource Mix

During the development of the dynamic resource mixes, R-squared values were employed twice: first, to identify trends in historical data, and later, to assess the fit of predictive equations against target values. While R-squared serves as a measure of goodness of fit, analyzing individual datasets and selecting appropriate functions for best-fit lines provides insights into different resource types. Notably, resource types with lower R-squared values exhibited greater historical volatility, marked by substantial fluctuations in their share of total energy production.
For instance, natural gas steadily increased its share from 2014 to 2020 but experienced a sharp decline in 2021, resulting in a lower goodness of fit. This pattern suggests that R-squared could serve as a useful metric for evaluating the validity of the dynamic resource mix as actual resource shares are recorded over time. Additionally, low R-squared values may highlight historically significant events that disrupt energy sourcing within sub-grids. For example, the decline in natural gas consumption after 2020 may be attributed to shifts in demand during the global COVID-19 pandemic (U.S. Energy Information Administration, 2024).

5.4 Implications of Results

The CO_2 emissions from ACNF production, while not unreasonable, remain substantial. Across all scenarios in this study, total emissions through 2035 and 2050 were lower than those in a static assessment scenario. Consequently, assessing the production phase is essential for evaluating ACNF's sustainability in comparison to traditional CNF. Two studies found that the energy consumption and environmental impacts of polymer-based CNF production are substantial (Khanna et al., 2008; Khanna & Bakshi, 2009). However, a full life cycle comparison, spanning algal cultivation requirements, the products useful life phase, and end-of-life impacts, are necessary to fully assess ACNF's environmental footprint. While this comprehensive analysis is beyond the scope of this thesis, the integration of more realistic grid emission projections provides a stronger foundation for DLCA studies. As demonstrated, even under low investment scenarios, industrial-scale ACNF production is expected to reduce GHG emissions over time. This decline could enhance the viability of high-energy algal biomass cultivation methods, such as photobioreactors, which require less land and water and could further improve raw material sustainability (Nogueira Junior et al., 2018).

Economic policy and carbon pricing frameworks will likely influence ACNF's long-term feasibility. Under the Inflation Reduction Act (2022), fines are currently imposed on methane (CH_4) emissions, while carbon dioxide (CO_2) emissions remain exempt. Although this study does not directly assess methane emissions, they are an inherent byproduct of energy production, particularly from natural gas-based electricity generation (Wood et al., 2023). Future policy developments and investment in renewable energy will play a pivotal role in shaping emissions trends, reinforcing the need for adaptive sustainability assessments. Legislative measures, such as the Inflation Reduction Act, are expected to accelerate the adoption of new energy technologies (Bistline et al., 2024). Additionally, the act incentivizes carbon capture, utilization, and storage (CCUS), meaning that ACNF systems utilizing flue gas could potentially qualify for carbon credit incentives (Chen & Quinn, 2021).

Economic feasibility is an essential consideration when evaluating sustainability strategies. Life cycle assessment (LCA) is frequently paired with techno-economic analysis (TEA) to capture both environmental and financial implications. However, no examples of dynamic TEA methodologies were examined in this review. While generating a dynamic TEA is beyond the scope of this study, it presents an interesting opportunity for future research, particularly in the context of dynamic carbon accounting. As carbon fines and credits become more prevalent, integrating economic factors into DLCA methodologies could provide a more holistic evaluation of ACNF's long-term viability in a changing regulatory landscape.

5.5 Comparison with similar products

Two separate evaluations of energy consumption were conducted on CNF polymer composites and carbon nanofiber production methods. Both studies highlight the high energy demand associated with production, comparing it to the energy required for manufacturing metals used in similar applications (Khanna et al., 2008; Khanna & Bakshi, 2009). Khanna et al. (2008) assessing polymer-based CNF found that continuous manufacturing over 300 days per year required approximately 20,000 MJ of energy, whereas the static assessment in this model estimated approximately 70,000 MJ. This LCA study mentioned challenges with industrial scale production but omits providing a specific scale thus not being comparable with this study. Similar Another study comparing CNF polymer composites to traditional metals found that, in a cradle-to-gate analysis, up to 65 percent of the total life cycle impacts were attributed to the manufacturing of the carbon nanofibers themselves (Khanna & Bakshi, 2009). This assessment found that electrospinning, a process also used in the production of polymer composite nanofibers, accounted for approximately 70 percent of the total energy use within the manufacturing phase of this gate-to-gate analysis.

CNF polymer composites are defined as materials containing at least one component within the nanoscale range. A specific study evaluating CNF polymer composites for automotive applications found that energy consumption within the cradle-to-gate boundary was significantly higher than that of traditional steel (Khanna & Bakshi, 2009). However, the authors noted the potential for reduced total life cycle energy consumption if the use-phase were included, as fuel savings could be achieved due to the lighter weight of CNF-based components. If ACNF were utilized in vehicles or aircraft electronics, similar energy savings could be realized, but further assessment would be needed to quantify energy savings per unit of weight.

CHAPTER 6 – CONCLUSION

This thesis aimed to contribute to the sustainability assessment of algal carbon nanofiber production by modeling its energy consumption at an industrial scale. The analysis quantified energy use and translated it into CO_2 emissions across four future energy scenarios and timelines. To account for the temporal dynamics of energy transitions, a dynamic normalization factor was applied, ensuring that emissions were evaluated within the context of evolving renewable energy adoption in a specific sub-grid. This approach provides a dynamic understanding of ACNF's environmental impact by integrating both static and time-dependent energy variables into an LCA assessment.

