Energy System Roadmap for Carbon Neutrality via Production Scheduling in Manufacturing

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Samuel Cuauhtli-Ollin Trevino Martinez

May 2022

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This PhD is dedicated to my family, booie and friends. This amazing journey wouldn't have been the same without their support. Thirty-years ago I first heard of what a PhD was, at the time it seemed something remote and out of reach, but thanks to my uncle, Dr. Miguel Martinez, he became an inspiration and a cornerstone along the way. Thank you.

Acknowledgments

This PhD degree was supported by Mexico's Consejo Nacional de Tecnologia y Ciencia (National Council of Science and Technology) through the Ministry of Energy. Special thanks to my advisor Dr. Rapinder Sawhney, for his support and advice to conduct research and education at the University of Tennessee-Knoxville. To the team at the Center for Advanced Research and Education (CASRE). Collaborating in diverse projects at CASRE shaped my career in unimaginable ways and led me to fulfilling opportunities and everlasting connections. Thanks to my committee members: Dr. John Kobza, Dr. Hugh Medal, Dr. Charles Sims, and the people behind this work that one way or another encouraged me along the way: Dr. Oleg Shylo, Dr. Lee Riedinger, Dr. Rodney Kizito, Bobbie Nettle, Phillip Scruggs, and Maximiliano Ferrari.

Abstract

Under the panorama of increasing energy costs and environmental policies, driven by global warming concerns, this research is aimed at creating an energy optimal production schedule model to minimize energy costs and reduce carbon footprint emissions. The proposed model is built under the context of a sequence-dependent single machine scheduling problem. Moreover, the scheduling decisions are assumed to be affected by independent time of use electricity prices and carbon footprint environmental policies forced by either corporate or governmental institutions. To this end, a multi-objective Energy-Carbon Aware Sequence Dependent Job Scheduling optimization model is developed under a Mixed Integer Linear Programming formulation. The value of the model when compared to classical scheduling optimization approaches and job scheduling heuristics. Results show that energy-carbon aware scheduling models have a conflicting nature with production performance metrics (e.g. completion time). However, by leveraging on energy policies, such as net metering which incentivizes on-site power generation, carbon-neutrality is achieved without compromising production performance. These results are further examined under different net-metering compensation structures and dynamics of solar photovoltaic systems with and without energy storage systems. Their cost-savings are contrasted with a baseline scenario of power consumption only from the grid. Research directions and proposed roadmap to energy-carbon neutrality are finally discussed.

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Chapter 1

Introduction

1.1 Overview

The manufacturing industry sector is a key pillar of economic growth for any country in the world. Particularly, it is one of the most important and dynamic sectors in the United States. It accounts for a gross output equivalent to 35.4% of U.S. GDP, 87.5% share of total goods exports, supports more than 12.5 million jobs or 8.7% of the total U.S. workforce [1] [2], and is responsible for producing 18.2% of the world's goods. The growth and outlook of manufacturing remains positive and is expected to continue this trend in the near future. After a disruptive 2020 headwinds, employers are anticipating growth in the manufacturing sector amid a surge in demand and mass customization. The McKinsey Global Institute finds that the United States manufacturing GDP could climb its value to $3 trillion by 2025 – a boost of 20% above the current trend [3]. Given the importance of manufacturing to the general economy, positioning the manufacturing sector to compete in the future is essential to capture these opportunities.

The above outlook and growth of manufacturing will certainly increase the global demand for energy. Considering that energy is an indispensable resource to power equipment, assets, services and processes which are necessary to make products, enterprises carry both financial and environmental pressures related to energy consumption and its associated carbon emissions - specially in energy-intensive industries. Thus, advancements in optimal energy consumption efficiency and carbon footprint mitigation are crucial for manufacturing systems to remain competitive. Understanding how energy is utilized and accessed by manufacturing processes is an important step towards the development of energy-carbon aware production models.

1.1.1 Energy in manufacturing

In manufacturing, machine tools are the basic energy consumption devices [4]. Machine drives, pumps, and fans, which are primarily powered by electric motors, account for about half of the manufacturing sector's delivered electricity use and 8% of the sector's total fuel consumption. Their wide use across many industries results in a substantial impact on the demand placed on power grids.

The level of electricity use in manufacturing or other activities has broader implications for total energy use. It takes three units of primary energy (from fuels such as coal, nuclear, and natural gas) to generate one unit of electricity, meaning that increased electricity use has a disproportionate effect on the amount of total primary energy required to support site-level energy use.

Electricity powers about 89% of motors in manufacturing [5]. Electric motors are used in a wide variety of materials handling and materials processing operations. One of the most energy-intensive and heavily used process in manufacturing systems for the production of plastic parts is injection molding. In this process, electricity is used to power motors to inject liquefied polymer at high pressure into a mold cavity. The polymer takes the shape of the cavity and is cooled. The resulting part is ejected from the mold cavity, and the molding machine is reset for the next injection cycle. These processes require significant power supply, and can consume large amount of energy in the ranges of 50-150 kWh depending on the type of material and production quantity [6].

In general, machine drives account for an average of close to 10% of delivered energy use in manufacturing. In some industries, such as textiles and plastics and rubber, this share can approach 25%, Figure 1.1. On the other hand, machine drives used in more energy-intensive industries, such as petroleum and coal products, food products, and chemicals, tend to account for a smaller share of energy use within that industry because of the significant amounts of energy needed for other parts of the manufacturing process. However, the use of machine drives in energy-intensive manufacturing processes accounts for about 70% of total manufacturing electric motor energy consumption.

The indirect emissions caused by machine tools using electricity can not be neglected. [7] pointed out that the indirect CO2 emissions of a numerical control machine tool with main shaft power in 22 kW operating one year was equivalent to the emissions of 61 SUV cars. Also, machine tools have been regarded as one of the regulatory priority categories in the European Union's Eco-design Directive [8]. That puts the pressure on manufacturer in meeting the eco-design targets and carbon emission policies in their operations.

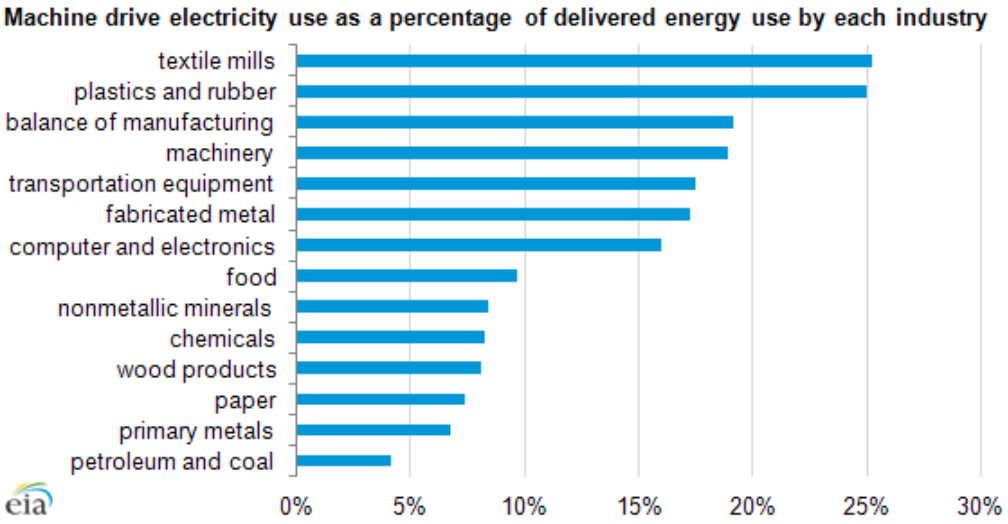


Figure 1.1: Electricity use by machine drives in manufacturing
Source: U.S. Energy Information Administration. https://www.eia.gov

1.1.2 The electric grid

Understanding the flow of electricity in energy markets to which manufacturers have access, provides pertinent information on the structure, relationships and dynamics that propel electricity costs and its associated carbon footprint. In its general form, shown in Figure 1.2, the supply of electricity in the power industry is mostly comprised by generation, transmission, distribution, and customer demand – commonly known as the *load*.

Electricity generated at power plants is transmitted through a complex network of electricity substations, power lines, and distribution transformers before it can reach consumers. In the United States, this power system – the grid – comprises 7,700 power plants, 3,300 utilities, and over 2.7 million miles of power lines which connect more than 145 million customers. At the highest level, three separate self-contained interconnections of power production and transmission constitute the U.S. grid. These are the Eastern, Western, and Texas interconnections, see Figure 1.3.

- The Eastern Interconnection covers the area east of the Rocky Mountains and a portion of northern Texas, and consists of 36 balancing authorities.
- The Western Interconnection encompasses the area to the west of the Rockies and consists of 37 balancing authorities.
- The Electric Reliability Council of Texas (ERCOT) supplies most of Texas and consists of a single balancing authority.

These interconnections delineate the physical system of the grid. The actual operation of the electric system is managed by entities called balancing authorities. Many of these balancing authorities are electric utilities that belong to important organizations such as the Regional Transmission Organizations (RTOs) and Independent System Operators (ISOs) with the responsibility of electric energy reliability across specific portions of the power grid, meaning that they ensure that sufficient supply of electricity is available to serve the expected demand in real time. Such balance is critical to maintain the safe and reliable operation of the grid; if demand and supply fall out of balance, blackouts can result and cause severe damage to the components of the grid.

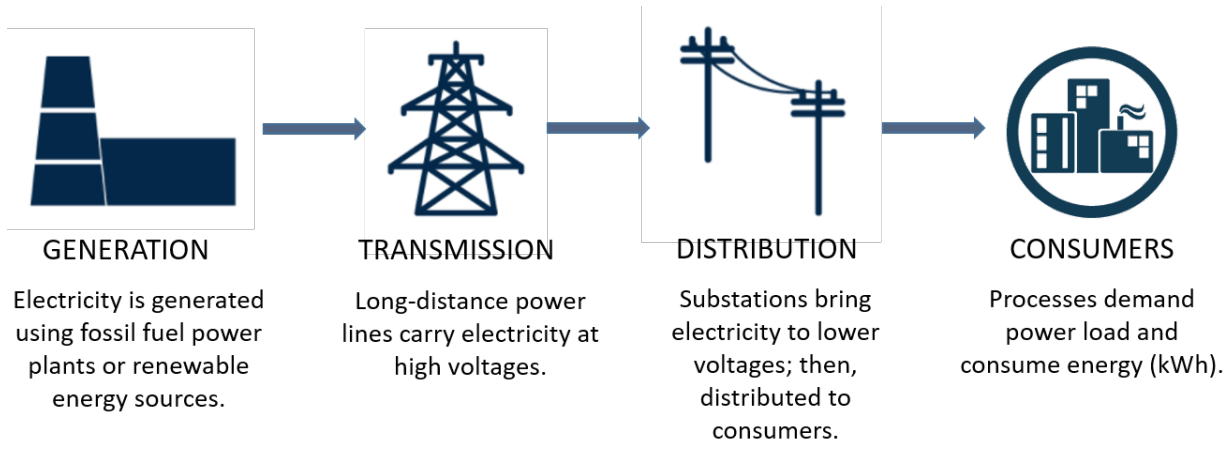


Figure 1.2: The electric grid

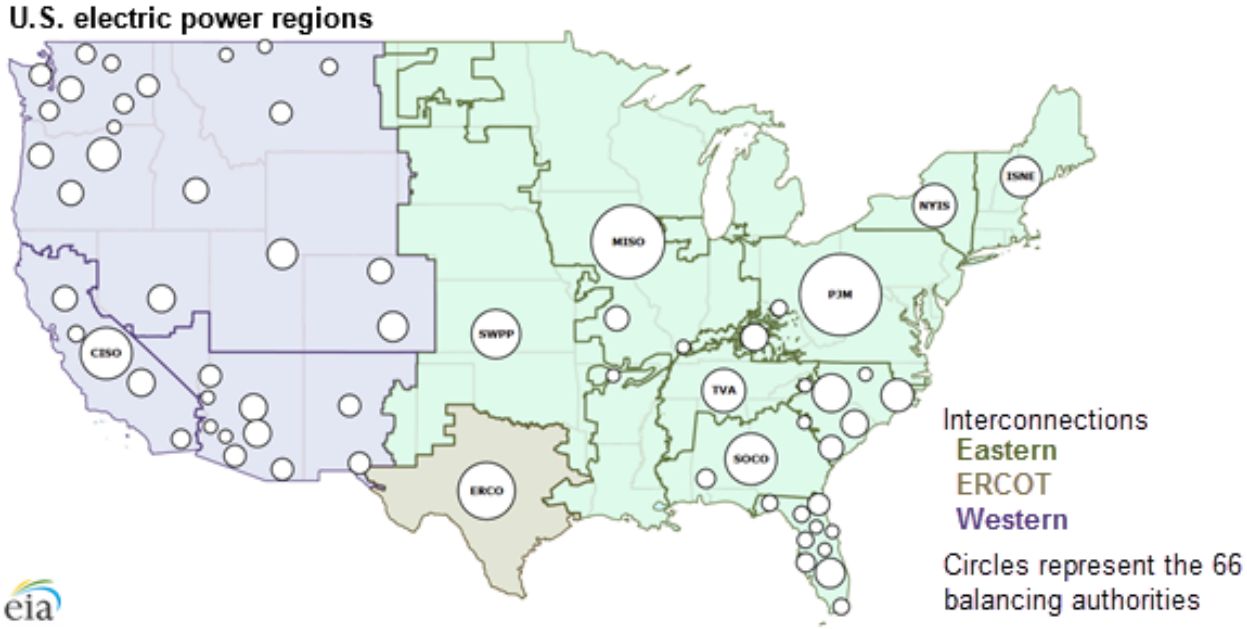


Figure 1.3: U.S. Electric System.
Source: U.S. Energy Information Administration. https://www.eia.gov

It is noteworthy to mention that regions belonging to RTOs and ISOs operate in a wholesale electric market giving consumers access to advancements in smart grid technologies making energy transmission more efficient, sustainable and cost effective. In the U.S., two thirds of the national load is served by RTO/ISO regions.

The network structure of the interconnections, under mandatory reliability standards issued by the North American Electric Reliability Corporation (NERC) and approved by the U.S. Federal Energy Regulatory Commission (FERC), helps maintain the reliability of the power system by providing multiple routes for power to flow and by allowing generators to supply electricity to many load centers.

To attain the above, electricity grids are highly dependant on fossil fuels to provide a base load. In the U.S., the electricity generation mix is mainly composed of 60% fossil fuels – primarily coal and natural gas –, 20% nuclear, and 20% renewables [9]. Moreover, Time-of-use (TOU) tariffs have emerged as one of the most common approaches adopted by utility companies to achieve more efficient and effective demand management.

Contingent on the utility power generation provider and the electric system operator in the U.S., consumers may pay a different rate during the day depending on how much it costs to generate power, this is known as time of use (TOU) electricity tariffs, Figure 3. For example, west coast utilities, i.e. PG&E, offer a 4-TOU rate plans: Peak, Partial peak, Off-peak, and Super off-peak [10]. Whereas, other utilities in the east, i.e. TVA [11], may offer only two rates in TOU plans. Compared to flat electricity rates, TOU tariffs provide users with an opportunity to cut costs by shifting their consumption to hours with lower rates. However, such shifts may increase carbon footprint for regions that use fossil-based fuel generation to meet the base load electricity of their grid. A snapshot on how each state in the U.S. generates power is shown in Figure 1.4.

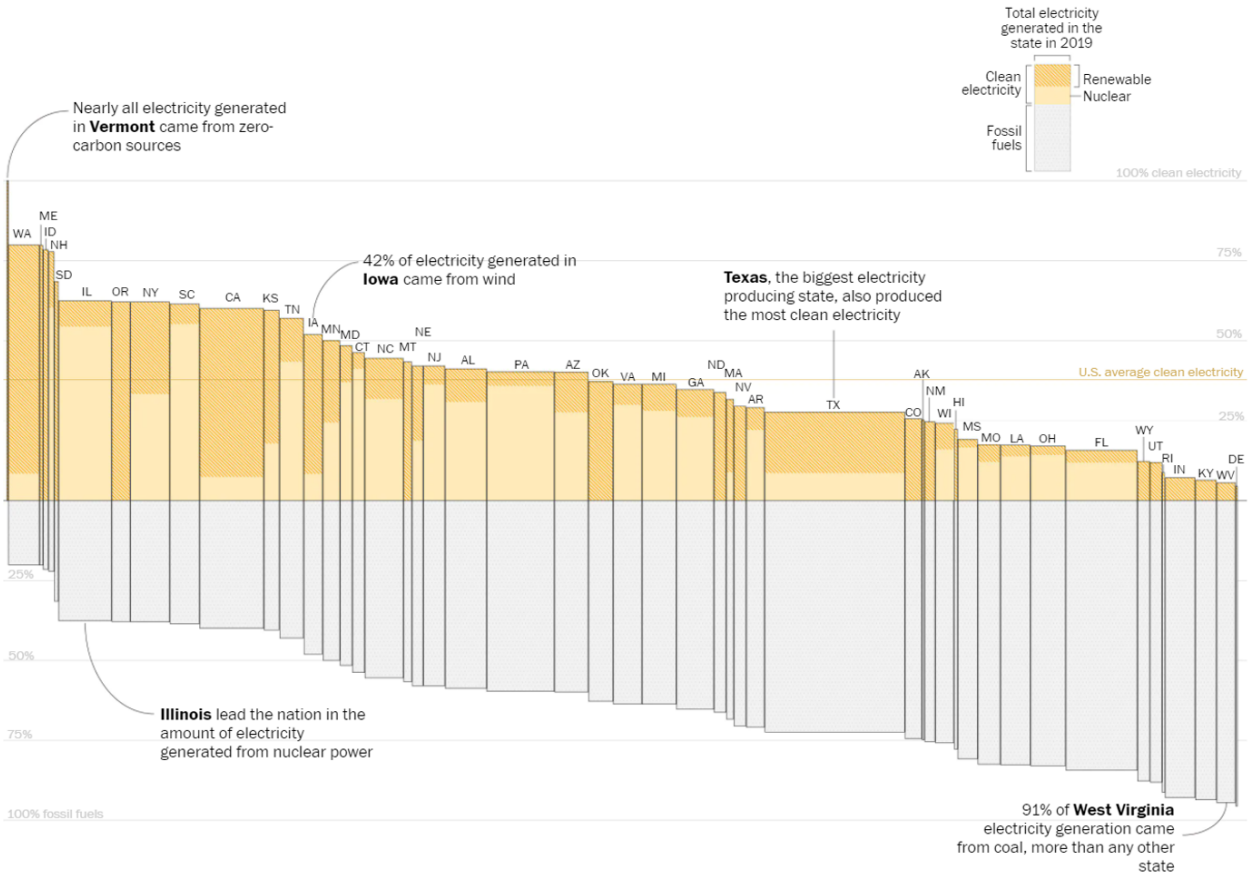


Figure 1.4: Power generation by state in 2019.
Source: Muyskens, J., Eilperin, J. (July 30, 2020). Biden calls for 100 percent clean electricity by 2035. Here's how far we have to go. *The Washington Post*. https://www.washingtonpost.com/climate-environment/2020/07/30/biden-calls-100-percent-clean-electricity-by-2035-heres-how-far-we-have-go/

1.2 Motivation

1.2.1 Energy consumption and climate change

In view that the manufacturing sector accounts for almost a third of the total electricity consumption, and that electricity is mostly generated through conventional fossil fuel power plants in the U.S., two things come to light. First, with the increase of energy prices as a result of the ever increasing fuel prices [12] and growth outlook in energy demand, energy-aware production models become relevant for the manufacturing industry since energy consumption represents a significant amount of energy costs to power operations in energy-intensive industries. As an example, the manufacturing industry in the U.S. has spent more than $80 billion on fuel and electricity annually, of which about $4 billion corresponded to energy expenditures in the automotive industry [13].

Second, the manufacturing sector is accountable for 24% of the global CO_2 emissions and a main contributor to one of the world's public problems, climate change [14]. Climate change resulting from anthropogenic direct or indirect CO_2 emissions [15] – also known as carbon footprint –, can contribute to climate hazards [16], resulting in interrupted production, raise of costs and prices, and lost corporate revenues and profits [17]. Recently, the winter storm in Texas on February 2021, demonstrated how vulnerable supply chains are when the access to electricity is disrupted and roads become impassable [18]. It became the costliest winter storm on record with an estimated damage of $22.5 billion (2021 USD). Other climate change related events can be equally prejudicial to organizations, triggering flooding, heat stress, water food scarcity, and given current trends, they are expected to become more and more frequent. Hurricanes with the intensity to disrupt supply chains, are expected to be two to four times more frequent by 2040, and the probability of disruption in rare earth production from extreme rainfall may increase 2 to 3 times by 2030 [19].

Due to the high risks that global warming and climate change has on public health and global stability, several nations around the globe prepare sustainability roadmaps to meet the agreed Paris Agreement to limit global warming to less than $2°C$ [20]. The two largest economies in the world, the United States and China, have committed to achieve carbon neutrality by year 2050 [21], and 2060 [22], respectively.

Ultimately, these environmental policies will push for a rapid adoption of clean energy technologies and demand high energy efficient and low carbon practices in powering the economy. As a result, enterprises are facing new constraints and challenges to reduce CO_2 emissions while maximizing production profit. It is clear that measures to enhance energy efficiency in manufacturing hold great potential for reducing energy consumption and energy-related CO_2 emissions, and that these approaches will only become more relevant in the near future.

Despite that world-class manufacturing best practices (e.g. Lean Manufacturing, Six Sigma, Total Quality) have been extensively analyzed for decades, there is a lack of clear and structured research in the study of energy utilization in production systems and their environmental impacts [23] [24]. Moving forward, energy and environmental metrics need to be fully integrated into the decision making within the performance measurement system of organizations [25] to achieve the concept of Sustainable Development envisioned by the United Nations [26]. This concept is defined in what is known as the Sustainable Triangle, Figure 1.5, depicting a balance among the economic aspects of productivity, social welfare and quality of life, and the preservation of natural resources of the environment. Given the continuous growing demand for goods, the development of energy-carbon aware models that can be integrated into the operational excellence systems of enterprises is essential to establish sustainability in the manufacturing sector, and transition into carbon-neutral processes.

1.2.2 Carbon footprint profile in energy

With the expansion of renewable energy technologies, studies in support of micro-grid penetration gain momentum [27] [28] [29]. As opposed to conventional power generation, distributed energy resources (DER) technologies soothe environmental problems through: reduction in emissions, higher energy efficiencies, reduced impact to public health, and conservation of natural resources [30]. DER systems typically use renewable energy sources, including small hydro, biomass, biogas, solar power, wind power, and geothermal power, and play an important role for the electric power distribution system.

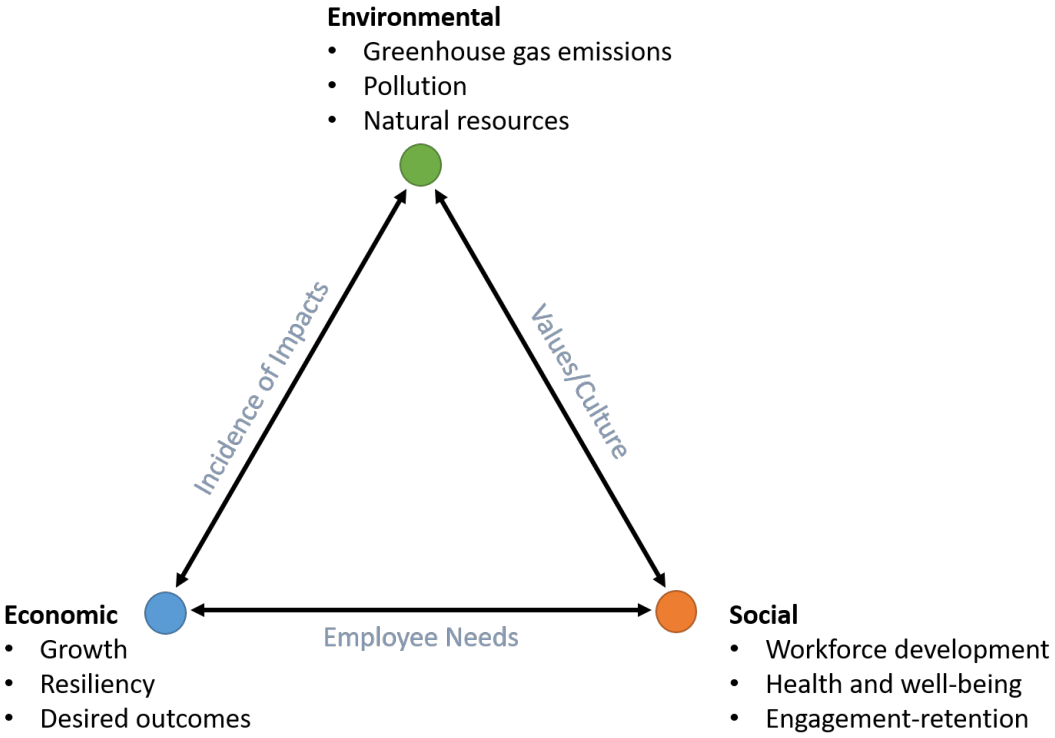


Figure 1.5: Sustainability Triangle.

Considering the above, the pathway towards carbon-neutrality in manufacturing via DER are promising. The integration of on-site renewable energy into factories from a real-time operations management perspective is a hot topic [31]. Other than sourcing from on-site renewable generation, manufacturing plants can also maximize the value of long-term electricity procurement plans through renewable energy certificates trading and power purchased from energy markets [32]. To some extent, these dynamics currently shape the way in which many of the top Fortune 500 companies realize their corporate sustainability goals [33].

The Intergovernmental Panel on Climate Change [34], and others [35], have conducted interesting assessments on life-cycle emissions equivalent per kWh for distinct electricity generation technologies. In ISO regions or utilities that integrate DER systems, the carbon footprint profile per kWh on the grid can be estimated. In the U.S., given the hourly electricity generation mix data for any regional grid and the estimates of content of equivalent CO2 in kg/kWh by source type (Table 1.1), we can obtain the content of carbon per kWh (kgCO2eq/kWh) emitted at each point in time. This is denoted as the carbon profile curve on the grid, and is a very important piece of information for production management decisions when it comes to designing carbon-aware models or energy systems that support carbon-neutrality for manufacturing processes.

1.2.3 Energy policy

The combination of climate change related events and renewable energy limitations have sparked debates in energy policy and energy regulatory frameworks around the globe (e.g. tax credits, incentives, carbon tax, cap-and-trade systems) [36] [37] [38]. As a result, these environmental regulations, mostly arising since the 2015 Paris Agreement on climate change to limit global warming to less than $2°C$ [20], in conjunction with institutional energy management standards (e.g. ISO 50001), put industry and manufacturing systems under pressure to meet sustainability targets and eco-friendly practices. For example, the approval of new companies, incentives for new investments, or prevention of opportunistic behavior decisions across eco-industrial parks are based on industrial symbiosis (IS) performance [39]. IS is an indicator related to the interchange of materials, energy, and water.

Table 1.1: Life-cycle emissions equivalent per kWh from selected electricity generation source technologies.

	Life-cycle emissions (gCO2eq / kWh)		
Technology	**Min**	**Median**	**Max**
Coal	740	820	910
Natural Gas - Combined Cycle	410	490	650
Biomass - dedicated	130	230	420
Geothermal	6.0	38	79
Hydropower	1.0	24	2200
Nuclear	3.7	12	110
Concentrated Solar Power	8.8	27	63
Solar PV - rooftop	26	41	60
Wind onshore	7.0	11	56
Wind offshore	8.0	12	35

Source: IPCC, 2014

Additional energy management performance indicators are proposed in [40]. To this end, analyses that provide insights to both policy-makers and production managers in determining whether replacing conventional manufacturing strategies with environmentally friendly ones is technically feasible and economically viable [41] are very much needed.

An interesting energy policy that could enable the adoption of renewable energy technologies to mitigate carbon emissions in the manufacturing industry, and alleviate the exposure to ever rising energy prices is in relationship to Net-Metering. Net-metering is a regulatory billing mechanism that credits renewable energy (i.e. solar and wind) system owners for the electricity they generate and give back to the grid [42]. If a system is net-metered, the electricity meter runs backwards to provide a credit when the generation exceeds consumption. Thus, customers are only billed for their "net" energy use. Although net-metering has portrayed economic and environmental benefits within residential applications [43] [44], little work has been done in demonstrating the same in the commercial and manufacturing sectors, and remains to be explored.

From a policy-maker perspective, energy policy plays an important role not only in determining how fast can we get to a carbon-free economy, but also in how these policies impact the economic competitiveness of the manufacturing sector. Analyses that provide technical feasibility and profitability in eco-friendly strategies are critical to support both environmental policy-makers and production managers. Certainly, energy policy should be geospatially-based in order to maximize the value of available clean energy resources and enhance energy security against uncertainty and inclement weather.

1.3 Approach

1.3.1 Production scheduling and energy

Life-cycle management is a pivotal part in addressing sustainability. The way in which business models and best practices are carried out determines, for the most part, the degree of energy consumption and carbon footprint of organizations. Nevertheless, while life-cycle analysis can lead to an extension in the product life-cycle and utilization of resources for

longer times, reducing demand for energy and carbon emissions [45], these solutions carry major barriers for implementation due to considerable capital expenditures, rigid business models, inflexible market preferences, and longer periods of time to restructure supply chains.

Alternatively, in production systems, key activities such as production planning and scheduling are frequent decisions that have a direct impact on the utilization of energy-intensive equipment. Without major capital investments, energy-carbon efficient solutions can emerge from production planning and scheduling optimization models [46]. The reduction and planning of idle-time in combination to the sequencing of jobs leads to a better prediction of the workflow and allow management to budget energy requirements and carbon emissions for the system. At the same time, less emissions and energy costs results in higher corporate results aligned with eco-social responsibility. It has been seen that enterprises that are more aligned to eco-social responsibility are more successful than those that are not [47]. In this regards, the development and inclusion of energy and carbon footprint indicators [40] into production scheduling objectives are key in supporting the transition to sustainable manufacturing.

Short-term production planning – or scheduling – has gained a lot of attention in the last years as an approach to address energy and carbon emissions related problems in manufacturing. With the emergence of renewables and smart grids, it is natural that the energy consumption of production processes has also become part of the operational scheduling problem, especially since the time of consumption may significantly affect the price of electricity and the amount of CO_2 content on the grid. Hence, the joint consideration of earlier isolated production scheduling problem aspects requires new ways of formulating and solving integrated problems where time-sensitive energy prices, carbon content on the grid, energy policy, and renewable technologies are considered. This an important mechanism in which manufacturing processes at developing nations can rely upon to achieve energy and sustainability targets in a short period of time at a minimum cost. The proposed framework in this dissertation falls within this approach as it addresses energy-carbon awareness in production scheduling decisions.

1.3.2 Research objectives and scope

The idea that electricity grids are increasing their distributed power generation mix portfolio [30] opens up the discussion that the content of carbon dioxide per kilowatt-hour fluctuates during the day. Consequently, at nights and early mornings the content of CO_2 per kWh is higher since power generation sources depend heavily on fossil fuel stations (i.e. coal-fired plants). Whereas during the day, when renewable energy sources are available, the content of CO_2 per KWh is lower. This creates the controversy that shifting production from on-peak hours, which occur in the middle of the day, to off-peak electricity pricing hours, early mornings and nights, may increase CO_2 emissions in regions where the grid base load is met with fossil-based power plants [48]. Minimizing electricity costs while reducing CO_2 emissions in production systems is a challenge, therefore, in alignment to this problem, the proposed PhD research work is aimed at creating an energy optimal production schedule model, integrating on-site power technologies, in order to:

1. Minimize energy costs.

2. Reduce CO_2 footprint.

A technology that can tackle the energy-carbon emissions problem in manufacturing is Mixed-Integer Linear Programming (MILP). MILP is a kind of optimization modeling approach to maximize, i.e. profit, or minimize, i.e. costs, a specific dependent function of interest (objective function) which in turn is a function of several integer-related variables subject to deterministic constraints. Considering that MILP solvers have advanced significantly in recent years and can solve faster and larger problems than before, this modeling approach will be key in the development of this dissertation in order to provide a framework to minimize energy costs and carbon footprint via production scheduling decisions.

To this end, an Energy-Carbon Neutral Sequence Dependent Job Scheduling optimization model is proposed. The proposed model is built under the context of a sequence-dependent single machine scheduling problem. How the jobs are sequenced in the process has an important influence on energy consumption [49] given the sequence-dependent setup times.

Moreover, the scheduling decisions are assumed to be affected by independent time of use electricity prices and carbon footprint environmental policies enforced by either corporate or governmental institutions. In addition, this research will seek to integrate on-site solar power decisions into the model as a mechanism to cap carbon footprint constraints.

The research objective/questions to be addressed in this study are:

a) Research objective 1: Develop an efficient mathematical model to provide optimal sequencing-scheduling decision variables in the production system that minimizes the objective of energy and carbon footprint.

b) Research objective 2: Measure the effect that energy-carbon aware scheduling strategies have on traditional production performance metrics.

c) Research objective 3: Compare the value of the proposed energy-carbon aware model to contemporary non energy-carbon aware scheduling models.

d) Research objective 4: Understand energy dispatching decisions in a carbon-neural manufacturing system that leverages on on-site solar energy and energy storage systems (ESS).

e) Research objective 5: Understand the effects of energy policies (i.e. carbon tax, net-metering regulations) in total energy costs and on-site solar power generation decisions.

1.3.3 Problem statement

This PhD research work features the single machine sequence-dependent scheduling problem. Machine scheduling is a short-term production planning task to determine the sequence of jobs allocated to machines, that is, a set of n jobs $J = \{J_j\}_{j=1}^{n}$ need to be sequenced and assigned on a set of of m machines $M = \{M_k\}_{k=1}^{m}$. Each job consists of a set of ϕ_i ordered operations $O_j = \{O_{j,g,i}\}$, where $O_{j,g,i}$ is the g-th operation of job j processed on machine i.

In addition, for each job $j \in N$ and machine $i \in M$, we are given a non-negative integer $p_{j,g,i}$, which corresponds to the processing time of $O_{j,g,i}$, and $c_{j,g,i}$ is the completion time of $O_{j,g,i}$. In a single operation or single machine production system, the aforementioned sets and variables are simplified to only $J = \{J_j\}_{j=1}^{n}$, $M = 1$, p_j, and c_j, accordingly [50] . An

important condition in the single machine problem is that N jobs are processed through one machine and there is no preemption allowed, that is, once a job starts, the machine must complete processing the job without interruption.

Sequence-dependent setup times

The study of single machine scheduling extends to include sequence-dependent setup times s_{jk} between jobs [51] [52] [53] . The graphical representation of this problem is exhibited in Figure 1.6. Based on the sequence in which jobs are processed in the machine, a sequence-dependent setup time s_{jk} applies when processing job k, $k \in N$, after having processed job j, $j \in N$.

1.3.4 Energy scope

In the integration of energy costs to the optimization model in the form of electricity costs, it is imperative to first denote the following mathematical definition of energy:

$$\textbf{Energy = Power x Time = kWh}$$

Energy is directly proportional to the rated power of the specific equipment times the duration of its utilization. The measure of electrical power of an equipment is to be measured in kilowatts (kW), and when utilized during a period of time t in the format of hours (hr), an energy consumption (kWh) in the form of electricity is incurred . Translating this definition to the sequence-dependent single machine job scheduling, the energy consumption of each job will be dependent on the specified machine power requirements ω_j when processing job j times its processing time p_j. Furthermore, the utilization of an equipment can be decomposed into four modes: ramp-up, idle, operating mode, and ramp-down. Similarly, the energy consumption relations dependant on machine mode are shown in Table 1.2.

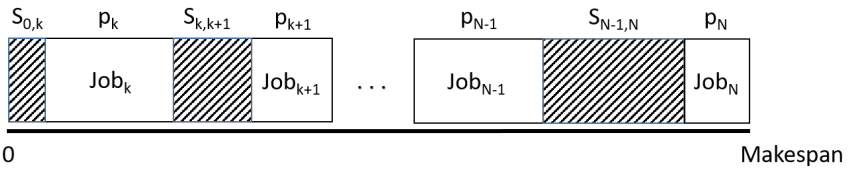


Figure 1.6: A single machine scheduling problem with sequence-dependent setup times.

Table 1.2: Machine mode parameters.

