AN ABSTRACT OF THE DISSERTATION OF

Arvind Shankar Raman for the degree of Doctor of Philosophy in Mechanical Engineering presented on March 11, 2022.

Title: An Information Modeling Framework for Support of Sustainable Manufacturing System Design Decision Making

Abstract approved: ____

Karl R. Haapala

Manufacturing technology has continuously evolved and advanced over the past century; this has led to an increase in the production of consumer and industrial goods driven by simultaneous growth in population and wealth. Despite the resulting economic and labor growth, environmental impacts of manufacturing have increased dramatically due to the dependence on exhaustible material and energy resources necessary to meet these growing product demands. Increasing awareness and concern over these impacts has encouraged sustainable thinking toward managing material resources, alternative energy sources, and advanced manufacturing technologies. However, the primary emphasis of manufacturing system design decision making has

remained focused on the reduction of cost of goods sold (in discrete part production) and total production cost (in continuous production). Manufacturing system design decision makers face challenges in defining, evaluating, and implementing sustainable manufacturing practices, which include the time-intensive nature of complex system design and analysis, data integrity, and deficiencies in assessment methods. In particular, the challenges of collecting, curating, analyzing, and presenting environmental, economic, and social metrics and indicators (sustainability performance information) remains a barrier to operational decision-making. Existing assessment methods and tools are not well-suited to evaluating the sustainability performance of manufacturing processes and systems, as they tend to be product-focused and have limited ability to adapt to changes at the manufacturing process or system level.

The objective of this dissertation research is to facilitate sustainable manufacturing system design decision making by integrating a systematic and structured information modeling framework with a manufacturing system design approach. To accomplish this goal, the research approach involves four steps: (1) Performing a review of recent literature to identify the existing challenges in the development and application of sustainable manufacturing methods, tool, models, algorithms, metrics, and indicators; (2) Introducing a functional and object-oriented information modeling methodology to characterize the sustainability performance of unit manufacturing processes (UMPs) using the concepts of abstraction and instantiation, which is demonstrated by reusing and extending a manual milling UMP model for two and a half-axis milling process; (3) Applying information modeling approaches in characterizing the sustainability performance of manufacturing process flows composed of UMPs, which is demonstrated for a discrete part manufacturing system; and (4) Synthesizing the results of the prior steps to provide an information modeling framework for sustainable manufacturing system design decision making. The framework is applied to discrete and continuous product manufacturing to demonstrate the flexibility of this system design approach. The framework provides an accessible approach for detailed analysis of the sustainability performance of manufacturing processes and systems by enabling the reuse, extension, and composability of new and previously developed UMP models. The coupling of information modeling concepts (e.g., abstraction, instantiation, and polymorphism) along with hierarchical, structured, and systematic manufacturing system design enables the framework to address the challenges stated above, namely: (1) Modeling complexity is simplified through a bottom-up approach for characterizing individual UMPs, which are built up for system-level characterization; (2) Model development, verification, and validation efforts are reduced by reusing and extending UMP models, thereby also reducing the time-intensity of modeling; (3) Data reliability is improved, since the framework is agnostic of existing process-specific data sources, rather than restricting data sources and types necessary for analysis; and (4) Multi-criteria decision-making is facilitated by using a hierarchical data structure for model-quantified metrics of interest, which supports analysis using decision trees. The research lays a foundation for developing an ontologies based decision support for sustainable manufacturing system design, as ontologies describe relationships and links between systems and sub-systems which enables the framework to have high-fidelity and understanding of the manufacturing system model and data.

An Information Modeling Framework for Support of Sustainable Manufacturing Systems Design Decision Making

by
Arvind Shankar Raman

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Presented March 11, 2022
Commencement June 2022

Doctor of Philosophy dissertation of Arvind Shankar Raman presented on March 11, 2022

APPROVED:

Major Professor, representing Mechanical Engineering

Head of the School of Mechanical, Industrial, and Manufacturing Engineering

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Arvind Shankar Raman, Author

ACKNOWLEDGEMENTS

First and foremost, I express my heartfelt gratitude and acknowledgement to my advisor and mentor, Dr. Karl R. Haapala for his expert professional guidance throughout my graduate program. His tremendous support, encouragement, insights, and integrity has been a great source of motivation both in academic and personal fronts. I am extremely honored and indebted to him for all that I have imbibed during my graduate studies. I look forward to having a continued working relationship for the rest of my professional career.

I would also like to acknowledge the help and support that I received from my committee members Dr. Andy Fan, Dr. Christopher Hoyle, Dr. David Porter, Dr. Prasad Tadepalli, who provided useful insights and recommendations during the course of this research. I would also like to extend my thanks to Dr. Brian Paul for providing his support and guidance for a research opportunity under his area of expertise. I express my sincere thanks to the National Institute of Standard and Technology, The Department of Energy, and School of Mechanical, Industrial, and Manufacturing Engineering for their support of this research.

Finally, I would like to express my sincere gratitude to my family especially my parents and in-laws for their unconditional support without which this journey would have not been possible. Most importantly, I am extremely thankful for the constant encouragement, admirable patience, and sacrifices by my wife Aarthi Venkatakrishnan, and the abundance of love from my son Shreyas.

CONTRIBUTION OF AUTHORS

Chapter 2: Manuscript 1

Arvind Shankar Raman led the authorship of a journal paper detailing the events and summarizing the findings of the RAMP (Reusable Abstractions of Manufacturing Processes) workshop conducted in June 2018. Based on the workshop findings, a follow-up investigation to uncover future research opportunities in smart and sustainable manufacturing was undertaken along with four collaborators: Dr. Barbara Linke (Conventional Manufacturing), Dr. Kamyar Raoufi (Nano-manufacturing), Dr. William Bernstein (Process and System Characterization), and KC Morris (Workforce Education and Training). Arvind Shankar Raman investigated Additive Manufacturing and subsequently summarized the findings from the identified research opportunities under each topic area. The design of the workshop, associated study, and paper organization and final editing was directed by Dr. Karl Haapala.

Chapter 3: Manuscript 2

Arvind Shankar Raman undertook the following tasks in leading the authorship of this paper: 1) performed a literature review to identify the limitations of prior work related to the sustainability characterization of Unit Manufacturing Processes (UMPs); 2) developed an information modeling methodology to reuse and extend UMP models by applying concepts of abstractions and instantiations for sustainability assessments; 3) demonstrated the methodology by developing energy models for a manual milling process and extended into a two and half axis milling model, by adding table feed and lubricant system models. KC Morris and Dr. Karl Haapala provided input and direction for the work as well as helpful review and feedback.

Chapter 4: Manuscript 3

Arvind Shankar Raman undertook the following tasks in leading the authorship of this paper: 1) developed an information modeling method for composition of UMPs to characterize manufacturing systems for sustainability assessments; 2) developed physics-based models to understand the shared information context between UMPs; 3) demonstrated the developed method using a trade-off analysis for a discrete part that undergoes a variety of physical and material transformations. KC Morris and Dr. Karl Haapala provided input and direction for the work, and helpful review and feedback.

Chapter 5: Manuscript 4

Arvind Shankar Raman led the authorship of this paper, which developed a sustainable manufacturing systems design decision support framework and demonstration cases for both discrete part manufacturing and continuous product manufacturing. To do so, he developed the underlying models (economic, energy, and social) that were used for sustainability assessments. Dr. Karl Haapala provided input and direction for the work as well as helpful review and feedback.

TABLE OF CONTENTS

Page

TABLE OF CONTENTS (CONTINUED)

Page

TABLE OF CONTENTS (CONTINUED)

Page

TABLE OF CONTENTS (CONTINUED)

Page

TABLE OF CONTENTS (CONTINUED)

Page

LIST OF FIGURES

LIST OF FIGURES (CONTINUED)

Figure | Page

LIST OF FIGURES (CONTINUED)

Figure Page

LIST OF TABLES

LIST OF TABLES (CONTINUED)

Table Page

LIST OF TABLES (CONTINUED)

LIST OF APPENDICES

LIST OF APPENDICES (CONTINUED)

Appendix Page

NOMENCLATURE

A	Heat transfer area
A_{Dav}	Cross-sectional area of uncut chip
A_f	Cross-sectional area of finished workpiece
A_i	Cross-sectional area of incoming workpiece
A_s	External surface area of the oven
C_{Bar}	Specific heat of extrusion barrel
C_c	Consumable cost per part
C_{design}	Capital cost of designed equipment
C_E	Total cost of energy
C_F	Facility cost
C_i	Specific heat of incoming workpiece
CI	Ratio of consistency index
$C_{Install}$	Tool installation cost
C_L	Labor cost per part
C_M	Maintenance cost per part
C_{mfg}	Cost of manufacturing space
COGS	Cost of goods sold
C_p	Specific heat of flue gas
C_q	Specific heat of quenchant
C_R	Raw material cost per part
C_r	Consistency ratio
C_{ref}	Capital cost of referenced equipment

NOMENCLATURE (CONTINUED)

C_S	Annual salary of labor
C_T	Capital cost per part
C_{Tool}	Capital cost of tool
d	Depth of cut
D_i	Incoming diameter of workpiece
E_{ag}	Energy at the agitator
E_c	Cutting energy
E_{off}	Offsite energy consumption
E_{on}	Onsite energy consumption
E_T	Total energy consumption
f	Feed
F_c	Cutting force
Fl	Flow rate exiting the vessel
F_{ram}	Force on the ram
GHG	Greenhouse gas emissions
GWP_{CH4}	Global warming potential of CH_4
GWP_{NO2}	Global warming potential of NO_2
h_{av}	Uncut chip thickness
H_B	Height of quench bath
H_f	Height of finished workpiece
k	Tool working hours per year
k_W	Thermal conductivity of workpiece

NOMENCLATURE (CONTINUED)

L_B	Length of quench bath
L_{annual}	Annual availability per laborer
L_f	Length of finished workpiece
L_i	Incoming workpiece length
L_R	Loaded labor cost rate
L_{ram}	Length of ram
$\dot{m}_f$	Mass flow rate of flue gas
m_{ng}	Mass of natural gas burnt
M_{Bar}	Mass of barrel
M_f	Mass of finished workpiece
M_i	Mass of incoming workpiece
MRR	Material removal rate
n	Equipment count
n_R	Amount of raw material use per part
ndc	Number of decision-criteria
N_b	Batch size
N_{labor}	Number of operators per tool
N_s	Number of personnel per tool
p	Extrusion pressure
P	Annual production volume
P_b	Basic power
P_{cut}	Power at cutting tool

NOMENCLATURE (CONTINUED)

P_{design}	Designed production volume
P_i	Power supplied to ram
P_m	Power at motor
P_{ref}	Reference production volume
Puc	Percentage of uncombusted fluw gas
P_{spec}	Specific power to cut material
P_t	Power at table motor
q_{f_loss}	Heat loss in flue gas
q_{o_loss}	Heat loss in oven
q_t	Total heat of the annealing process
Q	Heat supplied or removed
Q_i	Energy required to heat the workpiece
Q_{loss}	Heat lost by workpiece
Q_q	Energy required to heat quenchant
r_m	Fraction of tool capital cost
R	Extrusion ratio
R_{CO2}	Production rate of CO_2
R_{CH4}	Production rate of CH_4
RI	Random index
R_{NO2}	Production rate of NO_2
S_{design}	Designed size of equipment
S_{ref}	Referenced size of equipment

NOMENCLATURE (CONTINUED)

S_t	Kerf width
S_{tool}	Footprint area required for tool
T	Thickness of workpiece
T_{amb}	Ambient temperature
t_b	Batch setup time
t_c	Cycle time
t_{fac}	lifetime of facility
t_L	Lifetime of tool
t_{load}	Part load time
t_{unload}	Part unload time
T_b	Basic time
T_c	Cutting time
T_{des}	Desired temperature of workpiece
T_{oven}	Oven temperature
T_q	Temperature of quenchant
T_w	Incoming temperature of workpiece
u_{tool}	Tool utilization
u	Energy dissipated per unit volume
U	Heat transfer co-efficient of incoming chemical
UC_e	Unit cost of energy
UP_R	Unit price of raw material
U_f	Utilization factor

NOMENCLATURE (CONTINUED)

y	Yield
Y	Yield strength
YS_i	Incoming yield strength of workpiece
V	Volume of reactor/separator
V_B	Workzone of quench bath
V_c	Cutting speed
$\bar{\dot{V}}_c$	Volumetric flow rate of coolant
V_{cool}	Volume of coolant
V_i	Volume of incoming part
V_f	Volume of finished part
$\dot{V}_f$	Flow rate of flue gas
V_k	Heat transfer co-efficient of the oven wall
V_q	Volume of quenchant
V_r	Volume removed
V_{ram}	Speed of ram
W	Tool wear rate
W_B	Width of quench bath
W_f	Width of finished workpiece
W_i	Work done on stock
W_{ram}	Work done by ram
$\bar{X}$	Cooling rate of workpiece material

NOMENCLATURE (CONTINUED)

α	Die angle
ε	Strain
μ	Friction coefficient of die
τ	Residence time
ρ	Density of material
ρ_{flue}	Density of flue gas
ρ_q	Density of quenchant
λ_{max}	Maximum Eigen value
ΔH_{ng}	Enthalpy of natural gas
ΔT	Temperature change
ΔT_{Bar}	Change in temperature of barrel
ΔT_f	Change in temperature of workpiece

Chapter 1: INTRODUCTION

1.1 Motivation

Manufacturing industry is undergoing significant advancements in the fields of computing technology, architecture, and infrastructure; real-time (big) data analytics, instrumentation, and control; materials science, multi-scale physics-based manufacturing process modeling, and precision tooling and equipment; and many other synergies between facets of science, technology, engineering, and mathematics [1,2]. According to the U.S. Bureau of Economic Analysis (BEA), these technologies enabled manufacturing (e.g., in chemical, food, automobiles, metal fabrication, and petroleum industries) to have a combined contribution of 10.8% to the U.S. Gross Domestic Product in 2020 [3]. At the same time, according to the U.S. Energy Information Administration (EIA), the industrial sector consumed 35% [4] of total energy production (lagging only the transportation sector, at 37%), while employing 12.5% [5] of the total workforce.

Along with these technological advancements and economic growth, there has been increasing emphasis on sustainable manufacturing [6–8] due to governmental and global policies, international standards, and an increase in customer awareness and societal concerns [9,10]. Historically, economic factors such as reduced product cost, increased revenue, and market presence have been the driving forces in advancing manufacturing innovation and productivity. However, it has been projected that manufacturing technologies that promote economic and social sustainability will grow from a market value of $8.79 billion in 2019 to $48.36 billion by 2027 [11].

Sustainable development defined by the Brundtland report [12] states that "development which meets the needs of the present without compromising the ability of future generations to meet their own needs." Since the Brundtland report was published, academic researchers and industrial practitioners have developed a number of methods and tools to promote sustainable manufacturing practices. Sustainability thinking has paved the way to design and manufacturing practices, which in turn have aided environmentally responsible and sustainable manufacturing philosophies [13,14]. However, there continues to be a need for engineering decision-making approaches to accommodate the sustainable growth in manufacturing output, energy demand, and consumption, while conserving and sustaining resources for future generations.

Implementing sustainable manufacturing practices is attendant with several challenges due to the complex nature of interactions among the various processes and activities taking place within a manufacturing system. A number of key challenges inhibit the drive to incorporate sustainability thinking into manufacturing system design [15–18]:

(1) Difficulty of making manufacturing decisions that emphasize the three pillars of sustainability (i.e., economic, environmental, and social),

(2) Complexity of integrating sustainable manufacturing practices along with other manufacturing activities such as lean, quality control, manufacturing and regulatory standards, and supply chain management,

(3) Limited model accuracy and precision in sustainability assessment due to generic representations of manufacturing processes and a broad emphasis on all phases of the product life cycle,

(4) Difficulty of the industrial application of life cycle assessment (LCA), due to a lack of reliable and efficient models, methods, and tools, and

(5) Level of expertise required to develop and analyze sustainability assessment models for manufacturing systems and to apply LCA methods for process analysis.

1.2 Background

It can be noted that LCA remains at the forefront of the many methods developed to evaluate sustainability performance. LCA focuses on evaluating the environmental performance of a product from its cradle to grave. Existing LCA methods primarily address environmental impacts rather than focusing on all three pillars of sustainability. LCA methods/tools often focus on energy consumption and the challenges associated with reducing energy-related carbon footprint. The few tools that emphasize the three pillars of sustainability in product design and manufacturing lack supporting data and reliable models to enable multi-criteria decision-making [19]. Due to the complexity of manufacturing systems, the models within these LCA tools are often too generic for characterizing specific instances of known classes of manufacturing processes [20,21]. Additionally, LCA tools lack the robustness to assess sustainability performance at the manufacturing system level as these tools are unable to handle the myriad (information, data, and material) exchanges between manufacturing processes. As a result, LCA tools and supporting models are made in an ad hoc manner for sustainability assessment. Due to these limitations, LCA methods are not well-equipped for manufacturing system design decision support.

A manufacturing system is defined as “the arrangement and operation of elements (machines, tools, material, people, and information) to produce a value-added physical, information or service product whose success and cost is characterized by measurable parameters of the system design” [22]. As such, manufacturing system design focuses on designing the manufacturing process flow, organization of materials, and resources (people, tools, and information) required for producing a product. It is a subset of production system design, and focuses on designing the type of manufacturing system and processes that best suit the product design. The ability to evaluate the performance of a manufacturing system during its design through the integration of existing sustainability assessment methods/tools would support sustainability decision making. To address this need, several efforts have been pursued for evaluating product sustainability performance during the manufacturing phase of the lifecycle.

For nearly the past century, researchers have been investigating the performance measurement of the fundamental building blocks (distinct manufacturing processes) of manufacturing systems, termed unit manufacturing processes (UMPs) [23]. UMPs have been defined as “the individual steps required to produce finished goods by transforming raw material and adding value to the workpiece as it becomes a finished product” [24]. Formalized representations for characterizing the structure of UMPs have changed over time, beginning with Kim et al. [25], who applied IDEF0 functional modeling to represent the functions, constraints, and actions of UMPs. More recently, ASTM subcommittee E60.13 [26] has focused on disseminating knowledge, and developing and promoting information modeling-based standards for sustainable manufacturing assessment. Within the family of sustainability standards developed by the ASTM sub-committee, ASTM E3012-20 [27] defines UMPs as shown in Figure 1.1. While UMPs have been classified using a variety of taxonomies [28–30], the formalized representation is agnostic to the modeled manufacturing process.

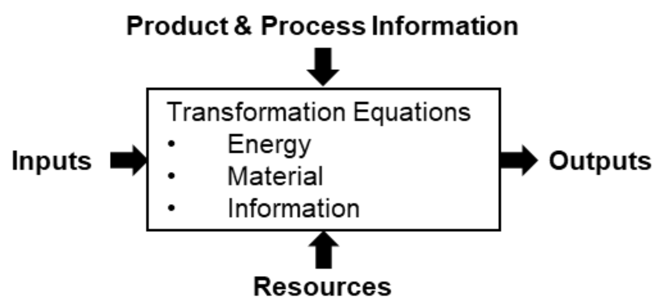


Figure 1.1. Graphical representation of a unit manufacturing process [27]

A manufacturing system consists of one or more UMPs arranged in sequential manner to output a finished product. Based on ASTM E3012-20, composability is defined as "the act of linking individual unit manufacturing process (UMP) models together to create a composite of UMP models that can characterize the metrics of interest of a production system or product" [27]. Composition is essential for establishing relationships between UMPs, tracking material and information exchanges, and defining a structured representation of a manufacturing system, all of which enable holistic manufacturing system design decision support through information modeling.

Existing sustainable manufacturing assessment methods/tools focus on characterizing and evaluating process-level performance, and have been applied to optimize process parameters for a variety of metrics of interest [31]. However, little effort has focused on sustainable manufacturing performance assessment through the evaluation and composition of UMPs to represent a manufacturing system. In particular, existing methods/tools are limited in their ability to reuse and compose UMP models, and thus, require analysts to devote significant time to model setup and deployment.

The formalized UMP information modeling structure is amenable to the fundamental blocks of object-oriented programming such as abstraction, instantiation, and polymorphism. Information models help in defining relationships, constraints, model structure, rules and operations [32]. The core attributes of object-oriented programming help in faster deployment of sustainability assessment for manufacturing systems, since models can be reused and modified (extended) with relative ease to suit any manufacturing process flow of interest. The application of information modeling for evaluating the sustainability performance of manufacturing systems has not been given much attention, which has led to ad hoc, non-standard practices. The advantages that arise from integrating UMP information modeling into sustainability performance evaluation have not been realized for multi-criteria manufacturing system design decision support.

1.3 Research Objective

The primary objective of the dissertation research presented herein is to facilitate sustainable manufacturing system design decision making by integrating a systematic and structured information modeling framework with manufacturing system design methodology. This integrated approach will enable systematic assessment of discrete and continuous manufacturing systems using a variety of sustainability metrics.

1.4 Research Questions

Four research questions were posed to address the research objective stated above:

- **Question 1**: What is the state-of-the-art in systemic sustainable manufacturing assessment, with regard to current metrics/indicators, methods/tools, and models/algorithms in use and opportunities for future research?
- **Question 2**: How can information modeling methods be leveraged to reuse and extend Unit Manufacturing Process (UMP) models to support sustainability assessments for specific instances of manufacturing process configurations?
- **Question 3**: How can information modeling methods be leveraged to define shared information context (linking information) for UMP model composition to support sustainability assessments of manufacturing systems?
- **Question 4**: How can information modeling methods be integrated within manufacturing system design decision-making to support sustainability performance characterization, evaluation, and improvement?

1.5 Research Tasks

To help answer these research questions, the following research tasks were pursued:

- **Task 1:** Conduct a review of the domain literature and gather input from the advanced manufacturing research community, including industry, academia, and government labs. This work helps in defining the state-of-the-art in smart and sustainable manufacturing as well as a basis for future research to support performance metrics, characterization models, and analysis methods attendant with conventional manufacturing, nanomanufacturing, and additive/hybrid manufacturing, and process-level and system-level characterization.
- **Task 2:** Develop an approach for extending and reusing UMP models to characterize a variety of sustainability metrics and indicators that applies core concepts of object-oriented information modeling, such as abstraction, inheritance, and polymorphism. Abstraction and inheritance enable the reuse of information models, and polymorphism helps in extending models to characterize process variants. Reuse and extension of existing UMP models enables modelers to more quickly develop new process models with better defined structure and with relative ease compared to developing models from scratch. The developed approach is demonstrated using an example of a manual milling UMP model, which is extended to represent a two and a half-axis milling process with a lubrication system. This is achieved by abstracting and instantiating the manual milling UMP model (template) and then adding instantiations of the table feed and the lubricant system, termed “layer models.”

- **Task 3:** Develop a method for representing a manufacturing system (a network of UMPs) by applying the composability principle of information modeling. Approaches for linking UMPs tend to be manual and open to subjective interpretation, which leads to inconsistencies in handling information flow and data exchange, unstructured representations, and significant time investment. Information modeling enables linking, handling, and processing of data in a hierarchical and structured sequence, as well as data traceability and potential automation using software applications. Composability enables the modeler to capture shared information context between the multiple UMPs that constitute a manufacturing system. In prior work, this information context has been represented as linking variables, which are further defined here as "specific" (associated with the two linked processes) and "generic" (associated with any instance of a particular process, independent of process links). The developed method is verified using a demonstrative case study of products manufactured using a distributed, cloud-based manufacturing system. The study details a trade-off analysis performed for a family of extruded parts using multi-criteria decision making to evaluate three procurement options/perspectives.
- **Task 4:** Integrate the information modeling framework developed in Tasks 2-3 along with manufacturing systems design methodology to facilitate sustainable manufacturing system design decision making. The integrated framework follows a systematic and structured information modeling approach for characterizing the sustainability performance of a manufacturing system. To verify the framework, a demonstrative case study is first undertaken to compare

the sustainability performance of two manufacturing systems producing the same aluminum product (wheel housing) across a range of production volumes. Next, to illustrate the application of the integrated framework beyond discrete part manufacturing, a case study for continuous manufacturing compares the environmental and cost performance for the production of a bulk chemical (ammonia) using two chemical process flows over a range of capacities.

1.6 Intellectual Merit

The foregoing research tasks help in addressing the research questions posed above and, thereby, aid in achieving the research objective of this dissertation. In so doing, this research advances the state-of-the-art in sustainable manufacturing systems design decision making, providing a number of contributions to the body of knowledge:

- Research Task 1 identifies the need for structured, repeatable, verifiable, and reliable methods and tools to characterize sustainability performance of manufacturing processes and systems to support manufacturing system design decision making. Further, this task helps identify barriers to advanced manufacturing process development, modeling, and analysis, as well as opportunities for future research to address these barriers with respect to metrics/indicators, models/algorithms, and tools/methods.
- Research Task 2 presents an approach for reusing and extending UMP models through information modeling methods such as abstraction, instantiation, and polymorphism to evaluate the sustainability performance of manufacturing processes. The novel approach provides a structured, repeatable, and reliable

method for characterizing sustainability performance of UMPs. The approach lays the foundation for evaluating system-level sustainability performance, as demonstrated under Research Task 3.

- Research Task 3 presents an information modeling approach for composing UMP models to characterize the sustainability performance of a manufacturing system. Composability of UMP models through functional block aggregation enables tracking of product and process information flows within the modeled manufacturing system. Such manufacturing systems models provide insights into the relationships between individual UMPs, which can support decision making for the design of new manufacturing systems, as demonstrated in Research Task 4.
- Research Task 4 presents a framework for integrating the information modeling approaches developed in Tasks 2-3 with manufacturing systems design methodology to facilitate multi-criteria decision making for the design of sustainable manufacturing systems. The utility of this framework is its flexibility and adaptability for modeling various manufacturing systems, as demonstrated for discrete and continuous production. Further, the information modeling basis of framework lends it to the realization of computer-based applications and tools to support systems engineers and other decision makers.

1.7 Dissertation Outline

This research conducted as part of this dissertation is reported in manuscript format and includes six chapters and several appendices, all of which are used to address the objective of this research.

Chapter 1 provides an introduction, motivation, and background to the research including objective, research questions, tasks, and intellectual merit.

Chapter 2 presents a review of the literature (published in the *ASTM Journal of Smart and Sustainable Manufacturing Systems*). A detailed summary of the near to long term research opportunities for advancing smart and sustainable manufacturing is presented. The identified gaps for sustainable manufacturing systems design established the research objective for this dissertation.

Chapter 3 is an article submitted to the *ASME Journal of Computing and Information Science in Engineering*. This chapter presents an information modeling methodology for reusing and extending UMP models for sustainability assessments using concepts of abstraction and instantiation which are core to information modeling. The methodology is demonstrated using an extension of manual milling UMP to a two and a half axis milling UMP.

Chapter 4 is an article to be submitted to the *ASME Journal of Manufacturing Science and Engineering* and develops a methodology to compose UMPs for evaluating the sustainability performance of manufacturing systems. Composition for a variety of processes under the manufacturing taxonomy were investigated to understand the characteristics of the shared information between UMPs for composition. This method was conceptually demonstrated for discrete part production using a trade-off analysis comparing the sustainability performance for making a design decision.

Chapter 5 is an article to be submitted to the *Journal of Cleaner Production*, and develops an information modeling framework to support decision making for manufacturing system design, with the methods developed in Chapter 3 and Chapter 4 as the foundation. The framework has been conceptually demonstrated for discrete part manufacturing and continuous product manufacturing.

Chapter 6 summarizes the findings from the research, and reports on the conclusions, contributions, and potential future research directions of the dissertation work.

Chapter 2: DEFINING NEAR-TERM TO LONG-TERM RESEARCH OPPORTUNITIES TO ADVANCE METRICS, MODELS, AND METHODS FOR SMART AND SUSTAINABLE MANUFACTURING

2.1 Abstract

Over the past century, research has focused on continuously improving the performance of manufacturing processes and systems – often measured in terms of cost, quality, productivity, and material and energy efficiency. With the advent of smart manufacturing technologies – better production equipment, sensing technologies, computational methods, and data analytics applied from the process to enterprise levels – the potential for sustainability performance improvement is tremendous. Sustainable manufacturing seeks the best balance of a variety of performance measures to satisfy and optimize the goals of all stakeholders. Accurate measures of performance are the foundation on which sustainability objectives can be pursued. Historically, operational and information technologies have undergone disparate development, with little convergence across the domains. To focus future research efforts in advanced manufacturing, the authors organized a one-day workshop, sponsored by the U.S. National Science Foundation (NSF), at the joint manufacturing research conferences of the American Society of Mechanical Engineers (ASME) and Society of Manufacturing Engineers (SME). Research needs were identified to help harmonize disparate manufacturing metrics, models, and methods from across conventional manufacturing, nanomanufacturing, and additive/hybrid manufacturing processes and

systems. Experts from academia and government labs presented invited lightning talks to discuss their perspectives on current advanced manufacturing research challenges. Workshop participants also provided their perspectives in facilitated brainstorming breakouts and a reflection activity. The aim was to define advanced manufacturing research and educational needs for improving manufacturing process performance through improved sustainability metrics, modeling approaches, and decision support methods. In addition to these workshop outcomes, a review of the recent literature is presented, which identifies research opportunities across several advanced manufacturing domains. Recommendations for future research describe the short-, mid-, and long-term needs of the advanced manufacturing community for enabling smart and sustainable manufacturing.

2.2 Introduction

Manufacturing has undergone rapid advancement in the past few decades, due to improvements in information technology, sensing methods and technologies, tooling and equipment, new and improved materials, and improved understanding of process characteristics through data analytics, all of which has enabled new manufacturing methods (e.g., cyber-manufacturing and distributed manufacturing) and manufacturing processes (e.g., additive manufacturing and hybrid manufacturing) [1]. Integration of current-day manufacturing methods, processes, and equipment with sensors, controls, computational methods, new materials, data analytics, artificial intelligence, and communication technologies drive smart manufacturing [33], an emerging manufacturing concept that has seen a variety of definitions. The U.S. National Institute for Standards and Technology (NIST), states, "[Smart manufacturing systems are] fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs" [34]. The U.S. Department of Energy (DOE) Clean Energy Smart Manufacturing Innovation Institute (CESMII) posits, "Smart Manufacturing (SM) enables all information about the manufacturing process to be available when it is needed, where it is needed, and in the form it is needed across the entire manufacturing value-chain to power smart decisions" [35]. Such technological advances will enable a broad range of industries to lower costs, improve quality, increase productivity, improve material management, increase efficiency, reduce energy use, and improve worker health and safety, among other performance measures [33,36].

Further, continuously monitoring and improving upon these key performance indicators (KPIs) helps in improving the sustainability performance of smart manufacturing systems beyond that previously attainable with asynchronous, manual collection and interpretation of performance data. Sustainable manufacturing requires a balance of KPIs that span the three pillars of sustainability (economic, environmental, and social) based on stakeholder preferences [37]. However, smart and sustainable manufacturing systems exhibit a complex nature, often due to varied, non-uniform manufacturing processes that make quantifying process metrics, ensuring data integrity, and establishing relationships between the systems and sub-systems extremely difficult [38,39]. Through the evolution of manufacturing, new processes, materials, and supporting technologies have been developed based on industry needs.

Complementary efforts were undertaken to quantify metrics, model systems and sub-systems, and develop methods of quantification for performance measures. These developments have been completed quite independently, however, and have had little to no convergence. To address this deficiency, NIST worked to (a) develop standard smart manufacturing measurement methods, (b) model and characterize smart manufacturing system complexity, (c) develop guidelines for methods, metrics, and tools that enable manufacturing stakeholders to assess and assure cybersecurity of smart manufacturing systems, and (d) develop methods and protocols for the integration of smart manufacturing systems [40]. In addition, recently developed ASTM standards led by NIST researchers guide companies in evaluating and characterizing the sustainability performance of manufacturing processes in their facilities and supply chains [41,42].

To support research efforts in smart and sustainable manufacturing, the authors organized a one-day workshop, sponsored by the U.S. National Science Foundation (NSF), at the joint manufacturing research conferences of the American Society of Mechanical Engineers (ASME) Society of Manufacturing Engineers (SME) held at Texas A&M University in June 2018. The workshop invited participants from the industry, academia, and government labs to engage in presentations and discussions of recent developments within emerging areas of advanced manufacturing. It aimed to identify the basis for future research in smart and sustainable manufacturing to support performance metrics, characterization models, and analysis methods attendant with conventional manufacturing, nanomanufacturing, and additive/hybrid manufacturing, as well as for process-level and system-level characterization. This approach enabled the research team to gather perspectives from across various domains of manufacturing and to synthesize these findings to address common research needs for advancing smart and sustainable manufacturing with an emphasis on the role of standards in advancing the field. Workshop activities undertaken to generate and synthesize this information are described in Section 3. To supplement the findings from the workshop presented in Section 4, the research team conducted a literature review which identifies the current state of several key domains of manufacturing and their relevant challenges. Section 5 reports future research opportunities and expected outcomes in short- to long-term time ranges. Section 2 provides background information in support of the work reported herein.

2.3 Background

The objective of the study reported herein aims to focus future research efforts in advanced manufacturing, with an emphasis on smart and sustainable manufacturing processes and systems. A foundational assumption for smart manufacturing is that models of manufacturing processes provide a basis for computationally improving manufacturing operations. The principles on which these models are organized are emerging. ASTM subcommittee E60.13 on Sustainable Manufacturing [26] has published an initial set of standards to codify these principles, yet more research is needed to understand the fundamental modeling concepts—the abstractions—needed to enable model reuse and composition across the variety of manufacturing processes and systems.

To provide an initial foundation for this work, the findings from a prior workshop on Reusable Abstractions for Manufacturing Processes (RAMP), held in 2017, and the purpose of the 2018 RAMP workshop are next introduced. Both workshops were held in conjunction with a competition for modeling manufacturing processes using standard methods under development by ASTM subcommittee E60.13. The competitions motivated application of the standards to several manufacturing processes and user experiences from which to generate meaningful feedback.

The first RAMP workshop also was supported by NSF and held in conjunction with the 13th ASME Manufacturing Science and Engineering Conference (MSEC) and the 45th SME North American Manufacturing Research Conference (NAMRC) on June 7, 2017 at the University of Southern California in Los Angeles, CA. The workshop was held in partnership also with NIST and ASTM International. The objectives of the workshop were to:

1) Familiarize the research community with standards from the ASTM E60.13 Subcommittee for modeling manufacturing processes, including the ASTM E3012 Standard Guide for Characterizing Environmental Aspects of Manufacturing Processes [42];
2) Provide an opportunity for participants to put those standards into practice in modeling processes of their own interest, and to share experiences in applying the standards; and

3) Provide a source of candidate models to populate an extensible repository of reusable manufacturing process models being developed by NIST and its academic partners.

The workshop attracted several dozen participants from industry, academia, and government labs. The workshop highlighted the opportunities for an open repository of process models [43], and identified emerging efforts, including both standards development and academic and industrial research, to outline a vision for coalescing such efforts towards an open process model repository. Lessons from the workshop led to a new information model that facilitates more consistent characterization of physical artifacts in production systems, leading to better reusability of models and reproducibility of environmental analyses. Based on the 2017 workshop results and findings from ongoing research, the follow-on workshop held in 2018 and reported here was designed to:

1) identify needs for education and research to support the characterization of unit manufacturing processes (UMPs) for sustainability assessment;
2) define current limitations in associated education and research practices; and
3) prioritize the challenges to be pursued by the manufacturing research community to best meet industry needs in adopting and applying analytical methods for improving smart and sustainable manufacturing process and system performance.

The outcomes of the workshop are expected to benefit basic research programs within NSF, for example by leading to funded research and advancements in topic areas such as sustainability of nanomanufacturing processes and nano-products, digitization of continuous and batch processes, fundamental models of manufacturing processes, and efficient process and system models for decision support in cloud manufacturing. Academic researchers with foci in smart and sustainable manufacturing systems, manufacturing machines and equipment, materials engineering and processing, nanomanufacturing, and engineering education were particularly encouraged to attend; the workshop attracted participants with broad interests in teaching undergraduate and graduate students and conducting basic and applied research in analytical methods for sustainable manufacturing.

2.4 Overview of the 2018 RAMP Workshop

The second RAMP workshop was comprised of two half-day sessions and an evening poster session. The first half of the day was dedicated to presentations that introduced a variety of perspectives on manufacturing metrics and process modeling. The second half of the day was designed to engage the participants in defining relevant advanced manufacturing research challenges. In addition to participants from academia, industry, and government labs, the workshop hosted 46 undergraduate and graduate student participants, including 23 student finalists comprising six teams from the NIST-sponsored RAMP competition [44]. The student participants presented posters reporting their research in manufacturing process modeling and sustainability performance assessment. Additional details of the sessions are described in the following sections.

2.4.1 Student presentations and expert lightning talks

In the first session of the workshop, RAMP competition finalists presented their projects, summarized in Table 2.1. In the following session, experts from across the advanced manufacturing domain presented lightning talks to report ongoing research activities and their personal perspectives on the current and future research challenges and modeling needs for advanced manufacturing. These expert talks were not meant to be comprehensive, but provided context for participants in the afternoon session of the workshop to identify and discuss extant challenges across manufacturing research domains.

Table 2.1: Summary of RAMP Competition finalist presentations

Presentation Topic	Author(s)	Affiliation
A Production Line for Polylactide Business Card	Ian Garretson and Barbara Linke	University of California, Davis
Sustainability Analysis of Stereolithography using UMP Models	Timothy Simon1, Yiran Yang1, Wo Jae Lee1, Jing Zhao1, Lin Li2, and Fu Zhao1	Purdue University1, University of Illinois-Chicago2
Aggregating UMP Models to Enable Environmental Impact Characterization of Polymer-Based Hybrid Manufacturing	Sriram Manoharan and Dustin Harper	Oregon State University
UMP Model for Flexible Manufacturing System	Feng Ju, Daniel McCarville, Hashem Alshakhs, Weihao Huang, Xuefeng Dong, Hussain Alhader	Arizona State University
Data Driven UMP Model for Monitoring Specific Energy in Surface Grinding Process	Zhaoyan Fan and Sai Srinivas Desabathina	Oregon State University
Grinding Analysis and Model	Justin Canaperi, Yongxin Guo, John Park, Jun Yang, and Yuki Yoshinaga	Stony Brook University

The talks in the second session started with Dr. Khershed Cooper of NSF presenting *Nanomanufacturing Research at NSF*. He discussed various NSF programs that address the growing demands and challenges of advanced manufacturing. He presented several specific approaches that have been pursued to address needs for scalability in nanomanufacturing under NSF funding. He also discussed avenues of NSF funding to support such work, including cyber-manufacturing and nanomanufacturing.

Next, Dr. Ajay Malshe of the University of Arkansas outlined key drivers for standardization of nanomanufacturing in his talk titled *Standardization and Scale-up of Nanomanufacturing Processes*. He provided his perspective on the future of nanomanufacturing and described some of the limitations, specifically noting increasing stress levels in the research lab because of a dramatically changing invention-to-product life cycle. He also highlighted the missing link between research and industrial application, a need to account for the frequency of products changing hands, and the value of students being exposed to industry perspectives before contributing to lab research.