6.1 Contributions and Implications of the Research

This research advances both the understanding of algal-based materials and the methodologies used to assess emerging products. The ACNF production model serves as a foundational tool for evaluating the machinery requirements and energy demands of fabricating a novel material. Additionally, this model highlights key challenges in industrial-scale assessments, particularly the lack of data on large-scale ACNF manufacturing.

The incorporation of dynamic assessment provides a new case study on the implications of temporally dynamic elements in life cycle assessments. This approach demonstrated that in a gate-to-gate analysis, total projected emissions varied substantially over time. The findings suggest that traditional LCA methodologies may overestimate CO_2 emissions in manufacturing by failing to account for changing energy landscapes.

This insight is crucial, as it indicates the potential resilience of algal-based products under shifting energy conditions. As emissions per kilowatt-hour decline over time, more energy-intensive cultivation methods, such as photobioreactors, may become viable. This shift could reduce the land, and water demands of open-raceway pond systems, while simultaneously improving growth rates and biomass yield, making algal-based materials more sustainable and scalable.

6.2 Limitations and Challenges

The process of developing this model and assessment method exposed some challenges adapting laboratory scale data to an industrial scale process. While utilizing published methods of creating ACNF, limited commercial scale equipment exists specifically for this application. Thus, assumptions had to be made about quantity and types of machines necessary to process large batches of algae derived oil. Additionally, it's expected that economies of scale may further influence the findings from this thesis.

Limitations in predicting future grid emissions are also substantial. Variability in investment trends, energy policies, and technological advancements introduces uncertainty in futuristic projections. Historical energy trends are neither linear nor consistent, meaning that the equations used for future projections likely represent averaged trends rather than precise year-to-year values. This is particularly relevant given the long development timelines for renewable energy projects, such as wind farms and solar installations, which can take years to become fully operational. Because future scenarios are projections, some degree of deviation is expected. However, within the scope of this project, the chosen approach suggests an approach and data-driven framework for estimating future emissions based on available grid trends. Despite these limitations, a key takeaway from this study is that energy resource mixes evolve over time, and environmental impact assessments must account for these dynamics rather than relying on static assumptions.

6.3 Future Research Directions

Future adaptations of this research should enhance verification and validation efforts by incorporating pilot or industrial-scale data to more accurately represent primary resource consumption and broadening the life cycle assessment. This would allow for refinements to the model, ensuring greater accuracy in assessing energy and material flows. Expanding the scope of the model could transition the study to a gate-to-gate assessment to a cradle-to-cradle approach, incorporating use-phase and end-of-life impacts for bio-based algal materials. This broader framework would provide a comprehensive understanding of the full life cycle environmental footprint beyond production. Additionally, a broader approach could help quantify total life cycle carbon consumption, particularly given algal-based materials' ability to utilize flue gas during cultivation.

Further expansion could also incorporate additional life cycle impact categories, such as water quality effects, land-use conversion impacts, and detailed emissions profiles. Beyond environmental impacts, dynamic resource mix projections could be extended to additional geographical regions, making this methodology applicable to other grid systems beyond the RMPA sub-grid. This would strengthen the generalizability of the approach and support its use in broader energy transition analyses.

6.4 Closing Statement

This research highlights the importance of dynamic life cycle assessment elements in evaluating the sustainability of emerging biomaterials, especially as energy systems continue to evolve. By combining industrial-scale energy modeling with future resource mix projections, this study takes a more realistic approach to assessing the environmental impact of ACNF production. The results show that energy transition trends substantially influence emissions and reinforce the need for flexible LCA methodologies that account for changing energy landscapes rather than relying on static assumptions.

While this study lays a strong foundation for ACNF environmental assessment, it also exposes key challenges in scaling lab-based data to industrial processes and highlights uncertainties in long-term energy forecasting. Future work should focus on validating these findings with pilot-scale data, expanding the life cycle boundaries beyond production, and incorporating more regional energy mix scenarios to strengthen the applicability of this approach.

As renewable energy adoption accelerates, materials like ACNF could play a role in low-carbon manufacturing and sustainable product development, but their feasibility depends on continued improvements in energy forecasting, production efficiency, and impact assessment methods. By bridging environmental modeling with energy system dynamics, this research provides a valuable tool for understanding the long-term sustainability of emerging materials and ensuring that environmental assessments evolve alongside technological advancements.

REFERENCES

Arvidsson, R., Tillman, A., Sandén, B. A., Janssen, M., Nordelöf, A., Kushnir, D., & Molander, S. (2018). Environmental Assessment of Emerging Technologies: Recommendations for Prospective LCA. *Journal of Industrial Ecology*, *22*(6), 1286–1294. https://doi.org/10.1111/jiec.12690

Beckstrom, B. D., Wilson, M. H., Crocker, M., & Quinn, J. C. (2020). Bioplastic feedstock production from microalgae with fuel co-products: A techno-economic and life cycle impact assessment. *Algal Research*, *46*, 101769. https://doi.org/10.1016/j.algal.2019.101769

Binderbauer, P. J., Woegerbauer, M., Nagovnak, P., & Kienberger, T. (2023). The effect of “energy of scale” on the energy consumption in different industrial sectors. *Sustainable Production and Consumption*, *41*, 75–87. https://doi.org/10.1016/j.spc.2023.07.031

Bistline, J., Blanford, G., Brown, M., Burtraw, D., Domeshek, M., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Marcy, C., Mayfield, E., McFarland, J., McJeon, H., … Zhao, A. (2023). Emissions and energy impacts of the Inflation Reduction Act. *Science*, *380*(6652), 1324–1327. https://doi.org/10.1126/science.adg3781