Machine mode i	**Status**	**Power requirements**	**Time length**
1	Ramp-up	ω_r	R
2	Idle	ω_i	I
3	Operating	ω_j	p_j
4	Ramp-down	ω_f	F

where: $\omega_f \leq \omega_i \leq \omega_j \leq \omega_r$.

The effectiveness of the proposed model is built on as a function of Time of Use (TOU) energy consumption and total CO_2 emissions. This is because electricity prices and emissions experience hourly variations during the day. These variables are optimized in the proposed Energy-Carbon Model, which in turn generate an optimal daily production schedule that provides not only the job sequencing and machine dispatching rules to operate the system, but also the hourly energy consumption plan and carbon footprint plan for the day. This becomes valuable information to production managers for budgeting purposes.

1.3.5 Assumptions

The described model is intended to optimally provide scheduling decisions in a production environment in which:

a) There exists a need to minimize energy and carbon footprint.

b) The process under study runs on electricity, is connected to the grid, and TOU electricity prices exist in the region.

c) Carbon footprint taxes/fees also apply and have a flat rate of \$/kgCO_2e (dollars per kilogram of carbon dioxide equivalent emissions into the atmosphere).

d) The manufacturing facility in located in a region where net-metering policy is available and has access to solar power generation.

e) The production environment is composed of a single machine or follows a TSP graphical representation of a sequence-dependent single machine job scheduling problem.

f) A set of jobs $J = \{1, ..., N\}$ can be defined as a set of batches in a manufacturing system, or a set of tasks/activities in a non-manufacturing system which must be performed.

g) All jobs $j \in N$ have deterministic processing times p_j and sequence-dependent setup times s_{jk}, and require unique power specifications ω_j from the equipment in order to be processed.

h) The set of jobs must be processed within a 24hr scheduling horizon. Under a manufacturing production planning environment, it is assumed that the Master Production Schedule of the day is feasible and enough capacity exists to finish all the jobs in a day.

i) Before the first job can be processed, a ramp-up time is needed and the equipment or process shuts-down only after the last job is completed.

j) Job preemption is not allowed, and for simplicity, ramp-down modes are neglected since the power requirement at this mode is assumed to be minimum.

Applications

The proposed model, tied with its assumptions, is envisioned to be of value and provide meaningful and insightful scheduling decisions in distinct applications and production environments where sustainability and energy costs are of relevance. In manufacturing, this applies to repetitive discrete manufacturing with energy-intensive processes, such as:

- painting-booths in the automotive industry,
- industrial furnaces used in heat treatment processes,
- drying chambers for curing processes,
- plastic injection molding machines.

Considering the sequence-dependent single machine job scheduling problem, electricity Time of Use, energy mix portfolio in the grid, and access to on-site power generation, the generalized optimization model presents insights on the impact that production and environmental policies have in the energy-carbon aware decisions of a production system. The ultimate goal is to fill the research gap between the production scheduling decisions existent in the single machine job scheduling literature and the energy management planning within manufacturing production systems.

1.3.6 Dissertation structure

This PhD dissertation has been structured in the form of three integrated papers. The work of each paper is presented as a chapter of its own in this document. Thus, chapter 2 of this documents presents the first article entitled: "Energy-Carbon Footprint in Manufacturing Systems - A Systematic Literature Network Analysis". This work illustrates the direction and distinct approaches of research associated with energy and carbon footprint in manufacturing systems. Chapter 3 presents the second article: "Energy-Carbon Footprint Optimization in Sequence-Dependent Production Scheduling". This article introduces an energy-carbon aware production scheduling model to optimize costs associated with energy and carbon footprint in a single machine.

Chapter 4, entitled: "Optimal Energy System for Energy-Carbon Neutrality in Production Scheduling via Net Metering", expands the work in Chapter 3 by presenting an optimization model that integrates on-site solar photovoltaic sizing decisions, energy storage conditions, and net metering policies, as a mechanism to achieve net zero footprint in manufacturing processes. Chapter 5 concludes this PhD dissertation and highlights its benefits to the stakeholders in the energy market. Other applications and considerations are discussed. Finally, future research directions are provided.

Chapter 2

The First Article: Energy-Carbon Footprint in Manufacturing Systems - A Systematic Literature Network Analysis

Disclosure Statement

This chapter corresponds to the manuscript "Energy-Carbon Footprint in Manufacturing Systems – A Systematic Literature Network Analysis" submitted to the *Renewable & Sustainable Energy Reviews* journal on January 09, 2022. The authors of this manuscript are: Samuel C. Trevino Martinez (main and corresponding author), and Dr. Rapinder Sawhney, both from the Department of Industrial and Systems Engineering at the University of Tennessee-Knoxville. Samuel C. Trevino Martinez was responsible for the conceptualization, methodology, software, validation, investigation, writing - original draft, and visualization of this article. Dr. Rapinder Sawhney was responsible for the supervision of the article.

2.1 Abstract

Considering a fast pacing growth in the manufacturing industry across the globe, and under the reality of high energy demand, rising energy costs, and environmental policies driven by global warming concerns, the proposed research aimed at studying the structure governed in the literature that addresses these issues in advancing towards sustainability in manufacturing. Thus, the evolution and research trends from 2003-2021 of sustainable manufacturing in relationship to energy and carbon footprint in manufacturing are presented. They were identified on the basis of scientific publications encompassed in the international Web of Science database and following the Systematic Literature Network Analysis. Through the use of semantic network maps, it was possible to observe the nonlinear development of concepts and brisk changes in thinking and conducting scientific research. Literature research results show that the direction of research in energy and carbon footprint in manufacturing is pointed towards focuses on life cycle management, production management and scheduling, renewable energy resources, and energy policy.

2.2 Introduction

Energy is an indispensable resource to power equipment, assets, services and processes which are necessary to drive economic growth. The manufacturing industry is a key pillar of economic growth accounting for a gross output equivalent to 35.4% of the U.S. Gross Domestic Product (GDP), an 87.5% share of total goods exports, and support to 8.7% of the total U.S. workforce [1] [2]. In this regards, amid a fast paced demand for energy to support different industries, the ever rising energy costs [12], and environmental policies driven by global warming concerns, advancements in energy efficiency and carbon footprint mitigation are critical for manufacturing systems to remain competitive.

Considering that most of the energy in manufacturing is supplied in the form of electricity, and that electricity is mostly generated through conventional fossil fuel power plants in the U.S. – 60% fossil fuels, 20% nuclear, and 20% renewables [9] –, two things become relevant: 1) that conventional electricity grids are vulnerable to environmental and severe

weather disasters causing energy outages and disrupting entire supply chains [54], and 2) climate change resulting from anthropogenic direct or indirect CO_2 emissions [15] – also known as carbon footprint –, can contribute to climate hazards [16], resulting in interrupted production, raise of costs and prices, and lost corporate revenues and profits [17]. Recently, the winter storm in Texas on February 2021, demonstrated how vulnerable supply chains are when the access to electricity is disrupted and roads become impassable [18]. It became the costliest winter storm on record with an estimated damage of $22.5 billion (2021 USD). Other climate change related events can be equally prejudicial to organizations, triggering flooding, heat stress, water food scarcity, and given current trends, they are expected to become more and more frequent. Hurricanes with the intensity to disrupt supply chains, are expected to be two to four times more frequent by 2040, and the probability of disruption in rare earth production from extreme rainfall may increase 2 to 3 times by 2030 [19].

Due to the high risks that global warming and climate change has on public health and global stability, several nations around the globe prepare sustainability roadmaps to meet the agreed Paris Agreement to limit global warming to less than $2°C$ [20]. The two largest economies in the world, the United States and China, have committed to achieve carbon neutrality by year 2050 [21], and 2060 [22], respectively. Ultimately, these environmental policies will push for a rapid adoption of clean energy technologies and demand high energy efficient and low carbon practices in powering the economy.

Considering the above, the concept of Sustainable Manufacturing is studied in this research. Since Sustainable Manufacturing is defined as the creation of products that use non-polluting processes, conserve energy and natural resources, and are economically viable and safe to society [55], it makes sense to understand the interaction of emissions, energy, and their related costs and risks in manufacturing systems. Therefore, the objective of this research is to depict the structure governed in the literature that addresses the issues of energy and carbon footprint existent in manufacturing that can unlock pathways towards sustainability in manufacturing, and consequently, a carbon-free economy.

In relationship to the idea under research, this work answers the following research questions:

Question 1. What has been the trend over the years?

Question 2. Which are the most influential scientific publications?

Question 3. Which researchers are the most influential?

Question 4. What has been the international contribution to scientific publications?

Question 5. What are the most popular related areas of knowledge?

Question 6. Which research centers have been torchbearers for the idea under research?

Question 7. What are the most important clusters identified in the literature and, and what has been their historical evolution over time?

This work is structured as follows. Section 2.3 describes the research methodology utilized for the literature review. Section 2.4 exhibits the results of the bibliometric analysis. Section 2.5 presents the evolution of research and discusses identified structures and research directions. Section 2.6 summarizes the findings and provides final remarks.

2.3 Research Methodology

Bibliometric analysis is a scientific computer-assisted methodology that evaluates research results through statistical methods to comprehensively capture and review scientific publications related to a given topic or concept [56]. Thus, allowing to observe the big picture in the development of science around the globe. Bibliometric analysis focuses on scientific work published by academics and practitioners. It can also be seen as a mechanism to enable the diffusion of knowledge as it is often cited by other researchers and indexed in the largest international databases.

The application and quantification of quantitative data referring to scientific publications and the use of quantitative indicators of various databases are part of bibliometric analyses. These indicators reflect the state of science around a topic [57]. Sometimes a large number of citations of the indicated scientific work can be determinant of a new idea, method, or discovery.

In order to examine the characteristics, as well as the underlying structures in science and technology, botch mathematical and statistical techniques were used in the bibliometric analysis.

The bibliometric analysis presented in this study follows the Systematic Literature Network Analysis (SNLA), which is based on a novel literature review and analysis and visualization of the bibliographic network. This allows readers to identify trends and uncover how scientific research has addressed a specific topic over time since its early conception [58]. The SNLA results would complement existing systematic literature review in the area of study, in the sense that it provides a synthesis of the dynamic development of the field, along with the set of research themes, thereby the understanding of the overall intellectual landscape over the years can be possible.

In the first phase of this study, a Systematic Literature Review (SLR) is conducted, and the scope of study is defined in three steps:

1. Scope of the analysis
2. Features selection (keywords, journals, time, type of documents, language)
3. Analysis and evaluation

The search for scientific publications was done using the Web of Science (WoS) Core Collection platform. This platform, supported by Clarivate Analytics, is a multidisciplinary research platform that provides access to multiple bibliographic databases for comprehensive coverage for over 82 million items from more than 20,000 journals, 126,000 books and 226,000 conferences proceedings records around the world [59]. WoS includes tools necessary to establish bibliometric indicators, parametric evaluation, and bibliography creation. It is one of the most used academic search engines, allowing researchers to analyze search results by authors, affiliation, country, journal/book title, citations, and broad subject categories. Compared to the Scopus database platform, WoS has a smaller overall content, however, the Natural Sciences and Engineering areas of knowledge are more represented in WoS [60]. This translates into a higher quality of data and detailed information on publications related to the scope of study of this research. Another advantage of WoS is the longer time-frame covered citations compared to Scopus. This appears to be more suitable for large-scale citation analysis, as citations are covered up to year 1900, while, in Scopus, citation coverage only extends to year 1970 [61]. Therefore, the WoS database platform was utilized in this research.

2.4 Bibliometric Analysis

Based on Figure 2.1, it can be observed that the creation of knowledge related to sustainable development continues to be widely disseminated. The very early publications on the idea of sustainable development date back as far as 1981, and has been following an exponential grow in the number of published scientific papers ever since. This is an indication that this is an important area of research and focus for the scientific community.

This growing trend requires research to systematize and rationalize the knowledge generated on the subject. For this purpose, it is ideal to reveal its evolution in time by studying the process of creating, transferring, and developing knowledge from a dynamic perspective.

Considering the above, it was decided to narrow on the subject of sustainable development to focus on the research evolution of sustainability in manufacturing over time from an energy and carbon footprint perspective. A set of keywords was selected to collect metadata from selected scientific databases. The search was conducted in June 2021 in the Web of Science database platform using the selected keywords. As an initial search, 90,946 scientific publications were found containing the keywords "Sustainable Manufacturing" in its title, abstract, or words.

Given that the manufacturing sector depends heavily on energy resources to power equipment and processes [62] and since energy has a high relationship to the concept of sustainability, a second round of search was conducted to narrow down on the keywords of "Energy" AND "Sustainable Manufacturing" to emphasize on the work done in transitioning manufacturing into an energy efficient activity. The first publication to address the importance of sustainability for companies and the awareness of high energy costs was presented in 1992 entitled *LCA - A Tool for Marketing Clean Products*. The authors present critical issues related to the application of the Life Cycle Analysis (LCA) as a tool for high-performance, quality management with a higher awareness of social and environmental responsibility.

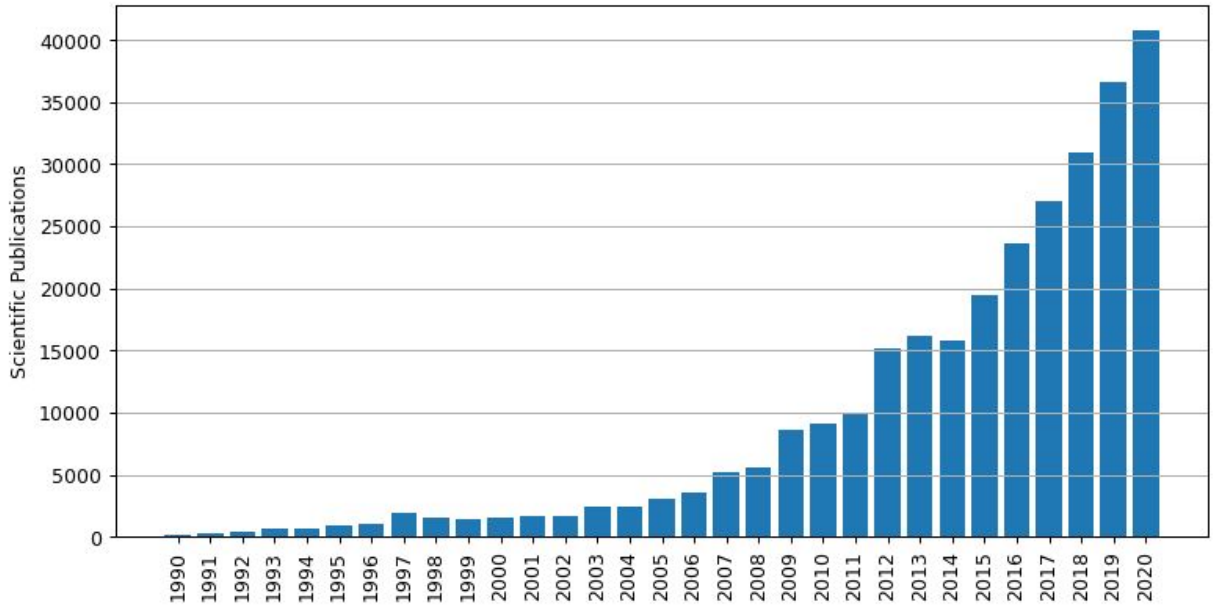


Figure 2.1: Number of Publications in the area of sustainable development from the Web of Science database.

To ensure that the main ideas of energy and carbon footprint were present in a manufacturing setting, a third and final round of narrowed search was reduced to three terms: "Energy" AND "Carbon Footprint" AND "Manufacturing". In total 848 scientific publications were published in the years 2003-2021. These results become the scope of our systematic analysis. Table 2.1 summarizes the results of the iterative searches.

As a result of the conducted activities, bibliometric dataframes were created from the latter 848 records and summarized in Table 2.2. These scientific publications comprehended 3,064 scientists for analysis. They published in 436 distinct sources - journals, conferences, and book chapters. The primary investigators identified in these records came from 69 countries and represented 980 research centers from around the world.

The journal with the largest number of published articles for the area under study is the *Journal of Cleaner Production* with a 107 record count, comprising 12.62% of all publications (Figure 2.2). The *Journal of Cleaner Production* is an international, trans-disciplinary journal focusing on Cleaner Production, Environmental, and Sustainability research and practice. *Sustainability* has been is identified as the second most important journal in publications related to the scope of this study. *Sustainability* is an international, cross-disciplinary, scholarly, peer-reviewed, and open-access journal of environmental, cultural, economic, and social sustainability. This journal has 34 records, around 4% of all publications.

We analyzed a sample of the 848 academic publications to identify the articles with high impact on the scientific community interested in energy and carbon footprint in manufacturing. The most important papers were cited more than 200 times, all of them dealing with research on "Energy" AND "Carbon Footprint" AND "Manufacturing".

Table 2.1: Initial search results.

Set of keywords	Search results
Clean Production OR Sustainable Manufacturing	90,946
Energy AND Sustainable Manufacturing	10,555
Energy AND Carbon Footprint AND Manufacturing	848

Source Own study based on WoS

Table 2.2: Scientific publications in the years 2003-2021.

Scientific publications in the years 2003-2021	
Number of records	848
Number of journals	436
Number or authors	3064
Number of countries	69
Number of scientific centers	980

Source Own study based on WoS

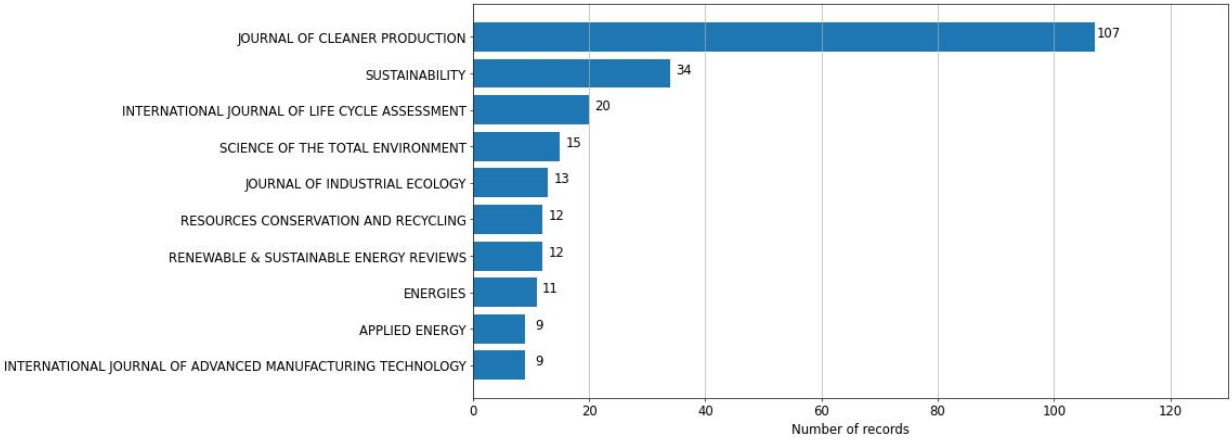


Figure 2.2: Top 10 most important scientific journals with the largest number of articles "Energy" AND "Carbon Footprint" AND "Manufacturing" .

Table 2.3 presents an overview of the ten most influential scientific papers with respect to their citation frequency in descending order. The most cited paper is titled Metal Additive Manufacturing: A Review, by Frazier, WE., published in the *Journal of Materials Engineering and Performance* in 2014. Interestingly, the concept of metal additive manufacturing has gained significant attention from the scientific community in relationship to its potential for energy and sustainability applications. It has been shown that additive manufacturing processes are a sustainable system due to their low energy consumption, minimal waste, and design optimization for weight savings in components [63]. It is noteworthy to mention that power consumption and carbon footprint reduction through scheduling optimization in manufacturing has also been a topic of interest in conjunction with the idea of renewable energy.

On the basis of the Web of Science database platform, the ranking of researchers can also be distinguished according to the number of scientific papers published by them indexed by the database. Taking into account the authors and co-authors as well as the number of their scientific publications, it should be emphasized that research into the keywords of "Energy" AND "Carbon Footprint" AND "Manufacturing" was contributed by 3,064 scientists from around the world. Due to the number of publications among researchers, attention is drawn primarily to those whose contributions as Principal Investigators (PI) include more than 4 scientific publications from the studied area (Table 2.4). They constitute 0.10% of the studied population. This results confirm the law of scientific productivity, commonly referred to as Lotka's Law – stating that a small number of researchers publish a large number of scientific papers, while most scholars only own a small number of publications.

The author with the most number of published papers identified in this study is Kucukvar, M. (Table 2.5). His work has been mostly focused on energy-climate related life-cycle analyses in global supply chains of manufacturing industries, with special interest in the food industry. He has stated that the contribution of the food industry to energy consumption and carbon footprint is considerably high compared to other manufacturing industries [64]. Other notable authors include, Egilmez, G., with related research in carbon, energy, and water footprint analysis of manufacturing, and Franchetti, M., expanding the energy footprint analysis into the healthcare and construction space.

Table 2.3: Top 10 most cited scientific papers.

Publication title	Year	Total citations
Metal Additive Manufacturing: A Review By: Frazier, WE	2014	2231
Carbon Footprint of Nations: A Global, Trade-Linked Analysis By: Hertwich, EG; Peters, GP	2009	864
Growth in emission transfers via international trade from 1990 to 2008 By: Peters, GP; Minx, JC; Weber, CL; Edenhofer, O	2011	778
Carbon dioxide equivalent (CO2-e) emissions: A comparison between geopolymer and OPC cement concrete By: Turner, LK; Collins, FG	2013	584
New technologies reduce greenhouse gas emissions from nitrogenous fertilizer in China By: Zhang, WF; Dou, ZX; He, P; Ju, XT; et al.	2013	335
A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction By: Fang, K; Uhan, N; Zhao, F; Sutherland, JW	2011	321
Carbon-Nanotube-Based Thermoelectric Materials and Devices By: Blackburn, JL; Ferguson, AJ; Cho, C; Grunlan, JC	2018	276
Integrating waste and renewable energy to reduce the carbon footprint of locally integrated energy sectors By: Perry, S; Klemes, J; Bulatov, I	2008	253
Forty years of Heat Integration: Pinch Analysis (PA) and Mathematical Programming (MP) By: Klemes, JJ; Kravanja, Z	2013	241
Global typology of urban energy use and potentials for an urbanization mitigation wedge By: Creutzig, F; Baiocchi, G; Bierkandt, R; Pichler, PP; Seto, KC	2015	216

Source Own study based on WoS

Table 2.4: Number of scientific papers published as PI.

Number of authors	Number of scientific papers published as PI
1	≥ 5
2	4
8	3
47	2
707	1

Source Own study based on WoS

Table 2.5: Authors with the higher count of publications

Author	PI	Co-author	Total count
Kucukvar, M.	8	8	16
Egilmez, G.	4	7	11
Franchetti, M.	7	0	7
Hertwich, EG.	4	3	7
Cucek, L.	3	3	6
Malmodin, J.	3	-	3
Wilson, JB.	3	-	3

Source Own study based on WoS

The most influential author in terms of total number of citations related to this study is Frazier, WE., with his work of *Metal Additive Manufacturing: A Review*, which also happened to be the most cited paper in Table 3. Next in line are academics Hertwich, EG., Peters, GP., and Turner, LK., with fascinating econometric studies around the carbon footprint of nations, emissions studies via international trade, and CO_2 analyses of materials, respectively. Table 2.6 shows the rest of the top 10 most influential authors.

Bibliometric results also show that the studied population of the 848 identified scientific publications is represented by a total of 69 countries, from which the United States, China, and the United Kingdom lead in number of publications. All-together, these three nations constitute 43.6% of the total number of publications identified in this study. These statistics indicate these countries contribute significantly and have a leadership role in the development of the studied area. Figure 2.3 shows a sample of the top countries by their number of scientific publications. The dominance of the top 3 countries becomes very evident when compared to the rest of the countries; 35 countries (roughly 50% of the countries in this study) have less than 5 publications each.

As one can imagine, the developed statistics show that the productivity, in terms of number of published articles, is primarily dominated by scientists from four leading scientific institutions (Table 2.7), which are included in the regions of the aforementioned top 3 countries. Combined, they published a total of 46 scientific papers, representing 5.42% of all published papers extracted from the studied area.

In order to compare the quality of work from these institutions, we computed for each of them a numerical weighted average based on the impact factor of the journals in which the papers were published. From this, we can visually identify that the institution with the highest quality of work per publication in the area under study is the Norwegian University of Science and Technology (NTNU), in Norway (Figure 2.4). This indicates that NTNU is a center of high quality research in the development of frameworks related to energy-carbon footprint in manufacturing, and a point of reference for any practitioner or researcher in the field. Conspicuously, the second most cited author, Hertwich, EG. (Table 2.6), conducts research at this institution.

Table 2.6: Top 10 most influential authors.

Author	Total citations as 1st author
Frazier, WE	2231
Hertwich, EG	985
Peters, GP	778
Turner, LK	584
Kucukvar, M	336
Zhang, WF	335
Fang, K	321
Onat, NC	320
Blackburn, JL	276
Perry, S	253

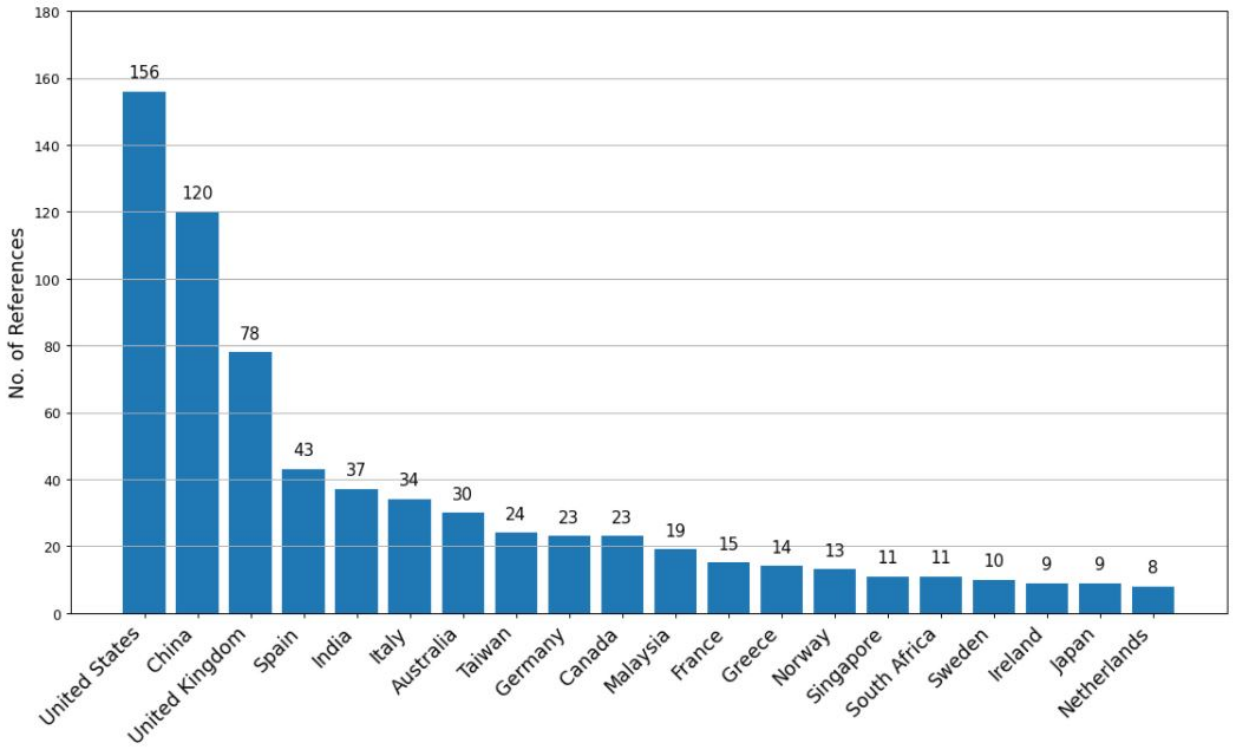


Figure 2.3: Top countries by number of scientific papers published as per first author.

Table 2.7: The most productive institutions identified in the set of scientific papers.

Organization	Record count	% of 848 (%)
Chinese Academy of Science, China	14	1.65
University of Manchester, United Kingdom	14	1.65
Norwegian University of Science Tech., Norway	12	1.42
University of Central Florida, USA	10	1.18

Source Own study based on WoS

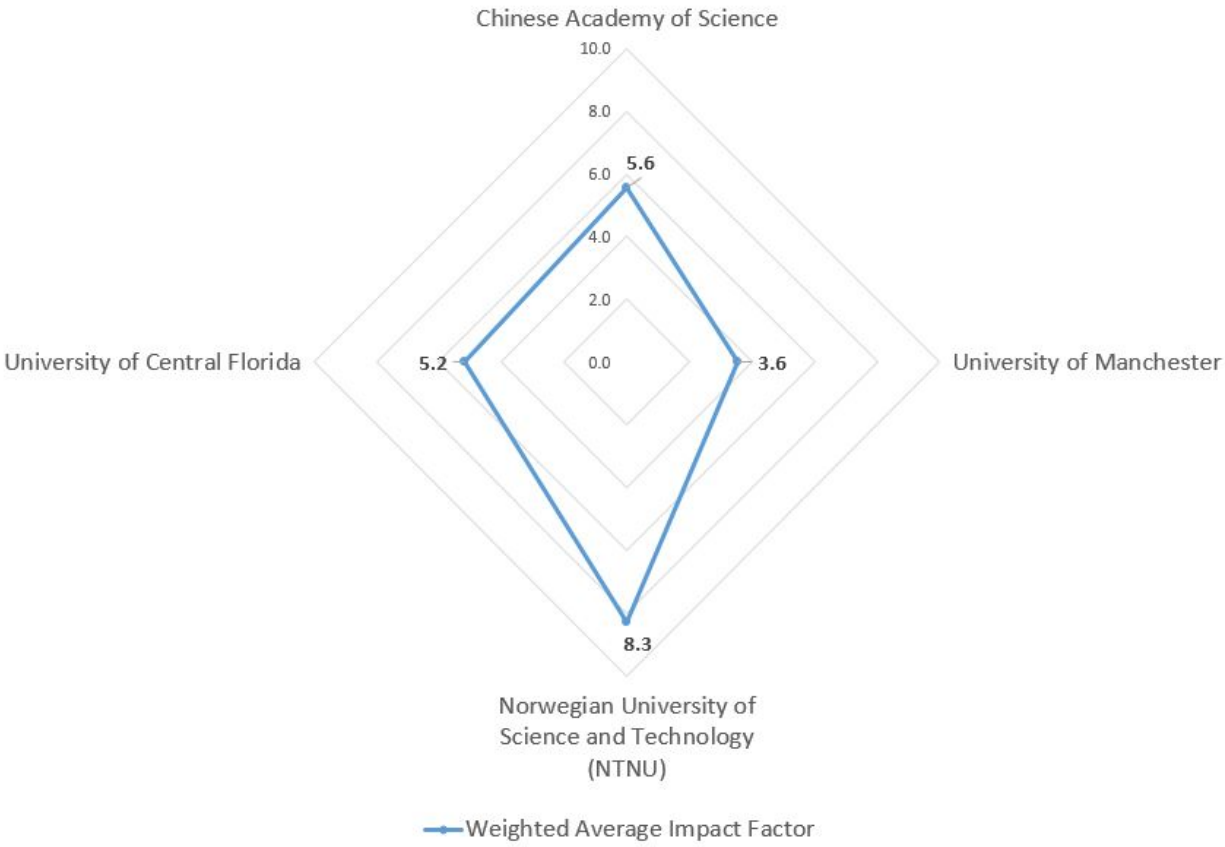


Figure 2.4: Comparison of top research institutions by weighted average impact factor per publication

The Web of Science database provided details into the areas of knowledge for the identified scientific papers. A total of 78 areas of knowledge are related to this study. Naturally, given the focus of this study, the most prominent area of knowledge is within the field of Environmental Sciences, followed by Green Sustainable Science & Technology and Environmental Engineering. As it can be seen in Table 2.8, the most popular areas connected to this research are in the disciplines of Engineering, from what it can be concluded the challenges associated with energy and carbon footprint in manufacturing is a topic of great interest among engineering related academics and practitioners.

In review of the presented bibliometric results and the dynamics of the studied area from 2003-2020, three periods were identified for further analysis on the evolution of research:

- Period 1: Initiation Period (2003-2009), comprised of 22 scientific published publications
- Period 2: Growth Period (2010-2015), covering 255 scientific publications
- Period 3: Diffusion Period (2016-2021), this period includes 571 scientific publications

For this analysis, semantic maps were utilized. The purpose of mapping and applying visualization methods is to highlight focus of interest, research directions and trends in the scientific community around a topic. When done at a longitudinal level, the evolution of research becomes much more clear and effectively understood, enabling the identification of the direction in which high quality research is being conducted.

Table 2.8: The most popular areas of knowledge for identified scientific papers.

Research Areas	Record count	% of 848 (%)
Environmental Sciences	270	32%
Green Sustainable Science Technology	236	28%
Engineering Environmental	200	24%
Energy Fuels	146	17%
Materials Science Multidisciplinary	86	10%
Engineering Manufacturing	82	10%
Environmental Studies	70	8%
Engineering Mechanical	53	6%
Engineering Chemical	48	6%
Engineering Industrial	46	5%

Source Own study based on WoS

2.5 Semantic Maps

Considering the boom of literature in recent years, the use of digital tools to analyze multi-disciplinary information is no longer a novel implementation, but a crucial task to do [65]. The digital visualization of knowledge allows to exploit value and extract meaningful features and information from bibliometric datasets. This can provide a better understanding of the cognitive structure of the data, and enable the discovery of interconnections, prevalence, and dimensions of science and research [66].

As part of this systematic literature research, semantic maps are created and analyzed, utilizing VOSviewer version 1.6.16 for the construction of network maps. VOSviewer is a software tool for visualizing and exploring bibliometric data. Developed and supported by the Centre of Science and Technologies Studies of Lieden University, VOSviewer permits the creation of maps based on any type of network data comprised of scientific publications, scientific journals, researchers, research organizations, countries, keywords, or terms [67].

In the construction of network maps, the Web of Science bibliographic database and reference manger files (i.e. RIS, EndNote) were inputs to VOSviewer. Maps created, visualized, and explored normally include only one type of item. These can be publications, researchers, or keywords, for example. Between any pair of items there can be a link, representing a relationship between the two. These links can be formed from bibliographic coupling between publications, co-authorship between researchers, or co-occurrence between terms. Each link has a strength indicated by a positive numerical value. This value may be denoted by the joint number of cited references of two publications (bibliographic coupling links), the number of publications two researchers have co-authored (co-authorship links), or the number of publications in which two keywords occur together (co-occurrence links). In our study, co-occurrence links were used to generate the network maps.

Within network maps, the use of clusters opens up new research perspectives in inter- and trans-disciplinary field. Using Cluster Analysis, a finite set of objects are grouped together into clusters that best describes and represents the data [68]. Clustering makes is possible to:

- identify and generalize the features for each set of groups of similar objects that coexist

- designate objects in isolation that do not relate to any other objects
- discover unknown structure in the analyzed data

A big advantage of VOSviewer is in its ability to group bibliometric data (items) into clusters using an intelligent clustering algorithm [69], and visualize it in a map. Clusters are non-overlapping, meaning that items may belong to only one cluster, or none. In the case items are assigned to clusters, a weight attribute is assigned to each item to characterize their importance.

In the network visualization, items are represented by their label and by a circle. The size of the circle of an item is determined by its weight attribute. The higher the weight of an item, the larger the label and the circle of the item. The weight attribute used for our network map visualizations was based on occurrences, indicating the number of documents in which a keyword occurs. Moreover, the color of an item is determined by the cluster to which the item belongs. In the visualization, the distance between two items depicts their relatedness. Items closer to each other share common features in which they occur.

Based on the bibliometric analysis described earlier, network maps were created for each of the periods of interest:

1. Initiation Period (2003-2009)
2. Growth Period (2010-2015)
3. Diffusion Period (2016-2021)

The visualization and discussion of the results of these network maps are presented next.

2.5.1 Initiation period

The first period for analysis in this study, the so-called Initiation period, belongs to scientific work published between 2003 and 2010. In this period, 22 scientific papers containing the keywords of "Energy" AND "Carbon Footprint" AND "Manufacturing" were published.