Mr. Kevin Lyons of NIST then presented *Standardization and Scale-up of Additive Manufacturing Processes*. He began by defining additive manufacturing processes and then providing his perspective on the key drivers for advancing additive manufacturing technology. He indicated that data handling and sharing, model development and adaptation, and design for additive manufacturing were key shortcomings to be addressed. He also introduced potential research opportunities in additive manufacturing, such as the need to integrate various process models while considering the inherent complexities, underlying assumptions, and constraints, the lack of a robust method to verify and validate process models for additive manufacturing, the need to develop an approach for capturing design rules for additive manufacturing, and the need to develop simulation testbeds for modelers to test their models against rigorous, highly-controlled additive manufacturing benchmark test data.

Moving away from the process-specific focus, Dr. Fazleena Badurdeen of the University of Kentucky next spoke about *Educating Engineers on Sustainable Manufacturing*. She presented several engineering education challenges, and emphasized that realizing sustainable manufacturing innovations requires developing an educated and skilled workforce. One research opportunity she noted was a need for a multi-disciplinary approach to address sustainable manufacturing challenges that incorporates convergent research and education. In order to achieve this vision, a continuous effort of collaboration between key stakeholders, such as universities, industry, and state and federal agencies is required. She introduced various NSF programs and other funding opportunities that could be used to facilitate such efforts to bolster sustainable manufacturing engineering education.

Dr. Barbara Linke of the University of California Davis next focused on *Modeling Manufacturing Processes*. She outlined the Unit Process Life Cycle Inventory (UPLCI) effort [45] to characterize a broad set of manufacturing processes. The UPLCI approach uses industrial information for each manufacturing process (machine) to estimate material inputs, energy use, and material losses for a particular product design. Linke also introduced a more involved approach for modeling process environmental performance metrics developed under the Cooperative Effort on Process Emissions in Manufacturing (CO2PE!) initiative [46]. She discussed the challenges encountered during the creation of UPLCI, including data quality and availability, reduction of complexity while remaining generic, managing empirical models, dependence of materials and energy on machine setup, and an unclear vision of how to capture impacts of auxiliary processes. To improve dissemination, Linke encouraged researchers to report their UPLCI models in standard format as peer-reviewed journal articles in *Production Engineering - Research and Development*, where recent UPLCI studies have appeared for grinding and welding [47,48].

Mr. Arvind Shankar Raman of Oregon State University next presented the talk titled, *Approach for Modeling of Manufacturing Processes and Manufacturing Systems*. He discussed the motivations for companies to pursue sustainable manufacturing practices, including social responsibility, investor demands, government regulations, international standards, and customer consciousness. However, he noted a considerable number of challenges; for example, analysis applications for sustainability assessments are often deficient in supporting integrated system-, process-, and machine-level manufacturing decisions. Data collection and reporting within and across supply chains remain a large challenge for manufacturers. Prior manufacturing process modeling efforts (e.g., UPLCI and CO2PE!) have focused on developing information models that are problem-specific, making them extremely limited in their extensibility. In addition, such approaches require technical understanding of the manufacturing processes, which makes them difficult to adopt and apply within different product designs and production settings. Shankar Raman presented an information modeling framework for reusing and extending existing models of manufacturing processes for sustainability characterization [49].

To close out the lightning talks, Dr. Alex Brodsky of George Mason University, in his presentation titled *Reusable Model Repository for Manufacturing Systems*, introduced a web-based system, called Factory Optima, being developed in his lab for composition and analysis of manufacturing service networks based on a reusable model repository [50]. This architecture aims to overcome the limitations of current decision-making tools and models for smart manufacturing. Most analysis and optimizations tools are currently developed from scratch, which leads to high cost, long-duration development, and restricted extensibility. Factory Optima is a high-level system architecture based around a reusable model repository and the Unity Decision Guidance Management System. Brodsky described this software framework and system for composition, optimization, and trade-off analysis of manufacturing and contract service networks. The work is unique in its ability to perform tasks on arbitrary service networks without manually crafting optimization models.

The expert lightning talks laid the foundation for the interactive afternoon sessions of the workshop. Three exercises were conducted to engage workshop participants: a schema refinement activity, brainstorming on process modeling challenges and opportunities, and a reflective activity to contemplate the lessons of the day.

2.4.2 Schema refinement activity

Researchers from NIST led the activity to gather feedback from 2018 RAMP Competition participants and others to support extending and strengthening of the schema standardized in the ASTM E3012-16 standard (recently superseded by ASTM E3012-19). One of the key goals of ASTM E3012-16 is to characterize and record UMP models in a consistent manner to promote model reuse and sharing. The schema provided in the standard did not explicitly support reuse, which was made apparent from the NIST-hosted RAMP Competition in 2017, where use of the standard was a requirement for process model development. The submissions rarely conformed to the standard. NIST designed a formal implementation schema [51] for the 2018 RAMP Competition to ensure that the standard was followed more closely by process modelers. NIST also proposed revisions to the standard that are captured in the new schema, including the inclusion of more specific elements within the product and process information element as well as other elements and attributes to promote model traceability.

The proposed revisions to the standard were reviewed and explained in a 15-minute presentation. Participants were then asked to navigate to the online tool, IdeaBoardz [52], on their personal devices (e.g., mobile phones, laptops, or tablets) and to respond under six categories of feedback: keep doing, start doing, stop doing, less of, more of, and action items. Participants were asked to anonymously post concepts, ideas, and suggestions related to each category. The online tool allowed for “up-votes,” wherein workshop participants could show their agreement with ideas posted by other participants. Once concepts were posted to the board, participants volunteered to provide a verbal explanation of their ideas, which led to a discussion and clarification of key ideas.

Based on the number of votes, it was evident that participants desired more modeling examples, specifically those that would be industry-relevant (19 total votes). There was also a considerable need for better definitions and documentations for the elements and attributes within the schema (7 total votes). With proper tools and frameworks, participants suggested that there would be fewer barriers to the use of UMP information models. Based on comments received, a critical future direction would be to demonstrate the use of the revised schema in industrial settings. In particular, validating the approach at scale would garner more interest and use of the standard. Validation could be facilitated by the generation of models (or adaptation of manufacturing process models) undertaken by the advanced manufacturing research community.

2.4.3 Brainstorming activity and results

Parallel brainstorming discussions that focused on the six lightning talk topic areas were each facilitated by a subject matter expert. The session was guided by Dr. Karl Haapala, of Oregon State University, and focused on advancing discrete manufacturing processes, nanomanufacturing at scale, additive manufacturing at scale, process-level sustainability assessment, system-level sustainability assessment, and manufacturing engineering education. The brainstorming session involved 26 participants from academia and three from government labs. Each of the groups discussed challenges and opportunities related to metrics and indicators, models and algorithms, and tools and methods for each topic area. Participants first distributed themselves among the topic areas and then advanced through facilitated discussion rounds to brainstorm ideas related to the topics in a timed manner. The structure of this session allowed for a continuous flow of perspectives and ideas that were guided toward identifying challenges and approaches to overcoming them for each topic. Results of the activity were synthesized and provided in Table 2.2 (metrics/indicators), Table 2.3 (models/algorithms), and Table 2.4 (methods/tools) for each topic area.

2.4.4 Reflection activity and results

The final stage of the afternoon workshop session involved an individual activity that allowed participants to reflect on what they had heard and to offer their own insights. As such, the workshop organizers posed two questions: (1) *What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?* and (2) *What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?*

Table 2.2. Results for metrics and indicators from the brainstorming activity

Topic	Metrics and Indicators
Discrete manufacturing	• Identified challenges, including product customization, standardization, and bolstering the flexibility of processes • Identified connecting process level controls and system level metrics as a key barrier
Nanomanufacturing at scale	• Identified key metrics and indicators which include (depending on the process) fluid type, electron beam power, scan rate, beam diameter, material removal rate, structural resolution, feature size, tolerances, nanoparticle medium, roll-to-roll speed, printing speed, ink spread, sintering conductivity, circuit device design, and reactor design • Identified a key barrier as control over process parameters to achieve defined dimensional tolerances, which is difficult due to the extreme sensitivity of nanomanufacturing processes
Additive manufacturing at scale	• Identified metrics included temperature, layer thickness, material uniformity, material density, extrusion rates, feed rates, internal geometries, product dimensional constraints, melt pool geometry, build time, profile, accuracy, surface finish, and repeatability, including preventative maintenance, post-processing operations, and control of multi-axis equipment • Noted a need for developing and implementing methods of non-destructive inspection for measuring features (internal and external). In addition, current indicators of process variables are deficient in their ability to control the melt pool within desired operating ranges of existing additive manufacturing processes
Process-level sustainability assessment	• Identified metrics and indicators at the process level, which broadly include cost, productivity, quality, energy, resources, waste, environmental impacts, personal health, and safety • Noted a difficulty in identifying and quantifying metrics at the process level, which requires sophisticated models for accurate characterization
System-level sustainability assessment	• Identified metrics included lead time, resource availability, material stability, and system reliability • Indicated importance of considering interactions of multiple manufacturing processes for accurate metric quantification and assessment, requiring integration of models across engineering domains and information-sharing across industries
Manufacturing engineering education	• Noted that an identifiable increase in confidence within manufacturing classes is a key indicator for education in advanced manufacturing • Identified the lack of sustainability topics in undergraduate studies is a weakness of advanced manufacturing education • Found metrics for engineering education in advanced manufacturing difficult to define

Table 2.3. Results for models and algorithms from the brainstorming activity

Topic	Models and Algorithms
Discrete manufacturing	• Noted that complexities in model composition and optimization are barriers to developing flexible models and algorithms, requiring support of related products with complementary models across multiple enterprises • Indicated that scheduling intricacies are a challenge for modeling flexible discrete product manufacturing systems • Noted that modeling dynamic processes and processes that are interdisciplinary (involving various engineering technologies) can be extremely difficult
Nanomanufacturing at scale	• Noted current modeling methods include modeling of nano-scale fluid dynamics, roll-to-roll modeling, circuit modeling, molecular dynamics, and density functional theory • Indicated a lack of models or algorithms for metrics and indicators of interest such as electron beam power, scan rate, beam diameter, structural resolution, feature size, nanoparticle medium, printing speed, ink spread, and sintering conductivity
Additive manufacturing at scale	• Indicated some of the existing modeling challenges include support structure optimization, design features (form, fit, and function), and model fidelity • Expressed a need for representing key performance indicators (KPIs) as a function of control parameters • Noted that cloud-based process design is needed, perhaps combining parameterized product design methods with new process design approaches
Process-level sustainability assessment	• Indicated limited availability of models and algorithms that enable the assessment of process-level sustainability metrics • Noted that exploration of physics-based and empirical models, predictive models, optimization methods, process planning, and sensor data collection and storage for data-driven models should be studied as disparate means to assess and improve process-level sustainability
System-level sustainability assessment	• Noted a need to develop models for risk assessment and evaluating system dynamics • Indicated models that describe manufacturing processes accurately have an important role in robust system-level sustainability assessment
Manufacturing engineering education	• Identified the need for models to apply sustainability concepts in real life, as well as the need for models that are easy-to-apply with existing software solutions and sustainability assessment methods • Indicated a need to incorporate design methodologies, especially Design for X concepts, into manufacturing engineering curricula

Participants recorded their answers to the two questions on individual notecards. The answers received were varied, but could be grouped into the following categories:

1) Connection between academia, industry, and government
2) Manufacturing engineering education improvement and workforce development
3) Development, verification, and validation of manufacturing process models
4) Development of advanced manufacturing technologies and novel materials
5) Scalability improvements and standardization for advanced manufacturing
6) Integration of advanced manufacturing with cross-functional engineering domains

The categorization of responses to the open-ended first question are indicated in Figure 2.1. More than one quarter (27%) of the participants reported that *manufacturing engineering education improvement and workforce development* efforts are most needed to advance manufacturing research or education. Individual responses indicated that participants perceived a lack of industry-relevant curricula in advanced manufacturing engineering education or a lack of adoption of basic engineering education in manufacturing industry. Key ideas shared by workshop participants included improving education, providing hands-on experience, promoting manufacturing education to inspire younger generation, and developing online resources for manufacturing education.

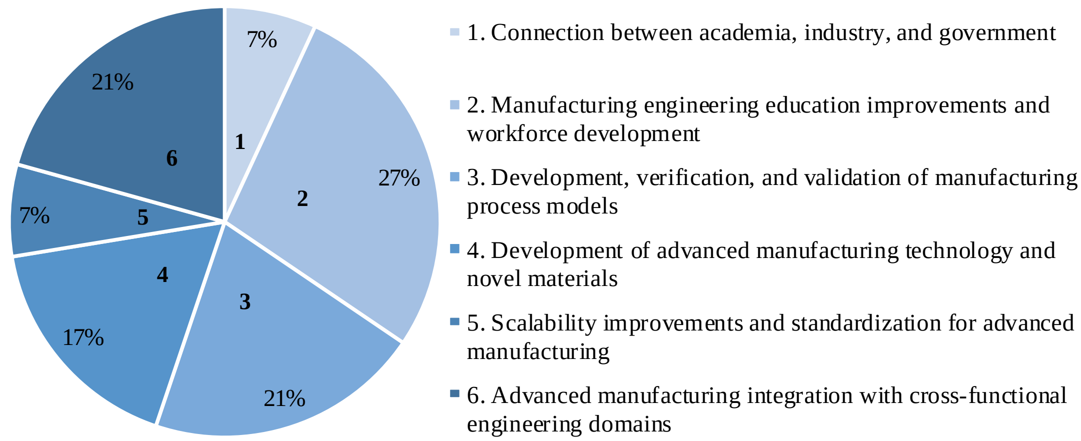


Figure 2.1. Summary of responses to Question 1: ***What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?***

The third category (*process model development, verification, and validation*) and the last category (*integrating manufacturing with cross-functional engineering domains*), scored high as well; 21% of respondents identified these areas as having the most pressing need. In particular, participants noted that process models with validated datasets, methods, and algorithms were needed. These responses may have been due to the workshop discussions tailored toward addressing a need for models to fill current characterization gaps and engineering education needs. Respondents indicated that fields of engineering such as design (*connecting design and manufacturing*) and computer science (*artificial intelligence, machine learning, and improvements in analytical tools*) play a critical role in advancing manufacturing industry and enabling smart manufacturing.

Table 2.4. Results for methods and tools from the brainstorming activity

Topic	Methods and Tools
Discrete manufacturing	• Identified a need to classify problems of existing manufacturing processes to advance the understanding and optimize the performance of discrete manufacturing processes using machine learning • Expressed a need to develop software for interpreting and linking disparate process models
Nanomanufacturing at scale	• Noted that common tools include mathematical solvers, computational fluid dynamics software, finite element analysis software, and finite volume methods, as well as analytical tools (e.g., scanning electron microscopes and transmission electron microscopes) • Noted that key barriers include the precision and accuracy of current metrological methods/tools and limited ability to control motion components with extreme precision
Additive manufacturing at scale	• Indicated a need for tools that aid selection of the process type, build orientation, and material, in addition to tools that support metrology, in-process monitoring, quality measurement, and verification and validation • Noted a need to develop/improve tools that perform cross-validation, and provide sustainability decision support, cost modeling, and product design optimization
Process-level sustainability assessment	• Indicated a need for tools that support teaching of sustainability assessment at the process level through adaptable, easy-to-use, open source methods of quantification • Identified skills training, societal influence, and social behaviors as approaches to communicate the importance of considering sustainability factors
System-level sustainability assessment	• Indicated current challenges include how to collect, sort, and validate data for system-level assessment • Noted a need to develop tools that establish and define process relationships between models for systemic assessments
Manufacturing engineering education	• Noted that manufacturing techniques that can be taught using in-house demonstrations would be highly beneficial for students to develop a physical understanding of processes • Indicated that basic technical knowledge should be included in physics-based classes, and taught using case studies in an interactive manner (e.g., labs associated with reading materials)

For the second question, the responses were coded using the same six categories (Figure 2.2). More than one-third of the participants felt that the key next step was related to *manufacturing engineering education improvement and workforce* *development*. In particular, workshop participants noted needs in providing internship opportunities for students, developing online educational tools on advanced manufacturing, promoting engineering at all levels of education, enabling education research, recruiting people for advanced manufacturing careers, and combining industry practice with traditional educational methods.

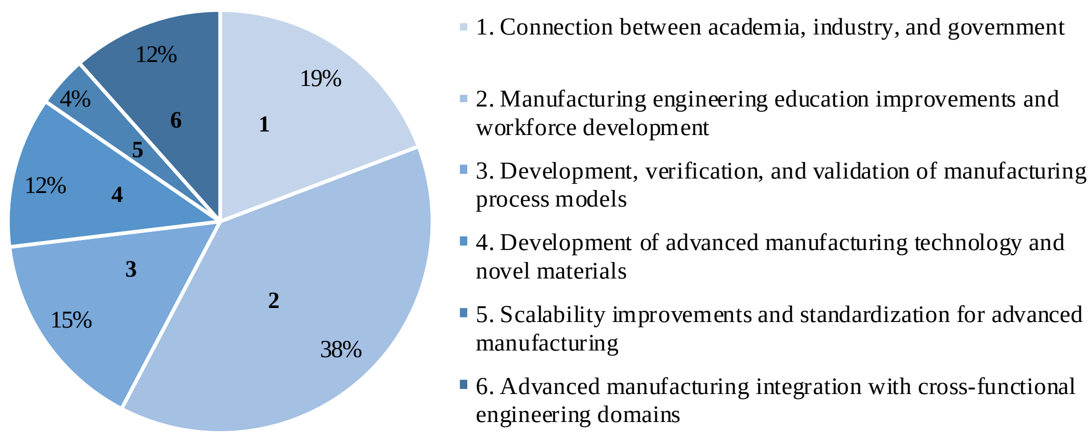


Figure 2.2. Summary of responses to Question 2: ***What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?***

A significant fraction of participants (19%) reported key next steps related to *connection between academia, industry, and government*, noting that academic research, government policies, and industry adoption need to work hand-in-hand for advancing manufacturing. Some of the key points mentioned by participants were needs for better communication between academia and industry, in addition to implementing policy changes for encouraging more sustainable practices, using industry-driven research to create value, and bridging the gap between people and technology through defined guidelines for practitioners.

2.5 Summary of Workshop Findings

The workshop activities identified potential directions for basic and applied research related to sustainability of nanomanufacturing processes and nano-products, digitization of continuous and batch processes, development of physics-based models of manufacturing processes, and efficient process and system models for cloud- and cyber-manufacturing. In particular, the following research directions emerged:

1) Machine learning methods can support understanding of a variety of discrete manufacturing processes, e.g., nanomanufacturing, as well as system-level sustainable manufacturing analysis and optimization.
2) Metrics and indicators for nanomanufacturing are plentiful and span process parameters, material properties, and part characteristics. They should be unified/harmonized to enable technology comparisons.
3) Scalability in nanomanufacturing needs to lead to reduced defects, improved metrology methods and tools, and measurement of moving parts and assemblies.
4) Scalability of additive manufacturing requires optimization methods for new material development, part geometry generation, and support structure design.
5) Additive manufacturing key performance indicators must be connected as a function of process controls.

6) Integration of in-situ and out-of-process metrology, sustainability decision tools, model selection tools, cost models, and product design optimization tools, are all areas of research need, especially in emerging domains, e.g., additive manufacturing.
7) Transient analysis of complex manufacturing systems can lead to robust manufacturing process models.
8) Bridging the gap between process-level controls and system-level metrics can enable deeper insight for discrete and bulk product manufacturing.
9) Systemic sustainable manufacturing requires insight from risk assessment and system dynamics methods to capture the emergent behaviors of interconnected, complex systems.
10) Societal influences of sustainable manufacturing, e.g., stakeholder behavior, must be better understood to enhance development and adoption of new materials, processes, and products.
11) Robust methods to characterize interactions of physical processes, human activities, and decisions across systems are needed to advance systemic sustainable manufacturing.
12) Problem identification and diagnostics can be aided through classification of physical asset degradation.
13) Innovative engineering education approaches are needed to address the growing urgency for accurate and meaningful sustainability assessment at the process and system levels. Engineering students often need a more physical connection

to the process, while technical students require more fundamental knowledge and skills for advanced manufacturing.

14) Developing and sharing knowledge (e.g., learning metrics, models, and approaches) for improving the effectiveness of learning in advanced manufacturing should be a focus of engineering education research.

15) Standards can support the reusability and replicability of research into advanced manufacturing processes.

2.6 A Review of Future Research Opportunities

Based on these workshop findings, the authors synthesized the research directions that emerged into five advanced manufacturing topics: conventional manufacturing, nanomanufacturing, additive/hybrid manufacturing, process and system characterization, and workforce education and training. These categories follow key NSF areas of research interest. Next, a review of the recent literature was undertaken with a goal of identifying future research opportunities in each of these domains. We focused on first defining the state of current research in each topic area by reviewing recent NSF advanced manufacturing projects and related literature from the manufacturing research community. Based on this work, we present short-, mid-, long-term research challenges raised to help define key gaps to be addressed by the advanced manufacturing community. Finally, we identify expected outcomes of successful research undertaken in each area. We caution that these findings are limited (specific technology development may not have broad consensus); the community should expand areas of research opportunity through continued discourse.

2.6.1 Conventional manufacturing

Conventional manufacturing commonly includes established processes, categorized as primary shaping, deformation, material removal, coating, heat treatment, and joining processes [28]. While the physical phenomena of each of these processes have not been completely characterized, a majority of recent phenomenological research has been directed at additive manufacturing, as discussed in Section 5.3. In addition, in the U.S., welding process research has been well-supported by the NSF. The emphasis has been on solid-state welding processes, which occur below the melting temperature of the components to be joined. These research efforts include advancements in friction stir welding (e.g., defect detection and prevention [53,54], joining dissimilar metals [55,56], and effects of temperature and force control [57,58]); hybrid ultrasonic resistance welding [59–61]; magnetic pulse welding and friction stir blind riveting [62–64]; and impact welding [65]. Fewer research efforts have tackled fusion welding processes, such as vibration-assisted laser keyhole welding [66].

Recent research in material removal operations have explored specific challenging phenomena, such as those attendant with ultra-precision machining of ceramics [67–69]; machining-induced distortion in milling [70,71]; through-tool minimum quantity lubrication drilling [72]; and atomized dielectric-based electro discharge machining [73]. Research in this domain is also directed at improving machine tools, such as software-supported improvement of speed and accuracy of vibration-prone machines [74–76]; at metrology, such as measurements of part features using freeform optics

[77–79], measurement of dynamic moving parts in manufacturing tools [80], and manufacturing of optics used in metrology [81]; and at non-destructive evaluation of composites [82]. Table 2.5 identifies the relevant potential research opportunities and expected outcomes in the short-, mid-, and long-term ranges.

Table 2.5. Research opportunities for conventional manufacturing processes

	Research Opportunity	Expected Outcome
1-3 years	• Develop physical process models, in particular for new and hybrid processes • Develop transient analysis models of complex systems, especially non-steady state manufacturing elements	• Optimized digital twins of processes • Robust models with easier transferability and scalability
4-5 years	• Develop robust and process-representative machine learning algorithms • Develop scheduling models for flexible discrete systems • Develop models and controls for integrating robots into manufacturing processes, and model interactions between robots and processes • Develop models of metrology processes to allow smart manufacturing control	• Optimized performance of discrete manufacturing through improved process understanding • Process and process chain improvements
5+ years	• Develop models for product categories across multiple enterprises, in particular the connection of physical process models across factories	• Higher competitiveness of various industry sectors

With the trend towards smart, automated, and cyber-integrated manufacturing, the need for realistic digital representations of conventional manufacturing processes is also gaining importance [38,83]. Though much insight can be gained through purely data-driven models, a hybrid approach, wherein physical knowledge is also leveraged, is preferred [84]. Emerging electronic, biomedical, and aerospace products are driving applications of new smart technologies, providing challenging material combinations, tolerances, and lot sizes for conventional manufacturing.

2.6.2 Nanomanufacturing

Nanomanufacturing has been used in producing materials and products in almost all major industry sectors, such as electronics, automobile, aerospace, biomedical, energy, and food, among others [85]. Nanomanufacturing is the production of nanoscale features (surface and sub-surface), materials (nanoparticles), parts (3D nanostructures, nanotubes, and nanowires), devices, and systems [86]. Scalable nanomanufacturing involves the high volume manufacturing of nanomaterials and nanostructures, assembly into parts, devices and sub-systems, and integration into a complete system. Nanomanufacturing generally has a minimum of one lateral dimension in the range of 1-100 nm [87].

Nanomanufacturing has been broadly classified into three categories: top-down (producing nanoscale features using physical processes that remove material from a larger mass), bottom-up (building up nanoscale features from an atomic or molecular scale using chemical synthesis and self-assembly), and hybrid (a combination of top-down and bottom-up) approaches [88]. Due to the application of nanomanufacturing in a variety of industry sectors, research of novel nanomanufacturing technologies focuses on scaling up from lab-scale to large volume production, lowering tooling and equipment cost, improving quality and reliability, increasing yields, reducing wastes, developing materials compatible for new techniques, and multi-material production [89–91].

Since nanomanufacturing relies on many fields of engineering for materials development, equipment and tool development, optical characterization of nanoscale features, and sensing and instrumentation, these fields need to work cohesively to advance new nanomanufacturing technologies. Current tools to characterize surface and sub-surface level topographical information are time-consuming [92], which is a bottleneck in high-volume manufacturing. Unlike discrete manufacturing processes, each nanoscale process is unique due to its complexity in controlling process variables, measurement, sensing, and material homogeneity at the nanoscale [89]. These variations result in products of varying quality, introduce large failures, and decrease the relative reliability of resulting products.

Mechanical components in nanomanufacturing devices and equipment are subjected to multiple failure patterns due to system complexities such as, multiple sub-systems, complex underlying physical phenomena, and rapid degradation of tool components [93,94]. Extensive research is often needed to troubleshoot equipment failures, occupying valuable human resources. Educating engineers in nanomanufacturing processes is a key to overcoming many of these barriers [93]. In particular, educational materials for design for manufacturing and assembly (DFMA) and failure modes and effects analysis (FMEA) should be developed for nanomanufacturing process technologies. Another key area of emerging nanomanufacturing research is self-assembly of nano-components to form nanoscale systems. Robust self-assembly methods are needed, for example, in order for nanoscale components developed though bottom-up approaches to have a hierarchically-ordered structure with high quality [95–97].

It should be noted, nanomanufacturing technologies require large amounts of in-process manufacturing data to support robust process modeling. To overcome this challenge, statistical tools and machine learning methods could be applied for real-time process control to achieve desired quality levels. Researchers would thus be able to correlate process parameters that are crucial to performance improvement, while developing scientific understanding of the underlying physical phenomena. Such knowledge would facilitate development of hybrid (combination of physics-based and data-driven) models of nanomanufacturing processes [98]. Table 2.6 identifies the potential research opportunities and expected outcomes for nanomanufacturing in the short-, mid-, and long-term ranges.

2.6.3 Additive manufacturing

Additive manufacturing is a process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies [99]. Additive manufacturing is at a turning-point due to its increasing application in manufacturing a wide range of products in various industrial sectors [100]. Industry sectors where innovations can be seen include food and consumer products, medicine and medical products, automotive, aviation, architecture, and construction [101,102]. Competitive advantages of additive manufacturing processes include their adaptability to the geometric complexity of shape-optimized components, suitability for production of customized or tailored products, flexibility for just-it-time production approaches, and ability to reduce the need for part transportation and storage [85,103]. Moreover, design for additive manufacturing approaches have enabled industry to generate lightweight product designs, reduce assembly errors, and improve sustainability performance of manufacturing by reducing waste and energy.

Table 2.6. Research opportunities for nanomanufacturing processes

	Research Opportunity	Expected Outcome
1-3 years	• Improve control of in-process parameters (e.g., melt pool temperature, flow rates, and power levels) to achieve desired feature tolerances • Reduce scan speeds to improve upon current metrology methods, which take a long time to scan and require frequent calibration • Develop an initial repository that contains design for manufacturing methods for varied nanomanufacturing processes	• Increased product quality • Reduced cost for metrology and quality inspection • Improved process selection and design
4-5 years	• Integrate more precise control in current optical methods employed in fabrication and metrology to overcome inconsistencies in part quality due to power, beam diameter, and machine precision • Improve optimization and control of real-time process parameters, e.g., via artificial intelligence methods, to improve efficiencies, and reduce costs, environmental impacts, and wastes	• Products with higher quality and reduced defects • Efficient, high-throughput metrology • Reduced cost of nano-products through high-volume production
5+ years	• Develop standard guidelines for establishing performance metrics, analytical models, and evaluation methods for nanomanufacturing	• Better understanding of process and system factors to be prioritized for efficient manufacturing and high quality products

These advantages of additive manufacturing processes are attendant with their own inherent disadvantages. While conventional manufacturing processes are capable of making thousands to millions of identical parts at low cost, for example, current additive manufacturing process technologies are better suited for high-value, low-volume production applications [100] due to their relatively high capital investment needed to achieve high production volumes [104]. Thus, the cost of products made using additive manufacturing is typically much higher than those made using conventional mass production methods. Current additive manufacturing equipment also imposes limitations on product size and part quality, and requires more highly skilled labor.

To address these challenges, new additive manufacturing capabilities have been investigated, including multi-material, multiscale, multiform, and multifunctional printing [105–107]. Nano-positioning in micro-scale additive manufacturing [108,109] has also gained attention from researchers. Process modeling [110], precision improvement [111], and cost reduction [112] are the other areas in micro-scale additive manufacturing that have been investigated recently. In addition to micro-scale, some researchers have focused on developing new materials for nano-scale additive manufacturing[113].

An extant challenge is the limited set of materials available for industrial additive manufacturing use. These materials generally have limited mechanical and thermal properties, which restricts their broader application [104]. Moreover, the sustainability performance of many materials in additive manufacturing is not well-understood [114]. It has been suggested that developing lower cost biocompatible materials can help improve economic and environmental aspects of sustainability [115]. In addition to material-related issues, the effect of different equipment and process technologies on various materials are poorly understood, often resulting in poor surface finish and tolerances, warping, and layer misalignment [116]. Table 2.7 identifies the potential research opportunities and expected outcomes for additive manufacturing in the short-, mid-, and long-term ranges.

Table 2.7. Future research opportunities for additive manufacturing

	Research Opportunity	Expected Outcome
1-3 years	• Develop automated geometric decomposition methods for efficient part buildup and assembly • Develop geometric dimensioning and tolerancing models for *a priori*, predictive analytics • Develop models to characterize product and process information (and/or performance) based on 3D model and 2D slice data	• Improved product quality by predicting warping and distortion • Better data sharing, storing, access, and modifying
4-5 years	• Develop new equipment and controls to reduce capital investment • Develop new materials and compatible deposition mechanisms to enable multi-material and multiscale additive manufacturing • Develop multifunctional processes to enable production of tailored alloys and microstructures	• Mass production of identical parts at low cost • Broad potential applications using new materials and equipment
5+ years	• Develop precision control strategies reduce cycle time while maintaining desired quality	• Rapid manufacturing of products with multiscale complex geometries

2.6.4 Process and system characterization

Characterizing manufacturing processes at an in-depth level of detail and understanding manufacturing systems have traditionally been considered mutually exclusive activities. Entire disciplines and research communities have been built around each one in isolation. Engineering teams to address each perspective reside in many organizations. As a result, the tools to support these activities do not easily relate to one another [117]. For example, manufacturing execution system (MES) and enterprise resource planning (ERP) software have been designed to singularly address the performance of manufacturing systems at different levels of control, while tools to assess manufacturing processes are often developed in an *ad hoc* manner within individual companies [118].

With the emergence of industrial internet of things (IIoT) and related smart manufacturing concepts [119], there has been a recent uptick in solutions to bridge the moat between these two domains. Realizing semantic interoperability across MES and ERP software is a current focus area in the manufacturing research, industry, and standards communities for characterizing manufacturing processes for sustainability assessment [24], developing repositories of manufacturing process information [43,120], and analyzing manufacturing processes for designing smart manufacturing systems [121]. For example, Industrie 4.0, a German effort to develop a common framework that facilitates vertical integration across the traditional ISA-95 perspective, has gained much attention across the rest of the world [122]. For manufacturers to remain competitive, react amid unforeseen disruptions, and become more environmentally efficient, a perspective that bridges these two traditionally separated domains is necessary. Table 2.8 identifies the potential research opportunities and expected outcomes for process and system characterization in the short-, mid-, and long-term ranges.

It is clearly beneficial to link perspectives related to manufacturing processes and manufacturing systems. Benefits include more accurate prediction in critical system objectives, e.g., cycle time, throughput, and cost estimation. However, there are significant challenges that must be overcome to realize these benefits. One challenge is the computational cost of simulating detailed, process-level models residing in large networks of manufacturing activities [123]. For example, in traditional operations management problems, process-level metrics, such as cycle time and energy consumption, are simplified, e.g., assumed to be fixed, in order to deal with the complexity on the systems level.

Table 2.8. Research opportunities in process and system characterization

	Research Opportunity	Expected Outcome
1-3 years	• Construct guidelines for training data for data-driven models • Develop methods for integrating between data contexts based on different standard information modeling paradigms (e.g., SysML, E3012, and Modelica) • Tightly integrate physical systems with analytical applications • Understand computational complexity of process-level and systems-level analyses	• Public manufacturing process datasets and models • Usability of the current smart and sustainable manufacturing standards • New guidelines for standards integration (e.g., CCOM and E3012, MTConnect and OPC-UA) • Better communication across engineering domains
4-5 years	• Devise methods for consistent predictive models for process-level optimization • Define standards for linking process-level simulation to systems-level optimization • Develop methods for real-time monitoring and control from sensor data • Improve sensor development/deployment for higher quality data	• Better manufacturing analysis tools • High quality systems-level analysis • Better adaptability to changes at the process level • Near real-time trade-off analysis for assessing sustainability performance • Better public datasets for education, training, and process improvement
5+ years	• Improve scalability, flexibility, and adaptability of process-level to systems-level approaches • Define model verification, validation, and uncertainty quantification (V&V) • Develop standards to port process-level to systems-level thinking in an automated manner • Integrate broad-based security methods with data flow for robust, trusted process and system analysis and optimization	• Clear understanding of limits of paired process-to-systems approaches and standards that link the two perspectives • Clear guidelines for characterizing uncertainty of models • Pilot studies that demonstrate potential to educators, researchers, and practitioners • Tools for secure and private data transfer (e.g., blockchain for manufacturing) • Improved standards for process model and manufacturing data security

Other process and system characterization challenges include the following:

(1) Validation modeling and uncertainty quantification methods across different abstraction levels (e.g., machines, processes, and systems) are not standardized[1].

(2) Even if process-level models are available, e.g., in a repository, appropriateness of their reuse for a specific instance is not well-understood [120]. Bridging the existing standards at the various levels is another open research question, e.g., relating MTConnect to the E3012 standard.

(3) To produce "what-if" scenario exploration in complex supply chain networks, relating disparate databases to one another is particularly challenging.

Privacy and security associated with sharing data across and between distributed manufacturing enterprises remains a primary concern of many manufacturing companies and an area of very rapid evolution. Applying best practices and known methods for incorporating levels of traceability, e.g., blockchain or digital signatures, is essential for enterprises to feel comfortable in sharing data. Articulating manufacturing needs is important to influencing ongoing development in these areas.

[1] ASME's Verification, Validation, and Uncertainty Quantification (VVUQ) initiative is an emerging standard area that provides guidance to develop, analyze, and enhance the credibility of computational models and simulations [124]

2.6.5 Workforce education and training

Beyond traditional engineering and technical curricula, the current and future manufacturing workforce needs to be educated in advanced manufacturing and provided with the skills that will enable decision making in smarter, more sustainable industrial environments. Process and system modeling are primary mechanisms to continuously improving broad-based manufacturing performance [101,125]. As noted above, manufacturing processes account for the most intensive energy use and waste production in many manufacturing facilities [126,127], yet are often overlooked because their solutions are complex and varied.

While process improvement based on Plan-Do-Check-Act cycles are well-established, technical standards for applying the practice routinely for improving individual manufacturing processes remain under development and deployment. ISO 14001 [128] provides guidelines for companies to establish environmental management systems that address waste and energy management, but stops short of offering guidance on improvements for individual processes. Engraining standards such as those from ASTM E60.13 [129,130] into widespread practice, first through standards education program development [131], will spur industry adoption of sustainability improvement practices [132]. These standard practices can be extended with a focus on individual manufacturing processes to enable more replicable and repeatable evaluation. In addition, techniques for applying foundational yet interdisciplinary (cross-cutting) technologies that promise revolutionary impacts to manufacturing performance need to be integrated into manufacturing education. These technologies include sensing technology, computational skills, artificial intelligence (AI), machine learning, data analytics, ontological definition, cognitive computing, augmented and virtual reality, and quantum computing, among others. Process modeling may serve as a platform for such integrations.

The challenges of workforce education and training are diverse, and include establishing practices in process and system modeling, sustainable thinking, life cycle assessment, and continuous improvement at all levels of the manufacturing enterprise as well as a need for personalized education and training experiences to inspire the next generation to pursue manufacturing careers [133]. Such efforts need to be undertaken at all educational levels. Often, the sustainability-related trade-offs of our decisions are unknown, either due to a lack of information at the time the decisions are made, a lack of metrics by which the factors can be quantified (i.e., the externalities), or lack of visibility of the trade-offs to the decision maker [134,135]. Standard practices for instilling manufacturing process modeling are lacking [118], and how such standards can by systemically employed in cyber-human systems must be better understood [40]. Early work has been done in this area, but more is needed to characterize manufacturing processes for sustainability [129,136], for representing manufacturing processes using information modeling [129,136], for reusing such information models variations of manufacturing processes [49,130]. What distinguishes these concepts from more traditional curricula is the heavy reliance on information to guide decision making. Information modeling and capture have traditionally not been part of manufacturing engineering curricula. The field of structural engineering has seen a similar transformation and several researchers have reported on educational aspects of this transformation [137–139].

While industry is in need of skilled workers in smart and sustainable manufacturing to enable the development, implementation, and continuous improvement of advanced manufacturing processes, interests in manufacturing careers has decreased due to the poor image young people have of industry [1]. Integrating sustainability concepts into engineering curricula has been shown to improve student perceptions, in particular for students underrepresented in engineering [140,141], as well as motivating students to pursue careers in sustainability [142,143] and increase student interest in the job opportunities in manufacturing [144,145]. A concerted effort is needed to synthesize existing resources through convergent research that raises the conscientiousness of sustainability objectives in the profession, develops the data and methods needed to inform effective decision making, and provides insight and intuition to externalities, while also focusing the educational objectives of the advanced manufacturing community. For instance, a key gap in existing science and engineering education is the lack of an appropriate learning environment for students to address technical solutions that consider the three aspects of sustainability [146]. Further, the more mundane aspects of manufacturing [147–149] and manufacturing education can be improved through the application of gamification techniques [150,151]. With a deep understanding of the principles of manufacturing processes themselves, in some cases these techniques may be applied to improve the performance of those processes.