Bistline, J. E. T., Brown, M., Domeshek, M., Marcy, C., Roy, N., Blanford, G., Burtraw, D., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Mayfield, E., McFarland, J., … Zhao, A. (2024). Power sector impacts of the Inflation Reduction Act of 2022. *Environmental Research Letters*, *19*(1), 014013. https://doi.org/10.1088/1748-9326/ad0d3b

Bixler, T. S., Houle, J., Ballestero, T., & Mo, W. (2019). A dynamic life cycle assessment of green infrastructures. *Science of The Total Environment*, *692*, 1146–1154. https://doi.org/10.1016/j.scitotenv.2019.07.345

Blanchard, B. S. (Ed.). (2014). *Systems Engineering and Analysis (5th edition)* (5th ed). Pearson.

Borah, A. R., Hazarika, P., Duarah, R., Goswami, R., & Hazarika, S. (2024). Biodegradable Electrospun Membranes for Sustainable Industrial Applications. *ACS Omega*, *9*(10), 11129–11147. https://doi.org/10.1021/acsomega.3c09564

Boulay, A.-M., Bare, J., Benini, L., Berger, M., Lathuillière, M. J., Manzardo, A., Margni, M., Motoshita, M., Núñez, M., Pastor, A. V., Ridoutt, B., Oki, T., Worbe, S., & Pfister, S. (2018). The WULCA consensus characterization model for water scarcity footprints: Assessing impacts of water consumption based on available water remaining (AWARE). *The International Journal of Life Cycle Assessment*, *23*(2), 368–378. https://doi.org/10.1007/s11367-017-1333-8

Carneiro, M. L. N. M., Pradelle, F., Braga, S. L., Gomes, M. S. P., Martins, A. R. F. A., Turkovics, F., & Pradelle, R. N. C. (2017). Potential of biofuels from algae: Comparison with fossil fuels, ethanol and biodiesel in Europe and Brazil through life cycle assessment (LCA). *Renewable and Sustainable Energy Reviews*, *73*, 632–653. https://doi.org/10.1016/j.rser.2017.01.152

Chen, P. H., & Quinn, J. C. (2021). Microalgae to biofuels through hydrothermal liquefaction: Open-source techno-economic analysis and life cycle assessment. *Applied Energy*, *289*, 116613. https://doi.org/10.1016/j.apenergy.2021.116613

Chen, Zhe. (2024, November 11). *Discussion of Algal CNF Processes* [Personal communication].

Chong, D., Wang, N., Su, S., & Li, L. (2023). Global warming impact assessment of asphalt pavement by integrating temporal aspects: A dynamic life cycle assessment perspective. *Transportation Research Part D: Transport & Environment*, *117*, N.PAG-N.PAG. Academic Search Ultimate.

Cimini, A., Borgioni, A., Passarini, E., Mancini, C., Proietti, A., Buccini, L., Stornelli, E., Schifano, E., Dinarelli, S., Mura, F., Sergi, C., Bavasso, I., Cortese, B., Passeri, D., Imperi, E., Rinaldi, T., Picano, A., & Rossi, M. (2023). Upscaling of Electrospinning Technology and the Application of Functionalized PVDF-HFP@TiO2 Electrospun Nanofibers for the Rapid Photocatalytic Deactivation of Bacteria on Advanced Face Masks. *Polymers*, *15*(23), 4586. https://doi.org/10.3390/polym15234586

Clarens, A. F., Resurreccion, E. P., White, M. A., & Colosi, L. M. (2010). Environmental Life Cycle Comparison of Algae to Other Bioenergy Feedstocks. *Environmental Science & Technology*, *44*(5), 1813–1819. https://doi.org/10.1021/es902838n

Collinge, W. O., Landis, A. E., Jones, A. K., Schaefer, L. A., & Bilec, M. M. (2013). Dynamic life cycle assessment: Framework and application to an institutional building. *The International Journal of Life Cycle Assessment*, *18*(3), 538–552. https://doi.org/10.1007/s11367-012-0528-2

Cruce, J. R., Beattie, A., Chen, P., Quiroz, D., Somers, M., Compton, S., DeRose, K., Beckstrom, B., & Quinn, J. C. (2021). Driving toward sustainable algal fuels: A harmonization of techno-economic and life cycle assessments. *Algal Research*, *54*, 102169. https://doi.org/10.1016/j.algal.2020.102169

Dębowski, M., Świca, I., Kazimierowicz, J., & Zieliński, M. (2022). Large Scale Microalgae Biofuel Technology—Development Perspectives in Light of the Barriers and Limitations. *Energies*, *16*(1), 81. https://doi.org/10.3390/en16010081

Denholm, P., Brown, P., Cole, W., Mai, T., Sergi, B., Brown, M., Jadun, P., Ho, J., Mayernik, J., McMillan, C., & Sreenath, R. (2022). *Examining Supply-Side Options to Achieve 100% Clean Electricity by 2035* (NREL/TP-6A40-81644, 1885591, MainId:82417; p. NREL/TP-6A40-81644, 1885591, MainId:82417). https://doi.org/10.2172/1885591

Donohoo-Vallett, P., Ryan, N., & Wiser, R. (2023). *On the Path to 100% Clean Electricity*. US Department of Energy.