In this period, a total of 91 concepts were identified. Due to the limited number of publications that exist in this period around these joint keywords, for purposes of building

the semantic network map the threshold for the minimal occurrence of keywords was set to 2. Thus, of the 91 concepts belonging to this period, only 11 meet the requirement. These are visualized in the network diagram shown in Figure 2.5.

It can be seen that three clusters are identified, with a scientific, thematically coherent area. From bottom-up clockwise, the first cluster contains three keywords: renewable energy, carbon footprint, and emissions. A second cluster is associated with the keywords of: life-cycle, life cycle assessment, energy, and products. The third cluster contains two keywords: international-trade and carbon.

The item that connects to all of the three clusters is the keyword of life-cycle. This gives the insight that the motivation to address energy and carbon footprint in manufacturing during the first decade of the XXI century was partially triggered by its connection to the understanding of life-cycle of products. In the first publication of this period, framed *A Methodology for Assessment of the Carbon Neutrality of Products* the authors present a number of case studies involving combined heat and power plants, solar photovoltaic cells, and wind turbines to assess the life-cycle of these products and their environmental footprints. It is argued that for the full environmental benefits of corporate strategic developments a shift in thinking towards a local manufacturing industry is necessary. This is due to the fact that the transportation of products has a severe impact on the environment; as the distance of transportation of products increases, the carbon emissions becomes larger.

The impact of international-trade and, specially, air travel became under the spotlight in this period, and still is. The aircraft fuel consumption consists of 10 percent of all transport sector emissions of carbon dioxide in the US [70]]. Globally, aviation produces 2.4 percent of total CO2 emissions, and could triple by 2050 given the projected growth of air travel and freight [71].

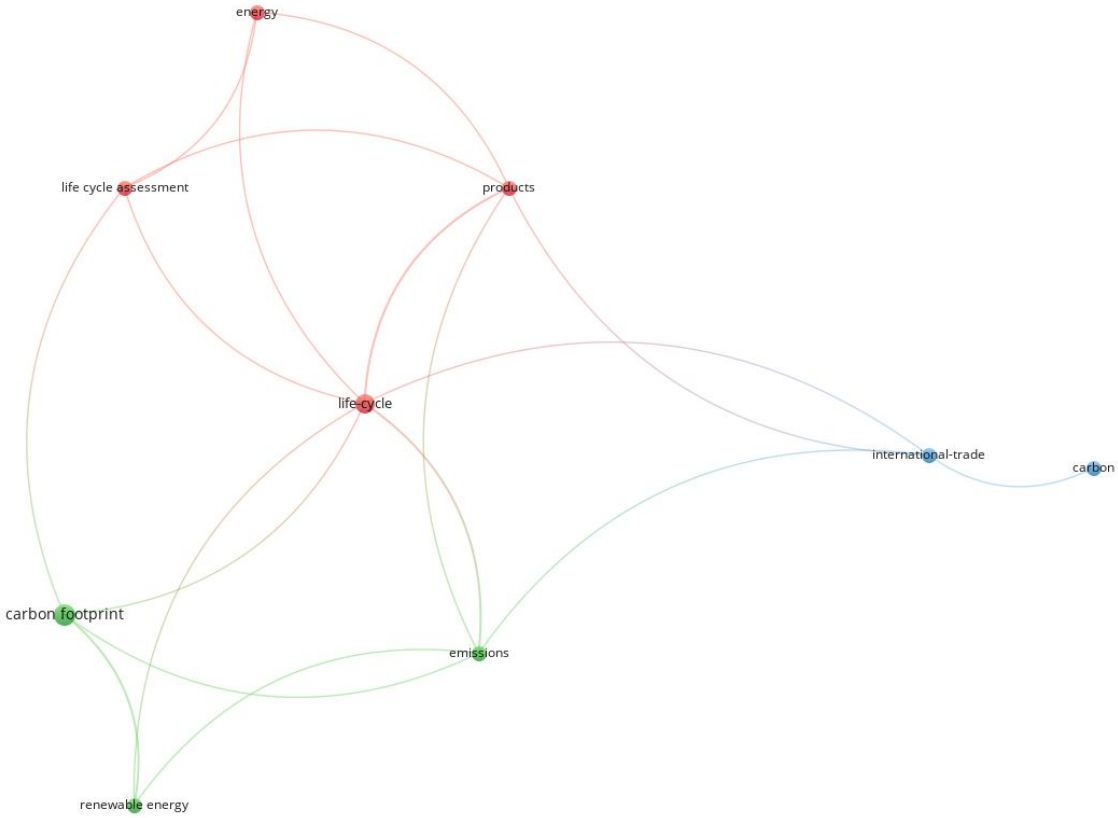


Figure 2.5: Network map on keywords for initiation period (2003-2009)

The most cited paper in the first decade of 2000 is the publication titled *Carbon Footprint of Nations: A Global, Trade-Linked Analysis*, by Hertwich and Peters, with 864 citations. In this work it is shown that carbon footprint is strongly correlated with per capita consumption expenditure, however this relationship is not equal across nations. Interestingly, the elasticity of carbon footprint per unit expenditure is lower in rich countries than in poor countries, suggesting that access to cutting-edge technology, improved quality of products, and more efficient production processes have a deceleration effect in carbon intensity.

2.5.2 Growth period

The specified second period, called the growth period, corresponding to the first half of the second decade of this century from 2010-2015, is comprised of 255 scientific publications. From there, 1,181 concepts were identified , of which 50 meet the threshold of minimal occurrence of keywords set at 6.

During the growth period, the extension and interconnection to additional concepts is clearly visible in the network map (Figure 2.6). The main drivers for research in this period are characterized into 5 clusters, represented by the areas of life-cycle assessment, energy, carbon footprint, management, and consumption, respectively.

All identified clusters are highly multi-directional. It can be seen that the concept of carbon footprint proliferates to the areas of optimization, energy-consumption, performance measurements, management, supply chain, inventory, and others. Approaches in the reduction of carbon footprint through renewable energy technology and energy efficiency practices now become part of the center of attention.

In the most cited publication of this period, the virtues of additive manufacturing in terms of environment, energy consumption and carbon footprint are discussed [63]. It is highlighted that additive manufacturing holds great potential to reduced energy consumption and total emissions produced when compared to conventional manufacturing, and that, beyond the manufacturing process itself, there is also potential to mitigate the life cycle carbon footprint of products through reduced material and weight savings.

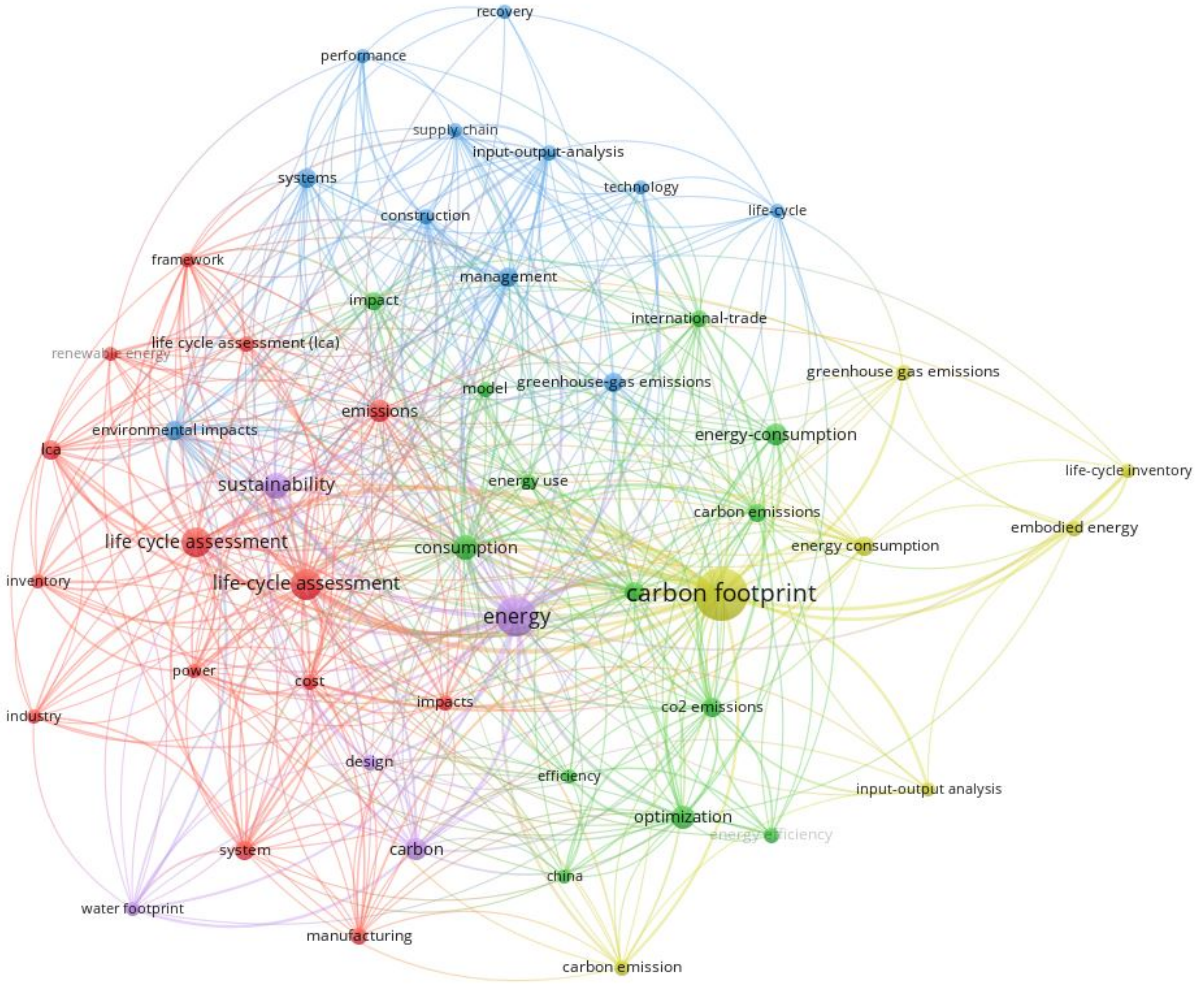


Figure 2.6: Network map on keywords for growth period (2010-2015)

Manufacturing strategies in relationship to production scheduling have also shown to have a significant breakthrough in energy efficiency and carbon footprint. For the first time, researchers begin to extend the well-known job shop scheduling problem to energy-related factors besides the traditional metric of cycle time [72], [73], and [74]. In [75], the inclusion of peak power load, energy consumption, and carbon footprint factors is presented in a multi-objective mathematical programming model. On a novel approach, [76] addresses a low-carbon production scheduling algorithm for a single machine considering renewable energy. [77] takes the flexible job-shop scheduling problem in a manufacturing setting to seek solutions that minimize production and energy costs, by considering renewable energy and energy storage. Other notable papers examine the effect of time-sensitive electricity prices, such as time-of-use electricity tariffs, on production planning [78] and scheduling decisions [48].

The idea that electricity grids are increasing their distributed power generation mix portfolio [30] opens up the discussion that the content of carbon dioxide per kilowatt-hour fluctuates during the day. In the US, the electricity generation mix is mainly composed of 60% fossil fuels, 20% nuclear, and 20% renewables [9]. Consequently, at nights and early mornings the content of CO_2 per kWh is higher since power generation sources depend heavily on fossil fuel stations (i.e. coal-fired plants). Whereas during the day, when renewable energy sources are available, the content of CO_2 per KWh is lower. This creates the controversy that shifting production from on-peak hours, which occur in the middle of the day, to off-peak electricity pricing hours, early mornings and nights, may increase CO_2 emissions in regions where the grid base load is met with fossil-based power plants. [48]. Hence, minimizing electricity costs while reducing CO_2 emissions in production systems is a challenge.

With the expansion of renewable energy technologies, studies in support of micro-grid penetration gain momentum [27] [28] [29]. The Intergovernmental Panel on Climate Change [34], and others [35], conduct interesting assessments on life-cycle emissions equivalent per kWh for distinct electricity generation technologies (Table 2.9).

Table 2.9: Life-cycle emissions equivalent per kWh from selected electricity generation source technologies.

	Life-cycle emissions (gCO2eq / kWh)		
Technology	**Min**	**Median**	**Max**
Coal	740	820	910
Natural Gas - Combined Cycle	410	490	650
Biomass - dedicated	130	230	420
Geothermal	6.0	38	79
Hydropower	1.0	24	2200
Nuclear	3.7	12	110
Concentrated Solar Power	8.8	27	63
Solar PV - rooftop	26	41	60
Wind onshore	7.0	11	56
Wind offshore	8.0	12	35

Source: IPCC, 2014

[30] examined the environmental impacts of the conventional power generation, and identified four areas in which distributed energy resources (DER) technologies could mitigate these environmental problems through: reduction in emissions, higher energy efficiencies, reduced impact to public health, and conservation of natural resources.

Given the above, the pathway towards carbon-neutrality in manufacturing via DER begins to look promising. The integration of on-site renewable energy into factories from a real-time operations management perspective is explored in [31]. Other than sourcing from on-site renewable generation, manufacturing plants can also maximize the value of long-term electricity procurement plans through renewable energy certificates trading and power purchased from energy markets [32]. To some extent, these dynamics continue to shape the way in which many of the top Fortune 500 companies realize their corporate sustainability goals [33].

2.5.3 Diffusion period

In the third analyzed period, called the Diffusion period, spanning from 2016 to 2021, 559 publications yielded a total of 3,000 keywords; a radical increase compared to the previous period. To visualize the network map, only 116 keywords met the minimum keyword occurrence threshold of 6.

As expected, this period presents a more dense and extensive inter-connectivity in the concepts related to energy and carbon footprint in manufacturing. Greater detail can be visualized on the interconnection of novel and distinct approaches and the prevalence of the forces that drive current research. These main forces are characterized into 6 clusters (Figure 2.7).

Two of the most important clusters for the diffusion period are related to energy policy and optimization strategies. Looking at the items that belong to these two clusters (Table 2.10), it can be suggested that, to a great degree, the contribution of optimization models and energy and international policy frameworks in the pursuit of a carbon-free economy remain predominant. Other clusters also present emerging concepts related to energy storage and a revamp interest around the concept of carbon-capture and sequestration among the scientific community.

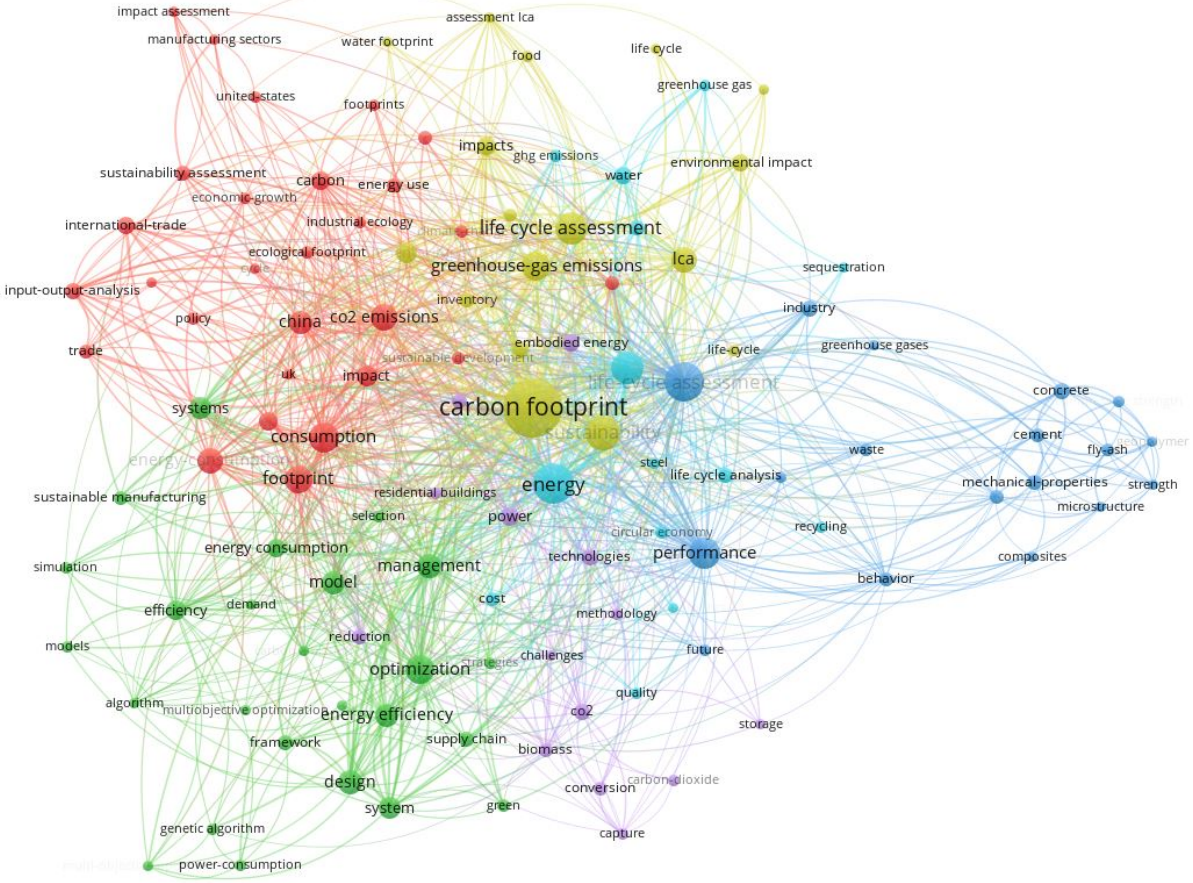


Figure 2.7: Network map on keywords for diffusion period (2016-2021)

Table 2.10: Two important clusters in the diffusion period.

Cluster 1	Cluster 2
Carbon emissions	Algorithm
China	Demand
Climate change	Design
Construction	Energy efficiency
Economic growth	Management
Energy consumption	Multi-objective optimization
Industrial ecology	Optimization
International trade	Simulation
Manufacturing	Strategies
Policy	Supply chain
Sustainability assessment	Sustainable manufacturing
United Kingdom	Sustainable production
United States	

Recently, stochastic programming has become popular in solving optimization problems where penetration of renewables significantly affects results. Stochastic programming is an optimization method that accounts for uncertainty in problem formulation, in which the component containing the stochastic outcome is represented by a selected group of scenarios. These scenarios each have a probability of occurring, and are weighted as such in the objective function. Because wind, solar, and other renewable energy sources have uncertain generation, stochastic programming is a natural way to integrate these into energy-intensive production and manufacturing systems [79] [80].

In [81], a stochastic-based planning framework for a production system utilizing DER is developed with the objective of improving energy efficiency with lower grid energy dependency and outage risk. An energy procurement plan for a flow shop scheduling problem considering on-site renewables uncertainty, day-ahead and real-time electricity prices, and energy storage is discussed in [82]. [83] extends the job shop scheduling problem as a multi-objective stochastic problem to minimize total completion time and energy costs for manufacturing plants that value on-site renewable generation and are faced with time-sensitive electricity prices. The power required for production is met by a combination of on-site renewable generation, supply form the grid, and energy storage systems. On a different approach, [84] formulates the scheduling problem to minimize the total CO_2 emissions, instead of energy costs, for a single-machine. In this study, the power obtained from renewable sources is modelled as interval numbers instead of probabilistic weights.

The consolidation of the findings in the diffusion period are presented in Table 2.11. As more intermittent energy production from DER is being incorporated into energy systems, the need for optimal Energy Storage Systems (ESS) sizing from an economical perspective becomes a challenging problem [85]. Different ESS architectures are presented in [86]. Strategies for integrating storage with respect to an energy market structure have also been proposed in vertically integrated utilities (VIU) and independent system operators (ISO) [79], and in behind-the-meter applications [86].

Table 2.11: Consolidation of the identified direction of research.

Fields	Research focus	Motivations	Approaches
Life Cycle	-Linear Economy -Circular Economy -Shared Economy	-Waste management -Recycling -Reuse -Repairing -Remanufacturing -Products as services -Stewarship rules	-Cost-benefit analysis -Reverse logistics -Supply chain analysis -Life cycle analysis
Production Management	-Production planning and control -Production scheduling -Energy procurement -Industry 4.0	-Capacity planning -Grid dependency -Energy costs -Total carbon emissions -Production costs -Demand charges	-Buffer size / Batch size -Load management -Load tracking -Job sequencing -Job shop scheduling optimization -Meta-heuristics -Digital twin
Renewable Energy	-Energy market dynamics -Distributed Energy Resources -Energy Storage Systems -Micro-grids	-Energy dispatch -On-site power generation -Power transmission -Unit commitment -Power generation mix -Energy pricing -Reserve power -Wind / Solar power -Grid resiliency -Energy disruptions -Energy footprint	-Robust optimization -Simulation -Wind / Solar sizing -Stochastic optimization -Forecasting -Machine Learning
Energy Policy	-Carbon regulations -Renewables incentives -Research and development -International trade	-Social cost of carbon -Climate change -Energy security -Energy resiliency	-Carbon tax -Carbon cap and trade -Renewable energy credits -Investment tax credits -Production tax credits -Net-metering

Manufacturing systems can also leverage on ESS to reduce energy costs via active demand side energy management when operating under an on-peak demand price structure [87]. Furthermore, when it comes to inclement and extreme weather, energy storage is capable of providing robustness to the grid infrastructure to enable resilient flow of quality and reliable power, preventing price spikes and blackouts to end users [88].

On the other hand, the combination of climate change related events and renewable energy limitations have sparked debates in ESS policy and energy regulatory frameworks around the globe (e.g. tax credits, incentives, carbon tax, cap-and-trade systems) [36] [37] [38]. As a result, these environmental regulations, mostly arising since the 2015 Paris Agreement on climate change to limit global warming to less than $2°C$ [20], in conjunction with institutional energy management standards (e.g. ISO 50001), put industry and manufacturing systems under pressure to meet sustainability targets and eco-friendly practices. For example, the approval of new companies, incentives for new investments, or prevention of opportunistic behavior decisions across eco-industrial parks are based on industrial symbiosis (IS) performance [39]. IS is an indicator related to the interchange of materials, energy, and water. Additional energy management performance indicators are proposed in [40]. To this end, analyses that provide insights to both policy-makers and production managers in determining whether replacing conventional manufacturing strategies with environmentally friendly ones is technically feasible and economically viable [41] are very much needed.

An interesting energy policy that could enable the adoption of renewable energy technologies in the manufacturing industry, and alleviate the exposure to ever rising energy prices is in relationship to Net Metering. Net metering is a regulatory billing mechanism that credits renewable energy (i.e. solar and wind) system owners for the electricity they generate and give back to the grid [42]. If a system is net-metered, the electricity meter runs backwards to provide a credit when the generation exceeds consumption. Thus, customers are only billed for their "net" energy use. Although net-metering has portrayed economic and environmental benefits within residential applications [43] [44], little work has been done in demonstrating the same in the commercial and manufacturing sectors, and remains to be explored.

While some researchers agree that renewable energy sources can realistically mitigate climate change by replacing fossil fuels [89] [90], others doubt that it is possible [91] [92] [93]. Unequivocally, not all countries face the same level of certainty as to what energy source to stress in the future. For manufacturing plants located in regions in the Middle East, hydro power is not an option, but large potential exists in solar energy. Conversely, solar energy is not the best choice for on-site generation in Nordic regions, but hydro and geothermal power are evident choices there. Moreover, it should be acknowledged that a sudden large-scale shift to renewable energy could bring adverse effects to the environment with respect to the utilization of land and depletion of minerals required for the manufacturing of components [94].

Other non-renewable climate change mitigation alternatives, such as carbon capture and sequestration (or storage) – also used for enhanced-oil recovery (EOR) applications [95]– are still in the early stages of development and commercialization. However, despite the broad recognition of having the potential to decarbonize the industry and its ability to facilitate the removal of CO_2 from the atmosphere [96], the technology costs for CO_2 capture and its underground storage effectiveness continue to be questionable [97].

As it can be seen, the diffusion period shows an interesting expansion of research, but more importantly, marks down the current direction of thinking in connection to energy-carbon footprint in manufacturing. The evolution of cleaner, efficient and affordable technologies, and their integration with smart and optimal decision-making processes will play a key role in meeting climate change targets as we move forward towards the crystallization of sustainable manufacturing.

2.6 Conclusions

Considering a fast pacing growth in the manufacturing industry across the globe, and under the reality of high energy demand, rising energy costs, and environmental policies driven by global warming concerns, the proposed research aimed at studying the structure governed in the literature that addresses these issues in advancing towards sustainability in manufacturing.

In this study, the evolution and research trends from 2003-2021 of sustainable manufacturing in relationship to energy and carbon footprint in manufacturing were presented. They were identified on the basis of scientific publications encompassed in the international Web of Science database. Through the use of semantic network maps, it was possible to observe the nonlinear development of concepts and brisk changes in thinking and conducting scientific research.

With respect to the research questions outlined for this work, the main takeaways of the visualization of knowledge regarding the field of Sustainable Manufacturing in connection with the concepts of Energy and Carbon Footprint in Manufacturing are the following:

- Life cycle management plays an important role in cutting emissions and lessen waste
- Production scheduling strategies have strong potential in reducing energy costs and carbon footprint in manufacturing
- Leveraging on on-site renewable energy sources is a clear pathway towards a carbon-neural manufacturing system
- Energy policy holds great influence in the direction of research towards a carbon-free economy
- Optimization and data-driven models are the backbone of current research in energy efficiency and distributed energy sources

Figure 2.8 portrays the above findings in a conceptual plot to represent the pathway towards sustainability and carbon-neutrality in manufacturing. Carbon footprint levels decreases with the initiation of a life cycle oriented business model (i.e. circular economy), followed by optimization in production planning and scheduling, and the integration of distributed energy resources. These reductions are influenced by energy policy and regulations, thus, creating oscillations down the way. Altogether, the above decisions are more reliable and effective when structured under a data-driven process. The fundamentals that support this pathway were identified in this study and are summarized here below.

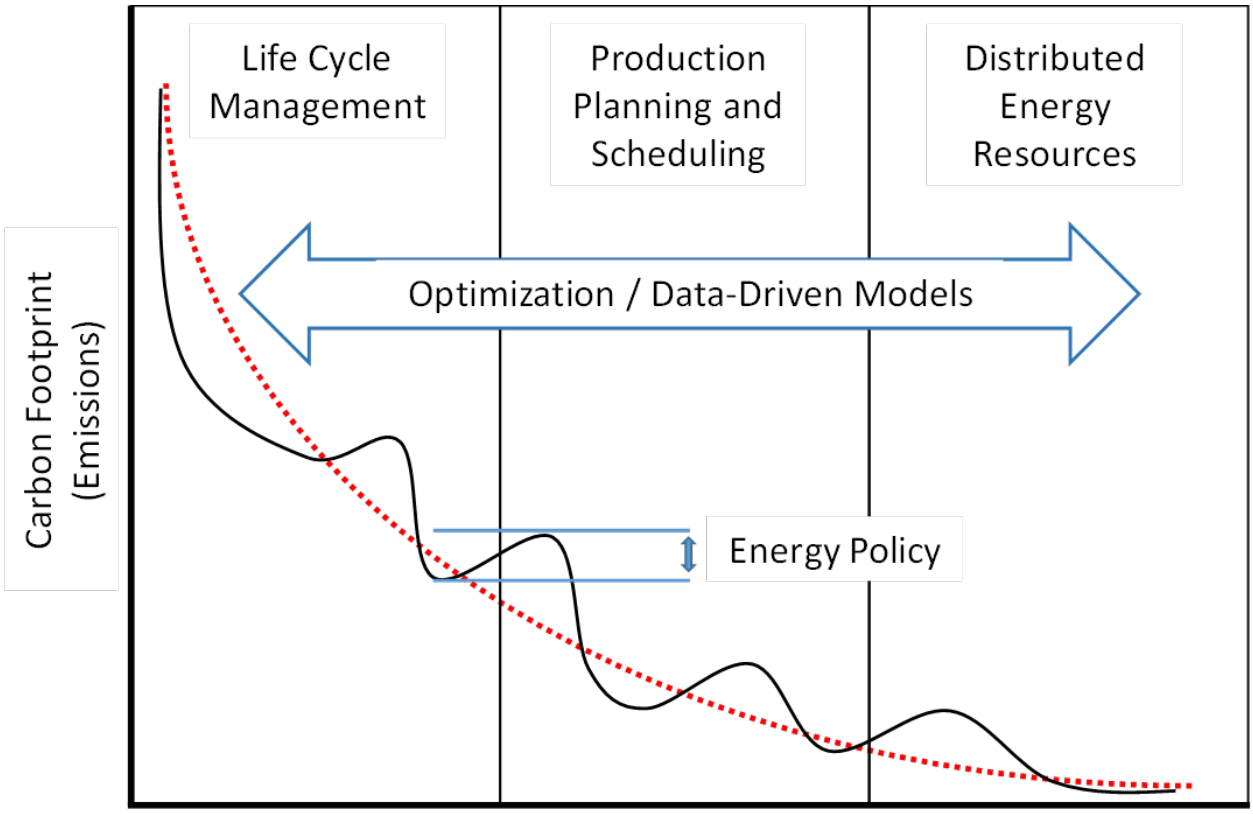


Figure 2.8: Conceptual pathway towards carbon-neutrality in manufacturing

As seen in the literature, life-cycle management is a pivotal part in addressing sustainability. The way in which business models and best practices are carried out determines, for the most part, the degree of energy consumption and carbon footprint of organizations. Extending the use of resources for longer times could cut nations' emissions by up to 70% [45]. Hence, advancements in the concept of circular economy will be necessary to extend the life of products and mitigate waste. The evolution towards a "shared" economy goes a step further in maximizing the value at each point in a product's life – companies can become more competitive by using innovative, cheap and reusable parts and equipment (e.g SpaceX [98]).

Without major capital investments, energy-carbon efficient solutions can emerge from production planning and scheduling optimization models. This an important mechanism in which manufacturing processes at developing nations can rely upon to achieve energy and sustainability targets in a short period of time at a minimum cost. This approach also enables the concept of energy procurement, allowing managers to include energy and carbon emissions as part of their enterprise resource planning for operations. At the same time, less emissions and energy costs results in higher corporate results aligned with eco-social responsibility. It has been seen that enterprises that are more aligned to eco-social responsibility are more successful than those that are not [47]. In this regards, the development and inclusion of energy and carbon footprint indicators [40] into operational performance measurement systems will be key in supporting the transition to sustainable manufacturing.

The adoption of distributed energy sources and on-site renewable generation provides a promising outlook towards carbon-neutral operations. Several companies (i.e. Microsoft, IKEA) have included the integration of renewable energy as part of their corporate strategy, and even go further into the idea of carbon-negative operations [99], meaning that the generation from renewable sources will account for the historical carbon emissions since the founding of the company.

From a policy-maker perspective, energy policy plays an important role not only in determining how fast can we get to a carbon-free economy, but also in how these policies impact the economic competitiveness of the manufacturing sector. Analyses that provide

technical feasibility and profitability in eco-friendly strategies are critical to support both environmental policy-makers and production managers. Certainly, energy policy should be geospatially-based in order to maximize the value of available clean energy resources and enhance energy security against uncertainty and inclement weather.

Finally, this study also points to the fact that optimization and data-driven research is currently of great interest in the scientific community for the development of energy efficiency and carbon mitigation frameworks. In this direction, we anticipate that the propagation of Internet of Things, Industry 4.0, and Artificial Intelligence within the global economy will boost the sustainability of manufacturing systems at levels yet to be seen.

Chapter 3

The Second Article: Energy-Carbon Footprint Optimization in Sequence-Dependent Production Scheduling

Disclosure Statement

This chapter corresponds to the manuscript "Energy-Carbon Footprint Optimization in Sequence-Dependent Production Scheduling" submitted to the *Applied Energy* journal on January 10, 2022. The manuscript reference number is **APEN-D-22-00293**, and has a current status of Under Review. The authors of this manuscript are: Samuel C. Trevino Martinez (main and corresponding author), Dr. Rapinder Sawhney, and Dr. Oleg Shylo. Samuel C. Trevino Martinez was responsible for the conceptualization, methodology, software, validation, investigation, writing - original draft, and visualization of this article. Dr. Rapinder Sawhney was responsible for the supervision of the article, and Dr. Oleg Shylo contributed to the conceptualization of the article.

3.1 Abstract

Under the panorama of increasing energy costs and environmental policies driven by global warming concerns, this research is aimed at creating an energy optimal production schedule model to minimize energy costs and reduce carbon footprint emissions. The proposed model is built under the context of a sequence-dependent single machine scheduling problem. Moreover, the scheduling decisions are assumed to be affected by independent time of use electricity prices and carbon footprint environmental policies forced by either corporate or governmental institutions. To this end, a Low Energy-Carbon Cost Sequence Dependent Job Scheduling optimization model (LEC-SDJS) is developed under a Mixed Integer Linear Programming formulation. Preliminary results show the value of the model when compared to classical scheduling optimization approaches and job scheduling heuristics. Research directions, and proposed validation are finally discussed.

3.2 Introduction

The manufacturing industry sector is a key pillar of economic growth for any country in the world and it is one of the most important and dynamic sectors in the United States. It accounts for a gross output equivalent to 35.4% of U.S. GDP, an 87.5% share of total goods exports, and supports 8.7% of the total U.S. workforce [1] [2]. Intrinsically bound with manufacturing activity, energy is one of the most vital resources to power operations and generate products. Over the past two decades, demand for industrial products has risen considerably leading to higher energy consumption. Growth in energy consumption, driven primarily by an ongoing long-term of rising production in energy-intensive industries, and the increase of energy prices [12], have sent energy costs to represent a significant amount of operational expenditures, thus, motivating the need for energy efficiency. In the U.S., the manufacturing sector consumes about one-third of the energy used [100], and spends over $80 billion on fuel and electricity annually [13].

Considering that the energy demanded by manufacturing enterprises industries is mostly generated from fossil fuel sources containing high levels of carbon, it has led them to

become accountable for 24% of the global CO_2 emissions and a main contributor to one of the world's public problems, climate change [14]. The serious risks that climate change possesses on the environment and to public health has prompted several main economies to formulate stringent legislation and regulations on carbon emissions, either in the form of a cap-and-trade or carbon tax [101]. As a result, enterprises are facing new constraints and challenges to reduce CO_2 emissions while maximizing production profit. It is clear that measures to enhance energy efficiency in manufacturing hold great potential for reducing energy consumption and energy-related CO_2 emissions, and that these approaches will only become more relevant in the near future.

Ironically, even though world-class manufacturing methodologies, such as Lean Manufacturing, Six Sigma, Total Quality, and The Sawhney Model [102], have been extensively analyzed for decades, there is a lack of clear and structured research in the study of energy utilization in production systems and their environmental impacts [23] [24]. Relatively new in the manufacturing field, energy and environmental metrics have not been fully included in productivity key performance indicators within enterprises [25], falling short of achieving the concept of Sustainable Development envisioned by the United Nations [26]. This concept is defined in what is known as the Sustainable Triangle, Figure 3.1, depicting a balance among the economic aspects of productivity, social welfare and quality of life, and the preservation of natural resources of the environment. Given the continuous growing demand for goods, the development of energy-carbon aware models that can be integrated into the operational excellence systems of enterprises is essential to establish sustainability in the manufacturing sector.

The Intergovernmental Panel for Climate Change (IPCC), and several authors [103] [104], have identified potential methods to improve energy efficiency and mitigate emissions in manufacturing. Such strategies can be categorized into three main dimensions, illustrated in Figure 3.2: 1) building eco-design, 2) renewable energy, and 3) operations.