Another fundamental distinction of future manufacturing systems is the interplay between the virtual and the physical worlds. This distinction is manifest throughout the discipline. AR and VR technologies are being applied in manufacturing training systems where significant training can take place without any physical engagement. Similarly, like the 3D product design models that came before it, the concept of the "digital twin" has emerged to describe the virtual model of operational systems that allow for monitoring and prognosis based on real-time data. What's more, the use of robotics throughout manufacturing systems will require sophisticated human machine collaborations. The next generation of manufacturing engineers will need to shift seamlessly and accurately between the virtual and actual world in a way that has not been previously practiced, opening up a new area of research exploration. Automation of systems means seeding control of those systems, yet human expertise and knowledge is necessary to maintain control though all types of failure modes. The aviation industry has witnessed some highly-visible unexpected consequences from the introduction of automated navigation into the cockpit in terms of pilot preparedness in emergency situations resulting in loss of human life [152,153]. Avoiding similar catastrophes in the manufacturing setting will take study and work towards implementing fail-safe solutions. Initial approaches to the problem have explored the form of interactions between humans and machines with the goal of identifying and optimizing those task for which a person's unique skills are best suited by providing access to data on demand to improve their decision making capabilities [154,155]. Table 2.9 identifies the potential research opportunities and expected outcomes for educational and training issues in the short-, mid-, and long-term ranges.

Table 2.9. Research opportunities in workforce education and training

	Research Opportunity	Expected Outcome
1-3 years	• Use the design of products, processes, and systems as a basis to capture K-12 students' imaginations and interests • Use web-based learning, augmented reality, and virtual reality technologies to promote advanced manufacturing technical skills • Create resources and tools for teaching process and information modeling in technical and engineering education programs • Integrate sustainable manufacturing and life cycle thinking into K-12 curricula	• Motivated young people toward engineering and making for the social good • More engagement in engineering and manufacturing for a more productive society and more sustainable industry • Better trained students, technicians, and engineers to support advanced manufacturing
4-5 years	• Innovate current online and virtual media to teach K-12 and undergraduate students about advanced manufacturing and build their confidence through learning by doing • Understand what is required of intuitive user interfaces to improve operational choices, including gamification • Integrate life cycle thinking and design for X methods in engineering education	• Prevention of unintended consequence through proactive planning and informed decision making • Expanded knowledge and engineering intuition surrounding sustainability objectives • Effective learning tools and methods
5+ years	• Make estimation of impacts available to designers and other decision makers, e.g., real-time analytics using cyber-technology • Develop frameworks for integration of real-time data into design decision making • Create tools that enable users to find relevant existing information and research, and perform trade-off assessment • Develop systemic approaches and methods for teaching smart and sustainable manufacturing	• Ease of impact assessment for manufacturing processes and product life cycles • Integration of life cycle costs into design and manufacturing planning • Facilitated exploration of impacts of production systems on society in the presence or absence of life cycle thinking

2.7 Summary

Over the past several decades, manufacturing industry has seen rapid development in sensing technologies, process equipment, and materials, among other areas, aided by the emergence of data and information technologies. These advancements have enabled new manufacturing methods (e.g., cyber-manufacturing and distributed manufacturing) and processes (e.g., additive manufacturing and hybrid manufacturing), but often experienced little or no convergence during their development, which has inhibited more systemic development and growth.

The foregoing presented the findings from a workshop organized within the manufacturing research community that aimed to identify challenges and barriers attendant with smart and sustainable manufacturing. The workshop activities (i.e., student presentations, expert talks, schema refinement feedback, and brainstorming and reflection) aided in defining challenges related to metrics and indicators, models and algorithms, and tools and methods across several advanced manufacturing fields. The ideas gathered from workshop participants reflect a range of potential opportunities for the manufacturing research and educational community to pursue.

To supplement workshop findings, a review of recent literature was completed under the following themes: (a) conventional manufacturing processes and systems; (b) nanomanufacturing processes and systems; (c) additive/hybrid manufacturing processes and systems; (d) process and system characterization methods; and (e) workforce education and training for advanced manufacturing industry. Existing challenges and barriers, potential research opportunities, and expected outcomes were presented from the short- to long-term range for each topic area. This study arrived at the following findings:

(1) Improvements in sensing, controls, metrology, and processes have been reported across the various manufacturing technology domains;

(2) There is a need for well-developed models, algorithms, and methods that can be utilized to improve process- and system-level performance for specific manufacturing applications;

(3) Artificial intelligence (e.g., reasoning and machine learning) and other emerging technologies can have a great impact in process- and system-level improvements across manufacturing domains; and

(4) Improved manufacturing education could inspire future generations into manufacturing engineering and research careers (e.g., through new hands-on, virtual, and off-site methods).

These findings can help stimulate future manufacturing research and benefit stakeholders across academia, government, and industry for advancing smart and sustainable manufacturing, as discussed in greater detail in Section 5. The fundamental and applied research opportunities identified under these themes can be undertaken by existing and emerging consortia (e.g., NSF Industry-University Collaborative Research Centers, Manufacturing USA, and EU Factories of the Future programs), as well as through conventional university, industry, and government agency funding mechanisms that are addressing emergent manufacturing challenges. It will be crucial that research solutions derive actionable implementation pathways for industrial organizations and educational institutions at all levels and scales in order to achieve the vision of academic, industry, and governmental leaders and policy makers for a smarter, more sustainable future.

Disclaimer

No endorsement of any commercial product by NIST is intended. Commercial materials are identified in this report to facilitate better understanding. Such identification does not imply endorsement by NIST nor does it imply the materials identified are necessarily the best for the purpose.

Acknowledgement

This material is based upon work supported by the National Science Foundation (NSF) under Grant No. 1831141. The authors wish to thank the NSF, the invited speakers, and workshop participants for their contributions. The authors also gratefully acknowledge the assistance of Mr. Dustin Harper from Oregon State University in transcribing the workshop notes.

Chapter 3: REUSING AND EXTENDING STANDARDS-BASED UNIT MANUFACTURING PROCESS MODELS FOR CHARACTERIZING SUSTAINABILITY PERFORMANCE

3.1 Abstract

Over the past two decades numerous efforts have characterized manufacturing processes for sustainability performance. These efforts have been pursued primarily by manufacturing researchers in academic and governmental labs, and involve the development of frameworks, methodologies, and standards for characterizing discrete manufacturing processes and their representation as information models. Further, characterization of sustainability performance of manufacturing process flows has been attempted through linking, or composing, these unit manufacturing process (UMP) models. This paper reviews these efforts and identifies existing research gaps that should be addressed by academic, industrial, and governmental researchers. The review includes the relevant sustainable manufacturing standards that have been recently published by ASTM International. A methodology for creating and extending composable models of UMPs that builds upon these standards is presented. This research demonstrates how formalization of these prior efforts can address the identified gaps. It is shown that reuse of UMP models can be enabled by encapsulating specific characteristics of complex processes into information models that can be applied for detailed process analysis and evaluation. This research proposes the concept of a template UMP information model, which can further be abstracted and customized

to represent an application-specific, higher-order manufacturing process model. The template model concept is illustrated for manual and computer numerically controlled (CNC) milling processes.

3.2 Introduction

Manufacturing has traditionally been oriented toward providing goods, increasing profits and securing market share, but manufacturing with a broader sustainability focus continues to gain momentum [156]. Globally, a number of sustainable manufacturing efforts have been pursued in response to growing societal concerns over the non-monetized impacts of manufacturing [8,10,9]. In particular, green, or environmentally-responsible design and manufacturing philosophies have paved the way for assessment tools that promote sustainable manufacturing during the conceptual and early design stages of the product life cycle [13,14]. A variety of software tools are available to perform product life cycle assessment (LCA) [157,158]. LCA tools are able to guide manufacturers in making more informed decisions about the environmental impacts of their production processes and supply-chain activities [21,159]. These tools can sometimes offer insight into product- and process-related economic and social impacts during design and, thus, aid manufacturers in developing and implementing sustainable product design and manufacturing modifications.

One major drawback of LCA tools, however, has been their limited ability to model specific manufacturing processes for analysis, which, in turn, limits their utility in evaluating the environmental impacts of changes to individual manufacturing processes [21,160]. Manufacturing phase, or gate-to-gate, LCA studies tend to utilize process models that are not representative of the machine tool setup in the setting evaluated [160,161]. These generic process representations lead to a lack of confidence in assessment results. For example, a comparative LCA for the same machining process type used to produce a one-kilogram pyramid and a one-kilogram cube would yield identical results, since the generic machining process model contained in the database reports impact based on the mass of the part processed and the mass of the material removed. However, due to variations in the machine setups, cutting paths, and other process-specific factors, environmental impacts may vary significantly for the two parts. In addition, there is a lack of quality and granularity of process data, which underpins process models in LCA tools.

To overcome these modeling limitations, efforts have been undertaken to improve manufacturing process characterization for sustainability assessment. One aim of these efforts is to enhance the ability of LCA tools to more accurately assess the environmental impacts of unit manufacturing processes (UMPs) [21,162,134,163]. UMPs have been defined as “the individual steps required to produce finished goods by transforming raw material and adding value to the workpiece as it becomes a finished product” [24], and as “the smallest elementary manufacturing activity required for a specific taxonomological [referring to a taxonomy of manufacturing process types] transformation and composed of machines, devices, or equipment” [164]. More accurate UMP models will also enhance evaluations for other metrics and indicators (e.g., cost and productivity).

The construction of a UMP model requires knowledge of process-specific data and information, including a familiarity with the process physical and/or chemical phenomena [162]. Thus, model development is cost- and time-intensive and has been largely ad hoc, leading to a lack of common structure, and inhibiting model transparency and reusability. These deficiencies have driven recent standards development through ASTM International and the International Organization for Standardization (ISO) [165] In particular, the ASTM E3012-20 standard provides an information modeling-based (hierarchical) structure for constructing process models, and offers a replicable method for representing UMPs [27]. Due to its structured approach, standards-based model development facilitates data handling within/between models and data sharing between business units/organizations, which will enable systemic sustainability assessment. However, these standards-based approaches do not remove the need for domain knowledge nor do they reduce the cost- and time-intensity of model development. The research present herein explores the application of two information modeling techniques (i.e., abstraction and instantiation) to support engineers and analysts lacking in-depth domain knowledge in the development of new UMP models through the reuse and extension of existing models. Related prior work is briefly introduced in Section 3.3. In Sections 3.4-3.5, a methodology for reuse and extension of existing models is presented and demonstrated for a machining process (manual and computer numerically controlled milling). Finally, advantages of this methodology are presented relative to existing approaches (Section 3.6).

3.3 Background

3.3.1 Prior efforts on characterizing manufacturing processes for life cycle assessment

Several efforts have pursued the development of methods for UMP characterization. One of the primary efforts has been under the Unit Process Life Cycle Inventory (UPLCI) project [163,166–168]. The goal of the UPLCI project is to formalize a systematic framework for inventory analysis of the manufacturing phase of LCA. This inventory analysis is performed by dividing a manufacturing process into sub-processes; the resulting representative models are much more reliable and precise. As such, the UPLCI project is pursuing the creation of a toolset that would help compile life cycle inventories (LCIs) of UMPs to support LCA. The framework could enable manufacturing system analyses by aggregating LCI data for individual manufacturing processes involved in the production of a part [31,45]. Developing a new UPLCI involves four steps: (1) preparing the UMP using illustrations and adding details of the UMP energy use phases by dividing the process into basic time, idle time, and peak energy time; (2) developing mass loss equations based on the type of process and ancillary systems used within the process; (3) developing a functioning model of the UPLCI to exhibit its capabilities; and (4) citing references to the obtained mechanistic models [45]. Recently, UPLCI efforts have been pursued to develop reusable manufacturing process models, and reported for grinding [47], gas metal arc welding [48], additive manufacturing [169], and metal injection molding [170]. In addition, Overcash and co-workers applied a UPLCI approach on an aviation assembly involving 67 manufacturing process steps and 14 sub-assemblies with four different materials

[163]. Other efforts have applied the UPLCI approach to develop product and process life cycle inventories [162,171,172]. Table 3.1 summarizes a number of other recent efforts undertaken to characterize manufacturing processes for sustainability performance, which span the manufacturing taxonomy.

Table 3.1: Recent efforts to characterize the sustainability performance of manufacturing processes

Process type	Description	Reference
Mass reduction	Environmental impacts of machining	Dahmus et al. [173]
	Environmental impacts of non-cylindrical grinding	Murray et al. [174]
	Environmental impacts of milling	Diaz et al. [175]
	Energy consumption of ball-end milling	Quintana et al. [176]
	Energy consumption of grinding	Linke et al. [47]
	Energy use in numerically controlled machining	He et al. [177]
	Environmental and cost analysis of stamping	Cooper et al. [178]
Mass conservation	Environmental impacts of sand casting	Dalquist et al. [179]
	Environmental impacts of steelmaking and casting	Haapala et al. [180]
	Sustainability assessment of die casting	Watkins et al. [181]
	Sustainability assessment of die casting	Singh et al. [182]
	Energy consumption of injection molding	Madan et al. [183]
	Exergy analysis of sheet metal forming	Dittrich et al. [184]
	Sustainability assessment of extrusion	Singh et al. [185]
	Energy consumption of metal injection molding	Raoufi et al. [170]
Heat treatment	Sustainability assessment of induction hardening	Eastwood et al. [171]
	Energy consumption of sintering process	Wang et al. [186]
Joining	Energy consumption of gas metal arc welding	Zhang et al. [48]
	Energy consumption of friction stir welding	Shrivastava [187]
Additive manufacturing	Energy consumption of stereolithography	Simon et al. [169]
	Energy consumption of laser powder bed fusion	Ramirez-Cedillo et al. [188]

Initial UPLCI framework development work was expanded in conjunction with the Cooperative Effort on Process Emissions (CO2PE!) in Manufacturing, an initiative undertaken by the International Academy for Production Engineering (CIRP) [21,160]. CO2PE! was launched to address the lack of precise and specific environmental impact data in LCI databases for manufacturing processes. The effort aimed to compile a repository of data from research labs and other organizations from various geographic locations. The focus was to emphasize the coordination of the various global efforts in consolidating and analyzing environmental impacts of UMPs toward sustainability characterization of manufacturing [31,161]. Objectives of the CO2PE! were to (1) evaluate energy consumption and CO_2 emissions with the focus of assessment of process-related environmental impacts, (2) develop a methodology for enabling data inclusion from multiple sources in LCI databases for sustainability assessments, (3) collaborate with machine tool designers to augment manufacturing processes for reduced environmental impact, and (4) incorporate eco-labeling for manufacturing systems.

An effort that combined UPLCI and CO2PE! with a focus on emphasizing the coordination of various global efforts in consolidating and analyzing environmental impacts of UMPs toward sustainability characterization of manufacturing was reported by Duflou et al. [31] and Kellens et al. [161]. In merging these two initiatives, UPLCI formed a screening method for building LCI databases, while CO2PE! presented an in-depth approach for quantifying LCI data. In spite of these efforts, manufacturing process characterization efforts have been siloed and have lacked a standard, structured modeling approach. This lack of standardization has inhibited model sharing and reuse. Further, model development, application, and interpretation necessitate domain expertise of modelers and end users.

3.3.2 Standards development for sustainable manufacturing assessment

A number of modeling efforts have been undertaken to evaluate the sustainability performance of manufacturing systems [189], and have been completed for a specific industry [190,191] or manufacturing system [192,193]. In addition, the resulting *ad hoc* models are often not scalable or transferable since they lack a common structure and/or standard model development approach. To aid in addressing these deficiencies, the International Organization on Standardization (ISO) published the ISO 20140:2019 standard [194]. The standard instituted a method for environmental performance evaluation (EPE) of individual manufacturing processes by assessing energy efficiency and other factors of manufacturing systems. The standard helps in conducting EPEs of manufacturing systems by aggregating relevant UMP data. The application of ISO 20140:2019 can be useful in (1) benchmarking environmental impacts of a UMP for producing a part, (2) improving an existing manufacturing process for better environmental impact performance, (3) establishing a goal for improving environmental impacts of a manufacturing system and breaking it down to the sub-system level for process improvement, and (4) improving the production process for evaluation of environmental impacts of shopfloor activities.

Collaborations within the ASTM International working group on sustainable manufacturing have also been engaged in standards development efforts to overcome the inherent gaps in manufacturing process and system modeling for sustainability performance assessment. These collaborations contributed to the ASTM E2986-18 standard, which provides a method for the evaluation of manufacturing process-related environmental impacts [41]. A second standard, ASTM E3012-20 [27], further developed ASTM E2986-18 to support analysts and decision makers in the systematic characterization of the environmental impacts of a UMP. The ASTM E3012 standard [27] defines a structure for representing a UMP, which is formalized in XML (eXtensible Markup Language) using XSD (XML Schema Definition). This formalization is meant to enable industry practitioners and researchers to more easily share UMP models [129,136]. The standard provides for the specification of variables for linking, or composing, multiple UMPs for sustainability characterization of manufacturing systems. However, implementation of the linking and composability concepts are not fully developed in the standard.

3.3.3 Limitations of prior work

Despite the fact that several efforts aid in characterizing discrete manufacturing processes for sustainability performance evaluation (Table 3.1), there has not been significant development of accompanying methods and tools leading to industry adoption. Prior work has often focused on developing distinct and specific UMP information models. Developing these information models from scratch requires a high-level of process knowledge and expertise in characterizing specialized manufacturing processes and, thereby, requires significant time and effort. Also, these methods do not provide a standardized platform to develop consistent and reliable models for sharing information between models for efficiently evaluating the sustainability performance of a manufacturing system. The LCI data available cannot be reliably reused for LCA, as they are subject to the quality of the reporting sources.

Having robust information models based on first principles, which can be reused and expanded upon to specify configurations of manufacturing processes would greatly benefit manufacturers and researchers alike. In particular, UMP model development efforts have not focused on creating reusable abstractions for information models that can be expanded for sustainability characterization in a variety of settings.

The methodology presented below extends prior framework development efforts based on the ASTM standards. Collaborative research with the U.S. National Institute of Standards and Technology (NIST) proposed an integrated methodology for assessing sustainability performance of manufacturing processes [164], in addition to terminology to facilitate manufacturing process characterization for sustainability assessment. Based on the methodology, a complimentary information modeling framework to capture UMP and workpiece information was demonstrated by characterizing process energy consumption. To extend the methodology, a complementary framework for composing UMPs to enable sustainability assessment of manufacturing systems was developed Smullin et al. [195,196]. However, the framework lacked aspects of model reusability and extensibility, which are addressed in this research. Related efforts have explored the need for an open repository of UMP models [43,50,197]. The reuse of models in such a repository is an ongoing challenge that this work addresses. Here, we posit that information models can be created for a specific manufacturing process and then abstracted to characterize variations of that manufacturing process. Using these open abstractions of UMPs, process model composability can be performed to conduct systemic sustainability assessment.

3.4 Research Method

The aim of the research presented here is to build on the existing ASTM E3012-20 standard to improve the reusability and extensibility of UMP models. The standard provides a graphical model structure to represent UMPs (Figure 3.1), and defines five aspects: inputs, outputs, resources, product and process information, and transformation equations. Inputs indicate the types of energy, materials, and consumables flowing into the process. Outputs indicate the product and, when relevant, co-products and by-products, types of wastes/emissions, and process feedbacks (e.g., status of consumables and tools) that flow from the process. Resources define information related to resources used by the process, such as tooling/fixtures, equipment, software, and people. Product and process information is needed to enable transformation functions (equations), and includes information related to the product (material), process plans, and control programs. Product and process information comprises four categories: (1) Fixed parameters, (2) Intermediate variables, (3) Control parameters, and (4) Metrics of interest (MOIs). Fixed parameters are parameters that do not change during the manufacturing process (e.g., workpiece density). Control parameters are the user-tunable parameters for the manufacturing process (e.g., feed and depth of cut). Intermediate variables are the calculable variables that are used for evaluating the key performance indicators (KPIs) and MOIs (e.g., cutting energy). The KPIs and MOIs are used in evaluating the sustainability performance of the UMPs and manufacturing systems under consideration. Transformation equations model the conversion of physical inputs to the UMP into the physical outputs from the UMP. These relationships are also used to calculate the KPIs and MOIs for the modeled UMP, and provide a physical basis for characterizing manufacturing sustainability performance.

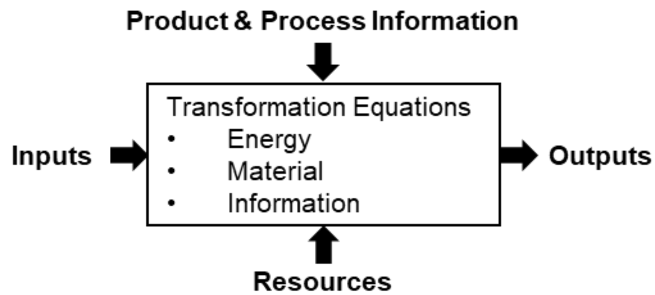


Figure 3.1. Graphical representation of a unit manufacturing process [27]

The ASTM standard provides a formal representation of all five UMP aspects using an XML schema [198]. Since these aspects are represented as element blocks in the standard model structure, they are easy to read, edit, and expand upon from a software programming perspective. The research herein contributes a methodology for abstracting an existing model and molding it into a specific model for a particular application (extension) using new layer models. Further proposed is the development of template models that can be reused, and extended to represent manufacturing processes. Figure 3.2 shows the activities comprising the methodology developed herein, which involve defining what constitutes a template model, devising a method to develop and represent a template model, presenting an approach for abstracting models for extensibility, and establishing a relationship between a template model and layer models.

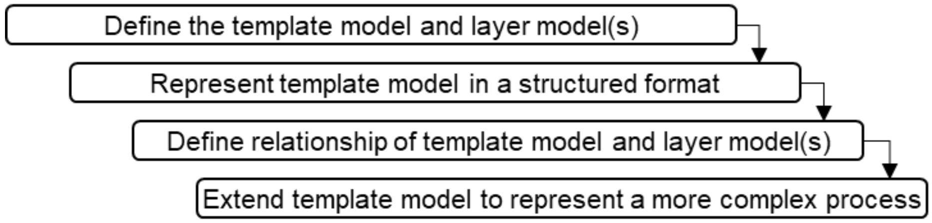


Figure 3.2. Methodology for abstracting unit manufacturing process models for reusability, extensibility, and composability

The remainder of this section discusses each of these activities in greater detail. Section 3.5 then demonstrates the activities using the case of milling operations.

3.4.1 Define the template model for the process

The ASTM E3012-20 standard guides researchers and industry practitioners in developing process-specific UMP models. Here, we present the concept of characterizing the most basic manufacturing process for a specific class or process type. We evaluate the feasibility of extending such basic UMP models to form configuration (machine)-specific models by layering subsystem models onto this template model. Thus, a template model can be defined as a model that completely characterizes the most simplistic instantiation of a manufacturing process class, where a process class comprises varying levels of machine configurations (complexity). The manufacturing process taxonomy defined by Todd et al. [30] can aid in establishing template models (abstractions) for the various process types. The taxonomy organizes manufacturing processes into two primary classes: shaping and non-shaping (Table 3.2).

Table 3.2: Manufacturing process taxonomy classification [30]

Class	Group	Family	Sub-class
Shaping	Mass reducing	Mechanical	Single-point, multi-point, abrasive machining, shearing, blanking, piercing
		Thermal	Torch cutting, electrical discharge machining, high energy beam machining
		Chemical	Chemical, electrochemical, photo-chemical
	Mass conserving	Consolidation	Molding, compacting, deposition, laminating
		Deformation	Forging, extruding, drawing, rolling, thread forming, knurling, bending, forming
	Joining	Mechanical	Pressure welding, friction welding, ultrasonic welding
		Thermal	Electric arc welding, gas welding, brazing, soldering, diffusion bonding
		Chemical	Adhesive bonding
Non-shaping	Heat treatment	Annealing	Recovery, recrystallization
		Hardening	Surface hardening, through hardening
		Other	Sintering, curing, bonding, cryogenic treatment
	Surface finishing	Surface preparation	Descaling, deburring, degreasing
		Surface coating	Mechanical coating, thermal coating, chemical coating
		Surface modification	Burnishing, peening, texturing

Shaping processes alter the workpiece geometry, while non-shaping processes alter the material properties of the workpiece. Shaping processes are grouped into mass reducing, mass conserving, and joining processes, while non-shaping processes are grouped into heat treatment and surface finishing. These groups have been classified into fourteen families, for example, mass reducing processes form mechanical reduction, thermal reduction, and chemical reduction processes. These fourteen families are broken into sub-classes of manufacturing processes that exhibit similar functionality/process physics. This classification of manufacturing processes provides insight for defining a template model for each sub-class. Once so defined, template models can then be developed by domain experts for the most basic machine forms for each manufacturing process sub-class, by using mechanistic (empirical), analytical (physics-based), and other modeling techniques.

As noted above, the template model should enable expansion to accommodate modeling of similar machine configurations or higher complexity machine configurations through extension. Model extension can be achieved through the addition (and/or removal) of layer models representing different process capabilities, including auxiliary equipment and other resources. This characteristic of template model expansion can be explained using the example of a milling process. A UMP model developed for machining using a manual mill would be considered as a template model for milling (a class of multi-point material removal processes); a manual knee and column mill is understood to be the basic physical representation of most vertical milling machines [28]. In this form, the spindle is electrically powered, while all other machine motions are manually controlled (e.g., spindle speeds, feed rates, and depths of cut). By adopting the manual knee and column mill to create the template model for milling, all other milling machine variants would be extensions of the template model. These extensions could be envisioned as additional transformation functions (e.g., spindle speed control, table feed control, or lubrication systems) that can be layered onto the base template model. From this example, it can be recognized that layer models represent sub-systems or auxiliary systems of a machine tool configuration, that are not directly involved in the processing of the workpiece. The layers add value to a manufacturing process by enhancing the capabilities of the machine tool through integration of mechanical (e.g., motion control systems), thermal (e.g., heating elements), chemical, and/or electrical sub-systems. Although definition and modeling of template models and layer models require subject matter expertise, once these models have been established for various process types and sub-systems/auxiliary equipment, the methodology presented herein for model reuse and extension can be applied by non-expert practitioners to model and analyze specific instantiations of more complex processes and systems. Table 3.3 identifies some of the template manufacturing processes for various manufacturing sub-classes.

Table 3.3: Example template models and layer models for several selected manufacturing processes configurations

Sub-class	Process configuration	Template model	Layer model(s)
Single point cutting	Lathe with lubrication system	Manual turning	Lubrication system
Multi-point cutting	Two-and-a-half axis milling	Manual milling	Table/spindle control systems
	Electrical discharge grinding	Surface grinding	Electrical power pulse generator
	4-axis jig boring	Manual jig boring	Table/spindle control systems; rotary table control system
Extruding	Hot extrusion	Cold extrusion	Barrel heating system
Friction welding	Friction stir welding with tool heater	Manual milling	Table/spindle control system; tool induction heater

While it is expected that template models can be applied to the majority of higher-order machine configurations, some complex machine/process models will require further development. Process information and transformation equations will require vetting and modification for configurations that are too complex in nature to facilitate extension from template models. For example, such cases could derive from machine configurations that are combinations of multiple manufacturing processes within a single machine, e.g., five-axis milling (milling machine, turning machine, and tool change system) or a hybrid machine tool (e.g., milling and wire feed additive manufacturing). The methodology presented is generally applicable to these complex configurations, but will require a complete and thorough understanding of the machine and process to model accurately.

3.4.2 Represent template model in a structured format

Next, the identified template model must be represented in a structured manner to enable software tool implementation. Software tools will facilitate adoption and use of manufacturing process and system modeling and analysis. We investigated how UMP models could be represented for software implementation using XML since it is capable of handling functional modeling of manufacturing systems [199,200]. XML schema can handle complex relationships and has a defined structure, which is beneficial for model development and is amenable to extension for software programming [201]. In addition, XML models are capable of handling the research-specific needs for model reusability, extensibility, and composability due to their structured and compartmentalized way of representing data [202]. By representing models as XML documents, parsing, analyzing, and processing data is software platform independent and can be handled by any language that can work with XML. The language is relatively easy to learn for non-expert practitioners, which can help promote adoption of the standard, broadening its use and impact. For industry practitioners and researchers to perform sustainability assessments, models are represented as real-time operational standardized XML documents. By conforming to common standards, template models can be used by other researchers and practitioners and expanded into application-specific process models.

3.4.3 Establish relationship between template model and layers

For extending the template model to a use-specific information model, it is critical to establish the relationship between the template model and the information pertaining to the new layer model. To better represent this relationship, we use a UML (Unified Modeling Language) class diagram for illustration (Figure 3.3). UML class diagrams are the fundamental building blocks for object-oriented programming [203]. A class diagram shows the elements and the flow of information between elements, and establishes a sematic relationship between these elements; XML applications are commonly modeled using UML [204]. UML class diagrams can be directly used for structuring the XML document or they can be created to model the structure of XML schema [205]. In the first case, the UML class diagram does not necessarily focus on the structure of the schema from which the XML document was created, but rather, the diagram enables inclusion of additional details to the XML document itself. The UML class diagram can be set to match the structure of the schema, if required. In the second case, the UML class diagram contains the information that will guide development of XML schema, meaning that the schema is the output deliverable of the UML. The delivered XML schema conforms to the conditions and relationships represented in the UML class diagram.

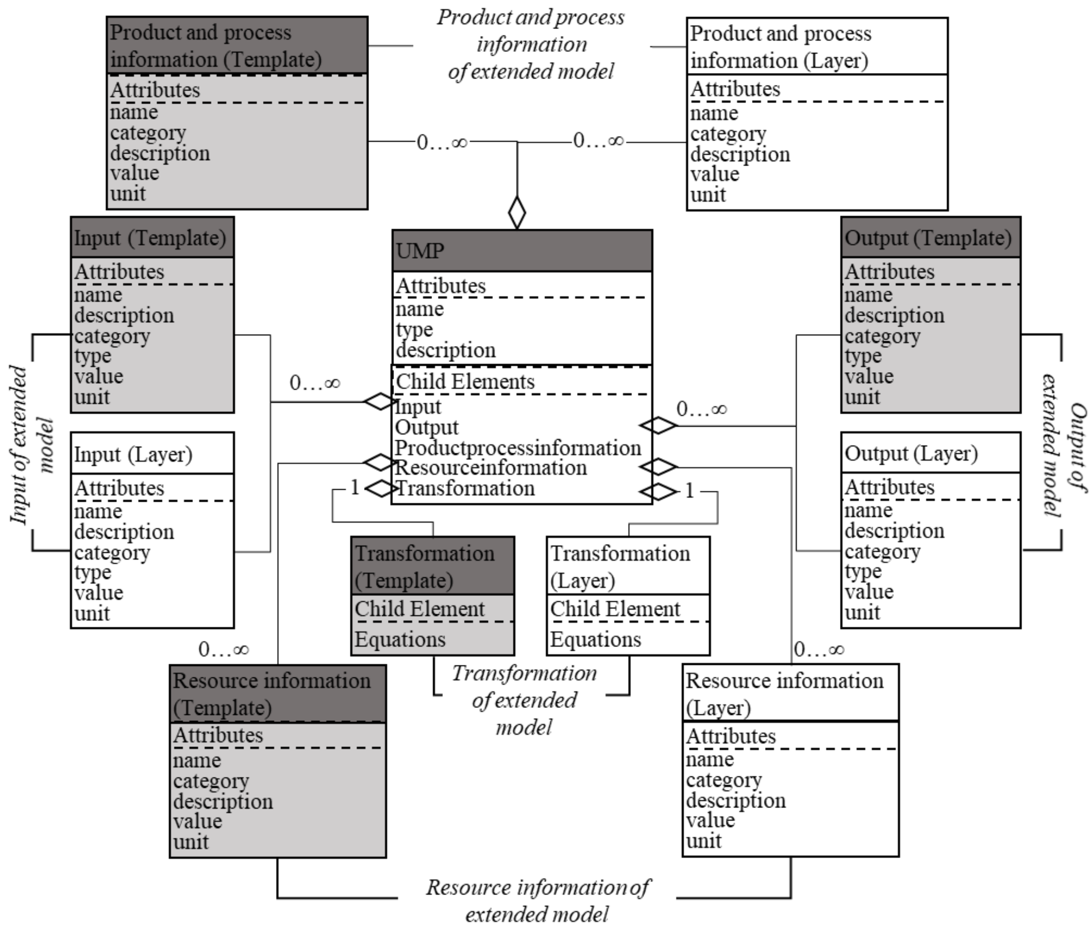


Figure 3.3. UML representation of extension of a template model using layers

For the purpose of extending standard information models, UML class diagrams can be used to add information to existing XML documents while still conforming to the specified schema. The UML class diagram in Figure 3.3 represents a method of extending an XML model of a manufacturing process by combining a template model for the process with information related to the auxiliary/support process(es) using layer models. Shaded boxes represent the template model, while unshaded boxes represent the information of the layer model to be added to the template model. The box at the center, titled UMP, is the extended model that represents aggregated information from both the template model and the layer models. This structure of the UML class diagram continues to follow the XML schema specified by the ASTM E3012-20 standard.

3.4.4 Extend template model to represent a more complex process

The next step focuses on extending a template model to represent more complex, use-specific manufacturing processes. The capability of extending template models to depict a complex variation of the process being modeled is called extensibility. Since template models are created based on ASTM E3012-20, the model structure inherently enables extension. For example, let model UMP A in Figure 3.4 be the template model for all similar manufacturing processes, A. Let UMP A1 be a complex variation of UMP A. To develop a model for UMP A1, an instance of the template model of UMP A is generated. This model is then extended using information related to UMP A1 as a layer (Layer A1) of template model UMP A. We posit that extensibility can be achieved by building upon template models using such layer models, and by building upon existing instantiations of extended template models using additional layer models to develop higher-order UMP models. This concept is illustrated for milling in Section 3.5.

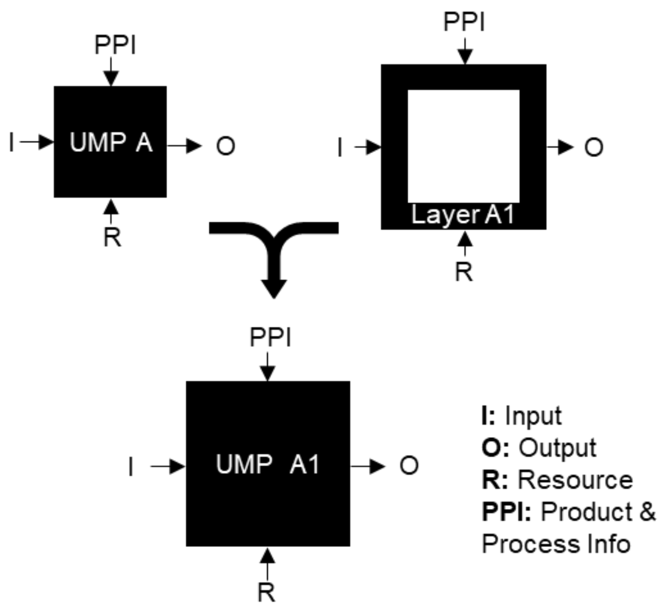


Figure 3.4. Extensibility of template model of UMP A using Layer A1 to form extended model UMP A1

An important aspect of extensibility is that layer models added to the template model need not only represent higher-order variants of the primary process. For example, auxiliary systems (e.g., exhaust gas pressure control systems, monitoring equipment, and electric boosting systems) that are essential to support the manufacturing process, but may not directly modify the workpiece, can be added as layers to model specific equipment in use. To be amenable for reuse, template models necessitate that certain information and characteristics be replicated to the extended model for expansion.

3.5 Demonstration Case: Milling Process

To demonstrate the application of the methodology described above for extending a template UMP model, we develop a template model for manual milling (Appendix A1), which we then extend to model milling using computer numerical control (CNC) of x-axis and y-axis movements (we refer to this variation as a “two-and-a-half axis milling machine”). The model is used to characterize and improve milling process energy use. Only the spindle is powered on the representative manual milling machine. The development of the template model began with capturing the physical inputs and outputs of the process (e.g., bar stock, work in process, electrical input, and waste). Next, product and process information was identified, which captures product data (e.g., part length, width, and thickness, and material density), process data (e.g., cutting speeds, feeds, and depths), and sustainability metrics of interest (e.g., energy consumption, energy cost, and greenhouse gas emissions) and KPIs (e.g., energy consumption per part). The transformation equations comprise the mathematical functions required to quantify the metrics of interest and KPIs. The UMP model also captures information pertaining to process resource needs (e.g., software, tools, fixtures, and workers), which may not have a direct effect on either the product or process, but are needed to aid in the functioning of the machine. An equivalent information model representation for the process is developed based on ASTM E3012-20, and reported for the manual milling case in XML format (Appendix A2). The model documents the five aspects of a UMP model (i.e., inputs, outputs, product/process information, resources, and transformation equations) as elements in the XML documents. Transformation equations for the milling process were drawn from the literature [206–209].

The template model for manual milling can be extended to accommodate the addition of a CNC table feed system (Layer 1) and lubrication system (Layer 2), as shown in Appendix A3. The extension is achieved by instantiating the template model and layer models using encapsulation (bundling of data using methods of aggregation), which results in a single model that represents a two-and-a-half axis milling process with lubrication system. The bold blue text in the figure indicates the information pertaining to the aggregated layer models for the table feed system and the lubrication system. Development of the layer models relied on prior research [173,210–212].

The XML representation of the template model for milling can be updated by editing individual elements of the XML instance (Appendix A2) to accommodate the table feed and lubrication system layer models. The updated XML instance (Appendix A4) captures the five UMP model aspects (i.e., inputs, outputs, product and process information, resources, and transformation equations) and adheres to ASTM E3012-20. This system also can be represented using functional modeling, e.g., IDEF0 (Integrated Computer Aided Manufacturing DEFinition for Functional Modeling), which is used for integrating information systems in manufacturing industry. IDEF0 models are used to comprehensively represent manufacturing systems, and can illustrate details of the aggregated template model and layer models. Additionally, IDEF0 models enable tracking of information flows between the higher-level system and sub-systems, which is valuable for characterizing a manufacturing system that contains multiple manufacturing process flows. Further, IDEF0 models help in establishing relationships between UMPs and sub-systems within the manufacturing facility. Appendix A5 illustrates and IDEF0 model for the two-and-a-half axis milling machine with lubrication system (Process A1), which is comprised of the manual milling process (A0) and the layer models for the table feed system (T0) and lubrication system (L0). These layer models are represented as sub-processes in the IDEF0 model. It can be noted that each sub-process has inputs, outputs, product and process information, resources, and transformation equations, which must be defined by the modeler.

3.6 Critique of UMP model Reusability, Extensibility, and Composability

As noted in Section 3.3.1, a number of manufacturing process models have been developed for sustainability performance characterization. A lack of a standardization for model development and the resulting unstructured representations leads to limited model reuse. Prior modeling efforts (e.g., UPLCI and CO2PE!) have not emphasized the integration of models into engineering tool applications. The methodology presented herein provides a means for analysts to reuse and extend existing information models of manufacturing processes. Template models provide a basis for users to instantiate more complex UMP models for their particular manufacturing process configuration. In addition, template models can be modified in order to evaluate different process performance metrics of interest and KPIs. The methodology can enable software application development to support abstraction and aggregation of template models and layer models into varied extensions. Though the methodology is demonstrated for a bottom-up approach for representing more complex machine configurations from a basic machine form, it can also be used to deconstruct information models developed for complex machine configurations in order to represent a simpler machine configuration. In this manner, layers can be removed that do not pertain to the simple machine form or that are not common among instantiations of a particular class of processes.