Dyckhoff, H., & Kasah, T. (2014). Time Horizon and Dominance in Dynamic Life Cycle Assessment. *Journal of Industrial Ecology*, *18*(6), 799–808. https://doi.org/10.1111/jiec.12131

Emissions & Generation Resource Integrated Database (eGRID). (2024, September 30). U.S. Environmental Protection Agency. https://www.epa.gov/egrid

Fort Collins Weather Station Data Access. (n.d.). Colorado State University. Retrieved March 6, 2025, from https://climate.colostate.edu/~autowx/fclwx_0700.php

Gagnon, P. (2024). *Long-run Marginal Emission Rates for Electricity—Workbooks for 2023 Cambium Data* [Workbook]. National Renewable Energy Laboratory. https://data.nrel.gov/submissions/230

Gagnon, P., Brown, M., Steinberg, D., Brown, P., Awara, S., Carag, V., Cohen, S., Cole, W., Ho, J., Inskeep, S., Lee, N., Mai, T., Mowers, M., Murphy, C., & Sergi, B. (2023). 2022 Standard Scenarios Report: A U.S. Electricity Sector Outlook. *Renewable Energy*.

Gagnon, P., & Cole, W. (2022). Planning for the evolution of the electric grid with a long-run marginal emission rate. *iScience*, *25*(3), 103915. https://doi.org/10.1016/j.isci.2022.103915

Greene, J. M., Quiroz, D., Compton, S., Lammers, P. J., & Quinn, J. C. (2021). A validated thermal and biological model for predicting algal productivity in large scale outdoor cultivation systems. *Algal Research*, *54*, 102224. https://doi.org/10.1016/j.algal.2021.102224

Hammadi, Y. (2024, October 9). *Discussion of Inovenso Electrospinning Processing Data* [E-Mail].

Hong, T., Pinson, P., Wang, Y., Weron, R., Yang, D., & Zareipour, H. (2020). Energy Forecasting: A Review and Outlook. *IEEE Open Access Journal of Power and Energy*, *7*, 376–388. https://doi.org/10.1109/OAJPE.2020.3029979

Isaac, B., Taylor, R. M., & Reifsnider, K. (2021). Mechanical and Dielectric Properties of Aligned Electrospun Fibers. *Fibers*, *9*(1), 4. https://doi.org/10.3390/fib9010004

Karaduman, F. R., Türk Çulha, S., & Horzum, N. (2022). Algal nanofibers: Current status and recent developments. *Materials Today Communications*, *33*, 104248. https://doi.org/10.1016/j.mtcomm.2022.104248

Kaur, R., Patsavellas, J., Haddad, Y., & Salonitis, K. (2023). The Concept of Carbon Accounting in Manufacturing Systems and Supply Chains. *Energies*, *17*(1), 10. https://doi.org/10.3390/en17010010

Kendall, A. (2012). Time-adjusted global warming potentials for LCA and carbon footprints. *International Journal of Life Cycle Assessment*, *17*(8), 1042–1049. https://doi.org/10.1007/S11367-012-0436-5/METRICS

Khanna, V., & Bakshi, B. R. (2009). Carbon Nanofiber Polymer Composites: Evaluation of Life Cycle Energy Use. *Environmental Science & Technology*, *43*(6), 2078–2084. https://doi.org/10.1021/es802101x

Khanna, V., Bakshi, B. R., & Lee, L. J. (2008). Carbon Nanofiber Production: Life Cycle Energy Consumption and Environmental Impact. *Journal of Industrial Ecology*, *12*(3), 394–410. https://doi.org/10.1111/j.1530-9290.2008.00052.x

Kumar, D., & Singh, B. (2019). Algal biorefinery: An integrated approach for sustainable biodiesel production. *Biomass and Bioenergy*, *131*, 105398. https://doi.org/10.1016/j.biombioe.2019.105398

Levasseur, A., Lesage, P., Margni, M., Brandão, M., & Samson, R. (2012). Assessing temporary carbon sequestration and storage projects through land use, land-use change and forestry: Comparison of dynamic life cycle assessment with ton-year approaches. *Climatic Change*, *115*(3–4), 759–776. https://doi.org/10.1007/s10584-012-0473-x

Levasseur, A., Lesage, P., Margni, M., Deschênes, L., & Samson, R. (2010). Considering Time in LCA: Dynamic LCA and Its Application to Global Warming Impact Assessments. *Environmental Science & Technology*, *44*(8), 3169–3174. https://doi.org/10.1021/es9030003

Lueddeckens, S., Saling, P., & Guenther, E. (2020). Temporal issues in life cycle assessment—A systematic review. *The International Journal of Life Cycle Assessment*, *25*(8), 1385–1401. https://doi.org/10.1007/s11367-020-01757-1

Ma, D. (2024, October 22). *Sourcing Stabilization and Annealing Furnaces for nanofiber finishing processes* [Phone Interview].

Mahmud, R., Moni, S. M., High, K., & Carbajales-Dale, M. (2021). Integration of techno-economic analysis and life cycle assessment for sustainable process design – A review. *Journal of Cleaner Production*, *317*, 128247. https://doi.org/10.1016/j.jclepro.2021.128247

Malara, A. (2024). Environmental concerns on the use of the electrospinning technique for the production of polymeric micro/nanofibers. *Scientific Reports*, *14*(1), 8293. https://doi.org/10.1038/s41598-024-58936-5

Mehariya, S., Goswami, R. K., Verma, P., Lavecchia, R., & Zuorro, A. (2021). Integrated Approach for Wastewater Treatment and Biofuel Production in Microalgae Biorefineries. *Energies*, *14*(8), 2282. https://doi.org/10.3390/en14082282

