

**NEXT LEVEL ENERGY MANAGEMENT THROUGH SMART
MANUFACTURING FOR ACHIEVING NET-ZERO 2050**

A Dissertation Presented for the

Doctor of Philosophy

Degree

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DEDICATION

This dissertation is dedicated to my parents for their constant and unwavering support.

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ABSTRACT

This research aims to guide energy management improvements using smart manufacturing concepts to achieve net-zero 2050 goals. The global manufacturing industry is undergoing a fourth industrial revolution. Simultaneously, the United States has set a goal of achieving net-zero greenhouse gas emissions by 2050. Navigating these two concurrent revolutions in manufacturing is the motivation for this research.

This multi-part dissertation focuses on understanding smart manufacturing for energy management through a review of the applicability of smart manufacturing maturity models, an application of a machine learning framework for energy prediction to show a real-world case of smart manufacturing for energy management, and an analysis of the Better Plants program to determine policy recommendations for achieving net-zero 2050. Smart manufacturing is a priority research area for many organizations, but there is no clear understanding of the terms and dimensions across industries, including energy management. This gap was addressed by reviewing twenty-four maturity models across ten categories of dimensions. The focus areas for companies and areas with weak guidance were identified.

Energy consumption predictions are typically performed using basic linear regression based on production or often naïve approximations. Better data fidelity and analytic methods are envisioned with the fourth industrial revolution. No existing study was identified that predicts energy consumption at the facility level using machine learning or at a time scale shorter than a year. A framework with machine learning and an automated data collection framework for energy prediction at the facility level is proposed to address this gap. The framework is used to test increasingly complex machine learning

models on daily, weekly, and monthly datasets. The complex models can be utilized for increased prediction accuracy. Still, significant challenges must be overcome to automate the process, such as the need for reliable and quality data and considerable human labor. The BP program was reviewed and accomplishments were outlined according to year and subsector. The BP program has been crucial for emission reductions, but acceleration is required to meet further goals. To maximize the effectiveness of the BP program, the US government should consider adopting additional incentives and combine them with disincentives.

Keywords

Smart manufacturing, energy management, energy efficiency, energy digital twin, net-zero 2050, machine learning

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INTRODUCTION

This multi-part dissertation consists of three separate research articles organized as chapters. They are interconnected by the goal of advancing energy management through smart manufacturing to help the U.S. industrial sector achieve its objective of net-zero carbon emissions by 2050. The section motivates this research, lists the research objectives and questions, and provides an overview of the rest of the dissertation.

Relevance of Research

Research Motivation

Smart manufacturing, also called Industry 4.0, is an important research topic right now, but there is no clear understanding of what the term means and how it should be applied, especially when viewed across industries. A major motivation for this research is the Industrial Decarbonization Roadmap published by (US DOE, 2022), shown in **Figure 1**, which outlines the necessary research and development for industrial decarbonization's net-zero 2050 goals. Interestingly, smart manufacturing is listed as a near-term commercial opportunity for energy efficiency, but in the author's experience, smart manufacturing is not clearly understood enough to consider it a near-term recommendation. This provided the necessary motivation to research smart manufacturing maturity and how it will relate to net-zero 2050 in general.

Other reviews exist of SM maturity models to develop a new maturity model, but Chapter I investigates the dimensions in more depth and focuses on how to select and apply the existing models. The author's goal was to distill the models into a simple enough survey that an undergraduate energy auditor could take it into a plant and make recommendations. A major result of this paper, which is included in the appendix of

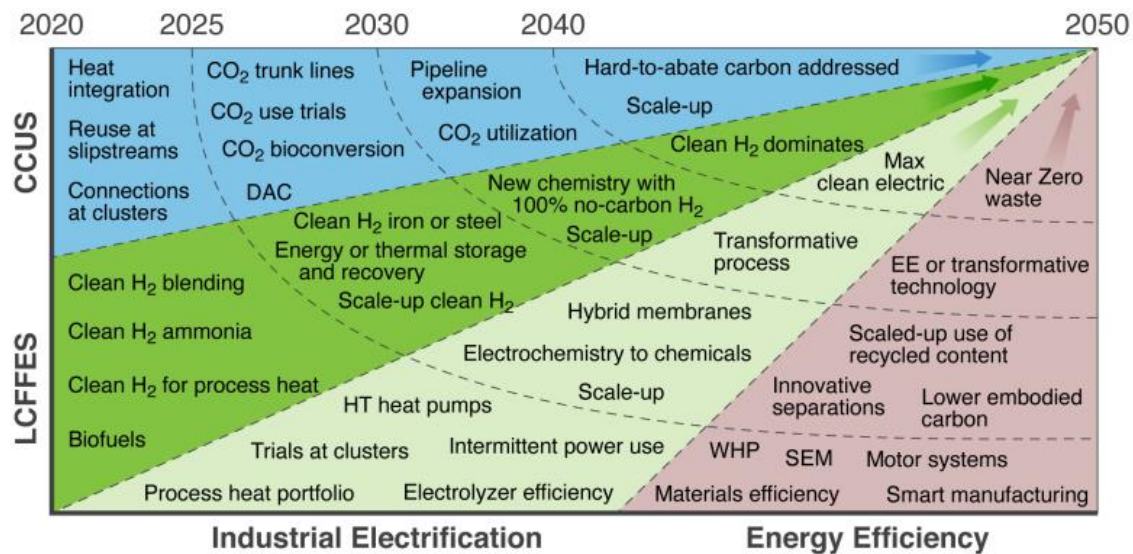


Figure 1: Major research and development opportunities for industrial decarbonization

Chapter I is a survey on smart manufacturing, which can be directed at small and medium manufacturers to assess smart manufacturing maturity and make actionable recommendations.

Figure 2 shows the number of research publications on data-driven energy savings by procedure. Too much research is focused on modeling and analysis and not enough research showing how to acquire, process, and implement data in industrial processes. This provides the initial motivation for Chapter II, which implements a data-driven energy management procedure in an actual industrial process.

For Chapter III motivation, the author realized that the Better Plants (BP) program provided an accessible data source for benchmarking industrial net-zero 2050 that had not yet been tapped. The author has experience with the BP program and knew that an in-depth review of its implementation and accomplishments could help other agencies develop their own voluntary emission reduction programs.

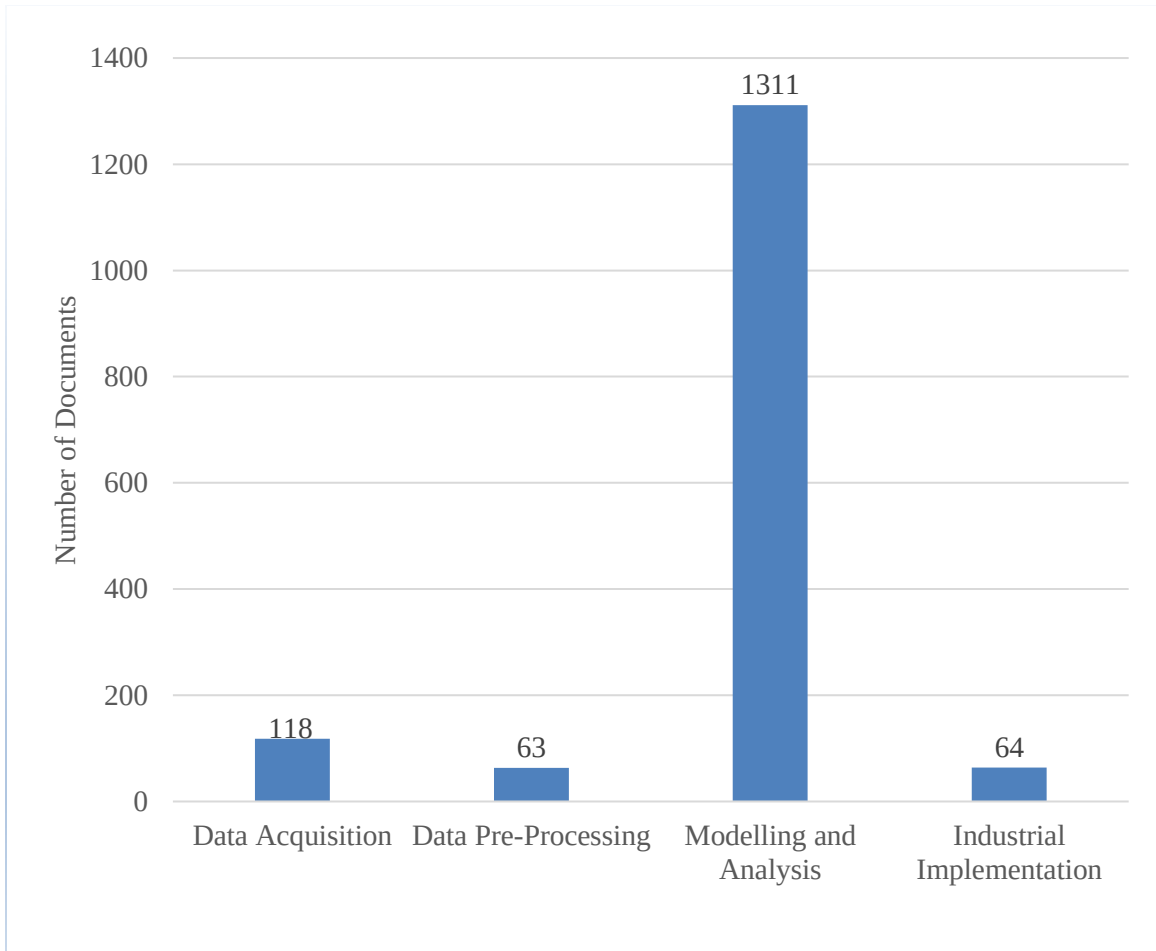


Figure 2: Number of research publications in data-driven energy savings by procedure

Research Questions

For Chapter I, which reviews smart manufacturing maturity models on their applicability to 10-dimension categories, the following questions guided the research:

1. Many smart manufacturing maturity models exist for different applications and industries. How can a small manufacturer know if one is applicable?
2. What are the most critical dimensions of smart manufacturing maturity?
3. What smart manufacturing dimensions are being overlooked or left out?
4. What are the weaknesses and strengths of existing models?

The research presented in Chapter II aims to answer the following questions:

1. Can industrial facility-level energy predictions be improved using weekly and daily energy data?
2. Can industrial facility-level energy predictions be improved by considering more advanced ML models such as Principal Component Regression (PCR), K-Nearest Neighbor (KNN), Random Forest (RF), and Bayesian Regularized Neural Network (BRNN)?
3. Because naïve predictions already perform well, does this indicate that data from one year prior could be used as an additional predictor for enhanced accuracy in facility-level energy predictions?
4. What are the significant challenges in implementing a facility-level automated energy prediction framework?

The study discussed in Chapter III seeks to address the following questions:

1. What type of company is likely to join the BP program?
 - a. Public or private?

- b. Small, Medium, or large? (Based on employees, amount of energy spending, revenue)
 - c. Specific sectors?
2. Which sectors have had the best energy intensity improvements?
 3. How effectively has the BP program targeted energy-intensive sub-sectors?
 4. What are the possible scenarios for the scope of the BP program and US progress toward net-zero 2050?

Research Objectives

The deliverables include (i) a survey for small and medium manufacturers to assess their smart manufacturing, (ii) a framework for industrial energy consumption predictions using machine learning and automated data collection, (iii) an assessment of the BP program regarding how it relates to net-zero 2050 goals.

Dissertation Outline

This dissertation is organized into three chapters, preceded by Introduction and followed by Conclusions.

Chapter I provides a review of smart manufacturing maturity models and their applicability to ten-dimension categories, including ‘Information Technology (IT) & Cyber-Physical System (CPS) & Data’, ‘Strategy & Organization’, ‘Supply Chain & Logistics’, ‘Products & Services’, ‘Culture & Employees’, ‘Technology & Capabilities’, ‘Customer & Market’, ‘Cybersecurity & Risk’, ‘Leadership & Management’, and ‘Governance & Compliance’.

Chapter II proposes a machine learning framework with automated data collection for energy prediction at the facility level. It uses it to test increasingly complex machine learning models on daily, weekly, and monthly datasets.

Chapter III develops a generic overview of the implementation and accomplishments of the US BP program to aid other government agencies in creating their own voluntary emission reduction programs. Chapter III is currently finished but not published, with the understanding that it will be published after graduation.

Figure 3 shows the gaps identified and filled by each chapter in this research.

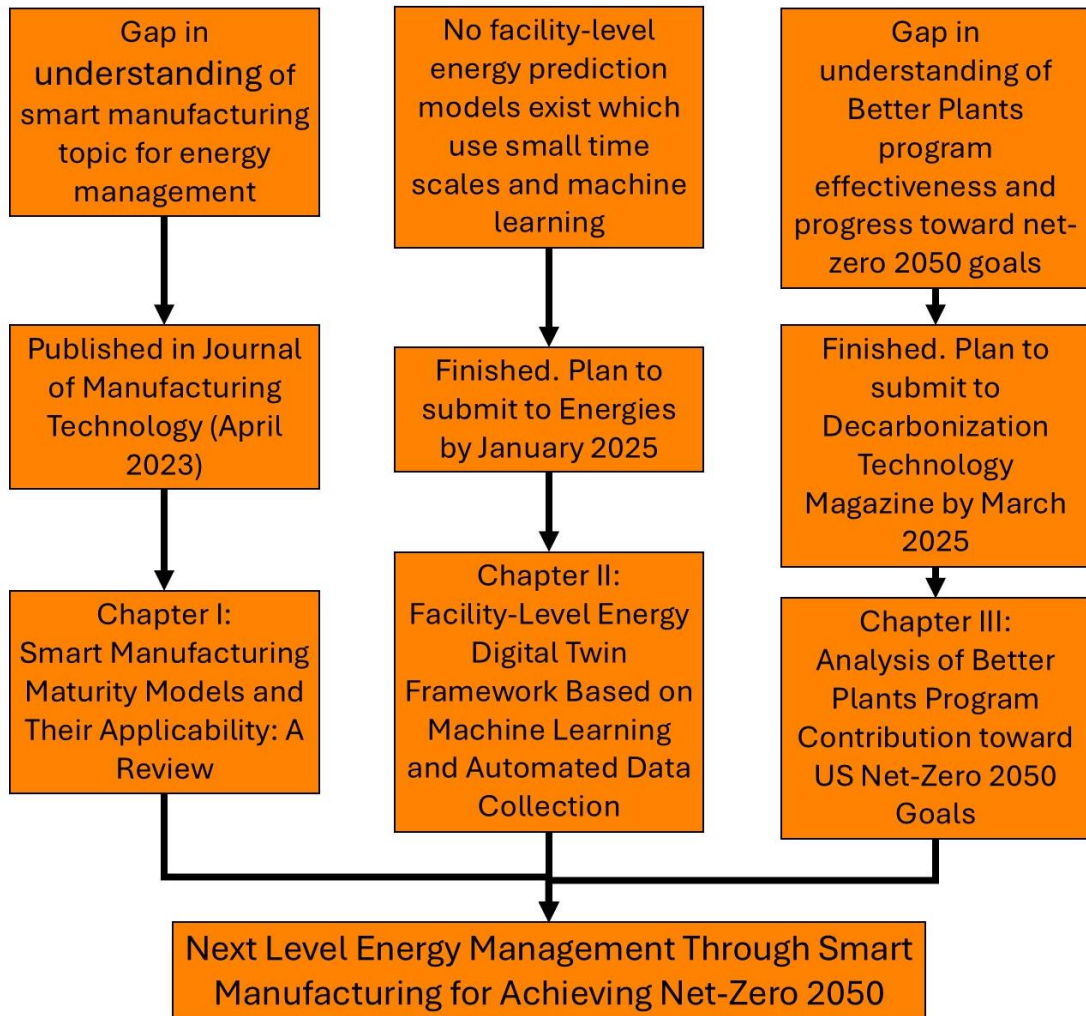


Figure 3: Dissertation outline including the research gaps identified and Chapter names

CHAPTER I

SMART MANUFACTURING MATURITY MODELS AND THEIR

APPLICABILITY: A REVIEW

A version of this chapter was published in the Emerald Publishing Limited “Journal of Manufacturing Technology Management” by David Vance, Mingzhou Jin, Christopher Price, Sachin U. Nimbalkar, and Thomas Wenning:

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Abstract

This paper reviews existing Smart Manufacturing (SM) maturity models’ dimensions and maturity levels to assess their applicability. Many maturity models are available but have not been validated or do not provide useful application guides. This gap creates the need for a review of their applicability and how to improve it.

Nineteen peer-reviewed maturity models related to ‘Industry 4.0’ or ‘Smart Manufacturing’ were selected based on a systematic literature review (SLR), and five consulting firm models were selected based on the author’s industry knowledge. The chosen models were analyzed to determine ten categories of dimensions. They are assessed on a 1 – 5 scale for their applicability in the ten dimensions categories.

The five ‘consulting firm’ models have a first-mover advantage, are more widely used, and are more applicable, but require payment, and lack published details and validation. The nineteen ‘peer-reviewed’ models are not as widely used and are not easy to apply,

but they are improving. The categories defined include ‘Information Technology (IT) & Cyber-Physical System (CPS) & Data’, ‘Strategy & Organization’, ‘Supply Chain & Logistics’, ‘Products & Services’, ‘Culture & Employees’, ‘Technology & Capabilities’, ‘Customer & Market’, ‘Cybersecurity & Risk’, ‘Leadership & Management’, and ‘Governance & Compliance’. The analyzed maturity models were particularly weak in cybersecurity, leadership, and governance.

Introduction

Smart Manufacturing (SM) was first called Industry 4.0 (i.e., the fourth industrial revolution) by (Kagermann et al., 2013) but is also sometimes called Industrial Internet, Smart Industry, Factory of the Future, Digital Manufacturing, and Integrated Industry. Even though SM is a priority research area for many organizations, there is no clear understanding of what all these terms mean across industries, and which one should be applied. This leads to miscommunication of the concept to manufacturing firms and difficulties clearly outlining the steps required for transitioning to a smart, digital enterprise (Ghobakhloo, 2018). SM adoption will be different for each application based on products, manufacturing processes, and enterprise goals. Consequently, scholars have identified some definitions, design principles, and technology trends for SM. (Kagermann et al., 2013), for example, identified quantitatively four design principles (interconnection, information transparency, decentralized decisions, and technical assistance) and core features (digitization and connectivity everywhere between machines, products, employees, suppliers, and customers enabling communication, self-management, and improved performance). Recently, Mubarok (2020) defined Industry 4.0 as “a seamless collaboration of diverse advanced technologies integrating smart

visualization and smart analytics of autonomous processes to grasp the vision of smart and intelligent factories as to produce smart connected products and provide smart services through real-time information transparency.” This paper considers any advanced technology that allows real-time information transparency, improved decision making, or interconnection between diverse processes an SM technology. Typical SM technologies include Radio Frequency Identification System (RFID), collaborative robotics, Industrial Internet of Things (IIoT), cloud computing, cyber-physical systems (CPS), big data analytics, blockchain, and additive manufacturing. Some other technologies associated with SM include digital-twin, advanced simulation, and cybersecurity.

There are numerous benefits of implementing SM (for example shorter lead times, increased revenue, reduced costs, increased productivity, improved product customization) but the main benefit of selecting the best maturity model for a specific application is improved decision making (Dalenogare et al., 2018). The claim is reinforced by Schuh *et al.* (2017), which states “The chief economic potential of Industry 4.0 lies in its ability to accelerate corporate decision-making and adaptation processes.” The challenges facing SM transformation include inadequacy of information technology (IT) technologies, limited knowledge, and expensive investment costs in addition to a need for integrating modern technologies, advanced machines, and automated workflows throughout the value chain (Erol et al., 2016). The following problems were identified from expert interviews when implementing SM (Schumacher et al., 2016): 1) Companies perceive the SM concept as highly complex and lacking strategic guidance; 2) Companies lack a clear understanding of SM outcomes and benefits; 3) Companies fail to assess their own capabilities in taking any coordinated measure.

To address these challenges, an SM maturity model conceptualizes and measures the maturity of a process or organization in terms of implementing SM technologies/strategies and describes a path to pursue a specific target state (De Carolis et al., 2017). The SM maturity model's purpose is to capture economic potential through informed corporate decision-making and guide the company through its challenges. Open questions remain on how to choose an SM maturity model for a specific purpose and how to assess the merits of a specific maturity model.

There are three distinct maturity model types: (1) Maturity grids; (2) Hybrids and Likert-like questionnaires; (3) Capability Maturity Models (CMM) (Fraser et al., 2002).

Maturity grids are of moderate complexity and contain text descriptions for each maturity level. Likert-like questionnaires are constructed from statements of 'good practice' in which the respondent scores their performance on a rating scale. A hybrid model combines the questionnaire approach with definitions for each maturity level. CMM, often the most complex type of maturity model, describes each process area and common features and specifies key practices for addressing a series of objectives. CMM often stipulates five maturity levels: initial, repeatable, defined, managing, and optimizing.

Good maturity models typically have the following features and evolution. Maturity models should follow a predictable linear pattern through discrete stages. All premises of the maturity model should be evaluated iteratively including its quality, usefulness, and effectiveness. There should be thorough documentation of the design process, including references to existing maturity models (Becker et al., 2009). Evolutionary phases of the maturity model development are descriptive, prescriptive, and comparative (De Bruin et al., 2005). Maturity models begins with descriptions of maturity levels and dimensions,

then through experience prescribes paths to get from one maturity level to another, and finally becomes comparative once enough data is available to make comparisons. Based on this process, the most useful and evolved maturity models have comparative capability combined with good descriptions of maturity items and specific paths through the levels. Problems with existing SM maturity models are mainly that the degree of application in real business is low, more maturity models are being proposed than are being implemented, and awareness is lacking for the ‘peer-reviewed’ maturity models within the corporate world (Felch et al., 2019). Considering the many models available, inconsistent human judgement, many industries and applications, and lack of awareness, one of the greatest challenges for a decision maker is selecting which maturity model to use. Altan Koyuncu *et al.* (2021) employed fuzzy methods considering the number of dimensions, maturity levels, release date, content, the definition of measurement properties, assessment expenditures, and assessment method to select an Industry 4.0 maturity model for solar cell manufacturers. This review article considers more models and focuses on not just the number of dimensions but the dimension focus so that manufacturers can select an SM maturity model for their specific purposes. Hajoary (2021) performed a systematic review to determine 9-dimension categories of SM maturity models (i.e., Organizational Strategy, People/Employee, Process, Technology, Customers, Products and Services, Manufacturing and Operations, Information Technology, and Culture). Dimensions related to supply chain, cybersecurity, and regulatory issues are notably absent. This review article determines more comprehensive dimension categories, including the new ‘Supply Chain &

Logistics', 'Cybersecurity & Risk' and 'Governance & Compliance' categories, and assesses applicability towards those dimensions.

Small and Medium Enterprises (SMEs) require special consideration. SMEs are characterized by resource limitation, low volume production, high flexibility, high specialization, and inclination toward niche markets. Typical SM maturity models and roadmaps are not applicable to SMEs which have smaller technology, infrastructure, employee, and financial capabilities (Mittal, Khan, et al., 2018). An SME is unlikely to have the capital to pay a consulting firm to perform a digital transformation for their enterprise. Multi-national enterprises (MNEs) typically start from a theoretical level 1 with no current adoption but the resources and employees available with some knowledge on the topic. An SME, however, typically begins at level 0 with no information and no resources available. The impact of SM on SMEs can be large if governmental agencies and associations assist with the process of digital transformation (Ghobakhloo, 2018). Four out of ten SMEs in a survey did not have a comprehensive SM strategy compared with two out of ten MNEs (Schröder, 2016). Williams *et al.* (2019) performed a systematic review of maturity models for SMEs and discovered six essential maturity model dimensions (1) strategy, (2) products/services, (3) technology, (4) people and culture, (5) management, and (6) processes with people and culture being the most important. However, Williams *et al.* (2019) did not cover several recent maturity models for SMEs, such as in Maturity model toward Industry 4.0 for SMEs (Ganzarain & Errasti, 2016) and Maturity Model of Digitization for SMEs (Blatz et al., 2018). Therefore, there is a need for an assessment of the applicability of all existing maturity models for SME considerations with more comprehensive dimension categories.

This review article characterizes existing maturity models based on relevant features and determines useful and comprehensive dimension categories to evaluate the maturity models' applicability for different situations. Models are scrutinized to determine specific drawbacks that need to be addressed. Each of the 10-dimension categories are discussed in detail to show how they can be improved and to illustrate exemplary maturity items.

Systematic Review of Smart Manufacturing Maturity Models

Methodology

The research presented follows the systematic literature review (SLR) methodology outlined by (Dekkers et al., 2021) to ensure transparency and replicability. The guiding research question is: “What are the most important dimension categories of existing Smart Manufacturing Maturity Models?” The research objectives are to determine a list of the most important dimension categories, evaluate SM maturity models applicability to those categories, determine specific drawbacks that need to be addressed, and develop future research directions. **Figure 4** outlines the methodology used to gather a corpus of SM related literature for the peer reviewed maturity models, and the structure of its analysis. This corpus was collected between the 1st and 5th of May 2022 using the first 80 most relevant results from Google Scholar, SCOPUS, and Web of Science and the search string (*“Industry 4.0” OR “Digital” OR “Smart Manufacturing”*) AND (*“Maturity Model” OR “Maturity Assessment”*). The time frame considered was from 2013 when the term Industry 4.0 was first introduced to the present. Only published studies in scholarly journals available in English were included. Maturity models not focusing on manufacturing at the enterprise level and instead focusing on the digital maturity of a person, country, region, city, or specific component were excluded. Models focusing

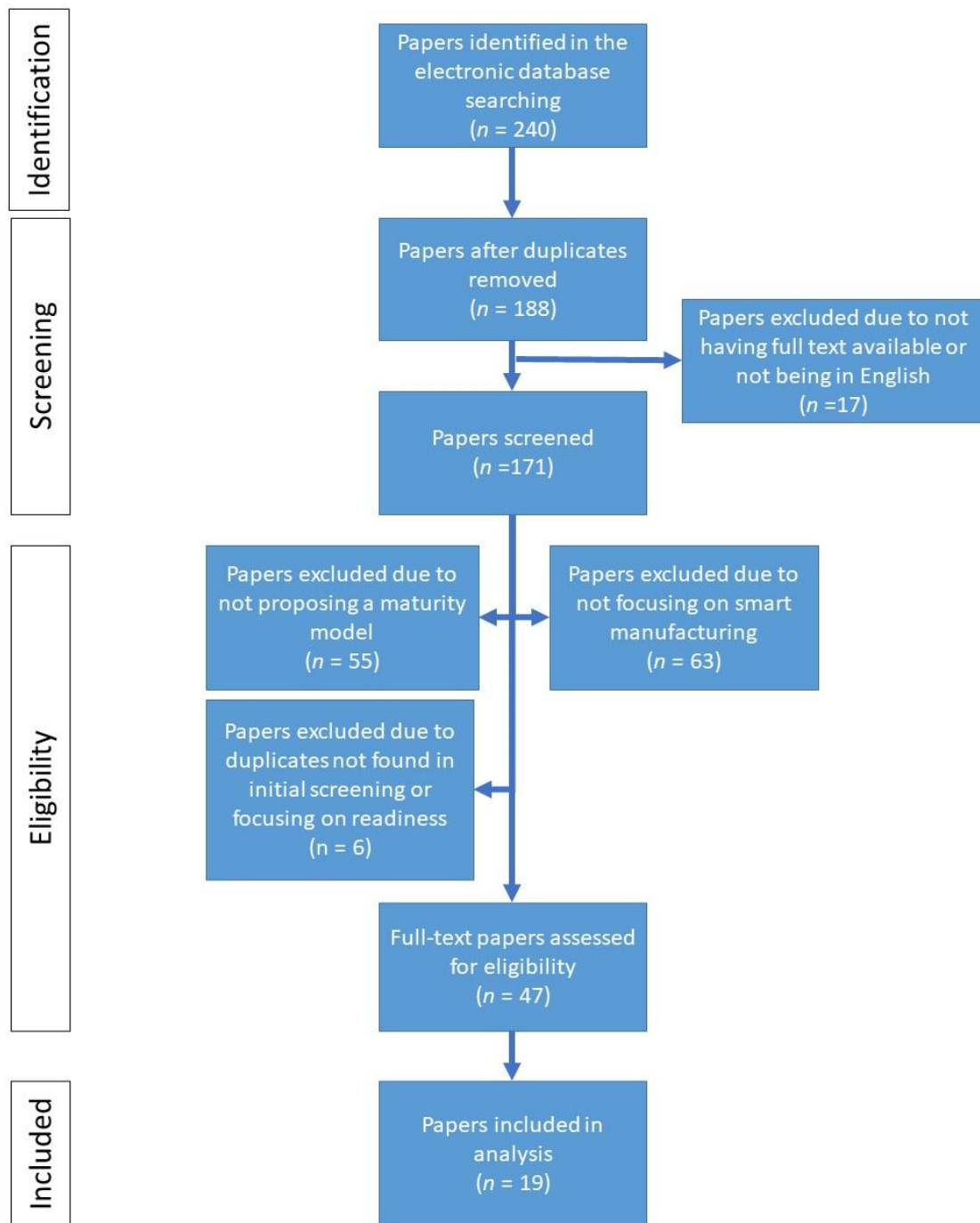


Figure 4: Systematic literature review methodology

on an enterprise's readiness were excluded. Maturity models not having adequate descriptions of their levels and dimensions were excluded. The final maturity model selection was based on quality.