Thus, the approach also enables selection and modification of an existing information model that closely represents a new machine configuration for customization, thereby reducing the time and effort needed for developing new UMP models. The inputs, product and process information, outputs, and resource elements from the template model are reused and extended by adding and aggregating information from the layer model(s). Reuse and extension of the transformation equations is also possible. Transformation equations related to the intermediate variables can be reused or extended, provided the naming conventions used in the template and layer models are distinct. For example, if the basic energy in the template models and the layer models are named in a distinguishable manner, the total basic energy for the extended model is simply the sum of individual values for basic energy in the template and layer models.

The same concept applies for aggregating most KPIs and metrics of interest (percentage and relative values must be aggregated separately). The reuse of transformation equations is desirable to save time and effort in model construction. Reuse and extension of these mathematical relationships is readily achievable if the template model and the layer models are structured for evaluating the same set of KPIs and metrics of interest. The validity of extending a template model using layer models is enabled through aggregation of the KPIs and metrics of interest. Information modeling techniques facilitate aggregation of model information, and can be realized through software integration when developing an engineering analysis tool. From the standpoint of a practitioner, extension of a template model is solely based on machine configuration. If the specific instance of a UMP (i.e., the machine under study) can be segmented into sub-systems that do not physically/chemically modify the workpiece, extension of the template model (i.e., through the use of layer models) is necessary to represent that specific machine configuration. Although the authors have demonstrated the method of reuse and extension using mechanistic model for a milling machine configuration, the method is not bound by the modeling approach. Underlying models can be physics-based, data-driven, or digital twins/simulations. To apply the methodology developed in this research, these underlying models must adhere to the structure defined by the standard.

This flexible modeling approach aligns with a recently developed UMP builder tool, which supports creation and storage of process information models for sustainability assessment [43,197]. This approach additionally offers an illustrative pathway for industry to develop, share, adapt, and adopt validated UMP models in a secure, curated manner. The presented methodology for model reuse and extension maintains the standard model structure by placing new information within layer models that integrally link with existing template models. Such model reusability and extensibility is important for sustainability assessment of manufacturing systems, since it enables composability of representative information models, while maintaining validated core relationships for the basic process.

3.7 Conclusions

The methodology presented herein establishes a mechanism to create reusable abstractions (template models) of unit manufacturing processes (UMPs) for characterizing the sustainability performance (e.g., materials/energy use and other impacts) for a variety of manufacturing processes and systems. The approach facilitates creation of reusable and extensible UMP information models and enables practitioners and researchers to develop more accurate models for process and system characterization by tailoring existing validated models for their specific needs. This approach offers several advantages over current practice, including:

(1) Straightforward development of template (base) and extended UMP models supported by a standard model structure;

(2) Simplified tracking of information for evaluating UMP models and validating modifications made to extend the models;

(3) Improved model reusability and extensibility through single and multi-layer buildup of existing validated UMP models; and

(4) Maintained reusability, extensibility, and composability characteristics of the UMP model after extension.

Further, the methodology presented in this research is portable (UMP models can be incorporated into computer-aided engineering tools) and scalable (models can be developed for processes and systems of varying complexity from a variety of domains). To realize the vision of facilitated model creation, extension, and application to sustainable manufacturing characterization, future work must build an open, secure repository of validated template models and extension layer models for a broad set of manufacturing processes. This effort can be accelerated through the creation of software tools capable of model verification and/or validation, as well as establishing a community of users capable of testing model functionality and accuracy. Additionally, being able to link characterized UMPs to form a manufacturing system model will enable system-level manufacturing characterization and enhance sustainability assessment from a systems perspective. Finally, tools must emerge that are capable of aiding decision makers from various manufacturing domains in composing the models for system analysis and optimization.

Acknowledgements

The academic authors gratefully acknowledge the National Institute of Standards and Technology (NIST) for its support of this research through NIST Award No. 70NANB16H223, with special thanks to Mr. Kevin Lyons, Dr. Swee Leong, Dr. Bill Bernstein, and Dr. David Lechevalier for their generous inputs to the research.

Chapter 4: COMPOSITION OF UNIT MANUFACTURING PROCESS MODELS FOR CHARACTERIZING SUSTAINABILITY PERFORMANCE OF MANUFACTURING SYSTEMS

4.1 Abstract

Recent efforts have undertaken characterization of manufacturing systems through information modeling. Information modeling offers the benefit of representing information in structured way. With an increasing emphasis on sustainable manufacturing, however, few efforts of modeling manufacturing systems for sustainability performance have been pursued using information modeling. The recent ASTM E3012-20 standard focuses on information modeling of unit manufacturing processes (UMPs) and can be applied to address this need. The research herein explores the concept of UMP composition for characterizing manufacturing systems to support sustainability assessments based on ASTM E3012-20. A review of research on process model composition is conducted to identify existing research gaps. A methodology for composing UMP models developed based upon the ASTM standard is also presented. Analysis of 42 different compositions of UMP models identifies patterns of information that is shared between UMPs. This shared information, termed linking variables, are classified under geometric properties and material properties; each variable defines key information about the workpiece required for composition. Linking variables are characterized by analyzing compositions of various processes based on manufacturing process type (mass reducing, mass conservation, heat

treatment, and surface finishing processes). Based on the characterizations, it is found that the standard linking variable definition should be modified, and two new terms are proposed: generic and specific linking variables. In conclusion, a standardized system model structure is proposed using two information modeling approaches. Demonstration cases for linking extrusion, machining, and heat treatment process models is presented to verify the proposed methodology for composing UMPs to represent a manufacturing system.

4.2 Introduction

Over the past century, manufacturing has advanced tremendously due to continuous improvements in computing technology and architecture, sensing and control, materials science, tooling and equipment, understanding of physical phenomena underlying manufacturing processes, real-time data analytics, and many other synergies between facets of science, technology, engineering, and mathematics [213,214,1]. Though manufacturing has continued to evolve, the focus has fundamentally been on reducing product cost and increasing profitability and market presence, essentially addressing economic competitiveness of manufacturing. Over the past two decades, increasing emphasis has been given to sustainable manufacturing [6,7,156] primarily due to social responsibility goals, investor demands, government regulations, international standards, and, perhaps most importantly, increased customer consciousness [8,10,9]. Many challenges have been introduced due to the complexity of implementing sustainable manufacturing practices and policies within industry. A challenge is in striking the right balance among the three pillars of sustainability, namely, consideration of environmental, economic, and social factors in decision making. Life cycle assessment (LCA) tools and methods have been developed for product-focused environmental impact analysis, and are limited in assessing manufacturing process and system level sustainability performance. Recent, but limited, LCA efforts have begun to develop and implement economic and social impact assessment [215]. Deficiencies in tools and methods are primarily due to the inconsistencies in data, approach, and generic representation of manufacturing processes [20,21]. These problems are exacerbated by complexities introduced when evaluating manufacturing performance at the system level.

Information modeling has been posited as one method to overcome inconsistencies in representation of information related to any process, as it has a well-defined structure [216]. Common information modeling languages are capable of working across software platforms and tools. Several recent efforts for modeling product design and manufacturing information are explored in Section 2. The ASTM E3012-20 standard defines information modeling as a method for characterizing manufacturing processes to evaluate sustainability performance [27]. Research efforts involving this standard methodology have been previously reported by the authors [49]. The goal of the research reported herein is to demonstrate standards-based information modeling for characterizing manufacturing systems for sustainability performance evaluation. The research is based on the composition of unit manufacturing process (UMP) models to form a manufacturing system model, as described in the ASTM E3012-20 standard. After a brief review of prior work, in Section 2, we present the proposed methodology for model composition and demonstrate the approach for composing an extrusion process with milling and annealing processes. In conclusion, we discuss the advantages of the proposed methodology relative to existing approaches, in addition to limitations of the approach and opportunities for future research.

4.3 Background

Product development involves on two stages in the product life cycle: design and manufacturing. Process planning links these two stages [217], and establishes the sequence of manufacturing processes and operations for the specified product design in order to produce the product in a cost-effective and resource-efficient manner. Recent focus on sustainable production has compelled process planning approaches to consider the three pillars of sustainability, involving environment, social, and economic factors. Detailed product design information must be transferred to the manufacturing processes used to transform raw material into a physical product, for example through the conversion of computer-aided design (CAD) data to machine control instructions (G-code). This information is evaluated during process planning activities to make informed decisions to align design and manufacturing objectives, as well as addressing external demands (e.g., internal/external policies or manufacturing performance goals). The development of computing technology over the past four decades, including information modeling approaches and standards, has greatly assisted such decision making through enhanced design and manufacturing collaboration.

Information modeling is a method of defining specific data of a domain using concepts, relationships, constraints, rules, and operations based on its application [32]. In particular, information modeling provides an organized structure for data to be shared, reused, and processed. The most commonly used modeling languages have been Integrated computer-aided DEFinition (IDEF0) [218] for function modeling, and Unified Modeling Language (UML) [203] and eXtensible Markup Language (XML) [219] for object-oriented modeling. These developments have laid the foundation for various modeling techniques that have been used in the design and manufacturing domains. Perhaps the most well-known information modeling frameworks have been in the integration of design data specific to CAD applications, including the Initial Graphics Exchange Specification (IGES) and the International Organization for Standardization (ISO) standard ISO 10303 [220], informally known as Standard for the Exchange of Product Model Data (STEP). STEP is able to capture information related to the entire life cycle of the product, while IGES captures information related to the geometry of the part/product [221]. Manufacturing has greatly benefitted from STEP data, since it is CAD platform agnostic and easy for manufacturers to interpret design needs, as it follows a defined structure.

Several efforts have pursued information modeling of manufacturing processes and systems for resource planning, cost modeling, and process planning. For instance, ISO 16100-2 [222] focuses on defining a standard method of information exchange between design and manufacturing software systems. The Core Product Model (CPM) led by the U.S. National Institute of Standards and Technology (NIST), was specific to the design phase and focused on representing product information such as function, form, behavior, and material, and their interrelationships [223–225]. The Open Assembly Model (OAM) expanded on CPM and provided a standard representation for assemblies [226]. In 1994, NIST initiated a program for representing the manufacturing phase of product development, called the Systems Integration for Manufacturing Application (SIMA), which focused on integrating software systems of design and manufacturing [227]. An effort undertaken by NIST to integrate design and process planning used an object-oriented manufacturing process information model through UML to support process planning activities [228]. The model contains classes of manufacturing information (workpiece, equipment, cost, time, and process sequence), which can be abstracted for manufacturing activities such as equipment setup, workpiece loading/unloading, and workpiece processing. None of these prior efforts emphasized sustainability performance characterization. However. Zhang et al. [216] demonstrated the integration of manufacturing process-oriented information related with sustainable manufacturing and product design information for model development to estimate energy consumption for sustainability evaluation using information modeling concepts.

As noted in Section 4.2, efforts have pursued sustainability performance characterization during the product design and manufacturing phases. Software tools such as SimaPro[2] [229] and GaBi [230] emerged to assist designers and other decision makers to improve product environmental performance. LCA tools, however, are limited in their ability to customize analysis for specific manufacturing applications, since their process model databases contain generic manufacturing process models, and tailored models are time- and resource-intensive to develop. To overcome this inherent gap, the Unit Process Life Cycle Inventory (UPLCI) effort focused on developing reusable manufacturing process models for sustainability assessment [45,167]. Recently, manufacturing process models developed for grinding [47], gas metal arc welding [48], metal injection molding [170] and additive manufacturing [169] have been reported using the UPLCI approach. An application of the approach was reported that assessed sustainability performance of a product comprised of 14 sub-assemblies and four different materials, requiring 67 manufacturing process steps [163]. A related effort was pursued under the Cooperative effort on Process Emissions (CO2PE!) initiative by the International Academy of Production Engineering (CIRP) [21]. The intent was to develop environmental impact data that would be precise and specific for individual manufacturing processes. The effort focused on developing a repository of life cycle inventory (LCI) information for manufacturing processes to facilitate the assessment of product environmental impacts [31].

[2] No endorsement of any commercial product by NIST is intended. Commercial materials are identified to facilitate better understanding. Such identification does not imply endorsement by NIST nor does it imply the materials identified are necessarily the best for the purpose.

Though applications of the research efforts reviewed above have been demonstrated, they are not structured for the purpose of integration into software tools to analyze sustainability performance. To address this need NIST initiated an effort within ASTM International under the sub-committee E60.13 on sustainable manufacturing that combines information modeling and development of UMP models for sustainability performance evaluation [129]. ASTM has subsequently published four standards related to sustainable manufacturing: ASTM E2987-20 provides terminology for sustainable manufacturing [231]; ASTM E2986-18 provides guidelines for evaluating environmental performance of manufacturing processes [41]; ASTM E3096-18 provides guidelines for choosing and organizing key performance indicators (KPIs) necessary for the evaluation of manufacturing processes [232]; and ASTM E3012-20 provides guidelines for characterizing manufacturing processes for environmental impacts [27]. ASTM E3012-20 combines both the information modeling and sustainability characterization in its approach and is the basis for this research.

Due to the complexity of manufacturing process information and the relationships with other processes in a manufacturing process flow, development of information models and meta-models for manufacturing are a large challenge [233]. Prior efforts based on ASTM sustainable manufacturing standards focused on developing frameworks/methodologies for evaluating sustainability performance of manufacturing systems. Garretson [164] explored the concept of composability (linking manufacturing processes in a sequence that becomes a manufacturing process flow) and demonstrated sustainability assessment using the approach. Smullin et al. [195]

built on this work by further investigating the composition of manufacturing processes and developing a software tool that performed process composition for evaluating sustainability performance of a process flow in a more automated fashion. Brodsky et al. [50] focused on evaluating manufacturing systems using a reusable information modeling repository. This approach explored manufacturing process model composition, optimization, and conducting trade-off analysis for manufacturing/contract service networks. Though these efforts focused on evaluating sustainability performance of manufacturing systems, they lacked a structured approach that could be generalized from the process to manufacturing facility level. A key barrier was a lack of a streamlined information tracking between individual manufacturing process models within the manufacturing system. This information exchange is desired to help industry practitioners understand the design and manufacturing drivers that impact key performance indicators and metrics of interest from a sustainability decision-making standpoint. The research herein is focused on addressing this inherent gap of information exchange by increasing traceability to enhance sustainability assessment of manufacturing systems.

Since the research herein builds on this prior work and the ASTM E3012-20 standard, it is important to define the basic terms within the standard. The standard provides a graphical representation of a UMP model (Figure 4.1). UMPs have been defined as “the individual steps required to produce finished goods by transforming raw material and adding value to the workpiece as it becomes a finished product” [24], and as “the smallest elementary manufacturing activity required for a specific taxonomological [referring to a taxonomy of manufacturing process types] transformation and composed of machines, devices, or equipment" [164]. A UMP representation has five key elements: inputs, outputs, resources, product and process information, and transformation equations. Inputs to a UMP are the various physical features flowing into the UMP (e.g., energy, materials, and consumables). Outputs of a UMP are the physical features that are of value or a waste at the end of the process (e.g., end product/work-in progress part, co-products and by-products, and wastes/emissions). Resources are process-related information that are intrinsic to the function of the manufacturing process (tooling/fixtures, equipment, software, and people). Product and process information contains information related to the workpiece and process (e.g., material, material properties, dimensional information, process parameters, control programs, and process feedbacks such as the condition of consumables and/or tools). Product and process information is essential for the transformation functions (equations) for establishing relationships between the physical inputs and the physical outputs of the UMP. Key performance indicators (KPIs) and other metrics of interest are also defined by the transformation functions, and support sustainability assessment.

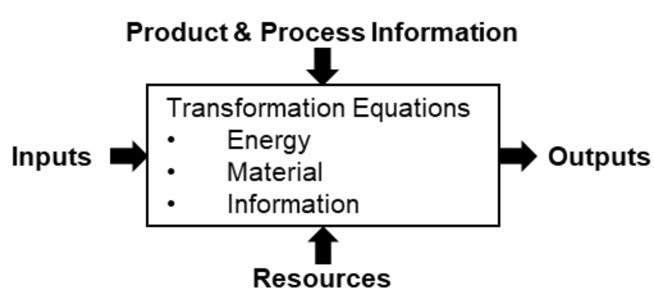


Figure 4.1. Graphical representation of a unit manufacturing process [27]

The ASTM E3012-20 standard introduces composability for characterizing the performance of manufacturing systems, as shown in Figure 4.2. The figure illustrates how multiple UMPs are defined in a sequence to represent the manufacturing process flow in a manufacturing system. Each UMP represents a manufacturing operation used to sequentially transform a workpiece(s) into the final desired product. Manufacturing process flows in real settings occur in series (e.g., from UMP 1 to UMP 2) and in parallel (e.g., UMP 3 and UMP4). The approach for composing two unique UMPs should not be dependent on the manufacturing flow. As per the standard, composition is "the act of linking individual unit manufacturing process (UMP) models together to create a composite of UMP models that can characterize the metrics of interest of a production system or product" [27]. The information that is shared between UMPs are called "linking variables." The standard also states that a linking variable is defined by its reference to a "source UMP" and a "target UMP."

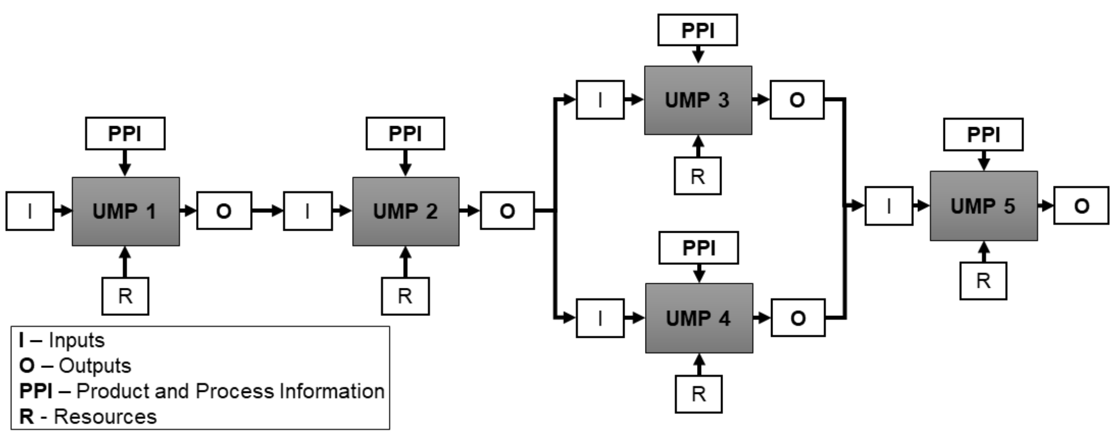


Figure 4.2. Graphical representation of composed unit manufacturing processes [27]

To achieve the goal of developing a manufacturing system model representation for sustainability characterization, the research builds upon the ASTM E3012-20 standard to explore the concept of composing UMP models. To enable characterization of information required for composition (linking variables), classification of linking variables, and development of a structure for composed manufacturing systems are needed. The methodological approach undertaken here is presented in Section 3. The scope of this work is restricted to performing UMP model composition for a single workpiece. Manufacturing processes that transform multiple workpieces, such as joining and assembly, are left for structural evaluation under future work.

4.4 Research Methodology

This research supports the characterization of complete manufacturing systems for sustainability performance evaluation by enabling UMP model composition. The approach pursued in this research involves several activities, summarized as follows: (1) Identifying information required for composition, (2) Classification of linking variables, (3) Characterizing linking variables and UMP model structure for composition, (4) Proposing a manufacturing system structure, and (5) Performing composition of UMPs using a case study. These activities are described in greater detail below.

4.4.1 Identify information required for composition of two UMPs

The ASTM E3012-20 standard mentions linking variables and that they would be used for composition. Accordingly, a linking variable is defined by its reference to the source

UMP, i.e., the preceding process step, and a target UMP, i.e., a subsequent process under consideration. Further, a linking variable is comprised of product and process information associated with the source UMP model needed to execute a model of the target UMP. In order to realize the concept of composability using linking variables, we first focused on identifying key information associated with UMP models (linking variables are crucial for characterizing a manufacturing system through UMP model composition). To accommodate the wide spectrum of manufacturing processes, we further examined composing UMP models by considering the full manufacturing process taxonomy defined by Todd et al. [30]. Their manufacturing process classification is divided into five categories: (1) Mass reducing, (2) Mass conserving, (3) Joining, (4) Heat treatment, and (5) Surface finishing. It should be noted that the scope of this work was limited to serial manufacturing process flows, thus joining processes (welding, soldering, assembly, etc.) were not evaluated. Representative source UMPs were selected (Table 4.1) to identify linking variables required for composition with a variety of target UMPs (Figure 4.4). These diverse process types were selected to support characterization and classification of a range of linking variables.

In order to analyze model composition for extracting patterns of linking variables, UMP models needed to be created for each of the selected manufacturing process. The ASTM E3012-20 standard provides guidelines for characterizing UMPs, which were used to develop energy-based mechanistic models for each of the selected manufacturing processes.

Table 4.1: Source manufacturing processes selected for composability evaluation

Manufacturing process category	Representative manufacturing processes	Selected source process
Mass reduction	Milling, turning, drilling, grinding, boring, shaping, blanking, and threading	Milling
Mass conservation	Injection molding, extrusion, molding, casting, drawing, forging, and bending	Extrusion and bending
Heat treatment	Tempering, annealing, hardening, and sintering	Annealing
Surface finishing	Shot peening, cleaning, deburring, degreasing, and spray painting	Shot peening

UMP models for milling, extrusion, and annealing used for composition evaluation are provided in Appendices B1, B2, and B3, respectively. The development of the model for milling was previously discussed by the authors [49]. Energy-based models for the target UMPs, were created as spreadsheet models using transformation equations specified by Groover [28]. To identify linking variables for different types of manufacturing processes, composition was performed using the selected UMPs as the source and target UMPs as shown in Figure 4.3.

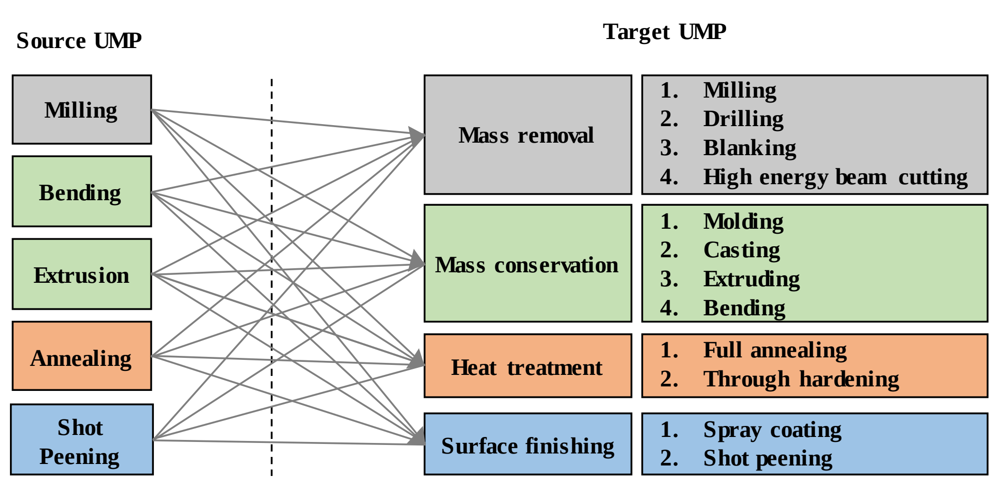


Figure 4.3. Selected combinations of source and target UMPs for linking variable analysis

Certain combinations of selected source and target UMPs are unlikely due to the nature of workpiece processing. For example, extrusion, which leads to extreme deformation, usually does not follow milling, which is typically used to achieve dimensional accuracy. Thus, of the 60 possible composition combinations, 42 were considered in this research. During UMP model development, multiple pieces of information from the source UMPs were identified that needed to be shared with the target UMPs for composition.

4.4.2 Classification of linking variables

Based on the composition of selected source and target UMPs, it was found that linking variables were either related to a geometric property (e.g., length, width, diameter, height, surface area, or volume) or a material property (e.g., ultimate tensile strength, yield strength, grain structure, or Young's modulus) of the workpiece. Potential linking variables were identified for geometric properties and material properties, as detailed in Table 4.2.

From the perspective of ASTM E3012-20, several patterns for linking variables were identified as listed below:

(1) Physical outputs of the source UMP feed as the inputs to target UMPs. Properties of these outputs always represent linking variables.

(2) Linking variables were only identified within product and process information for the source UMP.

a. Fixed parameters and intermediate variables were found to be linking variables, because they contain information related to the workpiece.

b. Control parameters and metrics of interests were not identified as linking variables, because they contain information related to the process parameters for the source UMP, and are not required by the target UMP.

(3) Resource information of the source and the target UMPs were not identified as linking variables; the aggregate information from both the source and the target UMP would constitute resource information of the composed system model.

Table 4.2: Potential linking variables defined by workpiece property type

Property type	Sub-classification	Potential linking variables
Geometric properties	Dimension	Length, width, height, thickness, diameter, radius, surface area, and volume
	Other geometric properties	Datum features, geometric tolerances, and part orientation
Material properties	Mechanical	Ultimate tensile strength, yield strength, density, hardness, viscosity, and creep
	Electrical	Conductance, resistance, capacitance, and inductance
	Thermal	Conductivity, resistivity, and specific heat capacity
	Chemical	Corrosion resistance, pH, surface tension, and surface energy
	Magnetic	Hysteresis, Curie temperature, and magnetic flux
	Atomic	Atomic mass, atomic number, and atomic weight
	Manufacturing	Castability and machinability ratings
	Environmental	Embodied water and embodied energy
	Optical	Refractive index, reflectivity, photosensitivity, and radiation index
	Radiological	Neutron cross-section, specific activity, and half life
	Acoustical	Absorption index and reflection capacity

The potential linking variables identified in Table 4.2, as well as the patterns identified by evaluating the selected combinations of composed processes, helped focus efforts on characterizing the linking variables required for UMP model composition.

4.4.3 Characterize linking variables

Further evaluation of linking variables was made based on the analysis of the compositions reported in Section 4.4.1. For the purpose of modeling manufacturing system structures, it is essential to understand the flow of information in composed UMPs. By consolidating the information from the 42 selected compositions, an illustration of the information flow is depicted in Figure 4.4.

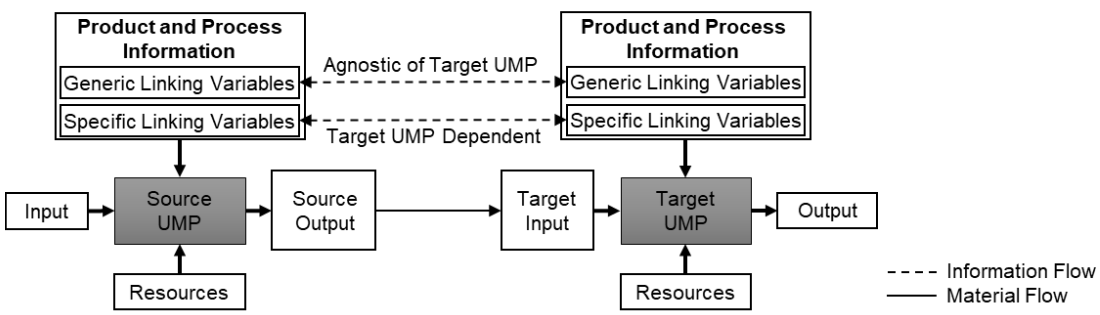


Figure 4.4. Information and physical flows between source and target UMPs

The dashed lines show the flow of information from the source UMP to the target UMP, while the solid lines show the physical workpiece flow between the two UMPs. From the compositions explored, it was found that there are linking variables that are target UMP agnostic (source UMP information that must be shared with any target UMP), as well as linking variables that are dependent on the target UMP (type of manufacturing process). As a result, we suggest a modification to the definition for linking variables found in the ASTM E3012-20 standard, as detailed in Table 4.3. In addition, we define two new terms – generic linking variable and specific linking variable – that further classify product and process information as being target UMP independent or dependent, respectively. The classification of linking variables helps in identifying information that is required for composition within a complex structure of UMPs. Classification of linking information sets up UMP models for systemic assessment and further enhances the expansion and reuse of the models through foundational template models, described by Shankar Raman et al. [49]. In particular, it should be noted that template models enable information required for composition to be reused, reducing model development effort and improving information traceability.

Table 4.3: Modifications to existing linking variable definitions

Term	Definition in the ASTM E3012-20 standard	Revised Definition
Linking variable	*A linking variable is defined by its reference to a "source UMP" and a "target UMP"*	Product and process information from the source UMP(s) that defines the state of workpiece(s) and establishes relationships (shared context) between output(s) of the source UMP(s) and input(s) of the target UMP.
Generic linking variable	Does not exist.	Product and process information from the source UMP(s) required to be shared to the target UMP(s), independent of the target manufacturing process type(s).
Specific linking variable	Does not exist.	Product and process information from the source UMP(s) required to be shared to the target UMP(s), dependent on the target manufacturing process type(s).

These linking variable definitions can be explained using an illustrative example of UMP model composition where extrusion is the source UMP and annealing is the target

UMP. The UMP model of extrusion in Appendix B indicates the generic linking variables for composition with any subsequent process and the specific linking variables for composition with heat treatment processes. Product and process information shown in bold indicates the generic linking variables. Product and process information highlighted in gray indicates the specific linking variables required by the target UMP (annealing) model. From this work, it was found that composition scenarios can exist where specific linking variables are not required by a target UMP, since the generic linking variables will convey sufficient information. For example, composition of two milling UMPs only requires generic linking variables; in this case, only a few dimensional properties (e.g., length, width, and height) and material properties (e.g., alloy and hardness) are needed. Section 4.5 details a demonstrative case study to evaluate a manufacturing process flow (Figure 4.7) in which an input rod stock is transformed into a corner bracket.

4.4.4 Proposed UMP structure to represent linking variables

Characterizing linking variables for composition facilitates development of a manufacturing system model structure that contains the compiled information for the associated manufacturing processes. The manufacturing system has a set of defined inputs, which are transformed into desired products, co-products, and by-products by utilizing a set of resources and product and process information relevant to UMPs comprising the manufacturing process flow. A manufacturing system model structure was pursued under this research that would mimic the UMP model structure as defined in ASTM E3012-20 to facilitate data tracking, information modeling, and model composability.

The aggregated physical inputs of each UMP in the manufacturing flow represent the physical inputs of the composed system. Similarly, the aggregated physical outputs of the UMPs in the manufacturing flow, not including the intermediate workpieces' states, represent the physical outputs of the composed system. It is understood that the workpiece(s) emerging from the last UMP in the manufacturing process flow is the output workpiece(s) for the composed system. The compiled resources for the attendant UMPs represent all of the resources required for the functioning of the composed system. The linking variables form a consolidated subset of product and process information from the attendant UMPs in the manufacturing process flow.

Therefore, for the purposes of information modeling, the product and process information element of the UMP model structure can be replaced with an element containing the compiled linking variables for each source/target UMP composition within the manufacturing system (Figure 4.5). In this representation, the boxes labeled with PPI highlight the linking product and process information variables shared between respective UMPs. It is important to note that the product and process information element of the structured system model contains the linking variables relevant to the UMP composition(s), and does not contain comprehensive information for each UMP within the system. However, all product and process information pertaining to individual processes is accessible from each associated UMP model. This system structure enables information exchange between UMPs if the manufacturing process flow is later modified.

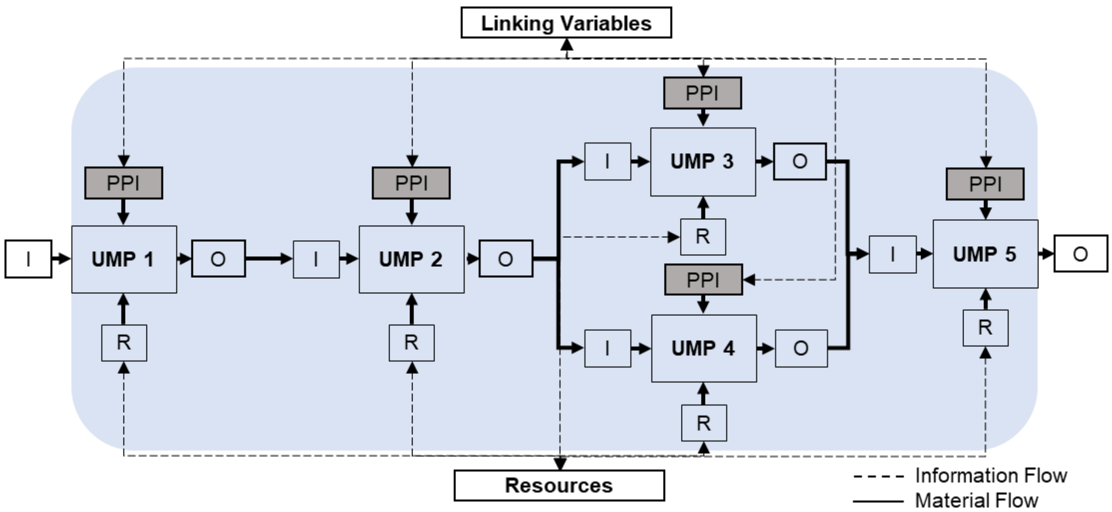


Figure 4.5: Manufacturing system model structure

As the number of UMPs increases in a manufacturing system, it would be difficult to track material and information flows using such a pictorial representation. The challenges of tracking and handling information for establishing relationships, constraints, rules, and operations between systems and sub-systems can be overcome by using a defined formal structure, or data semantics [234]. Functional modeling approaches (e.g., IDEF0 and Unified Modeling Language (UML)) help in structuring information using a bottom-up approach to define the functions of each system/sub-system. These approaches provide a graphical representation of the required software functions and modules to aid application design. To facilitate application development, the functions can be defined as classes and objects using object-oriented programming (e.g., using C++, C#, Java), which provides a top-down software development approach [235]. Combining functional modeling and object-oriented programming approaches can facilitate representation of UMPs and their relationships within a manufacturing system for rapid sustainability performance evaluation. In addition, since the structure of a manufacturing system mimics the UMP model structure, the system model can be represented using functional modeling (e.g., IDEF0 or UML) or object-oriented programming (e.g., XML), similar to UMP model representations provided by existing standard guidelines.

IDEF0 has been used in integrating information systems with manufacturing systems [236,237]. Due to a streamlined hierarchical structure that is specifically designed for interaction between multiple systems and sub-systems, the IDEF0 representation is effective in mapping information flows from upstream UMPs to downstream UMPs. Also, IDEF0 has a defined modeling language that includes both syntax and semantics along with a well-defined methodology for developing functional models [238]. Further, software tools are available to assist in developing and interpreting IDEF0 diagrams.

Similarly, XML offers a syntactic-based, encoded structure that can be used to represent a UMP or composed system model. XML Schema Definitions (XSDs) provide the rulesets that describe how XML files (specifications) need to be structured to represent a system(s) or sub-system(s) [219]. XML contains information in a hierarchical tree-like structure which is easy to parse for performing data handling and analysis. In addition, since XML is object-oriented, it is easy to abstract and reuse models for similar manufacturing processes and systems. The ASTM E3012-20 standard defines a formal XML structure for representing UMPs, comprised of five elements: Input, Linking Variables, Transformations, Resources, and Output. The Input, Output, and Resources elements have attributes defined by the standard. As noted above, linking variables can be identified within individual UMP models comprising a manufacturing system model. Since the linking variables are part of the product and process information for individual UMP models, they use the same attributes (i.e., name, description, category, and units) when specified as product and process information or the composed manufacturing system model.

4.5 Demonstration of the Methodology

The developed methodology for defining a manufacturing system model is illustrated here by performing a composition of energy-based UMP models comprising a manufacturing process flow. This section demonstrates (1) the transfer of information using physics-based representations of the UMPs and (2) how shared information from a number of composed UMPs can aid system-level sustainability assessment. An example is presented for a part that undergoes physical and material transformations. UMP models for extrusion, milling, and annealing (Appendices B1, B2, and B3) were selected to demonstrate the process physics-based case. For the second case, UMP models of extrusion, saw cutting, quenching, and annealing (Appendices B2, B7, B8, and B3) were selected.

4.5.1 Information transfer across composed UMP models

The three selected manufacturing processes (extrusion, milling, and annealing) are representative UMPs for three manufacturing taxonomy categories, namely, mass conservation, mass removal, and heat treatment, respectively. These three processes can be used to help illustrate how changes in the manufacturing process flow can affect geometric and material properties of the workpiece. The manufacturing process flow is comprised of extrusion, followed by milling and then annealing. Table 4.4 provides the literature basis for the UMP models developed.

Table 4.4: Selected manufacturing processes for composition

UMP Model	Modeling Aspect	Reference
Milling	Process physics	[28,208]
	Energy characterization	[206,207,209,239]
Extrusion	Process physics and energy characterization	[28,240–244]
Annealing	Process physics and energy characterization	[28,245–247]
Circular saw cutting	Process physics and energy characterization	[248,249]
Common for selected manufacturing processes	Sustainability KPIs	[185,250]

The composition of the three processes is shown in Appendix B4, which provides a graphical representation of composed system with the linking variables identified between the respective source and target UMP(s). For example, in the composition of extrusion (source UMP) and milling (target UMP) the linking variables of length, width, height, volume, mass, and density of the workpiece form the shared context (linking relationships) for the processes. However, when the workpiece is subsequently annealed (target UMP), the linking variables are shared from both the milling and extrusion UMP models. One key item to note is that the outputs of each upstream (source) UMP serve as inputs to the downstream (target) UMPs. For example, the work-in-process output of extrusion ($WIP_{Extrusion}$) becomes the input for milling, while the WIP output of milling (WIP_{Milled}) is an input for annealing. Thus, it can be seen that the linking variables are carried by the product and process information flow, and, in turn, are encoded by the material flow [251]. In effect, product and process information is carried through a process flow by the in-process material.

4.5.2 An application of process information modeling for energy cost and environmental impact assessment

To demonstrate an application of the proposed concept and method, a distributed cloud-based manufacturing system (DCMS) case study is presented. DCMS refers to a service where the consumers (small/medium companies) design, choose, and configure manufacturing by breaking down a product into its sub-components and/or related manufacturing processes. DCMS relies on an agile supply chain, robust manufacturing network distributed geographically, and a dynamic production planning system [252]. These systems offer benefits such as reduced costs, shorter production cycles, customized products, just-in-time manufacturing, and reduced inventory. However, as consumer demand grows, DCMS tends to be a less viable option than conventional manufacturing systems due to increased efforts required to manage the supply chain, manufacturing network, and production plans [253]. In spite of the potential disadvantages for scaling, DCMS has been on a recent upward trend, as it promotes sustainable manufacturing by sharing resources, reducing transportation, and increasing employment of the local workforce [254]. Due to their dynamic nature (in design, material, manufacturing process, and supply chain), sustainability assessment tools need to be dynamic to aid in characterizing and optimizing DCMS networks [255].

For this example, a national company that produces a family of extruded metal parts utilizes a DCMS network to reach potential customers. One of their customers is using the DCMS order fulfillment platform to specify and select corner brackets for constructing a set of new ergonomic assembly stations. Here, the brackets are representative of high-volume production, aluminum alloy (AA 6061) parts that have a wide application across industry. The company offers corner brackets with leg lengths ranging between 0.025m–0.125m in increments of 0.02m. The part wall thickness and width are parametric size dimensions related to leg length. The manufacturing process flow for the production of brackets reported in the DCMS platform by the supplier is illustrated in Figure 4.6, starting with the input raw material (rod stock) through final part processing. In this example, sustainability performance is impacted by the workpiece itself as well as the transformations the workpiece undergoes from hot extrusion through annealing.