Nogueira Junior, E., Kumar, M., Pankratz, S., Oyedun, A. O., & Kumar, A. (2018). Development of life cycle water footprints for the production of fuels and chemicals from algae biomass. *Water Research*, *140*, 311–322. https://doi.org/10.1016/j.watres.2018.04.046

OpenAI. (2024). *ChatGPT 4o* (Version GPT -4) [Computer software]. https://openai.com/chatgpt or https://chat.openai.com/

Osman, A. I., Mehta, N., Elgarahy, A. M., Al-Hinai, A., Al-Muhtaseb, A. H., & Rooney, D. W. (2021). Conversion of biomass to biofuels and life cycle assessment: A review. *Environmental Chemistry Letters*, *19*(6), 4075–4118. https://doi.org/10.1007/s10311-021-01273-0

Parsons, S., Allen, M. J., & Chuck, C. J. (2020). Coproducts of algae and yeast-derived single cell oils: A critical review of their role in improving biorefinery sustainability. *Bioresource Technology*, *303*, 122862. https://doi.org/10.1016/j.biortech.2020.122862

Pehnt, M. (2006). Dynamic life cycle assessment (LCA) of renewable energy technologies. *Renewable Energy*, *31*(1), 55–71. https://doi.org/10.1016/j.renene.2005.03.002

Persano, L., Camposeo, A., Tekmen, C., & Pisignano, D. (2013). Industrial Upscaling of Electrospinning and Applications of Polymer Nanofibers: A Review. *Macromolecular Materials and Engineering*, *298*(5), 504–520. https://doi.org/10.1002/mame.201200290

Quinn, J. C., & Davis, R. (2015). The potentials and challenges of algae based biofuels: A review of the techno-economic, life cycle, and resource assessment modeling. *Bioresource Technology*, *184*, 444–452. https://doi.org/10.1016/j.biortech.2014.10.075

Quiroz, D., Greene, J. M., Limb, B. J., & Quinn, J. C. (2023). Global Life Cycle and Techno-Economic Assessment of Algal-Based Biofuels. *Environmental Science & Technology*, *57*(31), 11541–11551. https://doi.org/10.1021/acs.est.3c02892

Quiroz, D., Greene, J. M., McGowen, J., & Quinn, J. C. (2021). Geographical assessment of open pond algal productivity and evaporation losses across the United States. *Algal Research*, *60*, 102483. https://doi.org/10.1016/j.algal.2021.102483

Quiroz, D., Greene, J. M., & Quinn, J. C. (2022). Regionalized Life-Cycle Water Impacts of Microalgal-Based Biofuels in the United States. *Environmental Science & Technology*, *56*(22), 16400–16409. https://doi.org/10.1021/acs.est.2c05552

Rosse Caldas, L., Bernstad Saraiva, A., Andreola, V. M., & Dias Toledo Filho, R. (2020). Bamboo bio-concrete as an alternative for buildings' climate change mitigation and adaptation. *Construction and Building Materials*, *263*, 120652. https://doi.org/10.1016/j.conbuildmat.2020.120652

Rossi, V., Cleeve-Edwards, N., Lundquist, L., Schenker, U., Dubois, C., Humbert, S., & Jolliet, O. (2015). Life cycle assessment of end-of-life options for two biodegradable packaging materials: Sound application of the European waste hierarchy. *Journal of Cleaner Production*, *86*, 132–145. https://doi.org/10.1016/j.jclepro.2014.08.049

Sacchi, R., Terlouw, T., Siala, K., Dirnaichner, A., Bauer, C., Cox, B., Mutel, C., Daioglou, V., & Luderer, G. (2022). PRospective EnvironMental Impact asSEment (premise): A streamlined approach to producing databases for prospective life cycle assessment using integrated assessment models. *Renewable and Sustainable Energy Reviews*, *160*. https://doi.org/10.1016/j.rser.2022.112311

Shen, W., Ao, F., Ge, X., Ning, Y., Wang, L., Ren, H., & Fan, G. (2022). *Effects of solvents on electrospun fibers and the biological application of different hydrophilic electrospun mats*. *30*. https://doi.org/10.1016/j.mtcomm.2021.103093

Sohn, J., Kalbar, P., Goldstein, B., & Birkved, M. (2020). Defining Temporally Dynamic Life Cycle Assessment: A Review. *Integrated Environmental Assessment and Management*, *16*(3), 314–323. https://doi.org/10.1002/ieam.4235

Su, S., Ju, J., Ding, Y., Yuan, J., & Cui, P. (2022). A Comprehensive Dynamic Life Cycle Assessment Model: Considering Temporally and Spatially Dependent Variations. *International Journal of Environmental Research and Public Health*, *19*(21), 14000. https://doi.org/10.3390/ijerph192114000

Su, S., Li, X., Zhu, C., Lu, Y., & Lee, H. W. (2021). Dynamic Life Cycle Assessment: A Review of Research for Temporal Variations in Life Cycle Assessment Studies. *Environmental Engineering Science*, *38*(11), 1013–1026. https://doi.org/10.1089/ees.2021.0052

Su, S., Li, X., & Zhu, Y. (2019). Dynamic assessment elements and their prospective solutions in dynamic life cycle assessment of buildings. *Building and Environment*, *158*, 248–259. https://doi.org/10.1016/j.buildenv.2019.05.008

Su, S., Li, X., Zhu, Y., & Lin, B. (2017). Dynamic LCA framework for environmental impact assessment of buildings. *Energy and Buildings*, *149*, 310–320. https://doi.org/10.1016/j.enbuild.2017.05.042

Subhadra, B. G., & Edwards, M. (2011). Coproduct market analysis and water footprint of simulated commercial algal biorefineries. *Applied Energy*, *88*(10), 3515–3523. https://doi.org/10.1016/j.apenergy.2010.12.051

Teymouri, A., Haji Hossein, A., Khoshnazar, R., & Guzmán, H. J. (2024). A review on carbon nanofiber production and application in cementitious mixtures. *Journal of Building Engineering*, *84*, 108519. https://doi.org/10.1016/j.jobe.2024.108519

Thomassen, G., Van Dael, M., Van Passel, S., & You, F. (2019). How to assess the potential of emerging green technologies? Towards a prospective environmental and techno-economic assessment framework. *Green Chemistry*, *21*(18), 4868–4886. https://doi.org/10.1039/c9gc02223f

U.S. Department of State. (2021). *The long-term strategy of the United States*.