List of Existing Maturity Models

The consulting firm maturity model list in **Table 1** was developed through existing industry knowledge. These consulting firm maturity models are popular because there is a tangible benefit to being a 'first mover' (Trotta & Garengo, 2019). 'Consulting firm' SM maturity models are described in **Table 1** according to the number of dimensions (denoted by D), number of levels (denoted by L), and model-defining characterizations. **Table 2** compares the peer-reviewed Industry 4.0 maturity models, generally offering clearer details on the development process, structure, and assessment methodology. The goal of a peer-reviewed model is to advance science and identify gaps in manufacturing knowledge, while the goal of a consulting firm model could be to sell a product or provide a solution. While peer-reviewed models have published more details, they often lack first-mover advantage, benchmarking capability, and industry partnership/validation. Peer-reviewed models are usually technology and industry-specific and either propose novel assessment methodology or build on an existing maturity model.

Analysis of Existing SM Maturity Models

Table 6 in this chapter Appendix describes the maturity levels of each of the models listed in **Table 1** and **Table 2**. Maturity models are organized by the method of defining maturity levels (not clearly defined, defined by organization performance,

Table 1: ‘Consulting Firm’ Industry 4.0 Maturity Models

Model	D	L	Characterizations
The Connected Enterprise Maturity Model (Rockwell Automation, 2014)	1	5	Focus on IT infrastructure. Organization level. Descriptive.
IMPULS- Industrie 4.0 Readiness (Lichtblau et al., 2015)	6	6	Online self-assessment. Likert questionnaire. Focus on SMEs. Prescriptive. Free. Organization level.
Industry 4.0 – Enabling Digital Operations Self-Assessment (PWC, 2016)	6	4	Self-assessment. Organization level. Comparative.
Warwick Industry 4 Readiness Assessment Tool (Agca et al., 2017)	4	6	Organization level. Comparative. Index. Comprehensive. Free. Self-assessment.
Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017)	4	6	Organization level. Comparative. Focus on German enterprises and business processes.

Table 2: ‘Peer Reviewed’ Industry 4.0 Maturity models

Model	D	L	Characterizations
Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises (Schumacher et al., 2016)	9	5	Likert questionnaire. Added organizational aspects to existing maturity model. Descriptive.
Maturity Model Toward Industry 4.0 for SMEs (Ganzarain & Errasti, 2016)	1	5	Focus on SMEs. Descriptive. Diversification strategy model for developing SM vision and specific project planning.
The IoT Technological Maturity Model (Jæger et al., 2016)	1	8	CMM like. Focus on adoption of IoT technology. Norwegian. Descriptive.
Smart Manufacturing System Readiness Level (SMSRL) Index (Jung et al., 2016)	4	10	Grid. Focus on technology adoption in manufacturing firm. Plant level. Descriptive.
System Integration Maturity Model Industry 4.0 (SIMMI) (Leyh et al., 2016)	4	5	Grid. Focus on classifying IT infrastructure maturity. Organization level. Descriptive. German.

Table 2: continued

Model	D	L	Characterizations
Maturity Model for Data-Driven Manufacturing (M2DDM) (Weber <i>et al.</i> , 2017)	1	6	Grid. Focus on data-driven manufacturing with a self-controlling and self-learning factory as the end goal. Descriptive.
Digital Readiness Assessment Maturity model (DREAMY) (De Carolis <i>et al.</i> , 2017)	4	5	Grid. Modular. Focus on processes (design & engineering, quality, production, maintenance, and logistics). Descriptive.
Industry 4.0 – MM (Gökalp <i>et al.</i> , 2017)	5	6	Grid. Focus on manufacturing processes. Clear development. Descriptive.
Maturity Model for Digitalization (Klötzer & Pflaum, 2017)	9	5	Hybrid. Focus on smart product realization and application in supply chain for data-driven manufacturing. Descriptive. Clear development.
Maturity Model for Data-Driven Manufacturing (M2DDM) (Weber <i>et al.</i> , 2017)	1	6	Grid. Focus on data-driven manufacturing with a self-learning and self-controlling factory as the end goal. Descriptive.
Digital Readiness Assessment Maturity model (DREAMY) (De Carolis <i>et al.</i> , 2017)	4	5	Grid. Modular. Focus on processes (design & engineering, production, quality, maintenance, and logistics). Descriptive.
Industry 4.0 – MM (Gökalp <i>et al.</i> , 2017)	5	6	Grid. Focus on manufacturing processes. Clear development. Descriptive.
Maturity Model for Digitalization (Klötzer & Pflaum, 2017)	9	5	Hybrid. Focus on smart product realization and smart product application in supply chain for data-driven manufacturing. Descriptive. Clear development.

Table 2: continued

Model	D	L	Characterizations
Maturity Model of Digitization for SMEs (Blatz et al., 2018)	6	3	Likert-questionnaire. Focus on medium-sized companies. Descriptive.
Smart Factory Maturity Model (Sjödén et al., 2018)	3	4	Unclear assessment method. Focus on smart factory. Descriptive. Validated through case study.
Maturity and Readiness Model for Industry 4.0 Strategy (Akdil et al., 2018)	3	4	Likert-questionnaire. Descriptive. Focus on developing organizational strategy.
Defense Sector Industry 4.0 Maturity Model (Bibby and Dehe, 2018)	3	4	‘Likert scale scoring system’. Focus on defense sector and ‘Factory of the Future’ technology adoption. Descriptive.
Digitalization Maturity Model for Manufacturing (Canetta et al., 2018)	5	4	Likert Questionnaire. Focus on manufacturing sector and workforce skill requirements. Descriptive. Maturity dimensions weighted according to importance to company.
SM3E (Mittal, Romero, et al., 2018)	5	5	Grid. SME Focus. Development but no validation. Full assessment details not included. Descriptive.
Industry 4.0 Maturity Model for Machine Tool Companies (Rafael et al., 2020)	6	6	Likert-questionnaire. Prescriptive. Focus on SME machine tool companies in Europe. Clear development.
An Industry 4.0 Maturity Model Proposal (Santos and Martinho, 2020)	5	6	Likert-questionnaire. Descriptive. Focus on initial diagnosis and roadmap. Clear development.
Maturity Model for Implementation of Industry 4.0 (Wagire et al., 2020)	4	7	Likert questionnaire. Descriptive. Focus on critical aspects of organizations, emerging technologies, & emerging economies.
Fuzzy Rule-Based Industry 4.0 Maturity Model (Caiado et al., 2021)	7	5	Hybrid. Fuzzy rule-based logic added. Focus on supply chain management and operations.

defined by technology, or like the CMM framework explained in the introduction.) Smart Manufacturing System Readiness Level (SMSRL) Index (Jung et al., 2016) is scored on a scale from 0 to 10, but a guide shows that a score of 0 is ‘Not performed’, 1 is ‘Initial’, 3 is ‘Managed’, 5 is ‘Defined’, 7 is ‘Qualitative’, and 9 is ‘Optimizing’, so it could have been included with CMM.

Table 7 in the Appendix of this chapter describes the dimensions of each of the models listed in **Table 1** and **Table 2**. The author filtered these dimensions through careful analysis into ten categories. Leyh *et al.* (2016) has two unique dimensions (horizontal and vertical integration) that were not easily placed into a category. Besides these two dimensions, the 10 identified categories include most possible dimensions.

Table 3 describes each of the ten categories, including possible keywords for each category and some example measurements and questions. The purpose of filtering the dimensions into the ten categories defined in **Table 3** is to evaluate which maturity models are applicable to which topics, discover if there are any gaps in the existing maturity models, and find ways to combine the best aspects from multiple models.

Table 4 assigns a score to each maturity model based on how applicable it is to that category.

- score of 0 means it is not mentioned,
- score of 1 means it is mentioned but there is no specific maturity item,
- score of 2 means there is a poorly described maturity item related to that category,
- score of 3 means there is a specific well-described maturity item
- score of 4 means there is a set of specific well-described maturity items
- score of 5 means the model stands out as focusing or applying to a specific category.

Table 3: Description of dimension categories

Category	Description
Information Technology & Data & Cyber-Physical System	Analysis of the enterprise's cyber-physical system (CPS), Information Technology (IT), and data management as they relate to SM. Dimension might measure how data is stored and used, which type of analytics are performed, if IT is integrated top to bottom, and CPS integration maturity.
Strategy & Organization	Analysis of the strategy and organization of the enterprise as they relate to SM. Dimension might measure degree of strategy implementation, how organizational hierarchy is changed with digitization, and how data informs strategy.
Products & Services	Analysis of the properties and characteristics of the products and services that will be developed, manufactured, used, or exploited as they pertain to SM. Dimension might measure product individualization, digitization of products, integration of products into other systems, ability to offer technology or information as a service, mix of services and products in company portfolio, and materials used.
Supply Chain & Logistics	Analysis of how the enterprise uses digitization to integrate their value chain and communicate supply and demand. Dimension might measure how supply chain is digitized, how visible supply chain is from end-to-end, how flexible supply chain is, how lead times are used, and how processes are integrated throughout supply chain.
Culture & Employees	Analysis of the enterprise's culture and employee skills as they relate to SM. Dimension might measure the willingness to change and accept new ideas, collaboration potential, employees understanding of SM, data-based employee development, and recognizing the value of mistakes.
Technology & Capabilities	Analysis of the SM technologies and capabilities the enterprise has. Dimension might measure which advanced technologies are used (Cloud, blockchain, robotics, additive manufacturing etc.).
Customer & Market	Analysis of how the enterprise targets customers and determines where it stands in the market. Dimension might measure how digitization affects market analysis and finds information on customer, determines the right time for sales and promotions, and analyzes competition.
Cybersecurity & Risk	Analysis of the enterprise's cybersecurity and risk as they relate to SM. Dimension might measure the network security, employee's education on cybersecurity, and existence of firewall.
Leadership & Management	Analysis of the leadership and management as it relates to SM. Dimension might measure the brand management, ecosystem management, support of executives, tracking of performance measures, and confidence in SM.
Governance & Compliance	Analysis of how the enterprise complies with standards, tax law, and legal issues as they relate to SM. Dimension might measure if compliance ensured and technically implemented? Are tax opportunities sought after and realized? Is a standard being followed?

Table 4: Maturity model applicability to dimension categories

Model	IT & Data & CPS	Strategy & Organization	Products & Services	Supply Chain & Logistics	Culture & Employees	Technology & Capabilities	Customer & Market	Cybersecurity & Risk	Leadership & Management	Governance & Compliance	TOTAL
Consulting Firm Maturity Models											
Connected Enterprise Maturity Model (Rockwell Automation, 2014)	5	0	0	1	0	1	0	1	0	0	8
Enabling Digital Operations Self-Assessment (PWC, 2016)	2	2	3	2	2	0	2	2	0	2	17
IMPULS (Lichtblau et al., 2015)	4	5	5	3	4	1	1	3	1	0	27
Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017)	3	3	4	4	5	3	3	3	3	1	32
Warwick Industry 4 Readiness Assessment (Agca et al., 2017)	0	5	5	5	4	3	3	3	3	5	36
Peer Reviewed Models											
Maturity Model Toward Industry 4.0 for SMEs (Ganzarain & Errasti, 2016)	0	1	0	0	0	0	1	1	0	0	3
SMSRL Index (Jung et al., 2016)	2	2	0	2	0	0	0	0	2	0	8
DREAMY (De Carolis et al., 2017)	0	2	0	2	0	2	0	0	2	0	8
Industry 4.0 Maturity Proposal (Santos & Martinho, 2020)	2	2	2	0	2	0	0	0	0	0	8
M2DDM (Weber et al., 2017)	5	0	1	1	0	2	0	0	0	0	9
Digitalization Maturity Model for Manufacturing (Canetta et al., 2018)	1	2	2	2	2	2	0	0	0	0	11
Fuzzy Rule-Based Industry 4.0 Maturity Model (Caiado et al., 2021)	1	1	0	5	0	1	3	0	0	0	11
SM ³ E (Mittal, Romero, et al., 2018)	1	3	3	1	3	0	0	0	1	1	13
The IoT Technological Maturity Model (Jæger et al., 2016)	5	3	0	3	0	3	0	0	0	0	14
System Integration Maturity Model Industry 4.0 (SIMMI) (Leyh et al., 2016)	5	0	3	1	0	3	0	3	0	0	15
Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises (Schumacher et al., 2016)	2	2	2	0	2	2	2	0	2	2	16
Industry 4.0 – MM (Gökalp et al., 2017)	2	2	2	2	2	2	2	2	0	0	16
Smart Factory Maturity Model (Sjödin et al., 2018)	1	1	1	5	5	5	1	0	0	0	19
Maturity Model of Digitization for SMEs (Blatz et al., 2018)	3	3	3	3	3	0	2	0	3	0	20
Maturity Model for Digitalization of Manufacturing Industry Supply Chain (Klötzer & Pflaum, 2017)	3	3	5	1	3	3	3	0	0	0	21
Defense Sector Industry 4.0 Maturity Model (Bibby & Dehe, 2018)	3	4	3	0	4	5	3	1	0	0	23
Industry 4.0 Maturity Model for Machine Tool Companies (Rafael et al., 2020)	4	5	5	3	4	1	1	3	1	0	27
Maturity Model for Implementation of Industry 4.0 (Wagire et al., 2020)	3	4	5	4	4	5	3	3	3	1	35
Maturity and Readiness model for Industry 4.0 Strategy (Akdil et al., 2018)	3	5	5	5	5	3	3	3	3	1	36
TOTAL	60	60	59	55	54	47	33	28	24	13	

A low score in **Table 4** does not mean a model is bad. It just means it does not cover a wide range of topics in detail or disclose enough information about its dimensions. All the maturity models included are worth consideration.

Table 5 highlights the applicable situations for each of the maturity models to help companies find a maturity model or models that work for their application.

A company should consider if it is a ‘good’ maturity model before considering any model for application. These are some common criteria that make a ‘good’ maturity model.

Maturity levels should follow a predictable linear pattern through discrete and clearly described stages. A good maturity model prescribes steps to advance from one maturity level to another and can be used to benchmark against competitors. All premises of a maturity model should be validated iteratively as well as its quality and effectiveness according to some measurable metric. For instance, a model focusing on the supply chain should validate that implementing the model improves supply chain efficiency and that it is desirable to move through the maturity levels. Each level for every dimension should be iteratively validated to show the logic. A clear and detailed vision that clarifies the end goal, costs, benefits, and challenges is necessary. Dimensions should cover the entire breadth of related topics and be modular, so that only related topics are included. Finally, a good maturity model should provide detailed documentation of the design, development, validation, and steps to implementation. Note that missing one or two of the 10 categories does not make a maturity model a ‘bad’ one. A company should develop/use a model or vision for the whole organization and then use a focused model for specific applications such as development of technology and connecting different

Table 5: Applicability of the considered SM maturity models

Models	Applicability	Drawbacks
Consulting Firm Maturity Models (Chronological)		
Connected Enterprise Maturity Model (Rockwell Automation, 2014)	Focus on IT architecture. No self-assessment.	Requires consultation. No clear details about the development process. Undefined maturity criteria.
IMPULS- Industrie 4.0 Readiness (Lichtblau et al., 2015)	Free, quick assessment through convenient web tool.	Widely used and cited by other researchers but no reference to initial development or validation. Not for in-depth assessment.
Industry 4.0 – Enabling Digital Operations Self-Assessment (PWC, 2016)	Global survey and blueprint for digital success with the organization level maturity evaluation	Self-assessment required. No details given about the development or validation process. Poorly defined maturity criteria.
Warwick Industry 4 Readiness Assessment Tool (Agca et al., 2017)	Convenient self-assessment template for 6 dimensions.	Maturity levels not clearly defined. Limited case studies available. No reference to development or validation. Limited prescriptions.
Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017)	Many details for development and assessment are included, but full assessment requires consultation.	Consultation required. ‘Stages’ of a company’s development described but lacking maturity levels for specific dimensions.
Peer Reviewed Models (Chronological)		
Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises (Schumacher et al., 2016)	Earliest, analyzed, peer-reviewed maturity model. Determined key problems in Industry 4.0 implementation in practice with 9 useful key dimension categories.	Not enough detail, and it is dated. No guidance for self-assessment.
Maturity model toward Industry 4.0 for SMEs (Ganzarain & Errasti, 2016)	Targeted at SMEs needing assistance developing their Industry 4.0 vision and strategy.	Not enough description of dimensions or maturity levels. No guidance for self-assessment. No clear development or validation. No prescription for maturing.
The IoT Technological Maturity Model (Jæger et al., 2016)	Focus on realizing IIoT through IT architecture. Summarizes idea of ‘automation pyramid’ consisting of IT system levels such as Plant Floor, MES, SCADA, and ERP.	Not recommended for being dated and lacking details. No clear development or validation. No prescription for maturing.
Smart Manufacturing System Readiness Level (SMSRL) Index NIST (Jung et al., 2016)	Recommended use is as a quick readiness assessment. The highest score is being connected by a standard data exchange.	Not well developed and does not include many details. Unable to access reference material. No guidance for self-assessment.
System Integration Maturity Model Industry 4.0 (SIMMI) (Leyh et al., 2016)	Identified cross-sectional technologies required for Industry 4.0 enterprise systems. Useful for IT architecture.	Incomplete development. No validation. Reference material in German.
Maturity Model for Data-Driven Manufacturing (M2DDM) (Weber et al., 2017)	One-dimensional IT architecture maturity model. Useful for digital twin vision.	No guidance for self-assessment. No validation. No prescription.

Table 5 Continued

Models	Applicability	Drawbacks
Digital Readiness Assessment Maturity model (DREAMY) (De Carolis et al., 2017)	Focus on manufacturing processes.	Not enough details. Development and validation performed but not clearly described. No guidance for self-assessment.
Industry 4.0 – MM (Gökalp et al., 2017)	Formation based on ISO/IEC 15504.	Not enough details given for application. Maturity levels and dimensions are partially defined. No validation. No guidance.
Maturity Models for Digitalization (Klötzer & Pflaum, 2017)	Useful for smart product focus.	Dimensions and maturity levels are not clearly defined. No validation. No guidance.
Maturity Model of Digitization for SMEs (Blatz et al., 2018)	Calculates an overall maturity level by weighing dimensions and then calculating the weighted mean.	Little development included. Maturity levels are not clearly defined. No assessment details. No guidance.
Smart Factory Maturity Model (Sjödin et al., 2018)	Focus on Process, People, and Technology. Identified challenges and benefits of smart factory implementation through interview.	Not enough detail. No prescription for moving through levels. No guidance for self-assessment. Development not based on existing maturity models.
Maturity and Readiness model for Industry 4.0 Strategy (Akdil et al., 2018)	Good development and plenty of detail. Focus on smart services & products, business processes, operations, marketing, and strategy. Questionnaire provided.	No validation. No prescription.
Defense Sector Industry 4.0 Maturity Model (Bibby & Dehe, 2018)	Specific to defense sector. Focuses on technology and capabilities.	Lists some good maturity assessment items but doesn't provide descriptions. No guidance for self-assessment. Validation and development performed but details aren't given. No prescription.
Digitalization Maturity Model for Manufacturing (Canetta et al., 2018)	Developed questionnaire not attached. Doesn't provide enough detail to be useful for assessment.	Questionnaire not included. Development performed but no mention of existing maturity models that were considered. No validation.
SM ³ E (Mittal, Romero, et al., 2018)	Focus on SME. Toolkit concept provides guidance to advance in maturity.	Details of all toolboxes not included. No validation. Self-assessment not possible.
Industry 4.0 Maturity Model for Machine Tool Companies (Rafael et al., 2020)	Good development and validation. Demonstrates how existing models (IMPULS) can be improved for a specific sector. Useful for machine tooling companies and adaptable.	No significant drawbacks to mention. No benchmarking capability.
An Industry 4.0 Maturity Model Proposal (Santos & Martinho, 2020)	Good development and some validation. Questionnaire included.	No benchmarking or prescription capability. Not very detailed. Doesn't provide specific level descriptions for each dimension.
Maturity Model for Implementation of Industry 4.0 (Wagire et al., 2020)	Good development, well-defined dimensions useful across the organization.	Too complex for SME self-assessment but useful for organization-wide assessment of MNE. No benchmarking capability. No prescription. Questionnaire not included.
Fuzzy Rule-Based Industry 4.0 Maturity Model (Caiado et al., 2021)	Complex but well developed and useful for supply chain management and operations.	Full questionnaire not included. Too complex for SME. Fuzzy logic approach is too complex for most applications. No benchmarking.

enterprise units. Model applicability may involve implementation factors, such as scope, industry, company size, geographic location, assessment method, cost/availability, and relevant dimensions.

Figure 5 shows a scatterplot and trendlines for the total score of the consulting firm and peer reviewed maturity models based on **Table 4**. The consulting firm models (blue dots) can be seen to be early movers and had high scores early. The peer reviewed models (orange triangles) have lower scores early on, but they seem to be improving. There have been more peer reviewed models in recent years than consulting firm models.

Discussion

This section discusses each of the ten categories in **Table 3**, presents some exemplary maturity items for each category, and identifies gaps for future research.

IT & CPS & Data

The ‘IT & CPS & Data’ category received a high amount of focus, possibly due to the large number of terms included but also because of its inherent importance. In general, internally connected systems for communication are necessary to develop smart products, logistics or manufacturing. Many of the reviewed maturity models consider IT as a first step or as a part of SM visions. This area usually requires major investment for most companies and is widely considered a foundation to implement SM. Beginning steps of this category focus on integrating existing systems so that they can communicate vertically and ensuring that the traditional information pyramid of manufacturing exists. The final steps focus on optimizing the factory through continuous improvement and developing predictive capability.

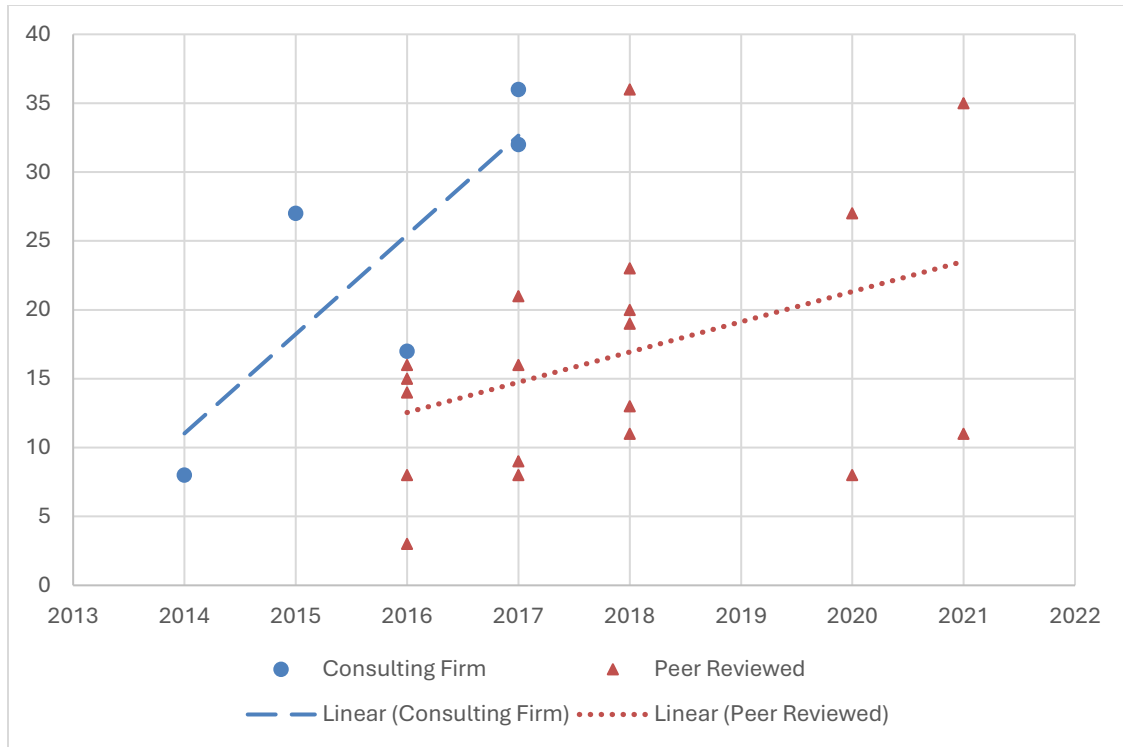


Figure 5: Scores for consulting firm and peer-reviewed maturity models

Some example maturity items showing the first steps of IT include:

- **Rockwell Automation** (2014): “During ‘Stage 2: Secure and Upgraded Network and Controls’ the organization evolves and/or builds an OT/IT backbone that will deliver secure connectivity from plant-floor operations to enterprise business systems.”
- **IoT Technological Maturity Model** (Jæger et al., 2016): “Level 2 – Initial to 4.0 Maturity: Have one 4.0 enabled object. Robots, machines, and IT-systems can communicate vertically. Assets can be remotely programmed, accessed, and managed using a PC, tablet, or smart phone connected to the Internet.”
- **SIMMI** (Leyh et al., 2016): “Stage 2 – Cross-Departmental Digitization: Information can be (partially) exchanged automatically among different departments and business areas. No data islands exist within the company. The company has started to implement a service-oriented architecture (SOA). Legacy systems are broken down, and their functionalities are encapsulated into services. An enterprise service bus (ESB) is implemented to replace enterprise application integration principles and to enable direct connection between new systems.”
- **M2DDM** (Weber et al., 2017): “Level 1 – Data and System Integration. At this level the traditional information pyramid of manufacturing is implemented. Machines are integrated and managed by a central instance, a Manufacturing Execution System (MES). Production orders are managed by a higher-level Enterprise Resource Planning System (ERP) which is directly connected to the MES to preserve time.”

Some example maturity items showing the vision of IT include:

- **Rockwell Automation** (2014): “Stage 5 of the maturity model is creating an environment that anticipates activities throughout the enterprise and through the supply and demand chain.”
- **IoT Technological Maturity Model** (Jæger et al., 2016): “Level 8 – 4.0 Maturity: All objects are connected to the Internet and seamlessly integrated, where objects communicate with other objects using common architectures, interoperability, and open standards, enabling human intervention. Production and warehouse environments are optimally automated, doing manual work only when it is considered most appropriate. Business Intelligence and continuous improvement characterize the organization. Continuous improvement is enabled by continuous monitoring of real-time performance discovering design problems that testing failed to reveal. Smart factories emerge. Organizations become predictive, meaning they can forecast what can happen in the future, through Big Data.”
- **SIMMI** (Leyh et al., 2016): “Stage 5 – Optimized full digitization: Each step inside and outside the company is digitized. Within the value networks physical value and information flows can be represented digitally, so the entire added value can be simulated in real time. It is possible to automatically perform necessary adjustments for all companies of the value network.”
- **M2DDM** (Weber et al., 2017): “Level 5 – Self-Optimizing Factory. The self-optimizing factory fully integrates all systems, devices and data across the entire product life cycle and uses insights about this data to automatically optimize the factory and all manufacturing processes. At this level, advanced analytics play a

major role in extracting valuable information from data. To enable real-time analytics, a new cloud hierarchy level on the shop floor must be implemented...”

Strategy & Organization

Strategy is a main consideration for selecting and developing a maturity model and involves many fundamental questions. What does a company want to achieve at the end? What do the stakeholders want the company to look like? How does a company provide value through digitization? IT, employees, process, supply chain, leadership, and customers should all be considered in an SM strategy. Some other associated maturity items or terms included within this category include business model, hierarchy, and vision. The company should be able to state their SM strategy and vision within one to two sentences and this strategy should be communicated and understood throughout the company. Not having a stated vision for the company is a clear sign of SM immaturity. The percentage of the budget used for digitization and SM can also give some indication of the SM maturity of the company. Spending 0% of a budget on technology investments is a sign that a company is not mature in terms of SM and has likely not even started. Some example maturity items from IMPULS (Lichtblau et al., 2015) related to this category include: “How would you describe the implementation status of your Industry 4.0 strategy? Do you use indicators to track the implementation status of your Industry 4.0 strategy? Which parts of your company have you invested in implementing Industry 4.0 in the past two years? What are your plans for the future?” IMPULS (Lichtblau et al., 2015) stands out in this category because it has straightforward questions.

Products & Services

The ‘Products & Services’ category received a high amount of focus. This category can be very different between industries (i.e., an automobile manufacturing company has a very different product from a concrete company). While several maturity models require that products be equipped with smart functionalities, this may not be immediately useful or possible. This dimension should be modified for an individual company’s needs.

IMPULS (Lichtblau et al., 2015), for example, asks if a company offers products equipped with the following functionalities: self-reporting, product memory, localization, integration, assistance systems, object information, monitoring, and automatic identification. Companies should decide if these functionalities make sense for them.

The most common maturity items within this category are flexible batch size, the ability to sense the environment, and the ability to store data and communicate it with other systems. Other considerations are enabling value and data-driven services and offerings through data gathered, customization, tracking through lifecycle, and incorporating SM technologies such as digital twin. Some example maturity items for this category include:

- ***The University of Warwick Model*** (Agca et al., 2017): Breaks their ‘Products and services’ dimension into 5 sub-dimensions including digital features of products, product customization, data-driven services, level of data usage, and revenue share.
- ***Maturity Models for Digitalization*** (Klötzer & Pflaum, 2017): Model focuses on smart product realization and application.
- ***Maturity and Readiness Model for Industry 4.0 Strategy*** (Akdil et al., 2018):
‘Smart products and services’ dimension with highest maturity described as follows:
“Company’s products can communicate with other systems, collecting data, and

keeping it on their system or in the cloud. Products have a platform on which the product or cloud applications are working. Products can perform descriptive, diagnostics, predictive and prescriptive data analysis. Products can be tracked along their complete lifecycle. Company can offer service/insights for its business, customers, and partners according to data obtained from the product improvements.”