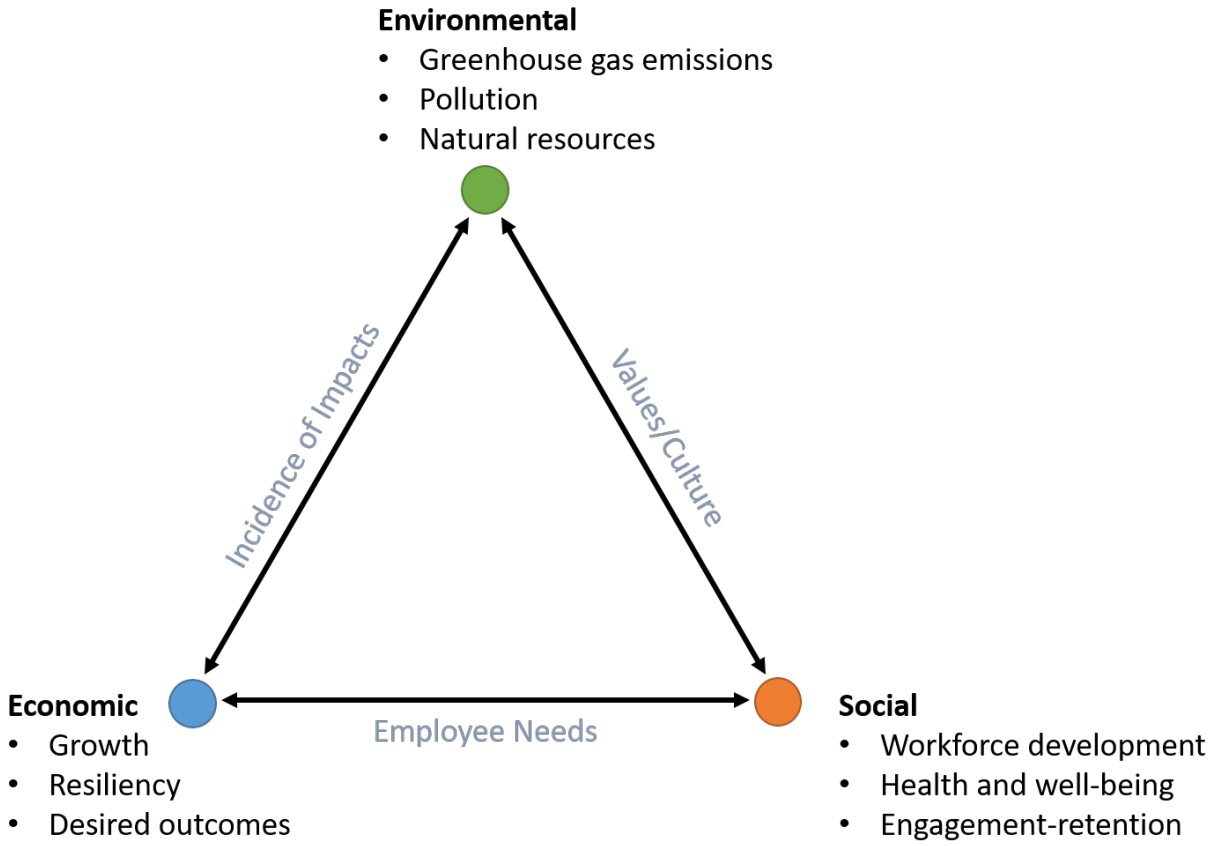


Figure 3.1: Sustainability Triangle.

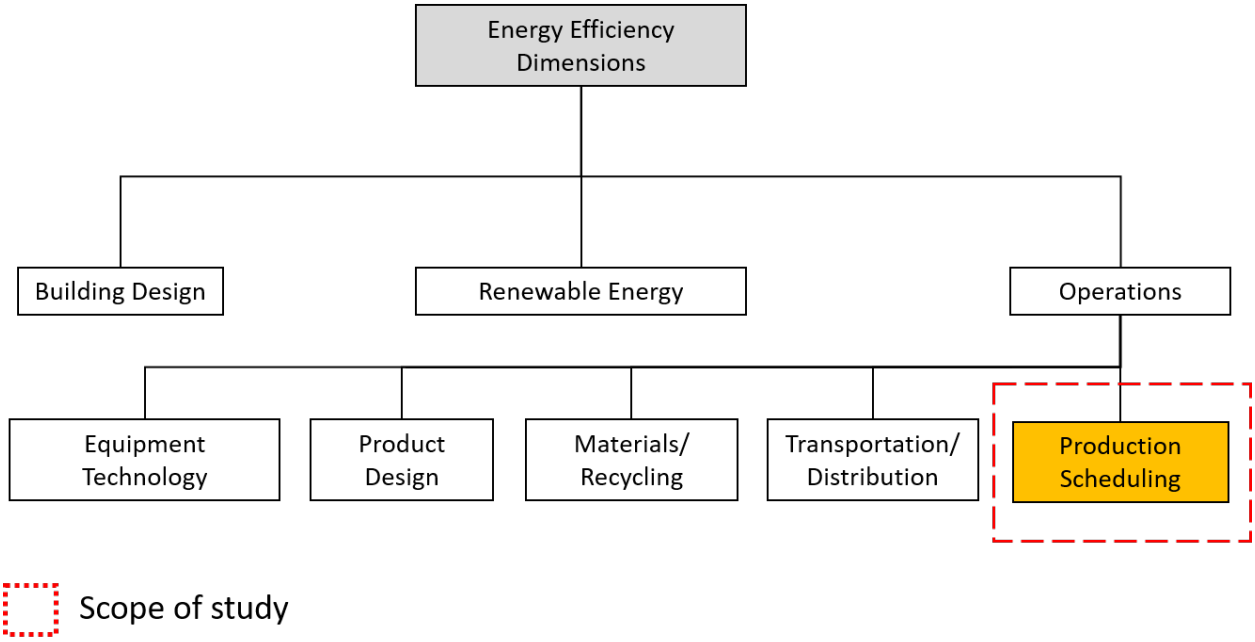


Figure 3.2: Energy Efficiency Dimensions.

Building redesign strategies can lead into the development of greener and more energy efficient facilities in terms of lighting, heating and air conditioning. Nevertheless, because a building and its environment are complex systems and carry major barriers to implementation such as lack of suitable legislation or life-cycle assessment (LCA) tools for designers to use, retrofit decisions are quite difficult to undertake [105] [106].

Renewable energy strategies address cost-benefit issues in the availability and utilization of distributed energy resources to enable production and transportation of goods. Although the leveraging of cleaner on-site power generation to cap energy and carbon footprint is promising, this topic is out of scope in this research.

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Strategies focused on operations embark solutions across the supply chain in regards to equipment technology, product design, materials and recycling, transportation and distribution, and production scheduling. In terms of equipment technology, upgrading and retrofitting into higher energy efficient equipment is a clear path towards sustainability. However, switching to new and advanced equipment often requires large capital investments [107]. Product redesign strategies can extend the lifetime of goods to lower its demand and production energy requirements, nonetheless, it has to be considered that extending lifetime may not be aligned with current market preferences or business model since enterprises are rewarded for growing sales. Material substitution/selection based on LCA and recycling are strategies within the circular economy that can reduce energy consumption and emissions. An important drawback to consider is that recycled/recovered materials can be limited by the type of manufacturing process and supply chain [108]. Furthermore, transportation and

distribution activities also require longer periods of time to achieve efficiency results, and, in many cases the supply chain can lower its performance while doing so [109].

Alternatively, in production systems, key activities such as production planning and scheduling are frequent decisions that have a direct impact on the utilization of energy-intensive equipment. Without major capital investments, it has been shown that the most energy-carbon efficient solution will emerge from optimal production planning and scheduling [46] as the reduction and planning of idle-time in combination to the sequencing of jobs leads to a better prediction of the workflow and allow management to budget the energy and emissions for the system. Our proposed model falls within this approach as it addresses production scheduling decisions to minimize energy-carbon costs.

The introduction of electricity tariffs, under Time of Use (TOU) contracts by utility companies, has further complicated the system's optimization scheduling problem since optimizing energy consumption does not necessarily lead to a reduction in the electricity cost [110].

To this end, an optimal production scheduling framework for a single machine production system is proposed in this research to minimize its energy consumption costs and CO_2 footprint. Considering the sequence-dependent single machine job scheduling problem, electricity Time of Use and energy mix portfolio in the grid, the optimization model presents insights on the impact that production and environmental policies have in the energy consumption behavior of a production system. The ultimate goal is to fill the research gap between the production scheduling decisions existent in the single machine job scheduling literature and the energy management planning within manufacturing production systems. Section 3.3 discusses previous production scheduling research in optimizing energy consumption in manufacturing and identifies research gaps in applied energy management models. Section 3.4 introduces the methodology to support the proposed optimal scheduling model to budget energy costs and foot print under the conditions of time of use electricity prices and carbon tax. Section 3.5 presents the preliminary results and sensitivity analysis obtained from the proposed model. Section 3.6 summarizes the findings and provides guidance for future work.

3.3 Literature Review

3.3.1 Energy management in production systems

General frameworks have been reported in literature to connect Energy and Green models into current world-class production practices. In [111], a five-step Lean and Green model is suggested to be implemented as part of a continuous improvement process at the manufacturing cell level. [112] proposed a Sustainable-Value Stream Mapping (Sus-VSM), to include metrics for evaluating the environmental and societal sustainability performance of a manufacturing line. Another framework by [113], the "lean ecosphere" framework, addresses human integration in lean for sustaining operations. After implementation, fewer cases of employee dissatisfaction, less conflict among departments, more cohesiveness among employees, and higher profits were found.

The effects of applying specific Lean tools on environmental impacts were studied by [114] and [115]. Likewise, [116] present a study to enlighten the contribution of Lean in achieving better environmental performance of production systems and identify this as an emergent business model for supporting eco-efficiency. In this study, the concept of eco-efficiency encompasses: i) minimizing energy intensity in both products and services; ii) reducing materials intensity; iii) reducing toxic emissions; iv) recycling and use of renewable energy; v) extending durability of products, and; vi) increasing service intensity. Similarly, in [117], a framework, "En-Lean", is presented to align Lean and green manufacturing in the metal cutting supply chain. In their study, the relationship between Lean practices and environmental outcomes is depicted. It is found that workplace design attributes of Lean such as Poka-Yoke, SMED, and Pull systems have a positive effect on environmental metrics, whereas efficient flow systems in Lot Sizing (i.e. "Single-Piece Flow") have a negative effect.

The divergences of Lean and Green, and their limitations as an integrated approach are further explored by [118]. Their study shows that Lean and Green are not completely compatible and conflicting objectives arise from their divergent definition of waste. The integration of Six Sigma into the creation of the concept of Green Lean Six Sigma as a unified approach is discussed as a possible solution to address these limitations, and enhance its effectiveness.

For the purpose of energy cost savings and environmental concerns, [119] showed that production systems can significantly reduce energy consumption and atmospheric emissions in automotive paint shops by applying optimal batch and scheduling policies. Also, previous research has shown that besides total energy consumption, peak energy demand affects directly total energy costs. In [120], the use of buffer inventory to minimize energy consumption in manufacturing systems during peak periods is suggested.

3.3.2 Energy cost optimization in machine scheduling

Although the single machine scheduling problem has been exhaustively studied in the literature since decades [121], the interest of extending the problem to include energy costs and/or carbon emissions has gained ground in recent years, motivated primarily by energy cost awareness and environmental concerns due to climate change. In this direction, existing research has particularly addressed multi-objective formulations and approaches to minimize classical scheduling objectives (i.e. completion time C_{max}, total weighted tardiness TWT, maximum lateness L_{max}, tardy jobs T) in combination to related energy and emissions objectives.

The single machine scheduling problem where n jobs have to be processed in the order of their arrival, and both C_{max}, and total energy consumption are minimized is studied in [122]. First, they developed dispatching rules which determine whether to leave the machine idle, or to turn it off between jobs. They develop a multi-objective mixed integer linear programming (MILP) formulation and solve it combining both objectives by adding a weighted sum to both objectives.

In [123], a multi-objective MILP optimization model is presented to illustrate the trade-off between minimizing C_{max} and total energy consumption. For it, Pareto frontier optimal solutions are constructed utilizing the ϵ-constraint method, and a constructive heuristic approach is presented to solve large instances.

[76] derived a general multi-objective mixed integer programming (MIP) formulation that considers both C_{max} and energy and energy-related criteria (i.e. peak load and carbon footprint) when optimising the operating schedule of a flow shop. The Pareto frontier was computed specifying upper bounds on the peak load and then searching for the minimum

C_{max}. Significant trade-offs between both objectives are reported. On the other hand, [72] generated an energy-aware scheduling algorithm based on MIP formulation to realise energy savings for a flexible flow shop that was required to keep its fixed job assignments and sequences.

Furthermore, a novel ant colony optimisation meta-heuristic to solve the hybrid flow shop scheduling problem by considering production efficiency and electric power cost with TOU electricity prices was applied by [124]. In the same direction, [73] considered a multi-objective optimization model of minimizing maximum completion time and total energy consumption in a flexible flow shop. In here, an improved heuristic based on genetic-simulated annealing algorithm is presented to solve the multi-objective optimization problem, in which the weighted sum utility function approach was used to generate the set of non-dominated solutions (Pareto optimal solutions).

[125] generalized the model of [122] by taking into account jobs with unequal release dates that do not necessarily need to be scheduled in the order of their arrival. Thus, the developed model not only determines the timing and length of turn off/turn on periods, but also sequences the jobs in such a way that both the total tardiness and total energy costs are minimized. [74] investigated the problem where different operating modes (processing, idle, off) with different machine energy consumption levels and TOU tariffs exist. The proposed model minimizes total energy costs under the constraint that all jobs have to be processed in the given time horizon. The same problem was also investigated by [126], under a multi-objective formulation to minimize C_{max} instead of total tardiness along with total energy costs.

3.3.3 CO_2 emissions awareness in machine scheduling

In connection to environmental-related criteria, [50] integrated CO_2 emission considerations into production scheduling of a single batch machine in the presence of dynamic job arrivals and assumed that jobs have unequal release times, due dates, processing times, and priorities. The developed two multi-objective models to minimize the TWT and the total carbon dioxide emissions by determining whether to start processing a batch or wait for more jobs to arrive in a given time interval. Thus, the models try to balance the negative effects of leaving a

machine idle and the negative effects of operating an underutilized machine. A triple criteria includes a hybrid flow shop scheduling problem of minimizing TWT, carbon footprint, and peak power.

A similar model to [122] was developed by [127]. Yet, instead of minimizing total energy costs, the model minimizes total CO_2 emissions, and assumes that CO_2 emissions can be related to the energy consumption by a constant factor. In [128], an ϵ-archived genetic algorithm (ϵ-AGA) for a multi-objective parallel machine problem is examined on two batch scheduling problems with the goal of minimising CO_2 emissions and the traditional due date-based objective of minimizing TWT is presented.

The inclusion of TOU electricity tariffs in conjunction with hourly CO_2 emissions is presented in [48]. In their work, a time-indexed integer programming formulation is developed, and Pareto optimal solutions using the ϵ-constraint method were constructed for the multi-objective flow shop scheduling problem to depict the trade-off between minimizing electricity costs and carbon footprint emissions.

[84] presented the first model that integrated renewable energy sources (RES) with an uncertain energy supply into a single machine scheduling problem. The energy supplied by the RES was assumed to be stored in a rechargeable battery. Supply uncertainty for the RES was modeled using interval numbers. To reduce CO_2 emissions, the machine does not use power from the electricity grid until the battery runs out of power. The author considered two cases. In the first case, the main objective is to explore how TWT and total carbon dioxide emissions are affected by the amount of power generated from RES in each time interval. Conversely, in the second case, the model solely minimizes TWT subject to a periodic as well as a rolling CO_2 emission constraint. The Pareto efficient solutions in this multi-objective MILP are solved comparing the Lexicograhic-Weighted Tchebycheff method and the weighted sum approach.

Using the frequently utilized three-field notation $\alpha/\beta/\gamma$ to describe a scheduling problem [129], where the first field (α) describes the shop (machine) setting, the second field (β) the setup information and conditions, and the third field (γ) the performance measure, we consider the sequence-dependent s_{jk} single machine scheduling problem from an energy-carbon footprint cost $TECFC$ with TOU electricity tariffs perspective, including release

dates r_j, hereafter, expressed in this proposed research as the $1 \mid r_j, s_{jk} \mid TOU - TECFC$ problem. The consideration of time variable slot costs in the single machine scheduling problem with variable time slot costs has been proven to be *NP-hard* [130].

In fact, those time variable conditions would resemble the TOU electricity tariffs in our energy-carbon problem.

Table 3.1 summarizes the aforementioned related research. As it can be seen, there is still rare research that has successfully integrated the time-of-use electricity prices and hourly carbon footprint emissions in a sequence-dependent scheduling structure. The proposed model presented ahead bridges this gap.

3.4 Methodology

This research is developed in the form of a Mixed Integer Linear Programming Model that can serve as a framework for a production system to minimize its energy costs and carbon footprint via its production scheduling decisions. To this end, a Low Energy-Carbon Cost Sequence Dependent Job Scheduling optimization model (LEC-SDJS) is proposed. The proposed model is built under the context of a sequence-dependent single machine scheduling problem. Moreover, the scheduling decisions are assumed to be affected by independent time of use electricity prices and carbon footprint environmental policies forced by either corporate or governmental institutions which are materialized in the form of carbon tax.

The research objectives/questions to be addressed in this study are:

- Research objective 1: Develop an efficient mathematical model to provide optimal scheduling decision variables in the production system that minimizes the objective of energy and carbon footprint costs.

- Research objective 2: Develop a model that has the ability to budget the optimal energy requirements for the production system in which the objective is met.

- Research objective 3: Compare the value of the proposed energy-carbon aware model to contemporary non energy-carbon aware scheduling models.

Table 3.1: Energy-carbon related literature on machine scheduling.

	α (Machine setting)			β (Conditions)									γ (Objectives)						
Author	Single Machine	Flow Shop	Parallel	Sequence dependent	Fixed precedence	Uneven processing times	Job-related power level	Due dates	Release dates	TOU	Hourly emissions	On-site power	Completion time	Weighted tardiness	Energy consumption	Carbon emissions	Peak power	Energy cost	Energy-Carbon Costs
Mouzon et al. (2007)	x												x		x				
Mansouri et al. (2016)		x											x		x				
Fang et al. (2011)		x											x			x	x		
Bruzzone et al. (2012)		x			x										x				
Luo et al. (2013)		x								x			x					x	
Dai et al. (2013)		x						x					x		x				
Mouzon et al. (2008)	x								x					x				x	
Shrouf et al. (2014)	x						x			x								x	
Yildrim et al. (2011)	x								x				x		x				
Liu and Huang (2014)	x					x		x	x					x		x	x		
Liu et al. (2013)	x												x			x			
Liu (2014)			x					x						x					
Zhang et al. (2014)		x								x	x					x		x	
Liu (2016)	x											x	x			x			
Our Proposal	**x**			**x**			**x**		**x**	**x**	**x**	**x**							**x**

- Research objective 4: Understand the effects of carbon tax in production scheduling decisions.

Before presenting the method and proposed optimization model, important contextual definitions around the job scheduling problem, energy, Time of Use electricity, and carbon footprint are presented ahead.

Let there be a single machine with a finite set of N jobs $J = \{J_i\}_{i=1}^{N}$, which require to be processed before the end of the day, where each job $j \in N$, is characterized by non-negative processing times p_j, power requirements w_j, and sequence dependent setup times s_{jk} that apply when the processing of job k, $k \in N$, occurs after having processed job j, $j \in N$. The equipment runs on electricity, and therefore, is subject to TOU electricity tariffs. Additionally, CO_2 footprint emissions per kWh vary during the day depending on the energy portfolio mix of the electric grid, and a fixed carbon tax exists to levy on them [131]. No preemption is allowed on jobs, and there exists feasibility in completing all jobs in a day. Thus, the objective is to develop an optimal sequencing schedule of the jobs such that electricity and carbon costs are minimized.

3.4.1 Definition of energy

Because the integration of energy costs into the optimization model is in the form of electricity costs, it is imperative to first denote the following mathematical definition of energy:

$$\text{Energy} = \text{Power x Time} = \text{kWh}$$

Energy is directly proportional to the rated power of the specific equipment times the duration of its utilization. The measure of electrical power of equipment is to be measured in kilowatts (kW), and when utilized during a period of time t in the format of hours (hr), an energy consumption (kWh) in the form of electricity is incurred . Translating this definition to the sequence-dependent single machine job scheduling, the energy consumption of each job will be dependent on the specified machine power requirements ω_j when processing job j times its processing time p_j. Furthermore, the utilization of an equipment can be decomposed

into four modes: ramp-up, idle, operating mode, and ramp-down. The energy consumption relations dependant on machine mode are shown in Table 3.2.

The effectiveness of the proposed model is built on as a function of Time of Use (TOU) energy consumption and total CO_2 emissions. This is because electricity prices and emissions experience hourly variations during the day. These variables are optimized in the proposed Energy-Carbon Model, which in turn generate an optimal daily production schedule that provides not only the job sequencing and machine dispatching rules to operate the system, but also the hourly energy consumption plan and carbon footprint plan for the day. This becomes valuable information to production managers for budgeting purposes.

3.4.2 Time-of-Use (TOU) electricity rate structure

Time-of-use (TOU) has emerged as an approach adopted by utility companies to achieve more efficient and effective demand management of electricity. Contingent on the utility power generation provider and the electric system operator in the U.S., customers may pay a different rate during the day depending on how much it costs to generate power, this is known as time of use (TOU) electricity tariffs (Figure 3.3). For example, west coast utilities, i.e. PG&E, offer a 4-TOU rate plans: Peak, Partial peak, Off-peak, and Super off-peak [10]. Whereas, other utilities in the east, i.e. TVA [11], may offer only two rates in TOU plans. For a given time period, the electricity cost is calculated based on the electricity consumption times the electricity price during the time period.

Compared to flat electricity rates, TOU tariffs provide users with an opportunity to cut costs by shifting their consumption to hours with lower rates. However, such shifts may increase carbon footprint for regions that use fossil-based fuel generation to meet the base load electricity of their grid.

Table 3.2: Machine mode parameters.

Machine mode i	Status	Power requirements	Time length
1	Ramp-up	ω_r	R
2	Idle	ω_i	I
3	Operating	ω_j	p_j
4	Ramp-down	ω_f	F

where: $\omega_f \leq \omega_i \leq \omega_j \leq \omega_r$.

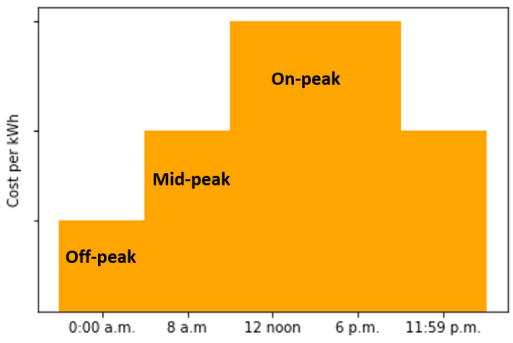


Figure 3.3: An example of time-of-use electricity rate ($/kWh) during a day.

3.4.3 CO_2 footprint emissions

In terms of carbon footprint, the indicator to this objective is the quantity of carbon dioxide CO_2 incurred in the overall energy utilized, that is, kilograms of CO_2 equivalent per kWh ($kgCO_2e/kWh$). The CO_2 emissions per kWh depend heavily on the power portfolio mix used by the utility to generate electricity throughout the day. Some of the most common energy sources utilized include coal, natural gas, nuclear, hydro, wind and solar. Depending on the location of the production facility, the electric grid may or may not have inclusion of low carbon technologies in their mix, i.e., nuclear, hydro, solar and wind, to offset the content of CO_2 per kWh supplied during the day. Thus, CO_2 levels per kWh vary during the day depending on the availability of these low carbon technologies.

Using the hourly electricity generation mix data contained in Figure 3.4 for any regional grid in the U.S. and the estimates of content of equivalent CO2 in kg/kWh by source type (Table 3.3), we can obtain the content of carbon per kWh (kgCO2eq/kWh) emitted at each point in time.

3.4.4 Carbon tax

A carbon tax is a tax levied on the carbon content of in the greenhouse gases (GHGs) emitted by humans (anthropogenic GHGs), and, like carbon emissions trading (calculated in tonnes of carbon dioxide equivalent or tCO_2e), is a form of pollution tax [132]. It is mechanism to have users of carbon fuels pay for the climate damage caused by releasing carbon dioxide into the atmosphere and it is intrinsically related to the social cost of carbon (SCC), which represents the marginal cost of the impacts caused by emitting one extra tonne of carbon (as carbon dioxide) at any point in time. If the carbon tax is set high enough, it becomes a powerful monetary disincentive that motivates switches to a cleaner economy, simply by making it more economically rewarding to move towards non-carbon fuels and energy efficiency practices.

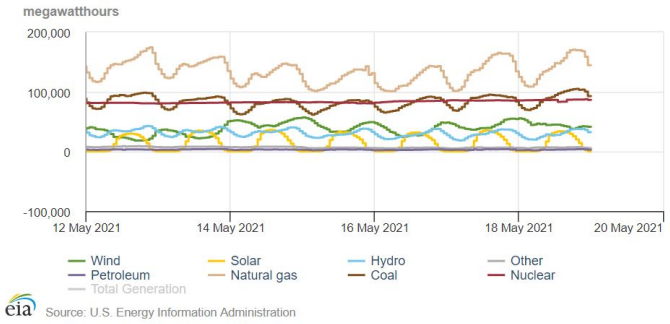


Figure 3.4: Hourly power generation in the grid by portfolio mix.

Table 3.3: Kg. of CO_2 equivalent per kWh per energy source.

Source	kgCO2eq/kWh
Coal	0.82
Natural Gas	0.50
Nuclear	0.01
Hydro	0.02
Solar	0.05
Wind	0.01

Finland was the first country to introduce a CO_2 tax in the 1990s, since then, the majority of the European nations and other nations in North America, South America and Australia have implemented a carbon tax, with Sweden leading the price at $131 USD per tCO_2e [101]. Hence, the inclusion of SCC into our model can help understand the sensitivity in scheduling decisions and the impact to costs and emissions with respect to the potential direction of carbon tax levies imposed to the industry.

3.4.5 Model overview

An overview of the proposed method that incorporates TOU, carbon emissions, into a sequence-dependent single machine scheduling problem is shown in Figure 3.5. Given a production system in which a set of jobs $j \in N$ are to be scheduled, and provided the equipment power (ω) parameters to process each job, p_j, the scheduling model takes into account a Cost Model $f(g)$, which is a function of the Time of Use of Electricity price π_t, and the carbon footprint profile ($kgCO_2e/kWh$) of the electric grid λ_t, at time t. Concurrently, the carbon footprint profile is a function of the power generation portfolio mix at the geographical region, and the physical content of equivalent CO_2 emitted per kWh of energy generated from source γ_s. Furthermore, the scheduling model is developed in a Mixed Integer Linear Programming (MILP) mathematical optimization approach, in which scheduling decision variables and feasibility equations are integrated. Subsequently, the MILP scheduling model is optimized using GUROBI v8.1 and compiled in Python3.6. The results of the optimization engine will provide the optimal schedule plan for each job and depict the hourly energy consumption, ψ_t, and carbon footprint, λ_t, for the day.

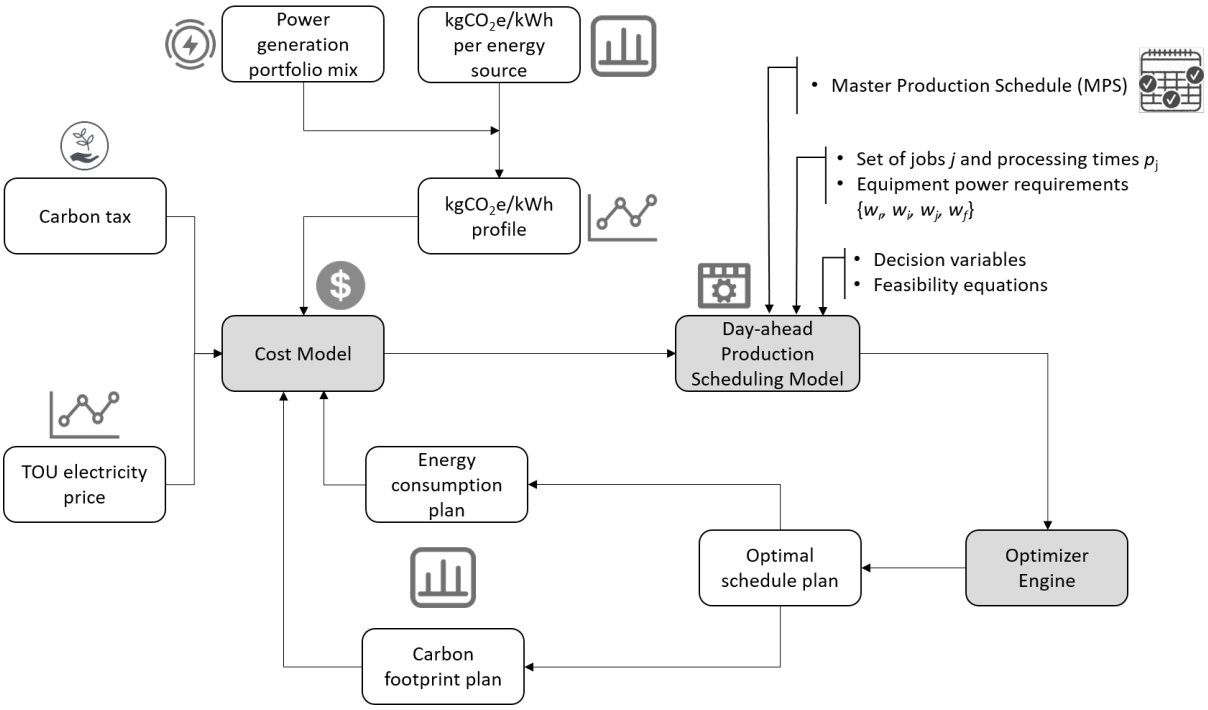


Figure 3.5: Model overview.

3.4.6 Model scope

The described model is intended to optimally provide scheduling decisions in a production environment in which:

a) There exists an energy-intensive process in which the minimization of energy and carbon costs is of interest.

b) The set of jobs are to be processed within a Day-Ahead scheduling horizon. It is assumed that the Master Production Schedule of the day provides enough capacity to process the jobs for the Day-Ahead time window. The Day-Ahead time window becomes a parameter and a constraint in the mathematical model.

c) The model does not consider other production costs that are not energy or carbon footprint related. Nevertheless, this study provides managerial insights into the value of the proposed model solution when compared to a minimum completion time solution.

d) All jobs are shipped at the end of the day, and, therefore, do not incur into delay penalty fees or inventory holding costs.

e) Before the first job can be processed, a ramp-up time is needed and the equipment or process shuts-down only after the last job is completed.

f) Job preemption is not allowed, and for simplicity, ramp-down modes are neglected since the power requirement at this mode is assumed to be near zero.

3.4.7 Energy-Carbon aware mathematical model

Under a multi-objective approach, the mixed integer programming (MILP) formulation of the proposed research model, which is built using completion-time and time-indexed variables, can be modified in the following way to seek the minimization of (3.1) total costs of electricity TEC and (3.2) carbon footprint emissions CFE. That is,

$$\min \quad TEC \tag{3.1}$$

$$\min \quad CFE \tag{3.2}$$

with the following set of constraints.

$$\text{s.t.} \quad TEC = \sum_{t\in\{T\}} \pi_t \psi_t, \qquad \forall\, t = 1, 2, ..., T \tag{3.3}$$

$$CFE = \sum_{t\in\{T\}} \psi_t \gamma_t \qquad \forall\, t = 1, 2, ..., T \tag{3.4}$$

$$c_j \geq p_j \qquad \forall j \in N \tag{3.5}$$

$$c_j + p_k + s_{jk} \leq c_k + M(1 - x_{jk}) \qquad \forall j < k \tag{3.6}$$

$$c_k + p_j + s_{jk} \leq c_j + M x_{jk} \qquad \forall j < k \tag{3.7}$$

$$c_0 = R \tag{3.8}$$

$$c_{max} \geq c_j \qquad \forall j \in N \tag{3.9}$$

$$\sum_{t\in\{T\}} t y_{jt} = c_j - p_j \qquad \forall j \in N \tag{3.10}$$

$$\sum_{t}^{t+p_j-1} z_{jt} \geq y_{jt} p_j \qquad \forall t \in (R, ..., T - p_j + 1) \tag{3.11}$$

$$\sum_{j\in\{N\}} z_{jt} = p_j \qquad \forall j \in N \tag{3.12}$$

$$1 - \sum_{j\in\{N\}} z_{jt} = u_t \qquad \forall t \in T \tag{3.13}$$

$$\sum_{t\in\{T\}} y_{jt} = 1 \qquad \forall j \in N \tag{3.14}$$

$$\sum_{j\in\{N\}} z_{jt} \leq 1 \qquad \forall t \in T \tag{3.15}$$

$$\sum_{j}\sum_{t} z_{jt}\omega_j + u_t\omega_i + \tau_t\omega_r = \psi_t \qquad \forall j \in N, t \in T \tag{3.16}$$

$$\psi_t \gamma_t = \lambda_t \qquad \forall t \in T \tag{3.17}$$

$$c_{max} \leq T \tag{3.18}$$

$$x_{jk}, y_{jt}, z_{jt}, u_t, \tau_t \in \{0, 1\} \qquad \forall j, k, t, j < k \tag{3.19}$$

Equations (3.3) and (3.4) define the total electricity costs and total carbon footprint emissions, respectively. For the next set of constraints, a dummy job 0 is added to the list of

jobs only to depict the starting point of production. Equation (3.5) provides a lower bound for completion times for all jobs according to their respective processing times. Equations (3.6) and (3.7) provide the completion times for all jobs, including their respective setups times depending on the decision on whether job j precedes job k or otherwise. Equation (3.8) depicts the ramp-up time before any job can start. Equation (3.9) gives the Makespan of the production schedule. Equation (3.10) defines the starting time for each job after the setup time of that particular job has been completed. Equations (3.11) and (3.12) are time index formulations to dictate the periods in which each job is being processed. Equation (3.13) indicates the periods of idle time in which the system is neither processing a job, nor is in ramp-up or shut-down mode. Equations (3.14) and (3.15) indicate that the starting of a job must be assigned to a point in time in the planning horizon T, and only one job can be processed at a time. Equation (3.16) provides the electricity consumption in kWh for each period t. Equation (3.17) provides the amount of carbon footprint incurred at period t. Finally, constraint (3.18) sets the binary conditions for the decision variables.

Alternatively, given the conflicted nature amid objectives (3.1) and (3.2), both objectives can be merged together into a single cost function, providing a single objective to the problem. Because a cost function may provide insightful information regarding the impact depending on the direction of cost policies, the proposed thesis research works in this path. Thus, the objective function becomes

$$\text{Min} \quad \left[\sum_{t\in\{T\}} \pi_t \psi_t\right] + \eta\left[\sum_{t\in\{T\}} \psi_t \gamma_t\right] \tag{3.20}$$

where, η depicts the carbon tax parameter applied for the total carbon footprint emissions. Equation (20) can further be simplified into:

$$\text{Min} \quad \sum_{t\in\{T\}} (\pi_t + \eta\gamma_t)\psi_t \tag{3.21}$$

Equations (3.5)-(3.18) would then complete the formulation.

3.5 Results: Validation via a Case Study

To demonstrate the performance of the energy-carbon model, a 10 job problem was constructed. While the values of this case study do not represent standard values of energy-intense equipment, they serve as a basis to validate the logic of the proposed model and it's effectiveness to other traditional job scheduling approaches.

3.5.1 Problem parameters

The processing times of each jobs p_j were randomly generated with a distribution $\sim$ Uniform(1,4); setup times s_{jk} distributed as $\sim$ Uniform(0,2); and power requirements in kW to process each job $w_j \sim$ Uniform(10,40). The resulting parameters are given in Table 3.4. Table 3.5 shows the symmetrical sequence dependent setup times (hrs) between jobs. During setups, the equipment is in stand-by mode at 1 kW; the same is true for idle times. Table 3.6 provides the TOU tariffs used and Table 3.7 reveals the hourly CO_2 emissions per kWh used in this example. The carbon tax was fixed at a cost of \$100 USD per Ton equivalent of CO_2 (tCO_2e).

To illustrate the value of the proposed Energy-Carbon model, the results of the optimal solution are compared to two classical scheduling methods: a) Shortest Processing Time (SPT) algorithm, and b) total completion time (C_{max}).

SPT is a greedy heuristic to sequence scheduling decisions based on the length of the processing time of each job. That is, priority are given to jobs with lower processing times to begin first. Alternatively, certain enterprises that follow production systems based on Lean Manufacturing have performance metrics around the concept of cycle time. Cycle time, also known as Lead Time, is the total completion time (C_{max}) that it takes to complete a set of task or a production schedule, and is of great importance in manufacturing . Linear Programming models exist in the literature to optimally solve this criteria.

Table 3.4: Job processing time (hrs) and power requirement (kilowatts) parameters.