U.S. Energy Information Administration. (2024, February 26). *Global natural gas markets expected to be tighter this winter*. Today In Energy. https://www.eia.gov/todayinenergy/detail.php?id=63804

U.S. Environmental Protection Agency. (2024). *2022 eGRID Data*. https://www.epa.gov/egrid/download-data

Van Vuuren, D. P., Stehfest, E., Gernaat, D. E. H. J., Doelman, J. C., Van Den Berg, M., Harmsen, M., De Boer, H. S., Bouwman, L. F., Daioglou, V., Edelenbosch, O. Y., Girod, B., Kram, T., Lassaletta, L., Lucas, P. L., Van Meijl, H., Müller, C., Van Ruijven, B. J., Van Der Sluis, S., & Tabeau, A. (2017). Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. *Global Environmental Change*, *42*, 237–250. https://doi.org/10.1016/j.gloenvcha.2016.05.008

Wang, L., Liu, J., Zhao, Q., Wei, W., & Sun, Y. (2016). Comparative study of wastewater treatment and nutrient recycle via activated sludge, microalgae and combination systems. *Bioresource Technology*, *211*, 1–5. https://doi.org/10.1016/j.biortech.2016.03.048

Wang, T., He, X., Gong, W., Kou, Z., Yao, Y., Fulbright, S., Reardon, K. F., & Fan, M. (2022). Three-dimensional, heteroatom-enriched, porous carbon nanofiber flexible paper for free-standing supercapacitor electrode materials derived from microalgae oil. *Fuel Processing Technology*, *225*, 107055. https://doi.org/10.1016/j.fuproc.2021.107055

Western Electricity Coordinating Council. (n.d.). *2024 State of the interconnection*. Western Electricity Coordinating Council. Retrieved December 3, 2024, from https://feature.wecc.org/soti/index.html

World Energy Outlook 2023. (n.d.).

Xie, Z., Huang, E., Garg, S., Hwang, S., Liu, P., & Chen, J. G. (2024). CO2 fixation into carbon nanofibres using electrochemical–thermochemical tandem catalysis. *Nature Catalysis*, *7*(1), 98–109. https://doi.org/10.1038/s41929-023-01085-1

Xue, D. (n.d.). *Strategies for mitigating the global energy and carbon impact of artificial intelligence*.

Yearout, R. (2025, February 1). *Solvent Recovery Systems Meeting* [Personal communication].