- ***Maturity Model for Implementation of Industry 4.0*** (Wagire et al., 2020): The ‘Smart Product’ dimension states that the company embeds intelligent sensors into its products, enabling them to sense the environment around them.

Supply Chain & Logistics

The ‘Supply Chain & Logistics’ category received a high amount of attention and there are many other maturity models not considered which use the terms ‘Logistics 4.0’, ‘Smart Logistics’, and ‘Smart Supply Chain’. There are several maturity models, such as Defense Sector Industry 4.0 Maturity Model (Bibby & Dehe, 2018), which could benefit from more supply chain considerations. At some point the company must shift focus from integrating internal operations to integrating the information between suppliers and customers. The University of Warwick model (Agca et al., 2017) states that “supply chain integration is the secret success factor of Industry 4.0.” because of the expanded potential for collaboration and integration of data. The organization must create a clear and effective supply chain that connects with suppliers and customers, adapting to market changes and customer needs.

At the highest maturity level, most maturity models require that the company and its partners completely automate, digitize, and integrate their supply chain and have predictive capability. Some example maturity items for this category include:

- ***The University of Warwick model*** (Agca et al., 2017): Breaks their ‘Supply Chain’ dimension into 5 sub-dimensions including inventory control using real-time data management, supply chain visibility, integration, flexibility, and lead times.
- ***Fuzzy Rule-Based Industry 4.0 Maturity Model*** (Caiado et al., 2021): Focuses on operations and supply chain management from the perspective of the customer, logistics, supplier, integration, planning and control of production systems, quality control, and maintenance. At the highest level, “the process is digital oriented relying on solid technology infrastructure and the organization has high growth potential. The company has completely digitalized their internal and inter-company processes, together with strong collaboration, integration of AI and self-learning skills in information systems, and creation of proactive processes for forecasting and planning future production, integrating data visualization and systems external partners to enable supply chain predictability and intelligent manufacturing.”
- ***Maturity and Readiness model for Industry 4.0 Strategy*** (Akdil et al., 2018): “Supply chain systems are fully integrated between company, suppliers, and customers, providing real-time planning.”

Culture & Employees

A company’s ability to successfully implement Industry 4.0 depends heavily on its employees' skills and behaviors and a culture that encourages collaboration and innovation. Implementing big data analytics and Industrial IoT requires employees with digital and analytics skills. The concepts of employee and culture could be separated, but they have enough relation to be included within the same category.

The ability to carry out employee training in a virtual environment and to share real-time information with employees in the field are two common maturity items in this category.

Some other example maturity items for this category include:

- ***Industrie 4.0 Maturity Index ACATECH*** (Schuh et al., 2017): Has a ‘Culture’ dimension with sub-dimensions of social collaboration and willingness to change.
- ***Smart Factory Maturity Model*** (Sjödin et al., 2018): At the highest level, the ‘People’ dimension requires “a culture of continuous smart factory innovation” and “having specialized roles and responsibilities geared toward predictable production.”
- ***Maturity and Readiness model for Industry 4.0 Strategy*** (Akdil et al., 2018): ‘Smart Business Processes Human Resources’ dimension has two questions including “Can your company share real-time data with employees in the field?” and “Can employee training be carried out in a virtual environment?”

Technology & Capabilities

Some maturity models include specific technologies and capabilities as maturity items.

This approach can be valuable for investigating if certain technologies could be useful as piece of a company’s SM strategy, but a manufacturer should be wary not to focus on the next best technology but on developing a long-term strategy and way of thinking and establishing the needed IT architecture. Multiple studies warn about focusing on technology without a vision and plan. One application where it makes sense to focus on technology is when the model is intended for a specific industry such as the Defense Sector Industry 4.0 Maturity Model (Bibby & Dehe, 2018). It would not make sense to apply this model intended for the defense sector to the automotive sector.

Some examples of maturity items for this category include:

- ***Maturity Model for Implementation of Industry 4.0*** (Wagire et al., 2020): Has a ‘Smart Manufacturing Technology’ dimension with sub-dimensions including many different technologies such as collaborative and autonomous robots and software systems. The model also has ‘Product and Services-Oriented Technology’ dimension with sub-dimensions including more technologies such as VR, AR, MR, additive manufacturing, mobile devices and wearables, and others. Finally, it has an ‘Industry 4.0 Base Technology’ dimension with even more technology requirements including cloud computing network for resource sharing and data storing, and others.
- ***The Defense Sector Industry 4.0 Maturity Model*** (Bibby & Dehe, 2018): Has dimensions including ‘Additive Manufacturing’, ‘Cloud’, ‘Manufacturing Execution System’, ‘Internet of Things and CPS’, ‘Big Data’, ‘Sensors’, ‘e-Value Chains’, and ‘Autonomous Robots’.
- ***Smart Factory Maturity Model*** (Sjödin et al., 2018): ‘Technology’ dimension has an objective of configuring modular technologies and at its highest maturity level can “create systems to monitor and visualize critical operational analytics” and “integrate digital system insights from external partners to enable supply chain predictability.” Wisely, this model does not focus on specific technologies and has a first step of “Apply a digital lens to map existing and new technologies.”

Customer & Market

The ‘Customer & Market’ category has not received much attention, and no maturity model clearly focused on it. Pricing, promotion, and sales could be taken to go with this category or with the ‘Products’ category. This category could be considered as closely related to the ‘Products’ and ‘Supply Chain’ categories but the authors believe that

‘Customer/Market’ is still a good category to include because several maturity models include it as an item and there is a distinction between it and the ‘Products’ category. A good question to summarize this category is “How well does a company know their customers and the market for their products?” One example of a maturity item for this category is the Maturity and Readiness model for Industry 4.0 Strategy (Akdil et al., 2018), which asks, “Which of the following studies are conducted within customer analytics?” Options include customer segmentation and lifetime value, campaign management, cross-selling, market basket analysis, product bundling and recommendation, customer churn analysis, and product portfolio management. This example shows how closely related the ‘Customer’ and ‘Products’ categories are when evaluating Industry 4.0 maturity.

Cybersecurity & Risk

The ‘Cybersecurity’ category has received little consideration. SM maturity models mostly mention that cybersecurity should be considered without articulating a vision and describing maturity levels. Fuzzy Rule-Based Industry 4.0 Maturity Model (Caiado et al., 2021), for example, has an ‘Industrial Cyber Security’ sub-dimension, which states that “The company has adopted various security measures like encryption, authentication, and authorization measures that help to establish secured communication protocols to ensure IT security and data protection, as a threat may arise due to connected ecosystem.” Industry 4.0 Readiness Assessment for SME (Harmoko & Axmann, 2020), a model not identified by the initial systematic literature review, adds “continuous monitoring and security analytics.” There is a need for an SM maturity model that clearly articulates the vision of cybersecurity and prescribes steps to move from outsider to expert.

Leadership & Management

Leadership is a topic that is only given minor consideration and is not the focus of any maturity model investigated. Yet, company transformation requires strong and continuous leadership support in all processes. Leadership may be included within a ‘Strategy and Organization’ sub-dimension, but it should be specifically evaluated. Warwick Industry 4 Readiness Assessment Tool (Agca et al., 2017), for example, has a ‘Leadership’ sub-dimension within its ‘Strategy and organization’ dimension with a highest level of “Widespread support for Industry 4 within both the leadership team and across the wider business.” For SM adoption, new management and leadership styles may be required for many manufacturers, especially small- and medium-ones. This dimension category needs more specific descriptions of maturity levels, a prescription for moving between the levels, and an understanding of how to determine the right leadership style.

Governance & Compliance

Considerations on legal, compliance, governance, and tax have received the least focus out of all the 10 categories evaluated. Industry 4 Readiness Assessment Tool (Agca et al., 2017) has a ‘Legal Considerations’ dimension with sub-dimensions related to contracting models and intellectual property. These sub-dimensions state that smart contracts may be enabled through blockchain with unique legal risks and benefits that must be clearly understood to be utilized, and that intellectual property must be secured and purchased if necessary. Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises (Schumacher et al., 2016) mentions that a company should follow all relevant labor regulations related to SM. PWC (2016) has a ‘compliance, security, legal & tax’ dimension that has the highest level of “value-chain network is

optimized for compliance, security, legal, and tax considerations.” Governance can be a sub-dimension, and not receive very much focus, but it should not be forgotten.

Conclusions

This review characterizes smart manufacturing (SM) maturity models based on their focus, levels, dimensions, assessment method, whether they are a product of a consulting firm or peer-reviewed, scope, whether they have prescriptive and comparative capability, validation, guidance for self-assessment, and whether clear development and assessment details are included. This analysis reveals features that can differentiate them.

This study fills a research gap by comparing SM maturity models’ dimensions to reveal the aspects that are being focused on and being left out. This research also determines the applicability of the reviewed maturity models based on their dimensions and potential for application. Through grouping similar dimensions, this review identified ten comprehensive categories of dimensions. These dimension categories are in order of the focus they received: 1. IT & CPS & Data; 2. Strategy & Organization 3. Products & Services; 4. Supply Chain & Logistics; 5. Culture & Employees; 6. Technology & Capabilities; 7. Customer & Market; 8. Cybersecurity & Risk; 9. Leadership & Management; 10. Governance & Compliance. Scores from 0 to 5 were assigned to the maturity models based on the level of detail in which they address each general category. ‘Governance & Compliance’, ‘Cybersecurity & Risk’, and ‘Leadership & Management’ were lacking focus in many of the maturity models. ‘Governance & Compliance’ and ‘Leadership & Management’ dimension categories require more research to clearly describe maturity levels and paths to maturity. There is existing cybersecurity research that could be added to existing SM maturity models, such as those models reviewed by

(Rabii et al., 2020). The ‘Leadership & Management’ category requires a better understanding of the styles of leadership to choose from and steps to transform leadership style effectively. ‘Governance & Compliance’ category is difficult to assess and provide guidance on because of lack of standardization, but still should not be overlooked. Suppose a company has no plan for SM and digital transformation. In that case, it is recommended to begin by developing a strategy, assessing readiness, taking inventory of its IT systems, and planning how it will create and use data. A company should focus on the area that it considers most valuable, but a comprehensive analysis of all 10-dimension categories helps select an appropriate SM maturity model.

Most consulting firms require payment for consultation to see their assessment details. This supports the idea that consulting firm and peer-reviewed models have different goals. Consulting firm models aren’t as helpful in developing new maturity models or adaptable for personal use, but they could provide a total solution for companies whereas you wouldn’t expect a researcher or graduate student to come into a company and overhaul all its operations. PWC (2016) is a useful survey of more than 2,000 executives in 26 countries and offers valuable advice for digital strategy and blueprint but the actual maturity model is not very well described. The IMPULS model (Lichtblau et al., 2015) serves as a useful day one assessment because an assessment can be completed online in 10 minutes. Among the consulting firms, the Warwick (Agca et al., 2017) and ACATECH (Schuh et al., 2017) maturity models stand out because they have published details about their development and assessment methods and validated effectiveness by publishing multiple case studies. A manufacturer might want to reconsider going with a

consulting firm because they may try to overhaul whole systems using only their products, increasing capital costs and reducing the system's openness.

The strengths of the peer-reviewed models are that they are conceptually useful, they build on each other, and they are becoming better. The peer reviewed models can be improved through more validation and case studies, web-based assessment tools, and by using the discussion of each of the categories to improve their weak dimensions. One research need is to identify dimensions of SM maturity that can be improved based on a plant visit or interview. This will enable engineers to offer practical guidance.

Maturity Model for Implementation of Industry 4.0 (Wagire et al., 2020), Maturity and Readiness model for Industry 4.0 Strategy (Akdil et al., 2018), Warwick Industry 4 Readiness Assessment Tool (Agca et al., 2017), and Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017) received high scores in **Table 4**, meaning that they cover the topics uncovered in detail and would be useful as general models or as starting points for new models. No model studied covered all the topics in detail. The lack of assessment and development details, case studies, and validation of the models' usefulness are the major weaknesses preventing the recommendation of a specific SM maturity model. Case studies and validation of models are more important than developing new models.

This review showed that no existing SM maturity model applies to every dimension, industry, or company size. There is no guide for practitioners in choosing an SM maturity model for their specific applications such as developing IT technologies, connecting their enterprise, or creating a smart supply chain. A decision framework is needed to aid decision-makers in selecting or creating an SM maturity model based on dimensions, scope, industry, size, geographic location, assessment method, and cost.

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APPENDIX

Survey Developed for Smart Manufacturing and Energy Management

The goal with conducting this survey is to understand the status and needs of manufacturers in the area for integrating smart manufacturing with energy management and emissions reduction (decarbonization). The identifying information such as company name, contact info, and address are only to ensure there are no repeat surveys, the surveys are valid, and will not be shared externally. The non-identifying information will be summarized to create a regional model for technical assistance and workforce training.

General Information

Company Name:

Click or tap here to enter text.

Contact Information:

Click or tap here to enter text.

Address:

Click or tap here to enter text.

North American Industry Classification System (NAICS) Code:

NAICS & SIC Identification Tools

Click or tap here to enter text.

Number of Employees:

Click or tap here to enter text.

Annual Revenue:

Click or tap here to enter text.

Annual Energy Costs:

Click or tap here to enter text.

Annual Energy Consumption:

Click or tap here to enter text.

Annual production:

Click or tap here to enter text.

Shift schedule:

Click or tap here to enter text.

Square footage of plant:

Click or tap here to enter text.

Energy Management

1. How established is your energy management system?

- ☐ Nonexistent
- ☐ Initial, some processes are established, but significant energy uses are only partly managed.
- ☐ Formally established based on ISO 50001 processes but not certified
- ☐ Certified and demonstrated to be effective but doesn't exceed ISO 50001 standard
- ☐ Perfectly integrated into the organization's managements systems. Internal standards exceed ISO 50001 standard.

2. Which smart manufacturing technologies have been adopted for energy management?

Select more than one if applicable.

- ☐ Real-time data availability
- ☐ Automated data collection
- ☐ Sub-metering
- ☐ Maintenance informed by energy consumption patterns
- ☐ Demand response
- ☐ Advanced simulation
- ☐ Digital Twin
- ☐ Blockchain
- ☐ Cloud data storage

3. What are the challenges for your company to implement 'smart energy management'?

- ☐ Lack of expertise
- ☐ Lack of vision / strategy
- ☐ Employee sentiment
- ☐ High investment costs
- ☐ Legacy equipment
- ☐ Inadequate IT technology
- ☐ Data security concerns
- ☐ Other: Click or tap here to enter text.

4. How effectively do you communicate sustainability issues within and outside your organization?

- ☐ Communication is nonexistent
- ☐ Communications are informal and ad hoc. Involvement is limited.
- ☐ Communication processes are documented. Employees are encouraged to make comments or suggest improvements.
- ☐ Regular reports are communicated to employees. Internal meetings and seminars on energy and emissions occur. Communication methods such as banners, posters, social media, and house journals are implemented.
- ☐ Annual report is published to all interested parties. All suggested improvements are recorded, and specific incentives exist. The organization is actively involved in industry networks, demonstrating best practices.

5. Do you hold senior management personally responsible for energy and/or emission metrics?

- ☐ No
- ☐ Yes

6. Is there a dedicated organization role for energy management team?

- ☐ No personnel assigned to energy management
- ☐ No, part-time responsibility of some employee with limited authority
- ☐ Responsibilities and authorities are assigned, but limited competence
- ☐ A dedicated and capable environmental manager exists
- ☐ A team of dedicated authorities with expertise are delegated

7. Do you have an energy policy statement that includes a clear definition of energy targets and shows management's commitment to the efficient use of energy?

- ☐ No energy policy exists
- ☐ Energy policy exists informally but it is not clear or communicated
- ☐ A stand-alone energy policy exists and commitments are in clear terms
- ☐ Energy policy is communicated and well-known. Periodic reviews occur.
- ☐ Energy policy is widely recognized. It is updated as necessary.

8. Do you gather your own energy data in the plant, separate from utility bills?

- ☐ No energy data gathered in the plant separate from utility bills
- ☐ Some energy data collected but not effectively used
- ☐ Some energy data infrequently collected and used
- ☐ Energy data collected at frequency greater than billing period and compared with utility bills to gather additional information to better understand consumption data

9. Do you systematically look for energy efficiency opportunities and take them if the cost and benefit analysis is positive?

- ☐ No process exists for identifying energy efficiency opportunities
- ☐ Process defined but not fully implemented
- ☐ Basic process implemented for identifying and analyzing energy efficiency opportunities
- ☐ Systematic process in place which prioritizes energy efficiency opportunities through internal mechanism such as carbon tax

10. How do you review your energy consumption?

- ☐ Never or no established process
- ☐ Irregularly only when a mandatory energy audit is required or irregularities occur.
- ☐ Periodically with documented results. Energy review includes analysis of energy use and consumption, identification of significant energy users and relevant variables, projection of future use, and identification of opportunities.

- ☐ Annual comprehensive energy and GHG emissions audits are performed by internal and external professionals with benchmarking.
- ☐ Quarterly or monthly energy and GHG emissions reviews, including statistical models and regression analysis.

11. In your energy review process, do you compare the consumption ratios or specific energy consumption against industry benchmarks?

- ☐ No
- ☐ Yes

12. In your energy review process how do you predict future energy consumption?

- ☐ No prediction
- ☐ Simple prediction based on previous year
- ☐ Regression analysis based on production but no other relevant variables
- ☐ Regression analysis including production and other relevant variables
- ☐ Machine learning, advanced simulation, or other advanced prediction method

13. Do you consider energy and/or emissions while developing standard operating procedures (SOPs) and procuring materials?

- ☐ No consideration of energy or emissions in SOP or procurement
- ☐ Low-cost options are prioritized over low-emission due to inefficient but existing policy
- ☐ Basic criteria are established and communicated to suppliers

- ☐ Procurement requirements are documented and fully communicated.
- ☐ Energy and emissions are highly prioritized while developing SOPs and procuring materials. Low and no global warming potential refrigerants are fully implemented.

Decarbonization

14. How established is your 'net-zero' emissions goal?

- ☐ No stated goal or emissions baseline assessment performed
- ☐ Scope 1 and 2 emissions are estimated and pilot energy efficiency projects underway but no goal setting
- ☐ The goal stated and scope 1 and 2 emissions comprehensively assessed
- ☐ The goal stated, and pilot studies for industrial electrification, low-carbon fuels, feedstocks, energy sources, and carbon capture, utilization, and storage are in progress as appropriate. Scope 3 emissions are defined and estimated.
- ☐ Measurable progress beyond pilot studies and continuous process in place for reviewing goal. The goal includes milestones, an implementation plan, comprehensive scope 1, 2, and 3 emission assessment, and is clear, robust, and scientifically-sound.
- ☐ Accomplished, and aiming for higher goals such as 'historic-zero' or negative emissions.

15. How would you evaluate your implementation of the following decarbonization strategies?

	Not planned	Pilot	Implemented
Energy efficiency	☐	☐	☐
Power purchase agreement includes clean generation guarantees	☐	☐	☐
On-site renewable power generation	☐	☐	☐
Combined heat and power	☐	☐	☐
Energy storage	☐	☐	☐
Electrification of vehicle fleet	☐	☐	☐
Electrification of process heat processes (heat pump)	☐	☐	☐
Electrification of hydrogen production	☐	☐	☐
Electrification of HVAC for domestic use	☐	☐	☐
Substitution of low-and-no carbon fuels and feedstocks (biofuels, biomass, hydrogen, nuclear, etc.) for fossil fuel	☐	☐	☐
Carbon accounting	☐	☐	☐
Purchase of carbon offset credits	☐	☐	☐
Carbon capture, utilization, and storage (CCUS)	☐	☐	☐

16. Which alternative energy sources are implemented on-site?

- ☐ Solar
- ☐ Wind
- ☐ Biomass
- ☐ Geothermal
- ☐ Biofuels
- ☐ Hydrogen
- ☐ Nuclear
- ☐ Other: Click or tap here to enter text.

Smart Manufacturing

17. Do you have a smart manufacturing strategy? (1 -2 sentences preferred, focusing on how smart manufacturing will drive value)

- ☐ No
- ☐ Yes (Include below)

Click or tap here to enter text.

18. Is there any organizational structure for data management? (Data scientists, analytics team, SM director, etc.)

- ☐ No
- ☐ Yes

19. How is your IT organized?

- ☐ Service provider (No in-house IT department)
- ☐ Central IT department
- ☐ Local IT departments in each area
- ☐ IT experts attached to each department

20. How would you evaluate the following functionalities when it comes to your equipment infrastructure?

	Not available	Yes, to some extent	Yes, completely
Machines and systems can be controlled through IT	☐	☐	☐
M2M: machine-to-machine communication	☐	☐	☐
Interoperability: integration and collaboration with other machines/systems possible	☐	☐	☐

21. Which machine and process data are you collecting during production?

- ☐ Inventory
- ☐ Manufacturing throughput times
- ☐ Equipment capacity utilization
- ☐ Production residue
- ☐ Error quota

- ☐ Employee utilization
- ☐ Data on remaining processing
- ☐ Overall equipment effectiveness (OEE)
- ☐ Energy consumption

22. How is the data you collect utilized in production?

- ☐ Predictive maintenance
- ☐ Optimization of production and logistics
- ☐ Transparency across production processes
- ☐ Quality management
- ☐ Production controlled automatically through use of real-time data
- ☐ Resource consumption optimization (material, energy, time)
- ☐ Click or tap here to enter text.

23. How far along are your solutions for IT security?

	Not relevant	Planned	In-progress	Implemented
Internal Data Storage	☐	☐	☐	☐
Cloud Services	☐	☐	☐	☐
In-house communications	☐	☐	☐	☐
Communications with business partners	☐	☐	☐	☐
Continuous Monitoring and Analysis	☐	☐	☐	☐

24. What level of support for smart manufacturing exists within the leadership team?

- ☐ Leadership do not acknowledge the value of smart manufacturing investments
- ☐ Leadership is investigating smart manufacturing benefits
- ☐ The leadership team understands the financial benefits of smart manufacturing and has a basic investment plan
- ☐ Leadership teams fully understand the financial benefits of smart manufacturing and demonstrate their support for smart manufacturing across the business

25. Which data is available in real-time for leadership / management to make decisions?

- ☐ Production
- ☐ Maintenance
- ☐ Finances
- ☐ Energy / Emissions
- ☐ Employee
- ☐ Supply Chain
- ☐ Market

Appendix Tables

Table 6: Comparison of maturity model maturity levels

Model	Maturity Levels					
Maturity Levels are not clearly defined or on a rating scale						
Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises (Schumacher et al., 2016)	Levels 1 -5 determined by weighted average formula. Levels not clearly defined.					
Smart Manufacturing System Readiness Level Index (Jung et al., 2016)	Score of 0 - 10					
Maturity Model of Digitization for SMEs (Blatz et al., 2018)	Overall maturity level is calculated by a weighted arithmetic mean. Levels 1 – 3.					
Defense Sector Industry 4.0 Maturity Model (Bibby & Dehe, 2018)	Each section is scored 1 -5 and then aggregated to provide a total organization score. Level 1: Minimal (23-46), Level 2: Development (47 – 69), Level 3: Defined (70 – 92), Level 4: Excellence (93 – 115)					
Digitalization Maturity Model (Canetta et al., 2018)	Numerical result obtained by equation considering maturity level, weighting factor, and number of questions. Overall maturity level calculated by an aggregated value of the results. Levels 0 – 3 not clearly defined.					
An Industry 4.0 Maturity Model Proposal (Santos & Martinho, 2020)	Levels 0 -5 described based on degree of implementation. Not clearly defined for each dimension.					
Maturity Model for Implementation of Industry 4.0 (Wagire et al., 2020)	Overall maturity level calculated by an aggregated value. Level 4: Expert indicates that the company has adopted all aspects of Industry 4.0 and has the application of emerging technologies.					
Maturity levels defined by organization performance						
IMPULS- Industrie 4.0 Readiness (Lichtblau et al., 2015)	Level 0 Outsider	Level 1 Beginner	Level 2 Intermediate	Level 3 Experienced	Level 4 Expert	Level 5 Top Performer
Industry 4.0 – Enabling Digital Operations Self-Assessment (PWC, 2016)	Level 1 Digital Novice	Level 2 Vertical Integrator		Level 3 Horizontal Collaborator	Level 4 Digital Champion	
Warwick Industry 4 Readiness Assessment Tool (Agca et al., 2017)	Level 1 Beginner	Level 2 Intermediate		Level 3 Experienced	Level 4 Expert	
Maturity Models for Digitalization (Klötzer & Pflaum, 2017)	1 Digitalization Awareness	2 Smart Networked Products	3 Service-oriented Enterprise	4 Thinking in Service Systems	5 Data-driven Enterprise	
Maturity levels defined by technology capability						
Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017)	1 Computerization	2 Connectivity	3 Visibility	4 Transparency	5 Predictive Capacity	6 Adaptability

Table 6 continued

Model	Maturity Levels															
(System Integration Maturity Model Industry 4.0) SIMMI (Leyh et al., 2016)	1 Basic Digitization		2 Cross-departmental Digitization		3 Horizontal and Vertical Digitization		4 Full Digitization		5 Optimized Digitization							
Maturity Model for Data-Driven Manufacturing (M2DDM) (Weber et al., 2017)	0 Nonexistent IT Integration		1 Data and System Integration		2 Integration of Cross-Life-Cycle Data		3 Service Orientation		4 Digital Twin		5 Self-Optimizing Factory					
Smart Factory Maturity Model (Sjödin et al., 2018)	1 Connected Technologies			2 Structured data gathering and sharing			3 Real-time process analytics and optimization			4 Smart, predictable manufacturing						
Maturity levels defined like Capability Maturity Model Framework																
Maturity model toward Industry 4.0 for SMEs (Ganzarain & Errasti, 2016)	1 Initial			2 Managed			3 Defined			4 Transformed			5 Detailed			
The IoT Technological Maturity Model (Jæger et al., 2016)	1 3.0 Maturity		2 Initial to 4.0 Maturity		3 Connected		4 Enhanced		5 Innovating		6 Integrated		7 Extensive		8 4.0 Maturity	
Digital Readiness Assessment Maturity Model (DREAMY) (De Carolis et al., 2017)	1 Initial			2 Managed			3 Defined			4 Integrated and Interoperable			5 Digital-oriented			
Industry 4.0 – MM (Gökalp et al., 2017)	0 Incomplete		1 Performed		2 Managed		3 Established		4 Predictable		5 Optimizing					
SM ³ E (Mittal, Romero, et al., 2018)	1 Novice			2 Beginner			3 Learner			4 Intermediate			5 Expert			
Maturity and Readiness model for Industry 4.0 Strategy (Akdil et al., 2018)	Level 0 Absence			Level 1 Existence			Level 2 Survival			Level 3 Maturity						
Fuzzy Rule-Based Industry 4.0 Maturity Model (Caiado et al., 2021)	Level 0 Nonexistent			Level 1 Conceptual			Level 2 Managed			Level 3 Advance			Level 4 Self-Optimized			

Table 7: Description of maturity model dimensions

REF	Dimensions	Description
Consulting Firm Maturity Models (Chronological)		
The Connected Enterprise Maturity Model (Rockwell Automation, 2014)	1. IT Network	1. The one dimension is not very well defined. “All facets of an organization’s existing IT network are evaluated including information infrastructure, controls and devices that feed and receive data, networks that move the information, and security policies.”
IMPULS- Industrie 4.0 Readiness (Lichtblau et al., 2015)	1. Employees 2. Strategy and Organization 3. Smart Factory 4. Smart Operations 5. Smart Products 6. Data-driven services	1. Measured by analyzing employees’ skills in various areas and the company’s efforts to acquire new skill sets. 2. Examines the company’s business model, openness, and culture regarding Industry 4.0. Measured by implementation of Industry 4.0 strategy, operationalization and review of strategy, investment activity relating to Industry 4.0, and use of technology and innovation management. 3. The Smart Factory is a production environment in which production systems and logistics systems organize themselves without human intervention. Measured by Digital Modeling, Equipment Infrastructure, Data Usage, and IT Systems. 4. The enterprise-wide and cross-enterprise integration of physical and virtual worlds. Measured by Cloud Usage, IT Security, Autonomous processes, and Information Sharing. 5. Smart Products are equipped with sensors to collect data on their environment and their own status. Measured by ICT add-on functionalities and Data analytics in usage phase. 6. Objective of data-driven services is to align future business models and enhance benefit to the customer. Measured by share of data used, share of revenues derived from data-driven services, and availability of data-driven services.
Industry 4.0 – Enabling Digital Operations Self-Assessment (PWC, 2016)	1. Business Models, Product & Service Portfolio 2. Market & Customer Access 3. Value Chains & Processes 4. IT Architecture 5. Compliance, Legal, Risk, Security & Tax 6. Organization & Culture	Some example questions to consider and examples of a ‘Digital Champion’ are given. 1. Development of new disruptive business models with innovative product and service portfolio, lot size of 1. How is the mix of products and services in the portfolio? Which digital features or service are offered? To which degree is engineering digitized? 2. Integrated customer journey management across all digital marketing and sales channels. Which channels are used for customer interactions? Which data is measured to understand customers? How are customer interactions tracked? 3. Fully integrated partner ecosystem with self-optimized, virtualized processes and decentralized autonomy. To which extent is manufacturing integrated with engineering internally? How is the supply chain managed? How are manufacturing capacities planned? 4. Partner service bus, secure data exchange. How are processes supported by digital technologies? How does IT infrastructure support digital services? 5. Optimized value chain network for legal, compliance, security, and tax. How is compliance assured and technically implemented? Are tax opportunities realized? How is cyber trust ensured? 6. Collaboration as a key driver. What is the organization’s ability to change? Which Industry 4.0 capabilities are available within the organization?