Job	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
Processing times p_j	1	2	1	4	1	1	2	1	2	3
Power-kW w_j	30	60	20	10	50	40	30	30	60	20

Table 3.5: Sequence-dependent job setup times matrix.

	Job 0	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6	Job 7	Job 8	Job 9	Job 10
Job 0	-	2	2	0	2	1	2	1	0	0	1
Job 1		-	2	1	2	1	2	1	2	0	1
Job 2			-	1	2	2	0	2	0	1	1
Job 3				-	2	0	2	1	2	0	0
Job 4					-	1	0	2	1	0	0
Job 5						-	0	1	1	2	2
Job 6							-	2	1	0	0
Job 7								-	2	1	1
Job 8									-	2	2
Job 9										-	2
Job 10											-

Table 3.6: TOU electricity prices.

TOU Tariffs	Time	Price ($/kWh)
Off-Peak	0:00-6:00 11:00-15:00	0.10
Peak-Hours	6:00-10:00 16:00-20:00	0.20

Table 3.7: Hourly CO_2 emissions per kWh.

Time	CO_2 emissions ($kgCO_2e/kWh$)
07:00-11:00 14:00-18:00	0.250
5:00-7:00 11:00-12:00 13:00-14:00 18:00-20:00	0.500
4:00-5:00 12:00-13:00 20:00-21:00	0.750
0:00-4:00 21:00-24:00	1.000

3.5.2 Model results

The comparative scheduling results and cost breakdown of each method are shown in Table 3.8 and Table 3.9, respectively. As it can be seen in Table 3.8, the Energy-Carbon Model has the lowest cost overall. This is possible because the Energy-Carbon Model assigns the most intense jobs to off-peak hours as much as possible, and in order to do so, setup planning for those jobs must occur prior to off-peak hours. Moreover, planned idle time, or waiting, becomes crucial to achieve cost optimality. From Table 3.8, the Energy-Cost Model is the only method that has periods of idle time (i.e. at 8:00, 9:00, and 18:00hrs). It is more cost-effective to wait idle during peak-hours prior to the next setup. From this, we establish the following paradigm shift in a production system.

A paradigm shift: Idle time is of strategic advantage, not a waste

Traditionally, operational excellence methodologies (i.e Lean Manufacturing) have described *idle time* as a waste, and thus, a non-value added activity that must be eliminated or reduced. This principle has led to performance metrics in which the shorter the cycle time, the better. However, from an Energy-Carbon production scheduling perspective this may not be true. Hence, we derive the following claim.

CLAIM: Planned idle time is of strategic advantage, not a waste.

PROOF: From Table 3.8, it can be shown that it is more cost-effective to have a process wait idle during electricity peak-hours, or during hours of high-carbon content per kWh, prior to the next setup, instead of continuing quickly with the next task, as the STP or C_{max} methods would do. Although the C_{max} method is able to complete faster and have no setups in its schedule, it fails to deliver the minimum energy-carbon costs since it neglects the hourly variations in energy prices and emissions. This logic is embedded in the Energy-Carbon Model and allows it to optimize energy and carbon costs.

Table 3.8: Scheduling results for SPT, C_{max}, and Energy-Carbon Model; I = Idle, S = Setup.

Hour	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
Price ($/kWh)	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
CO_2 emissions	1	1	1	1	0.75	0.5	0.5	0.25	0.25	0.25	0.25	0.5	0.75	0.5	0.25	0.25	0.25	0.25	0.5	0.5	0.75	1	1	1
Solutions																								
SPT	S	S	J-1	S	J-3	J-5	S	J-8	S	J-6	J-2	J-2	S	J-10	J-10	S	J-7	J-7	S	J-9	J-9	J-4	J-4	J-4
C_{max}	J-3	J-5	S	J-8	J-2	J-2	J-6	J-10	J-10	J-4	J-4	J-4	J-9	J-9	J-1	S	J-7	J-7						
Energy-Carbon Model	J-3	J-10	J-10	S	J-1	S	S	J-4	J-4	J-4	J-9	J-9	J-6	J-2	J-2	**I**	J-8	**I**	**I**	S	J-5	S	J-7	J-7

After computing the total energy and carbon costs warranted by these solutions, we obtain that the SPT and C_{max} methods have an optimality gap of 14% and 16%, respectively, compared to the schedule built on the Energy-Carbon Model (see Table 3.9).

Most firms are already cognizant of energy costs and are already making production decisions with those in mind. So the real value of the proposed model is to help firms adjust production to account for carbon costs. Thus, we further analyze the emission cost savings between a firm that minimizes only energy costs and a firm that minimizes both energy and carbon costs.

Depicted in Table 3.10, under a sole energy cost savings approach, jobs with higher energy requirements are produced during off-time peaks as much as possible, thus, the entire production schedule tends to shift at times were electricity prices are at their lowest (i.e. evenings). However, this action is not environmentally efficient; carbon footprint emissions per kWh are mostly high during those hours since renewable sources are not available and, therefore, high carbon power sources (i.e. coal plants) are in use to power the grid at those times.

Table 3.11 shows that, while a pure energy cost savings approach is only 2% away from the optimal cost, the emissions cost is approximately 11% higher than our model which minimizes both energy and carbon costs. Nevertheless, these savings are dependant on the established value of carbon tax.

Figure 3.6 shows the savings sensitivity on carbon tax for both approaches. It can be seen that minimizing for only energy costs is insensitive to increases on carbon tax, as it stays constant at a value of 360 $kgCO_2e$. Therefore, the production schedule remains the same regardless of a carbon tax.

Conversely, the Energy-Carbon Model shows that the production scheduling is responsive to carbon taxes. There is a decreasing pattern in emissions as carbon taxes increases, having the biggest drop when moving from \$150 to \$175 per Ton equivalent of CO_2 ($/Ton$CO_2e$). From an environmental policy perspective, this provides a direction to legislators on the flexibility of emissions depending on the value of carbon tax.

Table 3.9: Cost breakdown for SPT, C_{max}, and Energy-Carbon Model

	SPT	Cmax	Energy-Carbon Model
Completion time	24	18	24
Energy cost	79	76	61
Emissions cost	27	32	32
Total cost	106	108	93
Optimality Gap (%)	14%	16%	*

Table 3.10: Scheduling results for Energy cost savings and Energy-Carbon Model; I = Idle, S = Setup.

Hour	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
Price ($/kWh)	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
Emissions (eqkgCO2/kWh)	1	1	1	1	0.75	0.5	0.5	0.25	0.25	0.25	0.25	0.5	0.75	0.5	0.25	0.25	0.25	0.25	0.5	0.5	0.75	1	1	1
Solutions																								
Energy cost only	J-3	J-5	**I**	**I**	**I**	**I**	**I**	**I**	**I**	S	J-8	J-2	J-2	J-6	J-10	J-10	**I**	**I**	J-4	J-4	J-4	J-9	J-9	J-1
Energy-carbon Optimization	J-3	J-10	J-10	S	J-1	S	S	J-8	**I**	**I**	J-2	J-2	J-6	J-9	J-9	J-4	J-4	J-4	**I**	S	J-5	S	J-7	J-7

Table 3.11: Performance results on Energy-Carbon model and only Energy.

	Energy-Carbon	Only Energy
Completion time	24	24
Energy cost	61	60
Emissions cost	32	36
Total cost	93	95
Optimality Gap (%)	*	2%

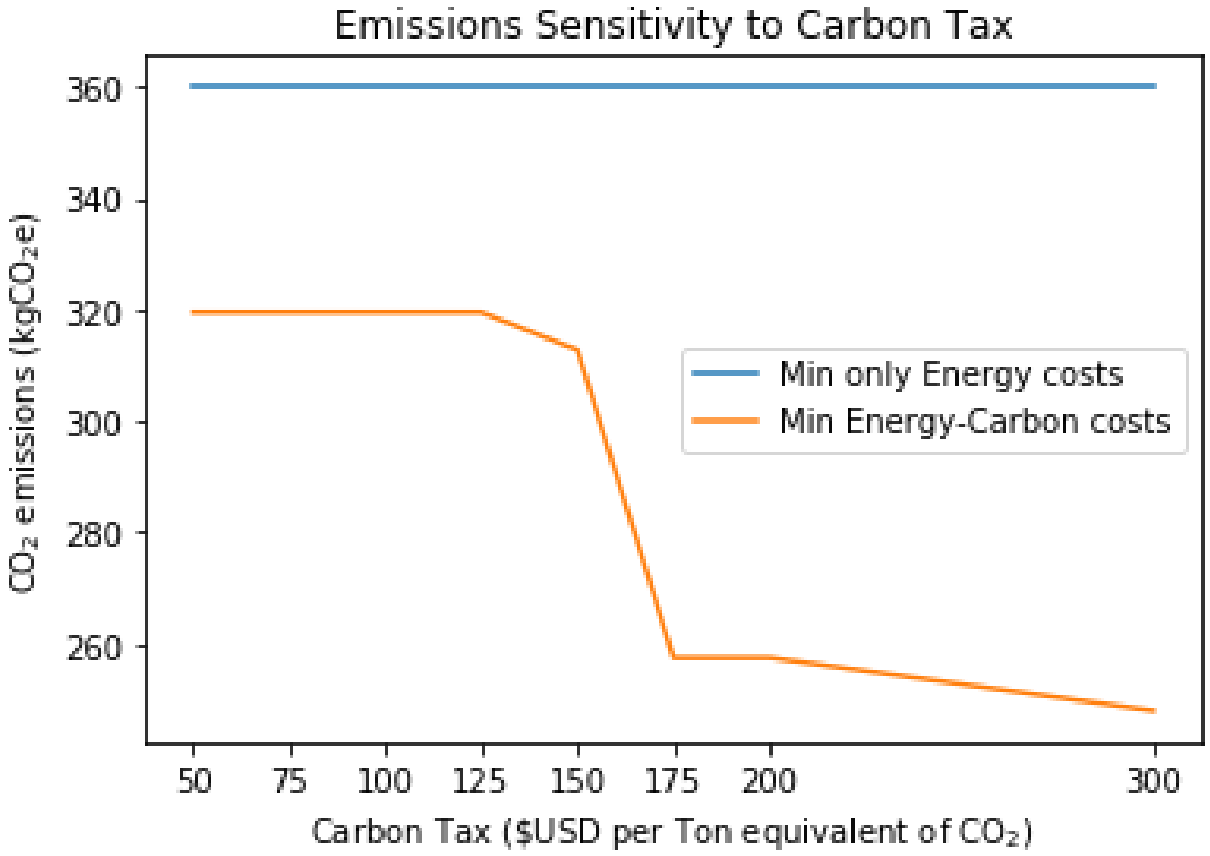


Figure 3.6: CO_2 footprint emissions sensitivity to carbon tax.

Interestingly, although the emissions in the Energy-Carbon model appear to be flat in the range of \$50/TonCO_2e and \$125/TonCO_2e, the production schedule does suffer modifications within this range. To verify this, Table 3.12 shows the production completion time decisions for each of the 10 jobs depending on the value of carbon tax. Observe that Job 8 changes its completion time when transitioning from \$50/TonCO_2e to \$75/TonCO_2e. Similarly, it can be visualized that the schedule in \$100/TonCO_2e is different to the one in \$125/TonCO_2e. This proves that the scheduling decisions to reach the minimum combined costs of energy and carbon emissions in the Energy-Carbon model are sensitive to the values of carbon tax.

3.5.3 Pareto optimal frontier

In order to examine the trade-off between the total energy costs *TEC* and total carbon footprint emissions *CFE*, Pareto optimal schedules were constructed for the multi-objective sequence dependant single machine scheduling problem. These Pareto optimal schedules are schedules for which no other schedule has both lower energy costs and a smaller carbon footprint. To obtain the Pareto optimal schedules, the ϵ-constraint method was utilized. A series of fixed upper and lower bounds were constructed. First, the problem was solved with the single objective of minimizing *TEC*, omitting *CFE*. And second, solved with respect to minimizing *CFE*, without considering *TEC*. Figure 3.7 shows the Pareto optimal frontier. As it can be seen, optimal *TEC* and *CFE* are found in two different schedules as an evidence that Objectives (3.1) and (3.2) cannot be optimized simultaneously. To achieve the lowest energy costs, jobs should be processed in off-peak hours as much as possible, which leads to higher carbon footprint emissions. On the other hand, if the objective is to minimize the total carbon footprint, jobs should be processed during the low-carbon hours to the maximum extend as possible. However, those low-carbon hours fall in peak-hours which elevate the energy price. Nevertheless, the Pareto frontier results suggests that a significant energy cost reduction can be achieved with minimal increase in carbon footprint emissions.

Table 3.12: Production scheduling completion times sensitivity by carbon tax.

Carbon Tax ($/Ton$CO_2$e)	50	75	100	125	150	175	200	300
Start	0	0	0	0	0	0	0	0
Job 1	5	5	5	24	5	5	5	5
Job 2	12	12	12	15	12	12	12	12
Job 3	1	1	1	4	1	1	1	7
Job 4	18	18	18	10	18	24	24	24
Job 5	21	21	21	5	21	8	8	8
Job 6	13	13	13	13	13	13	13	13
Job 7	24	24	24	22	24	18	18	18
Job 8	10	8	8	1	8	10	10	10
Job 9	15	15	15	12	15	15	15	15
Job 10	3	3	3	18	3	21	21	21
Emissions ($kgCO_2e$)	320	320	320	320	313	258	258	248

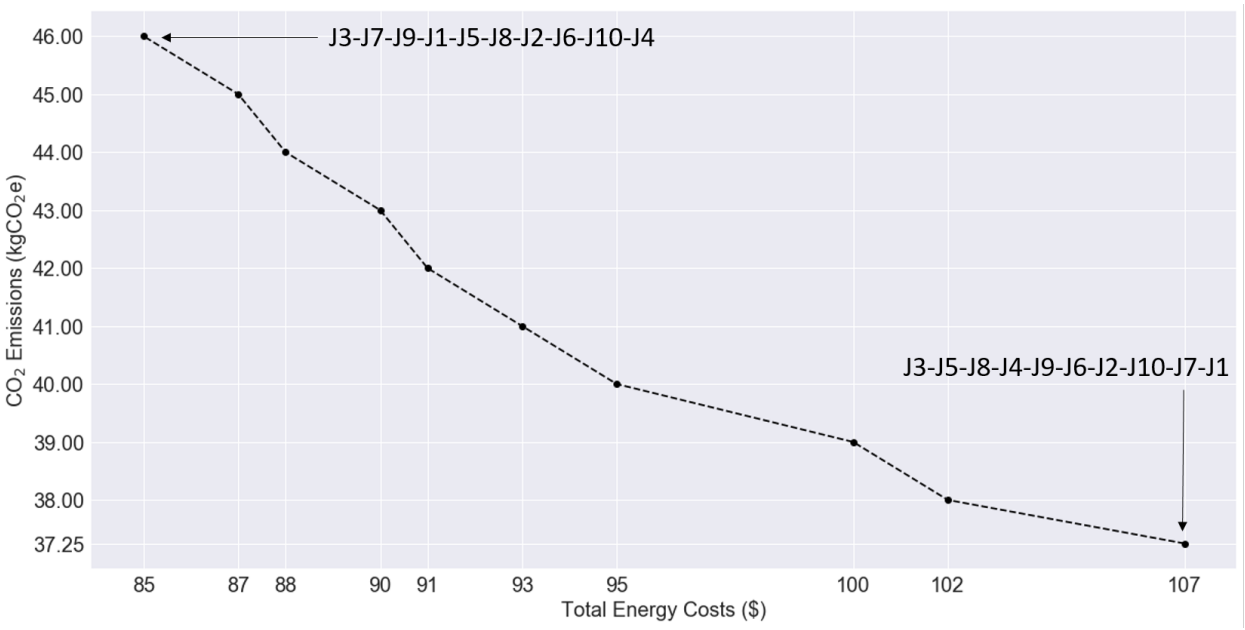


Figure 3.7: Pareto optimal frontier solutions for the example using the ϵ-constraint approach.

3.6 Conclusions

In the advent of a fast pacing growth of the manufacturing industry in the United States and worldwide, and under the panorama of increasing energy costs and environmental policies driven by global warming concerns, the proposed research work is aimed at creating an energy optimal production schedule model, integrating on-site power technologies, in order to minimize energy costs and reduce carbon footprint. The proposed model is built under the context of a sequence-dependent single machine scheduling problem. Moreover, the scheduling decisions are assumed to be affected by independent time of use electricity prices and carbon footprint environmental policies forced by either corporate or governmental institutions. To this end, a Low Energy-Carbon Cost Sequence Dependent Job Scheduling optimization model (LEC-SDJS) is developed under a Mixed Integer Linear Programming formulation. Preliminary results show the value of the model when compared to classical scheduling optimization approaches and job scheduling heuristics, and demonstrate that:

1. The integration of low-energy-carbon models can reduce the energy and carbon footprint costs in production systems.

2. The model can serve as an application to budget the required energy and carbon footprint ahead of time. This will open new opportunities within Enterprise Resource Planning systems (ERPs).

Per the discussion and findings in the literature, although there is novelty in the proposed research, it is of important to address the limitations of this proposed research.

Furthermore, although the results of the proposed model does offer an advantage in terms of energy and carbon footprint costs for production, its application in practice may face important drawbacks. In the presented case study, it was seen that the job completion time in the proposed model can exceed the minimum makespan, therefore, representing an overhead burden to the organization. These overhead costs may hinder the adoption of the proposed model and its sustainability benefits. On the bright side, the proposed model does offer a cleaner manufacturing culture that can drive belonging, pride and engagement to its employees. From a people-perspective, the idle times observed in the job sequencing solution

can be seen as an opportunity for training and enhancing the quality of life of employees by mitigating stress. At the same time, less emissions and energy costs results in higher sustainable corporate results aligned with eco-social responsibility. It has been seen that enterprises that are more aligned to eco-social responsibility are more successful than those that are not.

In terms of obtaining the TOU electricity prices, the utility provider may not offer the day-ahead electricity prices, in which case, average seasonal TOU prices can be estimated using historical data. Also, in the generation of the hourly carbon footprint profile of the grid, the information of the power generation portfolio mix is not available in real-time, hence, the profile would depend on the reported information from the past-day. The Energy Information Administration (EIA) constitutes a reliable resource in the U.S. to access energy related data, but this may not be the case in other countries.

Moreover, although the optimization structure of the proposed model is designed for a single machine scheduling problem, its implementation is not suitable if the selected machine is part of a production line that works under a "one-piece-flow" production system. Instead, the entire production line would need be treated as a "single machine". Under this approach the power requirements and cycle times of each machine in the line could be aggregated to define the processing times p_j for each production order j.

Finally future research calls for the development of meta-heuristics to solve large problem sets and the evolution of the proposed linear model to cover stochasticity in the carbon dioxide emissions from the grid.

Chapter 4

The Third Article: Optimal Energy System for Energy-Carbon Neutrality in Production Scheduling via Net Metering

Disclosure Statement

This chapter corresponds to the manuscript "Optimal Energy System for Energy-Carbon Neutrality in Production Scheduling via Net Metering" submitted to the *Journal of Cleaner Production* on January 12, 2022. The manuscript reference number is **JCLEPRO-D-22-00796**, and is currently under review by the Editor. The authors of this manuscript are: Samuel C. Trevino Martinez (main and corresponding author), Dr. Rapinder Sawhney, and Dr. Charles Sims, all from the University of Tennessee-Knoxville. Samuel C. Trevino Martinez was responsible for the conceptualization, methodology, software, validation, investigation, writing - original draft, and visualization of this article. Dr. Rapinder Sawhney was responsible for the supervision of the article, and Dr. Charles Sims contributed to the conceptualization, methodology, and writing of the article.

4.1 Abstract

Considering that energy is an indispensable resource to power equipment, assets, services and processes in manufacturing operations, and carries both financial and environmental pressures to enterprises - specially in energy-intensive industries -, this research presents an optimization framework that allows manufacturing processes to advance towards sustainability in operations by becoming energy-carbon neutral. This involves integrating renewable energy system decisions into production scheduling, in the form of solar photovoltaic modules and energy storage systems, and leveraging on energy policies that provide credits for net excess generation, such as net metering programs. The proposed optimization framework is built under a multi-objective MILP formulation, using time-indexed variables, and demonstrated in a case study of an energy-intensive injection molding process. Furthermore, a robust optimization approach using Monte Carlo simulations are suggested to construct confidence intervals for the lifespan of the solar installation. Results demonstrate that manufacturing systems that enable their solar photovoltaic system with energy storage dispatching capability are more cost-competitive to lower net metering compensation rates than those that do not.

4.2 Introduction

Energy is an indispensable resource in manufacturing operations. Rising energy costs and climate change related environmental regulations and policies cause enterprises to carry both financial and environmental pressures on energy consumption and its associated carbon footprint, particularly in energy-intensive industries. Commitments towards a carbon-free economy by 2050 [20] [21] are shaping organizational competitiveness in terms of how well enterprises attain sustainability goals and advance in methods to reduce energy costs, while still improving productivity performance levels. Thus, advancements in optimal energy consumption efficiency and carbon footprint mitigation are crucial for manufacturing systems to remain competitive, and these approaches will only become more relevant in the near future.

In manufacturing, machine tools are the basic energy consumption devices. [4]. Machine drives, pumps, and fans, which are primarily powered by electric motors, account for about half of the manufacturing sector's delivered electricity use and 8% of the sector's total fuel consumption [133]. Their wide use across many industries results in a substantial impact on the demand placed on power grids. The electricity use by machine drives in manufacturing has ample implications for total energy use. In total, electricity powers about 89% of motors in manufacturing [5].

Considering that the electricity demanded by manufacturing enterprises industries is mostly generated from fossil fuel sources containing high levels of carbon, it has led them to be accountable for 24% of the global CO_2 emissions [14] and a main contributor to one of the world's public problems, climate change. Thus, the indirect emissions caused by machine tools using electricity can not be neglected [7].

Despite that Operational Excellence practices, such as Lean Manufacturing, Six Sigma, Total Quality, among others, have been extensively analyzed for decades there is a lack of clear and structured research in the study of energy utilization in production systems and their environmental impacts [134]. Energy and environmental metrics need to be fully integrated into the decision making within the performance measurement system of organizations [25] to achieve the concept of Sustainable Development envisioned by the United Nations [26]. This concept is defined in what is known as the Sustainable Triangle, depicting a balance among the economic aspects of productivity, social welfare and quality of life, and the preservation of natural resources of the environment. Given the continuous growing demand for goods, the development of energy-carbon aware models that can be integrated into the operational excellence systems of enterprises is essential to establish sustainability in the manufacturing sector, and transition into carbon-neutral processes. It has been seen that enterprises that are more aligned to eco-social responsibility are more successful than those that are not [47].

Without major capital investments, energy-carbon efficient solutions can emerge from production planning and scheduling optimization models. The reduction and planning of idle-time in combination to the sequencing of jobs leads to a better prediction of the workflow and allow management to budget energy requirements and carbon emissions for the system

[46]. Given the emergence of renewables and smart grids, the production scheduling problems requires new ways of formulating and integrating aspects where time-sensitive energy prices, carbon content on the grid, energy policy, and renewable energy technologies are considered. Especially since the time of consumption may significantly affect the price of electricity and the amount of CO_2 content on the grid.

An interesting energy policy that could enable the adoption of renewable energy technologies to mitigate carbon emissions in the manufacturing industry, and alleviate the exposure to ever rising energy prices is in net metering. Net metering is a regulatory billing mechanism that credits renewable energy (i.e. solar and wind) system owners for the electricity they generate and give back to the grid [42].

Thus, customers are only billed for their "net" energy use. Figure 4.1 illustrates this mechanism. Although net metering has portrayed economic and environmental benefits within residential applications [43] [44], little work has been done in demonstrating the same in the commercial and manufacturing sectors, and remains to be explored.

In light of the above, this article presents a production scheduling optimization framework that allows manufacturing processes to advance towards sustainability in operations by becoming energy-carbon neutral, while also ensuring productivity metrics. The proposed model is built under the context of a sequence-dependent single machine scheduling problem, where scheduling decisions are assumed to be affected by independent time of use electricity prices. In addition, this research is one of a kind because of the integration of on-site solar photovoltaic (PV) sizing decisions, energy storage dispatching, and net metering policies, as a mechanism to achieve net zero footprint in manufacturing processes.

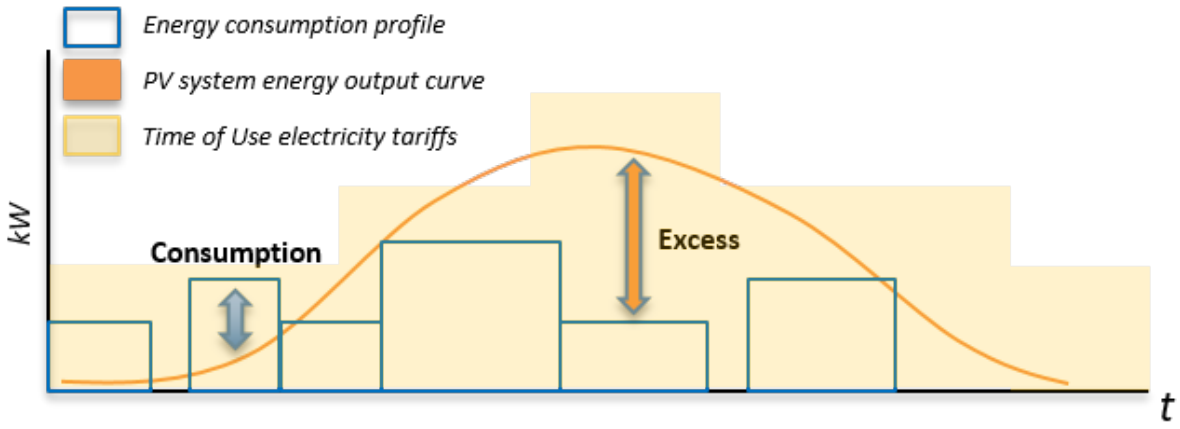


Figure 4.1: Net metering concept.

4.3 Literature Review

4.3.1 Single machine scheduling problem

Machine scheduling is a short-term production planning task to determine the sequence of jobs allocated to machines, that is, a set of n jobs $J = \{J_j\}_{j=1}^{n}$ need to be assigned to and sequenced on a set of of m machines $M = \{M_k\}_{k=1}^{m}$. Each job consists of a set of ϕ_i ordered operations $O_j = \{O_{j,g,i}\}$, where $O_{j,g,i}$ is the g-th operation of job j processed on machine i.

In addition, for each job $j \in N$ and machine $i \in M$, we are given a non-negative integer $p_{j,g,i}$, which corresponds to the processing time of $O_{j,g,i}$, and $c_{j,g,i}$ is the completion time of $O_{j,g,i}$. In a single operation or single machine production system, the aforementioned sets and variables are simplified to only $J = \{J_j\}_{j=1}^{n}$, $M = 1$, p_j, and c_j, accordingly [50] . An important condition in the single machine problem is that N jobs are processed through one machine and there is no preemption allowed, that is, once a job starts, the machine must complete processing the job without interruption.

Traditional objective functions studied in single machine scheduling problems include total weighted completion time [$\sum w_j C_j$], maximum lateness [L_{max}], number of tardy jobs [$\sum U_j$], and total weighted tardiness [$\sum w_j T_j$]. In the frequently utilized three-field notation $\alpha/\beta/\gamma$ to describe a scheduling problem [129], where the first field (α) corresponds to the number of machines, the second field (β) to the setup information and conditions, and the third field (γ) the performance objective, these problems are denoted as $1\|\sum w_j C_j$, $1\|\sum L_{max}$, $1\|\sum U_j$, and $1\|\sum w_j T_j$, respectively. The inclusion of the release date constrains r_j for any jobs make these problems NP-hard, as well as the total weighted tardiness problem with and without the release dates [135] [136].

The study of single machine scheduling has also being extended to include sequence-dependent setup times s_{jk} between jobs [51] [52] [53] . How the jobs are sequenced in the process has an significant influence on energy consumption given the sequence-dependent setup times [49]. Based on the sequence in which jobs are processed in the machine, a sequence-dependent setup time s_{jk} applies when processing job k, $k \in N$, after having processed job j, $j \in N$. In it's general form, the sequence-dependent single machine job scheduling problem, $1|s_{jk}|C_{max}$, is an *NP-hard* problem as well.

4.3.2 Energy-oriented models

Although the single machine scheduling problem has been exhaustively studied in the literature since decades [121], the interest of extending the problem to include energy costs and/or carbon emissions is a fairly new hot topic which has gained ground in recent years motivated primarily by energy cost awareness and environmental concerns due to climate change. In this regards, the direction of research has particularly addressed multi-objective formulations and approaches to minimize classical scheduling objectives (i.e. completion time C_{max}, total weighted tardiness TWT, maximum lateness L_{max}, tardy jobs T) in combination to related energy and emissions objectives.

In [122], they present the single machine scheduling problem in which both C_{max}, and total energy consumption, TEC, are minimized, $1||C_{max}TEC$. The proposed multi-objective mixed integer linear programming (MILP) formulation, solved by adding a weighted sum to both objectives, provides a framework for dispatching rules to determine when to leave a machine idle, or to be turned off in between jobs. This model was further generalized by constraining job release dates [125]. The proposed model, not only determines the timing and length of turn off/on decisions, but also the sequence of jobs, such that TWT and TEC are minimized, $1|r_j|\ TWT\ TEC$.

[74] investigated the single machine production scheduling problem considering different equipment modes (i.e. operating, idle) with different power requirements for each mode. Under the constraint that all jobs must be completed in a given time horizon, the proposed model minimizes the total energy costs and provides insights into the transitions between operating modes.

Even though energy-efficient practices are aligned with corporate sustainability targets and provide important cost-savings, there exists a conflicting nature between traditional operational performance metrics (i.e. throughput) and energy-oriented models [117] [118]. This divergence is explored by [123] in a production scheduling setting via a multi-objective MILP optimization model. Pareto frontier optimal solutions, utilizing the ϵ-constraint method, present the trade-off between minimizing C_{max} and total energy consumption.

Similarly, [76] derived a general multi-objective mixed integer programming (MIP) formulation that considers both C_{max} and energy and energy-related criteria (i.e. peak load) when optimising the operating schedule of a flow shop. The Pareto frontier was computed specifying upper bounds on the peak load and then searching for the minimum C_{max}. Significant trade-offs between both objectives are reported. On another approach, [72] generated an energy-aware scheduling algorithm based on MIP formulation to realise energy savings for a flexible flow shop that was required to keep its fixed job assignments and sequences.

Given the above, from a simple energy-oriented perspective, solutions that could potentially extend the completion time of jobs in return of energy-cost savings are unlikely to be embraced in a practical industrial setting in which on-time delivery and service levels are key metrics in the competitiveness of many enterprises. Therefore, production scheduling frameworks aiming at energy costs and sustainability in manufacturing must be robust enough to integrate leverage points in carbon emission costs, distributed energy resources and storage, and energy policy.

4.3.3 Carbon-emissions related models

Manufacturing strategies in relationship to production scheduling have also shown to have a significant breakthrough in energy efficiency and carbon footprint. For the first time, researchers begin to extend the well-known job shop scheduling problem to energy-related factors besides the traditional metric of cycle time [72], [73], and [74]. In [75], the inclusion of peak power load, energy consumption, and carbon footprint factors is presented in a multi-objective mathematical programming model. On a novel approach, [76] addresses a low-carbon production scheduling algorithm for a single machine considering renewable energy. [77] takes the flexible job-shop scheduling problem in a manufacturing setting to seek solutions that minimize production and energy costs, by considering renewable energy and energy storage. Other notable papers examine the effect of time-sensitive electricity prices, such as time-of-use electricity tariffs, on production planning [78] and scheduling decisions [48].

4.3.4 Renewable energy related models

With the expansion of renewable energy technologies, studies in support of micro-grid penetration gain momentum [27] [28] [29]. As opposed to conventional power generation, distributed energy resources (DER) technologies soothe environmental problems through: reduction in emissions, higher energy efficiencies, reduced impact to public health, and conservation of natural resources [30]. DER systems typically use renewable energy sources, including small hydro, biomass, biogas, solar power, wind power, and geothermal power, and play an important role for the electric power distribution system.

Given the above, the pathway towards carbon-neutrality in manufacturing via DER are promising. The integration of on-site renewable energy into factories from a real-time operations management perspective is a hot topic [31]. Other than sourcing from on-site renewable generation, manufacturing plants can also maximize the value of long-term electricity procurement plans through renewable energy certificates trading and power purchased from energy markets [32]. To some extent, these dynamics currently shape the way in which many of the top Fortune 500 companies realize their corporate sustainability goals [33].

In [81], a stochastic-based planning framework for a production system utilizing DER is developed with the objective of improving energy efficiency with lower grid energy dependency and outage risk.

4.3.5 Energy storage system related models

As more intermittent energy production from DER is being incorporated into energy systems, the need for optimal Energy Storage Systems (ESS) sizing from an economic perspective becomes a challenging problem [85].

Manufacturing systems can also leverage on ESS to reduce energy costs via active demand side energy management when operating under an on-peak demand price structure [87].

An energy procurement plan for a flow shop scheduling problem considering on-site renewables uncertainty, day-ahead and real-time electricity prices, and energy storage is discussed in [82]. [83] extends the job shop scheduling problem as a multi-objective stochastic

problem to minimize total completion time and energy costs for manufacturing plants that value on-site renewable generation and are faced with time-sensitive electricity prices. The power required for production is met by a combination of on-site renewable generation, supply form the grid, and energy storage systems.

4.3.6 Energy policy related models

The combination of climate change related events and renewable energy limitations have sparked debates in energy policy and energy regulatory frameworks around the globe (e.g. tax credits, incentives, carbon tax, cap-and-trade systems) [36] [37] [38]. As a result, these environmental regulations, mostly arising since the 2015 Paris Agreement on climate change to limit global warming to less than $2°C$ [20], in conjunction with institutional energy management standards (e.g. ISO 50001), put industry and manufacturing systems under pressure to meet sustainability targets and eco-friendly practices. For example, the approval of new companies, incentives for new investments, or prevention of opportunistic behavior decisions across eco-industrial parks are based on industrial symbiosis (IS) performance [39]. IS is an indicator related to the interchange of materials, energy, and water. Additional energy management performance indicators are proposed in [40]. To this end, analyses that provide insights to both policy-makers and production managers in determining whether replacing conventional manufacturing strategies with environmentally friendly ones is technically feasible and economicly viable [41] are very much needed.

From a policy-maker perspective, energy policy plays an important role not only in determining how fast can we get to a carbon-free economy, but also in how these policies impact the economic competitiveness of the manufacturing sector. Analyses that provide technical feasibility and profitability in eco-friendly strategies are critical to support both environmental policy-makers and production managers. Certainly, energy policy should be geospatially-based in order to maximize the value of available clean energy resources and enhance energy security against uncertainty and inclement weather.

4.4 Methodologyy

As seen in the literature, minimizing electricity costs while reducing CO_2 emissions in production systems is a challenge, therefore, the proposed research work is aimed at creating an energy optimal renewable energy system design, utilizing on-site solar power, to support production scheduling decisions to achieve this.

4.4.1 Solar photovoltaic power

One of the fastest growing renewable energy technologies are solar photovoltaic (PV) systems. According to the U.S. Energy Information Administration (EIA), solar PV capacity additions in the United States increased 25% from 2019 to 2020, and overall, solar is expected to account for the largest share of new capacity added to the grid in 2021 at 39%, followed by wind at 31% [137], shown in Figure 4.2. Markets for solar energy are maturing rapidly around the globe and are now making solar electricity economically competitive with conventional energy sources.

The proposed energy system design takes into account decisions about on-site solar PV capacity planning as a leverage mechanism for manufacturing enterprises to reduce energy costs and carbon footprint emissions. Hence, geospatial information regarding the solar radiation available at the facility's location is critical. Solar irradiance data is pulled from the National Solar Radiation Database (NSRDB) which is maintained by the National Renewable Energy Laboratory (NREL) . NSRDB is a database, covering the United States and a subset of international locations, with a complete collection of hourly and half-hourly values of metereological data and common measurements of solar radiation. In solar PV technology, the widely used measurement of solar radiation, is the global horizontal irradiance (GHI).

In solar PV capacity planning, the GHI at a location defines the average daily solar radiation in units of kilowatt-hour per square meter kWh/m^2 per day, also referred as "peak sun hours". The term "peak sun hours" refers to the amount of hours in which the intensity of solar irradiance (sunlight) reaches an average of 1,000 watts of energy per square meter per day at a particular location.