APPENDIX

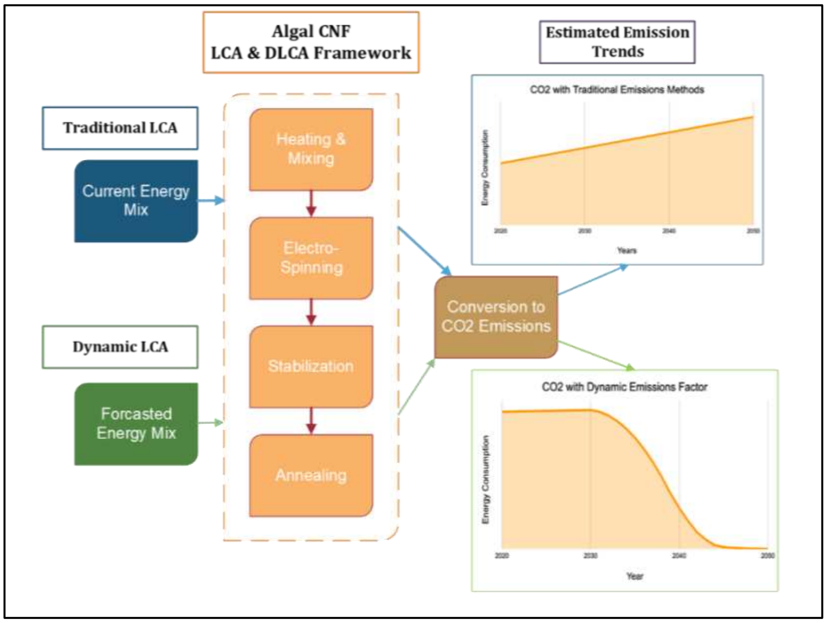


Figure 12 - ACNF LCA & DLCA Frameworks

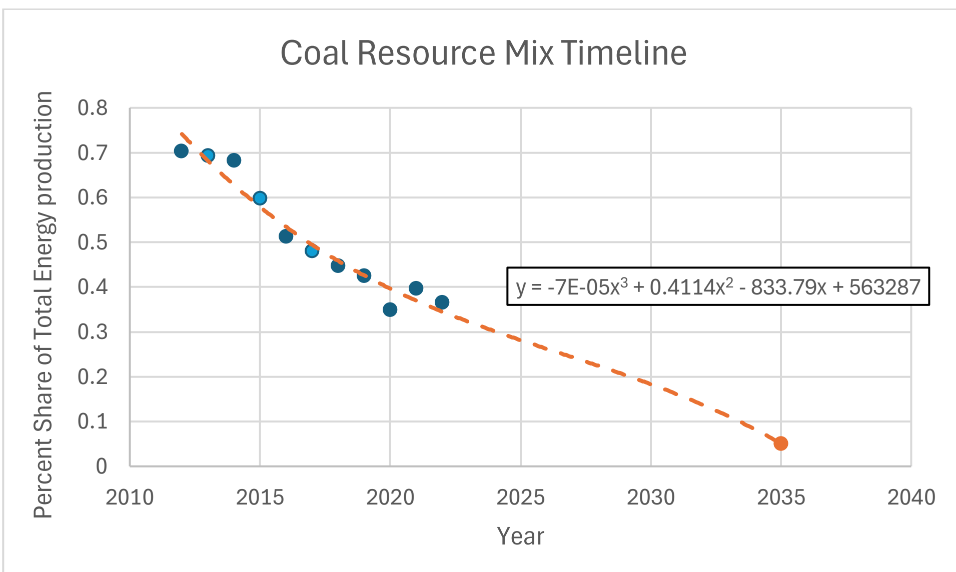


Figure 13 - Future resource mix development method

Table 5 - Dynamic emission factors (kg/kWh) in each timeline

Year	Historical	2035 - Mid Case	2035 - Low Invest	2050 - Mid Case	2050 - Low Invest	Static
2012	0.787394583					0.4880834
^2013	0.775584685					0.4880834
2014	0.763774787					0.4880834
^2015	0.690189524					0.4880834
2016	0.616604261					0.4880834
^2017	0.596957855					0.4880834
2018	0.577311449					0.4880834
2019	0.56005852					0.4880834
2020	0.495588781					0.4880834
2021	0.515167772					0.4880834
2022	0.488083369					0.4880834
2023		0.482190663	0.46481586	0.489585707	0.483351879	0.4880834
2024		0.459909041	0.446255893	0.470505596	0.468946971	0.4880834
2025		0.437803499	0.428956401	0.45170256	0.455972074	0.4880834
2026		0.415878862	0.413005471	0.433202713	0.444384812	0.4880834
2027		0.394149174	0.398480103	0.415025774	0.434118333	0.4880834
2028		0.372641222	0.385446203	0.397186029	0.425085841	0.4880834
2029		0.351400197	0.373958591	0.3796933	0.41718459	0.4880834
2030		0.330498149	0.364060996	0.362553901	0.410299358	0.4880834
2031		0.310046349	0.355786058	0.345771608	0.404305403	0.4880834
2032		0.290213145	0.349155326	0.329348654	0.399070886	0.4880834
2033		0.271249763	0.344179262	0.313286768	0.39445877	0.4880834
2034		0.253527638	0.340857235	0.297588283	0.390328201	0.4880834
2035		0.237591872	0.339177526	0.282257366	0.38653536	0.4880834
2036				0.267301399	0.382933788	0.4880834
2037				0.252732588	0.37937419	0.4880834
2038				0.238569849	0.375703717	0.4880834
2039				0.2248411	0.371764717	0.4880834
2040				0.211586044	0.367392963	0.4880834
2041				0.198859624	0.362415364	0.4880834
2042				0.18673633	0.356647139	0.4880834
2043				0.175315633	0.349888478	0.4880834
2044				0.16472886	0.341920671	0.4880834
2045				0.155147974	0.332501714	0.4880834
2046				0.146796812	0.321361394	0.4880834
2047				0.139965554	0.308195846	0.4880834
2048				0.135029425	0.292661582	0.4880834
2049				0.13247295	0.274369009	0.4880834
2050				0.132921551	0.252875402	0.4880834

Table 6 - CO_2 emissions per resource type with static scenario shares.

Type	Amount	Unit	2022 Share
Coal	1.0005	kg/kWh	0.366
Solar	0.0430	kg/kWh	0.035
Wind	0.0110	kg/kWh	0.275
Hydro	0.0210	kg/kWh	0.084
Natural Gas	0.4857	kg/kWh	0.236
Biomass	0.0520	kg/kWh	0.002
Oil	0.8395	kg/kWh	0.0004
Other - Petroleum	1.0794	kg/kWh	0.0008

Other - Battery Storage	0.0329	kg/kWh	0.0008
Static Emission Factor	0.4881	kg/kWh	1

ENERGY TOTALS			
Energy	14,738.03	kWh	
GWP (kg)	7,193.39	kg C02e	
GWP (tons)	7.19	tons CO2e	
Consumption per unit	0.01	kWh/m2 CNF	.5 g/m^2
ES - Consumption per unit	36,525.48	cm^2 / watt	Industrial
ES - Consumption per unit	5.70	cm^2/watt	Lab

SOLVENT CAPTURE EXPLORATION			
Energy	16,370.03	kWh	Daily
Emissions	9,583.04	kg CO2	Daily
Annual DMF before	8,158,823.53	liters	3X Reuse
Annual DMF after	2,719,607.84	liters	3X Reuse

MATERIAL IMPACTS			
N2 Gas	8640	liters	
	4.302542594	kg CO2	
DMF Solvent	22,352.94	liters	
	54,632.84	kg CO2	
PAN	1,510.33	liters	
	4,676.43	kg CO2	

WATER CONSUMPTION			
PAN Production	17,851.05	kg H2O	
CNF Production	131,473,478.44	kg H2O	

Figure 14 - ACNF process model results overview.