Parts are produced in several locations by size: 0.025m-0.045m (Chicago, IL), 0.065m-0.085m (Seattle, WA), and 0.105m-0.125m (New York City (NYC), NY). The three bracket options being considered by the customer's industrial engineer are (1) fifty 0.025m, thirty 0.065m, and twenty 0.125m brackets, (2) twenty 0.045m, thirty 0.085m, and fifty 0.105m brackets, and (3) thirty 0.025m, sixty 0.085m, and ten 0.125m brackets (each order consists of 100 brackets). The engineer is able to conduct trade-off analyses to evaluate the economic, environmental, and social performance of each option using a multi-criteria decision-making approach available through the DCMS platform. This approach enables the engineer to evaluate the three options under different sustainability perspectives using the following metrics:

(1) **Total energy** is the energy consumed to transform the input workpiece into an output/finished part. In this case, the total energy consumption is the energy spent to convert the stock to an annealed corner bracket.

(2) **Total cost** of manufacturing is the cost of goods sold (COGS) for the output/finished part. The typical cost elements of COGS include raw material, equipment/tool, utilities, consumables/tooling, facilities, maintenance, and labor costs [256,257].

(3) **Percent non-labor cost** is the ratio of all non-labor elements of COGS to the total cost of manufacturing the part (COGS).

(4) **Global warming potential (GWP)** is defined as "a measure of how much energy the emissions of 1 ton of a gas will absorb over a given period of time [usually 100 years], relative to the emissions of 1 ton of carbon dioxide (CO2)" [81].

(5) **Total mass** is the mass of all output/finished parts. This mass does not include the material removed during manufacturing, as it is an indicator of shipping-related impacts (e.g., transportation fuel and emissions).

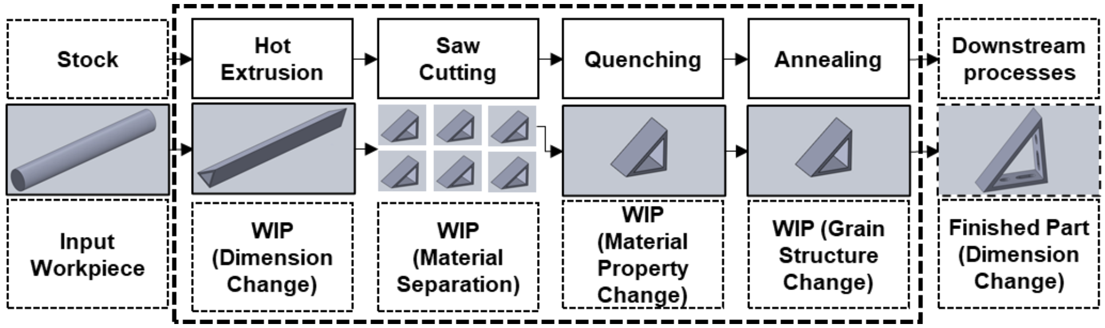


Figure 4.6: Manufacturing process flow demonstration case

Product design- and manufacturing process-related information pertaining to the workpiece transformations to convert the raw stock into finished corner brackets are detailed in Table 4.5. In applying the previously described sustainability performance evaluation methodology (Section 4.4), several modeling assumptions and considerations were made to assist in quantifying cost and environmental impacts of production. These considerations feed into UMP models for extrusion (Appendix B2), annealing (Appendix B3), saw cutting (Appendix B6), and quenching (Appendix B7).

Table 4.5: Assumptions and considerations for cost and environmental impact analysis of corner bracket production

Description	Assumptions	Additional Properties	References
Input workpiece (rod stock)	Material: Aluminum 6061 Diameter: 0.25 m Length: 1.2 m Chicago: $2.60/kg, Seattle: $2.90/kg, NYC: $3.10/kg	Yield strength: 276 MPa Density: 2768 kg/m^3 Thermal conductivity: 152 W/m K Mass: 163.11 kg	[258–260]
Extrusion process	Barrel material: Nitriding steel Barrel diameter: 0.175 m	Stock temperature: 400 °C Barrel temperature: 350 °C Ram speed: 0.006 m/s	[261,262]
Circular saw cutting process	Saw blade material: Steel with Carbide Tip Saw blade diameter: 0.406 m (16”) Saw blade kerf: 3.175 mm (0.125”) Saw blade hardness: > 30 HRC	Cutting speed: 122 m/min Feed: 0.20 m/min	[263,264]
Quenching process	Quench medium: Distilled water Quenchant temperature: 40 °C	Cooling rate: 150 °C/s (300 °F/s)	[265,266]
Annealing process	Annealing temperature: 420 °C Temperature hold time: 2 h	Cooling rate: 40 °C/h (air-cooled)	[260,267]
Input energy cost	Electricity: Seattle: $0.056/kWh, NYC: $0.06/kWh, Chicago: $0.07/kWh	Natural gas: $33.57/m^3 ($0.95/ft^3, national average)	[268]
Electrical energy emissions factor	Seattle: 0.090 kg CO_2e/kWh, Chicago: 0.368 kg CO_2e/kWh, NYC: 0.189 kg CO_2e /kWh		[269]
Labor cost	Chicago: $20.22/h, NYC: $21.28/h, Seattle: $25.29/h		[270]

The manufacturing process flow is composed of four UMPs as noted above (Figure 4.6). Product and process information associated with an upstream (source) UMP also serves as linking variables to the indicated downstream (target) UMP. Key product and process information (linking variables) found to have a high influence on sustainability performance are discussed below.

(1) **Rod stock (raw material) to hot extrusion:** Aluminum 6061 rod stock is extruded to form the cross-sectional shape of the corner bracket. Key product and process information with a direct impact on extrusion process sustainability performance are:

a. Extruded part cross-sectional area, which is generic linking variable that determines the extrusion ratio – defined as the ratio between the cross-sectional areas of the feed material (rod stock) and the extruded part. Extrusion pressure and, thus, ram power, are reduced as the extrusion ratio is reduced for a given stock diameter. Thus, larger size brackets will require less extrusion energy for a specified rod stock diameter and length.

b. Workpiece material microstructure, which is a specific linking variable that can lead to more energy use as hardness increases; some high-strength materials may also require preheating to facilitate extrusion. In this case, the Al 6061 rod stock is preheated to 400 °C for the hot extrusion process, which increases heating energy, but reduces ram power.

(2) **Hot extrusion to saw cutting:** Part blanks are cut to length using a saw cutting process. Key product and process information that drive saw cutting sustainability performance are:

a. Workpiece height, is a generic linking variable that defines the depth of cut, which, in turn, is taken into account when selecting the saw blade diameter and cutting feed rate. Depth of cut and feed rate determine time-related performance measures (e.g., cycle time and process energy use).

b. Workpiece hardness, which is a specific linking variable used to define the feed rate based on the characteristics of the blade used (e.g., tooth material hardness, tooth pattern, and kerf width). Harder workpiece materials require slower feed rates and exhibit increased specific cutting energy, both factors that negatively impact process sustainability performance.

(3) Saw cutting to quenching: The separated parts are then cooled in a quenching bath of distilled water. The key product and process information that influence quenching sustainability performance are:

a. Workpiece thickness, which is a generic linking variable that determines the required quench time for a specific part. Cooling time increases with part thickness, thereby increasing quenching cycle time.

b. Workpiece temperature, which is a specific linking variable of the incoming material that, along with the workpiece thickness and quenching medium, determines the workpiece cooling rate. For the corner bracket, a cooling rate of 150 °C/s will result in a workpiece hardness similar to AL6061 T6. Higher cooling rates tends to increase fatigue life, resistance to impact elongation, and strength. However, these conditions are not necessary for the corner brackets.

(4) **Quenching to annealing:** Full annealing must be done to achieve an "O" temper designation for the corner brackets. This condition allows the supplier to reach a broader market, and customers to apply their desired heat treatment regimen. The annealing process has three stages: (1) heating the workpiece to the specified annealing temperature, (2) holding the workpiece at the annealing temperature for a specified time, and (3) cooling the workpiece at a specified rate to achieve full annealing. The key product and process information that have a direct impact on the sustainability performance of annealing are:

a. Workpiece thickness, which is a generic linking variable used to determine the annealing temperature and hold time to achieve full annealing. This is the most energy intensive stage of the process, and lasts for a few hours. In this case, hold times of 2-3 hours at 420 °C have been estimated for the range of part wall thicknesses.

b. Workpiece material microstructure is a specific linking variable that determines the annealing temperature. The annealing temperature is critical for determining the amount of energy that needs to be provided to the oven. Also, the cycle time for the annealing process is dependent on the annealing temperature. Both natural gas consumed by the oven and cycle time are directly proportional to the annealing temperature of the workpiece material.

These linking variables aid in the composition of UMPs to form a model of the manufacturing process flow. Table 4.6 details the metrics of interests that have been quantified for the selected corner brackets in this demonstration case using the assumptions and considerations for each UMP (Table 4.5). This compiled information for each of the brackets creates a decision-making challenge for the engineer tasked with purchasing the corner brackets for the assembly station tables.

Table 4.6: Economic, environmental, and social impact analysis results

Part Size	Mass (kg)	Energy (kWh/part)	GWP (kg CO_2e/part)	Total Cost ($/part)	Labor Cost ($/part)
0.025	0.005	2.24	0.82	0.48	0.40
0.045	0.028	3.58	1.32	1.05	0.61
0.065	0.084	5.74	0.52	2.43	0.97
0.085	0.188	12.25	1.10	4.49	1.22
0.105	0.353	23.00	4.34	9.64	3.07
0.125	0.597	38.94	7.36	14.32	3.22

Thus, based on these quantified metrics of interest, the engineer is able to perform a trade-off study for the options under consideration. Figure 4.7 compares the three corner bracket procurement options by normalizing each metric of interest with respect to the worst-performing option. For example, the total mass of brackets in Option 1 is 62% of the total mass of brackets in Option 2. It can be seen that the metrics of interest (i.e., total energy (kWh), total cost ($), GWP (kg CO_2e), total mass (kg), and % non-labor cost) are equally weighted. It is interesting to note that the relative total energy and GWP performance vary due to the different energy mixes available at the manufacturing locations. These results indicate that Option 1 and Option 2 have better overall performance than Option 3 (28% and 26%, respectively), but it is not clear if a robust choice would be made based on this information, since different individuals would place different values on these decision-making criteria. It is important for the engineer to consider the choice using different perspectives – a capability available through the DCMS platform.

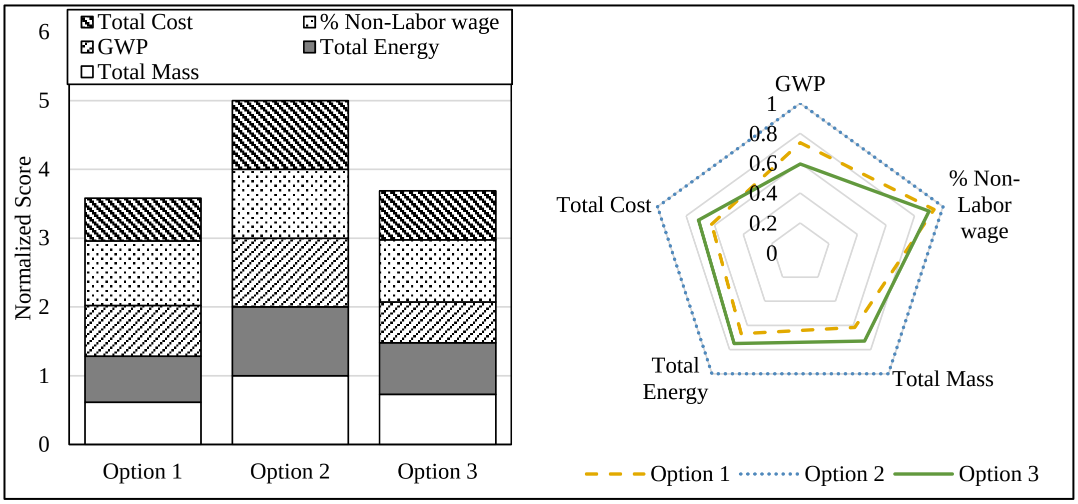


Figure 4.7: Trade-off analysis based on industrial engineer's weighting

Multi-criteria decision-making (MCDM) is an analysis technique that helps decision-makers distinguish among options (alternatives) based on potentially competing criteria. The Analytic Hierarchy Process (AHP), developed by Saaty [271] is a tool for MCDM that helps the decision-makers identify a solution that fits their objectives. AHP relies on subjective judgement from decision makers for assigning relative importance between the multiple criteria considered. Herein, it is assumed that the DCMS platform would collect information from a variety of users and generate a number of different decision-making perspectives (archetypes) based on the choices they make. However, absent such a marketplace, two perspectives are assumed here for illustration. In addition, AHP allows decision makers to evaluate the consistency of judgements made, which is well-suited for decision problems with multiple criteria spanning competing technical, social, and environmental domains [272]. MCDM using AHP involves a four-step process: (1) Defining the hierarchical structure, (2) Defining relative importance for pairwise comparison, (3) Computing criteria weights, and (4) Evaluating consistency. The MCDM approach is explained in more detail using the corner bracket demonstration case

The first step is to define the hierarchical structure, typically represented as a three-level model. Level 1 defines the goal of the model; Level 2 contains the decision criteria considered in decision-making, and Level 3 presents the decision alternatives (Figure 4.8).

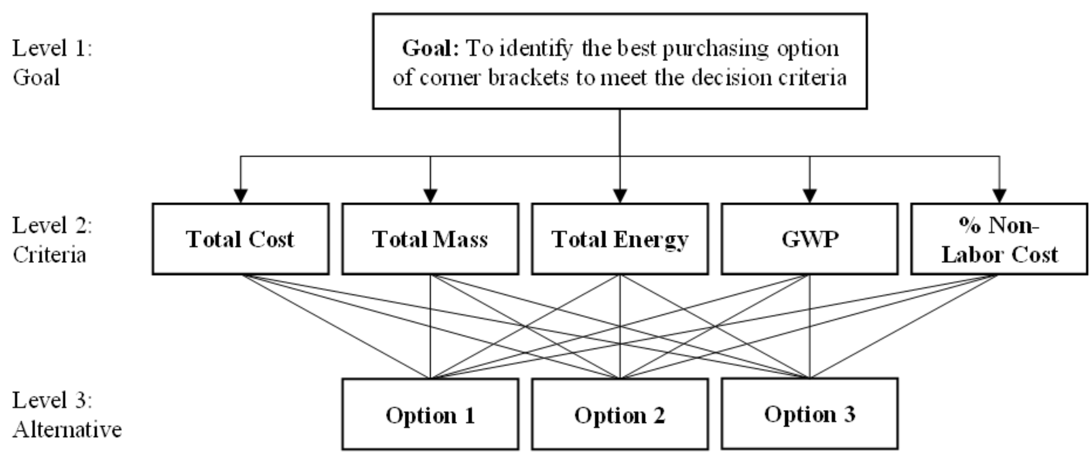


Figure 4.8: AHP hierarchical structure

Once the hierarchical structure is defined, pairwise relative importance (judgement) of the criteria needs to be evaluated. Typically, relative importance values range between 1 and 9, with 1 indicating equal importance, 3 and 5 indicating moderate importance, and 7 and 9 indicating extreme importance. The inverse of these scales, indicate moderately less importance (1/3 and 1/5) and highly less importance (1/7 and 1/9). Table 4.7 shows the pairwise comparison matrix from the first sustainability perspective selected by the industrial engineer. The first perspective represents that of a procurement manager, who is more likely to be focused on cost relative to other performance metrics. Here, for example, total cost is rated as being extremely more important (9 times) than GWP.

Table 4.7: Pairwise comparison matrix based on the procurement manager perspective

Criterion	Total Cost	Total Energy	GWP	Total Mass	% Non-Labor Cost
Total Cost	1	3	9	3	5
Total Energy	1/3	1	3	1/5	3
GWP	1/9	1/3	1	1/5	1/3
Total Mass	1/3	5	5	1	5
% Non-Labor Cost	1/5	1/3	3	1/5	1
Total	1.98	9.67	21	4.60	14.33

Based on the pairwise comparison matrix, the next step is to calculate the priority vector (Eigen vector) for assigning weights to the elements within the pairwise comparison matrix. The pairwise comparison matrix is normalized by dividing each matrix element by the total of each column. Table 4.8 shows the normalized pairwise comparison matrix.

Table 4.8: Normalized pairwise comparison matrix

Criterion	Total Cost	Total Energy	GWP	Total Mass	% Non-Labor Cost
Total Cost	0.51	0.31	0.43	0.65	0.35
Total Energy	0.17	0.10	0.14	0.04	0.21
GWP	0.06	0.03	0.05	0.04	0.02
Total Mass	0.17	0.52	0.24	0.22	0.35
% Non-Labor Cost	0.10	0.03	0.14	0.04	0.07
Total	1.00	1.00	1.00	1.00	1.00

The priority vector is then calculated by taking the average of each row of the normalized pairwise comparison matrix to estimate the weight assigned for each criterion in the decision-making process. For example, the weighting for total cost is 0.45 (Eq. 4.1).

$$Priority\ vector = \frac{1}{5}\begin{bmatrix} 0.51 + 0.31 + 0.43 + 0.65 + 0.35 \\ 0.17 + 0.10 + 0.14 + 0.04 + 0.21 \\ 0.06 + 0.03 + 0.05 + 0.04 + 0.02 \\ 0.17 + 0.52 + 0.24 + 0.22 + 0.35 \\ 0.10 + 0.03 + 0.14 + 0.04 + 0.07 \end{bmatrix} = \begin{bmatrix} 0.45 \\ 0.13 \\ 0.04 \\ 0.30 \\ 0.08 \end{bmatrix} \quad (4.1)$$

Next, the consistency ratio (C_r) is calculated to evaluate the acceptability of judgements. A consistency ratio of less than 10% is considered acceptable, whereas a higher ratio indicates subjective judgements need to be adjusted [271]. Consistency ratio is defined as the ratio of consistency index (CI) to the random index (RI). CI is calculated using the maximum Eigen value (λ_{max}), as shown in Eq. 4.2, where ndc is the number of decision-criteria (n=5). The random index specified for five metrics is 1.12.

$$CI = \frac{\lambda\max - ndc}{ndc-1} \tag{4.2}$$

To calculate the maximum Eigen value (λ_{max}), the weighted sum for each decision criterion (Eq. 4.3) needs to be computed based on calculated criteria weights in the priority vector (Eq. 4.1) and the pairwise comparison matrix (Table 4.7).

$$Weighted\ sum = 0.45 \begin{bmatrix} 1 \\ 1/3 \\ 1/9 \\ 1/3 \\ 1/5 \end{bmatrix} + 0.13 \begin{bmatrix} 3 \\ 1 \\ 1/3 \\ 5 \\ 1/3 \end{bmatrix} + 0.04 \begin{bmatrix} 9 \\ 3 \\ 1 \\ 5 \\ 3 \end{bmatrix} + 0.3 \begin{bmatrix} 3 \\ 1/5 \\ 1/5 \\ 1 \\ 1/5 \end{bmatrix} + 0.08 \begin{bmatrix} 5 \\ 3 \\ 1/3 \\ 5 \\ 1 \end{bmatrix} = \begin{bmatrix} 2.50 \\ 0.70 \\ 0.22 \\ 1.71 \\ 0.40 \end{bmatrix} \tag{4.3}$$

The maximum Eigen value (λ_{max}) is calculated as shown in Eq. 4.4, resulting in a consistency index (CI) of 0.10.

$$\lambda_{max} = \frac{\frac{2.50}{0.45} + \frac{0.70}{0.13} + \frac{0.22}{0.04} + \frac{1.71}{0.30} + \frac{0.40}{0.08}}{5} = 5.40 \tag{4.4}$$

For this example, the consistency ratio of the procurement manager judgements is 8.9% (Eq. 4.5), which is acceptable (<10%).

$$C_r = \frac{CI}{RI} = \frac{0.10}{1.12} = 0.089 \tag{4.5}$$

Using the criteria weights from the priority vector established for the procurement manager perspective (Eq. 4.1), a trade-off analysis for the three purchasing options is shown in Figure 4.9. Since higher importance was given to total cost and total mass compared to the other criteria, they have the highest influence on the performance of the options. From this perspective, it can be seen that the influence of energy consumption, GWP, and non-labor cost on sustainability performance are low relative to total cost and total mass. In addition, Option 1 performs slightly better (11%) than Option 3, while Option 2 is not preferable due to poor overall performance, as found without weightings applied, above.

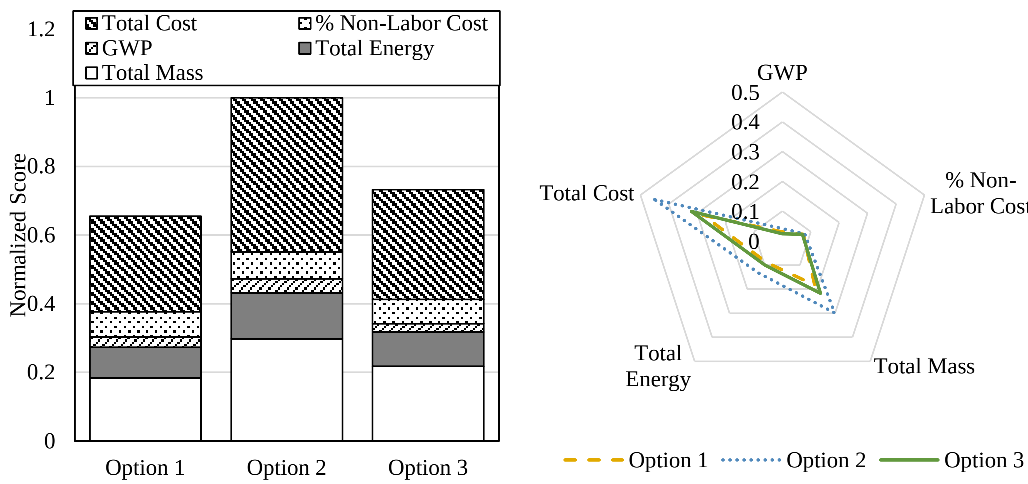


Figure 4.9: Trade-off analysis based on the procurement manager perspective

To test the validity of these results, the industrial engineer next applies the MCDM approach by taking the perspective of a sustainability manager (Table 4.9). The consistency ratio of the pairwise judgements was estimated as 8.0% (<10%), which is acceptable.

Table 4.9: Pairwise comparison matrix based on the sustainability manager perspective

Criterion	Total Cost	Total Energy	GWP	Total Mass	% Non-Labor Cost
Total Cost	1	1/5	1/7	1/3	1/3
Total Energy	5	1	1/2	5	3
Total Mass	7	2	1	5	3
GWP	3	1/5	1/5	1	1/5
% Non-Labor Cost	3	1/3	1/3	5	1

Based on the relative importance ratings from the sustainability manager perspective, the criteria weights were estimated and a trade-off analysis performed for the three purchasing options, as shown in Figure 4.10.

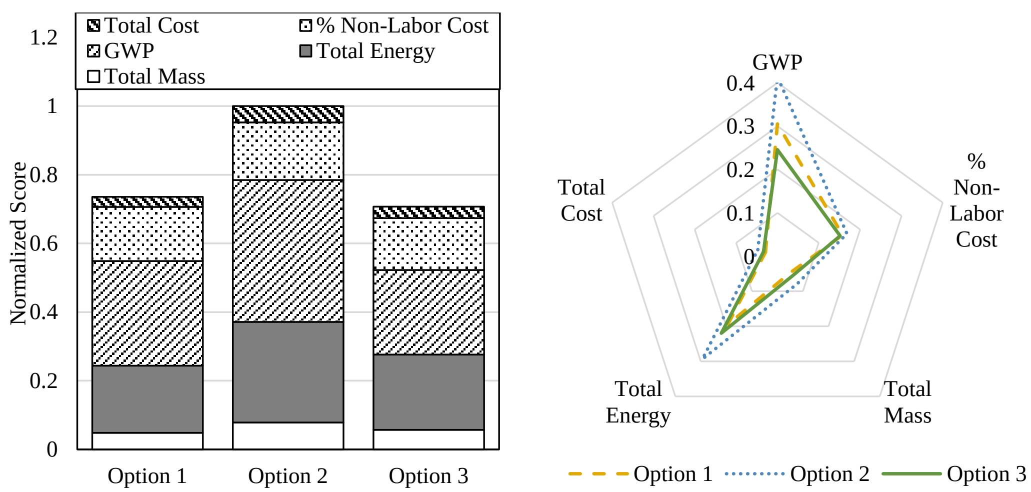


Figure 4.10: Trade-off analysis based on sustainability manager's judgement

Relatively higher importance was given to GWP, energy consumption, and percent non-labor cost. Thus, from this perspective, it can be seen that the influence of total cost and total mass are low relative to energy consumption, GWP, and non-labor cost on sustainability performance. In addition, Option 3 is found to perform only slightly better (3%) than Option 1, while Option 2 is not preferable due to poor overall performance.

Based on the trade-off analysis from the procurement manager and sustainability manager perspectives, Option 2 is not a viable procurement option. Option 1 is suited using the procurement manager judgements, and has a slight advantage over Option 3, whereas, for the sustainability manager's judgements, Option 3 is only slightly better than Option 1. From this analysis, Option 1 is the preferred choice selected by the industrial engineer for procurement.

In this demonstration, three perspectives were analyzed using different weighting schemes to make a product design decision (i.e., corner bracket specification for an assembly table) driven by manufacturing sustainability performance. The demonstration illustrates how the information exchange between individual UMPs in the defined manufacturing process flow can be used to characterize and quantify manufacturing process-/system-level metrics. Also, it is seen how the manufacturing system model can be used for performing a trade-off and sensitivity analysis. The structured representation of the system-level model helps in understanding the key product and process information and their effects on the defined sustainability KPIs/MOIs. This information enables design and manufacturing engineers to specify product or system design requirements for sustainability performance improvement.

4.6 Conclusions

The research presented herein investigates the concept of composability of unit manufacturing process (UMP) models to enable characterization of manufacturing systems for sustainability performance evaluation. Specific and generic linking variables are defined as the key information contained within a UMP model that enables its composition, or linking, with models of other UMPs. The concept of linking variables, previously defined in a cursory manner by the research community, was explored in more depth and several key characteristics of linking variables were defined. In so doing, the work provides two methods of representing a manufacturing system model structure (using IDEF0 and XML) that align with existing standard guidelines for structuring UMP models. From an information modeling standpoint, the manufacturing system model structure proposed in this research enables the following:

(1) Standardized representation of a manufacturing system in alignment with existing standards for UMP modeling developed by the ASTM sub-committee E60.13 on sustainable manufacturing.

(2) Tracking of information flows between UMPs through the use of functional modeling (e.g., IDEF0), which captures upstream and downstream data and information.

(3) Abstraction of UMP models (e.g., XML), which allows for instantiation of a process model developed for a particular application to be reused for related processes and process flow variants.

(4) Automatic adjustments to manufacturing system models, when realized through a software application, that reflect real-time or near real-time changes to the

processes used in the system through direct modifications to the underlying UMP models.

Though the methodology is demonstrated for a single workpiece flow, the approaches can be applied to manufacturing systems that handle multiple workpieces (e.g., parallel production flows) and utilize manufacturing processes such as joining and assembly. Composability of UMPs for sustainability performance evaluation enables manufacturers to gain a deeper understanding of the interrelationships between manufacturing processes, especially those that drive influencing factors for specific metrics of interest for engineering and business decision makers across operational, tactical, and strategic levels of an organization. Linking variables act as a medium in defining these relationships. Further, composability allows manufacturers to evaluate manufacturing systems to focus on desired sustainability objectives, including improving cost, productivity, energy efficiency, environmental performance, and social impacts. Since the concept of linking variables had not been previously explored in depth, the methodology developed provides a starting point for researchers and industry practitioners in implementing the ASTM sustainable manufacturing standard for evaluating system-level manufacturing sustainability performance.

This work supports ongoing research focusing on development of open manufacturing process model repositories [197,197] and promoting their broader adoption toward evaluating sustainability performance of manufacturing processes and systems [8,44,273,274]. The model composition method presented in this work eases development of software solutions and could be incorporated into existing computer-aided design software tools to support manufacturing systems design decision making. Software development is enabled by taking advantage of both functional modeling and object-oriented programming architecture, and can be structured by considering their respective frameworks. Understanding of manufacturing processes can be a limitation to software development, since the model development requires domain expertise of process parameters and the influence of geometric and material properties on manufacturing processes. Linking variables, which are identified based on process knowledge, establish relationships between UMPs, thereby improving insight into representing manufacturing system models. Integration of domain expert knowledge into UMP model development needs more attention. For example, the application of ontologies for linking variables that can map, link, and define rules and relationships for two or more UMPs, which will further unsupervised or semi-supervised sustainability assessments of manufacturing systems.

Acknowledgements

The authors gratefully acknowledge the National Institute of Standards and Technology (NIST Award No. 70NANB16H223) for its support of this research. We would especially like to thank our NIST collaborators for their generous inputs to the research.

Chapter 5: AN INFORMATION MODELING FRAMEWORK FOR SUPPORT OF SUSTAINABLE MANUFACTURING SYSTEM DESIGN DECISION MAKING

5.1 Abstract

Sustainable manufacturing system design constitutes the development and application of manufacturing processes towards making products with minimal economic, environment, and social impacts. Historically, manufacturing industry has been driven by the motivation to reduce costs. With increasing emphasis on energy and resource conservation, environmental impact reduction, and social responsibility, multi-criteria decision-making methods and engineering analysis tools have been developed to support sustainable manufacturing. These methods and tools are cumbersome, however, since they are developed in an ad hoc manner, typically to assess an existing manufacturing process, line, or facility. A lack of standard methodologies for model development and analysis limits the sharing and reuse of existing knowledge for the design of sustainable manufacturing processes and systems. This paper presents a framework for integrating information modeling-based sustainability assessment with manufacturing system design methodology to facilitate the design of sustainable manufacturing systems. The developed information modeling approach utilizes standards-based methods for characterizing the sustainability performance of unit manufacturing processes (UMPs) and manufacturing systems. Manufacturing system design defines the sequence and arrangement of UMPs for the intended product based on the expected customer demand. This framework enables multi-criteria sustainability

assessment of manufacturing systems through the information modeling concepts of abstractions, instantiation, and composition. A demonstrative case study compares the sustainability performance of two manufacturing systems producing an aluminum wheel housing. To illustrate the framework for continuous manufacturing, the economics of two chemical process flows are compared for the production of a bulk chemical (ammonia). These case studies highlight the utility, flexibility, and adaptability of the framework for modeling different manufacturing systems. The information modeling basis of this approach lends it to realization through computer-based applications and tools to support systems engineers and other decision makers.

5.2 Introduction

Manufacturing system design includes the estimation, analysis, and capacity planning, considering material flows, production type (job shop, batch, mass, and continuous), operations, and plant layout [275,276]. Manufacturing system design approach have applied conventional methods such as the axiomatic theory of design, extended general design theory, Taguchi robust design, theory of inventive problem solving, and total quality development with an intent of improving productivity, system efficiency, yield, and product quality [277]. The primary focus has been on reducing product cost, thereby increasing margins, revenue, and market penetrance to improve economic competitiveness. However, with increased consumer awareness, government regulations, and investor demands, the importance of sustainable manufacturing has increased [156]. Several definitions of sustainable manufacturing have been proposed, but none have been widely accepted. According to the United State Environmental

Protection Agency (U.S. EPA), sustainable manufacturing is "[t]he creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources. Sustainable manufacturing also enhances employee, community and product safety [278]." Several challenges are attendant with executing sustainable manufacturing practices in industry: (1) Sustainability analysis is cumbersome at the manufacturing system design phase due to the complex nature of manufacturing systems (interactions between manufacturing processes) [279]; (2) Engineering methods/tools have limited ability to address all three pillars of sustainability, namely, economic, environmental, and social impacts, simultaneously [215]; (3) Sustainability assessment methods/tools inhibit the transferability of knowledge since they typically focus on product impacts and are constrained to modeling the specific processes used in the manufacturing system under study; (4) Process models that underlie existing methods/tools are not easily tunable, limiting the ability to evaluate sustainability performance at the manufacturing system level; and (5) Existing methods/tools are unable to support multi-criteria sustainability decision making at the manufacturing system design phase, all of which hinder sustainable manufacturing.

Life cycle assessment (LCA) methods/tools aim to address several of these challenges at the product design and/or manufacturing system design phases [280]. LCA provides a framework for assessing the environmental impacts across the product lifecycle [281]. While LCA studies often span from cradle to grave, product designers and manufacturers are focused on assessing and improving the sustainability performance of the manufacturing phase of the lifecycle (gate-to-gate) [282]. Existing LCA tools apply process models for a particular manufacturing setting, however, these underlying models tend to be generic representations of an individual process or set of processes that are based on unique data sets [283]. Other deficiencies include inadequacies in assessment approach (little focus on cost and social impacts), inconsistency in data, and inability to perform multi-criteria decision analysis for a manufacturing system [284,285]. Due to these challenges, as well as the related challenges of consistent manufacturing process data representation, handling, and processing, adoption of LCA for manufacturing system design has not gained traction. These deficiencies can be addressed through the application of information modeling, which provides a well-defined structure and streamlined sequential handling and control over data exchange [165]. Information models define relationships, rules, functions, formal structure, and operations of entities (processes/subsystems) within the domain space (system) [32]. Further, information modeling provides an approach for defining functional and architectural requirements to represent data/information in the development of software platforms. By using this approach, underlying information models (metamodels) can be structured to facilitate data sharing between entities, model reuse and extension, and tracking and processing information in a reliable manner. In addition, these information modeling techniques can be leveraged for improving/adjusting existing metamodels with relative ease compared to developing new models from scratch.

Information modeling provides a foundational basis for development and modification of manufacturing process models to support parametric sustainability assessments. The benefits of integrating information modeling with manufacturing process modeling can be realized through development of sustainable engineering tools that enable efficient and accurate process/system analysis, while ensuring data privacy and operational confidentiality. The goal of this research is to facilitate multi-criteria sustainable manufacturing analysis and decision making by integrating information modeling-based sustainability assessment with manufacturing systems design (Figure 5.1).

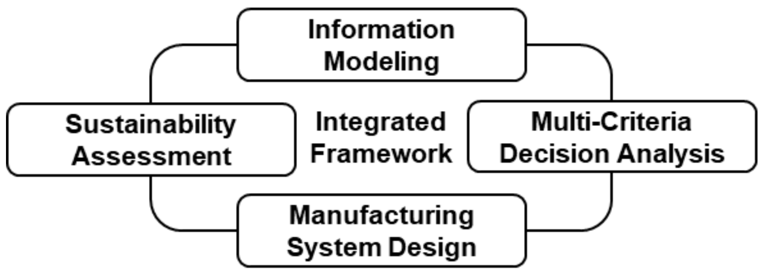


Figure 5.1. Conceptual model of the research

This research is based on the ASTM E3012-20 standard that describes information modeling as a means to evaluate sustainability performance of manufacturing processes [27]. Related research has reported the application of the standard for the sustainability performance characterization of manufacturing processes (e.g., material removal [173,174,286], heat treatment [171,186], mass conservation [180,182], injection molding [183,287], and sheet metal forming [178,184]) and systems [288,24,172]. The research herein extends this work by introducing an information modeling framework for sustainable manufacturing system design decision making. In Section 2 a brief review of prior work is detailed, followed by a description of the research methodology in Section 3, which presents the sustainable manufacturing system design decision support framework. Next, two demonstrative case studies are reported in Section 4, using a discrete manufacturing part and a continuous product manufacturing. Finally, in Section 5, the research findings, advantages/limitations of the framework, and recommendations are discussed.

5.3 Background

Manufacturing system design connects product design and manufacturing by establishing unit operations and process flows to efficiently and effectively produce the intended product, while meeting a defined set of desired objectives, or customer-driven functional requirements. A manufacturing system as "a subset of the production system – is the arrangement and operation of elements (machines, tools, material, people, and information) to produce a value-added physical, information or service product whose success and cost is characterized by measurable parameters of the system design" [22]. Thus, the design of a manufacturing system is driven by functional requirements, which are translated into engineering requirements that the system must fulfill under a set of constraints. In sustainable manufacturing system design, focus is placed on defining functional requirements that simultaneously address economic, environmental, and social performance objectives. In addition to production volume, which drives the size, cost, and complexity of manufacturing systems, sustainability performance depends on a variety of metrics interest that span the three pillars of sustainability, including direct costs (e.g., labor, consumables, and operations costs), indirect costs (e.g., maintenance, legal, safety, and administrative costs), capital cost, working conditions, worker safety, energy use, water use, solid waste, types of material handling equipment, and influence of geographic location [289].

With the wide range of metrics (environmental, economic, and social) that must be considered in the design and analysis of sustainable systems, holistic evaluation is challenging [290]. Multi-criteria decision analysis (MCDA) approaches have been applied to overcome the challenge of simultaneously comparing a number of competing metrics [291]. These include the Analytic Hierarchy Process (AHP), weighted sum method, weighted product method, Elimination and Choice Translating Reality (ELECTRE), Preference Ranking Organization Method (PROMETHE), Multi Attribute Utility Theory (MAUT), and Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS). However, existing assessment methods/tools do not support MCDA approaches for choosing alternatives to improve system sustainability performance [292,293]. In particular, for manufacturing system design, the underlying models for evaluating manufacturing processes are agnostic of production system attributes, such as production volume, labor utilization, the process plan and equipment, and geographic location. Several prior efforts in support of manufacturing system design have assessed environmental, economic, and social aspects independently in the decision-making process. Gao et al. [294] applied the manufacturing system design method along with LCA to identify key economic and environmental drivers for production of a microchannel device across a range of production volumes. Stoycheva et al. [295] presented a conceptual MCDA framework to evaluate the sustainability performance of various materials for the production of a set of automotive parts within an existing manufacturing system. Li et al. [296] applied the Decision Making Trial and Evaluation Laboratory (DEMATEL) method to determine key performance indicators that promote the development of a sustainable manufacturing system. A pairwise comparison was used to identify key indicators gathered through a survey of experts, which supported the design of an automotive part production system. Mokhtari et al. [297] demonstrated fuzzy goal programming to minimize production cost, transportation cost, and environmental impacts (i.e., generated waste, gas emissions, noise, worker injuries, and energy consumption) during production planning. Their approach was verified using manufacturing case studies for eight home appliances. It should be noted that these methods have been developed for specific applications in an ad hoc manner, and are not generalizable for reuse in the design of manufacturing systems. Advancements in software technology, including information modeling approaches and techniques, enable the structured and streamlined handling of product and process data in a manner that is complementary to manufacturing system design by bridging design and manufacturing decision making.