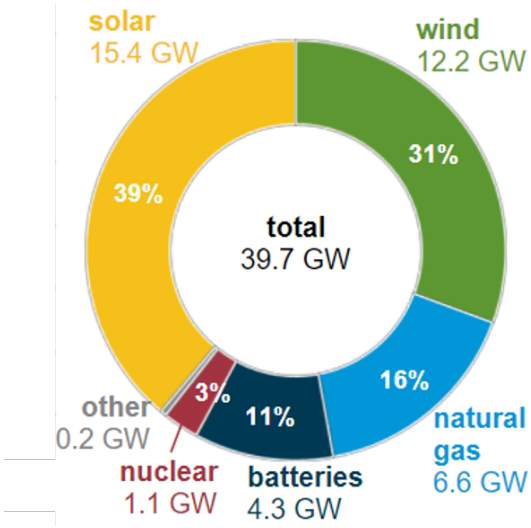


Figure 4.2: Planned U.S. utility-scale electricity generating capacity additions (2021). Source: U.S. Energy Information Administration

In Figure 4.3, the annual average peak hours per day is mapped across the United States. For example, a location that receives 5 kWh/m^2 per day can be said to have received 5 hours of sun per day at $1kW/m^2$. This allows to precisely measure the amount of sunlight that will hit solar panels installed in a given location. Solar panels are commonly rated by the amount of power it creates at Standard Test Conditions, or STC. These conditions include intensity of the sun (peak solar radiation), 1,000 W/m^2, and 25 degrees Celsius cell temperature.

Solar panels in PV technology are subject to energy losses that need to be accounted for in the performance efficiency expected in a real system. Since PV solar panels generate direct current (DC) output, an inverter is required to convert DC into alternate current (AC) output which motors and other forms of equipment can use. The inverter's nominal rated DC-to-AC conversion efficiency, defined as the inverter's rated AC power output divided by its rated DC power output is typically around 96%. Solar panels are also sensitive to temperature-related losses as a function of the cell temperature. Whenever solar panels are exposed beyond the reference temperature of $25°C$, a temperature coefficient loss of power occurs. Depending on the cell material (i.e. thin film with glass cover, crystalline silicon with anti-reflective coating), modules can experience a temperature coefficient loss ranging from $-0.20\%/°C$ to $-0.47\%/°C$.

Contingent on the location of the PV system, other system losses categories i may apply, such as: soiling, shading, snow, mismatch, wiring, connections, light-induced degradation, nameplate rating, age and availability. Soiling refers to dirt or other matter on the surface of the PV module that prevent solar radiation from reaching the cells. Soiling losses are greater in high-polluted areas with infrequent rain. Shading caused by objects near the modules (i.e. trees), or by self-shading when modules arranged in rows cause shadows on an adjacent row, reduce the solar radiation incidence. Snow reduces the energy produced, depending on the amount of snow and how long it remains on the PV modules. Mismatch are electrical losses due to slight differences in current-voltage characteristics caused by variations in PV manufacturing between modules in the array.

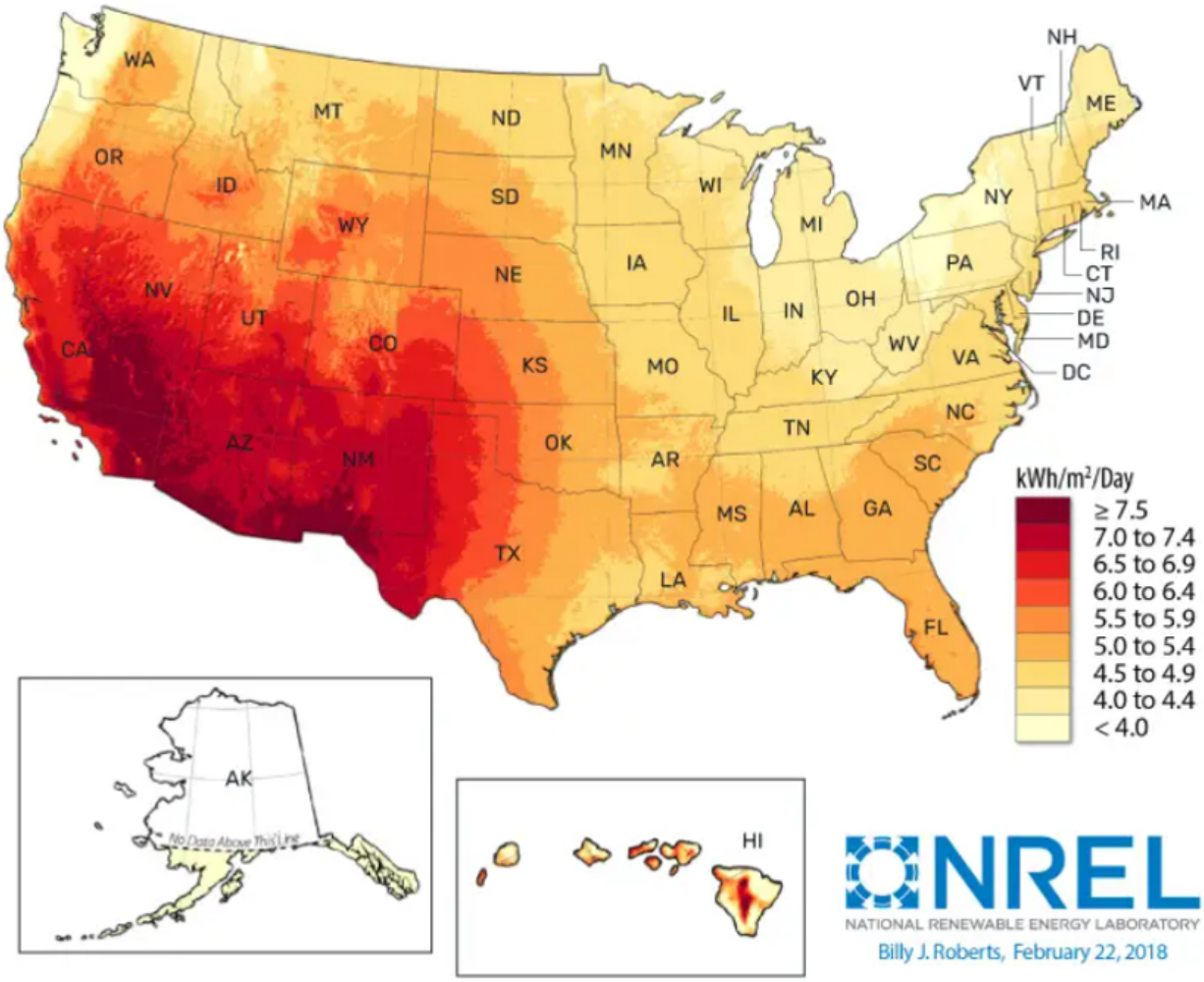


Figure 4.3: Annual average daily peak sun hours (kWh/m^2/day) based on data from 1998-2016 compiled by the National Solar Radiation Database. Image adapted from National Renewable Energy Laboratory (NREL).

Wiring losses relates to resistive losses in the DC and AC wires connecting modules, inverters, and other parts of the system. Connections yield resistive losses in electrical connectors in the system. Light-induced degradation is the loss of performance arising in the very first hours of exposition to the sun, with crystalline modules. The nameplate rating loss accounts for the accuracy in the testing yield power measurement at STC compared to the manufacturer's nameplate rating. Age refers to the effect of weathering of the PV modules on the array's performance over time. Availability losses are related to reductions in the system's output due to maintenance, grid outages, and other operational factors.

Considering the above, the PV system loss L is expressed as follows:

$$L = 1 - \prod_{i} \left(1 - \frac{l_i}{100}\right), \qquad \forall i \tag{4.1}$$

where: l_i is the percentage loss category i of the panels.

Equation (4.1) can further be used to determine the PV efficiency PV_{eff_t} of the system at each period t:

$$PV_{eff} = \begin{cases} I(1-L), & T_{cell_t} \leq T_{ref} \\ I(1-L) + \theta(T_{cell_t} - T_{ref}), & T_{cell_t} > T_{ref} \end{cases} \tag{4.2}$$

where: I is the inverter efficiency, θ is the temperature coefficient loss applied to the temperature difference of the cell T_{cell} and the reference temperature T_{ref} of $25°C$.

The above is later used to estimate the solar energy generation PV_{G_t} at any point in time t, as a function of solar PV capacity size PV_z in kilowatt (kW), equivalent sun-peak (full sun ratio at $1kW/m^2$) S_t during time t, and the system efficiency PV_{eff_t} :

$$PV_{G_t} = PV_z \cdot S_t \cdot PV_{eff_t}, \qquad \forall t \tag{4.3}$$

4.4.2 Model overview

An overview of the proposed model to design an energy system to support carbon-neutrality in operations from a machine scheduling perspective is presented in Figure 4.4. This model integrates the key aspects of time-sensitive energy prices – TOU –, carbon content per kWh on the grid, net metering policy, on-site solar power generation and energy storage systems into the single machine production scheduling problem. Under the assumption that a Master Production Schedule exists in which the production orders (jobs) are known and planned ahead in advance, and that enough production capacity exists to process the jobs in the day-ahead horizon, the set of jobs $j \in N$ are sequenced in the day-ahead production scheduling model. Each job carries a processing time p_j, and sequence-dependent setup times s_{jk} between jobs. A single machine process the jobs and has different power requirements (ω_j) for each job. This is the case of energy-intensive equipment used in discrete processes in manufacturing systems (i.e. plastic injection molding), where depending on the type of part, material used and quantity produced, the machine drive demands different power levels and setups are needed in between jobs to process the next batch of parts.

The energy system to support the day-ahead production setting comprehends TOU electricity tariffs, considering non-peak and peak hours, the net metering compensation rate policy, and the available solar power generation. The available solar power is dependant upon the solar irradiance GHI and temperature conditions of the region where the production facility is located. The integration of the production scheduling problem and the energy system provides an optimal job sequencing for minimum completion time c_{max}, dictating the hourly energy requirements, and the optimal renewable energy system size, in terms of solar PV module size PV_z and battery size as energy storage. Given the solar PV energy generation PV_{G_t}, hourly dispatching decisions are provided which instruct the times at which solar power should be exported to the grid for net metering credits PV_{NM_t}, or stored at the battery for later consumption B_{P_t} or dispatch to the grid B_{NM_t}.

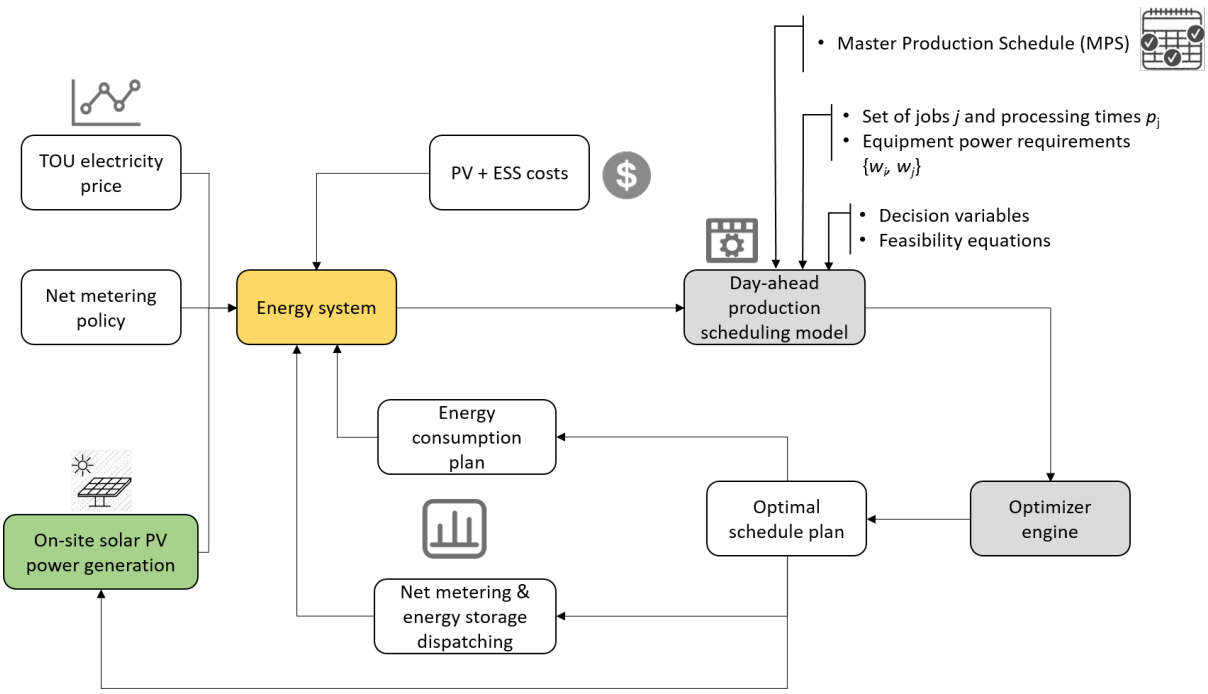


Figure 4.4: Model overview.

4.4.3 Model scope

The described model is intended to optimally provide scheduling decisions in a production environment in which:

a) There exists an energy-intensive process in which energy costs and carbon neutrality is of interest.

b) The set of jobs are to be processed within a Day-Ahead scheduling horizon. It is assumed that the Master Production Schedule of the day provides enough capacity to process the jobs for the Day-Ahead time window.

c) The model does not consider other production costs that are not energy related.

d) All jobs are shipped at the end of the day, and, therefore, do not incur into delay penalty fees or inventory holding costs.

e) Job preemption is not allowed.

4.4.4 Energy-Carbon neutral mathematical model

Considering that productivity metrics are essential for the competitiveness of any organization and that they should be attained while in parallel reaching sustainability targets, a multi-objective mixed integer programming (MILP) formulation is presented as a framework towards energy-carbon neutrality in manufacturing operations. The proposed multi-objective MILP model seeks to minimize the total completion time of all jobs C_{max}, while also minimizing the required solar PV system size PV_z required to offset the incurred energy consumption from the grid and its associated carbon footprint. That is,

$$\min \quad C_{max} \tag{4.4}$$

$$\min \quad PV_z \tag{4.5}$$

In order to treat the conflicting nature between productivity metrics in production scheduling, such as completion time C_{max}, and related sustainability targets, the approach

towards the multi-objectives (4.4) and (4.5) of the proposed model is to first guarantee that the job sequencing decisions x_{jk} minimize the total completion time C_{max}, and subsequently, solve the second problem on solar PV system size (4.5) using the optimal completion time C^*_{max} as a constraint. Therefore, the objective function (4.4) is solved first with the following set of constraints:

$$
\begin{aligned}
\text{s.t.} \quad & c_j \geq p_j && \forall j \in N && (4.6)\\
& c_j + p_k + s_{jk} \leq c_k + M(1 - x_{jk}) && \forall j < k && (4.7)\\
& c_k + p_j + s_{jk} \leq c_j + M x_{jk} && \forall j < k && (4.8)\\
& c_{max} \geq c_j && \forall j \in N && (4.9)\\
& \sum_{t \in \{T\}} t y_{jt} = c_j - p_j && \forall j \in N && (4.10)\\
& \sum_{t}^{t+p_j-1} z_{jt} \geq y_{jt} p_j && \forall t \in (R, ..., T - p_j + 1) && (4.11)\\
& \sum_{j \in \{N\}} z_{jt} = p_j && \forall j \in N && (4.12)\\
& 1 - \sum_{j \in \{N\}} z_{jt} = u_t && \forall t \in T && (4.13)\\
& \sum_{t \in \{T\}} y_{jt} = 1 && \forall j \in N && (4.14)\\
& \sum_{j \in \{N\}} z_{jt} \leq 1 && \forall t \in T && (4.15)\\
& x_{jk}, y_{jt}, z_{jt}, u_t \in \{0, 1\} && \forall j, k, t, j < k && (4.16)
\end{aligned}
$$

Equation (4.6) provides a lower bound for completion times for all jobs according to their respective processing times. Equations (4.7) and (4.8) provide the completion times for all jobs, including their respective setups times depending on the decision on whether job j precedes job k or otherwise. Equation (4.9) gives the Makespan, total completion time of the production schedule. Equation (4.10) defines the starting time for each job after the setup time of that particular job has been completed. Equations (4.11) and (4.12) are time

index formulations to dictate the periods in which each job is being processed. Equation (4.13) indicates the periods in which the machine is idle. Equations (4.14) and (4.15) specify that the starting of a job must be assigned to a point in time in the planning horizon T, and only one job can be processed at a time. Finally, constraint (4.16) sets the binary conditions for the decision variables.

For the second problem (4.5), in the minimization of the solar PV system size, it is considered that the energy generated by the PV system can be stored at a battery bank for later usage to support production. The set of constraints for this problem include equations (4.3) and (4.6)-(4.16) and the following:

$$\text{s.t.} \quad PV_{NM_t} + PV_{B_t} \leq PV_{G_t} \qquad \forall t \in T \qquad (4.17)$$

$$\sum_t \pi_t(policy * PV_{NM_t} - G_t) \geq 0 \qquad \forall t \in T \qquad (4.18)$$

$$\sum_t (PV_{NM_t} - G_t) \geq 0 \qquad \forall t \in T \qquad (4.19)$$

$$B_t = min\left(Q, max\left(0, B_{t-1} + PV_{B_{t-1}} - e_{t-1}\right)\right) \qquad \forall t \in (2, ..T) \qquad (4.20)$$

$$B_1 = 0 \qquad \forall t = 1 \qquad (4.21)$$

$$\sum_j \sum_t z_{jt}\omega_j + u_t\omega_i = e_t \qquad \forall j \in N, t \qquad (4.22)$$

$$e_t \leq G_t + B_t \qquad \forall t \in T \qquad (4.23)$$

$$c_{max} \leq c^*_{max} \qquad (4.24)$$

$$PV_z, PV_{NM_t}, PV_{B_t}, B_t \geq 0 \qquad \forall t \in T \qquad (4.25)$$

Equation (4.17) restricts that the amount of electricity sent back to the grid from the solar PV system PV_{NM_t} and/or used to recharge the battery PV_{B_t} at time t cannot exceed the amount generated by the solar PV system during the same period. Equation (4.18) ensures energy cost neutrality in the sense that, depending on the region's net metering compensation policy, the total compensation received from net metering must be at least equal to the energy costs incurred by consuming electricity from the grid G_t. Equation

(4.19) ensures carbon neutrality specifying that the overall carbon footprint γ_t derived from consuming electricity from the grid must be offset by the equivalent amount sent back to the grid. Equation (4.20) defines the amount of energy stored in the battery B_t and available to support production at time t as a function of battery capacity Q and energy stored, recharged and discharged in the previous period. Equation (4.21) establishes that there is no initial energy in the battery bank at the beginning of the first period of the day. Equation (4.22) describes the energy required for consumption at time t. Equation (4.23) constrains that the energy consumed e_t during period t must come from either the grid or the energy stored at the battery. It is noteworthy to mention that the energy generated from the solar PV system at time t is not considered for consumption due to the power quality issues in solar panels which can damage motors [138]. Equation (4.24) limits the completion time to the optimal C^*_{max} previously obtained. Equations (4.24) and (4.25) ensures no-negativity values in the solar PV system and battery related decision variables.

MILP variant for energy storage dispatching

As ESS (i.e. batteries) become more integrated with solar PV systems and micro-grids, this opens up the possibility to use energy stored in batteries to export to the grid in return for compensation credits under net metering. Under this condition, manufacturing sites could use energy stored in the battery bank B_t to support production B_{P_t} and/or send it back to the grid B_{NM_t} at any given period t, that is:

$$B_{P_t} + B_{NM_t} \leq B_t, \qquad \forall t \tag{4.26}$$

These energy dispatching decisions can be included in the formulation of problem (4.5) by adding equation (4.26) and replacing equations (4.18), (4.19), (4.20), (4.23), and (4.25) with the following constraints:

$$\sum_t \pi_t \Big(policy(PV_{NM_t} + B_{NM_t}) - G_t \Big) \geq 0, \qquad \forall t \tag{4.27}$$

$$\sum_{t}(PV_{NM_t} + B_{NM_t} - G_t) \geq 0, \qquad \forall t \tag{4.28}$$

$$B_t = min\Bigg(Q, max\Big(0, B_{t-1} + PV_{B_{t-1}} - B_{P_{t-1}} - B_{NM_{t-1}}\Big)\Bigg), \forall t \in (2, ..T) \tag{4.29}$$

$$e_t \leq G_t + B_{P_t}, \qquad \forall t \tag{4.30}$$

$$PV_z, PV_{NM_t}, PV_{B_t}, B_t, B_{P_t}, B_{NM_t} \geq 0, \qquad \forall t \tag{4.31}$$

Equation (4.27) incorporates the ability to send energy back to the grid at a given period directly from the on-site solar PV power generation and/or from the energy stored at the battery. Equation (4.28) ensures the net-zero carbon condition of the process, where the solar energy exported back to the grid, either from the PV system or battery, must exceed consumption from the grid. Equation (4.29) updates the battery discharge modes, which includes battery energy sent back to the grid for net metering credits. Equation (4.30) updates the source for energy consumption to be the grid and the amount of energy from battery decided to be assigned to support production. Equation (4.31) includes lower-bound constraints on battery dispatching decisions.

MILP variant for time-sensitive carbon content per kWh on the grid

Depending on the region where electricity is drawn from, its generation may occur through DER on the grid, causing the carbon content per kWh to fluctuate during the day depending on the type of power generator used. To account for this time-based carbon profile curve, the carbon-neutrality equations (4.19) and (4.28) would need to be updated as follows:

$$\sum_t \gamma_t (PV_{NM_t} - G_t) \geq 0, \qquad \forall t \tag{4.32}$$

$$\sum_t \gamma_t (PV_{NM_t} + B_{NM_t} - G_t) \geq 0, \qquad \forall t \tag{4.33}$$

where, γ_t is the equivalent carbon content on the grid at period t in kg per kWh ($kgCO_2e/kWh$). Since the life cycle carbon content per kWh of solar PV technology is near zero, solar power is assumed to be carbon-free.

4.5 Results: Validation via a Case Study

To demonstrate the implementation of the proposed framework towards energy-carbon neutrality in manufacturing systems, a case study involving an energy-intense manufacturing process is presented. One of the most energy-intensive processes in manufacturing systems is injection molding. Injection molding is heavily used in the production of plastic parts and consumes a significant amount of energy. In this process, electricity is used to power motors to inject liquefied polymer at high pressure into a mold cavity. The polymer takes the shape of the cavity and is cooled. The resulting part is ejected from the mold cavity, and the molding machine is reset for the next injection cycle. These processes require significant power supply; the peak power of energy consumption can go above 200 kW on certain high clamping force machines depending on the type of material and production quantity [139].

4.5.1 Problem description

The problem has been constructed with the following assumptions and considerations:

Job processing parameters

In this case, a set of 10 different customer batches, or jobs, are scheduled for production at a single injection molding machine. The setup times between jobs are sequence-dependent and are required for cooling, change molding, and adjust plastic injection settings for the next batch. The scheduling periods are hourly-based, thus, 24 periods are available for the day-ahead production schedule. The required processing times of each job p_j were randomly generated with a distribution $\sim$ Uniform(1,4); setup times s_{jk} distributed as $\sim$ Uniform(0,2). Processing and setup times are hourly data. The average power requirements in kW to process each job w_j were generated as $\sim$ Uniform(10,40). The resulting parameters are given in Table 4.1. Table 4.2 shows the symmetrical sequence dependent setup times (hrs) between jobs. During setups, the equipment is in stand-by mode at 1 kW; the same applies for idle times.

Net metering region and electricity tariffs

The manufacturing facility is assumed to be located in Asheville, North Carolina, USA. North Carolina has a regulatory policy in place in net metering allowing customers connected to the grid to be credited for net excess generation on installed solar PV systems. Credits rollover month-to month and compensation rates are assumed to be lower than the average retail cost of electricity, therefore, $policy = 80\%$. Electricity prices in the region are also assumed to be under TOU tariffs. The off-peak and peak demand hours and respective electricity prices are shown in Table 4.3.

Solar irradiance

The solar irradiance dataset for the region was pulled from NSRDB downloading hourly intervals for GHI and atmospheric temperature from years 1998 to 2020. The data was processed using Python v3.8.10. Since net metering programs allow to rollover credits, it makes sense to estimate hourly solar irradiance and temperature averages for the year.

Table 4.1: Job processing time (hrs) and power requirement (kilowatts) parameters.

Job	J1	J2	J3	J4	J5	J6	J7	J8	J9	J10
Processing times p_j	1	2	1	4	1	1	2	1	2	3
Power-kW w_j	30	60	20	10	50	40	30	30	60	20

Table 4.2: Sequence-dependent job setup times matrix.

	Job 0	Job 1	Job 2	Job 3	Job 4	Job 5	Job 6	Job 7	Job 8	Job 9	Job 10
Job 0	-	2	2	0	2	1	2	1	0	0	1
Job 1		-	2	1	2	1	2	1	2	0	1
Job 2			-	1	2	2	0	2	0	1	1
Job 3				-	2	0	2	1	2	0	0
Job 4					-	1	0	2	1	0	0
Job 5						-	0	1	1	2	2
Job 6							-	2	1	0	0
Job 7								-	2	1	1
Job 8									-	2	2
Job 9										-	2
Job 10											-

Table 4.3: TOU electricity prices.

TOU Tariffs	Time	Price ($/kWh)
Off-Peak	0:00-6:00 11:00-15:00	0.10
Peak-Hours	6:00-10:00 16:00-20:00	0.20

The hourly average irradiance W/m^2 was further converted into a sun-peak fraction, also known as full suns ($1000W/m^2$), by dividing the hourly average irradiance by 1000. Figure 4.5 depicts the average full sun factions for each hour across the years. The hourly averages for each year were further combined into a single hourly average. For simplicity, the values were rounded to the nearest significant decimal. Table 4.4 shows the hourly full suns and temperature averages for a given day.

Solar PV module type

Crystalline silicon is the dominant semiconductor material used in PV technology for the production of solar cells. Thus, crystalline silicon is the module type for the solar PV system in this study. The temperature coefficient loss of power of this cell material is $-0.35\%/^{\circ}C$. Moreover, the default solar PV system losses l_i for the model are depicted in Figure 4.6.

4.5.2 Model results

The described problem above was solved using Gurobi v9.5 on an Intel Core i7 processor. The solution provides energy consumption, generation, and dispatching decisions of the optimal energy system to support energy-carbon neutrality in agile manufacturing conditions. The profile of the optimal energy system, presented in Figure 4.7, contrasts solutions when net metering is valued at 80% and 100% the retail cost of electricity. Both solutions are constrained to the optimal completion time, C_{max}, obtained. Meaning that the set of jobs are completed by period 18. In addition, the battery energy storage condition was set to only be used for production and not for net metering. In both scenarios, the obtained optimal solar PV system size was 137.2 kW and 126.4 kW, respectively.

In Figure 4.7(a), it can be seen that during the first periods of the day the required energy for production is drawn from the grid, since the availability of solar power is null. However, early in the morning, while still consuming energy from the grid, the optimal solar PV size begins to generate energy to send back to the grid under net metering. Towards the middle of the day, it becomes more efficient to utilize the solar generation to charge the battery to support production and store energy instead of exporting it under net metering.

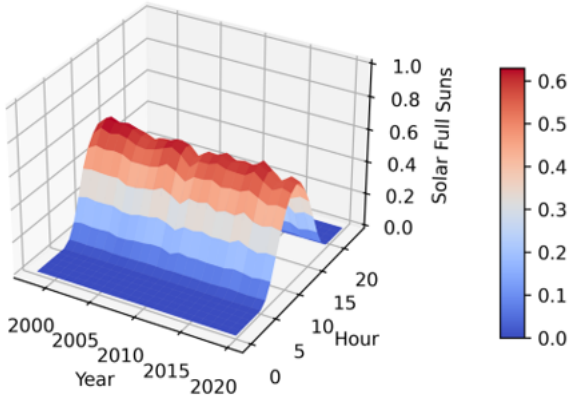


Figure 4.5: Equivalent full suns per hour for the region (1998-2020).

Table 4.4: Hourly solar full suns and temperature averages.

Time	Full suns	Temperature ($^{\circ}C$)
0:00	0	12
1:00	0	12
2:00	0	11
3:00	0	11
4:00	0	11
5:00	0	11
6:00	0	12
7:00	0.1	13
8:00	0.3	15
9:00	0.4	17
10:00	0.6	18
11:00	0.7	19
12:00	0.7	20
13:00	0.7	20
14:00	0.6	20
15:00	0.5	20
16:00	0.4	19
17:00	0.2	17
18:00	0.1	16
19:00	0	15
20:00	0	14
21:00	0	13
22:00	0	13
23:00	0	12

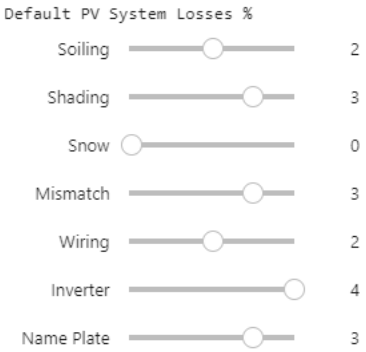
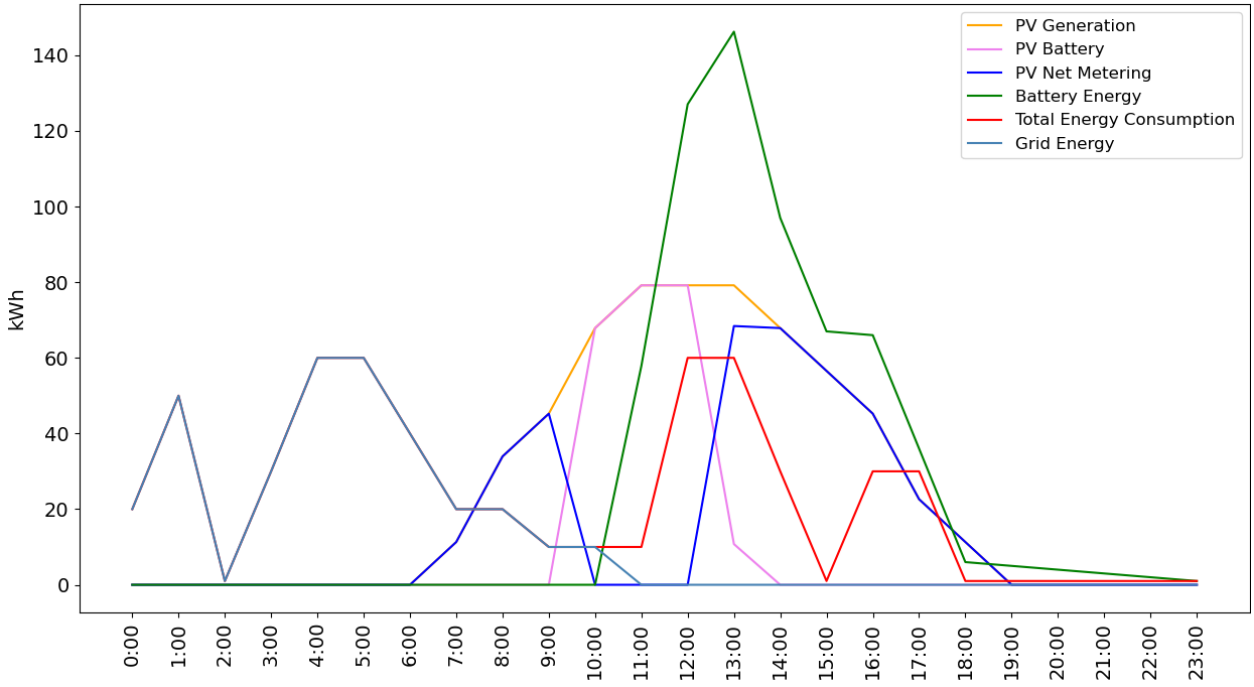
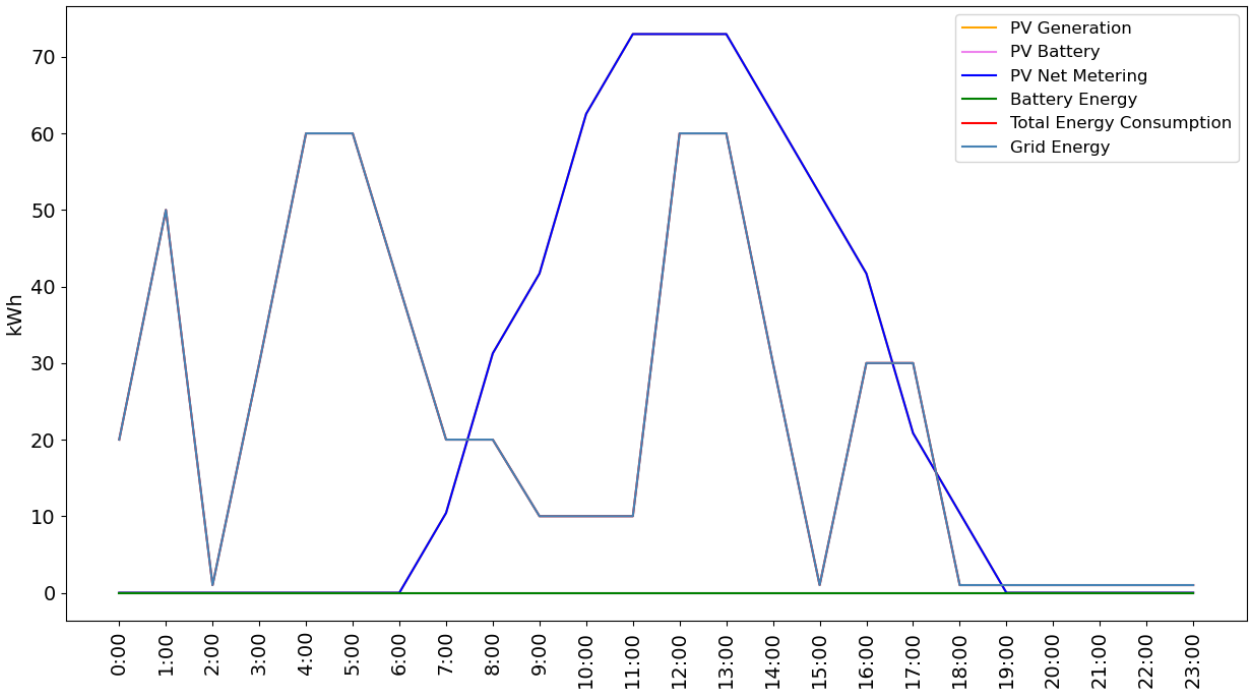


Figure 4.6: Default solar PV losses in %.



(a) Energy dispatching profile at 80% net metering retail value.



(b) Energy dispatching profile at 100% net metering retail value.

Figure 4.7: Optimal energy consumption, generation and dispatching profile solutions.

As the generation from the solar PV system reaches its climax, enough energy is stored in the battery bank to support production for the rest of the day, so there is no longer need to consume electricity from the grid. Notice the change in color for energy consumption in the plot. Once enough energy is stored in the battery bank, the rest of the energy generated by the solar PV system is again exported to the grid for credits.

In contrast, Figure 4.7(b) shows that when the net metering credits are equally valued at the TOU electricity costs, there is no motivation to store energy. Hence, energy consumption is always drawn from the grid to support the production schedule, and all the generation provided by the solar PV system is net metered as a mechanism for decarbonization to account for the energy costs and kWh consumed. This scenario provides an interesting insight to net metering consumers that are located in regions where the net metering credits are valued at full retail price. From a net metering perspective, the integration of energy storage systems only becomes relevant when the value of net metering credits is below electricity retail rates.

4.5.3 Robust optimization and Monte Carlo simulations

Although there are no specific end-dates on the productive life of solar PV panels, the industry standard warrants the electricity generation output of modules for 20-30yrs [140]. Solar installations are typically commissioned for 25 years before a new repower decision is made. Given this lifespan, it is imperative to make solar PV sizing decisions based on the expected solar conditions for the next 20-25 years.