EQUIPMENT LIST			
Equipment	**Phase**	**Version**	**Source/note**
"industrial heated tank with mixer"	Dope Solution	GPT Estimate	
Inovenso Stream Spinners	Electro Spinning	Inovenso SS-1600	Continuous Operation
Stabilization Zones	Stabilization	HSA7009-1007ZN Belt Furnace	Stabilization
Annealing Belt Furnace	Annealing		HSA7009-1007ZN Belt Furnace
Solvent Recycling Unit - Solvent Was	Electrospinning	Model SW 55	Brochure PDF

ELECTROSPINNING COMPONENT BREAKDOWN			
Component	**Price**	**Power Rating**	**Efficiency**
HIGH VOLTAGE POWER:SL80P10/11	4075	130W	75%
Roller Motor	1200		
Dehumidifier	2000	1.5-5kW	1.5 - 2.5 L/kWh
Parts Total Cost	7275		
Housing and Assembly (30%)	2182.5		
Final Machine Cost Estimate	9457.5		

Figure 15 - ACNF production equipment list with electrospinning primary component breakdown.

Figure 16 - Laboratory scale ACNF production sample

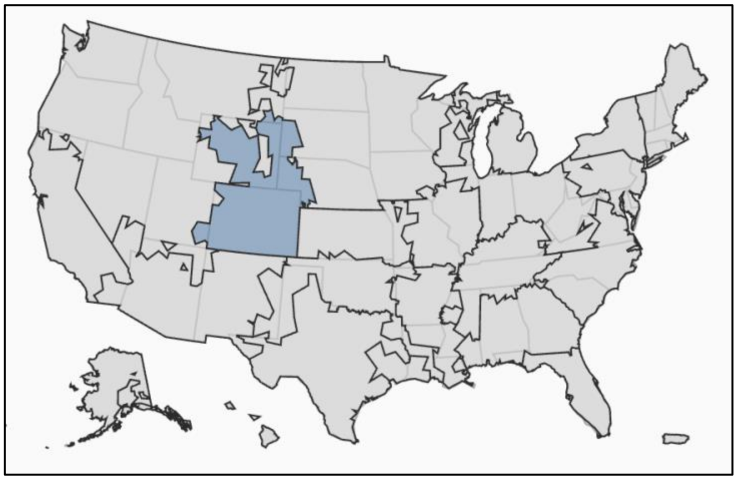


Figure 17 - Rocky Mountain Power Area sub-grid (US-EPA)

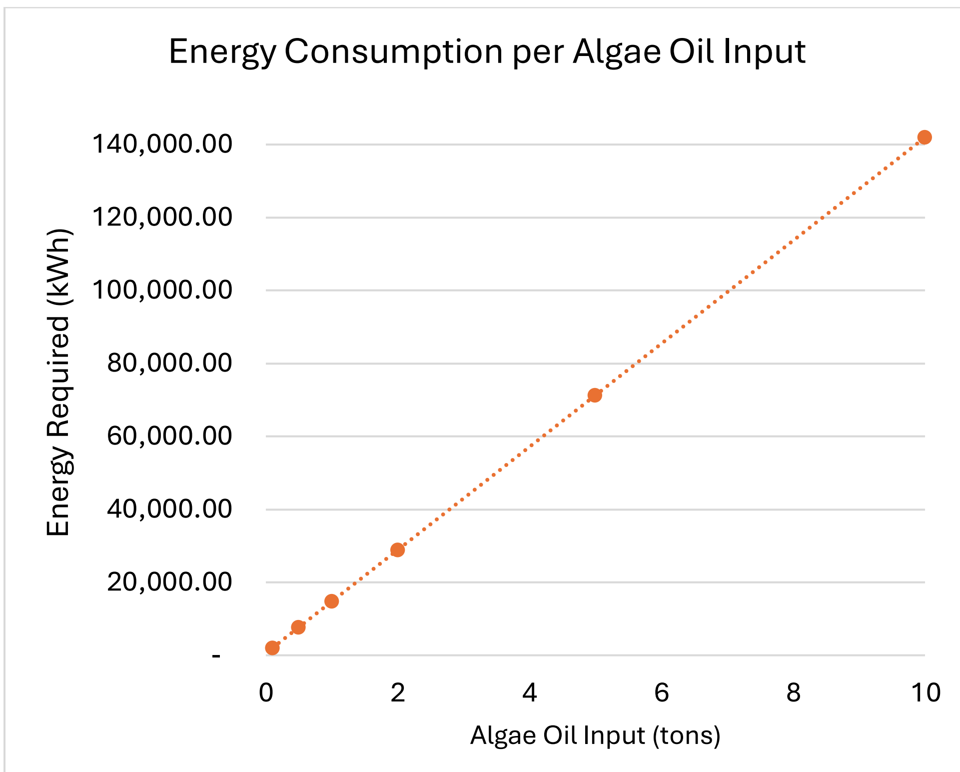


Figure 18 - Energy consumption per algae oil input

LIST OF ABBREVIATIONS

ACNF – Algal carbon nanofiber

AWARE – Available Water Remaining

CNF - Carbon nanofibers

DLCA – Dynamic life cycle assessment

DMF - Dimethylformamide

DNF – Dynamic normalization factor

EPA – Environmental protection agency

GHG – Greenhouse gas

GWP – Global warming potential

LCA – Life cycle assessment

PAN - Polyacrylonitrile

RMPA – Rocky Mountain Power Administration

WECC – Western Electricity Coordinating Council

WSCC – Western Systems Coordinating Council