Since information modeling provides a hierarchical structure to the data, it has been applied for data exchange in a number of design and manufacturing software frameworks. Some of the most commonly used information modeling languages are Integrated computer-aided DEFinition (IDEF0) [218] for function modeling, and Unified Modeling Language (UML) [203] and eXtensible Markup Language (XML) [219] for object-oriented modeling. Several past efforts have undertaken information modeling of manufacturing processes and systems for production planning, design data exchange schematics for manufacturing processes, and cost modeling [233,298]. The Systems Integration of Manufacturing Application (SIMA) developed by the National Institute of Standards and Technology (NIST) aimed to support the integration of design and manufacturing software systems using object-oriented representations of manufacturing process information to assist process planning. The Core Product Model (CPM), another effort by NIST, focused on representing design information such as product form, fit, function, dimensional details, and material. The Open Assembly Model (OAM) built upon CPM to expand the representation of design data for sub-system/system assemblies. These efforts laid the foundation for development of standards that emphasized representation of design and manufacturing data in computer applications. Well-known information modeling-based data exchange frameworks include Initial Graphics Exchange (IGES), Standard for the Exchange of Product Model Data (STEP), ISO 10303 (Standard for representing product manufacturing information for computer interpretation) [220], ISO 16100-2 (Standard for information exchange between design and manufacturing software applications) [299]. The Open Platform Communications (OPC) standard is a set of specifications and software protocols developed for the sharing of information in a secure and reliable way between manufacturing tools/equipment [300]. Despite these efforts to represent product and process data as information models and to improve data exchange between design and manufacturing, none were intended to facilitate sustainable manufacturing system design.

Simultaneously with these efforts, methods for supporting sustainability performance characterization at the product design and manufacturing stage were independently under development. Noteworthy efforts led to a number of software applications, such as SimaPro [301] and GaBi [230], developed to support design engineers in estimating the environmental impacts based on product design and manufacturing information. These software applications enabled decision makers to choose from among several alternatives to reduced product environmental impacts. However, these applications had a few drawbacks: (1) they did not allow decision makers to evaluate metrics related to all three pillars of sustainability, (2) estimated impacts had high level of uncertainty because the underlying models and data were broad representations of the associated manufacturing processes, and (3) they were not developed to support manufacturing system design decision making. To overcome these shortcomings, the Unit Process Life Cycle Inventory (UPLCI) initiative emerged with a focus on developing an inventory of reusable manufacturing process models for LCA [45]. Subsequently, manufacturing process models have been developed to estimate material and energy consumption for various manufacturing processes, including grinding [47], gas metal arc welding [48], additive manufacturing [169], metal injection molding [170], and laser powder bed fusion [188], among others. A similar effort, the Cooperative Effort on Process Emissions (CO2PE!), focused on developing life cycle inventories of manufacturing process data to enable product environmental impact assessments [46].

To support these efforts for analyzing manufacturing phase environmental impacts, several ISO and ASTM standards have been developed. ISO 20140 provides a five-part standard for environmental performance evaluation (EPE) of manufacturing systems [302]. Part 1 presents an overview and the general principles for such evaluation of manufacturing processes/systems, which are applicable to discrete, batch, and continuous manufacturing. Part 2 describes the EPE process, which includes defining the objective and scope of the evaluation, assessment of specified environmental KPIs, and value (inputs, outputs and services) of the manufacturing process/system. Part 3 presents a method for EPE data aggregation by defining the underlying mathematical relationships, data inputs, data structures, and manufacturing process functions, as well as the aggregation techniques (i.e., decomposition, conversion, summation, and allocation). Part 4 has not yet been published. Part 5 specifies the types of EPE data for evaluating the environmental performance of manufacturing systems. To demonstrate the functionality of the standard, a collaboration between researcher at the NIST and the National Institute of Advanced Industrial Science and Technology (AIST) of Japan evaluated an energy performance KPI (energy demand per unit workpiece) for machining a test part using two different process plans [303]. Another effort by researchers from Morocco proposed the application of ISO 20140 in the context of digital twin technology to enable real-time LCA and the environment performance optimization of manufacturing systems [304]. It should be noted EPE data is specific to the type of industry, manufacturer, and equipment/processes. Further, data types, quality, and availability are governed by the data acquisition method. Thus, similar to LCA, EPE studies are necessarily completed in an ad hoc manner. ISO 20140 suggests mapping EPE data into information models defined by the IEC 62264 standard. The IEC 62264 standard provides a protocol for defining the functions and information exchanges between enterprise, manufacturing, and control systems using information modeling techniques (e.g., hierarchical models, functional data flow models, object models, and operation activity models). No efforts have been reported that integrate the two standards to define syntactic representations of data and accompanying information models for data exchange between manufacturing processes to perform EPEs. This lack of a common structure for data communication inhibits application of the standard into a software architecture for environmental performance characterization of a manufacturing system.

In parallel with ISO standard development efforts for manufacturing environmental performance evaluation, recent standards released by the ASTM E60.13 sub-committee on sustainable manufacturing provide an information modeling-based methodology to analyze the environmental performance of manufacturing processes. The sub-committee has published four related standards: (1) ASTM E2987-20 defines relevant terminology applicable to sustainable manufacturing [231]; (2) ASTM E2986-18 provides procedures for evaluating the environmental performance of manufacturing processes [41]; (3) ASTM E3096-17 provides a process for defining, identifying, selecting, and managing key metrics of interest (MOIs) needed to evaluate process environmental performance [232]; and (4) ASTM E3012-20 presents a systematic approach to characterize manufacturing process environmental performance through a formal representation of the process (Figure 5.2), termed a unit manufacturing process (UMP) model [27]. ASTM E3012-20 defines a UMP as “the smallest element or subprocess in manufacturing that adds value through the modification or transformation of shape, structure, or property of input material or workpiece." UMPs have been also been defined as "the individual steps required to produce finished goods by transforming raw material and adding value to the workpiece as it becomes a finished product" [24].

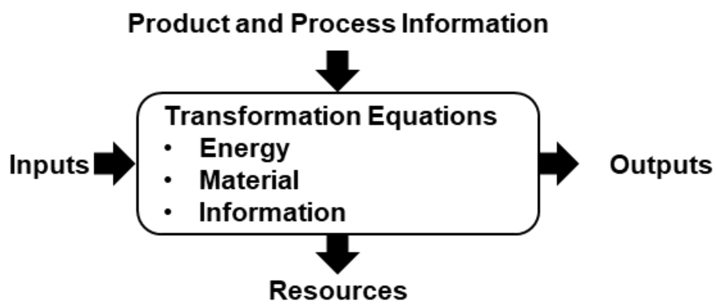


Figure 5.2. Graphical representation of a unit manufacturing process [27]

The ASTM standards enable industry practitioners and researchers to better understand the influence of various product and process variables (e.g., part geometry, materials, geographic location, energy mix, and manufacturing process settings) on environmental performance. This standards-based information modeling approach lays a foundation for facilitating manufacturing process and system design decision support. The standard UMP structure is defined by five elements: inputs, outputs, product and process information, resources, and transformation equations. Inputs (I) to the UMP include raw materials and/or work-in-process parts, consumables (e.g., lubricants and welding gas/fluxes), energy (e.g., electrical, heat, and chemical), and external factors (e.g., humidity, pressure, and temperature). Outputs (O) from the UMP include all physical outputs from the processing of inputs, which constitute the product(s), waste(s), and by-product(s), as well as energy losses and emissions. It is important to note that the outputs from a prior UMP could serve as inputs to a subsequent UMP in the manufacturing process flow. Product and process information (PPI) is comprised of all necessary information that either defines the product (e.g., design features and material properties) and the process. As such, PPI defines process parameters, e.g., fixed parameters, control parameters, intermediate variables, metrics of interest, and supporting information. Fixed parameters are process properties that do not change during the processing of inputs (e.g., oven wall thickness). Control parameters are process parameters that can be tuned or adjusted during the process (e.g., annealing temperature or temperature hold time). Intermediate variables are interim parameters used to calculate metrics of interest (e.g., drilling time, which can be calculated based on hole depth and drill feed, to estimate drilling energy). Metrics of interest are the desired process performance metrics evaluated using the UMP model (e.g., cost or mass of greenhouse gas emissions per part). Resources (R) comprise all information related to other resources used by the UMP, such as tooling, fixtures, equipment, software, and people, to convert inputs to outputs. Transformation equations are the governing functions (e.g., mathematical or data-driven relationships) used to model the conversion of inputs to outputs using the defined product/process information and resources, as well as quantifying the desired metrics of interest.

In addition to defining a structure for representing UMPs, the ASTM E3012-20 standard provides a theoretical definition of composition, which is “the act of linking individual unit manufacturing process (UMP) models together to create a composite of

UMP models that can characterize the metrics of interest of a production system or product" [27]. Figure 5.3 illustrates a manufacturing system structured using a sequence of UMPs that transforms inputs to desired outputs, including intermediate process inputs and outputs. Manufacturing systems utilize UMPs in series (e.g., UMP 1 and UMP 2) or in parallel (e.g., UMP 3 and UMP 4). UMPs models are connected to each other using "linking variables," or information exchanged/shared between UMPs, to represent the manufacturing system.

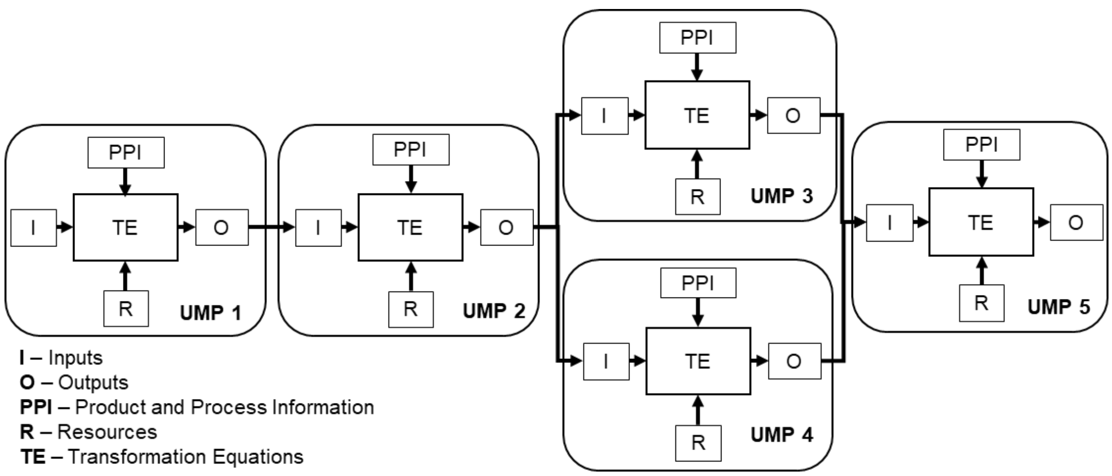


Figure 5.3. Graphical representation of composed UMPs [27]

Though the ASTM E3012-20 standard was developed to characterize manufacturing environmental performance, researchers have applied its methods to quantify a variety of metrics of interest to support sustainability performance evaluation of manufacturing processes and systems. For instance, the conceptual standard was applied in developing a method for assessing the sustainability performance of discrete part manufacturing processes [164]. The method was demonstrated to support design for manufacturing decision making of a representative aircraft subassembly. The concept of composition through linking variables was demonstrated in this initial work. Subsequently, a proof-of-concept software application was developed to explore the composition of manufacturing processes for assessing the sustainability performance of manufacturing flows [195]. A collaborative effort of Brodsky and NIST researchers developed an optimization approach to facilitate trade-off analysis of manufacturing process/service networks [50]. Their approach was demonstrated using a web-based software tool to optimize the contract manufacturing supply chain for the production of a heat sink on the basis of cost, throughput, and CO2 emissions. To enhance trade-off analysis in design for manufacturing, NIST researchers studied the feasibility of mapping the ASTM E3012-20 standard structure to the ecoSpold2 format (a data structure used for creating life cycle inventories) [165]. Due to the difficulty in applying the standard for consistent representation of manufacturing processes, a web-based tool was developed to assist analysts in creating standard-conforming UMP models [197].

This prior work has been attendant with a number of limitations. The standard provides a structure for consistent development of UMP models for specific instantiations of a process, but it does not facilitate model transferability (reusability) to characterize variations of the process [197]. Further, while the standard defines the concept of a linking variable, it has been recognized during the composition of UMP models that the linking variables depend upon the types and sequence of operations in the manufacturing process flow [305]. In applying the standard to model manufacturing systems, investigated linking variables and their interactions are often limited to only those relevant to specific demonstrative cases. Since such studies intend to characterize the performance of existing or proposed systems, they are not well-suited for supporting process planning or manufacturing system design. In particular, these methods were not developed with a foundational basis to support multi-criteria decision analysis, but rather for simultaneous quantification of selected metrics of interest [306]. Although structured UMP models help overcome the challenge of developing shareable life cycle inventories to support LCA studies, little effort has been placed in understanding the dynamic influences of product design or manufacturing process changes on the sustainability performance of manufacturing systems [134].

This research aims to address the limitations of existing sustainability assessment approaches by integrating a systematic and structured information modeling framework with manufacturing system design. This integrated framework will facilitate sustainable manufacturing system design decision making. The research presented herein builds upon prior efforts of the authors that (1) developed a methodology for reuse and extension of UMP models through information modeling approaches such as instantiation, polymorphism, and aggregation [49] and (2) applied information modeling techniques for composing UMP models to characterize and evaluate the sustainability performance of manufacturing systems [307]. A resulting integrated framework for sustainable manufacturing system design through multi-criteria decision making is presented and demonstrated using case studies for discrete and continuous production.

5.4 Research Method

The integrated framework developed in this research is agnostic of the type of manufacturing system under study (e.g., continuous manufacturing, batch production, or cellular manufacturing). The underpinning methodology follows a sequence of steps (Figure 5.4): (1) For the specified product, multiple manufacturing process flow options can be designed for sustainability performance evaluation, (2) Equipment sizes and quantities need to be estimated based on the intended production volume, which are based on the cycle time for discrete manufacturing and flow rates for continuous manufacturing, (3) The manufacturing system is then designed based on these equipment sizes and quantities and the manufacturing process flow (sequence), (4) Models of UMPs (discrete production) and unit operations (continuous production) are instantiated (reused and extended) and composed to quantify selected metrics of interest for the manufacturing system design alternatives, and (5) These disparate metrics are then evaluated using an MCDA approach to provide insights into the alternatives, enabling selection of the most desirable option.

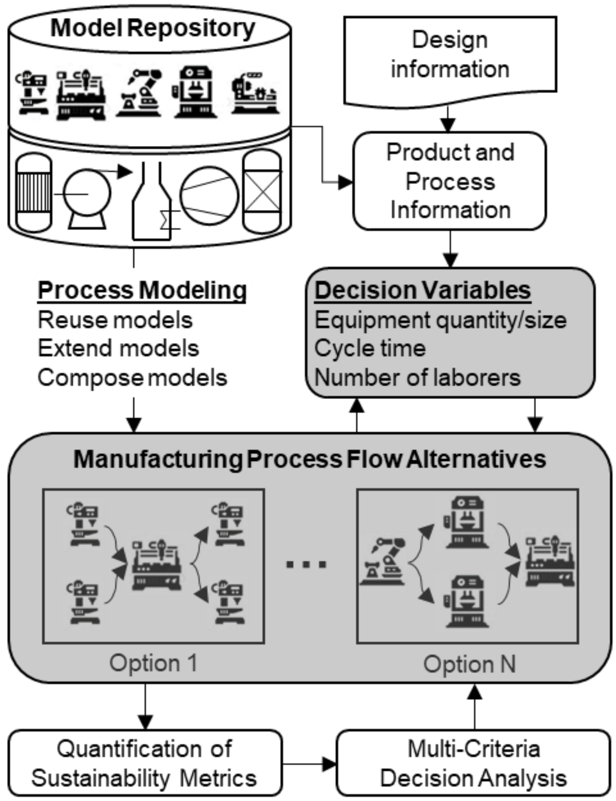


Figure 5.4. Integrated framework for sustainable manufacturing system design

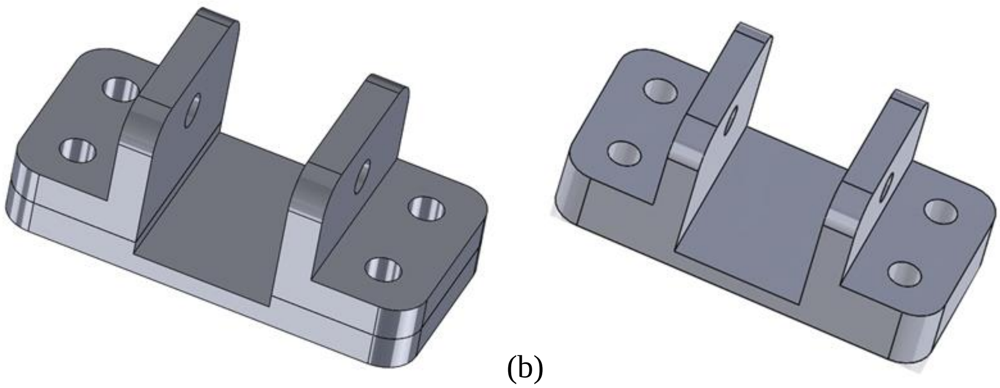
Thus, the framework provides a basis for integrating information modeling approaches of reusability, extensibility, and composability for sustainability assessment of manufacturing systems, previously reported as part of this research. Specifically, a method was developed to enable the reuse and extension of UMP models by encapsulating product- and process-specific characteristics in a template UMP model [49]. A template model was defined as "a model that completely characterizes the most simplistic instantiation of a manufacturing process that comprises varying level of machine configurations." Extension of a template model into a more complex machine configuration is done by aggregating the template model with appropriate layer models, which include models of auxiliary systems (e.g., monitoring equipment, exhaust gas systems, and pressure control systems) that do not modify the workpiece. This method for UMP model extension was demonstrated for a two and a half axis milling process model, and extended a manual milling process model with layer models representing a control system and cutting fluid system. Building upon this work, a method for composing UMP models was then developed using the information modeling technique of model aggregation, enabling sustainability characterization of a manufacturing process flow [307]. Further, linking variables (context information shared between UMPs) that establish relationships between UMPs in a manufacturing system were identified and characterized. This composition method was demonstrated to support the sustainable design and manufacturing of a corner bracket (discrete part manufacturing).

To address the overarching objective of the research, the work presented herein builds upon these prior methods, as indicated by the shaded boxes in Figure 4. The previously presented methods (reuse, extension, and composition) are maintained to provide decision support for manufacturing system design based on desired metrics of interest. This framework lacks a structure that would facilitate its transition into software architecture. Appendix C1 provides a conceptual structured definition of the framework using a UML class diagram, which would be the cornerstone for future development of an engineering decision support tool. UML class diagrams are central to object-oriented programming, and used to represent the structure of a system by describing its various classes, along with their associated interrelationships, attributes, and operations, as conceptual diagrams [308]. Thus, the UML diagram here defines the classes of the integrated framework as model repository, design information, design decision variables, UMP/unit operations, linking variables, metrics of interest, weights, and MCDA methods. Each class box specifies its associated attributes or methods. Relationships between classes, instantiated as objects, are shown using a connecting line with a diamond arrowhead. An associated phrase defines the object actions, e.g., the unit processes/operations class “accepts” product design information. Numbers at either end of the connecting lines define the instantiation constraints of the two classes, e.g., “1..*” at the arrow origin means a minimum of one instance (object) is required as output of the originating class, and “1” at the arrow terminus indicates one instance is required as input to the terminating class). This integrated framework and class diagram structure, lays a foundation for future software architecture that enables development of engineering decision support tools for manufacturing system design. Demonstrations of the integrated framework are provided in Sections 5.5 and 5.6 for discrete and continuous product manufacturing, respectively, and describe how the framework can be applied in engineering software tool development.

5.5 An Application of the Integrated Framework for Sustainable Manufacturing System Design for Discrete Part Manufacturing

Manufacturing system design is driven by product design requirements, production requirements, and the resultant engineering requirements that satisfy various metrics of interest, including sustainability performance measures, as captured within the integrated framework for sustainable manufacturing system design developed above. In the development of an engineering decision support tool that follows this information modeling paradigm, these system elements would define software functional requirements. In order to illustrate the application of the framework, a step-by-step approach is presented below that mimics the core functions of an envisioned engineering software tool to be used in the sustainable design of a discrete part manufacturing system.

For this demonstration, the premise is of a medium-sized metal product manufacturer exploring a new business opportunity in the industrial furniture market. The manufacturer has developed a design for a wheel housing that can be purchased by manufacturers or customers who wish to add casters to an existing workbench to improve workspace flexibility. From market research, customer requirements have been translated into product design, production, and engineering requirements (metrics of interest), resulting in two product designs (Figure 5.5). The company is interested in the following performance metrics cost, energy use, and labor wage. In addition to deciding from among these two product designs, company leadership is considering whether to implement a pilot production cell producing 1,000 parts annually or to launch a low-volume production line, which would manufacture 10,000 parts/year. Based on the product designs and expected annual production volumes, the manufacturing system design decision variables (i.e., equipment count and number of laborers) need to be estimated for the corresponding process flows.



(a) (b)

Figure 5.5. Wheel housing (a) Part design alternative 1 (b) Part design alternative 2

Two process flow alternatives have been conceptualized for the two part designs, respectively, and involve (a) assembly of a bottom plate with two L brackets (Figure 65.) and (b) production of a monolithic part (Figure 5.7). The manufacturing system design for Part Design 1 includes two manufacturing process flows. Manufacturing Line 1 produces the top plate, and Manufacturing Line 2 produces the two L-brackets that will be attached to the top plate. The parts will be subsequently packaged and shipped to the customer who will complete the assembly. Material input to Manufacturing Line 1 is an aluminum plate, which is first milled to create an open pocket and to add radii to the corners. Through holes are then drilled into the top plate. Material input to Manufacturing Line 2 is aluminum rod stock for extrusion into an L-shaped cross-section. Following extrusion, the material is water quenched and saw cut to the desired length. The L-bracket is then annealed, milled, and drilled to achieve the design specifications.

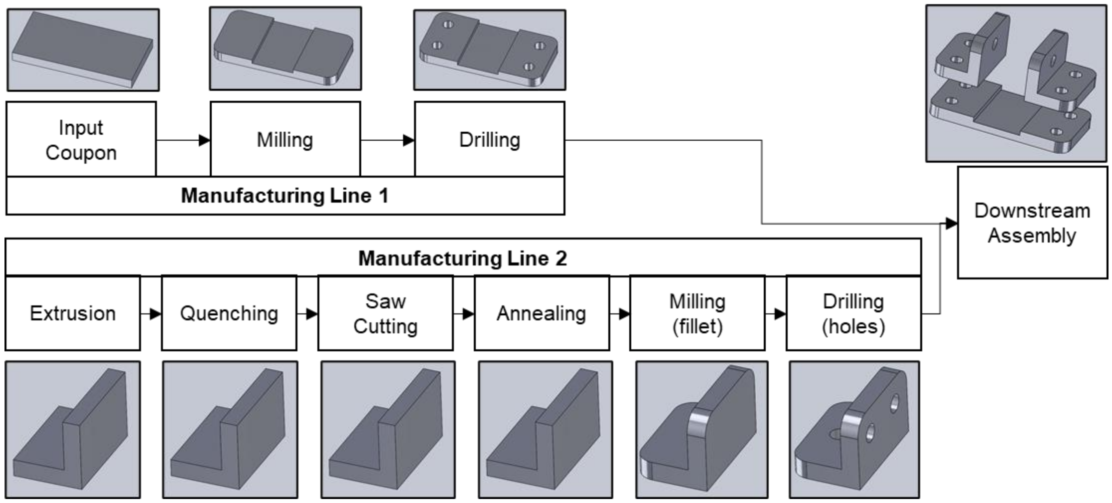


Figure 5.6. Manufacturing system design alternative 1 (MSD 1)

Using the information presented in Table 5.1, an example functional model of Manufacturing System Design Alternative 1 (MSD 1) is presented in Appendix C2, assuming an annual production capacity of 10,000 parts. The corresponding UMP models are instantiated to estimate the cycle time of each manufacturing process step in the manufacturing process flow. Based on process cycle times and annual demand, the equipment quantity required for each process step is estimated (Equation 1). As shown in Table 5.2, for Manufacturing Line 1, two mills and one drill press are required to meet the desired annual production. Similarly, for Manufacturing Line 2, one extruder, one quench tank, and two each of saw cutters, annealing oven, and drill presses, and three mills are estimated. These quantities correspond to the number of UMP model instantiations required for each process step within the manufacturing system model. The manufacturing system design is illustrated using an IDEF0 functional diagram (Appendix C2). In the diagram, solid arrows indicate the physical flows and dashed arrows indicate the information exchanges between the UMP model instantiations. The functional models define the manufacturing system design alternatives that can be used for evaluating the sustainability performance.

Table 5.1: Assumptions and considerations for manufacturing system design alternatives MSD 1 and MSD 2

Description	MSD 1	MSD 2	References
Input workpiece (coupon)	Material: Aluminum 6061 Length: 0.178 m Width: 0.1016 m Height: 0.0254 m Yield strength: 276 MPa Density: 2768 kg/m3 Thermal conductivity: 152 W/m K	Not applicable	[258–260]
Input workpiece (rod stock)	Material: Aluminum 6061 Diameter: 0.25 m Length: 1.2 m Yield strength: 276 MPa Density: 2768 kg/m3 Thermal conductivity: 152 W/m K Mass: 163 kg	Material: Aluminum 6061 Diameter: 0.25 m Length: 1.2 m Yield strength: 276 MPa Density: 2768 kg/m3 Thermal conductivity: 152 W/m K Mass: 163 kg	
Extrusion process	Barrel material: Nitriding steel Barrel diameter: 0.175 m Stock temperature: 400 °C Barrel temperature: 350 °C Ram speed: 0.06 m/s Tool cost: $12,000	Barrel material: Nitriding steel Barrel diameter: 0.400 m Stock temperature: 400 °C Barrel temperature: 350 °C Ram speed: 0.005 m/s Tool cost: $24,000	[261,262]
Circular saw cutting process	Saw blade material: Steel with carbide tip Saw blade diameter: 0.406 m Saw blade kerf: 3.175 mm Saw blade hardness: > 30 HRC Cutting speed: 122 m/min Feed: 0.20 m/min Tool cost: $4,000	Same as alternative 1	[263,264]
Quenching process	Quench medium: Distilled water	Same as alternative 1	[265,266]

Description	MSD 1	MSD 2	References
	Quenchant temperature: 40 °C Cooling rate: 150 °C/s Tool cost: $7,500		
Annealing process	Annealing temperature: 420 °C Temperature hold time: 2 h Cooling rate: 40 °C/h (air-cooled) Tool cost: $7,500	Same as alternative 1	[260,267]
Milling process	Feed rate: 0.032”/revolution Cutting speed: 950 SFM Tool diameter: 1/4” RPM: SFM X 3.82 X Tool diameter Tool cost: $7,000	Feed rate: 0.016”/revolution Cutting speed: 550 SFM Tool diameter” 1/4” RPM: SFM X 3.82 X Tool dia Tool cost: $15,000	
Drilling process	Tool diameter: 1/2” Feed rate: 0.01”/revolution Cutting speed: 300 SFM RPM: SFM X 3.82 X Tool diameter Tool cost: $5,500	Tool diameter: 1/2” Feed rate: 0.004”/revolution Cutting speed: 200 SFM RPM: SFM X 3.82 X Tool diameter Tool cost: $10,500	
Input energy cost	Electricity: $0.061/kWh (US national average) Natural gas: $33.57/m3 (US national average)		[268]
Electrical energy emissions factor	0.43 kg CO2e/kWh (US national average)		[269]
Annual labor cost	$60,000 (US national average per worker)		[270]

Similarly, Part Design Alternative 2, where the wheel housing is a single workpiece, is produced using Manufacturing System Design Alternative 2 (MSD 2), as shown in Figure 5.7. Input stock is extruded using a hot extrusion process, quenched, and saw cut into the near net shape of the final wheel housing. This intermediate part is subsequently milled and drilled to achieve the design specifications. Due to the change in manufacturing process flow, the two alternatives have key differences in the manufacturing equipment employed for the extrusion, milling, and drilling processes.

For this demonstration case, it is assumed that there are no fundamental differences in the equipment used for quenching, saw cutting, and annealing

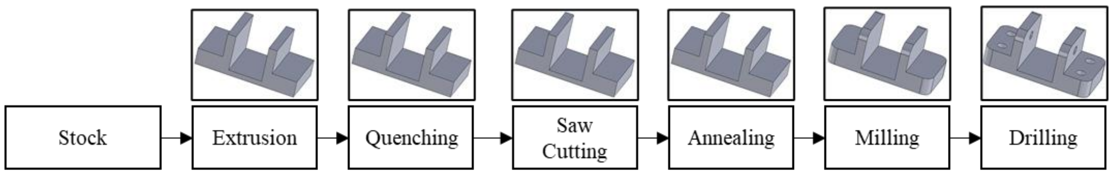


Figure 5.7. Manufacturing system design alternative 2 (MSD 2)

.

The manufacturing system design for discrete part manufacturing is driven by the expected annual production volume (customer demand) and cycle time for each process step in the manufacturing process flow. Process cycle time depends on the part design (e.g., geometry and material), machine capability (e.g., feed rate, cooling rate, or heating time), and load and unload time. Process cycle time can be estimated using UMP modeling techniques [49]. The equipment count (n) for each manufacturing process step can be estimated based on annual production volume (P), tool working hours per year (k), yield (y), cycle time (t_c), and tool utilization (u), as shown in Eq. 5.1. Within an information modeling system, these parameters would be stored as product and process information.

$$n = \frac{P/k}{y \times \left(\frac{1}{t_c}\right) \times u} \tag{5.1}$$

The equipment count for each process step will determine the facility layout in designing a dedicated manufacturing plant. For the purposes of manufacturing systems sustainability performance evaluation, the requisite UMP models will be instantiated based on the equipment count for each process. These UMPs must then be composed based on the manufacturing process flow. A product design can be produced by following a number of manufacturing process flows. Information modeling principles of reuse, extension, and composition aid in evaluating these alternative manufacturing process flows with relative ease, compared to the conventional approach of developing such models from scratch. It should be noted for products produced using contract manufacturers, the manufacturing system will already be in place and selected metrics of interest would depend on the process flow. Equipment and labor are shared across a mix of products based on changing customer demands. Thus, metrics of interest are driven by the utilization factor for each piece of equipment and associated labor, and calculated assuming complete utilization across a mix of products. The utilization factor (U_f) per part for the product under consideration is dependent on the batch size (N_b), batch setup time (t_b), cycle time (t_c), and tool availability per year (k), as shown in Eq. 5.2. Therefore, evaluation of sustainability performance is typically performed for the manufacturing process flow to identify the best alternative without consideration of production capacity.

$$U_f = \frac{\left(\frac{t_b}{N_b}\right) + t_c}{k} \tag{5.2}$$

Estimating the number of operators is a key aspect to sustainable manufacturing system design as labor influences economic and social metrics. The number of operators per tool (N_{labor}) for discrete part manufacturing depends on the cycle time (t_c), part load time (t_{load}), part unload time (t_{unload}), annual availability per laborer (L_{annual}), and annual production volume (P), as shown in Eq. 5.3.

$$N_{labor} = P \times \left[\frac{t_c + t_{load} + t_{unload}}{L_{annual}} \right] \tag{5.3}$$

Based on assumptions and considerations combined with the product design details, the equipment count for each of the manufacturing step within the manufacturing system design alternatives are estimated (Table 5.2). T he UMP models are then instantiated for reuse or extension based on an information modeling approach reported as part of this research [49]. The instantiated UMPs are then composed relative to the process flow to quantify the metrics of interest [307].

Table 5.2: Equipment count for two manufacturing system design alternatives for two annual production capacities

Manufacturing equipment (line)	MSD 1: Equipment quantity (utilization) for an annual production capacity of:		MSD 2: Equipment quantity (utilization) for an annual production capacity of:	
	1,000	10,000	1,000	10,000
Milling (1)	1 (13%)	2	1 (31%)	2
Drilling (1)	1 (14%)	1	1 (20%)	2
Extrusion	1 (8%)	1	1 (14%)	1
Quenching	1 (10%)	1	1 (10%)	1
Saw cutting	1 (7%)	2	1 (9%)	1
Annealing	1 (28%)	3	1 (28%)	2
Milling (2)	1 (24%)	3	NA	NA
Drilling (2)	1 (9%)	2	NA	NA

For this demonstration case, the sustainability metrics of interest considered to compare the two manufacturing system design alternatives, are indicated in Table 5.3.

Table 5.3: Sustainability metrics of interest for discrete part demonstrative case

Sustainability pillar	Metric of interest	Unit
Economic	Capital cost/part	$
	Raw material cost/part	$
	Facility cost/part	$
	Labor cost/part	$
	Consumable cost/part	$
	Utility cost/part	$
	Maintenance cost/part	$
Environmental	Energy use	kWh
	Waste	kg
	% Material conversion	
	Global warming potential (GWP)	kg CO_2 eq
Social	% labor-wage	

The seven economic metrics of interest indicated in Table 5.3 constitute Cost of Goods Sold (COGS). As indicated in Appendix C1, metrics of interests are a separate class that can be instantiated for each of the UMPs in the manufacturing process flow and aggregated as for evaluating the sustainability metrics of the entire manufacturing system. This aggregation has been presented as part of the previous reported work of adding layers to information models of UMPs. This reduces the effort by subject matter experts to focus more on the developing models that can characterize UMPs for their specific instantiations in the manufacturing process flow rather than focus on developing the sustainability metrics.

Based on the estimates (Table 5.2), the manufacturing system design has been represented using IDEF0 diagram for manufacturing system design alternative 1 (Appendix C2) and manufacturing system design alternative 2 (Appendix C3). Representative UMP models instantiations for milling, extrusion, saw cutting, quenching, annealing, and drilling have been illustrated in Appendix C4 through Appendix C9. The aggregated metrics of interest for two production capacities have been detailed in Table 5.4 by composing the UMPs within the manufacturing system design alternatives.

Table 5.4: Economic, environmental, and social impact analysis results on a per part basis for two production capacities

Sustainability pillar	Description	Annual production capacity of 1,000 parts/year		Annual production capacity of 10,000 parts/year	
		MSD 1	MSD 2	MSD 1	MSD 2
Economic ($)	Capital cost/part	4.34	7.32	0.71	1.14
	Raw material cost/part	1.56	1.38	1.56	1.38
	Facility cost/part	2.40	2.40	0.40	0.36
	Labor cost/part	0.29	0.19	0.17	0.11
	Consumable cost/part	0.80	0.60	0.80	0.60
	Utility cost/part	2.05	1.55	2.05	1.55
	Maintenance cost/part	2.53	3.65	0.38	0.55
	Total Cost/part ($)	13.97	17.09	6.07	5.69
Environmental	Energy use (kWh)	33.6	25.4	33.6	25.4
	Waste (kg)	0.08	0.06	0.08	0.06
	% Material conversion	91.4%	92.7%	91.4%	92.7%
	Global warming potential (kg CO_2e)	14.45	10.92	14.45	10.92
Social	% labor-wage	2%	1%	3%	2%

Based on the sustainability metrics evaluated for each of the manufacturing system design alternatives, it can be seen that at a production capacity of 1,000 parts per year, economically and socially, MSD 1 is better compared to MSD 2. From an environmental perspective, MSD 2 performs better compared to MSD 1, due to lower energy use, reduced waste, and better material conversion. At a production capacity of 10,000 parts per year, MSD 2 performs better compared to alternative one from an economic and environmental standpoint. At the social level, the margin of difference is negligible.

5.6 An Application of the Integrated Framework for Sustainable Manufacturing System Design for Continuous Product Manufacturing

In order to demonstrate the integrated framework to support the design of continuous product manufacturing systems, the Haber Bosch process is considered for the production of ammonia (Figure 5.8). The Haber Bosch process is typically comprised of nitrogen, hydrogen, and ammonia sub-systems. The economic performance of the Haber Bosch process is evaluated for a range of production capacities by using reference capacities available in the literature for the nitrogen [309], hydrogen [310], and ammonia [311] sub-systems.

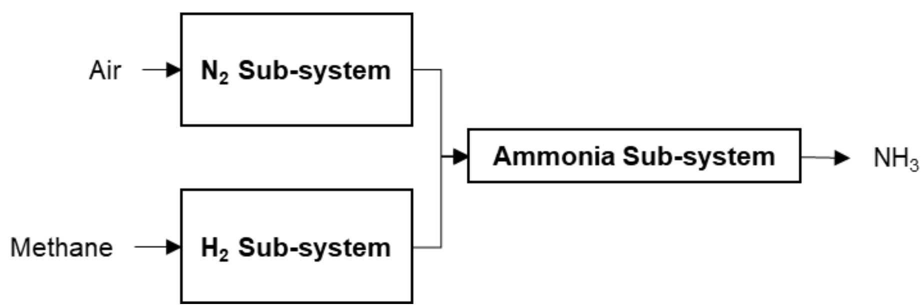


Figure 5.8: Subsystems of the Haber Bosch process for ammonia production

For the Haber Bosch process, the chemical equilibrium is expressed in Eq. 5.7. As indicated in Figure 5.8, nitrogen and hydrogen are the input feedstocks at a ratio of 1:3. A compressor delivers the nitrogen and hydrogen mix to the reactor at a pressure of 20

MPa. Iron (Fe) or aluminum trioxide (Al_2O_3) are typically used as the catalyst within the reactor.

$$N_2(g) + 3H_2(g) \rightleftharpoons 2\,NH3(g),\ \Delta H = -92\ {}^{kJ}/_{mol} \tag{5.7}$$

The reaction is exothermic with an enthalpy (ΔH) of 92 KJ/mol, making heat a by-product of the process. The ammonia is then separated in the separator and the residual nitrogen and hydrogen mix is fed back to the reactor. The reactor operates at a temperature of 700k. Haber Bosch process have been historically energy intensive due to chemical operating requirements of high pressure and high temperature. The goals of this demonstration case are to understand the influence of production capacity on system economic performance, and to highlight the adaptability of the integrated framework for design and analysis of continuous production systems.

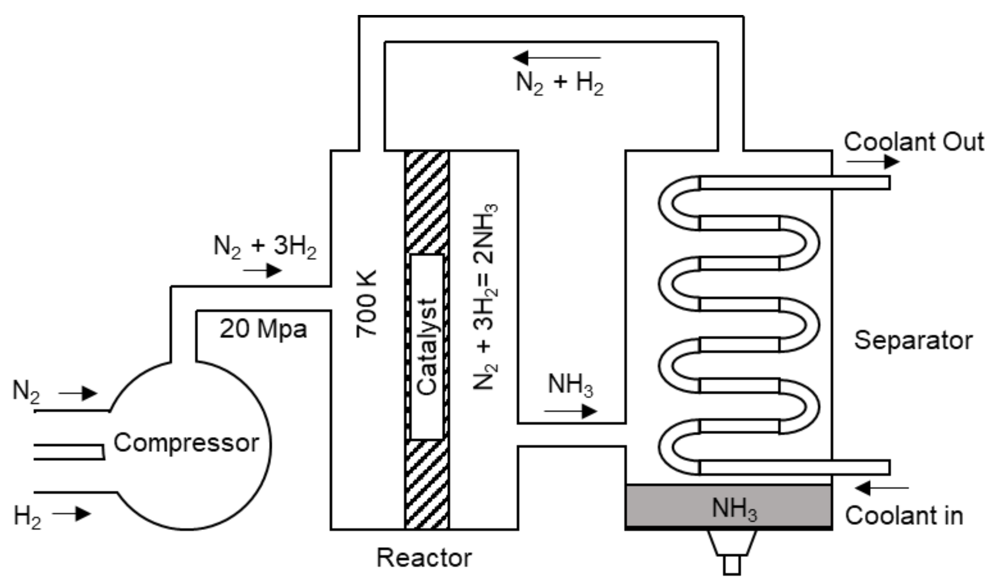


Figure 5.9: Haber Bosch process for ammonia production

Manufacturing system design for continuous product manufacturing (e.g., chemical production) is driven by customer demand (production volume). Chemical engineers must consider reaction kinetics to size the equipment needed for each unit operation. The unit operations are defined by the sets of inputs (feedstocks) that undergo transformations (e.g., reactions and separations) to generate outputs (products and by-products) utilizing provided resources (e.g., equipment and labor), which can be documented in its product and process information. In order to size major equipment, typically vessels (e.g., reactors and separators) and heat transfer (e.g., exchangers and mixers) equipment, required flowrates and heat supplied must be determined from the chemical design [312]. Once major equipment sizing is finalized, the metrics of interest, e.g., cost, environmental impacts, and worker safety, can be estimated for the entire system based on historical data and reaction chemistries.