Table 7 continued

REF	Dimensions	Description
Warwick Industry 4 Readiness Assessment Tool (Agca et al., 2017)	1. Products and Services 2. Manufacturing and Operations 3. Strategy and Organization 4. Supply Chain 5. Business Model 6. Legal Considerations	1. Sub-dimensions include product customization, digital features of products, data-driven services, level of product data usage, and share of revenue. 2. Sub-dimensions include automation, machine and operation system integration, equipment readiness for Industry 4.0, autonomously guided workpieces, self-optimizing processes, digital modelling, operations data collection, operations data usage, cloud solution usage, IT and data security. 3. Sub-dimensions include degree of strategy implementation, measurement, investments, people capabilities, collaboration, leadership, and finance. 4. Sub-dimensions include inventory control using real-time data management, supply chain integration, supply chain visibility, supply chain flexibility, and lead times. 5. Sub-dimensions include 'as a service' business model, data driven decisions, real-time tracking, real-time and automated scheduling, integrated marketing channels, and IT supported business. 6. Sub-dimensions include contracting models, risk, data protection, and intellectual property.
Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017)	1. Resources 2. Information Systems 3. Organizational Structure 4. Culture	1. Tangible, physical resources including a company's workforce (human resources), machinery and equipment, tools, materials, and final product. Measured by digital capability and structured communication. 2. Socio-technical systems in which information is provided based on economic criteria. They prepare, process, store and transfer data and information. Measured by two principles: data should be prepared and processed in a manner that supports decision making, and integration to enhance data use and increase agility. Includes governance and IT security. 3. Both the company's internal organization and its position within the value network. Established mandatory rules that organize collaboration both within the company and externally. Measured by two principles: organic internal organization and dynamic collaboration. 4. Includes behavior of employees, stated company vision, and corporate culture. Measured by two principles: willingness to change and social collaboration.

Table 7 continued

REF	Dimensions	Description
Industrie 4.0 Maturity Index ACATECH (Schuh et al., 2017)	1. Resources 2. Information Systems 3. Organizational Structure 4. Culture	1. Tangible, physical resources including a company's workforce (human resources), machinery and equipment, tools, materials, and final product. Measured by digital capability and structured communication. 2. Socio-technical systems in which information is provided based on economic criteria. They prepare, process, store and transfer data and information. Measured by two principles: data should be prepared and processed in a manner that supports decision making, and integration to enhance data use and increase agility. Includes governance and IT security. 3. Both the company's internal organization and its position within the value network. Established mandatory rules that organize collaboration both within the company and externally. Measured by two principles: organic internal organization and dynamic collaboration. 4. Includes behavior of employees, stated company vision, and corporate culture. Measured by two principles: willingness to change and social collaboration.
Peer Reviewed Maturity Models (Chronological)		
Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises (Schumacher et al., 2016)	1. Products 2. Customers 3. Operations 4. Technology 5. Strategy 6. Leadership 7. Governance 8. Culture 9. People	1. 62 maturity items are unequally grouped into nine organizational dimensions. 'Exemplary items to support understanding' are included for each dimension but there are no clear definitions given.
Maturity model toward Industry 4.0 for SMEs (Ganzarain & Errasti, 2016)	Unclear	Dimensions of the maturity model are intended to be 'company specific.' Company decides a specific vision informed by network, processes, product, and market and then Industry 4.0 projects are enacted.
The IoT Technological Maturity Model (Jæger et al., 2016)	Adoption of IoT Technology	Study is limited to IoT technologies without considering their use on business process change, smart materials, and smart manufacturing. Taken literally, definition is an object which communicates via the Internet. From manufacturing perspective, is defined as a commercial product with five specific characteristics: a unique identity, communication abilities, storage, a deployed language, and decision-making capabilities.
Smart Manufacturing System Readiness Level (SMSRL) Index NIST (Jung et al., 2016)	1. Organization 2. IT 3. Performance Management Information Connectivity	1. Defined as the comprehensiveness of the activities in the reference activity model performed by the manufacturers. Measured by (1) whether there is a process that formally manages each activity; and (2) whether there is a responsible human resource assigned to these activities. 2. Defined as the degree to which IT resources are available and working. 3. Defined as the degree to which the performance measures are used and monitored.

Table 7 continued

REF	Dimensions	Description
(System Integration Maturity Model Industry 4.0) SIMMI (Leyh et al., 2016)	1. Vertical Integration 2. Horizontal Integration 3. Digital Product Development 4. Cross-sectional Technology Criteria	Dimensions are unlike any other maturity model. 1. Focuses on the components of the lowest level of an enterprise, where different physical things need to exchange information throughout the level itself and the levels above. Most important criterion is that exchange is possible in both directions. 2. Industry 4.0 requires horizontal integration across the different value networks. Without an automated and integrated information flow a business-wide value network is not possible. Main criterion is a continuous and consistent information flow. 3. At least one enterprise system should be integrated into each respective process step. Resulting data and information of each step must be forwarded to the next and previous step. Main criterion is that each process step is presented digitally. 4. Focuses on assessing the extent to which technologies are used across all different fields of Industry 4.0. Also evaluates the level of support that enterprise systems can provide.
Maturity Model for Data-Driven Manufacturing (M2DDM) (Weber et al., 2017)	1. IT architecture for data-driven manufacturing	1. Three reference architectures are described which serve as a foundation for understanding IT architecture in general.
Digital Readiness Assessment Maturity model (DREAMY) (De Carolis et al., 2017)	1. Process 2. Monitoring and Control 3. Technology 4. Organization	1. The way in which processes are carried out. 2. The way in which these processes are monitored and controlled through the evaluation of feedbacks received from their execution. 3. The technologies that support these processes. 4. The organizational structures behind these processes.
Industry 4.0 – MM (Gökalp et al., 2017)	1. Asset Management 2. Data Governance 3. Application Management 4. Process Transformation 5. Organization Alignment	1. Covers IT systems of the organization, and technological readiness for Industry 4.0, usage of emerging business technologies, and security issues for smart technologies. Measures the level of support that the organization can provide for cutting-edge technology. 2. Investigates the capability level of the following: data collection, usage, data analytics and big data tools, and data-driven services. 3. Application capabilities provide an abstract perspective on the functional behavior required to support the business. Interfaces and information flow of applications should be structured, connected, standardized, controlled and interoperable. 4. Covers the transformation of the basic processes of each enterprise system which are Planning, Acquisition, Production, and Sale & Distribution. 5. Refers to the management of enterprises through Enterprise Architecture in terms of organizational structure, and strategy of the business.
Maturity Models for Digitalization (Klötzer & Pflaum, 2017)	1. Strategy Development 2. Offering to the customer 3. “Smart” product/factory 4. Complementary IT system 5. Cooperation 6. Structural organization 7. Process organization 8. Competencies 9. Innovation culture	1. Refers to the essential adjustments of a company’s strategic orientation. 2. Describes the customer value resulting from the respective level of maturity, whereby a customer can be of both internal and external nature. 3. The technological adaptations in the sense of a CPS, either with regard to actual products or to CPPS being utilized within production processes. 4. Related to the preceding dimension. Describes the associated technological framework regarding a new metacontext of digitalization. 5. Measure of cooperation with supply chain partners. 6. Identifies essential adaptations concerning the organizational anchoring of digitalization inside a company. 7. Refers to the adaptations necessary with respect to the company’s core business processes. 8. Identifies relevant knowledge and skills, on which a company must assure direct access to realize digital transformation. 9. Measure of innovation within the company culture.

Table 7 continued

REF	Dimensions	Description
Maturity Model of Digitization for SMEs (Blatz et al., 2018)	1. Strategy and Leadership 2. Company Culture and Organization 3. IT Infrastructure 4. Data Maturity 5. Process and Operations 6. Product	1. General foundation of the company in relation to its attitude towards digital transformation. The awareness and acknowledgement of the relevance of digitization is pivotal. 2. The attitude of the company as a whole. 3. Infrastructure needs to be capable of storing and processing big volumes of data. This data has to be protected. 4. Deals with the usage of data. Data needs to be protected and data protection policies need to be established and enforced. Effective audit procedures have to be defined and documented. 5. Concerned with the execution of activities and tasks within the company and their interdependencies. 6. Concerned with the product and the customer. In order to allow data collection, the product needs to be equipped with the appropriate sensor, computing and communication technology.
Smart Factory Maturity Model (Sjödin et al., 2018)	1. People 2. Process 3. Technology	1. Factory staff frequently lacked a common vision for and understanding of smart factory implementation. 2. The highly complex nature of smart factory technologies and systems makes it hard to gauge the potential benefits, creating an uncertain business case for implementation. 3. Manufacturing companies face difficulties in changing traditional routines and work process to effect the digital transformation.
Maturity and Readiness model for Industry 4.0 Strategy (Akdil et al., 2018)	1. Smart Products and Services 2. Smart Business Processes 3. Strategy and Organization	1. Smart products can do computations, store data and be involved in an interaction with their environment as well as they can give information about their identity, properties, status, and history. These features create a chance to obtain data from products and interpret data to offer services. No sub-dimension. 2. Dimension containing functional operations of companies to assess their maturity level regarding Industry 4.0 principles and triggering technologies. Three sub-dimensions including Smart production and operations, Smart marketing and Sales Operations, and Supportive Operations. Associated fields include after sales service, R&D, production, logistics, Sales and Distribution channels, HR, IT, and Smart finance. 3. Has no sub-dimension but has 4 associated fields including business models, strategic partnerships, technology investments, and organizational structure and leadership.
Defense Sector Industry 4.0 Maturity Model (Bibby & Dehe, 2018)	1. Factory of the Future 2. People and Culture 3. Strategy	1. Focuses on the eight key technologies and concepts related to Industry 4.0 including Additive Manufacturing, Cloud, Manufacturing Execution System, Internet of Things and CPS, Big Data, Sensors, and e-Value Chains. 2. Two sub-dimensions include Innovation Openness and Continuous Improvement Culture. 3. Focuses on having a robust and clear manufacturing strategy, an ambitious and well thought out technology investment plan, and an agility vision.
Digitalization Maturity Model for Manufacturing (Canetta et al., 2018)	1. Strategy 2. Processes 3. Technologies 4. Products & Services 5. People	1. Maturity dimensions not clearly defined, and assessment details not included.
SM ³ E (Mittal, Romero, et al., 2018)	1. Finance 2. People 3. Strategy 4. Process 5. Product	1. Focuses on how the SME is managing its economics. 2. Considers different organizational and cultural aspects such as encouraging “leadership” and vision towards SM. 3. Most importantly how to utilize data strategically. 4. The steps involved in the transformation of a product from raw material to final product. 5. Includes the business activities of “logistics”, “new product development”, “packaging”, “product modularity”, and “time to market.”

Table 7 continued

REF	Dimensions	Description
Industry 4.0 Maturity Model for Machine Tool Companies (Rafael et al., 2020)	1. Employees 2. Strategy and Organization 3. Smart Factory 4. Smart Operations 5. Smart Products 6. Data-driven services	Same dimensions as the IMPULS model with new sub-dimensions. 1. No new dimensions 2. New sub-dimension 'IT Strategy' added. 3. New sub-dimension 'Digital Modelling and Simulations Systems' added. 4. Autonomous processes boundaries changed to respond to alignment of robotization and automation facts within the context of the machine tool sector. 5. Three new sub-dimensions added including Adaptive and learning capabilities, Digital Twins, and Tracking the product. 6. New sub-dimension 'Product-Service System Model' added.
An Industry 4.0 Maturity Model Proposal (Santos & Martinho, 2020)	1. Organizational strategy, structure, and culture 2. Workforce 3. Smart factories 4. Smart processes 5. Smart products & services	1. The evolution toward Industry 4.0 needs a change of paradigms of the administration board through the promotion and dissemination of an innovative culture and continuous improvement, the disposability of required resources to implement new information and operation technologies, the adequacy of the organization structure, and of the constant pursuit of customer's satisfaction. 2. The digital transformation and the intensive use of innovative technologies are not possible without proper qualification and constant updating of the technical and management skills and of the workforce. The teams need to be opened for innovative technologies, and to have flexibility and autonomy for fast changes in context. 3. The factories of the future, compound by smart sensors and actuators, installations and equipment with embedded systems and connectivity, will enable the communication in real time between machines, products, people and infrastructures, forming a digital network environment. 4. The connectivity and interoperability of information and operation systems, and of equipment and installations, will enable the existence of autonomous systems and processes. Embedded with advanced algorithms of artificial intelligence, will contribute to the continuous machines learning, allowing the self-optimization and self-configuration of processes of production, maintenance, logistics, and support processes. 5. Products with intelligent embedded systems will constitute the base for data acquisition in real time, allowing the constant communication with customers, with the factory and with the productive processes through the value chain. Complementary services, based on acquired data, and enabled by connectivity technologies, will be an important source of the company's revenue
Maturity Model for Implementation of Industry 4.0 (Wagire et al., 2020)	1. People and Culture 2. Industry 4.0 Awareness 3. Organizational Strategy 4. Value Chain and Process 5. Smart Manufacturing Technology 6. Product and Services Oriented Technology 7. Industry 4.0 Base Technology	1. Sub-dimensions include Leadership Support, Continuous Improvement Culture, Dedicated teams, and Digital skills and qualification. 2. Sub-dimensions include Familiarity with Industry 4.0, Sensitivity towards the impact of digital transformation, Usefulness of Industry 4.0 to company, and Preparedness for Industry 4.0 adoption. 3. Subdimensions include digital vision and roadmap, customer integration, collaboration, zero paper strategy, and Financial investment. 4. Sub-dimensions include digitalization of vertical value chain, real-time monitoring and control, end-to-end IT-enabled planning and steering process, digitalization of production equipment, and digitalization of horizontal value chain. 5. Sub-dimensions include Autonomous and Collaborative robots, Software systems like ERP, MES, CRM and PLM, Identifiers like Bar code, QR code or RFID, Intelligent sensors, Machine to Machine and Human to Machine communication, Digital platforms for supplier integration, Digital platforms for customer integration, and AR, VR, and MR. 6. Sub-dimensions include Additive Manufacturing, Mobile devices and wearables, Blockchain technology, and Smart Product. 7. Sub-dimensions include Cloud computing network for resource sharing, cloud computing network for data storing, Internet of Things, Internet of Services, Big data, Simulation tools, Artificial Intelligence, Machine Learning and Deep Learning, and Industrial Cyber Security.

Table 7 continued

REF	Dimensions	Description
Fuzzy Rule-Based Industry 4.0 Maturity Model (Caiado et al., 2021)	1. Customer 2. Logistics 3. Supplier 4. Integration 5. PPC 6. Quality 7. Maintenance	1. “Refers to advances in customer’ relationship, segmentation, and satisfaction, as well as, marketing and sales strategies through different channels (e.g., social media); as the organization increases its maturity, it increases the level of digital interaction/ participation between the clients and the products/services offered. 2. Refers to advances in delivery, transportation, distribution, asset, and inventory management; as maturity increases, processes become more structured and standardized, while logistical models become more autonomous and optimized. 3. Refers to advances in supply network coordination, supplier(s) relationship management, and flexibility; with increasing maturity, there is greater cooperation and collaboration between partners, technologies and processes, enabling greater flexibility and decentralization. 4. Refers to advances in the level of integration of physical and computational processes, communication between actors, the connection between technologies, and interoperability; it identifies how processes and systems evolve from isolated silos to fully-connected ecosystems that support the remaining SCM and POM domains. 5. Refers to advances in the planning and control of production systems and the value chain of OM; the evolution of more intelligent systems follows the adoption of increasingly sophisticated Lean methods, exploring the synergies between technologies and methodologies. 6. Refers to advances in quality control systems, the performance of quality management tools; it describes a combination of technological and methodological evolutions working together to improve efficiency and accuracy. 7. Refers to advances in reliability, repair and maintenance plans, strategies and techniques; the increase in maturity leads to increasing automation in diagnostics combined with remotely-operated machines that gradually replace humans in specialized or high-risk activities.”

CHAPTER II

NEXT-LEVEL ENERGY MANAGEMENT IN MANUFACTURING: FACILITY- LEVEL ENERGY DIGITAL TWIN FRAMEWORK BASED ON MACHINE LEARNING AND AUTOMATED DATA COLLECTION

A version of this chapter is submitted for publication in the MDPI Open Access Journal “Energies” by David Vance, Mingzhou Jin, Christopher Price, Sachin U. Nimbalkar, and Thomas Wenning.

Concept creation, data collection and analysis, and original manuscript draft were prepared by David Vance. Mingzhou Jin, Christopher Price, Sachin U. Nimbalkar, and Thomas Wenning provided review.

Abstract

With the Fourth Industrial Revolution underway, better data fidelity, analytic methods, and tools such as Digital Twin (DT) and Internet of Things (IoT) are envisioned for industrial energy management. In a typical industrial energy management process, an energy consumption prediction is performed for the next year by employing basic linear regression based on production or a historical naïve approximation (i.e., the energy consumption in the last year is the prediction for the next year). There are only 12 data points per year at a monthly frequency, and thus, limited analytic methods are available. More methods can be investigated using daily and weekly data. The research proposes a framework for implementing machine learning with automated data collection at the facility level for energy prediction according to the ISO 50001:2018 energy management process and tests if reducing the time scale of predictions allows more complex machine learning methods. To test those machine learning methods, an electric vehicle Original Equipment Manufacturer (OEM) provided 15-minute energy and daily production data from 5 shops, including assembly, battery, body (electric), body (gas), and paint, which were combined into a sitewide dataset. Increasingly complex machine learning models, including naïve, simple linear regression, net regularized generalized linear regression,

principal component regression, k-nearest neighbor, random forest, and Bayesian regularized neural network models were tested on daily, weekly, and monthly datasets. It was discovered that complex monthly models require at least a year and a half to work, whereas complex weekly models could operate with a year of data for improved accuracy. Daily models could operate with only six months of data but did not perform as well because the production prediction accuracy was low. Significant challenges of automating energy management at the facility level were discovered, including the availability of reliable and quality energy and production data and the need for much human labor initially.

Introduction

The potential for future energy savings in manufacturing is in executing energy efficiency projects and developing new energy monitoring and management approaches (Weinert et al., 2011). The Internet of Things (IoT) and digital twin (DT) paradigms allow increased visibility, awareness, and energy efficiency improvements because of connected intelligent sensors and meters. This improved real-time energy consumption data can enhance the capability of Energy Management Systems (EnMS) to produce sustained energy savings (Lee & Cheng, 2016). With sufficient data through an energy data collection process, opportunities for energy efficiency become plentiful at each level of the manufacturing process. The state-of-the-art energy efficiency increasing methods in discrete part manufacturing are distinguished based on unit, multi-machine, factory, multi-facility, and supply chain levels (Duflou et al., 2012). The effectiveness of incorporating energy management into any of these levels depends on calculating the present and historical consumption, and the system's reaction to changes. In this study,

creating a data-gathering framework was guided by this ability to incorporate energy management for energy savings at each level. Energy prediction is an obligation of the ISO 50001:2018 energy management process, the industry standard for implementing EnMS (IOS, 2018), but manufacturers commonly use naïve or simple linear regression models if they perform any prediction. Several industrial energy management regression software packages are available, but none were identified which combine machine learning models with daily data inputs to make predictions. For example, the U.S. Department of Energy (DOE) Energy Performance Indicator Tool (DOE AMO, 2018) does not make predictions, only accepts monthly data inputs, and uses basic regression analysis. The DOE VERIFI (beta) tool (DOE AMO, 2019) can use more advanced regression analysis and generate visualizations and reports automatically. However, it does not currently accept daily or weekly input or make predictions.

Original Equipment Manufacturers (OEMs) are pressured to show how each stage of their manufacturing process operates sustainably. Suppose an OEM cannot track and predict the emissions during each manufacturing process. In that case, it will be unable to avoid unnecessary energy use, costs through carbon taxes, and adverse effects on corporate image.

Smart manufacturing (SM), another word for the fourth industrial revolution or Industry 4.0, covers any advanced technology that allows real-time information transparency, improved decision-making, or interconnection between diverse processes (Vance et al., 2023). Typical SM technologies include robotics, Industrial Internet of Things (IIOT), cloud computing, and, importantly for this research, DT, machine learning (ML), and big data analytics.

DT is a virtual or digital counterpart to a real system. In a factory, DT is Level 4 of six levels beginning with 0 and ending with the final Level 5 called “Self-Optimizing Factory.” (Weber et al., 2017). The essential aspect of DT is that it is a uniform data model for describing manifold assets. Data and system integration, integration of cross-life-cycle data, and a service orientation are requirements for advancing to the DT level. A systematic review of machine learning applications for industrial energy efficiency by Narciso and Martins (2020) showed that publications are increasing and are dominated by petrochemical production research. Only one of the forty-two papers reviewed predicts future energy consumption based on historical energy consumption, and it focuses on a specific process instead of the facility (Liu et al., 2019). Recently, Moghadasi et al. (2021) applied ML techniques to implement an ISO 50001:2018 energy management system. Moghadasi’s method fulfills all the requirements of ISO 50001 except the facility-level energy prediction: identifying significant energy users, defining energy performance indicators, developing a baseline, analyzing current energy performance, quantifying energy conservation opportunities, determining energy targets, and defining the energy action plan. Moghadasi et al. (2021) focuses on highly detailed process parameters such as steam temperature and pressure while this study investigates production and previous year's energy data as predictors for energy consumption in this study. Process parameters do not allow for prediction in the same way as production. Moghadasi’s framework could be helpful in conjunction with this research, but it doesn’t fulfill the energy prediction requirement.

Based on the above-identified research gaps, this research aims to answer the following questions: 1) Can industrial facility-level energy predictions be performed using weekly

and daily energy data? 2) Can industrial facility-level energy predictions be improved by considering more advanced ML models such as Principal Component Regression (PCR), K-Nearest Neighbor (KNN), Random Forest (RF), and Bayesian Regularized Neural Network (BRNN)? 3) Because naïve predictions already perform well, does this indicate that data from one year prior could be used as an additional predictor for enhanced accuracy in facility-level energy predictions? 4) What are the significant challenges in implementing a facility-level automated energy prediction framework?

Literature Review

This literature review reveals the research questions and status of combining Smart Manufacturing (SM) concepts of Digital Twin (DT), Internet of Things (IoT), and big data analytics with energy management and facility-level energy predictions.

IT, IoT, and advanced enterprise systems are essential for future energy management research and provide great potential for innovation (Shrouf et al., 2014). Real-time data is becoming available for factory management research. However, collecting, transforming, integrating, modeling, storing, securing, analyzing, and presenting big data sets presents challenges (Khan et al., 2017).

IoT has enabled many new energy and efficiency advantages, yet there has not been enough research to combine the ideas at the industrial plant level. Medojevic *et al.* (2018) stated that “without energy management overall at the center of Industry 4.0, there is no Industry 4.0,” pointing to the fundamental role energy availability and energy reliability play in manufacturing processes. There are considerable benefits to combining Industry 4.0 with energy management, but this has not been realized because plant managers lack awareness of the intimate connection between the two themes, and software tools need to

be upgraded (Medojevic et al., 2018). Shrouf and Miragliotta (2015) reviewed production management practices enhanced by SM technology and found six groups of benefits that can be achieved including 1) identifying and reducing energy, 2) improving production scheduling, 3) reducing energy costs through demand response and reduced energy purchasing cost, 4) efficient management of maintenance, 5) increasing environmental reputation by meeting stakeholder expectations and obtaining environmental certification, and 6) supporting decentralization in decision-making at the production level to increase energy efficiency.

Several reviews exist on the interaction between energy management and advanced data analytics. Sievers and Blank (2023) reviewed the state-of-the-art in data-driven residential and industrial energy management systems, including the system infrastructure's design, wireless and wired communication protocols, real-time and historical data, forecasting algorithms, and objectives and optimization techniques. A detailed assessment of the research literature on energy management in manufacturing is presented by (May et al., 2017). Six main lines of research in the field include (i) drivers and barriers, (ii) information and communication technologies, (iii) strategic paradigms, (iv) supporting tools and methods, (v) manufacturing process paradigms, and (vi) manufacturing performances in the trade-off. Since 2009, the number of publications has increased consistently until 2016, the last date in the study, and the authors expect it to continue increasing.

Energy Management

Some notable frameworks have been proposed for implementing an energy management DT. Schulze et al. (2016) proposed a framework for energy management in various

contexts based on overarching themes, including strategy/planning, implementation/operation, organization, control, and culture. The Schulze framework does not go in-depth into data collection or mention the DT concept, but it provides a comprehensive approach that can be used as a basis for development. Vihkorev et al. (2013) proposed an energy monitoring and management framework for the plant floor level, including data exchange standards, virtual energy data analysis, performance analysis, and energy usage dashboard. The Vihkorev framework focuses on the Manufacturing Execution System (MES) and complex event processing for providing real-time energy performance information. Data reduction is proposed through extracting key events from data streams due to large continuous datasets. The case study is implemented in a prototype information system in a machining line for a major automotive company. The result is a state recognition evaluation by a pattern machine to estimate the average time in different operation modes and the average energy used in idling. Zhang et al. (2018) proposed a framework for equipment energy consumption management (EECM) with a DT shop floor consisting of physical equipment, virtual equipment, EECM services, and data using a machine tool as an example. The potential applications of EECM with DT shop floor are energy consumption monitoring, analysis, and optimization. They believe that future work in this area will involve DT shop floor case studies and modeling, the fusion of multiple data sources, and establishing an EECM system on the DT shop floor. Wei et al. (2016) developed an energy management platform based on IoT for industrial facilities that includes a use case for energy consumption measurement in a facility. However, it doesn't consider multiple facilities, isn't implemented in an actual industrial process, and

focuses on demand responses. There are plenty of DT energy applications for the shop floor, but there is a lack of research for implementing DT energy at the plant level. Not many data acquisition platforms have been proposed or implemented for the energy management of intelligent manufacturing plants. Mahir et al. (2023) proposed a data acquisition platform for energy management in smart factories or buildings using openHAB, MQTT, and Node Microcontroller Unit (NodeMCU). They focus on improving communication security, and the proposed platform is not implemented.

Digital Twin (DT)

The capability of a manufacturer to produce DT applications is a crucial goal for SM (Weber et al., 2017). The term ‘digital twin’ was introduced by Michael Grieves in a 2002 product lifecycle management (PLM) presentation, although virtual replication of a product had been realized in the aerospace industry (Grieves, 2014). A widely used definition from Glaessgen and Stargel (2012) reads: “DT is an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin.”

Another definition for DT in manufacturing terms given by Garetti et al. (2012) reads: “DT consists of a virtual representation of a production system that can run on different simulation disciplines characterized by the synchronization between the virtual and real system, thanks to sensed data and connected smart devices, mathematical models and real-time data elaboration. The topical role within Industry 4.0 manufacturing systems is to exploit these features to forecast and optimize the behavior of the production system at each life cycle phase in real-time.”

In the next phase of DT research, references reviewed DT applications to determine a more specific definition of DT and specific use cases and terminology. For example, Kritzinger et al. (2018) categorically reviewed the DT in manufacturing applications to classify existing publications according to their type, level of integration, area of focus, and technology used. Before Kritzinger et al. (2018), DT was viewed simply as a digital counterpart to a physical object, and the terms digital model, digital shadow, and DT were often used synonymously. Now, the terms can be distinguished by the level of data integration between the physical and virtual counterparts. A digital model provides a virtual representation of a planned or existing physical object without an automated data exchange. A change in a physical object's state does not affect a digital object, and vice versa.. The digital shadow is where there is a one-way data flow between the state of a physical object and a virtual object. A change in the state of the physical object leads to a change in the virtual object, but not vice versa. If, and only if, data flows are fully integrated into both directions between the physical and virtual object, Kritzinger et al. (2018) determines that you can accurately refer to it as a DT. The authors found that most papers used the term DT, while only 18% accurately described a DT with bidirectional data transfer. Using the Kritzinger et al. (2018) framework, a real-time energy information model would not be characterized as DT unless it had bidirectional data-transfer capability. Shao and Helu (2020) characterized DT perspectives based on the definition proposed, relevant viewpoint, fidelity of the virtual representation (complete or partial), and temporal integration (real-time or offline). An offline DT would be where real-time communication is not critical and periodic connection is sufficient. The authors argue that the DT concept should depend on the viewpoint and context for the specific

use case and propose three critical factors for assessing the scope and requirements of a DT, including (1) Application, (2) Viewpoint, and (3) Context. A DT only needs to collect the relevant data to the use case of interest rather than all existing data. The Shao and Helu (2020) framework would allow practitioners to consider an energy information model given data in 15-minute steps as a DT application without the real-time bidirectional data-transfer capability. The currently under development ISO 23247 will provide a generic DT manufacturing development framework that considers the context and viewpoint for specific use cases. Yu et al. (2022). proposed the Energy Digital Twin (EDT) concept, aiming to manage and optimize site operations to minimize specific energy consumption through four attributes including 1) looks-like, 2) behaves-like, and 3) connected-to, and 4) timescale. Yu et al. (2022) classified EDT subtly shifts from Kritzinger *et al.* (2018) by introducing the term ‘Digital Manager’ to describe the connected-to attribute and avoid the requirement for bi-directional transfer. The argument is that many EDT applications, such as plant evolution and retrofit, do not rely on bi-directional, real-time data communication but should still be counted under the broader class of DT. Also, enabling communication from the DT back into the production environment for bi-directional data transfer requirements could require some disruption to production, which is ruthlessly avoided in manufacturing. For this research, automated data collection and integration into the digital model is the goal for energy management DT and not bidirectional data transfer, and so the application will be referred to as a DT according to the DT definition from Shao and Helu (2020) and the EDT definition from Yu et al. (2022).