In this study, assuming that the production process remains repetitive with similar job requirements and specifications, it is of interest to provide a confidence interval (CI) on the solar PV sizing decision to account for solar variations in the lifetime of the project. To establish a CI on the solar PV size decision, a robust optimization approach is carried out using Monte Carlo simulations. Robust optimization is a well known technique to deal with uncertainty and problem complexity [141]. To do this, the prescribed optimization framework was solved using historical data on the average hourly GHI and temperatures for each of the available years in the NSRDB for the location, from 1998 to 2020 (23 years).

Optimal solar PV size solutions are shown in Figure 4.8. These solutions consider a net metering compensation of 100% of retail rate, and work as a construct for the study.

Before a CI can be established, it is important to first conduct a normality test and use this information in accordance to the central limit theorem. Figure 4.9 presents the Q-Q plot of the solutions for the past 23 years. It can be seen that the solutions are very close to the normality line. The Saphiro-Wilk and D'Agostino's K^2 normality tests depict a p-value > 0.05, therefore, it can be concluded that the solutions follow a Gaussian distribution, from which a CI can further be set.

Under the assumption that the sunlight in the past would have a similar behavior in the future, these solutions are then randomly bootstrapped 10,000 times to create multiple replications that would represent solutions for the next 23 years. Figure 4.10 shows the probability density distribution of the Monte Carlo bootstrapping simulations, where X stands for the optimal solar PV size, PV_z. From there, a box-plot is to delimit the upper and lower limits of the simulations at a 95% CI, Figure 4.11. The obtained limits are: upper limit (UL) = 153.5 kW, lower limit (LL) = 148.2 kW. These limits provide an zone in which the decision of solar PV system size could provide enough solar generation to offset energy consumption from the grid and be energy-carbon neutral during the lifespan of the on-site solar installation.

Moving forward, it is pertinent for decision-makers to also be cognizant of the degradation rate in the solar panel output over time. The productive life of solar panels and the electricity production from these panels over time depend on factors such as climate, module type, and racking system, among others. NREL has shown that solar panels have a median degradation rate of about 0.5% per year but could be higher in hotter climates and in roof mounting systems [140]. Using the following exponential continuous function, solar panel degradation PV_D (%) can be explained as:

$$PV_D = (1 - e^{-d \cdot t}) \cdot 100 \tag{4.34}$$

where, d is the degradation rate per year and t is the number of years in the future.

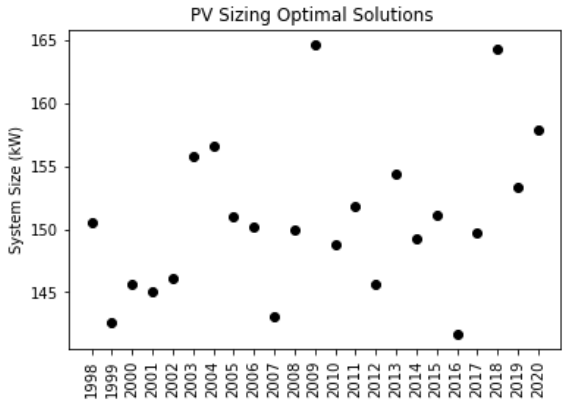


Figure 4.8: Solar PV system size optimal solutions by year.

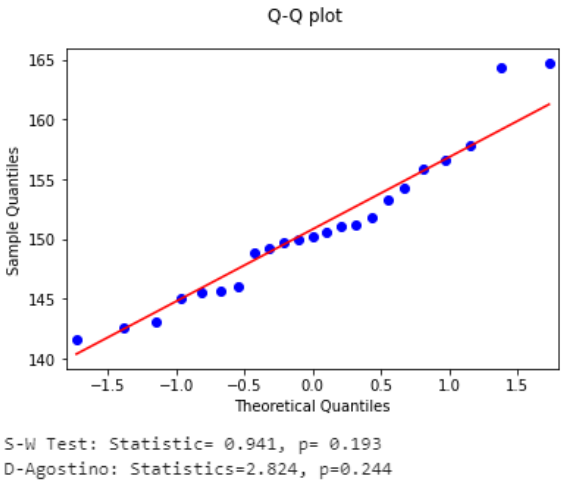


Figure 4.9: Normality test on yearly optimal solutions.

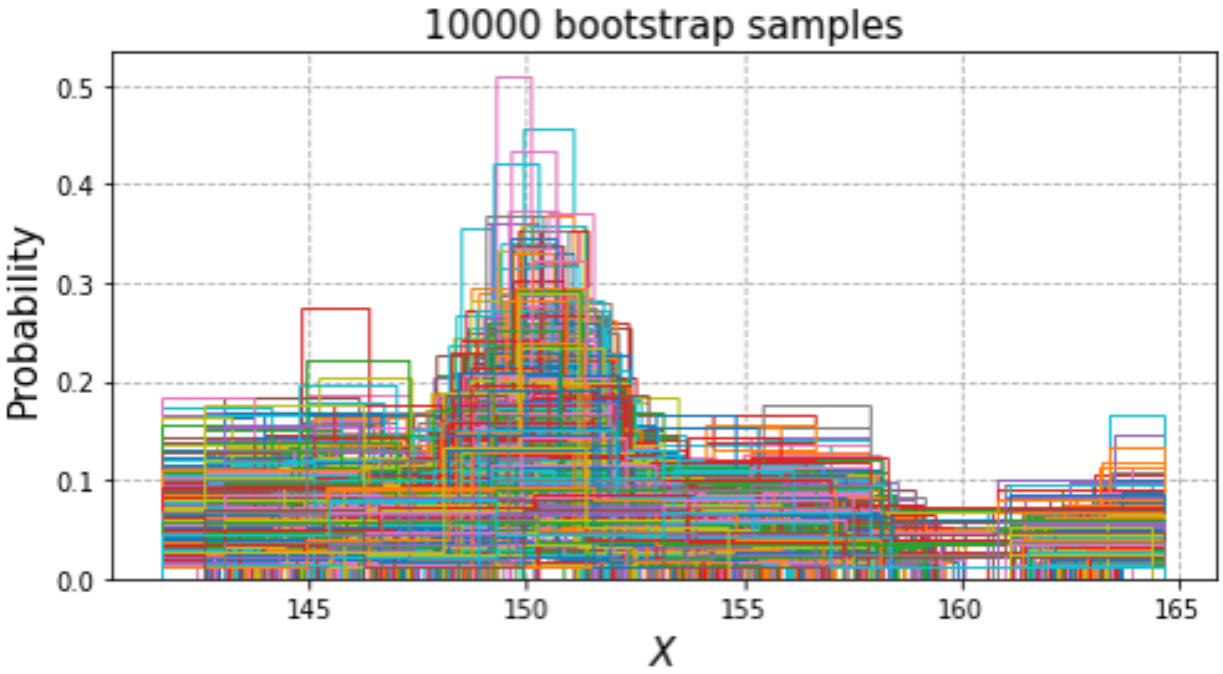


Figure 4.10: Optimal solar PV system sizes - Monte Carlo bootstrapping.

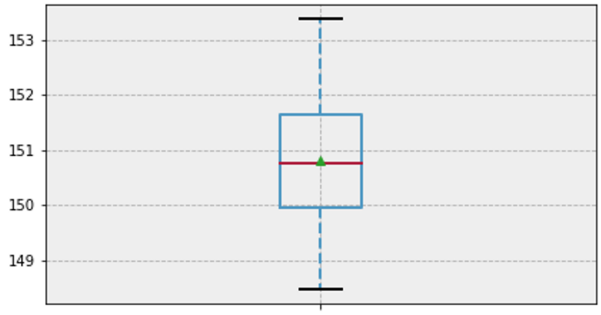


Figure 4.11: Monte Carlo Bootstrap 95% CI.
Upper limit: 153.5 kW
Lower limit: 148.2 kW

From the above, a degradation rate d of 0.5% per year implies that in year $t = 23$, the module is producing approximately 89% of the electricity it produced in year 1. In consequence, the CI defined earlier needs to account for this loss. The upper and lower limits are then updated dividing them by (1-PV_D). Hence, the limits UL = 170.2 kW and LL = 166.26 kW, would ensure at a 95% confidence that, by year 23, the on-site solar PV system is still capable of supporting energy-carbon neutrality for the manufacturing process.

4.5.4 Sensitivity analysis

Although many states and utilities in the United States allow net metering and have certain compensation rules, not all utilities credit net excess generation at retail rate. To understand the impact that different compensation rates have on the optimal solar PV system size decision, the described problem is solved for net metering compensation rates at 100%, 90%, 80%, 70% and 50% of retail value. Furthermore, as part of the analysis, the effect of battery storage dispatching rule policies, whether stored energy can be used for production and net metering or only for production, are also considered. The results of this analysis are shown in Figure 4.12, and summarized in Table 4.5.

It can be seen that net metering compensation rates that are lower than the retail rate increase the required solar PV system size for the manufacturing process to achieve energy-carbon neutrality. This effect is predominant and more significant in an energy system without energy storage since more solar generation is needed to account for the energy consumption from the grid. On the other hand, such effect is lower in systems that integrate ESS, and much lower when the ESS is enabled to have dispatching decisions to store energy for production and/or to export excess energy to the grid.

In this example, the optimal solar PV system size without ESS doubles from 126.4 kW to 252.8 kW when compensation rates drop from 100% to only 50% of the retail value. This depicts a linear relationship between system size and compensation rates when ESS are not integrated.

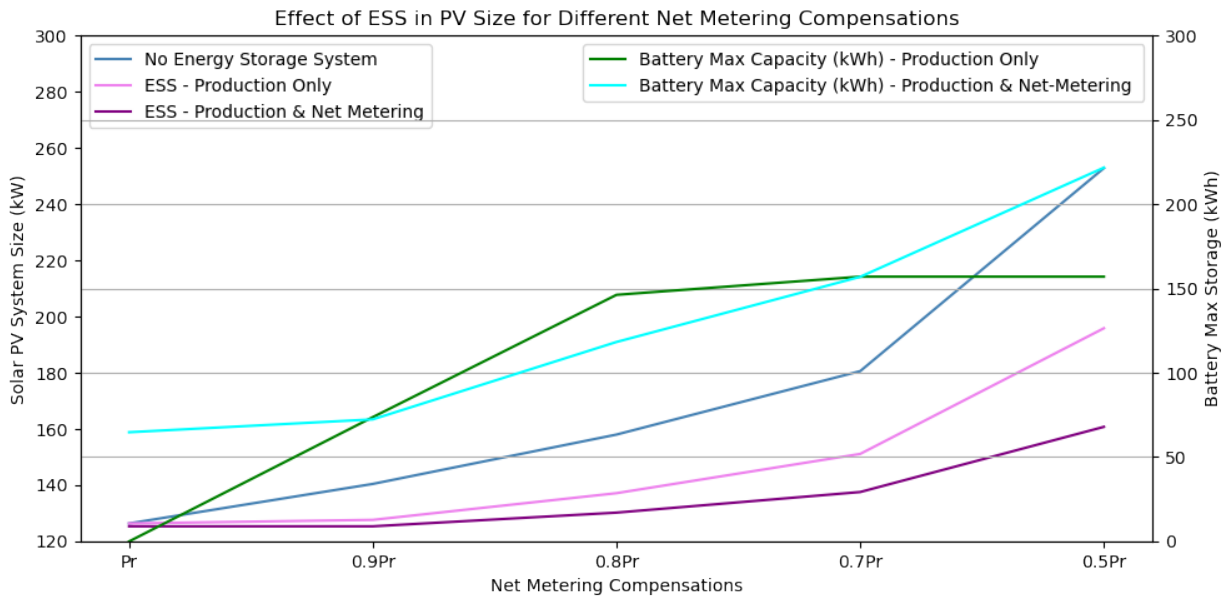


Figure 4.12: Effect of net metering compensation rates on solar PV system size and ESS.

Table 4.5: Energy system results for different net metering compensations.

	Net metering compensation rates				
	Pr	0.9Pr	0.8Pr	0.7Pr	0.5Pr
No ESS					
PV size (kW)	126.4	140.5	158.0	180.6	252.8
PV generation (kWh)	552.5	613.9	690.6	789.3	1105.0
Net metering (kWh)	552.5	613.9	690.6	789.3	1105.0
Grid consumption (kWh)	548.0	548.0	548.0	548.0	548.0
ESS - Production only					
PV size (kW)	126.4	127.7	137.2	151.1	195.9
PV generation (kWh)	552.5	558.0	599.5	660.6	856.0
Net metering (kWh)	552.5	327.0	362.5	423.6	619.0
Grid consumption (kWh)	548.0	327.0	321.0	321.0	321.0
Battery max capacity (kWh)	0.0	73.7	146.2	157.0	157.0
ESS - Production and net metering					
PV size (kW)	125.4	125.4	130.3	137.6	160.8
PV generation (kWh)	548.0	548.0	569.3	601.3	702.7
Net metering (kWh)	361.7	362.8	300.3	299.7	287.7
Grid consumption (kWh)	361.7	362.8	300.3	299.7	287.7
Battery max capacity (kWh)	64.8	72.4	118.3	156.9	221.7

Conversely, a solar PV system that includes ESS with dispatching capabilities experiences only a 27% increase to 160.8 kW at a 50% retail value. This translates into a savings of around 90 kW in installed solar PV capacity when compared to a system that does not integrate ESS. These results highlight the importance of integrating ESS when compensation rates are below the retail rate because solar PV systems can store energy during setup times and periods of excess generation, which can later be dispatched back to the grid at times when the cost of electricity is higher, as in peak-hours in TOU.

While the integration of ESS can reduce the required size of solar PV systems when compensation rates are low, it must be acknowledged that the battery max capacity (kWh) will naturally increase at lower compensation rates. This certainly brings extra burden to manufacturing sites in terms of capital, space and maintenance requirements. However, rather than estimating exact burden costs, in this case study it is of particular interest to understand the behavior of battery capacity requirements at different compensation rates to support energy-carbon neutrality in the manufacturing process.

As visualized above, in solar PV systems that integrates ESS only to support production, the max battery bank capacity reaches a near-limit when compensation rates are at 80% the retail value. At 70% and 50% retail value compensation rates, the battery max capacity remains unchanged at 157 kWh. This capacity limit can be explained by the fact that there is only a certain given amount of production that demands energy during the day. Nevertheless, in an ESS that supports both production and net metering, this limit does not exists. In this case, at a compensation equal to retail rate the battery maximum capacity starts at around 64.7 kWh, and reaches up to 221.7 kWh when the compensation rate is at 50% the retail rate. This is because more energy that the required for production can be stored and later dispatched to the grid, thus, gaining valuable credits at higher electricity rates during peak-hours. Given this behavior, this ESS setting will very likely require higher battery bank sizes if compensation rates drop below 50% the retail rate. This is the case of utilities or regions that only compensate at the avoidance cost of electricity, which value credits at a certain level to account for the adverse effects (i.e. pollution) of generating electricity using fossil fuels.

4.5.5 Economic analysis

While DER systems are valuable technologies to reduce energy costs and mitigate carbon emissions and footprint, these systems are also costly to install and maintain. It is imperative to quantify their economic cost and compare it to their economic benefits.

The following economic analysis compares the discounted energy costs (DEC) of alternative solar PV systems under different net metering compensation rates to a baseline situation where the production process described in our case study is only supplied with power from the grid. This comparison is done for a 20 year benchmark, which is close to the lifetime of a solar PV system.

The economic analysis starts by estimating the DEC of the baseline case (no PV/ESS) for the next 20 years. Under the assumption that the described process is repetitive on a daily basis, and that the process is optimal in its completion time, the daily energy consumption and costs under TOU are translated into annual costs by multiplying them by 365. This annual energy costs represent yearly cash flows, and are subject to increases in energy prices. According to the EIA, electricity prices have increased on average 1.8% per year in the U.S. over the past 25 years [142]. Hence, these annual cash flows are adjusted to account for this inflation. Subsequently, the twenty-year cash flows are discounted at an annual rate of 3% and 5%. The equation to calculate the DEC of the baseline case follows the net present value formulae [143], and is expressed as:

$$DEC_{baseline} = \sum_{t=1}^{20} \frac{c_t}{(1+r)^t} \tag{4.35}$$

where, c_t is the annual net energy cost at the end of year t, and r is the annual discount rate.

In contrast, the alternative optimal solar PV systems are: 1) a PV system without ESS capability, 2) a PV system plus ESS, where the battery bank that can only be used to power production (Prod), and 3) a PV system plus ESS in the form of a battery bank that can power production and also export energy to the grid for net metering (Prod, NM). The configuration of these solar PV systems is shown in Figure 4.13.

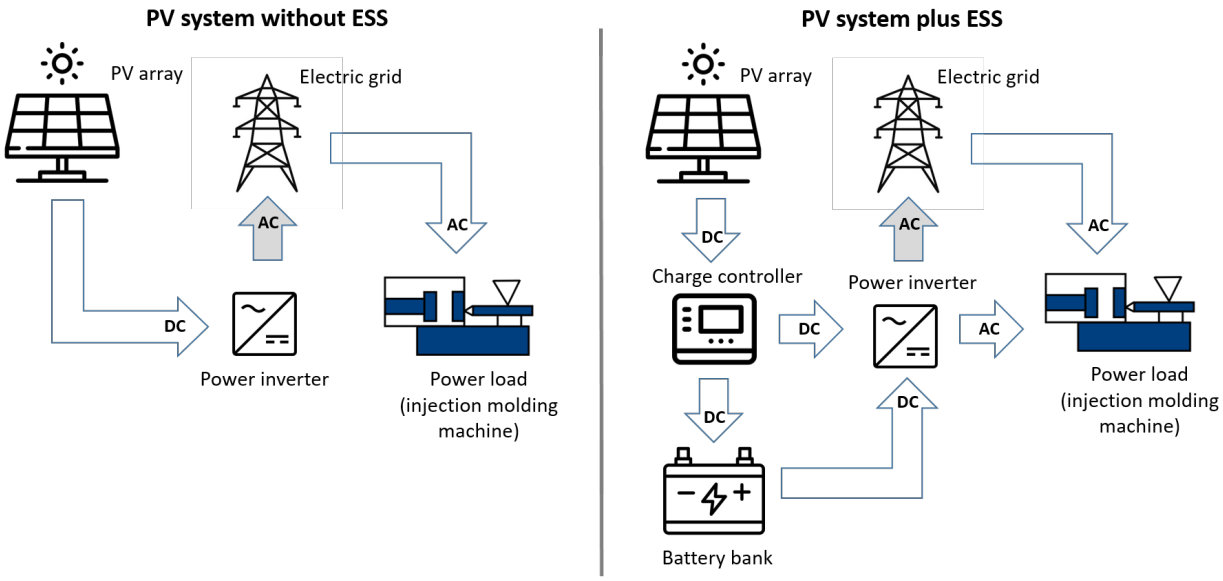


Figure 4.13: Solar PV configurations used in the economical analysis. PV system plus ESS configuration applies for both Production and Net Metering energy dispatch.

Optimization costs

To build this economic analysis, the objective function presented previously in equation (5) is modified to account for the current installation costs of solar PV panels and battery ESS systems. That is,

$$\min \quad C_{PV} \cdot PV_z + C_B \cdot B_{cap} \tag{4.36}$$

where C_{PV} is the cost of installation of a solar PV module in \$/kW, and C_B is the installation cost of a Li-Ion battery system in \$/kWh. Since the solar sizing PV_z is given in kW, and the battery capacity required size (B_{cap}) is measured in kWh, objective function (34) ensures that our solar PV and battery sizing decisions minimize the respective installation costs. If the DEC of a solar PV system (with or without ESS) is less than the DEC of the baseline, then the investment in these DER systems can save companies money while being carbon-neutral.

Based on the NREL cost benchmark report for solar PV system and energy storage [144], we consider the installed cost of commercial PV to be \$1.72/W (\$1,720/kW), with operational and maintenance costs (O&M) of \$19/kW-yr. This includes module, inverter, balance of system, labor, and soft cost (i.e. permit, inspection and interconnection costs). For energy storage, the total cost of installed Li-Ion batteries was assumed at \$469/kWh [145], which includes the capital costs of energy capacity of \$271/kWh and construction and commissioning costs. Energy storage adds \$10/kW-yr to PV O&M costs.

Assuming a lifetime in the PV system of 20 years, the yearly cash flows of O&M in PV and ESS are discounted at an annual rate of 3% and 5%. 20% of the batteries are replaced after 10 years due to battery capacity dropping 20%. It is assumed that battery costs drop 20% in the next 10 years [144]. This battery replacement cost in year 10 is also discounted at a 3% and 5% annual rates. To ensure that the lifetime of batteries is extended, a depth-of-discharge (DOD) of 80% is assumed. Thus, the following constraint is added to the model:

$$0.8B_{cap} \geq B_t, \qquad \forall t \tag{4.37}$$

The net metering constraint included in the proposed optimization model balances the costs of TOU electricity from the grid with the credits received for exporting energy to the grid (equations 4.18 and 4.27). Thus, the annual net energy costs are zero for all net metering compensation rates, and the only costs included in the DEC of each solar PV system alternative are its installation costs, O&M, and battery replacement (if applicable). The DEC of a solar PV system is calculated as:

$$DEC_{solar} = \sum_{t=1}^{20} \frac{c_{om}}{(1+r)^t} + \frac{c_{br}}{(1+r)^{10}} \tag{4.38}$$

where c_{om} are fixed yearly O&M costs, and c_{br} is the battery replacement cost in year 10 to replace 20% of the initial battery capacity assuming a battery capital cost drop of 20%. That is,

$$c_{br} = (0.2B_{cap}) \cdot (0.8 \cdot \$271/kWh) \tag{4.39}$$

Economic analysis results

The results from the economic analysis are presented in Table 4.6. The economic analysis show that solar PV system alternatives are cost competitive compared to the baseline, provided the compensation rate is high enough. At a 3% discount rate, a solar PV system is cost competitive if compensation rates are 60% of the retail value of electricity or higher. Even at a lower net metering compensation rate of 50% the retail value of electricity, a solar PV system coupled with ESS to support production and export energy back to the grid has a DEC lower than the baseline.

Table 4.6: Economic analysis

		Net Metering Compensation Rate = 1			Net Metering Compensation Rate = 0.8			Net Metering Compensation Rate = 0.6			Net Metering Compensation Rate = 0.5		
	Baseline (No PV/ESS)	PV w/o ESS	PV + ESS (Prod)	PV + ESS (Prod, NM)	PV w/o ESS	PV + ESS (Prod)	PV + ESS (Prod, NM)	PV w/o ESS	PV + ESS (Prod)	PV + ESS (Prod, NM)	PV w/o ESS	PV + ESS (Prod)	PV + ESS (Prod, NM)
PV/ESS sizing decisions													
PV size, optimal solution (kW)	0	150.5	150.5	150.5	188.3	164.2	168.0	251.0	203.4	192.4	301.2	234.7	218.6
ESS capacity (kWh)	0	0.0	0.0	0.0	0.0	60.0	30.0	0.0	60.0	60.0	0.0	60.0	60.0
ESS adjusted for DOD 80% (kWh)	0	0.0	0.0	0.0	0.0	75.0	37.5	0.0	75.0	75.0	0.0	75.0	75.0
Energy generation/consumption													
Daily PV generation (kWh)	0.0	553.6	553.6	553.6	692.0	603.6	618.0	922.6	747.6	707.6	1107.2	862.8	804.1
Daily net metering (kWh)	0.0	553.6	553.6	553.6	692.0	370.6	424.2	922.6	514.6	450.8	1107.2	626.8	542.7
Daily grid consumption (kWh)	548.0	548.0	548.0	548.0	548.0	325.0	354.2	548.0	325.0	291.2	548.0	322.0	286.6
Daily net consumption (kWh)	548.0	-5.6	-5.6	-5.6	-144.0	-45.6	-70.0	-374.6	-189.6	-159.6	-559.2	-304.8	-256.1
Energy costs/credits													
Annual energy costs	$ 31,427	$ 27,777	$ 27,777	$ 27,777	$ 27,777	$ 17,338	$ 27,777	$ 27,777	$ 17,338	$ 14,870	$ 27,777	$ 17,228	$ 14,644
Annual net metering credits	$ -	$ 27,777	$ 27,777	$ 27,777	$ 27,777	$ 17,338	$ 27,777	$ 27,777	$ 17,338	$ 14,870	$ 27,777	$ 17,228	$ 14,644
Annual net energy costs	$ 31,427	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
PV/ESS installation costs													
PV installation cost	-	$ 258,860	$ 258,860	$ 258,860	$ 323,790	$ 282,441	$ 288,994	$ 431,720	$ 349,796	$ 330,928	$ 518,064	$ 403,701	$ 376,044
ESS installation cost	-	-	-	-	-	$ 35,175	$ 17,588	-	$ 35,175	$ 35,175	-	$ 35,175	$ 35,175
DEC, 3% discount													
PV + ESS O&M expenses	-	$ 42,542	$ 42,542	$ 42,542	$ 53,213	$ 70,848	$ 72,492	$ 70,951	$ 87,743	$ 87,743	$ 85,141	$ 101,265	$ 94,327
Battery replacement cost	-	-	-	-	-	$ 2,420	$ 1,210	-	$ 3,252	$ 2,420	-	$ 2,420	$ 2,420
DEC (3% discount)	**$ 547,180**	$ 301,402	$ 301,402	$ 301,402	$ 377,003	$ 390,884	$ 380,283	$ 502,671	$ 475,967	$ 456,266	$ 603,205	$ 542,561	$ 507,966
Cost Savings (3% discount)		**$ 245,778**	**$ 245,778**	**$ 245,778**	**$ 170,177**	$ 156,296	$ 166,896	$ 44,509	$ 71,213	**$ 90,914**	$ (56,025)	$ 4,619	**$ 39,214**
DEC, 5% discount													
PV + ESS O&M expenses	-	$ 35,636	$ 35,636	$ 35,636	$ 44,574	$ 59,346	$ 60,723	$ 59,432	$ 73,499	$ 69,534	$ 71,319	$ 84,825	$ 79,014
Battery replacement cost	-	-	-	-	-	$ 2,420	$ 998	-	$ 1,996	$ 1,996	-	$ 1,996	$ 1,996
DEC (5% discount)	**$ 453,249**	$ 294,496	$ 294,496	$ 294,496	$ 368,364	$ 379,382	$ 368,303	$ 491,152	$ 460,467	$ 437,634	$ 589,383	$ 525,698	$ 492,229
Cost Savings (5% discount)		**$ 158,753**	**$ 158,753**	**$ 158,753**	$ 84,884	$ 73,867	**$ 84,945**	$ (37,904)	$ (7,218)	**$ 15,615**	$ (136,134)	$ (72,449)	$ (38,980)

However, at a 5% discount rate, compensation rates must be 60% or larger to make a solar PV system coupled with ESS for net metering cost competitive. If compensation rates are 50% or lower, a solar PV system is never cost competitive even in the presence of ESS. This highlights the fact that as the value of solar energy lessens in net metering programs, the competitiveness of solar PV systems weakens, since larger PV system sizes are required to generate enough power to match the energy costs of consuming electricity from the grid.

It is also interesting to see that when net metering compensation rates fall below the full retail value of electricity, coupling energy storage with solar PV systems is of relevance. In the presented case study, ESS allows the production system to store energy for later usage when electricity costs are high. This causes a drop in daily grid energy consumption compared to a solar PV system without ESS. From a utility and policy maker point of view, this shows that offering manufacturing enterprises a full retail value for their solar energy surplus discourages the adoption of ESS technologies, and grid consumption would remain the same as in the baseline scenario of only relying on power from the grid. Under this perspective, we can state that there exists a trade-off that needs to be considered in net metering compensation rates. Lower compensation rates would yield higher energy storage and lesser grid consumption, which can translate into greater independence from fossil fuels and, ultimately, a low-carbon economy, but the energy cost savings in integrating solar PV systems would also fall. The smaller the cost savings, the less likely a company is to adopt any of these technologies. Under such grim conditions, in order to move in the direction of decarbonizing the industry, incentives for solar energy and ESS installations (i.e., solar investment tax credits) would need to be considered in addition to net metering credits.

4.6 Conclusions

In light of environmental and rising energy costs pressures, this research presents an optimization framework that allows manufacturing processes to advance towards sustainability in operations by becoming energy-carbon neutral. This involves integrating renewable energy system decisions into production scheduling, in the form of solar PV modules and ESS,

and leveraging on energy policies that provide credits for net excess generation, such as net metering programs.

The proposed optimization framework was built under a multi-objective MILP formulation, using time-indexed variables, and demonstrated in a case study of an energy-intensive injection molding process. A first problem solves the job sequencing decisions for optimal completion time C_{max}. Once job scheduling decisions are known, a second problem is solved to obtain optimal solar PV sizing and energy dispatching decisions. Along with this, a robust optimization approach using Monte Carlo simulations was carried out to construct a CI for the lifespan of the solar installation.

To show the value of optimal solar PV system sizing decisions, a 20-year economic analysis on the case study was conducted to compare the DEC of solar PV systems against the baseline situation where only electricity from the grid is consumed. The economic analysis show that a solar PV system with ESS is cost competitive compared to the baseline when net metering credits are at least 60% the retail value of electricity.

To policy-makers and legislators, the analysis of this study provides insights unto how sensitive manufacturing enterprises can become to compensation credits in their quest towards energy-carbon neutrality. Clearly, manufacturing systems that enable their solar PV system with ESS dispatching capability are more cost-resilient and grid-independent at lower net metering compensation rates than those that do not. This opens up the discussion whether regions and utilities should also provide incentives for ESS capacity in exchange of lower valued net metering credits. Utilities can benefit from interconnected ESS, enabling resilient flow of quality and reliable power to the grid [88].

Chapter 5

Conclusions

Energy is an indispensable resource in manufacturing operations. Rising energy costs and climate change related environmental regulations and policies cause enterprises to carry both financial and environmental pressures on energy consumption and its associated carbon footprint, particularly in energy-intensive industries. Current domestic and international commitments towards a carbon-free economy by 2050 are shaping competitiveness in terms of how well companies attain sustainability goals and advance in methods to reduce energy costs, while still improving productivity performance levels. If companies are able to manage and optimize their energy consumption in the manufacturing process and reduce their carbon footprint, they will be able to spearhead important competitive advantages.

5.1 Discussion

In production systems, key activities such as production planning and scheduling are frequent decisions that have a direct impact on the energy consumption due to the utilization of energy-intensive equipment. As seen in the literature, without major capital investments, energy-carbon efficient solutions can emerge from production planning and scheduling optimization models. The reduction and planning of idle-time in combination to the sequencing of jobs has shown to lead to a better prediction of the workflow and allow management to budget energy requirements and carbon emissions for the system. At the same time, less emissions and energy costs can result in higher corporate results aligned with eco-social responsibility. It has been proven that enterprises that are more aligned to eco-social responsibility are more successful than those that are not, inciting that the need for the development and inclusion of energy and carbon footprint indicators [40] into production scheduling objectives are key in supporting the transition to sustainable manufacturing.

In light of the above, this PhD dissertation presented a production scheduling optimization framework that allows manufacturing processes to advance towards sustainability in operations by becoming energy-carbon neutral, while also ensuring productivity metrics. Minimizing electricity costs while reducing CO_2 emissions in production systems is a challenge, therefore, in alignment to this problem, the proposed PhD research work developed an Energy-Carbon Neutral Sequence Dependent Job Scheduling optimization model. The

proposed model is built under the context of a sequence-dependent single machine scheduling problem, where scheduling decisions are assumed to be affected by independent time of use electricity prices and carbon footprint environmental policies are enforced by either corporate or governmental institutions. In addition, this research is one of a kind because of the integration of on-site solar power decisions into the model as a mechanism to cap carbon footprint constraints. The outcome of this research resulted into the contribution of three articles of value for the scientific community and general operational excellence practitioners.

The first paper is entitled "Energy-Carbon Footprint in Manufacturing Systems - A Systematic Literature Network Analysis". In this work, a study is presented on the structure governed in the literature that addresses the concept of sustainability in manufacturing in relationship to energy and carbon footprint that can unlock pathways towards sustainability in manufacturing, and consequently, a carbon-free economy. Following a Systematic Literature Network Analysis, it was possible to observe the evolution and brisk changes in thinking and conducting scientific research around the concepts of energy and carbon footprint in manufacturing. The interaction of emissions, energy, and their related costs and risks in manufacturing systems was presented in network diagrams, depicting the most important areas of research and their evolution over time in the last two decades.

This systematic literature research concludes that the direction of research in energy and carbon footprint in manufacturing is pointed towards focuses on life cycle management, production management and scheduling, renewable energy resources, and energy policy. With the largest economies in the world committed to achieve carbon neutrality into the near future, energy policies will push for a rapid adoption of clean energy technologies and demand high energy efficient and low carbon practices in powering the economy. Thus, amid the expansion of renewables and smart grids, it is natural that the energy consumption of production processes has also become part of the operational scheduling problem, especially since the the cost of electricity and the amount of CO_2 content on the grid has a significantly effect on the time of consumption. Hence, the joint consideration of earlier isolated production scheduling problem aspects requires new ways of formulating and solving integrated problems where time-sensitive energy prices, carbon content on the grid, energy policy, and renewable technologies are considered. This an important mechanism in

which manufacturing processes at developing nations can rely upon to achieve energy and sustainability targets in a short period of time at a minimum cost.

Considering the above, the presented framework in this dissertation falls within this approach as it addresses energy-carbon awareness in production scheduling decisions. Such work was presented into two articles - the second and third paper.

The second article: "Energy-Carbon Footprint Optimization in Sequence-Dependent Production Scheduling", introduces an energy-carbon aware production scheduling model to optimize costs associated with energy and carbon footprint in a single machine. TOU electricity tariffs and carbon content per kWh on the grid are fundamental considerations to the model. A novel multi-objective Mixed Integer Linear Programming formulation is presented and compared to classical scheduling optimization approaches and job scheduling heuristics. Results show a conflicting nature between energy-carbon footprint related costs and productivity metrics, such as total completion time. Solving a production schedule to minimize energy and carbon footprint costs increases the total completion time of jobs. Although carbon taxes are imposed and job sequencing decisions are indeed sensitive to different values of carbon tax, the production schedule seeks lower energy costs early in the day and late in the evening, avoiding peak-hours, thus, extending the production makespan. This result brings questionable insights on the value of the proposed model in practice. In this form, high resistance in enterprises in adopting energy-aware models are expected, since lowering organizational performance in pro of sustainability goals can have adverse effects in profitability. To address this issue, an expansion of the proposed energy-aware production model is developed and presented in the third article.

The third article, entitled: "Optimal Energy System for Energy-Carbon Neutrality in Production Scheduling via Net Metering", expands the previous work by presenting an optimization model that integrates on-site solar photovoltaic sizing decisions, energy storage conditions, and net metering policies, as a mechanism to achieve net zero footprint in manufacturing processes. The proposed optimization framework is built under a multi-objective MILP formulation, using time-indexed variables, and demonstrated in a case study of an energy-intensive injection molding production process. Results demonstrate that manufacturing systems that enable their solar photovoltaic system with energy storage

dispatching capability are more resilient to lower net metering compensation rates than those that do not. Furthermore, a robust optimization approach using Monte Carlo simulations are suggested to construct confidence intervals for the lifespan of the solar installation, giving important considerations to the solar panel degradation curve.

5.2 Energy-Carbon Neutrality Roadmap

An important outcome of this dissertation is to provide a roadmap in which manufacturing enterprises can rely upon to achieve energy-carbon neutrality via production scheduling and distributed energy resources (DER). Illustrated in Figure 5.1, the consolidation of the proposed framework in this work is presented in the form of a systematic roadmap.

The proposed roadmap towards energy-carbon neutrality comprehends four phases: define, align, enhance, and sustain. In the define phase, upper management initiates the strategic corporate sustainability goal of net zero emissions. Next, mapping the energy intensity of the manufacturing process is needed to prioritize and effectively assign project resources to the critical energy-intensive processes. In the alignment phase, given the conflicting nature between environmental and productivity metrics, the inclusion of energy-carbon related metrics to the operational performance indicators is fundamental. This phase seeks to align energy-carbon decisions (i.e. energy consumption, carbon footprint) to key productivity metrics (i.e. completion time). The enhance phase looks into the data of the product-mix of the selected process, their required processing times, and its related equipment power specifications at different modes: ramp-up, processing, idle, and ramp-down. These inputs are necessary to compute the first-stage optimization of the proposed mathematical model, and obtain the minimum completion time. Subsequently, data extraction from the grid composition in terms of time-of-use electricity tariffs and carbon content profile per kWh is done. In addition, the identification of regional incentives and carbon emission policies at the location of the facility is performed. In conjunction with this, the DER geospatial information (i.e. solar global irradiance and temperature) provides the necessary information to run the second-stage optimization of the proposed model and obtain the production sequencing/scheduling and energy dispatching optimal decisions.