Sizing of heat transfer equipment is based on the area over which heat transfer occurs (A), which is dependent on the heat to supplied or removed (Q), heat transfer coefficient of the chemical (U), and the needed temperature change (ΔT) (Eq. 5.4). Heat transfer coefficients for the majority of the chemical products are readily available [313]. To ensure process safety, a design criterion is observed by convention, where the rated pressure of the equipment needs to be 1.5 times the expected actual pressure of the chemical process.

$$A = \frac{Q}{(U \times \Delta T)} \tag{5.4}$$

Vessels are sized according to volume (V) using the flowrate (Fl) exiting the vessel, chemical density (ρ), and residence time of reactants in the vessel (τ), which are parameters determined from the chemical design, as shown in Eq. 5.5.

$$V = 2\left[Fl \times \frac{\tau}{\rho}\right] \tag{5.5}$$

For established chemical production technologies, equipment is sized based on a scaling law, which is a factor of the referenced production volume (P_{ref}), as detailed in Eq. 5.6.

$$S_{design} = S_{ref} \times \left[\frac{P_{design}}{P_{ref}}\right]^{sf} \tag{5.6}$$

The designed size (i.e., area or volume) of the equipment (S_{design}) is dependent on the size of the equipment referenced in literature (S_{ref}), the designed production volume (P_{design}), the referenced production volume (P_{ref}), and a scaling factor (sf). Scaling factors range between 0.4-0.8 depending on the type of the unit operation [312].

Operating labor requirements are driven by the equipment type (Table 5.5) and, for continuous product manufacturing, are calculated based on the number of unit operations in the manufacturing process flow [312]. This approach differs from discrete part manufacturing, where labor is calculated based on process cycle time for each step in the manufacturing process flow. Labor requirements scale nonlinearly with equipment size; typically, a 0.20-0.25 scaling law proportional to the production volume is applied.

Table 5.5: Labor requirements per shift for common equipment types used in continuous product manufacturing [312]

Equipment Type	Labor/shift
Continuous Reactor	0.5
Batch Reactor	1
Evaporator	0.25
Separator	0.5
Crystallizer	0.16
Dryer	0.5
Steam plant (100,000 lb./h)	3
Filter	0.2-0.25

The Haber Bosch process for manufacturing ammonia is represented using IDEF0 in Appendix C10. Since Haber Bosch is a well-established process, details related to the capital and operating costs have been obtained from literature review. Table 5.6 details the operating volume and capital cost for each of these sub-systems, as identified from literature. Based on the underlying mass flow rates, 0.82 metric tons of nitrogen and 2.46 metric tons of hydrogen are required to produce one metric ton of ammonia. For estimating the capital cost of the individual sub-systems at desired capacity of production, economies of scale are applied based on a 0.6 scaling law [314], as described in Eq. 5.8.

$$\frac{C_{design}}{C_{ref}} = \left(\frac{P_{design}}{P_{ref}}\right)^{0.6} \tag{5.8}$$

Table 5.6 captures reference capital costs for the sub-systems (nitrogen delivery, hydrogen delivery, and ammonia production) in the Haber Bosch process from the literature. For example, a 300 MT/day sub-system producing nitrogen requires a capital investment of $140M. For a design capacity of 100MT/day of ammonia production, ~82 MT of nitrogen is required for the Haber Bosch process. By applying Eq. 5.8, for the designed production capacity, the capital cost of the nitrogen plant is $61M. Similarly, based on these reference subsystems, capital cost for the designed capacity of 100 MT/day for the ammonia plant is estimated using the 0.6 scaling law (Eq. 5.8).

Table 5.6: Capital cost for ammonia production

Sub-System	Reference Production Capacity (P_{ref}) in MT/day	Reference Capital Cost ($)	Capacity for 1 MT of Ammonia (MT)	Capital cost of Ammonia for 100 MT/day	Reference
Nitrogen	300	$140M	0.82	$61M	[309]
Hydrogen	50	$68M	2.46	$176M	[310]
Ammonia	4.5	$4.9M	1.00	$32M	[311]

Figure 5.10 shows the capital cost for a range of production capacities estimated using the approach described above. The drop in the capital cost with increase in capacity results from the scaling of equipment cost. Since ammonia is a bulk chemical product, operating at lower production volumes is typically not suited because the economics are not viable at lower production volumes.

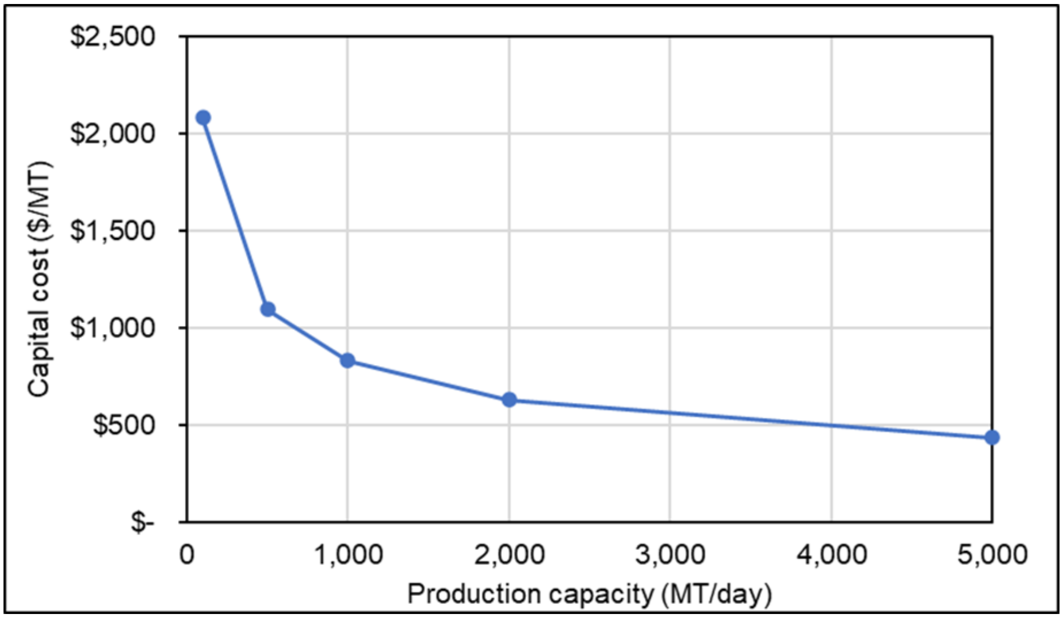


Figure 5.10: Capital cost over a range of production capacities

Based on scaling-law estimates, capital cost can be broken into cost categories using the Lang factorial model [315], as described in Table 5.7. The application of the Lang factorial method is standard practice in the design of chemical production facilities. Typically, the mean of the ranges are used for preliminary estimates which account to an error of ±10%.

Table 5.7: Capital cost factors for each cost category

CAPEX Cost Category	Factorial Range (% of CAPEX)
Purchased Equipment	15-40%
Equipment Installation	6-14%
Instrumentation and Controls	2-8%
Piping	3-20%
Electrical Systems	2-10%
Buildings (ISBL)	3-18%
Engineering	4-21%
Contingency	5-15%

Similarly, the operating costs for chemical processes were established from literature for the Haber Bosch process [316] as shown in Figure 5.11. Typically, the operating costs are comprised of raw material, energy, labor, maintenance, and overhead costs. Similar to capital costs, operating costs improve with increasing capacity, primarily since labor utilization increases with increasing capacity. Additionally, capital overhead costs reduce with increasing capacity, which contributes to the relative decrease in operating costs.

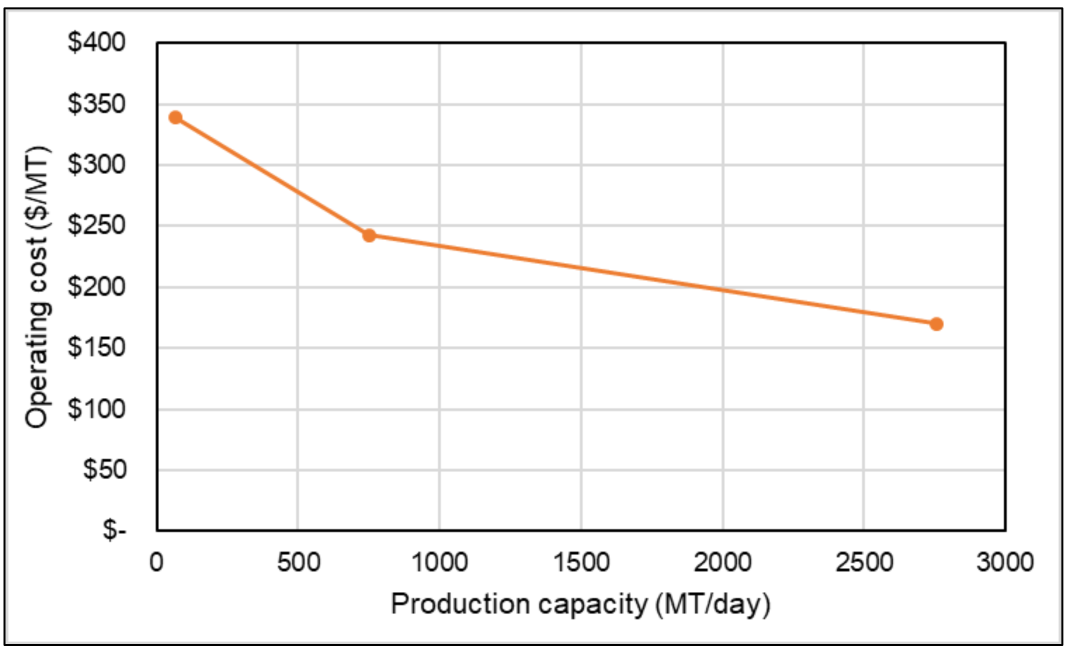


Figure 5.11: Operating cost over a range of production capacities

The application of the integrated information modeling framework to continuous product manufacturing is a novel approach for manufacturing system design. The framework enables practitioners to account for uncertainty and risk associated with preliminary design to evaluate the investment risk. Additionally, it facilitates future integration of environmental and social aspects as part of modeling efforts, which will promote sustainable manufacturing.

5.7 Conclusions

The integrated framework presented herein provides a systematic and structured approach that leverages information modeling techniques (e.g., abstraction, instantiation, and aggregation) for manufacturing sustainability performance assessment. The reuse, extension, and composition of unit processes is unified with a manufacturing system design approach to facilitate decision support during manufacturing system design. The framework follows a class-based structure, which streamlines data handling, sharing, and traceability and provides handles for a multi-criteria decision making. This integrated approach provides a foundation for repeatable and reliable manufacturing system model development. Key findings of this research are as follows:

1. Reuse, extension, and composition of formalized representations provides consistent and hierarchical structures for models of unit processes and manufacturing systems. The resulting models improve assessment accuracy for specific process configurations. Further, the composition of process models using linking variables streamlines the assessment of manufacturing systems, which addresses the challenge of *post hoc* performance metric aggregation.
2. Data and information tracking is facilitated by using information modeling techniques that establish relationships, constraints, rules, and functions between

entities within the framework (e.g., unit operations, design decision variables, design information, sustainability assessment, and metrics of interest). This attribute of the framework enables data access, handling, and sharing, which are important functions of model-based decision support at the enterprise level.

3. Flexible adaptability of the product, process, and system design, design decision variables, and decision methods is possible since the entities underpinning the framework are distinguished by specific functions. Further, interdependencies between these elements are established using information modeling.
4. The framework is founded upon object-oriented programming techniques, which will enable realization as engineering software tools for manufacturing process and system design.

The bottom-up approach and structure of the framework supports decision-makers in the early design phase in understanding the influence of design information (customer demand, product design requirements, and process information) on the manufacturing system design. Thereby, application of the framework can elucidate the drivers and barriers that influence the proposed manufacturing system design alternatives. Further, its structured approach can support integration of uncertainty quantification, risk assessment, and other investment analysis approaches. The framework can be expanded to support manufacturing systems optimization, for example by enabling real-time data analytics. Real-time data can be used to enhance existing models by integrating elements such as equipment state (tool/component wear, process drifts, and excursion) and external factors (temperature, humidity, and other operating conditions) that directly impact sustainability performance. Data-driven models would enable closed-loop and continuous improvement of manufacturing systems for a potentially varying set of objectives.

Chapter 6: CONCLUSION

Sustainable development focuses on meeting present demands, while conserving resources to meet the needs of future generations. Sustainable thinking has led to increased emphasis on sustainable manufacturing over the past few decades. A key part of sustainable manufacturing encompasses the design and development of manufacturing systems which create products that are economically, environmentally, and socially beneficial to society today and in the long run. Sustainable manufacturing methodologies are still in developmental stages of research. Existing philosophy has emphasized improving the economics of production, which makes it difficult to adapt and implement broader sustainability concepts into manufacturing practices. Sustainable manufacturing practices have recently gained traction in industry through the influence of various stakeholders. However, radical change is required to bring sustainable thinking into an industry-wide practice. A key aspect of industrial adoption is the need to educate business decision makers on the importance of environmental and social dimensions of sustainability, in addition to economics. Another way to overcome the challenge of industrial adoption is to demonstrate the long term value of sustainable manufacturing practices. To do so, the onus lies on manufacturing researchers to develop readily and easily accessible sustainable manufacturing methods and tools that enable engineers and other decision makers to realize the long term benefits of near term investments. The research reported in this dissertation helps to address this need by facilitating sustainable manufacturing system design decision making using an integrated systematic, structured information modeling framework and manufacturing system design methodology.

6.1 Summary

The integrated framework developed herein supports systematic assessment during the design of discrete and continuous product manufacturing systems for a variety of sustainability performance metrics. A lack of structured and repeatable methods/tools for sustainability assessment of manufacturing processes and systems was identified from literature review and through an academic/industry workshop, which motivated this research. First, a reliable and repeatable method for sustainability assessment was presented by using an information modeling-based approach of reuse and extension of manufacturing processes. The method was then extended to facilitate composition of UMP models in order to characterize the sustainability performance of manufacturing systems. The method supports multi-criteria decision making and was demonstrated for discrete part manufacturing. Based on this foundational work, an integrated framework was conceptualized for manufacturing system design decision making by unifying the information modeling techniques of model reuse, extension, and composition along with a manufacturing system design approach. This conceptual integrated framework was demonstrated for discrete part manufacturing and continuous product manufacturing to showcase the applicability of the framework to different manufacturing processes and systems.

6.2 Conclusions

Learnings from this research facilitate sustainable manufacturing system design decision making as follows: (1) The literature review and workshop guided understanding and identifying the current state-of-the-art in sustainable manufacturing assessment methods, models, and tools as well as identifying opportunities for future research; (2) The standards-based method developed for reuse and extension of UMP models provides an adaptable approach for evaluating the sustainability performance for instance-specific manufacturing process configurations; (3) Linking variables for a number of process classes under the manufacturing process taxonomy were defined and characterized by investigating shared context information between candidate UMPs for composition, which supports standards-based structural representation of manufacturing systems; and (4) Information modeling methods for UMP characterization were integrated with manufacturing system design methodology, leading to the development of a conceptual sustainable manufacturing decision support framework. Detailed findings of the research are provided below.

First, the literature review and the workshop outcomes identified a need for structured methods and tools to support process model development and application. Such methods/tools should enable model reuse and extension to reduce the need for domain expertise and time-intensive validation and rework. This industry need provided the motivation for the research underpinning the development of the integrated framework presented herein. Additionally, the outcomes of these studies provided further insights into potential future research opportunities that the advanced manufacturing community could pursue.

Second, the method developed for reuse and extension of UMP models to represent complex process configurations was enabled by using the information modeling techniques of abstraction, instantiation, and aggregation. The concept of manufacturing process template models for process sub-classes defined by manufacturing process taxonomy, as well as the concept of layer models for process sub-systems and auxiliary systems, were presented. Identification and description of template models and layer models is imperative for reuse and extension of UMP models for a variety of instantiations. Information modeling also helps in differentiating the template model and layer models for a complex process configuration, thereby enabling layer removal. These concepts define a foundational basis for plug-and-play UMP model development and application, thereby reducing significant efforts for industrial practitioners and analysts.

Third, the investigation of UMP model composition led to the characterization of linking variables that can be used for sharing information between UMPs within a manufacturing system. The sub-classifications of generic linking variables and specific linking variables guides practitioners in establishing process variable relationships for their specific application. The method for UMP model composition also provides a class-based structure for representing a manufacturing system. The flow of information is streamlined and traceable since UMP model composition follows an information modeling-based approach. The hierarchical structure of UMPs within the modeled manufacturing system facilitates rapid and robust multi-criteria decision analysis, by allowing decision makers to evaluate different system abstractions and a variety of performance metrics.

Fourth, the integrated framework provides a structured and systematic approach for evaluating manufacturing system design alternatives. The concepts of UMP model reuse, extension, and composition aid in evaluation of a manufacturing system design for selected metrics of interest. In addition, the manufacturing system design approach helps define the structuring of process information models (e.g., number and sequence) to evaluate sustainability performance of different system design alternatives. Select use cases demonstrate that the information modeling approach can provide a streamlined structure for software integration. Evaluation of manufacturing system design alternatives with relative ease and rapid turnaround is made possible through information modeling approaches that can be realized through a software architecture.

6.3 Research Contribution

This research advances the state-of-the-art in sustainable manufacturing systems design decision making, providing a number of contributions to the research community, as detailed below.

Contribution 1: The review of the current state-of-the-art in metrics/indicators, methods/tools, and models/algorithms for characterizing manufacturing processes for evaluating sustainability performance provided insights into a number of research opportunities. It identified the need for structured, repeatable, verifiable, and reliable methods and tools to characterize sustainability performance of manufacturing processes and systems to support manufacturing system design decision making. In addition, findings from the literature review and workshop identified research opportunities for supporting short-, mid-, and long-term needs for smart and sustainable manufacturing across the advanced manufacturing domains, including advanced manufacturing process development, modeling, and analysis.

Contribution 2: A novel information modeling-based approach was presented for the reuse and extension of UMP models, which leverages techniques such as abstraction, instantiation, and polymorphism to evaluate the sustainability performance of manufacturing processes. The method offers a structured, repeatable, and reliable approach for characterizing specific instances of manufacturing process configurations of varying complexity. The method provides a foundation for software architecture to abstract, instantiate, and extend existing UMP models for engineering analysis and decision-making tools for sustainability assessment.

Contribution 3: A novel information modeling-based approach was presented for aggregating (composing) UMP models to characterize manufacturing systems for sustainability performance evaluation. Composability of UMP models through functional block aggregation enables tracking of product and process information flows within the modeled manufacturing system. The research explored and characterized the information (linking variables) to be shared between the UMPs, thereby providing general guidelines and insights for practitioners conducting sustainability performance assessments. In addition, the approach enables data exchange and handling to streamline evaluation of the sustainability performance of manufacturing systems. The approach can serve as a building block for future software application development.

Contribution 4: An integrated information modeling framework for the support of manufacturing system design decision making was conceptualized that builds upon the standards-based methods of reuse, extension, and composition of UMPs for characterizing sustainability performance of manufacturing systems. The framework offers a flexible and adaptable approach for manufacturing system design decision support by combining information modeling techniques with a manufacturing system design approach. The standard-based framework will help reduce informal efforts of sustainable manufacturing system design. The framework is agnostic of the type of manufacturing and has been structured for software implementation to aid manufacturing system design, as demonstrated for discrete part manufacturing and continuous production.

6.4 Opportunities for Future Research

Several opportunities for future research arise from this work that would be of interest to the sustainable manufacturing community.

Opportunity 1: The integrated framework developed in this research provides an approach for sustainable manufacturing system design decision making. While the framework is demonstrated using multi-criteria decision analysis, its application can be extended for optimizing sustainability performance of manufacturing systems. Since the framework offers a structure for data handling that supports manufacturing system modeling, integration of real-time data and analytics in derivative engineering software tools will enable closed-loop optimization and control of system performance. This manufacturing system control can be achieved through software that is built upon the integrated framework, and takes in process data as model inputs and feeds these inputs to an optimization engine. Outputs of optimization would then inform the control system of required changes to process settings.

Opportunity 2: Manufacturing system design alternatives are driven by dynamic changes in customer requirements, functional requirements, and engineering requirements (e.g., product design, customer demand, and supply chain partners). While a conceptual framework has been developed in this research to accommodate this manufacturing system design flexibility, there is a paucity of analysis tools to support engineers in comprehensively evaluating manufacturing system design decision variables. This design decision support can be realized through the development of a software application that leverages machine learning-based evaluation techniques (e.g., decision-tree, rulefit, and neural network analysis) for evaluating manufacturing system design alternatives and suggesting the best alternative for a set of desired customer, design, and engineering requirements.

Opportunity 3: The framework developed in this research integrates product design information, manufacturing design decision variables, and manufacturing process information using information modeling techniques. This data exists as separate information sources absent of common semantics, which would necessitate a variety of communication protocols. Future work can develop an ontology to generate common semantics that establish the definitions, relationships, constraints, and data exchanges between the interdependent aspects of the conceptual framework. These ontologies can be leveraged in the design of a manufacturing system to provide rules, relationships, and constraints that define operating limits, process conditions, and scheduling. With further development, these ontologies would be able to support automated process control.

The research herein enables design decision support for sustainable manufacturing. The scope could be further expanded to include other important phases of the product life cycle, such as raw material extraction and processing, product use, and product end-of-life management (e.g., reuse, remanufacturing, and waste management), for more comprehensive sustainability assessment and decision making. The engineering research community can leverage the learnings from this work to formulate future collaborative efforts that will address global sustainable development goals.

REFERENCES CITED

[1] PCAST, 2014, Report to the President: Accelerating U.S. Advanced Manufacturing, President's Council of Advisors on Science and Technology, Executive Office of the President, Washington, D.C., USA.

[2] Baily, M. N., and Bosworth, B. P., 2014, "US Manufacturing: Understanding Its Past and Its Potential Future," Journal of Economic Perspectives, 28(1), pp. 3–26, doi:10.1257/jep.28.1.3.

[3] US Department of Commerce, 2021, Percentage added to the Gross Domestic Product (GDP) of the United States of America in 2020, by industry, Bureau of Economic Analysis, U.S. Department of Commerce1.

[4] U.S. Energy Information Administration, Monthly Energy Review (April 2021), U.S. Energy Information Administration, Washington D.C.

[5] U.S. Bureau of Labor Statistics, 2020, Employment by major industry sector, Bureau of Labor Statistics, Washington D.C.

[6] Haapala, K. R., Zhao, F., Camelio, J., Sutherland, J. W., Skerlos, S. J., Dornfeld, D. A., Jawahir, I. S., Clarens, A. F., and Rickli, J. L., 2013, "A Review of Engineering Research in Sustainable Manufacturing," Journal of Manufacturing Science and Engineering, 135(4), pp. 041013-1-041013–16, doi:Stability and Biological Responses of Zinc Oxide Metalworking Nanofluids.

[7] Jovane, F., Westkämper, E., and Williams, D., 2008, The ManuFuture road: towards competitive and sustainable high-adding-value manufacturing, Springer Science & Business Media.

[8] Sutherland, J. W., Skerlos, S. J., Haapala, K. R., Cooper, D., Zhao, F., and Huang, A., 2020, “Industrial Sustainability: Reviewing the Past and Envisioning the Future,” J. Manuf. Sci. Eng, 142(11), doi:10.1115/1.4047620.

[9] Allouche, J., 2011, “The sustainability and resilience of global water and food systems: Political analysis of the interplay between security, resource scarcity, political systems and global trade,” Food Policy, 36, pp. S3–S8.

[10] Stock, T., and Seliger, G., 2016, “Opportunities of Sustainable Manufacturing in Industry 4.0,” Procedia CIRP, 40, pp. 536–541, doi:10.1016/j.procir.2016.01.129.

[11] “Green Technology and Sustainability Market Statistics | Forecast - 2026,” Allied Market Research.

[12] Brundtland, G. H., 1987, Report of the World Commission on environment and development:" our common future.", United Nations.

[13] Hallstedt, S. I., 2017, “Sustainability criteria and sustainability compliance index for decision support in product development,” Journal of Cleaner Production, 140, pp. 251–266, doi:10.1016/j.jclepro.2015.06.068.

[14] Dornfeld, D., and Wright, P., 2007, “‘Technology Wedges’ for Implementing Green Manufacturing,” Transactions of NAMRI/SME, 35(1), pp. 193–200.

[15] Tanco, M., Kalemkerian, F., and Santos, J., 2021, “Main challenges involved in the adoption of sustainable manufacturing in Uruguayan small and medium sized companies,” Journal of Cleaner Production, 293, p. 126139, doi:10.1016/j.jclepro.2021.126139.

[16] Mathiyazhagan, K., Sengupta, S., and Mathivathanan, D., 2019, "Challenges for implementing green concept in sustainable manufacturing: a systematic review," OPSEARCH, 56(1), pp. 32–72, doi:10.1007/s12597-019-00359-2.

[17] Anand, C. K., and Amor, B., 2017, "Recent developments, future challenges and new research directions in LCA of buildings: A critical review," Renewable and Sustainable Energy Reviews, 67, pp. 408–416, doi:10.1016/j.rser.2016.09.058.

[18] Kuczenski, B., Marvuglia, A., Astudillo, M. F., Ingwersen, W. W., Satterfield, M. B., Evers, D. P., Koffler, C., Navarrete, T., Amor, B., and Laurin, L., 2018, "LCA capability roadmap—product system model description and revision," The International Journal of Life Cycle Assessment, 23(8), pp. 1685–1692, doi:10.1007/s11367-018-1446-8.

[19] Mathiyazhagan, K., Sengupta, S., and Poovazhagan, L., 2018, "A decision making trial and evaluation laboratory approach to analyse the challenges to environmentally sustainable manufacturing in Indian automobile industry," Sustainable Production and Consumption, 16, pp. 58–67, doi:10.1016/j.spc.2018.05.007.

[20] Duflou, J., and Overcash, M., 2012, "Unit Process Life Cycle Inventories CO2PE!-UPLCI Workshop, May 23, Berkeley, CA."

[21] Kellens, K., Renaldi, Dewulf, W., and Duflou, J. R., 2010, "The CO2PE!-Initiative (Cooperative Effort on Process Emissions in Manufacturing): International Framework for Sustainable Production," Knowledge Collaboration & Learning for Sustainable Innovation, Delft, The Netherlands, p. 13.

[22] Cochran, D. S., Arinez, J. F., Duda, J. W., and Linck, J., 2001, “A decomposition approach for manufacturing system design,” Journal of Manufacturing Systems, 20(6), pp. 371–389, doi:10.1016/S0278-6125(01)80058-3.

[23] Little, A. D., 1925, “The Contribution of Science to Manufacturing,” Annals of the American Academy of Political and Social Science, 119, pp. 1–9.

[24] Mani, M., Madan, J., Lee, J. H., Lyons, K. W., and Gupta, S. K., 2014, “Sustainability Characterization for Manufacturing Processes,” International Journal of Production Research, 52(20), pp. 5895–5912, doi:10.1080/00207543.2014.886788.

[25] Kim, C., Kim, K., and Choi, I., 1993, “An object-oriented information modeling methodology for manufacturing information systems,” Computers & Industrial Engineering, 24(3), pp. 337–353, doi:10.1016/0360-8352(93)90031-R.

[26] ASTM, 2019, “Subcommittee E60.13: Published standards under E60.13 jurisdiction.”

[27] ASTM, 2020, “Standard Guide for Characterizing Environmental Aspects of Manufacturing Processes (ASTM E3012-20),” doi:10.1520/E3012-20.

[28] Groover, M. P., 2015, Fundamentals of Modern Manufacturing, Wiley, New York.

[29] German Institute for Standardization, 2003, “DIN 8580: Manufacturing Processes - Definitions, Classification.”

[30] Todd, R. H., Allen, D. K., and Alting, L., 1994, Fundamental Principles of Manufacturing Processes, Industrial Press, New York.

[31] Duflou, J. R., Sutherland, J. W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., Hauschild, M., and Kellens, K., 2012, “Towards Energy and Resource Efficient Manufacturing: A Processes and Systems Approach,” CIRP Annals - Manufacturing Technology, 61(2), pp. 587–609, doi:10.1016/j.cirp.2012.05.002.

[32] Lee, Y. T., 1999, An overview of information modeling for manufacturing systems integration, Citeseer, Gaithersburg, MD, USA.

[33] Kusiak, A., 2018, “Smart manufacturing,” International Journal of Production Research, 56(1–2), pp. 508–517, doi:10.1080/00207543.2017.1351644.

[34] NIST, 2014, “Smart Manufacturing Operations Planning and Control Program,” National Institute of Standards and Technology.

[35] CESMII, 2019, “CESMII - What We Do,” What is Smart Manufacturing?

[36] Nižetić, S., Djilali, N., Papadopoulos, A., and Rodrigues, J. J. P. C., 2019, “Smart technologies for promotion of energy efficiency, utilization of sustainable resources and waste management,” Journal of Cleaner Production, 231, pp. 565–591, doi:10.1016/j.jclepro.2019.04.397.

[37] Kibira, D., Brundage, M. P., Feng, S., and Morris, K. C., 2018, “Procedure for Selecting Key Performance Indicators for Sustainable Manufacturing,” Journal of Manufacturing Science and Engineering, 140(1), p. 011005, doi:10.1115/1.4037439.

[38] Jeschke, S., Brecher, C., Song, H., and Rawat, D. B., 2017, Industrial Internet of Things: Cybermanufacturing Systems, Springer International Publishing, doi:10.1007/978-3-319-42559-7.

[39] Feeney, A. B., Frechette, S., and Srinivasan, V., 2017, "Cyber-Physical Systems Engineering for Manufacturing," Industrial Internet of Things, S. Jeschke, C. Brecher, H. Song, and D.B. Rawat, eds., Springer International Publishing, Cham, pp. 81–110, doi:10.1007/978-3-319-42559-7_4.

[40] Lu, Y., Morris, K. C., and Frechette, S., 2016, Current Standards Landscape for Smart Manufacturing Systems, National Institute of Standards and Technology, doi:10.6028/NIST.IR.8107.

[41] ASTM, 2018, "Standard Guide for Evaluation of Environmental Aspects of Sustainability of Manufacturing Processes (ASTM E2986-18)," doi:10.1520/E2986-18.

[42] ASTM, 2019, "Standard Guide for Characterizing Environmental Aspects of Manufacturing Processes (ASTM E3012-19)."

[43] Bernstein, W. Z., Bala Subramaniyan, A., Brodsky, A., Garretson, I. C., Haapala, K. R., Libes, D., Morris, K. C., Pan, R., Prabhu, V., Sarkar, A., Shankar Raman, A., and Wu, Z., 2018, "Research directions for an open unit manufacturing process repository: A collaborative vision," Manufacturing Letters, 15, pp. 71–75, doi:10.1016/j.mfglet.2017.12.007.

[44] NIST, 2018, "RAMP: Reusable Abstractions of Manufacturing Processes," National Institute of Standards and Technology.

[45] Overcash, M., and Twomey, J., 2012, "Unit Process Life Cycle Inventory (UPLCI) – A Structured Framework to Complete Product Life Cycle Studies," Leveraging Technology for a Sustainable World, D.A. Dornfeld, and B.S. Linke, eds., Springer Berlin Heidelberg, pp. 1–4.

[46] CO2PE!, 2015, “CO2PE! (Cooperative Effort on Process Emissions in Manufacturing).”

[47] Linke, B., and Overcash, M. R., 2017, “Reusable Unit Process Life Cycle Inventory for Manufacturing: Grinding,” Prod. Eng. Res. Devel., 11(6), pp. 643–653, doi:10.1007/s11740-017-0768-x.

[48] Zhang, H., and Zhao, F., 2019, “Reusable Unit Process Life Cycle Inventory for Manufacturing: Gas Metal Arc Welding,” Prod. Eng. Res. Devel., 13(1), pp. 89–97, doi:10.1007/s11740-018-0869-1.

[49] Shankar Raman, A., Haapala, K. R., and Morris, K. C., 2018, “Towards a Standards-Based Methodology for Extending Manufacturing Process Models for Sustainability Assessment,” ASME 2018 13th International Manufacturing Science and Engineering Conference, ASME, College Station, Texas, p. V001T05A024, doi:10.1115/MSEC2018-6707.

[50] Brodsky, A., Nachawati, M. O., Krishnamoorthy, M., Bernstein, W. Z., and Menascé, D. A., 2019, “Factory optima: a web-based system for composition and analysis of manufacturing service networks based on a reusable model repository,” International Journal of Computer Integrated Manufacturing, 32(3), pp. 206–224, doi:10.1080/0951192X.2019.1570805.

[51] Bernstein, W. Z., and Lechevalier, D., 2019, “A Reference Schema for the Unit Manufacturing Process Information Model,” Journal of Research of NAtional Institute of Standards and Technology, 124, doi:https://doi.org/10.6028/jres.124.011.

[52] Agrawal, A., Nayak, A., Maiti, A., Doshi, C., Doshi, D., and Mohan, D., 2009, "IdeaBoardz - Brainstorm, Retrospect, Collaborate."

[53] NSF, 2018, "Understanding How Aluminum Moves Around a Friction Stir Welding Tool in order to Prevent Welding Defects (NSF Award #1826104)."

[54] Shrivastava, A., Dingler, C., Zinn, M., and Pfefferkorn, F. E., 2015, "Physics-based interpretation of tool-workpiece interface temperature signals for detection of defect formation during friction stir welding," Manufacturing Letters, 5, pp. 7–11, doi:10.1016/j.mfglet.2015.04.002.

[55] NSF, 2015, "Joining of Dissimilar Materials through a Novel Hybrid Friction Stir Resistance Spot Welding Process (NSF Award #1537582)."

[56] Fei, X., Jin, X., Ye, Y., Xiu, T., and Yang, H., 2016, "Effect of pre-hole offset on the property of the joint during laser-assisted friction stir welding of dissimilar metals steel and aluminum alloys," Materials Science and Engineering: A, 653, pp. 43–52, doi:10.1016/j.msea.2015.11.101.

[57] Fehrenbacher, A., Duffie, N. A., Ferrier, N. J., Pfefferkorn, F. E., and Zinn, M. R., 2014, "Effects of tool–workpiece interface temperature on weld quality and quality improvements through temperature control in friction stir welding," The International Journal of Advanced Manufacturing Technology, 71(1–4), pp. 165–179, doi:10.1007/s00170-013-5364-4.

[58] Fehrenbacher, A., Smith, C. B., Duffie, N. A., Ferrier, N. J., Pfefferkorn, F. E., and Zinn, M. R., 2014, "Combined Temperature and Force Control for Robotic Friction Stir Welding," Journal of Manufacturing Science and Engineering, 136(2), p. 021007, doi:10.1115/1.4025912.

[59] NSF, 2019, “An Innovative Hybrid Ultrasonic Resistance Welding Process for Joining Advanced Lightweight and Dissimilar Materials (NSF Award #1853632).”

[60] Yang, J., and Cao, B., 2015, “Investigation of resistance heat assisted ultrasonic welding of 6061 aluminum alloys to pure copper,” Materials & Design, 74, pp. 19–24, doi:10.1016/j.matdes.2015.02.028.

[61] Liu, H., Hu, Y., Du, S., and Zhao, H., 2019, “Microstructure characterization and mechanism of acoustoplastic effect in friction stir welding assisted by ultrasonic vibrations on the bottom surface of workpieces,” Journal of Manufacturing Processes, 42, pp. 159–166, doi:10.1016/j.jmapro.2019.04.028.

[62] NSF, 2016, “CAREER: Surface Interactions in Dissimilar Material Joining (NSF Award #1651024).”

[63] Wang, W.-M., Ali Khan, H., Li, J., Miller, S. F., and Zachary Trimble, A., 2017, “Classification of Failure Modes in Friction Stir Blind Riveted Lap-Shear Joints With Dissimilar Materials,” Journal of Manufacturing Science and Engineering, 139(2), p. 021005, doi:10.1115/1.4034280.

[64] Khan, H. A., Wang, W.-M., Wang, K., Li, S., Miller, S., and Li, J., 2019, “Investigation of mechanical behavior of dissimilar material FSBR joints exposed to a marine environment,” Journal of Manufacturing Processes, 37, pp. 376–385, doi:10.1016/j.jmapro.2018.12.011.

[65] Lee, T., Zhang, S., Vivek, A., Kinsey, B., and Daehn, G., 2018, “Flyer Thickness Effect in the Impact Welding of Aluminum to Steel,” Journal of Manufacturing Science and Engineering, 140(12), p. 121002 (7 pages), doi:10.1115/1.4041247.

[66] NSF, 2018, "CAREER: Vibration-Assisted Laser Keyhole Welding to Improve Joint Properties (Award #1752218)."

[67] NSF, 2019, "CAREER: Material Removal Mechanism of Ceramic Materials in Ultra-Precision Machining (NSF Award #1844821)."

[68] Mizumoto, Y., Maas, P., Kakinuma, Y., and Min, S., 2017, "Investigation of the cutting mechanisms and the anisotropic ductility of monocrystalline sapphire," CIRP Annals, 66(1), pp. 89–92, doi:10.1016/j.cirp.2017.04.018.

[69] Yoon, H.-S., Kwon, S. B., Nagaraj, A., Lee, S., and Min, S., 2018, "Study of stress intensity factor on the anisotropic machining behavior of single crystal sapphire," CIRP Annals, 67(1), pp. 125–128, doi:10.1016/j.cirp.2018.04.114.

[70] Weber, D., Kirsch, B., D'Elia, C. R., Linke, B., Hill, M., and Aurich, J. C., 2019, "Concept to Analyze Residual Stresses in Milled Thin Walled Monolithic Aluminum Components and Their Effect on Part Distorsion," Proceedings of the WGP Annual Congress 2019, Hamburg, Germany.

[71] Chighizola, C. R., D'Elia, C. R., and Hill, M. R., 2019, "Intermethod Comparison and Evaluation of Near Surface Residual Stress in Aluminum Parts Subject to Various Milling Parameters," Proceedings of the 2019 SEM Annual Conference and Exposition on Experimental and Applied Mechanics, Society for Experimental Mechanics, Reno, Nevada, USA, p. 6 pp.

[72] Raval, J., Hung, W. N. P., and Tai, B. L., 2019, "Multiphase flow distribution in MQL drilling using optical intensity distribution based approach," Proceedings of the ASME 14th Manufacturing Science and Engineering Conference,

American Society of Mechanical Engineers, Erie, PA, p. V002T03A033; 9 pages, doi:10.1115/MSEC2019-2926.