The DT concept has been fully implemented and proven in several applications, though no plant-level energy management DT has been identified. Haag and Anderl (2018) prove the DT concept with a physical twin of a bending beam test bench, a DT CAD model, an MQTT broker to connect the physical and DT, a web-based dashboard, and a finite element method (FEM) simulation. The results demonstrate that the DT concept can be applied to real systems. A challenge for DT applications is that current CAx models are used in product development and are not constructed to live on as DTs, which adapt to the product characteristics throughout its entire operational phase. Additionally, conventional data gathering and processing methods are inadequate.

Tao *et al.* (2018) reviewed DT's state-of-the-art research and development history and summarized its industrial applications. The most popular application area is prognostics and health management (PHM). Energy efficiency or energy monitoring were not explicitly identified. Assad *et al.* (2021) showed the implementation of a web-based DT (WDT) for improving sustainability in industrial cyber-physical systems, proving that the energy management DT is feasible at the machine level. The three steps are a) reading the control parameters influencing energy consumption, b) recording the energy consumption data, and c) making predictions using an algorithm. An industrial case study in a battery manufacturing line demonstrates the WDT architecture, which has WebGL, Node.js, OPC UA server, and PLC as its major components and uses WebSocket as the communication protocol. This paper proposes an energy management DT framework for the plant level rather than the machine level.

Sustainability motivates energy management. Pater and Stadnicka (2021) reviewed twenty papers related to DT and sustainability to determine what types of problems are

included within the two topics. They concluded that there are many areas where the potential of DT for sustainability has not been realized and that this gives a signal to combine DT with sustainability. From the Pater and Stadnicka (2021) review, only one paper concerns real-time energy monitoring and forecasting, and none of them are related to energy management at the facility level.

Methodology

Framework Overview

Figure 6 provides a high-level framework for predicting energy consumption. Program #1 integrates data into a usable format for ML models based on historical energy consumption, weather, and production data. The output of Program #1 is a formatted dataset plus an initial variable analysis of each data source and scatter plots of energy vs. production and energy vs. temperature. Program #2 uses that formatted dataset to train ML models. Program #2 output is the ML models plus model info, including coefficients, best tuning parameters, and training and holdout results such as RMSE and R^2 and their standard deviations. Program #3 uses the created ML models with planned production data and forecasted weather data to predict energy consumption. The output of Program #3 is a dataset of each of the model's predictions and calculations of the RMSE and R^2 if the actual data is available.

This research uses 15-minute energy consumption data and daily weather and production data, but this framework could be employed at different time scales and scopes, such as at the area or line level. The electric vehicle manufacturing case described in this paper includes data from five shops: Assembly, Battery, Body Shop (Electric), Body Shop

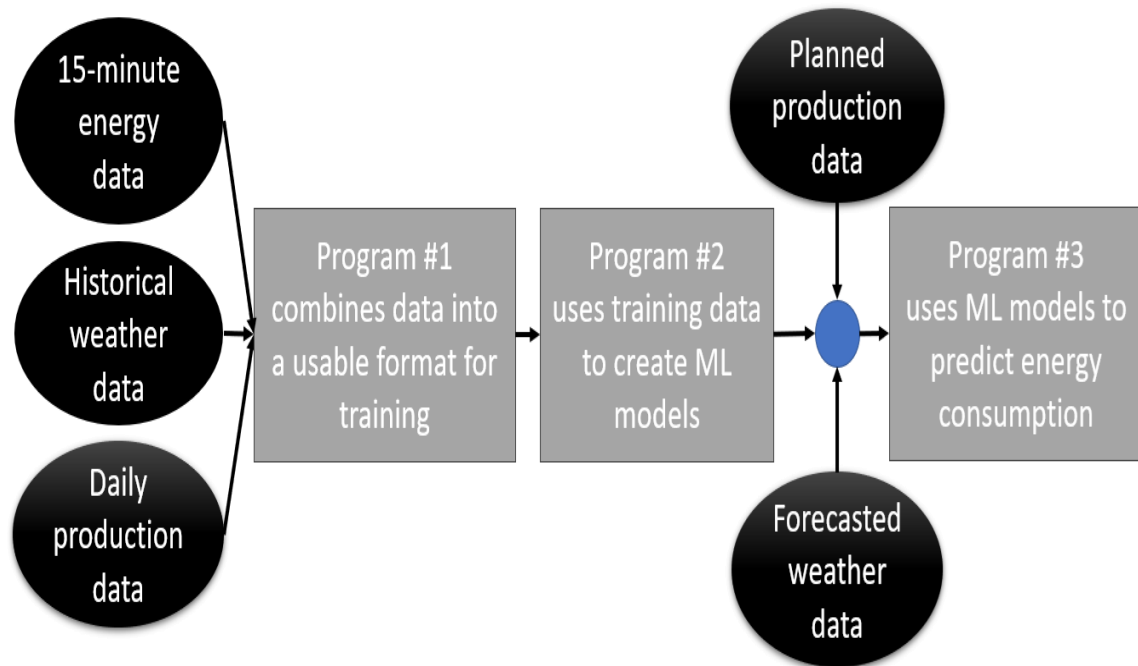


Figure 6: Framework for energy consumption prediction of a manufacturing facility

(Gas), and Paint. Sitewide energy is expressed as Assembly + Battery + Body Shop (Electric) + Body Shop (Gas) + Paint. The utility provided 15-minute energy data at the end of each week, which could be integrated into a communication architecture.

Weather impacts manufacturing energy consumption, and weather data is available from many sources. (Sitterson et al., 2020) demonstrated that an online web services tool can automatically retrieve and preprocess precipitation data. An Application Programming Interface (API) like the one developed by BizEE Software could be implemented to automate this data retrieval (BizEE Software, 2013).

Energy consumption heavily depends on production volumes. In this case, weekly production data is compiled into daily and monthly datasets for Assembly, Battery, Body Shops, Paint, and Sitewide. Sitewide production data is expressed as Assembly + Battery + Body Shop (Electric) + Body Shop (Gas) + Paint. Production data will likely be this framework's most challenging automated data collection implementation.

The ML model training can be performed through an open-source and free statistical environment such as R (R, 2015). In this environment, packages such as Caret can be utilized to develop machine-learning models quickly (Prabhakaran, 2018). A thorough overview of statistical learning using R is provided by (James et al., 2013).

Prediction Models

This section provides explanations of the prediction models. These well-known models were chosen because they can be roughly sorted from simple to complex. More information about each of the models can be found at (James et al., 2013) and their parameters are explained at (Caret Documentation, 2023). Chosen models include:

- **Naïve (Average)** – A naïve model does not use any sophistication to make a prediction and is often used as a benchmark for testing ML models. An average naïve model takes the average of the training dataset and applies it to all future forecasts. If a model cannot achieve a lower root mean square error (RMSE) than the naïve model, it is not as good as random chance. The R^2 of an average naïve model is 0.
- **Naïve (Historical)** – A historical naïve model takes data from one year prior and applies it to the future forecast. This is an industry practice that often improves upon the naïve average method.
- **Linear** – A simple linear regression model involving only one variable, in this case, production. The equation for a line of best fit is $y = m \cdot x + b$, where (x, y) represents any point that satisfies the equation. The y-intercept, b , is the y-value when $x = 0$. The slope, m , is the change in y when x increases by 1.
- **GLMNET (Net Regularized Generalized Linear Regression Model)** – Considers all variables and gives a reasonable estimation of the significant predictors. Fits lasso and elastic-net models for linear, logistic, and multinomial regression using coordinate descent. Extremely fast, exploits sparsity in the input x matrix, and can make various predictions accurately. For an $\alpha = 0$, ridge regression is employed, which tends to give equal coefficients and never fully throws out predictors. For an $\alpha = 1$, lasso regression picks fewer correlated predictors and discards the rest. For values between 0 and 1, it blends the two methods. A Generalized Linear Model (GLM) was also performed, but the results were close to GLMNET, and were omitted.

- **PCR (Principal Component Regression)** – In principal component analysis (PCR), an analysis is first performed on the original data, then dimension reduction is performed by selecting principal components using cross-validation and test error, and finally, regression is conducted using the first n dimension reduced principal components. PCR performs better than previous models on massive datasets and can accurately handle variables like ‘day of the week’ and ‘month of the year.’ Partial Least Squares Regression (PLSR) was also performed, but the results were close to PCR, and were omitted.
- **KNN (K-Nearest Neighbor)** – A non-parametric, supervised learning classification model that uses proximity to make classifications or predictions about the grouping of an individual data point. KNN is typically used as a classification algorithm for pattern recognition, from the assumption that related points can be found near one another. It can sometimes perform better on large datasets than previous models if there is an understanding to be developed based on neighborhoods or groupings that simple linear regression cannot determine.
- **Random Forest (RF)** – Random forest is a popular ML algorithm which combines the output of decision trees to reach a result. It is popular due to its ease of use, flexibility, and ability to handle classification and regression problems.
- **Bayesian Regularized Neural Net (BRNN)** – A neural network that incorporates posterior inference to reduce overfitting and can be trained based on just one parameter, the number of neurons.

Determining Best Model

To determine the best model, R^2 and RMSE metrics are used to compare them. R^2 is a ‘goodness-of-fit’ statistical measure demonstrating the percentage of the variance for a dependent variable explained by an independent variable in a regression model. The higher the R^2 value, the stronger the association between the dependent and independent variables. If the R^2 of a model is 0.5, then half of the studied variation can be explained by the model’s inputs. What qualifies an R^2 value as “good” depends on context. Naïve (average) models have an R^2 value of 0 associated with them because they have no variance. Root mean square error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals measure how far from the regression line data points are. Essentially, RMSE tells you how clustered data is around the line of greatest fit. The lower the RMSE, the better a given model can “fit” a dataset. A general rule of thumb is: If the prediction from one model is not a standard deviation more accurate than another, you might as well choose the simpler model.

It is helpful to use both RMSE and R^2 when deciding which model to use. RMSE describes the typical distance or error between the predicted and actual values. R^2 describes how well the predictor variables explain the change in the response variable. RMSE should be prioritized over R^2 when testing predictions because it is preferable to have a smaller error than to have the right shape but a larger error. This is apparent in several of the naïve models, where it has a good R^2 because the shape is correct, but a large RMSE because production has increased. Our partner prioritized R^2 , requiring 0.85 for analysis, but lower R^2 can be appropriate if RMSE is a small percentage of the total.

Experimental Processes

In initial variable testing of dry bulb temperature, wet bulb temperature, heating degree days, and cooling degree days, it was decided that average dry bulb temperature was the most significant. Heating and cooling degree days are helpful in many energy management processes, but here, they did not perform as well as dry bulb temperature. Also, predicting heating and cooling degree days is not as straightforward as predicting temperature. Dry bulb temperature is used as a predictor for weather in all models besides naïve and linear. From here on, temperature refers to the average dry bulb temperature. Production and temperature are used in every model besides linear, which only uses production, and naïve, which doesn't use either. Week of the year, month, and day of the week were implemented as predictors in PCR, KNN, RF, and BRNN models unless the program gave an error stating that the predictors were rank-deficient, meaning they did not contribute to the model's accuracy. There is insufficient space to document which predictors were chosen in each model. For the shop models, the predictors are its production data, temperature, month, week of the year for weekly and daily models, and day of the week for daily models. For the sitewide models, the predictors are production data for each shop plus sitewide, temperature, month, week of the year for daily and weekly models, and day of the week for daily models. Month and week of the year were almost always excluded, but the day of the week was included in most daily models. The weekly and daily models were cross-validated ten times, while the monthly models would not work in this way due to data size, and fewer cross-validations were performed. Some monthly models would not accept cross-validation, including KNN and BRNN for shop models and PCR, PLSR, KNN, and BRNN for sitewide models. The RF would not

function for any monthly sitewide models except in testing scenarios where there were more than two years of data. Because of the limited cross-validation, data confidence is not high for those monthly models. The data was randomly partitioned into 75% training and 25% holdout to ensure best practices, but holdout results are not included here.

Results

This section gives the daily, weekly, and monthly results for temperature, production, and sitewide energy for 2023 Q1, 2023 Q4, and 2024 Q1. Analysis for specific shops is included in the appendix.

For the results labeled 2023 Q1, data was collected from 2022 and then tested against the first quarter of 2023. For 2023 Q4 A, training data are from 2022 and 2023 up to September 1st, 2023, and tested in the last quarter of 2023. For 2024 Q1 A, training data are from 2022 and 2023 and tested in the first quarter of 2024. For 2023 Q4 B and 2024 Q1 B, energy data from one year prior is included as a predictor. This made the training dataset smaller because no data existed from 2021. So, for 2023 Q4 B, the training data is from 2023 up to September 1st, 2023, and does not include any training data from 2022 because the energy from last year's predictor does not have data from 2021. For 2024 Q1 B, training data are from 2023 and tested against the first quarter of 2024. The monthly and weekly models would not perform when they were first tested in 2022 Q4, so at least one year of data must exist to perform this analysis.

Production

Table 8 gives the production prediction's R^2 , which measures how accurate the partner companies' forecasts for production were. The projections were conducted at the

Table 8: Summary of production prediction accuracy

Shop	Time Period	2023 Q1 R^2	2023 Q4 R^2	2024 Q1 R^2
Assembly	Daily	0.92	0.03	0.91
	Weekly	0.88	0.52	0.98
	Monthly	1.00	0.04	1.00
Battery	Daily	0.96	0.07	0.69
	Weekly	0.88	0.08	0.88
	Monthly	1.00	0.00	0.94
Body (Electric)	Daily	0.80	0.06	0.60
	Weekly	0.76	0.28	0.52
	Monthly	1.00	0.02	0.74
Body (Gas)	Daily	0.88	0.03	0.85
	Weekly	0.74	0.32	0.97
	Monthly	1.00	0.00	1.00
Paint	Daily	0.91	0.02	0.90
	Weekly	0.88	0.52	0.97
	Monthly	1.00	0.05	1.00
Sitewide	Daily	0.92	0.03	0.91
	Weekly	0.86	0.53	0.96
	Monthly	1.00	0.06	0.99

beginning of each year, so there was a larger period between the 2023 Q4 predictions than the 2023 Q1 and 2024 Q1. Monthly and weekly production estimates were much more accurate than daily, which makes sense because the daily forecasts were derived. Daily production is more volatile due to many factors, such as maintenance, shift change, and weather. In addition, the company might miss daily goals but would make up for them through overtime on the weekend to still meet weekly and monthly goals.

Temperature

Table 9 gives the temperature prediction's R^2 , which measures how accurate our forecasts for temperature were. Historical averages from NCEI U.S. Daily Climate Normals (2006 – 2020) closest to the partner companies' location are used to forecast future temperatures (National Centers for Environmental Information, 2021). For monthly, the R^2 are high enough to use for predictions comfortably. However, there are low R^2 for some daily and weekly predictions, so it is up to the data scientist running the models to determine if it's appropriate. This study assumes that the temperature prediction accuracy did not significantly affect energy consumption prediction accuracy because the RMSE is small, and the temperature predictor importance was less than 20%.

Table 9: Summary of temperature prediction accuracy

Time Period	2023 Q1 R^2	2023 Q4 R^2	2024 Q1 R^2
Daily	0.26	0.83	0.42
Weekly	0.50	0.92	0.62
Monthly	0.92	0.99	0.86

Sitewide

The sitewide energy metric comes from 6 different shop meters combined. Some significant processes, equipment, and even whole shops were added between 2022 and 2023. Daily sitewide results are given in **Table 10**. The average sitewide daily energy consumption was 363,040 kWh, and RMSE standard deviation was around 5,000 kWh. Prediction accuracy was above 0.85 R^2 in 2023 Q1, less than 0.05 in 2023 Q4, and greater than 0.75 R^2 in 2024 Q1. This result also played out in the assembly and paint processes and is assumed to result from low production prediction accuracy for 2023 Q4. Adding the energy data from one year ago as a predictor, shown in 2023 Q4 B and 2024 Q1 B, improved the prediction accuracy. The ML models improved on the naïve results in 2023 Q1 and 2024 Q1 but not in the 2023 Q4 analyses. In these results tables, the yellow highlight indicates the lowest RMSE model when compared against actual data, and the orange highlight indicates the highest R^2 model.

Table 11 shows weekly sitewide results. The average weekly energy consumption was 2,355,600 kWh, and the standard deviation of RMSE was around 90,000. Prediction accuracy was not as bad in 2023 Q4 as in other models. As in previous models, RMSE decreased from 2023 Q1 to 2023 Q4 and increased from 2023 Q4 to 2024 Q1, but not as severely. Comparing 2023 Q4 A with 2023 Q4 B shows that prediction accuracy did not improve based on the actual or training results from adding the ‘energy data from the previous year’ predictor. The RMSE of the Historic model in 2023 Q1 was very good and could not be achieved, but the ML models improved on the linear model in that period.

Table 10: Results of daily sitewide model training

Time Period	Parameter	Model Type							
		Historic	Average	Linear	GLMNET	PCR	KNN	RF	BRNN
2023 Q1	RMSE (Training)		105,629	54,291	34,989	33,881	45,848	58,329	33,456
	R^2 (Training)		0.00	0.73	0.89	0.90	0.88	0.88	0.91
	RMSE (Actual)	78,852	74,088	181,577	54,026	53,378	33,078	49,524	31,823
	R^2 (Actual)	0.70	0.00	0.87	0.92	0.92	0.89	0.92	0.87
2023 Q4 A	RMSE (Training)	113,657	103,478	54,356	34,990	34,845	32,749	30,351	27,950
	R^2 (Training)	0.19	0.00	0.73	0.89	0.89	0.90	0.92	0.93
	RMSE (Actual)	112,459	124,464	160,524	132,719	135,631	135,333	140,233	143,182
	R^2 (Actual)	0.44	0.00	0.00	0.03	0.02	0.01	0.01	0.00
2023 Q4 B	RMSE (Training)	113,657	101,958	54,356	40,698	40,274	36,105	28,857	26,677
	R^2 (Training)	0.19	0.00	0.73	0.84	0.84	0.87	0.91	0.92
	RMSE (Actual)	112,459	120,878	160,524	129,048	124,096	131,786	142,825	127,605
	R^2 (Actual)	0.44	0.00	0.00	0.03	0.04	0.03	0.00	0.02
2024 Q1 A	RMSE (Training)	113,028	103,345	68,079	42,906	42,834	37,580	30,844	31,530
	R^2 (Training)	0.29	0.00	0.56	0.85	0.85	0.88	0.92	0.92
	RMSE (Actual)	114,349	107,524	58,084	57,842	60,113	78,928	67,846	58,269
	R^2 (Actual)	0.05	0.00	0.74	0.78	0.76	0.65	0.79	0.79
2024 Q1 B	RMSE (Training)	113,028	103,345	68,079	39,529	35,924	40,251	31,939	33,243
	R^2 (Training)	0.29	0.00	0.56	0.85	0.87	0.86	0.91	0.89
	RMSE (Actual)	114,349	107,524	58,084	52,544	46,197	57,928	57,711	56,881
	R^2 (Actual)	0.05	0.00	0.74	0.78	0.81	0.78	0.79	0.81

Table 11: Results of weekly sitewide model training

Time Period	Parameter	Model Type							
		Historic	Average	Linear	GLMNET	PCR	KNN	RF	BRNN
2023 Q1	RMSE (Training)		456,963	297,607	186,355	183,373	160,581	205,657	107,720
	R^2 (Training)		0.00	0.73	0.84	0.85	0.79	0.89	0.95
	RMSE (Actual)	230,610	1,806,313	1,321,370	252,767	534,254	391,638	290,422	350,465
	R^2 (Actual)	0.40	0.00	0.45	0.41	0.45	0.23	0.17	0.27
2023 Q4 A	RMSE (Training)	507,147	406,336	293,128	160,703	160,628	150,152	193,717	95,710
	R^2 (Training)	0.18	0.00	0.55	0.88	0.87	0.91	0.83	0.96
	RMSE (Actual)	564,164	697,198	553,789	384,559	384,182	403,828	461,169	333,189
	R^2 (Actual)	0.67	0.00	0.21	0.75	0.74	0.73	0.63	0.77
2023 Q4 B	RMSE (Training)	507,147	406,336	293,128	235,608	230,918	242,368	296,876	244,444
	R^2 (Training)	0.18	0.00	0.55	0.96	0.96	0.99	0.25	0.53
	RMSE (Actual)	564,164	697,198	553,789	385,571	367,732	540,490	578,331	321,153
	R^2 (Actual)	0.67	0.00	0.21	0.72	0.75	0.59	0.54	0.78
2024 Q1 A	RMSE (Training)	532,016	474,094	419,285	157,103	158,933	150,871	173,645	110,520
	R^2 (Training)	0.37	0.00	0.39	0.90	0.90	0.91	0.90	0.95
	RMSE (Actual)	500,572	609,475	251,523	280,070	279,656	222,876	273,626	262,489
	R^2 (Actual)	0.44	0.00	0.85	0.77	0.77	0.83	0.82	0.83
2024 Q1 B	RMSE (Training)	532,016	474,094	419,285	201,078	198,221	263,295	262,053	184,889
	R^2 (Training)	0.37	0.00	0.39	0.87	0.88	0.87	0.81	0.95
	RMSE (Actual)	500,572	609,475	251,523	322,663	363,583	304,783	464,141	424,085
	R^2 (Actual)	0.44	0.00	0.85	0.79	0.79	0.76	0.57	0.85

The ML models improved on the naïve models in all other time periods. In 2024 Q1 A and B the ML models only beat the linear model once. The sitewide model uses more predictors because it includes production data from each shop. This seems to translate to improved ML models, especially in training. In 2023 Q1, the ML models were several standard deviations better than the naïve and linear. The sitewide weekly ML models could be used for annual predictions, such as required for ISO 50001 certification. These results show that the naïve and linear models can have large and unpredictable errors. Sitewide monthly model results are given in **Table 12**. This is perhaps the most important result because this is the time period that the industry typically performs yearly predictions for ISO 50001 certification. The average sitewide monthly energy consumption was 11,012,000 kWh for 2023, and the standard deviation of RMSE was 500,000. For the ML models, prediction accuracy compared to actual results decreased from 2023 Q1 to 2023 Q4 and increased from 2023 Q4 to 2024 Q1. Prediction accuracy was not as terrible in 2023 Q4 compared to other time periods, with R^2 above 0.75 and RMSE less than 15% of the average monthly energy consumption. The ML models improved on the naïve models in every period besides 2023 Q1 and the linear besides 2024 Q1 A. The RF model ran in 2024 Q1 A for the first time in a monthly model, but it was the worst-performing model, and the results are not included. RF is not a good candidate for initial ML testing in monthly models because it takes more than two years of available data to perform. The BRNN did perform in 2024 Q1 B because it had a higher dimensionality with all the individual shop production data plus the ‘energy from

Table 12: Results of monthly sitewide model training

Time Period	Parameter	Model Type						
		Historic	Average	Linear	GLMNET	PCR	KNN	BRNN
2023 Q1	RMSE (Training)		1,747,3113	1,227,409	682,160	737,764		
	R^2 (Training)		0.00	0.66	0.91	0.92		
	RMSE (Actual)	748,792	1,445,674	4,219,015	3,263,449	1,159,504		
	R^2 (Actual)	0.89	0.00	0.82	0.12	0.72		
2023 Q4	RMSE (Training)	1,706,915	1,378,826	1,431,324	607,102	558,804	1,026,088	1,286,387
	R^2 (Training)	0.58	0.00	0.38	0.97	0.97	0.64	0.69
	RMSE (Actual)	2,288,114	2,544,555	2,272,790	1,388,637	1,302,062	1,346,754	1,212,710
	R^2 (Actual)	0.68	0.00	0.15	0.77	0.79	0.86	0.80
2024 Q1 A	RMSE (Training)	1,970,030	1,533,310	1,757,608	585,057	606,529	1,021,876	567,022
	R^2 (Training)	0.51	0.00	0.98	0.96	0.94	0.74	0.95
	RMSE (Actual)	1,067,821	1,625,809	630,998	680,560	966,446	1,009,443	758,261
	R^2 (Actual)	0.51	0.00	1.00	0.96	0.95	0.71	0.97
2024 Q1 B	RMSE (Training)	1,970,030	1,533,310	1,757,608	1,024,396	1,301,112		1,339,096
	R^2 (Training)	0.51	0.00	0.98	0.97	0.99		0.97
	RMSE (Actual)	1,067,821	1,625,809	630,998	1,250,344	428,949		291,403
	R^2 (Actual)	0.51	0.00	1.00	0.99	0.99		0.96

last year’ predictor, and it had the best prediction by RMSE. The BRNN monthly model did not perform in the 2024 Q1 B shop models.

Summary

Table 13 summarizes the best models and their R^2 for each shop and time period. The ‘best model’ is chosen according to the lowest RMSE because this indicates the model with the lowest expected error. It might be the case that another model besides the one chosen as ‘best model’ had a higher R^2 . Battery and Body (Electric) shops had just come online in 2023 Q1, so there was no model. Models with a (B) indicate the ‘energy data from last year’ predictor included. The monthly models in 2023 Q4 did not work with the ‘energy data from last year’ predictor because there wasn’t enough training data.

Discussion

Framework

Figure 7 shows an ideal application of the framework proposed in **Figure 6**. In this case, internal data such as production history and production predictions are automatically acquired, organized, and stored within a unified namespace (UNS), allowing access to data anywhere it is needed using a common data interface. David et al. (2019) presents the unified namespace architecture concept for integrating business data. Outside data, such as weather, is automatically acquired through HTTP / API.

The framework can be used at different levels of the plant, given that there is good production data. For example, the framework could be applied to an area level of the plant, given that the lines have good production data. The framework could be applied at the line level if each cell has good data. Finally, the framework could be applied at the

Table 13: Summary of the best models for each plant area.

Plant Area	Time Step	Time Period					
		2023 Q1		2023 Q4		2024 Q1	
		Best Model	R^2	Best Model	R^2	Best Model	R^2
Assembly	Daily	Linear	0.83	KNN (B)	0.40	Linear	0.77
	Weekly	GLMNET	0.42	BRNN (B)	0.78	Linear	0.83
	Monthly	PCR	0.76	Historical	0.72	Linear	0.95
Battery	Daily			KNN (B)	0.49	Linear	0.42
	Weekly			GLMNET (B)	0.72	RF (B)	0.58
	Monthly			BRNN	0.78	Average	0
Body (Electric)	Daily			KNN (B)	0.23	RF (B)	0.78
	Weekly			BRNN (A)	0.77	RF (A)	0.81
	Monthly			BRNN	0.85	GLMNET (B)	0.86
Body (Gas)	Daily	PCR	0.93	KNN (B)	0.46	GLMNET (A)	0.79
	Weekly	Linear	0.59	BRNN (B)	0.69	Linear	0.81
	Monthly	Linear	0.96	KNN	0.66	PCR (B)	0.98
Paint	Daily	RF	0.90	KNN (B)	0.34	RF (B)	0.54
	Weekly	BRNN	0.14	BRNN (A)	0.62	BRNN (A)	0.82
	Monthly	Linear	0.73	KNN	0.34	PCR (B)	1.00
Sitewide	Daily	PCR	0.92	Historical	0.44	PCR (B)	0.80
	Weekly	Historical	0.40	BRNN (B)	0.78	Linear	0.85
	Monthly	Historical	0.89	GLMNET	0.75	BRNN (B)	0.96

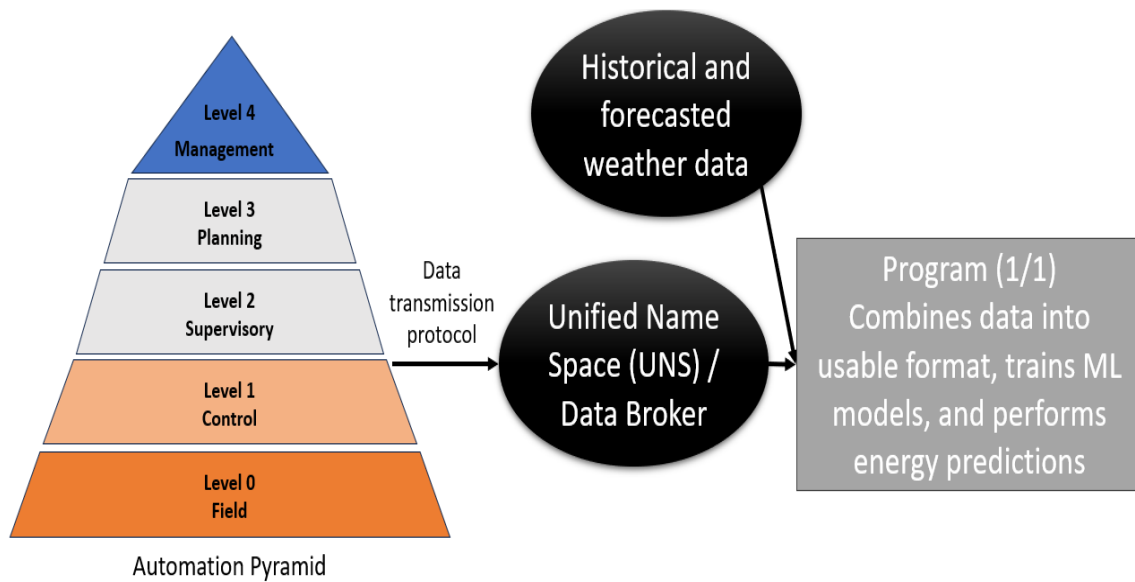


Figure 7: Ideal situation of the energy prediction framework

cell level, given that all equipment has good data. In these scenarios, temperature may or may not be a significant predictor, but others would reveal themselves with research.