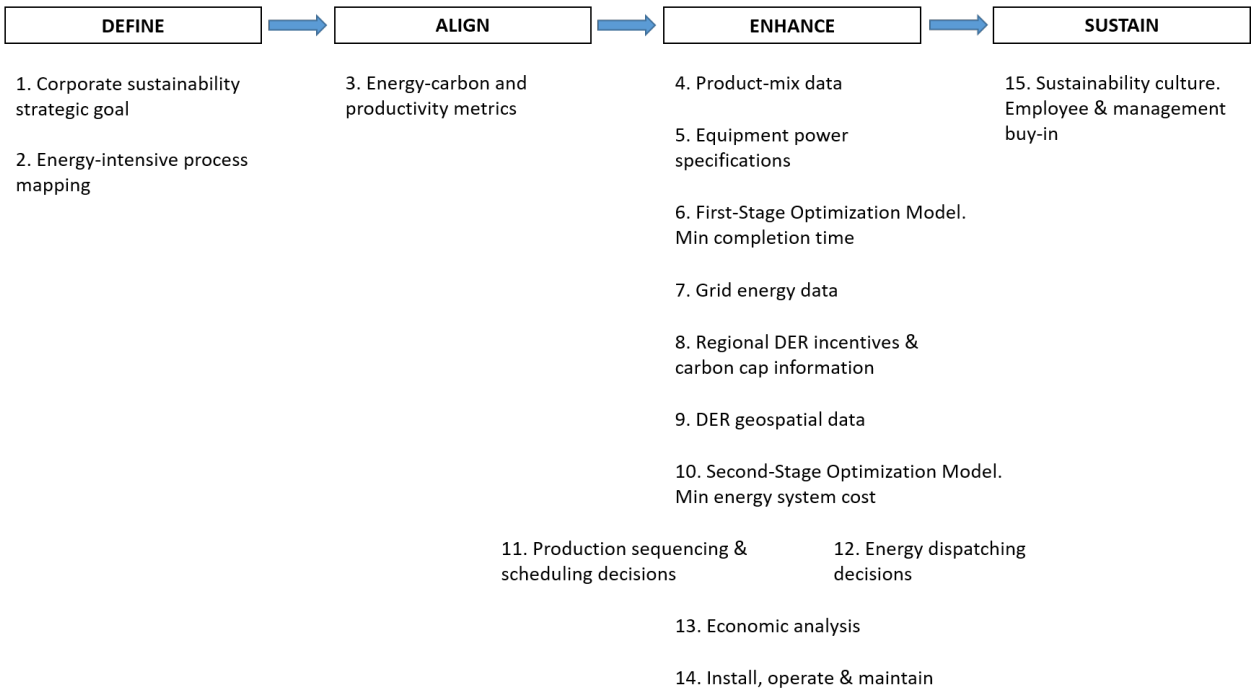


Figure 5.1: Energy-carbon neutrality roadmap.

The last part of the enhance phase is to compute an economic analysis to validate the cost-savings of the energy system obtained compared to a baseline of power consumption only from the grid. If cost-competitive, then the installation, operation and maintenance of the energy system follows. Finally, the sustain phase highlights the need to disseminate the awareness of the benefits of energy-carbon neutrality in production systems and, ultimately, utilize the proposed model in the design of a system that supports the sustainability culture across the organization.

5.3 Novelty of Work and Future Research

This PhD work contributes to the scientific community beyond production management and optimization models, looking at environmental and renewable energy applications for industry. It is noteworthy to mention some of the key points in which this dissertation provides novelty of work:

- Solar PV sizing decisions has not been seen at commercial and manufacturing industries applications from a production scheduling perspective. Rare research has been done integrating production scheduling and solar PV sizing. This research closes this gap and presents a novel framework to integrate both.

- Net metering applications have been widely discussed at a residential level, but not thoroughly investigated at the manufacturing level. This work certainly advances the study of expanding net metering into other industrial applications. From an energy perspective, if gives policy makers a perspective into compensation rates for manufacturing, and even the possibility of including incentives for ESS systems.

- Given the expansion of DES, energy dispatching decisions are more and more relevant in smart grids and production environments that integrate IoT devices. This work provides a direction for upcoming Industry 4.0 applications in terms of Net Zero production and renewable energy systems. Since PV systems and ESS at industrial sites are a natural expansion to the grid, a new research opportunity arises in including

the exchange of energy-related information between utilities and enterprises to optimize dispatching decisions and provide energy security to the grid.

- With the expansion of IoT and smart devices, the energy-carbon neutral framework presented here can certainly also be expanded to other non-manufacturing applications, as long as there is a need to perform tasks that require power, there exists access to internet, solar energy and renewable energy incentives. For example, in the residential sector, at home, smart electric appliances (i.e dishwasher, washer, drier, fridge, AC, heating) would require power to perform certain needs. Given TOU tariffs and user-specified schedule, the proposed model can size the optimal PV system and perform dispatching decisions between grid-PV system-ESS. This represents a new area of research that could be very likely integrated with smart home devices in the future (i.e Alexa, Google Home).

- Although the proposed model adds robustness into the solar PV decisions over the lifetime of the project, given the nature of the uncertainty and intermittent generation of renewables, stochastic programming is a natural way to formulate PV sizing and dispatching decisions into energy-intensive production and manufacturing systems. Stochastic programming is becoming a hot topic in solving optimization problems where the penetration of renewables significantly affects results.

5.4 Dissertation Benefits

The ultimate goal of this PhD dissertation is to achieve energy-carbon neutrality in manufacturing processes, also known as Net-Zero, by bolstering the energy efficiency and reduction of carbon footprint into the operational excellence of enterprises. The proposed work provides interesting benefits and insights to managers and operational excellence practitioners as follows:

a) Through the proposed mathematical model, it is shown that sequencing-scheduling decisions variables in the production system have a direct effect on the energy and carbon footprint of the system. Therefore, optimal scheduling decisions minimize overall energy and carbon footprint costs.

b) In comparing the value of energy-carbon aware production scheduling to contemporary non energy-carbon aware scheduling models, the effect that energy-carbon aware scheduling strategies have on traditional production performance metrics is assessed. The conflicting nature of productivity and energy-carbon awareness suggests that sustainability goals must support productivity goals, not displace them.

c) The proposed framework can serve as an application to budget the required energy and carbon footprint ahead of time. This opens up new opportunities within the area of Enterprise Resource Planning systems (ERPs). Given the world trend in sustainability, energy and carbon footprint management will become part of the competitive advantage of enterprises.

d) This research provides a road-map to energy-carbon neutrality by understanding energy dispatching decisions in a manufacturing system which leverages on on-site solar energy and energy storage systems (ESS). The implementation of this research provides insightful information to enterprises into cleaner on-site power generation decisions to meet their energy and carbon footprint budget.

e) This work portrays the effects of energy policies and economic incentives (i.e. carbon tax, net-metering regulations) have in total energy costs and on-site solar power generation decisions. To manufacturing enterprises, this highlights the importance of ESS to minimize capital costs in on-site solar capacity at locations where utilities do not provide full retail rate. To policy-makers and legislators, the analysis of this study provides insights unto how sensitive manufacturing enterprises can become to compensation credits in their quest towards energy-carbon neutrality.

f) For fortune 500 companies and enterprises seeking Net Zero production, this work provides insights in the development of partnerships and pathways that will enable organizations to influence renewable energy adoption to their suppliers and help develop the execution of global energy strategies centered on a supply portfolio of cost competitive clean and renewable energy sources consistent with corporate strategic objectives.

g) Utilities also benefit from this study. Through production scheduling and energy dispatching decisions, consumer demand becomes more predictable and the energy demand forecasting accuracy increases for day-ahead markets. Thus, energy purchasing and unit commitment and generation can synchronise much better knowing the consumption profile from electricity consumers (i.e, manufacturing enterprises).

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Appendices

A Jupyter Notebook Gurobi Optimization Codes

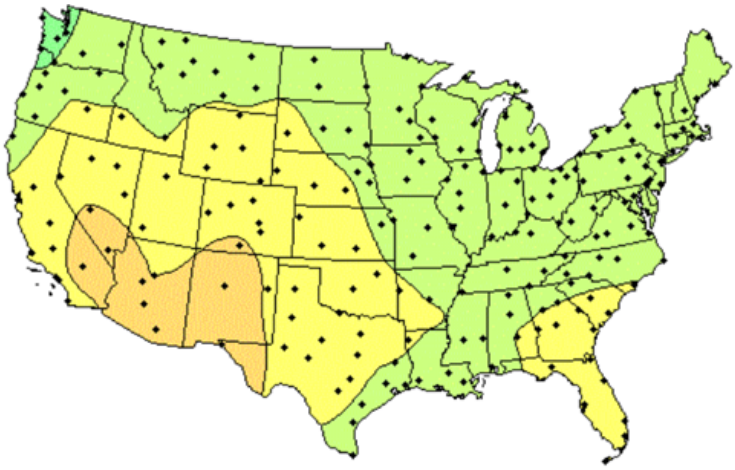
The following optimization codes were utilized in this research to solve the energy-carbon footprint optimization in production scheduling problem. These were written in python v3.8.10 in Jupyter Notebook using the Gurobi v9.5 optimization software.

Validation - Carbon-Neutral Production Scheduling under Net-Metering 2.0 - PV & ESS (Production and Net Metering)

In [ ]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
import math
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
from matplotlib import pyplot
from statsmodels.graphics.gofplots import qqplot
import statsmodels.api as sm
import pylab

from ipywidgets import interact, interactive, fixed, interact_manual
import ipywidgets as widgets
from gurobipy import *
```

Goegraphical Location (Average kilowatt-hours per square meter for an average yearly day)



Source: NREL, Spatial interpolation of solar radiation values derived from the National Solar Radiation Database (NSRDB).

1. Solar Irradiance

In [ ]:
```
#Reading irradiance data
os.chdir('/Users/User/Documents/Backup/Energy Carbon Optimization Research/Thesis/Energy F

#creating solar_irradiance dictionary
solar_irr = {}
for i in range(1998,2020+1):
    solar_irr[i]= (pd.read_csv(f"979952_35.97_-83.94_{i}.csv", header=2,usecols=[0,1,2,3,7

solar_irr[2020]
```

In [ ]:
```
#Average hourly sun peak across 1998-2020
sun_peak={}
for t in range(24):
    hour = []
    for i in range(1998,2020+1):
        hour.append(solar_irr[i].iloc[t][0])
    sun_peak[t] = round((np.mean(hour)/1000),2)

sun_peak
np.sum(sun_peak)
```

In [ ]:
```
#Average hourly Temperature across 1998-2020
temp = {}
for t in range(24):
    t_hour = []
    for i in range(1998,2020+1):
        t_hour.append(solar_irr[i].iloc[t][1])
    temp[t] = np.mean(t_hour)

temp
```

2. PV System efficiency

In [ ]:
```
print("\n")
print('Default PV System Losses %')

soiling = widgets.IntSlider( min=0, max=4, step=1, description="Soiling", value=2)
shading = widgets.IntSlider( min=0, max=4, step=1, description="Shading", value=3)
snow = widgets.IntSlider( min=0, max=4, step=1, description="Snow", value=0)
mismatch = widgets.IntSlider( min=0, max=4, step=1, description="Mismatch", value=3)
wiring = widgets.IntSlider( min=0, max=4, step=1, description="Wiring", value=2)
inverter = widgets.IntSlider( min=0, max=4, step=1, description="Inverter", value=4)
name_plate = widgets.IntSlider( min=0, max=4, step=1, description="Name Plate", value=3)

display(soiling)
display(shading)
display(snow)
display(mismatch)
display(wiring)
display(inverter)
display(name_plate)
```

Total Loss is calculated by multiplying the reduction due to each loss $L_i(\%)$:

$$L_{total}(\%) = 100\left[1 - \prod_i 1 - \frac{L_i}{100}\right]$$

In [ ]:
```
losses = (1-soiling.value/100)*(1-shading.value/100)*(1-snow.value/100)*(1-mismatch.value/
print(f"System Total Loss is: {(1-losses)*100 : .2f} %")
# losses
```

3. Manufacturing process data

In [ ]:
```
#Reading production data
os.chdir('/Users/User/Documents/Backup/Energy Carbon Optimization Research/Thesis')
```

```
df_req = pd.read_excel("10_jobs_TOU_CARBON_NetMetering2.0.xlsx", "requirements", index_col
df_costs = pd.read_excel("10_jobs_TOU_CARBON_NetMetering2.0.xlsx", "costs", index_col=[0])
df_set = pd.read_excel("10_jobs_TOU_CARBON_NetMetering2.0.xlsx", "setups", index_col=[0])
df_eq = pd.read_excel("10_jobs_TOU_CARBON_NetMetering2.0.xlsx", "equipment", index_col=[0]
df_specs = pd.read_excel("10_jobs_TOU_CARBON_NetMetering2.0.xlsx", "hourly_data", index_co

print('\n')
print("--------------------------------")
print("Job Specifications")
print("_____________________________")
print(df_req)
print('\n')

print("--------------------------------")
print("Setup times")
print("_____________________________")
print(df_set)

print("\n")
print("-------------------------------------------------------------")
print("TOU Electricity Price")
print("_____________________________________________________________")
print(df_specs)
```

4. Mixed Integer Linear Programming

4.0 Input parameters

In [ ]:

```
################################################################################
### INPUT PARAMETERS
################################################################################

#Energy system planning horizon
T=24

#Job requirements
jobs={}
for j in range(df_req.shape[0]):
    jobs[j]=j

#Processing times
p={}
for j in jobs:
    p[j]=df_req.iloc[j][0]

#Power requirements
pw={}
for j in [j for j in jobs if j>0]:
    pw[j] = df_req.iloc[j][1]


#Setups
s = {}
for k in jobs:
    for j in [j for j in jobs if j<k]:
        s[j,k]=df_set.iloc[j][k]

#Big M
L = 10000

#Electricity rates
price={}
```

```
for t in range(T):
    price[t] = df_specs.iloc[t][0]

#Emissions
emissions = {}
for t in range(T):
    emissions[t] = df_specs.iloc[t][1]

#Equipment ramp-up and idle mode rated power
Wr = 10
Wi = 1

#Ramp-up time
R = 0

#Battery energy capacity
Q = 1000000
```

4.4 Model ~ PV System Sizing & ESS (Production and Net Metering)

In [ ]:

```
###############################################################################
### OPTIMIZATION MODEL
###############################################################################

tou = Model("TOU")

##DEPENDENT VARIABLES
c={}
for j in jobs:
    c[j] = tou.addVar(vtype=GRB.INTEGER, lb=0)

c_max = tou.addVar(vtype=GRB.INTEGER, lb=0)

#idle time
idle_time = tou.addVar(vtype=GRB.INTEGER)

#Electricity costs
e_work = tou.addVar(vtype=GRB.CONTINUOUS)
e_idle = tou.addVar(vtype=GRB.CONTINUOUS)
e_ramp = tou.addVar(vtype=GRB.CONTINUOUS)

grid_costs = tou.addVar(vtype=GRB.CONTINUOUS)
nm_credits = tou.addVar(vtype=GRB.CONTINUOUS)

#Emissions costs
t_emissions = tou.addVar(vtype=GRB.CONTINUOUS)

##INDEPENDENT DECISION VARIABLES
x={}
for k in jobs:
    for j in [j for j in jobs if j<k]:
        x[j,k] = tou.addVar(vtype=GRB.BINARY)

y={}
for t in range(T):
    for j in [j for j in jobs if j!=0]:
        y[j,t] = tou.addVar(vtype=GRB.BINARY)

z={}
for t in range(T):
    for j in [j for j in jobs if j>0]:
        z[j,t] = tou.addVar(vtype=GRB.BINARY)

u={}
```

```
for t in range(T):
    u[t] = tou.addVar(vtype=GRB.BINARY)

#Energy requirement
G={}
for t in range(T):
    G[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#PV System related variables (PVz = System Size, PVg = System Energy Output)
PVz = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

PVg={}
for t in range(T):
    PVg[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

PVnm={}
for t in range(T):
    PVnm[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

PVb={}
for t in range(T):
    PVb[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)


#Battery Energy Availability at time t
B={}
for t in range(T):
    B[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#battery charging variable
Bc={}
for t in range(T):
    Bc[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#auxilary battery charging variable
Bc_scaled={}
for t in range(T):
    Bc_scaled[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb = -1000000, ub=GRB.INFINITY)


#auxiliary variable to represent energy consumption
e={}
for t in range(T):
    e[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)


#New variable on energy used from battery to power production (Bp)
Bp={}
for t in range(T):
    Bp[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#New variable on energy used from battery to net metering (Bnm)
Bnm={}
for t in range(T):
    Bnm[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#Maximum battery size ESS required
B_max = tou.addVar(vtype=GRB.CONTINUOUS, lb=0)


#Battery capacity size ESS required
B_cap = tou.addVar(vtype=GRB.CONTINUOUS, lb=0)


tou.update()
```

```
##CONSTRAINTS

#Disjunctive constraints
for k in jobs:
    for j in [j for j in jobs if j<k]:
        tou.addConstr(c[j] + p[k] + s[j,k] <= c[k] + L*(1-x[j,k]))

for k in jobs:
    for j in [j for j in jobs if j<k]:
        tou.addConstr(c[k] + p[j] + s[j,k] <= c[j] + L*x[j,k])

#Completion time
for j in jobs:
    tou.addConstr(c[j] >= p[j])

#dummy variable
for j in [j for j in jobs if j==0]:
    tou.addConstr(c[j] == R)


#total completion time
for j in jobs:
    tou.addConstr(c_max >= c[j])

# tou.addConstr(c_max <= T)
tou.addConstr(c_max <= 18) #Setting the completion cap according to min makespan

#Idle constraint
tou.addConstr(idle_time == c_max - c[0] - quicksum(p[j] for j in jobs if j!=0)) #not consi

#Start time of job
for j in [j for j in jobs if j!=0]:
    tou.addConstr(quicksum(t*y[j,t] for t in range(R,T)) == c[j] - p[j])

for j in [j for j in jobs if j!=0]:
    tou.addConstr(quicksum(y[j,t] for t in range (R,T)) == 1)


#Machine processing at times t
for j in [j for j in jobs if j!=0]:
    for t in range(R,T-p[j]+1):
        tou.addConstr(quicksum(z[j,k] for k in range(t,t+p[j])) >= (y[j,t]*p[j]))

for t in range(R,T):
    tou.addConstr(quicksum(z[j,t] for j in jobs if j!=0) <= 1)

#The times that the machine is working on a job should be equal to the job's processing ti
for j in [j for j in jobs if j!=0]:
    tou.addConstr(quicksum(z[j,t] for t in range(R,T)) == p[j])

#Machine idle at times t
for t in range(R,T):
    tou.addConstr(quicksum(z[j,t] for j in jobs if j!=0) == 1-u[t])

#Energy source
for t in range(R):
#    tou.addConstr(quicksum(ramp[j,t]*Wr for j in jobs if j==0) <= G[t])
    tou.addConstr(quicksum(Wr*R for j in jobs if j==0) <= G[t])


#Energy consumption
for t in range(R,T):
    tou.addConstr(quicksum(z[j,t]*pw[j] for j in jobs if j!=0) + u[t]*Wi == e[t])
#     tou.addConstr(e[t] <= G[t])
    tou.addConstr(e[t]-Bp[t] <= G[t]) #Included the Battery storage usage for production
```

```
#Energy costs/credits
tou.addConstr(grid_costs == quicksum(price[t]*G[t] for t in range(T)))
tou.addConstr(nm_credits == quicksum(0.5*price[t]*(PVnm[t]+Bnm[t]) for t in range(T)) )


#PV Solar Generation
for t in range(T):
    tou.addConstr(PVg[t] == sun_peak[t]*PVz*(losses))

for t in range(T):
    tou.addConstr(PVnm[t] + PVb[t] <= PVg[t]) #PV generation output can go to net meter or

#System Energy-Emissions Balance
# tou.addConstr(quicksum(price[t]*(PVnm[t]-G[t]) for t in range(T)) >= 0) #Balancing credi
# tou.addConstr(quicksum(price[t]*(0.6*PVnm[t] - G[t]) for t in range(T)) >= 0)
tou.addConstr(quicksum(price[t]*(0.5*(PVnm[t] + Bnm[t]) - G[t]) for t in range(T)) >= 0) #
# tou.addConstr(quicksum(price[t]*(PVg[t]-G[t]) for t in range(T)) >= 0)
tou.addConstr(quicksum((PVnm[t]+Bnm[t]-G[t]) for t in range(T))  >= 0) #CO2 emissions bala
# tou.addConstr(quicksum(emissions[t]*(PVnm[t]+Bnm[t]-G[t]) for t in range(T))  >= 0) #CO2
# tou.addConstr(quicksum(PVg[t]-G[t] for t in range(T))  >= 0) #CO2 emissions balance

#Energy Storage System equations

#Battery energy can be used for production or net metering
for t in range(R,T):
    tou.addConstr(Bp[t] + Bnm[t] <= B[t])

for t in range(1,T):
#   tou.addConstr(Bc_scaled[t] == B[t-1]+PVb[t-1]-e[t-1]) #auxilary constraint for battery
    tou.addConstr(Bc_scaled[t] == B[t-1]+PVb[t-1]-Bp[t-1]-Bnm[t-1]) #added option to use s
    tou.addConstr(Bc[t] == max_(0,Bc_scaled[t]))
    tou.addConstr(B[t] == min_(Q, Bc[t])) #energy balance in battery at time t

tou.addConstr(B[0] == 0) #battery energy at time 0

for t in range(T):
    tou.addConstr(B_max >= B[t]) # Maximum battery capacity required

tou.addConstr(0.8*B_cap == B_max) # Maximum battery capacity required


#Objective
# objective = PVz
objective = 1720*PVz + 469*B_cap

tou.setObjective(objective)
tou.modelSense = GRB.MINIMIZE

# Solve

tou.update()
tou.optimize()
# tou.write("tou.lp")
```

4.4.0 Results - PV & ESS (Production and Net Metering)

In [ ]:

```
##########################################################################
### SOLUTION PRINTOUT
##########################################################################

if tou.status==GRB.OPTIMAL:
    print("Completion time is:", c_max.x)
    print("-------------------------------------")
    print(f'Optimal PV System Size: {tou.objVal : .2f} kW')
```

```
    print('\n')
    for j in [j for j in jobs if j>0]:
        print("Job", j, ": starts at", c[j].x - p[j], "completes at", c[j].x)

    print('\n')

    #energy consumption
    print('\n')
    print("---------------------------------------")
    print(f'Optimal PV System Size: {PVz.x : .2f} kW')

    eGrid = []
    PVgen = []
    PVbattery = []
    PVnet_meter = []
    B_net_meter = []
    B_prod = []
    Battery = []
    eConsumption = []

    for t in range(T):
        eGrid.append(G[t].x)
        PVgen.append(PVg[t].x)
        PVbattery.append(PVb[t].x)
        PVnet_meter.append(PVnm[t].x)
        B_net_meter.append(Bnm[t].x)
        B_prod.append(Bp[t].x)
        Battery.append(B[t].x)
        eConsumption.append(e[t].x)

    print(f'Max Battery Capacity: {max(Battery) : .2f} kWh')
    print(f'Value of B_max is: {B_max.x : .2f} kWh')
    print(f'Value of B_cap is: {B_cap.x : .2f} kWh')
    print("---------------------------------------")
    print(f"Total Solar PV generation: {sum(PVgen): .2f} kWh")
#     print(f"Total Energy consumption: {sum(eConsumption)} kWh ")
    print(f"Total Net Metering energy: {sum(PVnet_meter)+sum(B_net_meter): .2f} kWh")
    print(f"Total Grid energy: {sum(eGrid)} kWh ")
    print("---------------------------------------")
    print(f"Total Energy Costs: ${grid_costs.x : .2f}")
    print(f"Total Energy Credits: ${nm_credits.x : .2f}")
    print('\n')

    for t in range(T):
        print(f'Energy consumed in time {t}: {e[t].x}')
    print('\n')
    for t in range(T):
        print(f'Energy drawn from grid in time {t}: {G[t].x}')
    print('\n')
    for t in range(T):
        print(f'Solar PV generation at time {t}: {PVg[t].x}')
    print('\n')
    for t in range(T):
        print(f'Solar PV net metering at time {t}: {PVnm[t].x}')
    print('\n')
    for t in range(T):
        print("Battery charge from PV at time", t, ":", PVb[t].x)
    print('\n')
    for t in range(T):
        print("Battery energy balance at time", t, ":", B[t].x)
    print('\n')
    for t in range(T):
        print("Battery energy for production at time", t, ":", Bp[t].x)
    print('\n')
    for t in range(T):
```

```
        print("Battery energy for net metering at time", t, ":", Bnm[t].x)
```

5. Confidence Interval - PV & ESS

In [ ]:

```
###############################################################################
### 1998-2020 Simulation
###############################################################################

PV_size = []
for i in range(1998,2020+1):


    ###############################################################################
    ### OPTIMIZATION MODEL
    ###############################################################################

    tou = Model("TOU")

    ##DEPENDENT VARIABLES
    c={}
    for j in jobs:
        c[j] = tou.addVar(vtype=GRB.INTEGER, lb=0)

    c_max = tou.addVar(vtype=GRB.INTEGER, lb=0)

    #idle time
    idle_time = tou.addVar(vtype=GRB.INTEGER)

    #Electricity costs
    e_work = tou.addVar(vtype=GRB.CONTINUOUS)
    e_idle = tou.addVar(vtype=GRB.CONTINUOUS)
    e_ramp = tou.addVar(vtype=GRB.CONTINUOUS)

    grid_costs = tou.addVar(vtype=GRB.CONTINUOUS)
    nm_credits = tou.addVar(vtype=GRB.CONTINUOUS)

    #Emissions costs
    t_emissions = tou.addVar(vtype=GRB.CONTINUOUS)

    ##INDEPENDENT DECISION VARIABLES
    x={}
    for k in jobs:
        for j in [j for j in jobs if j<k]:
            x[j,k] = tou.addVar(vtype=GRB.BINARY)

    y={}
    for t in range(T):
        for j in [j for j in jobs if j!=0]:
            y[j,t] = tou.addVar(vtype=GRB.BINARY)

    z={}
    for t in range(T):
        for j in [j for j in jobs if j>0]:
            z[j,t] = tou.addVar(vtype=GRB.BINARY)

    u={}
    for t in range(T):
        u[t] = tou.addVar(vtype=GRB.BINARY)

    #Energy requirement
    G={}
    for t in range(T):
```

```
    G[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#PV System related variables (PVz = System Size, PVg = System Energy Output)
PVz = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

PVg={}
for t in range(T):
    PVg[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

PVnm={}
for t in range(T):
    PVnm[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

PVb={}
for t in range(T):
    PVb[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)


#Battery Energy Availability at time t
B={}
for t in range(T):
    B[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#battery charging variable
Bc={}
for t in range(T):
    Bc[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#auxilary battery charging variable
Bc_scaled={}
for t in range(T):
    Bc_scaled[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb = -1000000, ub=GRB.INFINITY)


#auxiliary variable to represent energy consumption
e={}
for t in range(T):
    e[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#New variable on energy used from battery to power production (Bp)
Bp={}
for t in range(T):
    Bp[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)

#New variable on energy used from battery to net metering (Bnm)
Bnm={}
for t in range(T):
    Bnm[t] = tou.addVar(vtype=GRB.CONTINUOUS, lb=0, ub=GRB.INFINITY)



tou.update()

##CONSTRAINTS

#Disjunctive constraints
for k in jobs:
    for j in [j for j in jobs if j<k]:
        tou.addConstr(c[j] + p[k] + s[j,k] <= c[k] + L*(1-x[j,k]))

for k in jobs:
    for j in [j for j in jobs if j<k]:
        tou.addConstr(c[k] + p[j] + s[j,k] <= c[j] + L*x[j,k])

#Completion time
for j in jobs:
```

```
        tou.addConstr(c[j] >= p[j])

    #dummy variable
    for j in [j for j in jobs if j==0]:
        tou.addConstr(c[j] == R)


    #total completion time
    for j in jobs:
        tou.addConstr(c_max >= c[j])

    # tou.addConstr(c_max <= T)
    tou.addConstr(c_max <= 18) #Setting the completion cap according to min makespan

    #Idle constraint
    tou.addConstr(idle_time == c_max - c[0] - quicksum(p[j] for j in jobs if j!=0)) #not c

    #Start time of job
    for j in [j for j in jobs if j!=0]:
        tou.addConstr(quicksum(t*y[j,t] for t in range(R,T)) == c[j] - p[j])

    for j in [j for j in jobs if j!=0]:
        tou.addConstr(quicksum(y[j,t] for t in range (R,T)) == 1)


    #Machine processing at times t
    for j in [j for j in jobs if j!=0]:
        for t in range(R,T-p[j]+1):
            tou.addConstr(quicksum(z[j,k] for k in range(t,t+p[j])) >= (y[j,t]*p[j]))

    for t in range(R,T):
        tou.addConstr(quicksum(z[j,t] for j in jobs if j!=0) <= 1)

    #The times that the machine is working on a job should be equal to the job's processi
    for j in [j for j in jobs if j!=0]:
        tou.addConstr(quicksum(z[j,t] for t in range(R,T)) == p[j])

    #Machine idle at times t
    for t in range(R,T):
        tou.addConstr(quicksum(z[j,t] for j in jobs if j!=0) == 1-u[t])

    #Energy source
    for t in range(R):
    #    tou.addConstr(quicksum(ramp[j,t]*Wr for j in jobs if j==0) <= G[t])
        tou.addConstr(quicksum(Wr*R for j in jobs if j==0) <= G[t])


    #Energy consumption
    for t in range(R,T):
        tou.addConstr(quicksum(z[j,t]*pw[j] for j in jobs if j!=0) + u[t]*Wi == e[t])
    #     tou.addConstr(e[t] <= G[t])
        tou.addConstr(e[t]-Bp[t] <= G[t]) #Included the Battery storage usage for producti

        #Energy costs/credits
        tou.addConstr(grid_costs == quicksum(price[t]*G[t] for t in range(T)))
        tou.addConstr(nm_credits == quicksum(0.8*price[t]*(PVnm[t]+Bnm[t]) for t in range


#PV Solar Generation
    for t in range(T):
#         tou.addConstr(PVg[t] == sun_peak[t]*PVz*(losses))
        tou.addConstr(PVg[t] == (solar_irr[i].iloc[t][0]/1000)*PVz*(losses))

    for t in range(T):
        tou.addConstr(PVnm[t] + PVb[t] <= PVg[t]) #PV generation output can go to net mete
```

```
        #System Energy-Emissions Balance
        # tou.addConstr(quicksum(price[t]*(PVnm[t]-G[t]) for t in range(T)) >= 0) #Balanci
        # tou.addConstr(quicksum(price[t]*(0.6*PVnm[t] - G[t]) for t in range(T)) >= 0)
        tou.addConstr(quicksum(price[t]*(0.8*(PVnm[t] + Bnm[t]) - G[t]) for t in range(T))
        # tou.addConstr(quicksum(price[t]*(PVg[t]-G[t]) for t in range(T)) >= 0)
        tou.addConstr(quicksum((PVnm[t]+Bnm[t]-G[t]) for t in range(T))  >= 0) #CO2 emissi
        # tou.addConstr(quicksum(emissions[t]*(PVnm[t]+Bnm[t]-G[t]) for t in range(T))  >=
        # tou.addConstr(quicksum(PVg[t]-G[t] for t in range(T))  >= 0) #CO2 emissions bala

    #Energy Storage System equations

    #Battery energy can be used for production or net metering
    for t in range(R,T):
        tou.addConstr(Bp[t] + Bnm[t] <= B[t])

    for t in range(1,T):
    #    tou.addConstr(Bc_scaled[t] == B[t-1]+PVb[t-1]-e[t-1]) #auxilary constraint for bat
        tou.addConstr(Bc_scaled[t] == B[t-1]+PVb[t-1]-Bp[t-1]-Bnm[t-1]) #added option to t
        tou.addConstr(Bc[t] == max_(0,Bc_scaled[t]))
        tou.addConstr(B[t] == min_(Q, Bc[t])) #energy balance in battery at time t

    tou.addConstr(B[0] == 0) #battery energy at time 0


    #Objective
    objective = PVz

    tou.setObjective(objective)
    tou.modelSense = GRB.MINIMIZE

    # Solve

    tou.update()
    tou.optimize()
    # tou.write("tou.lp")

    PV_size.append(tou.objVal)
```

In [ ]:

```
#Statistical Analysis
years = []
for i in range(23):
    years.append(f"{1998+i}")

#Dispersion plot
plt.plot(years,PV_size,'o', color='black')
plt.xticks(rotation='vertical')
plt.ylabel("System Size (kW)")
plt.title("PV Sizing Optimal Solutions ")
plt.show()
```

5.1 Monte Carlo Bootstrapping

In [ ]:

```
r = 10000
monte_boot = [np.random.choice(PV_size, len(PV_size)) for _ in range(r)]
# monte_boot
```

In [ ]:

```
monte_boot_mean = [np.mean(np.random.choice(PV_size, len(PV_size))) for _ in range(r)]
```

In [ ]:

```
styling = {'sym': '',
           'whis': [2.5, 97.5],
           'showfliers': False,
           'vert': True,
           'boxprops': dict(linewidth=2.0, color='#4e98c3'),
           'whiskerprops': dict(linewidth=2.0, color='#4e98c3', linestyle='--'),
           'capprops': dict(linewidth=2.0, color='k'),
           'medianprops': dict(linewidth=2.0, color='#ad203e')
}

fig,  ax = plt.subplots()

ax.boxplot([monte_boot_mean],showmeans=True, **styling)
# axes[1].boxplot([monte_boot_std, monte_boot_skew, monte_boot_kurtosis], **styling)
ax.set_xticklabels(['Mean'], fontsize=20)
# axes[1].set_xticklabels(['Stdev', 'Skew', 'Kurtosis'], fontsize=20)
# for ax in axes:
ax.set_facecolor('#eeeeee')
ax.grid(True, linestyle='--', color='#acacac')
# ax.text(0.25, 0.85, fontsize=17, ha='center', va='center',
#         transform=ax.transAxes, color='grey', alpha=0.5);
fig.tight_layout(rect=[0, 0.03, 1, 0.92])
fig.suptitle('Monte-Carlo bootstrap C.I. 95%', fontsize=25)
```

In [ ]:

```
monte_boot_mean = [np.mean(np.random.choice(PV_size, len(PV_size))) for _ in range(r)]

from matplotlib.cbook import boxplot_stats
stats = boxplot_stats(monte_boot_mean)
print(f"Upper limit: {np.percentile(monte_boot_mean, 97.5)}")
print(f"Lower limit: {np.percentile(monte_boot_mean, 2.5)}")
print(f"Mean: {np.mean(monte_boot_mean)}")
```

In [ ]:

```
alpha = 0.05                        # significance level = 5%
df = len(PV_size) - 1               # degress of freedom = 20
t = stats.t.ppf(1 - alpha/2, df)    # t-critical value for 95% CI = 2.093
s = np.std(PV_size, ddof=1)             # sample standard deviation = 2.502
n = len(PV_size)

lower = np.mean(PV_size) - (t * s / np.sqrt(n))
upper = np.mean(PV_size) + (t * s / np.sqrt(n))

print(f"Upper Limit: {upper: .2f} kW")
print(f"Lower Limit: {lower: .2f} kW")
np.mean(PV_size)
```

Vita

Samuel Trevino received his B.S in 2004 and M.S in 2008, in Industrial and Systems Engineering at Tecnologico de Monterrey in Mexico, and University of Missouri-Columbia, respectively. He is currently a PH.D student and research assistant in the Industrial and Systems Engineering department at University of Tennessee, Knoxville. Previously, he served at Tecnologico de Monterrey as Director of the Industrial and Systems Engineering academic program. He has professional experience in the application of operational excellence (OPEX) methodologies in diverse industry applications, such as lean manufacturing, Six Sigma, supply chain and logistics, working for international companies, such as Valeo Automotive Group, Scholastic Inc., and Hallmark Cards Inc. His research interests include the application of optimization and statistical data analysis models to address energy efficiency and decision-making in energy source mixes for manufacturing.