Challenges

Accurate production data and production predictions constitute a significant challenge. At one point, production data were given in a different format with different values from previous data already received. It was determined this was because one dataset was from the line, and another was derived up the line. Production data must be consistently formatted, reliable, and high-quality. Also, production prediction accuracy was much better at the beginning of the year than in the last quarter. This result indicates that energy managers should be careful about predicting production.

Energy data quality and reliability were two more challenges in implementing this research. There were several occasions when data was unavailable when it was expected,

or there were gaps, albeit small, that had to be filled by the researchers. The utility quickly fixed these gaps, which might have prevented a real-time energy digital twin from functioning. The manufacturer's capability to receive automated energy data weekly and view it in real-time on a shop level was excellent and bodes well for the future of energy data in manufacturing. However, it needs work to be more reliable.

Another challenge was the amount of human labor involved. This research aimed to reduce the human input needed in energy prediction. However, automating the data retrieval, ML model training, and prediction resulting in a facility-level EDT requires many human hours. The following list details the tasks that need to be automated for the automated energy prediction framework:

- Data transmission and retrieval
- Data formatting
- ML model training and retraining
- Energy consumption predictions

One reason for the large amount of human labor was that several ML models were tested. It is worth researching which ML models work best with your problem. In this case, no study that had implemented an ML model to predict energy consumption at the manufacturing plant level was identified. The authors knew from personal experience that manufacturers use historic or average naïve models in many cases and sometimes use basic linear regression with production or multiple linear regression with production and temperature, but no case was identified of using a more complex ML model. In the future, the RF would be our first candidate for removal from this process, especially for

the monthly models, though it seems to perform well for the daily paint models. The next candidate would be GLM because the GLMNET is similar and improved upon the GLM in almost every model. PCR and PLSR would be our next candidates for removal from the process because they were not the best performing.

The BRNN has high complexity and promising initial results. It works with smaller datasets than the RF or KNN. The BRNN model was chosen because, compared to other neural net models, it requires less tuning. It worked well with the sitewide models with many predictors but was also the best-performing of several shop models. The KNN also had promising initial results in many of the models.

The amount of machine learning knowledge required could be challenging for real-world applications. The practitioner needs a fundamental understanding of automated data retrieval, machine learning model selection, tuning parameters, and what the results mean for energy management.

Lessons Learned

In some situations, historic and average models perform well, mainly where the system is steady, no new processes or equipment are added, and production is stable. **Table 12** shows a case where historic and average models have high and low prediction errors. The problem is that there is no confidence in your prediction. Manufacturers that rely on historic and average models for predictions typically do not follow good data science practices, such as maintaining a holdout dataset or testing variables. The historic and average models are sometimes necessary for a quick estimate but can easily be improved. Manufacturers might view energy consumption prediction for energy management as

unimportant and want to make the quickest estimate. The authors urge the industry to consider this as a chance to improve SM capability and inform predictions.

Daily models benefit from abundant data and perform well in 2023 Q1, with R^2 above 0.7. However, their performance decreased significantly in 2023 Q4 to the point of having R^2 approaching zero. This is likely because production prediction accuracy decreases with a more extended forecast period. Also, daily datasets were derived from the weekly data provided, and if there is a shutdown or missed production target, that production is shifted to the next day. To make a good prediction, you should first have good data to input. The daily model's application in practice will not be the same as in this research, over months or years, but rather testing for a specific scenario of a day or week. Still, the daily model results show that more flexible ML models are available with more data. One strength of the daily models is that the more complex models can run with less than a year of data.

The weekly PCR, KNN, RF, and BRNN models required at least one year of data to perform. Although they require more data, they showed that more complex methods can outperform simple ones. For example, RF and BRNN for Assembly 2023 Q1, KNN for Paint 2023, and BRNN for Sitewide 2023 all performed a standard deviation better than counterpart linear and naïve models. The research goal wasn't to show that complex models are always better than simple models but that it is possible. Good big data analytics requires quality data and a proper understanding of tuning and model selection. Usually, energy consumption predictions are performed monthly, but if production data is provided weekly, it makes sense to perform these predictions weekly. Also, if production

is delayed by a day, it could be pushed into next month's analysis, but since the weekly starts on Sunday, this could be avoided with weekly analysis.

The monthly prediction accuracy results showed that complex models require at least a year of data and two years to include the 'energy from last year' predictor. However, accuracy improvements are possible once that data is available, such as in 2024 Q1 Sitewide Monthly BRNN and 2023 Q4 Paint Monthly KNN.

The energy data from last year predictor had mixed results. It requires at least a year and a half of data to run, and some models, such as 2024 Q1 B Sitewide KNN, where adding the predictor made the training and actual RMSE significantly worse. Just because adding a predictor decreases the RMSE by a small amount does not mean it should be included for fear of overfitting. However, there were models such as 2024 Q1 B Paint KNN where adding the energy data from last year predictor decreased the RMSE of training and actual by a standard deviation, indicating it should be included. There were more of the best models that included the energy data from last year predictor. This type of case-by-case analytics thinking is essential for improving predictions.

Almost every model improved prediction accuracy over the naïve models, except in the sitewide 2023 Q1 weekly and monthly and sitewide 2023 Q4 daily models. With continued experimentation, the authors expect to consistently improve upon the naïve and linear regression, which is employed frequently in manufacturing energy management. One problem with using complex models is that they are not as easily interpretable. With linear regression, you can point to a coefficient and explain why it makes a prediction based on the production, but this isn't possible with PCR, KNN, RF, or BRNN, though they are more flexible and can improve predictions in some instances. The best ML

models vary by shop and perhaps because of the nature of each shop. More research is needed to explain why specific models perform well for a specific shop.

Conclusions

This paper proposes a framework for a facility-level Energy Digital Twin (EDT). This framework enables real-time energy data gathering, automated integration, and energy predictions and can be modified to work in any area of the plant. It was tested on daily, weekly, and monthly datasets for shops and sitewide processes.

The proposed framework advances the state-of-the-art in energy management. It enables manufacturers to move beyond the limitations of traditional energy management processes, which rely on inconsistent human input for naïve approximation and maybe basic linear regression or, at best, a GLM model that considers temperature. The framework's ability to provide near real-time and accurate energy predictions can help manufacturers identify energy-saving opportunities, better understand their processes, make data-driven decisions, and automate a piece of their ISO 50001 certification. The framework's straightforwardness and adaptability make it applicable to various manufacturing processes and industries. A limitation of the framework is the requirement for accurate and available production data and predictions. This framework could be applied throughout the plant if production data and predictions are accurate and available. The research showed that ML models could be successfully applied to facility-level energy predictions at smaller time scales for improved accuracy. Complex models, such as random forest and principal component regression, were sometimes but not always more accurate than simpler models, such as naïve approximation and linear regression.

For manufacturers, the effort is better spent automating the data collection framework and improving data quality and reliability than optimizing model selection. For future research, the authors recommend investigating different artificial intelligence methods in larger datasets, implementing the automated data collection framework, developing use cases besides ISO 50001 certification, and testing other predictors besides production, dry bulb temperature, week of the year, month, and day of the week. A sensitivity analysis of temperature prediction should also be considered. The authors used the historical average for temperature to make predictions, but this does not consider extreme weather, so different prediction sets could be developed for extreme weather.

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APPENDIX

Assembly

The assembly process is more hand-tool-driven than robotics. No significant equipment changes occurred between 2022 and 2023, but production increased, and moved to more electric vehicle production. The daily results of the assembly process are given in **Table 14**. The average daily energy consumption was 58,600 kWh, and the standard deviation of RMSE was $\sim 1,000$. Prediction accuracy decreased from 2023 Q4 to 2023 Q1 and improved for 2024 Q1. Prediction accuracy decreased when comparing Daily 2023 Q4 and Daily 2024 Q1 A and B, where B uses the energy data from one year ago as a predictor. The ML models were able to improve on the naïve models but could not improve on the linear model in 2023 Q1 or 2024 Q1.

Table 15 shows the weekly results of the assembly process. The average weekly energy consumption of the assembly shop was 408,000 kWh in 2023, and the standard deviation of RMSE was about 13,000 kWh. Prediction accuracy decreased from 2023 Q4 to 2023 Q1, though not as severely as in **Table 14** for daily prediction, and then improved for 2024 Q1. Adding the data from one year prior as a predictor in 2023 Q4 improved the training performance but had mixed results when used for prediction. The ML models improved on the naïve and linear models in 2023 Q1 and 2023 Q4 but not in 2024 Q1.

Table 16 gives the monthly results of the assembly process. The average monthly energy consumption of the assembly shop was 1,750,000 kWh, and the standard deviation of RMSE was about 100,000 kWh. Prediction accuracy decreased from 2023 Q4 to 2023 Q1 and increased to a high level in 2024 Q1. The energy data from last year was not added as a predictor to 2023 Q4 because there wasn't enough training data, but it was added for

Table 14: Results of daily assembly shop model training

Time Period	Parameter	Model Type							
		Historic	Average	Linear	GLMNET	PCR	KNN	RF	BRNN
2023 Q1	RMSE (Training)		15,312	7,657	4,733	4,775	9,920	11,266	4,534
	R^2 (Training)		0.00	0.76	0.91	0.91	0.73	0.89	0.91
	RMSE (Actual)	16,080	13,191	7,300	7,627	7,679	10,659	9,617	7,834
	R^2 (Actual)	0.73	0.00	0.83	0.85	0.85	0.79	0.86	0.83
2023 Q4 A	RMSE (Training)	17,409	15,396	7,965	5,783	5,756	7,260	5,734	6,220
	R^2 (Training)	0.24	0.00	0.73	0.86	0.86	0.78	0.87	0.83
	RMSE (Actual)	16,436	19,472	24,411	18,633	18,608	14,538	18,757	23,882
	R^2 (Actual)	0.39	0.00	0.00	0.09	0.09	0.36	0.08	0.00
2023 Q4 B	RMSE (Training)	17,409	15,396	7,965	6,001	4,780	6,298	4,267	3,897
	R^2 (Training)	0.24	0.00	0.73	0.84	0.90	0.80	0.93	0.93
	RMSE (Actual)	16,436	19,472	24,411	21,822	21,271	13,972	18,950	23,251
	R^2 (Actual)	0.39	0.00	0.00	0.02	0.01	0.40	0.08	0.01
2024 Q1 A	RMSE (Training)	16,988	15,908	9,575	6,740	10,356	13,893	8,471	6,568
	R^2 (Training)	0.32	0.00	0.63	0.83	0.61	0.40	0.84	0.84
	RMSE (Actual)	20,120	16,804	8,321	10,044	13,692	19,672	14,192	9,985
	R^2 (Actual)	0.03	0.00	0.77	0.81	0.64	0.61	0.78	0.81
2024 Q1 B	RMSE (Training)	16,988	15,908	9,575	5,302	5,263	7,573	4,659	4,923
	R^2 (Training)	0.32	0.00	0.63	0.89	0.89	0.80	0.92	0.91
	RMSE (Actual)	20,120	16,804	8,321	8,441	8,341	12,438	9,249	9,355
	R^2 (Actual)	0.03	0.00	0.77	0.81	0.81	0.70	0.85	0.84

Table 15: Results of weekly assembly shop model training

Time Period	Parameter	Model Type							
		Historic	Average	Linear	GLMNET	PCR	KNN	RF	BRNN
2023 Q1	RMSE (Training)		52,182	35,366	33,472	30,211	26,820	32,923	24,567
	R^2 (Training)		0.00	0.66	0.70	0.66	0.74	0.75	0.67
	RMSE (Actual)	75,220	34,297	31,968	21,609	27,232	34,451	31,692	36,957
	R^2 (Actual)	0.18	0.00	0.35	0.42	0.45	0.12	0.28	0.09
2023 Q4 A	RMSE (Training)	78,096	56,150	38,932	32,244	33,718	29,433	31,986	31,164
	R^2 (Training)	0.21	0.00	0.45	0.69	0.64	0.73	0.73	0.71
	RMSE (Actual)	75,803	103,924	83,733	70,474	68,693	73,895	70,567	67,713
	R^2 (Actual)	0.67	0.00	0.23	0.70	0.72	0.63	0.78	0.79
2023 Q4 B	RMSE (Training)	78,096	56,150	38,932	29,435	29,515	28,280	36,526	24,926
	R^2 (Training)	0.21	0.00	0.45	0.93	0.93	0.89	0.42	0.72
	RMSE (Actual)	75,803	103,924	83,733	61,223	57,416	74,220	83,150	49,462
	R^2 (Actual)	0.67	0.00	0.23	0.72	0.73	0.66	0.61	0.78
2024 Q1 A	RMSE (Training)	77,134	66,623	57,635	33,170	32,774	30,512	34,024	32,100
	R^2 (Training)	0.42	0.00	0.42	0.71	0.71	0.80	0.75	0.76
	RMSE (Actual)	86,288	88,004	36,587	68,900	70,096	61,070	65,864	50,578
	R^2 (Actual)	0.38	0.00	0.83	0.75	0.75	0.79	0.74	0.84
2024 Q1 B	RMSE (Training)	77,134	66,623	57,635	30,910	30,910	32,955	37,381	25,074
	R^2 (Training)	0.42	0.00	0.42	0.79	0.79	0.79	0.75	0.85
	RMSE (Actual)	86,288	88,004	36,587	67,905	74,861	61,521	73,195	81,244
	R^2 (Actual)	0.38	0.00	0.83	0.74	0.74	0.80	0.59	0.84

Table 16: Results of monthly assembly shop model training

Time Period	Parameter	Model Type						
		Historic	Average	Linear	GLMNET	PCR	KNN	BRNN
2023 Q1	RMSE (Training)		197,900	240,919	227,904	199,246		
	R^2 (Training)		0.00	0.65	0.78	0.71		
	RMSE (Actual)	309,741	326,770	141,556	56,614	55,116		
	R^2 (Actual)	0.18	0.00	0.80	0.75	0.76		
2023 Q4	RMSE (Training)	245,553	113,581	160,298	118,651	113,108	95,892	112,953
	R^2 (Training)	0.85	0.00	0.77	0.71	0.73	0.81	0.49
	RMSE (Actual)	342,804	398,250	374,923	338,428	333,659	313,087	347,613
	R^2 (Actual)	1.00	0.00	0.15	0.67	0.61	0.65	0.71
2024 Q1 A	RMSE (Training)	263,020	205,093	237,222	121,327	118,610	141,539	149,992
	R^2 (Training)	0.60	0.00	0.99	0.76	0.81	0.63	0.64
	RMSE (Actual)	217,806	151,258	59,200	198,204	210,728	249,189	206,641
	R^2 (Actual)	0.25	0.00	0.95	0.93	0.91	0.88	0.93
2024 Q1 B	RMSE (Training)	263,020	205,093	237,222	204,262	198,608		
	R^2 (Training)	0.60	0.00	0.99	1.00	0.99		
	RMSE (Actual)	217,806	151,258	59,200	108,648	100,846		
	R^2 (Actual)	0.25	0.00	0.95	0.94	0.94		

2024 Q1 B, which explains why the KNN and BRNN models did not work for 2024 Q1 B. The RF model did not work in any of the time periods. KNN became available with more than one year of data. ML models significantly improved accuracy compared to naïve and linear in 2023 Q1, insignificantly improved RMSE in 2023 Q4, and did not improve against linear in 2024 Q1.

Paint

The painting process is almost entirely robotic. No significant process changes occurred between 2022 and 2023, but production increased, and robotics were added. **Table 17** shows the daily prediction results for the paint process. The average daily energy consumption of the paint shop was 137,000 kWh in 2023, and the standard deviation of RMSE was about 3,500 kWh. Prediction accuracy fell significantly from 2023 Q1 to 2023 Q4 but improved in 2024 Q1. The most likely cause is the larger time period between production predictions. Adding the energy data from one year ago as a predictor had mixed results when comparing Daily 2023 Q4 A with Daily 2023 Q4 B. The ML models improved on the naïve and linear in most models, but it is unclear which model will be best in advance. Comparing 2023 Q4 A and B and 2024 Q1 A and B, in this case, it is better to have fewer data points and add the energy from last year's predictor.

Table 18 shows the weekly results of the paint process. The average weekly energy consumption in the paint shop was 956,000 kWh, and the standard deviation of RMSE was about 100,000 kWh. The prediction accuracy was best in 2023 Q1 according to RMSE, decreased in 2023 Q4, and stayed about the same in 2024 Q1, though R^2 improved. The 'energy data from the previous year' predictor decreased the prediction

Table 17: Results of daily paint shop model training

Time Period	Parameter	Model Type							
		Historic	Average	Linear	GLMNET	PCR	KNN	RF	BRNN
2023 Q1	RMSE (Training)		44,368	19,378	20,837	20,384	30,314	16,229	17,829
	R^2 (Training)		0.00	0.80	0.77	0.78	0.71	0.87	0.82
	RMSE (Actual)	48,017	38,083	18,475	17,080	17,804	23,335	15,754	17,468
	R^2 (Actual)	0.63	0.00	0.86	0.86	0.86	0.86	0.90	0.89
2023 Q4 A	RMSE (Training)	48,959	42,474	19,001	18,980	18,812	15,731	22,087	15,588
	R^2 (Training)	0.10	0.00	0.81	0.80	0.80	0.86	0.83	0.87
	RMSE (Actual)	44,075	42,849	60,281	54,436	54,818	59,459	41,851	58,686
	R^2 (Actual)	0.37	0.00	0.00	0.01	0.01	0.02	0.11	0.00
2023 Q4 B	RMSE (Training)	48,959	42,474	19,001	16,465	16,398	21,848	13,160	15,536
	R^2 (Training)	0.10	0.00	0.81	0.82	0.82	0.65	0.88	0.83
	RMSE (Actual)	44,075	42,849	60,281	58,745	59,753	33,828	49,966	55,902
	R^2 (Actual)	0.37	0.00	0.00	0.00	0.00	0.34	0.03	0.00
2024 Q1 A	RMSE (Training)	46,950	38,894	20,466	21,258	21,216	28,645	17,084	17,585
	R^2 (Training)	0.20	0.00	0.71	0.77	0.77	0.59	0.85	0.84
	RMSE (Actual)	51,195	45,512	34,246	52,924	52,962	42,894	41,670	40,496
	R^2 (Actual)	0.04	0.00	0.50	0.26	0.26	0.24	0.30	0.32
2024 Q1 B	RMSE (Training)	46,950	38,894	20,466	18,438	18,247	20,213	14,835	14,810
	R^2 (Training)	0.20	0.00	0.71	0.76	0.76	0.77	0.84	0.84
	RMSE (Actual)	51,195	45,512	34,246	35,670	35,744	38,636	30,729	33,414
	R^2 (Actual)	0.04	0.00	0.50	0.50	0.54	0.39	0.54	0.49

Table 18: Results of weekly paint shop model training

Time Period	Parameter	Model Type							
		Historic	Average	Linear	GLMNET	PCR	KNN	RF	BRNN
2023 Q1	RMSE (Training)		146,524	62,475	61,884	63,412	82,614	82,291	64,279
	R^2 (Training)		0.00	0.85	0.84	0.84	0.75	0.80	0.84
	RMSE (Actual)	180,142	343,888	79,420	70,357	78,674	66,431	66,089	63,193
	R^2 (Actual)	0.12	0.00	0.23	0.24	0.23	0.25	0.07	0.14
2023 Q4 A	RMSE (Training)	209,886	154,557	61,519	62,394	70,766	73,959	81,432	58,131
	R^2 (Training)	0.01	0.00	0.81	0.81	0.78	0.75	0.73	0.82
	RMSE (Actual)	189,218	228,054	153,305	151,124	151,124	146,692	159,584	138,733
	R^2 (Actual)	0.63	0.00	0.50	0.51	0.51	0.64	0.52	0.62
2023 Q4 B	RMSE (Training)	209,886	154,557	61,519	61,665	61,694	71,290	91,609	68,477
	R^2 (Training)	0.01	0.00	0.81	0.89	0.89	0.73	0.44	0.74
	RMSE (Actual)	189,218	228,054	153,305	176,921	176,916	211,926	181,527	152,407
	R^2 (Actual)	0.63	0.00	0.50	0.32	0.32	0.02	0.41	0.51
2024 Q1 A	RMSE (Training)	201,401	169,952	93,298	51,997	52,582	62,606	62,235	52,162
	R^2 (Training)	0.17	0.00	0.88	0.82	0.82	0.78	0.80	0.83
	RMSE (Actual)	242,688	261,967	137,637	156,351	165,697	125,986	139,460	111,233
	R^2 (Actual)	0.41	0.00	0.81	0.66	0.67	0.76	0.69	0.82
2024 Q1 B	RMSE (Training)	201,401	169,952	93,298	85,256	86,346	108,465	95,284	87,986
	R^2 (Training)	0.17	0.00	0.88	0.82	0.85	0.72	0.78	0.86
	RMSE (Actual)	242,688	261,967	137,637	130,600	132,931	183,532	168,898	126,133
	R^2 (Actual)	0.41	0.00	0.81	0.78	0.78	0.78	0.74	0.89

accuracy on training and actual results. The ML models nearly always improved on the naïve models, and some of the ML models improved on linear models. The monthly paint process model results are given in **Table 19**. Prediction accuracy was fair in 2023 Q1, decreased significantly in 2023 Q4, and then was at the highest levels seen in this research for 2024 Q1. Because the historical naïve model fits the actual results' shape but consistently predicts too low, the R^2 of the historical naïve model is better than other models, but the RMSE is not. The results show that it is possible to improve on linear and naïve predictions by using ML models.

Table 19: Results of monthly paint shop model training

Time Period	Parameter	Model Type						
		Historic	Average	Linear	GLMNET	PCR	KNN	BRNN
2023 Q1	RMSE (Training)		411,711	87,117	80,919	86,222		
	R ² (Training)		0.00	0.97	0.97	0.97		
	RMSE (Actual)	746,943	555,007	133,179	230,830	179,902		
	R ² (Actual)	0.71	0.00	0.73	0.68	0.69		
2023 Q4	RMSE (Training)	661,834	382,636	118,913	131,181	126,773	134,763	122,933
	R ² (Training)	0.00	0.00	0.93	0.95	0.95	0.79	0.94
	RMSE (Actual)	760,446	607,307	505,900	453,618	454,308	402,379	436,012
	R ² (Actual)	0.15	0.00	0.03	0.01	0.01	0.34	0.03
2024 Q1 A	RMSE (Training)	704,602	368,219	222,891	90,046	90,729	218,414	134,467
	R ² (Training)	0.01	0.00	0.97	0.98	0.98	0.65	0.93
	RMSE (Actual)	543,199	608,067	311,394	571,267	576,672	251,302	500,319
	R ² (Actual)	0.29	0.00	1.00	0.65	0.65	0.80	0.71
2024 Q1 B	RMSE (Training)	704,602	368,219	222,891	328,567	342,848		
	R ² (Training)	0.01	0.00	0.97	0.97	0.97		
	RMSE (Actual)	543,199	608,067	311,394	152,201	132,343		
	R ² (Actual)	0.29	0.00	1.00	1.00	1.00		

CHAPTER III
IMPLEMENTATION, IMPACT, CHALLENGES, AND OPPORTUNITIES OF
THE DOE BETTER PLANTS PROGRAM

This article is finished but hasn't been published anywhere, and it will not be before I turn in the final version of my ETD, so I didn't include a publication statement.

Concept creation and original manuscript draft were prepared by David Vance. Thomas Wenning prepared data collection and analysis and provided review. Mingzhou Jin, Christopher Price, and Sachin U. Nimbalkar provided review.

Abstract

This research reviews the United States Better Plants (BP) program, which aids the industrial sector in reducing emissions and improving efficiency through voluntary partnerships. A generic overview of the implementation of the BP program is presented to aid other government agencies in developing voluntary emission reduction programs. The status and future challenges of voluntary emission reduction programs for deep decarbonization are reviewed. The partners' historic and predicted emissions are assessed considering the net-zero 2050 goal. The authors discuss how the decarbonization landscape will change and how the BP program can effectively serve its partners. This goal of reaching net-zero emissions by 2050 in the U.S. industrial sector is of utmost importance, and this research aims to ensure the right path to achieve it.

Introduction

This article presents an overview of the Better Plants (BP) program, operated by the US Department of Energy (DOE) under the Industrial Efficiency & Decarbonization Office (IEDO). The BP program aids the United States industrial sector in setting and meeting energy, water, waste, and carbon emission reduction targets. Manufacturers participating in the program pledge to reduce one of these metrics by 25% over 10 years in exchange for recognition, technical support, and energy-saving resources (IEDO et al., 2023). The

BP program releases annual progress updates that showcase partners and highlight specific high-level metrics. This research aims to provide a deeper analysis than has been performed in those progress updates, aimed at the scientific community so that they may reproduce the results. The research presents a generic overview of the implementation of the BP program so that other government agencies can develop their own voluntary emissions reporting programs. Finally, the research assesses the historic and predicted emission reductions of the BP program in consideration of the net-zero 2050 goal.

The BP program is a partner of the Better Buildings Initiative, as shown in **Figure 8**. The Better Buildings Initiative also includes the Better Climate Challenge, which challenges companies from any sector to an increased 50% emissions reduction, and the Better Buildings Challenge, which focuses on commercial and residential sectors. The mission of the Better Buildings Initiative is to “Improve energy efficiency in the commercial, industrial, and residential sectors and accelerate cost-effective decarbonization solutions across the economy.” The authors have provided technical support to the BP program, and the BP program and industrial sector was chosen based on this experience.

U.S. Goal of Net-Zero Greenhouse Gas Emissions by 2050

The United States has established a goal of net-zero greenhouse gas emissions by no later than 2050 across all sectors, as outlined in (US Whitehouse, 2021). The core strategies of this ambitious goal are decarbonizing electricity, electrifying end uses and switching to clean fuels, cutting energy waste, reducing methane and other non-carbon dioxide greenhouse gas emissions, and scaling up carbon dioxide removal (Fam & Fam, 2024).

Figure 9 shows the United States' historic and projected emissions under the 2050 net zero goal. The 26-28% reduction from 2005 levels milestone for 2025 is next year.



225+ partners commit to reduce portfolio-wide GHG emissions at least 50% over 10 years



285+ partners commit to reduce portfolio-wide energy-use intensity at least 20% over 10 years



270+ industrial partners commit to reduce portfolio-wide energy-use intensity at least 25% over 10 years

Figure 8: Overview of the Better Buildings Initiative

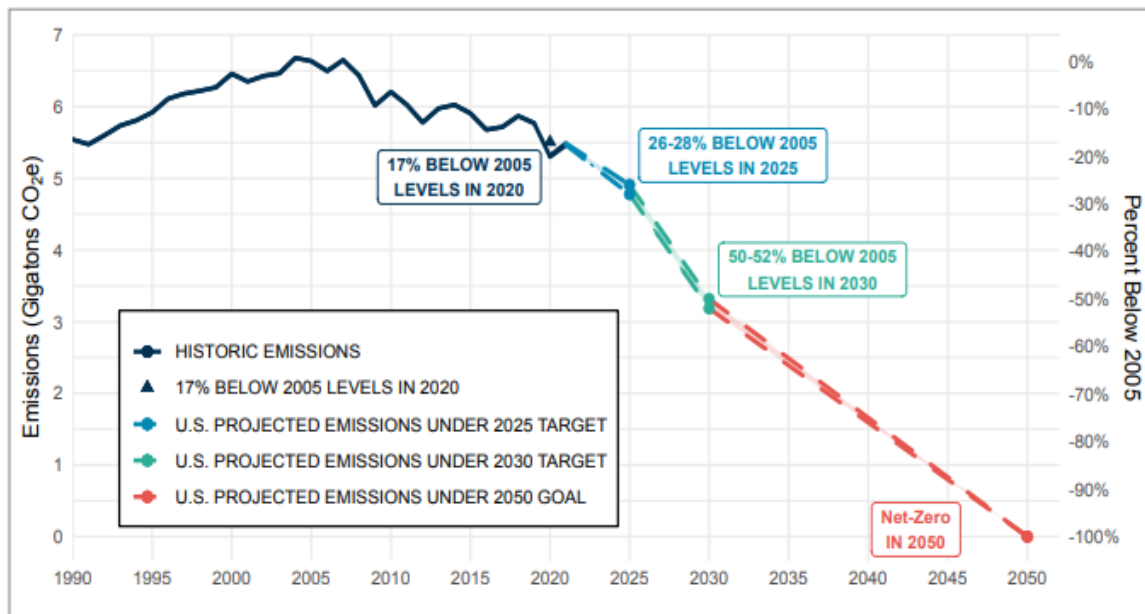


Figure 9: Historic and predicted US emissions under the 2050 goal for net-zero (US Whitehouse, 2021)

Greenhouse Gas Emissions Reporting in the United States

The U.S. Greenhouse Gas Reporting Program (GHGRP), the Manufacturing Energy Consumption Survey (MECS), and the Inventory of U.S. Greenhouse Gas Emissions and Sinks are the three primary involuntary greenhouse gas emissions reporting programs in the United States. Each program collects nationwide emissions data but doesn't work in partnership with industry and has different scopes.

The GHGRP was implemented in 2020 through the U.S. Environmental Protection Agency (EPA) to guide future GHG policies. The program directs thousands of U.S. facilities to report their annual emissions by GHG and production activity and sometimes goes to the process or unit levels (Tomar, 2023). In 2023, the US program covered over 7,500 facilities that emitted a combined 2.58 billion tons of carbon dioxide equivalent (T CO₂e), roughly half of total U.S. emissions (US EPA, 2024b). The GHGRP requires facilities that emit 25,000 T CO₂e per year, inject CO₂ underground, and providers of certain fossil fuels and industrial gases to report annually for as long as they fall within those criteria (US EPA, 2024a).

Figure 10 shows a summary of the GHG Reporting Program according to the number of facilities reported by subsector and their average emissions per reporter. The GHG Reporting Program covers the majority of U.S. emissions. Still, the focus is on power plants, petroleum and natural gas systems, and heavy direct emitting facilities and not directly on the industrial sector. The GHG Reporting Program does not require the entire parent company to report their emissions, only select facilities. The purpose is for businesses and others to trace and assess facilities' GHG emissions and for communities to identify high-emitting operations in their region (US EPA, 2024a). The BP

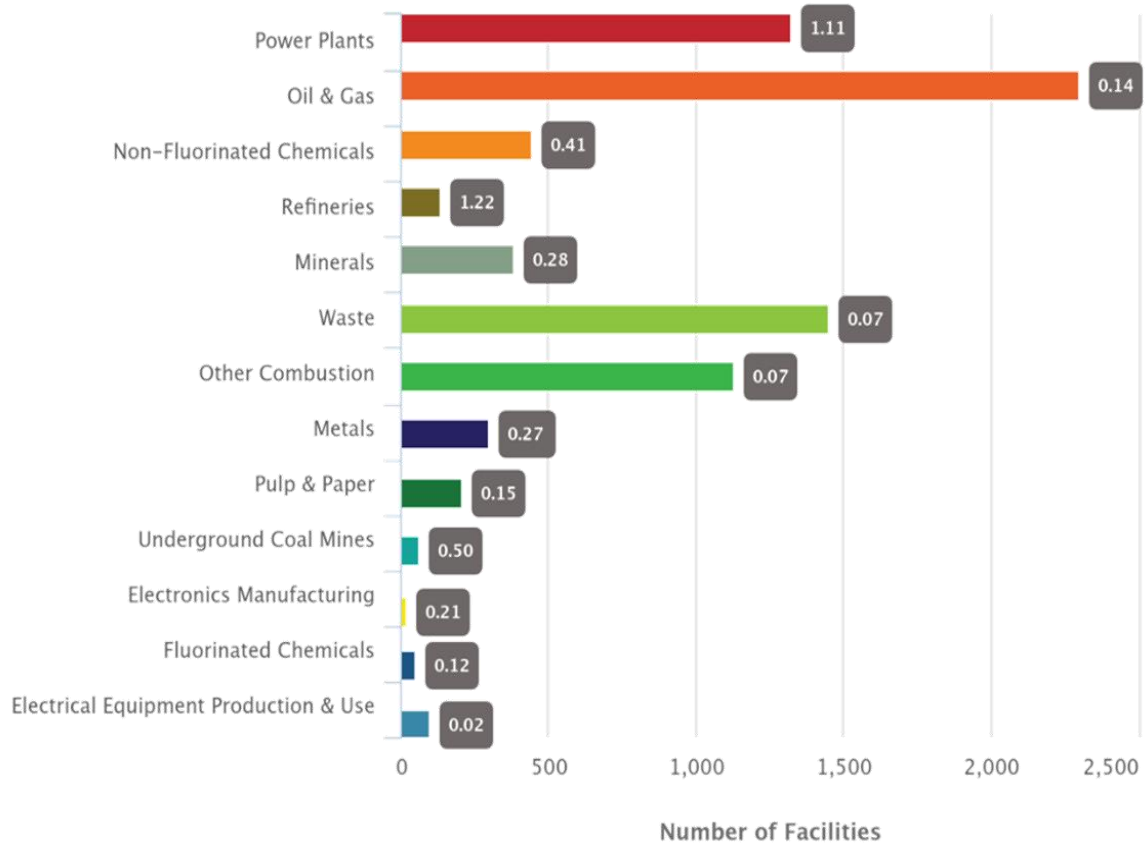


Figure 10: GHG Reporting Program number of facilities by sub-sector (US EPA, 2024b)

program is necessary because a mechanism is needed for reporting and reducing emissions that aren't included in the GHG Reporting Program. Avenues for technical support and industry collaboration are also needed.

The U.S. Energy Information Administration (EIA) performs national sample studies for residential, commercial building, and manufacturing sectors every 4 years. The Manufacturing Energy Consumption Survey (MECS) focuses on energy-related characteristics, energy usage, expenditures, and other questions involving energy activities for the industrial sector. The MECS results on participation in energy management programs and summaries of specific industrial subsectors are interesting for this research. MECS, like GHGRP, doesn't provide partnerships or technical assistance. The 2018 MECS survey reviewed the industrial subsectors' energy consumption in several ways, summarized in **Table 20**. According to MECS, the top 5 subsectors by total energy consumption are Chemical Manufacturing, Petroleum and Coal Products Manufacturing, Paper Manufacturing, Primary Metal Manufacturing, and Food Manufacturing. MECS 2018 reviewed the most common energy consumption improvement programs in the United States, as shown in **Figure 11**. ENERGY STAR was the most popular energy consumption improvement program, with 43% of manufacturing establishments participating, while BP had 9% (U.S. EIA, 2021). The 2018 MECS was based on the respondents' answers, not the BP dataset.

The final GHG reporting program in the US is the 'Inventory of U.S. Greenhouse Gas Emissions and Sinks' (Inventory) developed by the US EPA. The 'Inventory' is an annual report that tracks US GHG emissions and sinks by source, sector, and type of gas, tracing back to 1990. The purpose of the inventory is to provide a comprehensive

Table 20: Summary of 2018 MECS industrial subsector analysis

Sub-sector	# of Establishments	Total Energy Consumption (TBtu)
325 - Chemical Manufacturing	8,902	7,141
324 - Petroleum and Coal Products Manufacturing	1,883	4,245
322 - Paper Manufacturing	3,009	2,041
331 - Primary Metal Manufacturing	3,226	1,511
311 - Food Manufacturing	15,842	1,161
327 - Nonmetallic Mineral Product Manufacturing	12,035	846
321 - Wood Product Manufacturing	9,435	388
336 - Transportation Equipment Manufacturing	7,103	348
326 - Plastics and Rubber Manufacturing	8,317	257
332 - Fabricated Metal Product Manufacturing	37,949	257
333 - Machinery Manufacturing	14,919	148
312 - Beverage and Tobacco Product Manufacturing	3,938	118
334 - Computer and Electronic Product Manufacturing	6,646	110
335 - Electrical Equipment, Appliance, and Component Mfg.	3,295	85
313 - Textile Mills	1,360	64
323 - Printing and Related Support Activities	12,614	60
337 - Furniture and Related Product Manufacturing	8,347	37
314 - Textile Product Mills	4,116	22
315 - Apparel Manufacturing	3,856	4
316 - Leather and Allied Product Manufacturing	655	2
339 - Miscellaneous Manufacturing	13,679	61
TOTAL	181,126	18,907

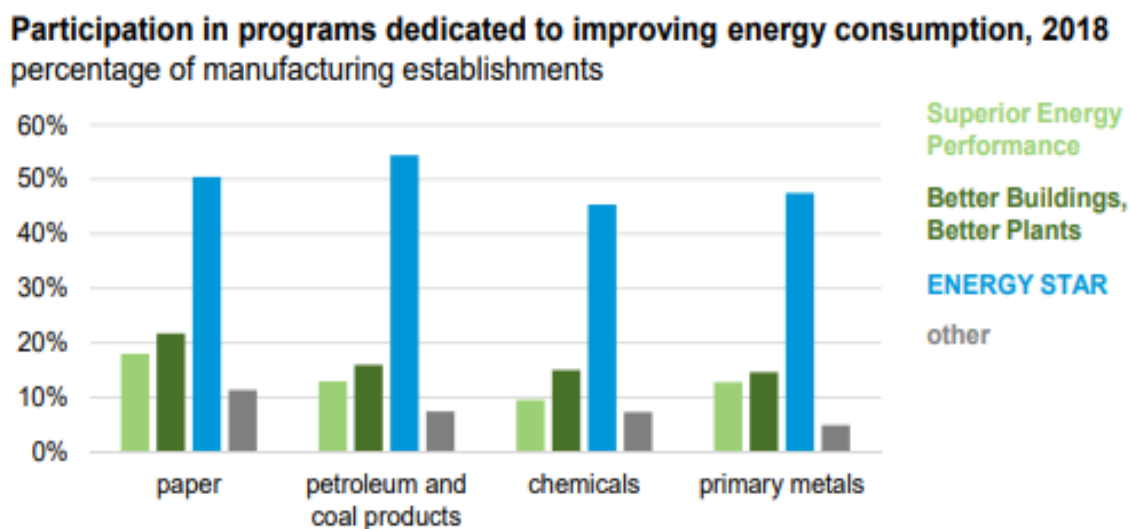


Figure 11: Participation in programs dedicated to improving energy consumption according to 2018 MECS (U.S. EIA, 2021)

accounting of total GHG emissions for all man-made sources in the US, including carbon dioxide removal by “sinks” from the management of lands in their current use or as lands converted to other uses (US EPA, 2024c). Like GHGRP and MECS, it is involuntary, not focused on the industrial sector, and doesn’t provide partnership or support.

Industrial Sector

The U.S. Department of Energy’s (DOE) “Industrial Decarbonization Roadmap” (US DOE, 2022) outlines the four key pillars for the US goal of net-zero GHG emissions, more specifically for the industrial sector, including (i) energy efficiency, (ii) industrial electrification, (iii) low-carbon fuels, feedstock, and energy sources (LCFFES), and (iv) carbon capture, utilization, and storage (CCUS). **Table 21** describes these pillars.

Although the importance and applicability of these pillars vary across industrial subsectors, all four are required.

Table 21: Four Industrial Decarbonization pillars (US DOE, 2022)

Energy Efficiency	Industrial Electrification	Low-Carbon Fuels, Feedstocks, and Energy Sources (LCFES)	Carbon Capture, Utilization, and Storage (CCUS)
Energy efficiency advancements minimize industrial energy demand, directly reducing the GHG emissions associated with fossil fuel combustion	Industrial process technologies that utilize electricity for energy rather than combusting fossil fuels directly, enable the sector to leverage advancements in low-carbon electricity from both grid and onsite generation sources.	Substitution of low- and no-carbon fuels and feedstocks for fossil fuels can further reduce combustion-associated emissions for industrial processes.	This multi-component strategy for mitigating difficult-to-abate emissions involves capturing generated CO ₂ before it can enter the atmosphere; utilizing captured CO ₂ whenever possible; and storing captured CO ₂ long-term to avoid atmospheric release.

The Industrial Decarbonization Roadmap (US DOE, 2022) identifies and directs research focus to the five largest CO₂ emitting industries that decarbonization technologies can have the most significant effect: petroleum refining, chemicals, iron and steel, cement, and food and beverage. Those sectors represent about 51% of energy-related CO₂ emissions in the U.S. industrial sector. **Figure 12** shows an example scenario for reaching net zero in 2050, including impacts from the four decarbonization pillars. In this scenario, the industrial sector must act quickly to evolve through several stages, including realizing early emission reductions, advancing and demonstrating technologies, and building knowledge and capacity for future technologies. The industrial decarbonization roadmap outlines the research and development focuses for industrial decarbonization from 2020 to 2050 across the decarbonization pillars (US DOE, 2022). Early opportunities set the stage for later transformative and crosscutting impacts, and preparation is necessary for an extended period of research and development and commercialization of decarbonization technologies. The BP program historically focuses on energy efficiency, but the other three pillars must become core activities.

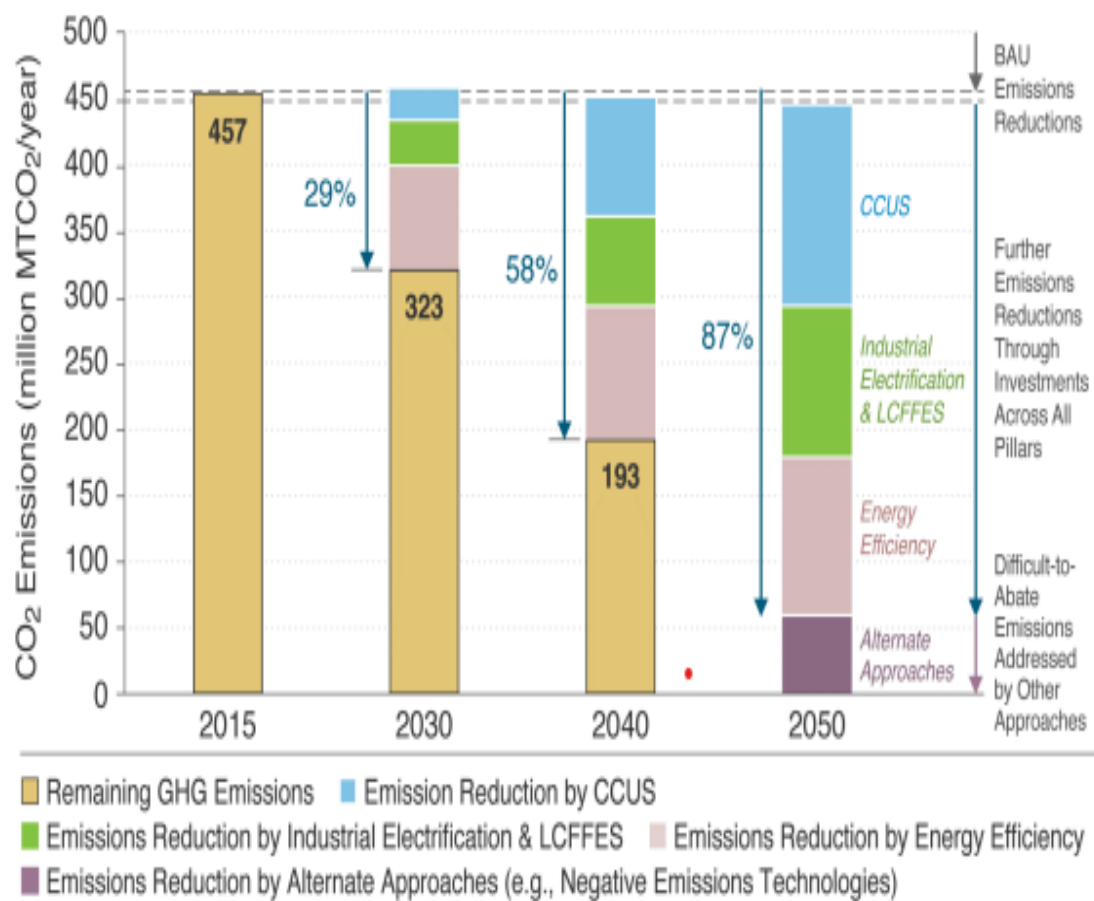


Figure 12: The Path to Net-Zero Industrial CO₂ emissions in the US for five industrial subsectors, 2015 – 2050. (US DOE, 2022)

According to White House research, the technology investments for non-carbon fuels, energy efficiency, and electrification are estimated to lower overall industrial sector CO₂ emissions by 69 – 95% by 2050 (US Whitehouse, 2021). The industrial sector's projected final energy use from 2005 – 2050, shown in **Figure 13** demonstrates the pathway from fossil fuels to clean hydrogen, electricity, and biofuels.

This research aims to analyze the Better Plants program's impact on the Industrial Decarbonization Roadmap and the White House Industrial Net-Zero 2050 goal and make policy recommendations to maximize the program's effectiveness.

Industry Classification Schemes (ICS)

Industry Classification Schemes (ICS) must be introduced as they are fundamental for many types of business and economic research (Phillips & Ormsby, 2016). The most widely used ISCs are the Standard Industrial Classification (SIC) system and the North American Industry Classification System (NAICS). The SIC is obsolete, and NAICS is preferred, but the four-digit SIC codes are still used today. For this research, the focus on NAICS because it is the most used and allows progress on the MECS 2018 analysis, but there are other ISC schemes. There are some well-documented challenges with using NAICS, including that large conglomerates have many NAICS codes, a significant percentage (~8%) of manufacturing was reclassified to “Services” in the change from SIC to NAICS (Fort & Klimek, 2016), NAICS is a self-assigned system with over 19,000 possible codes, resulting in many small businesses and startups choosing the wrong category, and there is sometimes confusion about what is meant by primary business activity (is it by square foot, revenue, energy, employees?).

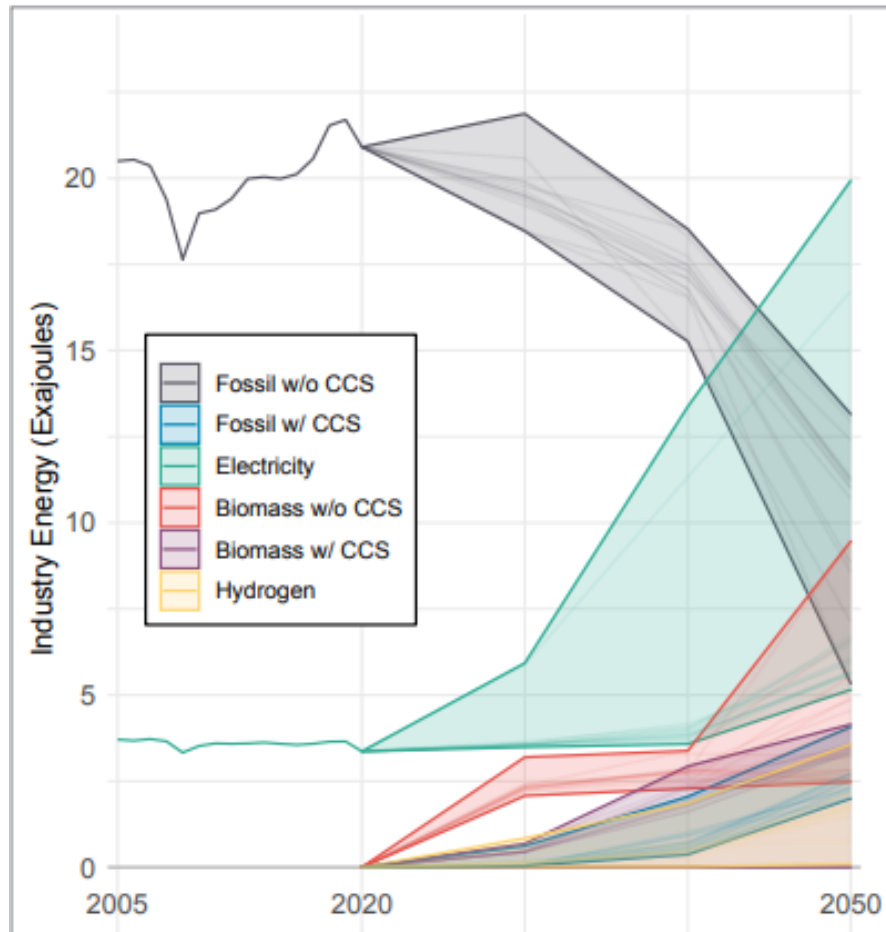


Figure 13: Industrial sector final energy use 2005 – 2050 (US Whitehouse, 2021)

Research Questions

The study is guided by the following research questions:

1. What lessons and implementation advice can be given to other government agencies?
2. What are the upcoming challenges presented by net-zero 2050 and deep decarbonization for voluntary emission reduction programs?
3. What type of company is likely to join the BP program?
 - a. Public or private?
 - b. Small, Medium, or large? (Based on employees and revenue)
 - c. Specific sectors?
4. What are the possible scenarios for the scope of the BP program and progress toward net zero 2050?

Overview of the BP Program

This section provides an overview of the BP program, including its history, offerings, and research highlights. The purpose is to include enough generic details on the implementation so that other government agencies may establish voluntary emission programs. **Figure 14** and **Figure 15** track the history of the BP program from 2009 to 2020. The BP program began in 2009 as the ‘Save Energy Now LEADER’ program with 32 industrial partners. More information about the early history and success of the Save Energy Now program can be found at (Wright et al., 2007). In 2011, the program merged with the Better Buildings Initiative to become the BP program. Since then, the BP program has consistently added process equipment initiatives, partnerships, and technology pilot programs. Water and wastewater treatment agencies were included because similar expertise is required. Pilot programs are necessary to scale and offer new



Figure 14: History of the BP program from 2009 to 2014 (BP Progress Update 2021)

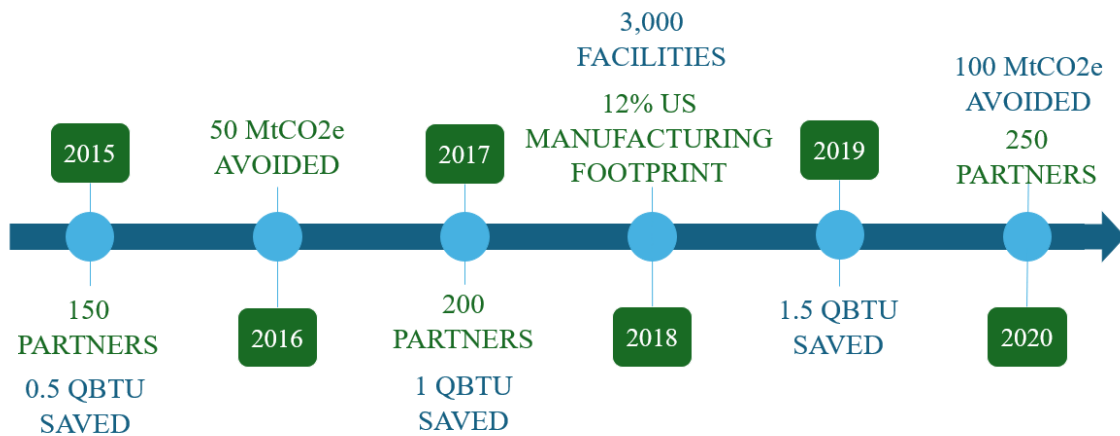


Figure 15: History of the BP program from 2015 to 2021 (BP Progress Update 2021)

resources. As partnerships grow and savings are realized, the goal is to develop a momentum that will propel the program so that its usefulness is apparent. The program provides value by strengthening manufacturing, reducing costs, and improving efficiency without considering emissions.

Program Offerings

This section will explain the current BP program offerings and essential components so that other government agencies may implement them effectively. The program aims to provide energy and emission reduction expertise to a range of manufacturing companies and highlight their accomplishments. The program is public-facing and open-source. The tools and research are intended to be shared to benefit manufacturing efficiency.

The partnership levels include Better Plants, Better Plants Challenge, and Better Climate Challenge. They are designed with a low entry level and a higher level to aspire to.

The offerings include recognition, technical support, training and education, energy-saving resources, peer exchange opportunities, and additional opportunities such as access to research and development through the DOE's national lab network. The essential components of each offering and their success so far will be described.

Recognition

The BP program highlights partner achievements and leadership by featuring case studies, highlighting success stories in materials and publications, facilitating recognition from DOE leadership, and highlighting partner accomplishments at events and site visits.

The annual progress update highlights goal achievers, new program and challenge partners, new case studies, and Better Project and Better Practice winners.

The Better Buildings Solution Center is available at (US DOE, 2024b) and is organized into implementation models, showcase projects, and solutions at a glance. The description of each solution type and the number of solutions is included in **Table 22**. Each year, Better Practice and Better Project Awards are presented during the Better Buildings, Better Plants Summit, recognizing leadership and innovation in adopting emissions, energy, water, and waste savings projects. The Better Practice Award is given to partners for achievements in applying and encouraging energy management practices, principles, and procedures. The Better Project Award recognizes partners for accomplishments in applying energy, water, and waste projects at specific facilities. Award winners are selected based on magnitude, replicability, innovation, and additional benefits. **Table 23** summarizes the Better Practice Awards given in 2024. **Table 24** summarizes the Better Project Awards given in 2024. These awards are the result of innovation and progress. They should be celebrated because they prove efficiency improvements and encourage US manufacturing to collaborate, share ideas, and compete beneficially. None of these are publishable independently, but they show the type of projects and practices that a similar program should highlight and celebrate.

Table 22: Contributions of BP program to the Better Buildings Solution Center

Solution Type	Description	Quantity
Implementation Models	Corporate-level solutions that overcome specific barriers to energy efficiency	45
Showcase Projects	Near-term energy-saving projects at individual facilities	72
Solutions at a Glance	Short and informative snapshots of a successful or innovative idea or practice	11

Table 23: Summary of Better Practice Awards given in 2024.

Company	Project Title	Estimated Savings
General Mills	Driving Efficiency Improvements Without Financial or Staff Investment	45,000 MTCO ₂ e, \$8 million
Oxychem	Helping Community School Districts Reduce Energy Consumption	375,000 kWh, \$34,000
Stellantis	Energy Treasure Hunt 2.0 Results in Energy Savings	2,800,000 kWh
Texas Instruments	An LED Best Practice Roadmap Program for Global Operations	27,000 MTCO ₂ e, \$5.3 million
The Chemours Company	Energy Efficiency Improvements through an Internal Bonus Metric	288,500 MWh
Toyota	Achieving Energy, Water, and Waste Reductions Through the Dealership Environmental Excellence Program (D.E.E.P)	7,000 MTCO ₂ e

Table 24: Summary of Better Project Awards given in 2024

Company	Project Title	Estimated Savings
3M	Hutchinson Steam-Traps Monitoring and Communication System	4,000 MTCO ₂ e
The Chemours Company	Distillation Column Waste Reduction via Increased Recycling	\$1 million
EnerSys	Cold Cube Production System Eliminates Energy-Intensive Process	20,000 kg (lead) 500,000 gallons (water)
PepsiCo Foods	PepsiCo Foods North America's Air Compressor Heat Recovery	400 MTCO ₂ e 500,000 gallons (water)
FMC Corporation	Cooling Tower Water and Energy Optimization	\$72,000
General Motors	Steam Elimination and Heat Recovery at Fort Wayne Assembly Plant	140,000 MTCO ₂ e
HNI Corporation	New Air Curtain Reduces Natural Gas Consumption	30% reduction of natural gas demand
Intralox	A Sustainable Approach to Injection Mold Optimization	60% reduction of waste produced, \$60,000
Nestle Health Science	State-of-the-Art Water Savings Project at Eau Claire, Wisconsin Factory	26 million gallons (water) 37 MTCO ₂ e
Nissan	Compressor Control Optimization	7% reduction in electricity demand
The Sherwin-Williams Company	Orlando Solar Pilot Reduced Carbon Emissions	680 MTCO ₂ e
Trane Technologies	Water Savings at La Crosse, Wisconsin Campus	53 million gallons (water)
Volvo Group	Renewable Diesel (HVO100) for Production Testing at Hagerstown Plant	14% reduction in emissions
Waupaca Foundry, Inc.	Smart Ventilation System	1,600 MTCO ₂ e

Technical Support

Every program partner is assigned a technical account manager (TAM) with energy management and efficiency expertise. The TAMs guide partners in establishing energy baselines, developing energy management goals, identifying energy-saving prospects, and tracking metrics. TAMs also provide support in using the DOE software tools and connecting partners with federal, state, and local resources. The selection of TAMs is critical for the implementation of the program because these are the experts chosen to represent the program in the field. TAMs should be selected based on the following criteria: energy management, technical assistance, energy efficiency, and process knowledge.

Training and Education

Partners can participate in three different learning experiences, including In-Plant Training (INPLT), virtual training, and decarbonization and energy boot camps.

Virtual training is an online version of an INPLT led by an expert that trains participants on identifying, implementing, and replicating energy-saving projects. The sessions range from 4 to 8 weeks and are available to all US manufacturers. There have been 39 courses.

The BP program offers a decarbonization and energy boot camp. This three-day workshop, which is open to anyone, combines classroom instruction, demonstration of diagnostic equipment and software, hands-on activities, and tours.

INPLTs are unique events led by professionals who train plant employees in various energy processes. So far, there have been 204 INPLTs, resulting in \$54 million in energy cost savings and 2,800+ workers. The topic list includes 50001 Ready, energy treasure hunts, compressed air, process heating, steam systems, fan systems, refrigeration, pump

systems, water efficiency, and wastewater treatment. The focus of an INPLT is training and building capacity among participants.

The BP program has assembled shared knowledge, resources, and best practices into an online learning library. The library has 3 BP program, 7 general efficiency, 7 system-specific, 4 tool and resource, 10 learn from your peers, 9 pre-INPLT, and 9 miscellaneous webinars. These resources are freely available and not restricted to partners.

Energy Saving Resources

The BP program has developed many tools to increase efficiency. The categories of tools and calculators are energy management, energy systems, and carbon, water, and waste management. The energy management tools include 50001 Ready Navigator, VERIFI, Plant Energy Profiler, Energy Footprint Tool, Energy Performance Indicator (EnPI), EnPI Lite, Project Implementation Toolkit, and Automated Register of Implemented Actions. The energy systems analysis tools include MEASUR and REopt. The carbon management tools include Carbon Inventory Calculator, Carbon Project Implementation Tracker, Electrification Impact Calculator, and Low Carbon Pilot Action Plan Tool. The waste management tools include Waste Stream Energy Content Calculator. The water management tool is Plant Water Profiler Tool. There are several tools coming soon. The VERIFI and MEASUR tools were built using open-source framework so that other programs can more easily develop their own versions.

The BP Diagnostic Equipment Program (DEP) loans diagnostic equipment to partners free of charge. Currently, 23 different tools can be loaned to collect energy data and improve system performance. **Table 25** summarizes the available tools and their use so that another program can determine the best equipment to include. A DEP provides value

Table 25: List of diagnostic equipment available from BP DEP

Equipment	Purpose
Acoustic Imager	Creates a sound map of an area to identify leaks
Anemometer	Measures wind speed
Combustion Analyzer	Quantifies excess oxygen in boiler/combustion process exhaust
Conductivity Meter	Quantifies dissolved solids in boiler water
Current Transformer	Quantifies the electric current flowing to a system or component
Digital Manometer	Used with a pitot tube to measure differential pressure
Digital Thermometer	Measures temperature when combined with a thermocouple
HOBO Data Logger	General purpose data logger with multiple inputs
Infrared Camera	Camera for evaluating structures, seals, insulation, hot spots, etc.
Infrared Thermometer	Used for non-contact temperature measurements
Laser Distance Meter	Records distance with a laser
Light Meter	Records lighting measurements in footcandles and lumens.
Pitot Tube	Measures airflow velocity
Power Logger	Logs power in low voltage electrical components
Pressure Transducer	Records pressure for use with a data logger
Pyrometer	Measures temperature in high-temperature applications
Strobe Tachometer	Determines the rotating speed of a shaft without contact
Temp/RH Logger	Measures and logs temperature and relative humidity
Thermocouple	Measures temperature for various applications
Thermocouple Logger	Records process temperature when combined with a thermocouple
Time of Use Logger	Logs on/off status of processes for time-of-use calculations
Ultrasonic Flow Meter	Measures the flow rate in fluid systems
Ultrasonic Leak Detector	Identifies leaks in compressed air or steam systems

to partners by allowing them to try out energy-saving equipment before purchasing, enabling participation in system-specific training events, and removing an equipment purchase from the payback calculations for some energy-saving tasks. A DEP also provides value to the program by testing new equipment and keeping equipment available for demonstration and application purposes. This list should not be considered exhaustive because equipment could be added, including, for example, a blower door, vibration sensor, and borescope. The DEP program should evolve naturally as companies have specific needs, funding becomes available, and new technologies emerge.

Highlights of BP Program Research

(Guo et al., 2023) discusses the various workforce development pursuits, including INPLT virtual INPLT, and in-person boot camps. (Guo et al., 2020) shares some practices that BP program partners applied for COVID-19 mitigation, including symptom screening, maintaining physical distance, sanitizing surfaces, wearing appropriate face masks, maintaining excellent personal hygiene, and configuring HVAC.

The BP program has published several reports focusing on providing guidance to companies including:

- Demand Response in Industrial Facilities: Peak Electric Demand
- Energy Intensity Baseline and Tracking Summary Guide
- Industrial Energy Management During a Pandemic
- Practices Implemented by DOE BP Program Partners to Mitigate COVID-19
- US DOE BP Program Energy Treasure Hunt Exchange Toolkit
- US DOE BP Program's Approach to Manufacturing Workforce Development

Literature Review

This review analyzes the literature on voluntary and involuntary energy and emission programs for the industrial sector, upcoming challenges, and methods for determining their effect on the net-zero 2050 goal.

Voluntary Emission Reduction Programs for Industrial Sector

Voluntary energy efficiency and GHG emissions reduction agreement programs can be divided into three broad categories: entirely voluntary, programs using a threat of imminent regulations or taxes as motivation, and programs that are implemented in conjunction with present tax policy or regulation (Price, 2005). (Sundaramoorthy et al., 2023) showed the effect of select industrial decarbonization programs worldwide and their uptake by companies from energy-intensive industries.

The EnergyStar program has the longest history and most involvement of any voluntary energy-related program worldwide. For this reason, it is used as an example, and the literature review begins by assessing how EnergyStar has reviewed its success.

(Brown et al., 2002) reviewed the status of the Energy Star program on its 10-year anniversary in 2002 and estimated its impact on emissions for the next 10 years.

Assessment of Net Zero 2050 Challenges

Much of the literature focuses on reviewing policy and technologies for deep decarbonization in energy-intensive industries. For example, (Nurdiawati & Urban, 2021) reviewed the status, technologies, and policies for deep decarbonization of energy-intensive industries, including steel, mining and minerals, cement, pulp and paper, and refinery, using Sweden as a reference case. (van Sluisveld et al., 2021) assessed the decarbonization pathways of iron & steel, clinker & cement, chemicals, and pulp & paper

sectors in the context of a global 2050 net-zero carbon emissions objective using the IMAGE integrated assessment model. Huo et al. (2023) analyzed the feasibility of utilizing captured unabatable industrial waste CO₂ as a feedstock for the global chemical industry transition to net-zero.

(Browning et al., 2023) provides an overview of the Energy Modeling Forum (EMF) 37 study on deep decarbonization and high electrification, documents the scenario design, provides a roadmap for future research, and summarizes and compares results for net-zero CO₂ by 2050 scenarios for the United States. In all of the 37 studies, negative emissions technologies, in addition to land sinks, were required to achieve net-zero CO₂ emissions. For industry, all models predict the replacement of petroleum and natural gas with a different mix of electricity, hydrogen, and biomass-based fuels.

(Worrell & Boyd, 2022) performs a bottom-up approach to estimate the emission reduction potential from the four “pillars” that support deep decarbonization of manufacturing (DDM): energy efficiency, material efficiency, industry-specific, and power grid. The analysis showed a feasible 86% reduction in carbon emissions in the industrial sector. The paper summarizes opportunities for selected industry subsectors. Another area of research in the field of assessing net-zero 2050 challenges involves discussing how global climate policy should develop based on pathways and priorities. (Åhman et al., 2017) discusses how global climate policy for decarbonization should develop. (C. G. F. Bataille, 2020) reasons for the formation of regional and sectoral transition policies, implemented through comprehensive policy packages. The research describes the physical and policy routes to a net-zero emissions industry and discusses the priorities and responsibilities for developed, in-transition, and less developed

countries. (C. Bataille et al., 2021) outlines the options, geography implications, system modelling implications, and policy for heavy industry global net-zero emissions.

Approach for Progress Updates

This section will discuss the analysis methodology of BP annual progress updates, found at (US DOE, 2024a), including calculations for the percent of U.S. manufacturing energy footprint, cost savings, annual energy intensity improvement, and amount of avoided CO₂ emissions.

Calculation of % of U.S. Manufacturing Energy Footprint

The following calculation for % of US manufacturing energy footprint is performed using the available MECS data for total US manufacturing energy consumption. The 2018 MECS was published in 2021, the 2014 MECS was published in 2017, and the 2010 MECS was published in 2013. This could also be accomplished using the EIA Monthly Energy Outlook dataset.

% of US Manufacturing Energy Footprint

$$= \frac{\text{Total Partner Primary Energy Consumption}}{\text{Total US Manufacturing Energy Consumption}}$$

Calculation of Cost Savings

Because the cost savings from a blended dataset includes several fuel types, a calculation is performed for blended energy cost, which is multiplied by the amount of energy saved to determine a cost savings. The calculation for cost savings is performed according to the following equation:

$$\begin{aligned}
& \text{Energy Cost Savings} \left(\frac{\text{Million \$}}{\text{year}} \right) \\
&= \text{Energy Used} \left(\frac{\text{TBtu}}{\text{year}} \right) \times \text{Blended Energy Cost} \left(\frac{\$}{\text{MMBtu}} \right) \\
&\quad \times \frac{1,000,000 \text{ MMBtu}}{\text{TBtu}} \times \frac{\text{Million \$}}{1,000,000 \$}
\end{aligned}$$

Table 26 provides an overview of the % energy savings by fuel type and unit energy costs used for calculations in BP progress updates from 2018 to 2020. The source for ‘% Energy Source Energy Savings by Fuel Type’ is data collected from the Save Energy Now Program from 2006 to 2010 (Wright et al., 2010). The source for the unit energy costs comes from EIA annual energy updates.

The formula for blended energy cost is:

$$\begin{aligned}
& \text{Blended Energy Cost} \left(\frac{\$}{\text{MMBtu}} \right) \\
&= \sum_{\text{For each fuel type}} (\% \text{ Energy Savings}) \times (\text{Unit Energy Cost})
\end{aligned}$$

Calculation of Average Annual Energy Intensity Improvement

The process for this calculation is explained in the DOE BP Report titled “Energy Intensity Baseline and Tracking Guidance”, which can be used with the companion tool Energy Performance Indicator software tool (EnPI). The company first chooses a boundary and baseline year. Then, relevant variables are identified, and data is gathered. A regression analysis is performed to normalize the facility data, and then, finally, the change in energy intensity from the baseline year is calculated. Each year, the baseline is

Table 26: Energy Cost Assumptions used in Progress Reports from 2018 to 2020

Fuel Type	% Energy Savings by Fuel Type	2018 Unit Energy Costs (\$/MMBtu)	2019 Unit Energy Costs (\$/MMBtu)	2020 Unit Energy Costs (\$/MMBtu)
Natural Gas	64.79%	\$4.08	\$3.80	\$3.20
Electricity	20.82%	\$5.97	\$5.89	\$5.74
Coal	9.88%	\$2.45	\$2.45	\$2.56
Residual fuel oil	4.41%	\$11.10	\$10.58	\$8.32
Distillate fuel oil	0.10%	\$16.93	\$15.80	\$11.34
Propane	0.01%	\$10.67	\$6.98	\$5.81
Other - Blended	-	\$4.64	\$4.41	\$3.90

adjusted based on relevant variables, usually weather and production, and also adjustments may be made to the boundary, such as when a facility is added or removed.

$$\text{Annual Energy Intensity Improvement (\%)} = \frac{\text{New Energy Savings}}{\text{Adjusted Baseline}}$$

Calculation of Avoided CO₂ Emissions

Avoided CO₂ emissions are calculated using the % Energy Savings by Fuel Type assumption from the cost savings calculation with an avoided CO₂ emissions coefficient. For electricity, the emissions factor is calculated from regional output emission rates according to eGRID. For all other fuel types, the emissions factor is provided by the Inventory of U.S. Greenhouse Gas Emissions and Sinks as shown in **Table 27**. The calculations must be repeated for each year.

Avoided CO₂ emissions

$$= \sum_{\text{For each fuel type}} (\text{Energy Savings}) \times (\text{Avoided CO}_2 \text{ emissions factor})$$

The formula used in **Table 27** to convert lb CO₂ / MWh to Metric Ton CO₂ / MMBtu is:

$$\frac{1 \text{ lb CO}_2 \text{ e}}{\text{MWh}} = \frac{1 \text{ lb CO}_2 \text{ e}}{\text{MWh}} \times \frac{1 \text{ Metric Ton}}{2204.6 \text{ lb}} \times \frac{1 \text{ MWh}}{3.412 \text{ MMBtu}} = \frac{0.000133 \text{ Metric Ton CO}_2 \text{ e}}{\text{MMBTu}}$$

To convert from kg Co2 /MMBTu to Metric Ton Co2 e/MMBTu, the formula is:

$$\frac{1 \text{ kg CO}_2 \text{ e}}{\text{MMBTu}} = \frac{1 \text{ kg CO}_2 \text{ e}}{\text{MMBTu}} \times \frac{1 \text{ Metric Ton CO}_2 \text{ e}}{1000 \text{ kg}} = \frac{0.001 \text{ Metric Ton CO}_2 \text{ e}}{\text{MMBTu}}$$

Table 27: Avoided CO₂ emissions factor for different fuel types (Updated for 2023)

Fuel Type	Avoided CO ₂ Emissions Factor	Unit	Avoided CO ₂ Emissions Factor (Metric Ton CO ₂ e/MMBtu)
Natural Gas	52.91	kg CO ₂ / MMBtu	0.053
Electricity	1,412.5	lb CO ₂ / MWh	0.055
Coal	95.99	kg CO ₂ / MMBtu	0.096
Residual Fuel Oil	75.09	kg CO ₂ / MMBtu	0.075
Distillate Fuel Oil	74.14	kg CO ₂ / MMBtu	0.074
Propane	62.88	kg CO ₂ / MMBtu	0.063

2023 Case Study

The BP dataset was provided with an agreement of confidentiality for all company data. Because the data is voluntary and self-reported, checks and explanations are required at each step of the reporting process. Checks are required for reporting and baseline year, number of plants, energy consumption, baseline adjustments, energy savings, change in energy intensity, and total change in energy intensity vs. cost savings.

In some years, the annual updates did not report all the metrics. This analysis includes data from 2008 to 2020 for the number of partner companies, approximate number of facilities, percent of U.S. manufacturing energy footprint, annual energy savings, annual cost savings, annual energy intensity improvement, and cumulative avoided CO₂ emissions. Numbers may be different from published progress updates. This is because the progress updates are released in the Fall of the following year, some companies report late, or the data was determined unverifiable.

Program Accomplishments

This section shows the outcomes of the analysis of the 2023 BP dataset, including a summary by year, NAICS classification, company size, and energy use. At the end of this section, some general findings are discussed.

Table 28 shows a summary of the BP program by year. It was created from a combination of BP annual progress updates, a 2020 BP performance report, and the 2023 raw BP dataset. Because some of the values from 2021 to 2023 are estimates that haven't been confirmed, it was decided not to include them here. These values haven't been collectively displayed anywhere before.

Table 29 shows a summary of the BP program by manufacturing sector NAICS for the year 2023. Some self-reported values, such as Total Partner Energy Consumption, have not yet been verified. Subsectors with less than five partners have not been included to protect the companies' identity. The transportation equipment subsector has the most partner companies and the chemical manufacturing subsector accounts for the most partner energy consumption. The BP program has captured the highest percentage of the transportation equipment subsector. Companies outside of the manufacturing sector have not been included.

Industry Net-Zero 2050 in Perspective

This section will discuss historical and predicted emission reduction scenarios to put the net zero 2050 goal in perspective. Assuming that the industrial sector follows the milestones of the overall US economy according to (US Whitehouse, 2021), then the following milestones exist for Industrial Net Zero 2050:

Table 28: Summary of the BP program by year

Year	# of Partner Companies	Approximate # of Facilities	% of U.S. Manufacturing Energy Footprint	Total Energy Savings (TBtu)	Total Cost Savings (Billion)	Average Annual Energy Intensity Improvement (%)	Cumulative Avoided CO ₂ Emissions (Million Metric Ton)
2009	13	332	~1%	27	0.1	8.8%	1.6
2010	96	1,880	4.4%	32	0.2	7.0%	1.9
2011	107	1,931	4.0%	99	0.5	5.1%	6.0
2012	116	2,114	4.0%	200	1.0	4.6%	12.1
2013	143	2,219	10.5%	320	1.7	4.1%	19.2
2014	160	2,337	10.8%	458	2.4	3.1%	27.6
2015	186	2,611	11.1%	637	3.3	3.1%	38.4
2016	191	2,845	11.4%	853	4.3	3.1%	51.5
2017	206	2,900	11.4%	1,097	5.5	2.7%	66.2
2018	234	3,172	12.0%	1,364	6.8	2.8%	82.3
2019	246	3,355	12.9%	1,653	8.2	2.6%	99.7
2020	256	3,464	13.8%	1,915	9.5	2.5%	115.6

* Data from 2021 to 2023 was not included because some values were estimated

Table 29: Summary of the BP program by manufacturing subsector

Subsector	#of Partner Companies	#of Facilities	Total Partner Energy Consumption (TBtu)
325 - Chemical	35	578	755
322 - Paper	11	91	180
331 - Primary Metal	22	90	577
311 - Food	25	468	287
327 - Nonmetallic Mineral Product	10	159	130
336 - Transportation Equipment	44	362	196
326 - Plastics and Rubber	16	141	51
332 - Fabricated Metal Product	27	150	30
333 – Machinery	20	493	30
312 - Beverage and Tobacco Product	7	76	11
334 - Computer and Electronic Product	12	194	52
335 - Electrical Equipment, Appliance, and Component	13	180	44
337 - Furniture and Related Product	5	59	11
TOTAL	254	2,451	1,424

* Data for Miscellaneous, Leather, Petroleum & Coal Products, Textile Products, and Printing subsectors were removed to protect individual company information.

- 2005 – 1,687 MtCO₂e (Baseline)
- 2020 – 1,400 MtCO₂e (17% below Baseline)
- 2025 – 1,248 MtCO₂e (26% below Baseline)
- 2030 – 844 MtCO₂e (50% below Baseline)
- 2050 – 0 MtCO₂e (Net Zero 2050)

Table 30 shows the result of a rolling 3%, 4%, and 5% reduction from 2023 levels. The US has already achieved the 17% below 2005 levels in 2020 milestone, so the following analysis looks to the 2025, 2030, and 2050 milestones. A ‘rolling’ reduction is performed because the value will never approach zero if a 3% reduction year to year is assumed.

From **Table 30**, a 3% reduction can meet the 2025 goal, but a 5% reduction is required to meet the 2030 goal, and a greater than 5% reduction is required to meet the 2050 goal.

Table 31 compares the BP program vs. the total industrial sector. The industrial sector GDP data comes from Bureau of Economic Analysis data. The total industrial sector energy and emissions data comes from EIA monthly energy outlook data. The annual emissions reduction is calculated by the following equation:

$$\text{Annual Emissions Reduction (\%)} = \frac{\text{Emissions}_{\text{current}} - \text{Emissions}_{\text{previous}}}{\text{Emissions}_{\text{previous}}} \times 100$$

The BP program annual energy intensity reduction (%) comes from the summary of the BP program by year in **Table 28**, plus estimates for 2021 to 2023. The total industrial sector's average annual energy intensity reduction (%) is 2.5%, while the BP program's annual energy intensity reduction is 3.8%.

Table 30: Results of a rolling 3%, 4%, and 5% reduction from 2023

YEAR	Industrial Total MtCO ₂ e (Rolling 3% Reduction)	Industrial Total MtCO ₂ e (Rolling 4% Reduction)	Industrial Total MtCO ₂ e (Rolling 5% Reduction)
2023	1,331	1,331	1,331
2025	1,242	1,213	1,183
2030	1,030	929	829
2035	832	667	503
2040	665	459	261
2045	528	305	104
2050	419	198	16

Table 31: BP vs. the total industrial sector

FY	Total Industrial Sector						BP
	GDP (Billion \$)	Emissions (MtCO ₂ e)	Total End Use Consumption (TBtu)	Energy Intensity (TBtu / Billion \$)	Emissions Reduction (%)	Energy Intensity Reduction (%)	Energy Intensity Reduction (%)
2005	1,693	1,687	24,799	14.65	-	-	-
2006	1,794	1,673	24,886	13.87	-0.8%	-5.3%	-
2007	1,845	1,672	24,780	13.43	-0.1%	-3.2%	-
2008	1,799	1,619	23,887	13.28	-3.2%	-1.1%	-5.7%
2009	1,696	1,409	21,787	12.85	-13.0%	-3.3%	-8.8%
2010	1,788	1,512	23,631	13.22	7.3%	2.9%	-7.0%
2011	1,863	1,503	23,876	12.82	-0.6%	-3.0%	-5.1%
2012	1,921	1,486	24,128	12.56	-1.1%	-2.0%	-4.6%
2013	1,971	1,505	24,719	12.54	1.3%	-0.1%	-4.1%
2014	2,010	1,516	24,853	12.36	0.7%	-1.4%	-3.1%
2015	2,071	1,457	24,777	11.96	-3.9%	-3.2%	-3.1%
2016	2,035	1,426	24,882	12.23	-2.1%	2.2%	-3.1%
2017	2,110	1,432	25,309	11.99	0.4%	-1.9%	-2.7%
2018	2,262	1,459	26,278	11.62	1.9%	-3.1%	-2.8%
2019	2,269	1,432	26,366	11.62	-1.9%	0.0%	-2.6%
2020	2,150	1,328	25,403	11.82	-7.3%	1.7%	-2.5%
2021	2,409	1,385	26,247	10.90	4.3%	-7.8%	-2.0%
2022	2,685	1,359	25,970	9.67	-1.9%	-11.2%	-1.8%
2023	2,840	1,331	26,041	9.17	-2.1%	-5.2%	-1.8%
AVERAGE:					-1.2%	-2.5%	-3.8%

[1] FY = Fiscal Year

[2] GDP = Gross Domestic Product

Discussion

Acceleration

The total industrial sector has had an average 1.2% reduction in emissions, but a 3% reduction is required to meet the 2025 goal, and a 5% reduction is required to meet the 2030 goal. For this reason, emissions reductions must accelerate by 2030.

In the short term, reducing energy intensity is equivalent to reducing emissions, but once energy efficiency is no longer viable, the other three decarbonization pillars are required.

Deep Decarbonization

The BP program's scope should not be restricted to energy efficiency and management. As decarbonization and net-zero 2050 progress, the BP program's importance should also progress. There are not enough experts in deep decarbonization to be at every manufacturing facility. The current framework encourages energy intensity reductions in the BP program and the Better Climate Challenge program is used for emissions reduction.

Incentives

There are two incentives that have historically been used by voluntary emissions reduction programs that the BP program has not implemented: access to an emissions trading market and relief from regulations and taxes.

Disincentives

So far, the BP program has operated completely using incentives, but there is historical precedent for combining them with disincentives such as taxes and regulations.

General Recommendations

This type of voluntary program must sometimes evolve its goals and offerings to match the current national and industrial landscape. The recent decarbonization and smart manufacturing movements have allowed the program to develop new technical offerings and realize new relevance. Staying on top of technological trends will make the program more valuable for its partners.

Ultimately, because it is a voluntary program, a certain amount of marketing and outreach is required. The goal is to provide clear value so companies feel confident recommending the program. Some companies will stay for three or four goal periods or even to net-zero emissions corporation-wide. Other companies will seek help with one specific goal and feel they have learned what they need from the program. The goal of net zero has an end, and the BP program wants to see companies reach that goal. Once a company reaches net-zero, it should realize this success and focus on other companies. The program should be developed with the Pareto Principle or 80/20 rule. This suggests finding 20% of companies in the country that will make 80% of emission reductions. Of those companies that join the program, 20% will aspire to an even higher goal, and the program motivates them to do so with the Better Climate Challenge. It would be great if 100% of the companies in the country joined the program, but it may be more effective to focus on the 20%. Some companies can independently reduce emissions, but BP program partners are expected to reduce emissions at a higher rate than the rest of the industry. These companies' emission reductions will naturally change over time according to their progress. Many companies can make significant emission reductions through energy efficiency and management, but those savings may not persist.

The political pendulum might swing away from emission reductions, and the program should highlight its cost savings and benefit to US manufacturing competitiveness. It is essential that the program exhibit resilience and value even without political support for emissions reductions. A long-term goal like net zero 2050 requires periods of rebuilding and resilience and periods of all-out effort.

Some regions of the world may prioritize water or waste savings over energy. Partners often come to the program with a specific goal and should receive help to achieve it.

Conclusions

A generic overview of the Better Plants (BP) program was presented to assist other government agencies in developing a voluntary emission reduction program of their own. Then, the approach for calculations in the annual progress updates was explained. Finally, the industrial net zero 2050 goal was put into perspective by comparing current reduction achievements from the total industrial sector and BP program with what will be necessary to achieve 2030 and 2050 goals.

The industrial sector has made progress towards emissions reductions and has already met the 17% reduction target from 2005 levels for 2020. However, more aggressive measures will be needed to meet future milestones, specifically aiming for a 3% reduction to meet the 2025 goal, 5% to meet the 2030 target, and even greater than 5% to meet the 2050 target.

The BP program has demonstrated an average 3.8% annual energy intensity reduction compared to the total industrial sector annual energy intensity reduction of 2.5%. In the short term, energy intensity improvement is a useful metric. However, as energy

efficiency measures are exhausted, there is a growing need for the BP program to evolve beyond energy efficiency.

Historically, two incentives have been implemented which the BP program could consider adopting, including access to emissions trading markets and regulatory relief. The US government has never integrated disincentives into emissions reduction policy, and it will be tricky politically, but research has shown that combining disincentives could yield better program participation and emissions reductions.

The focus should shift toward preparing the industry for deep decarbonization by fostering an environment of innovation and collaboration. Enhancing expertise in decarbonization and leveraging existing frameworks will be vital for accomplishing the ambitious net-zero 2050 target.

In conclusion, the BP program has been vital for the progress that has been made, but emissions reduction must accelerate to achieve net zero 2050 goals. To maximize the effectiveness of emission reduction efforts, the US government should consider adopting additional incentives and combining them with disincentives.

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CONCLUSION

This dissertation is motivated by the two concurrent revolutions occurring in manufacturing: the fourth industrial revolution and the goal of net-zero greenhouse gas emissions by 2050 per the Paris Climate Accord. The aim of this multi-part dissertation is to guide energy management improvements according to smart manufacturing concepts to achieve the net-zero 2050 goals.

Through three chapters, the research reviews the applicability of smart manufacturing maturity models, demonstrates an application of a machine learning framework for energy prediction, and analyzes the Better Plants (BP) program to determine policy recommendations for achieving net-zero 2050 goals.

The major research gaps identified include: 1) there is a lack understanding of the smart manufacturing topic, especially across industries and including energy management; 2) there have not been any studies identified that predict energy consumption at the facility level using machine learning or at a time scale shorter than a year; 3) there is a lack of research showing how to acquire, process, and implement data in industrial processes; 4) the BP program has not been reviewed in some time and the progress toward net-zero 2050 should be analyzed periodically.

Chapter I, “Smart Manufacturing Maturity Models and Their Applicability: A Review”, reviewed existing smart manufacturing maturity models’ dimensions and maturity levels to assess their applicability. The research uncovered 10 critical dimensions of SM maturity: 1) Information Technology (IT) & Cyber-Physical System (CPS) & Data; 2) Strategy & Organization; 3) Supply Chain & Logistics; 4) Products & Services; 5) Culture & Employees; 6) Technology & Capabilities; 7) Customer & Market; 8)

Cybersecurity & Risk; 9) Leadership & Management; and 10) Governance & Compliance. Each dimension is discussed, and some example maturity items are outlined. Governance & Compliance, Cybersecurity & Risk, and Leadership & Management were lacking focus in many of the models. IT & CPS & Data, Strategy & Organization, and Products & Services were the most important dimensions.

The research in Chapter I resulted in the survey for smart manufacturing in the Chapter I Appendix, which was used to develop a program called the East Tennessee Initiative for Smart Energy Management (ETISE).

Chapter II, “Next-Level Energy Management in Manufacturing: Facility-Level Energy Digital Twin Framework Based on Machine Learning and Automated Data Collection”, proposes a facility-level energy digital twin framework based on machine learning and automated data collection and implements it with an automotive OEM partner.

Increasingly complex models were tested on daily, weekly, and monthly datasets. The conclusions from Chapter II are that the naïve prediction can be improved upon in almost every case, complex models require more data to work, and it is possible to improve prediction accuracy using complex models. The significant challenges discovered include the availability of reliable and quality energy and production data and the human effort required to implement the model. The future work recommended from Chapter II is to investigate different artificial intelligence methods in larger datasets, implement more pieces of the automated data collection framework, test other predictors, perform a sensitivity analysis of temperature prediction, and use different temperature prediction datasets that consider extreme weather.

Chapter III, “Implementation, Impact, Challenges, and Opportunities of the Department of Energy Better Plants Program”, reviews the Department of Energy (DOE) Better Plants (BP) program. The BP program aids the US industrial sector in reducing emissions and improving efficiency through voluntary partnerships. A generic overview of the program and its offerings was presented so that another government agency could reproduce the results. The calculations performed in BP annual progress updates are explained. The BP program accomplishments are summarized according to year and subsector. The BP program has averaged an annual energy intensity reduction of 3.8% per year, while the total industrial sector has an average annual energy intensity reduction of 2.5% and annual emission reduction of 1.2%. Analysis of what is needed to meet different milestones showed that a 3% annual emission reduction is required to meet the 2025 goal, 5% reduction to meet the 2030 goal, and reductions exceeding 5% to meet the net-zero 2050 goal. In conclusion, the BP program has been crucial for emissions reductions, but acceleration is required to meet further goals. To maximize the effectiveness of the BP program, the US government should consider adopting additional incentives and combining them with disincentives.

The industrial sector is at a crucial point in its history, and the concurrent revolutions of smart manufacturing and net-zero 2050 must be navigated to ensure US competitiveness and leadership. This research has discussed the intersection of energy management and smart manufacturing, developed a case study showing smart manufacturing for energy management, and demonstrated the challenges of industrial net-zero 2050.

VITA

David Vance was born on October 20th, 1993, in Hopkinsville, Kentucky. He became interested in math and engineering at an early age through working for his father's construction company and grandfather's workshop. When considering colleges, he was set on studying renewable energy, and so he decided to attend Indiana University Purdue University (IUPUI). David graduated with a bachelor's degree in energy engineering in 2016 and a master's degree in mechanical engineering in 2018. While at IUPUI he became involved in the Industrial Assessment Center (IAC) program which shifted his research passion to energy topics in the industrial sector. He joined an IAC internship program which placed him at Oak Ridge National Laboratory. After completing his ORNL internship, joining the Bredesen Center at the University of Tennessee, Knoxville seemed like a natural progression. After graduation, David plans a career in energy policy and program management in Washington D.C. David is excited to apply his passion for sustainability and commitment to supporting U.S. manufacturing to contribute to ambitious challenges, such as achieving net-zero U.S. industrial sector emissions.