[73] Mujumdar, S. S., Kapoor, S. G., and Curreli, D., 2017, "Experimental Investigation of Atomized Dielectric-based MicroEDM Plasma Characteristics," Proceedings of the 2017 World Congress on Micro and Nano Manufacturing, Kaohsiung, Taiwan.

[74] NSF, 2018, "Boosting the Speed and Accuracy of Vibration-Prone Manufacturing Machines at Low Cost through Software (NSF Award #1825133)."

[75] Dong, X., and Okwudire, C. E., 2019, "Semi-active joint for ultra-precision positioning using sliding/rolling bearings," CIRP Annals, 68(1), pp. 385–388, doi:10.1016/j.cirp.2019.04.021.

[76] Duan, M., Yoon, D., and Okwudire, C. E., 2018, "A limited-preview filtered B-spline approach to tracking control – With application to vibration-induced error compensation of a 3D printer," Mechatronics, 56, pp. 287–296, doi:10.1016/j.mechatronics.2017.09.002.

[77] NSF, 2018, "CAREER: Breaking the Freeform Optics Metrology Barrier with Synthetic Wavelength Interferometry (NSF Award #1851739)."

[78] Villarraga-Gómez, H., Lee, C., and Smith, S. T., 2018, "Dimensional metrology with X-ray CT: A comparison with CMM measurements on internal features and compliant structures," Precision Engineering, 51, pp. 291–307, doi:10.1016/j.precisioneng.2017.08.021.

[79] Wang, C., Zhong, F., and Ellis, J. D., 2017, "Two-dimensional straightness measurement based on optical knife-edge sensing," Review of Scientific Instruments, 88(9), p. 095109, doi:10.1063/1.5002711.

[80] Lee, C., Zolfaghari, A., Kim, G. H., and Jeon, S., 2019, "An optical measurement technique for dynamic stiffness and damping of precision spindle system," Measurement, 131, pp. 61–68, doi:10.1016/j.measurement.2018.08.049.

[81] Ellis, J. D., Brooks, D. R., Wozniak, K. T., Gandara-Montano, G. A., Fox, E. G., Tinkham, K. J., Butler, S. C., Zheleznyak, L. A., Buckley, M. R., Funkenbusch, P. D., and Knox, W. H., 2017, "Manufacturing of Gradient Index Lenses for Ophthalmic Applications," Optical Design and Fabrication 2017 (Freeform, IODC, OFT), OSA, Denver, Colorado, p. OW1B.3, doi:10.1364/OFT.2017.OW1B.3.

[82] Crall, M. D., Laney, S. G., and Keller, M. W., 2019, "Multimodal Damage Detection in Self-Sensing Fiber Reinforced Composites," Advanced Functional Materials, 29(12), p. 1806634, doi:10.1002/adfm.201806634.

[83] Feng, S. C., Bernstein, W. Z., Hedberg, T., and Barnard Feeney, A., 2017, "Toward Knowledge Management for Smart Manufacturing," Journal of Computing and Information Science in Engineering, 17(3), p. 031016, doi:10.1115/1.4037178.

[84] Yao, H., Ren, Y., and Liu, Y., 2019, "FEA-Net: A Deep Convolutional Neural Network with Physics Prior for Efficient Data Driven PDE Learning," AIAA Scitech 2019 Forum, American Institute of Aeronautics and Astronautics, San Diego, California, USA, pp. 1–11, doi:10.2514/6.2019-0680.

[85] Esmaeilian, B., Behdad, S., and Wang, B., 2016, "The evolution and future of manufacturing: A review," Journal of Manufacturing Systems, 39, pp. 79–100, doi:10.1016/j.jmsy.2016.03.001.

[86] Cooper, K., and Wachter, R. F., 2013, "Nanomanufacturing: path to implementing nanotechnology," International Journal of Nanomanufacturing, 9(5/6), p. 540, doi:10.1504/IJNM.2013.057598.

[87] Li, L., Hong, M., Schmidt, M., Zhong, M., Malshe, A., Huis in'tVeld, B., and Kovalenko, V., 2011, "Laser nano-manufacturing – State of the art and challenges," CIRP Annals, 60(2), pp. 735–755, doi:10.1016/j.cirp.2011.05.005.

[88] Liddle, J. A., and Gallatin, G. M., 2016, "Nanomanufacturing: A Perspective," ACS Nano, 10(3), pp. 2995–3014, doi:10.1021/acsnano.5b03299.

[89] Cooper, K., 2017, "Scalable Nanomanufacturing—A Review," Micromachines, 8(1), p. 20, doi:10.3390/mi8010020.

[90] Busnaina, A. A., Mead, J., Isaacs, J., and Somu, S., 2013, "Nanomanufacturing and sustainability: opportunities and challenges," Nanotechnology for Sustainable Development, Springer, Cham, pp. 331–336, doi:10.1007/978-3-319-05041-6_26.

[91] Dimov, S., Brousseau, E., Minev, R., and Bigot, S., 2012, "Micro- and nano-manufacturing: Challenges and opportunities," Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 226(1), pp. 3–15, doi:10.1177/0954406211422972.

[92] Morita, S., Giessibl, F. J., Meyer, E., and Wiesendanger, R., eds., 2015, Noncontact Atomic Force Microscopy, Springer International Publishing, Cham, doi:10.1007/978-3-319-15588-3.

[93] Bukkapatnam, S., Kamarthi, S., Huang, Q., Zeid, A., and Komanduri, R., 2012, "Nanomanufacturing systems: opportunities for industrial engineers," IIE Transactions, 44(7), pp. 492–495, doi:10.1080/0740817X.2012.658315.

[94] Hornyak, G. L., Moore, J. J., Tibbals, H. F., and Dutta, J., 2008, Fundamentals of Nanotechnology., CRC Press, Hoboken.

[95] Chen, Y., Wang, Z., He, Y., Yoon, Y. J., Jung, J., Zhang, G., and Lin, Z., 2018, "Light-enabled reversible self-assembly and tunable optical properties of stable hairy nanoparticles," Proceedings of the National Academy of Sciences, 115(7), pp. E1391–E1400, doi:10.1073/pnas.1714748115.

[96] Chen, Y., Yang, D., Yoon, Y. J., Pang, X., Wang, Z., Jung, J., He, Y., Harn, Y. W., He, M., Zhang, S., Zhang, G., and Lin, Z., 2017, "Hairy Uniform Permanently Ligated Hollow Nanoparticles with Precise Dimension Control and Tunable Optical Properties," Journal of the American Chemical Society, 139(37), pp. 12956–12967, doi:10.1021/jacs.7b04545.

[97] Li, X., Li, B., He, M., Wang, W., Wang, T., Wang, A., Yu, J., Wang, Z., Hong, S. W., Byun, M., Lin, S., Yu, H., and Lin, Z., 2018, "Convenient and Robust Route to Photoswitchable Hierarchical Liquid Crystal Polymer Stripes via Flow-Enabled Self-Assembly," ACS Applied Materials & Interfaces, 10(5), pp. 4961–4970, doi:10.1021/acsami.7b16001.

[98] NSF, 2017, "Network for Computational Nanotechnology - Hierarchical nanoMFG Node (NSF Award #1720701)."

[99] ASTM, 2012, "Standard Terminology for Additive Manufacturing Technologies (Designation: F2792–12a)."

[100] Tofail, S. A. M., Koumoulos, E. P., Bandyopadhyay, A., Bose, S., O'Donoghue, L., and Charitidis, C., 2018, "Additive manufacturing: scientific and technological challenges, market uptake and opportunities," Materials Today, 21(1), pp. 22–37, doi:10.1016/j.mattod.2017.07.001.

[101] Huang, Y., Leu, M. C., Mazumder, J., and Donmez, A., 2015, "Additive manufacturing: Current state, future potential, gaps and needs, and recommendations," Journal of Manufacturing Science and Engineering, 137(1), p. 014001.

[102] Gibson, I., Rosen, D., and Stucker, B., 2015, Additive Manufacturing Technologies: 3D Printing, Rapid Prototyping, and Direct Digital Manufacturing, Springer-Verlag, New York.

[103] Nagarajan, H. P. N., Malshe, H. A., Haapala, K. R., and Pan, Y., 2016, "Environmental Performance Evaluation of a Fast Mask Image Projection Stereolithography Process Through Time and Energy Modeling," J. Manuf. Sci. Eng, 138(10), doi:10.1115/1.4033756.

[104] Chen, L., He, Y., Yang, Y., Niu, S., and Ren, H., 2017, "The research status and development trend of additive manufacturing technology," Int J Adv Manuf Technol, 89(9), pp. 3651–3660, doi:10.1007/s00170-016-9335-4.

[105] Leung, Y.-S., Kwok, T.-H., Li, X., Yang, Y., Wang, C. C. L., and Chen, Y., 2019, “Challenges and Status on Design and Computation for Emerging Additive Manufacturing Technologies,” J. Comput. Inf. Sci. Eng, 19(2), p. 021013, doi:10.1115/1.4041913.

[106] NSF, 2012, “CAREER: Mask Video Projection Based Additive Manufacturing at the Micro-scale over Large Areas (NSF Award #1151191).”

[107] NSF, 2017, “Additive Manufacturing of Controlled Anisotropic Materials via Electrically Assisted Nanocomposite Fabrication (NSF Award #1663663).”

[108] NSF, 2019, “Collaborative Research: Towards a Fundamental Understanding of a Simple, Effective and Robust Approach for Mitigating Friction in Nanopositioning Stages (NSF Award: CMMI 1855354).”

[109] NSF, 2016, “Vibration Assisted Nanopositioning: An Enabler of Low-cost, High-throughput Nanotech Processes (NSF Award #1562297).”

[110] NSF, 2014, “CAREER: Pushing the Boundaries: Advancing the Science of Micro-Additive Manufacturing (NSF Award: CMMI 1351469).”

[111] NSF, 2014, “Collaborative Research: A Novel Control Strategy for 3D Printing of Micro-Scale Devices (NSF Award #1434693).”

[112] NSF, 2013, “High Fidelity Additive Manufacturing at the Micro-scale (NSF Award #1334204).”

[113] NSF, 2017, “SNM: Manufacturing Autonomy for Directed Evolution of Materials (MADE-Materials) for Robust, Scalable Nanomanufacturing (NSF Award #1727894).”

[114] Rejeski, D., Zhao, F., and Huang, Y., 2018, "Research needs and recommendations on environmental implications of additive manufacturing," Additive Manufacturing, 19, pp. 21–28, doi:10.1016/j.addma.2017.10.019.

[115] Ngo, T. D., Kashani, A., Imbalzano, G., Nguyen, K. T. Q., and Hui, D., 2018, "Additive manufacturing (3D printing): A review of materials, methods, applications and challenges," Composites Part B: Engineering, 143, pp. 172–196, doi:10.1016/j.compositesb.2018.02.012.

[116] Abdulhameed, O., Al-Ahmari, A., Ameen, W., and Mian, S. H., 2019, "Additive manufacturing: Challenges, trends, and applications," Advances in Mechanical Engineering, 11(2), doi:10.1177/1687814018822880.

[117] Tao, F., Qi, Q., Liu, A., and Kusiak, A., 2018, "Data-driven smart manufacturing," Journal of Manufacturing Systems, 48, pp. 157–169, doi:10.1016/j.jmsy.2018.01.006.

[118] Smullin, M. M., Haapala, K. R., Mani, M., and Morris, K. C., 2016, "Using Industry Focus Groups and Literature Review to Identify Challenges in Sustainable Assessment Theory and Practice," American Society of Mechanical Engineers Digital Collection, p. V004T05A048; 10 pages, doi:10.1115/DETC2016-60216.

[119] Lee, J., Bagheri, B., and Kao, H.-A., 2015, "A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems," Manufacturing Letters, 3, pp. 18–23, doi:10.1016/j.mfglet.2014.12.001.

[120] Bernstein, W. Z., Mani, M., Lyons, K. W., Morris, K. C., and Johansson, B., 2016, "An Open Web-Based Repository for Capturing Manufacturing Process

Information," Volume 4: 21st Design for Manufacturing and the Life Cycle Conference; 10th International Conference on Micro- and Nanosystems, American Society of Mechanical Engineers, Charlotte, North Carolina, USA, p. V004T05A028; 8 pages, doi:10.1115/DETC2016-59265.

[121] Choi, S., Jung, K., Kulvatunyou, B., and Morris, K., 2016, "An analysis of technologies and standards for designing smart manufacturing systems," J. RES. NATL. INST. STAN., 121, p. 422, doi:10.6028/jres.121.021.

[122] Hankel, M., and Rexroth, B., 2015, "The reference architectural model industrie 4.0 (rami 4.0)," ZVEI, April.

[123] Ouelhadj, D., and Petrovic, S., 2008, "A Survey of Dynamic Scheduling in Manufacturing Systems," J Sched, 12(4), pp. 417–431, doi:10.1007/s10951-008-0090-8.

[124] ASME, 2019, "Verification, Validation and Uncertainty Quantification (VVUQ)," Verification, Validation and Uncertainty Quantification (VVUQ).

[125] Seliger, G., Khraisheh, M. M. K., and Jawahir, I. S., 2011, Advances in Sustainable Manufacturing, Springer Science & Business Media.

[126] Cunliff, C., 2018, An Innovation Agenda for Deep Decarbonization: Bridging Gaps in the Federal Energy RD&D Portfolio, Information Technology and Innovation Foundation, Washington D.C, USA.

[127] Center for Climate and Energy Solutions, 2018, "Decarbonizing U.S. Industry," Center for Climate and Energy Solutions.

[128] ISO 14000, 2019, "ISO 14000 family – Environmental management," ISO.

[129] Mani, M., Larborn, J., Johansson, B., Lyons, K. W., and Morris, K. C., 2016, "Standard Representations for Sustainability Characterization of Industrial Processes," Journal of Manufacturing Science and Engineering, 138(10), p. 101008, doi:10.1115/1.4033922.

[130] Mani, M., Morris, K., Lyons, K. W., and Bernstein, W. Z., 2018, "Reusable Models of Manufacturing Processes for Discrete, Batch, and Continuous Production - ProQuest," Journal of the Washington Academy of Sciences, 104(4), pp. 21–30.

[131] Choi, D., 2013, "Standards in Public Policy and Education," ASTM Standardization News, pp. 20–22.

[132] Ramanujan, D., Zhou, N., and Ramani, K., 2019, "Integrating environmental sustainability in undergraduate mechanical engineering courses using guided discovery instruction," Journal of Cleaner Production, 207, pp. 190–203, doi:10.1016/j.jclepro.2018.09.191.

[133] Reber, R., Canning, E. A., and Harackiewicz, J. M., 2018, "Personalized Education to Increase Interest," Curr Dir Psychol Sci, 27(6), pp. 449–454, doi:10.1177/0963721418793140.

[134] Brundage, M. P., Bernstein, W. Z., Hoffenson, S., Chang, Q., Nishi, H., Kliks, T., and Morris, K. C., 2018, "Analyzing environmental sustainability methods for use earlier in the product lifecycle," Journal of Cleaner Production, 187, pp. 877–892, doi:10.1016/j.jclepro.2018.03.187.

[135] Kumar, V., Haapala, K. R., Rivera, J. L., Hutchins, M. J., Endres, W. J., Gershenson, J. K., Michalek, D. J., and Sutherland, J. W., 2005, "Infusing

Sustainability Principles into Manufacturing/Mechanical Engineering Curricula," Journal of Manufacturing Systems, 24(3), pp. 215–225, doi:16/S0278-6125(06)80011-7.

[136] Rebouillat, L., Barletta, I., Johansson, B., Mani, M., Bernstein, W. Z., Morris, K. C., and Lyons, K. W., 2016, "Understanding Sustainability Data through Unit Manufacturing Process Representations: A Case Study on Stone Production," Procedia CIRP, 57, pp. 686–691, doi:10.1016/j.procir.2016.11.119.

[137] Sacks R. and Barak R., 2010, "Teaching Building Information Modeling as an Integral Part of Freshman Year Civil Engineering Education," Journal of Professional Issues in Engineering Education and Practice, 136(1), pp. 30–38, doi:10.1061/(ASCE)EI.1943-5541.0000003.

[138] Sacks R. and Pikas E., 2013, "Building Information Modeling Education for Construction Engineering and Management. I: Industry Requirements, State of the Art, and Gap Analysis," Journal of Construction Engineering and Management, 139(11), p. 04013016, doi:10.1061/(ASCE)CO.1943-7862.0000759.

[139] Irizarry, J., Meadati, P., Barham, W. S., and Akhnoukh, A., 2012, "Exploring Applications of Building Information Modeling for Enhancing Visualization and Information Access in Engineering and Construction Education Environments," International Journal of Construction Education and Research, 8(2), pp. 119–145, doi:10.1080/15578771.2011.647247.

[140] Zimmerman, J. B., and Vanegas, J., 2007, "Using Sustainability Education to Enable the Increase of Diversity in Science, Engineering and Technology-

Related Disciplines," The International Journal of Engineering Education, 23(2), pp. 242–253.

[141] Klotz, L., Potvin, G., Godwin, A., Cribbs, J., Hazari, Z., and Barclay, N., 2014, "Sustainability as a Route to Broadening Participation in Engineering," Journal of Engineering Education, 103(1), pp. 137–153, doi:10.1002/jee.20034.

[142] Clark II, C. J., and Gragg III, R. S., 2011, "Evaluation of Initial Environmental Engineering Sustainability Course at a Minority Serving Institution," Sustainability: The Journal of Record, 4(6), pp. 297–302, doi:10.1089/SUS.2011.9646.

[143] McCormick, M., Bielefeldt, A. R., Swan, C. W., and Paterson, K. G., 2015, "Assessing students' motivation to engage in sustainable engineering," International Journal of Sustainability in Higher Education, 16(2), pp. 136–154, doi:10.1108/IJSHE-06-2013-0054.

[144] Thürer, M., Tomašević, I., Stevenson, M., Qu, T., and Huisingh, D., 2018, "A systematic review of the literature on integrating sustainability into engineering curricula," Journal of Cleaner Production, 181, pp. 608–617, doi:10.1016/j.jclepro.2017.12.130.

[145] Raoufi, K., Park, K., Hasan Khan, Md. T., Haapala, K. R., Psenka, C. E., Jackson, K. L., Kremer, G. E. O., and Kim, K.-Y., 2019, "A Cyberlearning Platform for Enhancing Undergraduate Engineering Education in Sustainable Product Design," Journal of Cleaner Production, 211, pp. 730–741, doi:10.1016/j.jclepro.2018.11.085.

[146] Ferster, B., 2014, Teaching Machines: Learning from the Intersection of Education and Technology, JHU Press.

[147] Oprescu, F., Jones, C., and Katsikitis, M., 2014, “I PLAY AT WORK—ten principles for transforming work processes through gamification,” Front Psychol, 5, doi:10.3389/fpsyg.2014.00014.

[148] Markopoulos, A. P., Fragkou, A., Kasidiaris, P. D., and Davim, J. P., 2015, “Gamification in engineering education and professional training,” International Journal of Mechanical Engineering Education, 43(2), pp. 118–131, doi:10.1177/0306419015591324.

[149] Korn, O., and Schmidt, A., 2015, “Gamification of Business Processes: Re-designing Work in Production and Service Industry,” Procedia Manufacturing, 3, pp. 3424–3431, doi:10.1016/j.promfg.2015.07.616.

[150] Paravizo, E., Chaim, O. C., Braatz, D., Muschard, B., and Rozenfeld, H., 2018, “Exploring Gamification to Support Manufacturing Education on Industry 4.0 as an Enabler for Innovation and Sustainability,” Procedia Manufacturing, 21, pp. 438–445, doi:10.1016/j.promfg.2018.02.142.

[151] Despeisse, M., 2018, “Teaching Sustainability Leadership in Manufacturing: A Reflection on the Educational Benefits of the Board Game Factory Heroes,” Procedia CIRP, 69, pp. 621–626, doi:10.1016/j.procir.2017.11.130.

[152] Wise, J., 2019, “4 Other Times Plane Automation Software Went Haywire,” Popular Mechanics.

[153] Oliver, N., Calvard, T., and Potočnik, K., 2017, "The Tragic Crash of Flight AF447 Shows the Unlikely but Catastrophic Consequences of Automation," Harvard Business Review.

[154] Oborski, P., 2004, "Man-machine interactions in advanced manufacturing systems," Int J Adv Manuf Technol, 23(3), pp. 227–232, doi:10.1007/s00170-003-1574-5.

[155] Gorecky, D., Schmitt, M., Loskyll, M., and Zühlke, D., 2014, "Human-machine-interaction in the industry 4.0 era," 2014 12th IEEE International Conference on Industrial Informatics (INDIN), pp. 289–294, doi:10.1109/INDIN.2014.6945523.

[156] Bag, S., Gupta, S., and Kumar, S., 2021, "Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development," International Journal of Production Economics, 231, p. 107844, doi:10.1016/j.ijpe.2020.107844.

[157] Lopes Silva, D. A., Nunes, A. O., Piekarski, C. M., da Silva Moris, V. A., de Souza, L. S. M., and Rodrigues, T. O., 2019, "Why using different Life Cycle Assessment software tools can generate different results for the same product system? A cause–effect analysis of the problem," Sustainable Production and Consumption, 20, pp. 304–315, doi:10.1016/j.spc.2019.07.005.

[158] Silva, D., Nunes, A. O., da Silva Moris, A., Moro, C., and Piekarski, T. O. R., 2017, "How important is the LCA software tool you choose Comparative results from GaBi, openLCA, SimaPro and Umberto," Proceedings of the CILCA 2017 – VII International Conference on Life Cycle Assessment in Latin America, Medellin, Colombia, pp. 10–15.

[159] Reap, J., Roman, F., Duncan, S., and Bras, B., 2008, "A Survey of Unresolved Problems in Life Cycle Assessment: Part 2: Impact Assessment and Interpretation," The International Journal of Life Cycle Assessment, 13(5), pp. 374–388, doi:10.1007/s11367-008-0009-9.

[160] Overcash, M., Duflou, J., Kellens, K., Looman, K., Dewulf, W., Sutherland, J., Twomey, J., and Isaacs, J., 2012, "Unit Process Life Cycle Inventories CO2PE! - UPLCI Workshop," 45th CIRP Conference on Manufacturing Systems 2012, Berkeley, CA.

[161] Kellens, K., Duflou, J., Renaldi, Guo, Y., and Dewulf, W., 2012, "Critical Comparison of Methods to Determine the Energy Input for Discrete Manufacturing Processes," CIRP Annals - Manufacturing Technology, 61(1), pp. 63–66, doi:10.1016/j.cirp.2012.03.025.

[162] Bernstein, W. Z., Boettjer, T., and Ramanujan, D., 2021, "Quantifying Life Cycle Inventories for Machining Processes at Detailed Design," Procedia CIRP, 98, pp. 370–375, doi:10.1016/j.procir.2021.01.119.

[163] Overcash, M., Griffing, E., Vozzola, E., Twomey, J., Flanagan, W., and Isaacs, J., 2018, "Advancements in Unit Process Life Cycle Inventories (UPLCI) Tools," Procedia CIRP, 69, pp. 447–450, doi:10.1016/j.procir.2017.11.138.

[164] Garretson, I. C., 2015, "A Unit Manufacturing Process Characterization Methodology and Supporting Terminology for Sustainable Manufacturing Assessment," Master of Science, Oregon State University.

[165] Brundage, M. P., Lechevalier, D., and Morris, K., 2018, “Towards Standards-Based Generation of Reusable Life Cycle Inventory Data Models for Manufacturing Processes,” JMSE, doi:10.1115/1.4041947.

[166] Luttikhuis, E. O., Toxopeus, M. E., and Overcash, M., 2013, “Applying Unit Process Life Cycle Inventory (UPLCI) Methodology in Product/Packaging Combinations,” Re-engineering Manufacturing for Sustainability, A.Y.C. Nee, B. Song, and S.-K. Ong, eds., Springer Singapore, pp. 15–20.

[167] Overcash, M., Twomey, J., and Kalla, D., 2009, “Unit Process Life Cycle Inventory for Product Manufacturing Operations,” ASME International Manufacturing Science and Engineering Conference, ASME, West Lafayette, IN, pp. 49–55, doi:10.1115/MSEC2009-84065.

[168] Jiménez-González, C., Kim, S., and Overcash, M., 2000, “Methodology for Developing Gate-to-Gate Life Cycle Inventory Information,” The International Journal of Life Cycle Assessment, 5(3), pp. 153–159, doi:10.1007/BF02978615.

[169] Simon, T., Yang, Y., Lee, W. J., Zhao, J., Li, L., and Zhao, F., 2019, “Reusable Unit Process Life Cycle Inventory for Manufacturing: Stereolithography,” Prod. Eng. Res. Devel., doi:10.1007/s11740-019-00916-0.

[170] Raoufi, K., Harper, D. S., and Haapala, K. R., 2020, “Reusable unit process life cycle inventory for manufacturing: metal injection molding,” Production Engineering Research and Development, 14(5), pp. 707–716, doi:10.1007/s11740-020-00991-8.

[171] Eastwood, M. D., and Haapala, K. R., 2015, “An Induction Hardening Process Model to Assist Sustainability Assessment of a Steel Bevel Gear,” International

Journal of Advanced Manufacturing Technology, 80(5), pp. 1113–1125, doi:10.1007/s00170-015-7053-y.

[172] Eastwood, M. D., and Haapala, K. R., 2015, “A Unit Process Model Based Methodology to Assist Product Sustainability Assessment During Design for Manufacturing,” JCP, 108, pp. 54–64, doi:10.1016/j.jclepro.2015.08.105.

[173] Dahmus, J. B., and Gutowski, T. G., 2004, “An Environmental Analysis of Machining,” ASME 2004 International Mechanical Engineering Congress and Exposition (IMECE2004), Anaheim, CA, pp. 643–652, doi:10.1115/IMECE2004-62600.

[174] Murray, V. R., Zhao, F., and Sutherland, J. W., 2012, “Life cycle analysis of grinding: a case study of non-cylindrical computer numerical control grinding via unit-process life cycle inventory approach,” Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, p. 0954405412454102, doi:10.1177/0954405412454102.

[175] Diaz, N., Ninomiya, K., Noble, J., and Dornfeld, D., 2012, “Environmental Impact Characterization of Milling and Implications for Potential Energy Savings in Industry,” Procedia CIRP, 1, pp. 518–523, doi:10.1016/j.procir.2012.04.092.

[176] Quintana, G., Ciurana, J., and Ribatallada, J., 2011, “Modelling Power Consumption in Ball-End Milling Operations,” Mater. Manuf. Process., 26(5), pp. 746–756, doi:10.1080/10426910903536824.

[177] He, Y., Liu, F., Wu, T., Zhong, F.-P., and Peng, B., 2012, “Analysis and estimation of energy consumption for numerical control machining,” Proc. Inst.

Mech. Eng. Part B-J. Eng. Manuf., 226(B2), pp. 255–266, doi:10.1177/0954405411417673.

[178] Cooper, D. R., Rossie, K. E., and Gutowski, T. G., 2017, “An Environmental and Cost Analysis of Stamping Sheet Metal Parts,” J. Manuf. Sci. Eng, 139(4), p. 041012, doi:10.1115/1.4034670.

[179] Dalquist, S., and Gutowski, T., 2004, “Life Cycle Analysis of Conventional Manufacturing Techniques: Sand Casting,” Proceedings of ASME 2004 International Mechanical Engineering Congress and Exposition (IMECE2004), ASME, Anaheim, CA, pp. 631–641, doi:10.1115/IMECE2004-62599.

[180] Haapala, K. R., Catalina, A. V., Johnson, M. L., and Sutherland, J. W., 2012, “Development and Application of Models for Steelmaking and Casting Environmental Performance,” Journal of Manufacturing Science and Engineering, 134(5), pp. 051013-1-051013–13, doi:10.1115/1.4007463.

[181] Watkins, M. F., Mani, M., Lyons, K. W., and Gupta, S. K., 2014, “Sustainability Characterization for Die Casting Process,” American Society of Mechanical Engineers Digital Collection, doi:10.1115/DETC2013-12634.

[182] Singh, P., Madan, J., Singh, A., and Mani, M., 2012, “A Computer-Aided System for Sustainability Analysis for the Die-Casting Process,” ASME 2012 International Manufacturing Science and Engineering Conference, American Society of Mechanical Engineers, pp. 1087–1096, doi:10.1115/MSEC2012-7303.

[183] Madan, J., Mani, M., Lee, J. H., and Lyons, K. W., 2015, “Energy Performance Evaluation and Improvement of Unit-Manufacturing Processes: Injection

Molding Case Study," Journal of Cleaner Production, 105, pp. 157–170, doi:10.1016/j.jclepro.2014.09.060.

[184] Dittrich, M. A., Gutowski, T. G., Cao, J., Roth, J. T., Xia, Z. C., Kiridena, V., Ren, F., and Henning, H., 2012, "Exergy analysis of incremental sheet forming," Prod. Eng. Res. Devel., 6(2), pp. 169–177, doi:10.1007/s11740-012-0375-9.

[185] Singh, K., and Sultan, I. A., 2018, "Modelling and Evaluation of KPIs for the Assessment of Sustainable Manufacturing: An Extrusion process case study," Materials Today: Proceedings, 5(2, Part 1), pp. 3825–3834, doi:10.1016/j.matpr.2017.11.636.

[186] Wang, J., Qiao, F., Zhao, F., and Sutherland, J. W., 2016, "A Data-Driven Model for Energy Consumption in the Sintering Process," J. Manuf. Sci. Eng, 138(10), p. 101001, doi:10.1115/1.4033661.

[187] Shrivastava, A., Overcash, M., and Pfefferkorn, F. E., 2015, "Prediction of unit process life cycle inventory (UPLCI) energy consumption in a friction stir weld," Journal of Manufacturing Processes, 18, pp. 46–54, doi:10.1016/j.jmapro.2014.10.006.

[188] Ramirez-Cedillo, E., García-López, E., Ruiz-Huerta, L., Rodriguez, C. A., and Siller, H. R., 2021, "Reusable unit process life cycle inventory (UPLCI) for manufacturing: laser powder bed fusion (L-PBF)," Prod. Eng. Res. Devel., 15(5), pp. 701–716, doi:10.1007/s11740-021-01050-6.

[189] Gbededo, M. A., Liyanage, K., and Garza-Reyes, J. A., 2018, "Towards a Life Cycle Sustainability Analysis: A systematic review of approaches to sustainable

manufacturing," Journal of Cleaner Production, 184, pp. 1002–1015, doi:10.1016/j.jclepro.2018.02.310.

[190] Cai, W., and Lai, K., 2021, "Sustainability assessment of mechanical manufacturing systems in the industrial sector," Renewable and Sustainable Energy Reviews, 135, p. 110169, doi:10.1016/j.rser.2020.110169.

[191] Hegab, H. A., Darras, B., and Kishawy, H. A., 2018, "Towards sustainability assessment of machining processes," Journal of Cleaner Production, 170, pp. 694–703, doi:10.1016/j.jclepro.2017.09.197.

[192] Huang, A., and Badurdeen, F., 2017, "Sustainable Manufacturing Performance Evaluation: Integrating Product and Process Metrics for Systems Level Assessment," Procedia Manufacturing, 8, pp. 563–570, doi:10.1016/j.promfg.2017.02.072.

[193] Huang, A., Badurdeen, F., and Jawahir, I. S., 2018, "Towards Developing Sustainable Reconfigurable Manufacturing Systems," Procedia Manufacturing, 17, pp. 1136–1143, doi:10.1016/j.promfg.2018.10.024.

[194] International Organization for Standardization, 2019, "ISO 20140-3:2019 - Automation systems and integration — Evaluating energy efficiency and other factors of manufacturing systems that influence the environment — Part 3: Environmental performance evaluation data aggregation process."

[195] Smullin, M. M., 2016, "An Information Modeling Framework and Desktop Application to Compose Unit Manufacturing Process Models for Sustainable Manufacturing Assessment," M.S. Thesis, Oregon State University.

[196] Smullin, M. M., Iman, Z., and Haapala, K. R., 2017, “A Desktop Application for Sustainability Performance Assessment of Composed Unit-Based Manufacturing Systems,” Proceedings of the 12th International Manufacturing Science and Engineering Conference, ASME, Los Angeles, CA, p. V004T05A022; 11 pages.

[197] Bernstein, W. Z., Lechevalier, D., and Libes, D., 2018, “UMP Builder: Capturing and Exchanging Manufacturing Models for Sustainability,” Volume 1: Additive Manufacturing; Bio and Sustainable Manufacturing, ASME, College Station, Texas, USA, p. V001T05A022, doi:10.1115/MSEC2018-6331.

[198] Lósio, B. F., Salgado, A. C., and do Rêgo GalvĐo, L., 2003, “Conceptual Modeling of XML Schemas,” Proceedings of the 5th ACM International Workshop on Web Information and Data Management, ACM, New York, NY, USA, pp. 102–105, doi:10.1145/956699.956722.

[199] Sung, R. C., Ritchie, J. M., Lim, T., and Kosmadoudi, Z., 2012, “Automated generation of engineering rationale, knowledge and intent representations during the product life cycle,” Virtual Reality, 16(1), pp. 69–85.

[200] Meihua, Z., Aiping, L., and Liyun, X., 2008, “Integrated Modeling and Information Interaction Mechanism of Collaborative Production Information,” Proceeding of the International Conference on Information Management, Innovation Management and Industrial Engineering, IEEE, Taipei, Taiwan, pp. 67–70, doi:10.1109/ICIII.2008.236.

[201] Yadong, F., Ping, K., and Lei, Z., 2009, “Research and application of machine tools life-cycle management system based on web,” Proceedings of the ISECS

International Colloquium on Computing, Communication, Control, and Management, IEEE, Sanya, China, pp. 117–120, doi:10.1109/CCCM.2009.5267803.

[202] Guha, R. V., Brickley, D., and Macbeth, S., 2016, "Schema.org: evolution of structured data on the web," Communications of the Association for Computing Machinery, 59(2), pp. 44–51, doi:10.1145/2844544.

[203] Dennis, A., Wixom, B. H., Tegarden, D. P., and Seeman, E., 2015, System analysis & design: an object-oriented approach with UML, Wiley, Hoboken, NJ.

[204] Carlson, D., 2001, Modeling XML applications with UML: practical e-business aplications, Addison-Wesley, Boston, MA.

[205] van der Vlist, E., 2004, RELAX NG, O'Reilly, Sebastopol, CA.

[206] Kara, S., and Li, W., 2011, "Unit process energy consumption models for material removal processes," CIRP Annals - Manufacturing Technology, 60(1), pp. 37–40, doi:10.1016/j.cirp.2011.03.018.

[207] Avram, O. I., and Xirouchakis, P., 2011, "Evaluating the use phase energy requirements of a machine tool system," Journal of Cleaner Production, 19(6–7), pp. 699–711, doi:10.1016/j.jclepro.2010.10.010.

[208] Kalla, D., Twomey, J., and Overcash, M., 2009, MR 3 Milling Process Unit Process Life Cycle Inventory.

[209] Branker, K., 2011, A study of energy, carbon dioxide emissions and economics in machining: milling and single point incremental forming, Queen's University (Canada).

[210] He, Y., Liu, B., Zhang, X., Gao, H., and Liu, X., 2012, “A modeling method of task-oriented energy consumption for machining manufacturing system,” Journal of Cleaner Production, 23(1), pp. 167–174.

[211] Overcash, M., Twomey, J., Isaacs, J., Duflou, J., and Sutherland, J., 2010, “Energy efficiency improvements in manufacturing life cycle technology for analysis of machines and products,” Society of Manufacturing Engineers Technical Paper, TP10PUB8, Dearborn, MI, p. 5.

[212] Li, W., Zein, A., Kara, S., and Herrmann, C., 2011, “An investigation into fixed energy consumption of machine tools,” Glocalized solutions for sustainability in manufacturing, pp. 268–273.

[213] Raman, A. S., Haapala, K. R., Raoufi, K., Linke, B. S., Bernstein, W. Z., and Morris, K. C., 2020, “Defining Near-Term to Long-Term Research Opportunities to Advance Metrics, Models, and Methods for Smart and Sustainable Manufacturing,” Smart Sustain. Manuf. Syst., 4(2), p. 20190047 (25 pages), doi:10.1520/SSMS20190047.

[214] Vaidya, S., Ambad, P., and Bhosle, S., 2018, “Industry 4.0 – A Glimpse,” Procedia Manufacturing, 20, pp. 233–238, doi:10.1016/j.promfg.2018.02.034.

[215] Zimek, M., Schober, A., Mair, C., Baumgartner, R. J., Stern, T., and Füllsack, M., 2019, “The Third Wave of LCA as the ‘Decade of Consolidation,’” Sustainability, 11(12), p. 3283, doi:10.3390/su11123283.

[216] Zhang, H., Zhu, B., Li, Y., Yaman, O., and Roy, U., 2015, “Development and Utilization of a Process-Oriented Information Model for sustainable

manufacturing," Journal of Manufacturing Systems, 37, Part 2, pp. 459–466, doi:10.1016/j.jmsy.2015.05.003.

[217] Munoz, A. A., and Sheng, P., 1995, "An Analytical Approach for Determining the Environmental Impact of Machining Processes," Journal of Materials Processing Technology, 53(3–4), pp. 736–758, doi:10.1016/0924-0136(94)01764-R.

[218] Demirag, O., Johnson, A., Nazzal, D., and Wan, Y., 2008, "Integrated Definition (IDEF) Modeling Techniques," Georgia Institute of Technology, www2. isye. gatech. edu/~ lfm/8851/IDEF_V4. ppt.

[219] Cowan, J., Paoli, J., Yergeau, F., Maler, E., Sperberg-McQueen, C. M., and Bray, T., 2002, "Extensible Markup Language (XML) 1.1," W3C CR CR-xml11-20021015.

[220] International Organization for Standardization [ISO], 2020, "ISO 10303-242:2020 - Industrial automation systems and integration — Product data representation and exchange — Part 242: Application protocol: Managed model-based 3D engineering."

[221] Pratt, M. J., 2001, "Introduction to ISO 10303—the STEP Standard for Product Data Exchange," Journal of Computing and Information Science in Engineering, 1(1), pp. 102–103, doi:10.1115/1.1354995.

[222] International Organization for Standardization, 2003, "ISO 16100-2:2003 Industrial automation systems and integration -- Manufacturing software capability profiling for interoperability -- Part 2: Profiling methodology."

[223] Fenves, S. J., Foufou, S., Bock, C., and Sriram, R. D., 2008, “CPM2: A Core Model for Product Data,” Journal of Computing and Information Science in Engineering, 8(1), pp. 014501–014501, doi:10.1115/1.2830842.

[224] Fenves, S. J., Foufou, S., Bock, C., Sudarsan, R., Bouillon, N., and Sriram, R. D., 2004, CPM 2 :: a revised core product model for representing design information, National Institute of Standards and Technology, Gaithersburg, MD, doi:10.6028/NIST.IR.7185.

[225] Fenves, S. J., 2001, A core product model for representing design information, National Institute of Standards and Technology, Gaithersburg, MD, doi:10.6028/NIST.IR.6736.

[226] Baysal, M. M., Roy, U., Sudarsan, R., Sriram, R. D., and Lyons, K. W., 2004, “The Open Assembly Model for the Exchange of Assembly and Tolerance Information: Overview and Example,” Volume 4: 24th Computers and Information in Engineering Conference, ASME, Salt Lake City, Utah, USA, pp. 759–770, doi:10.1115/DETC2004-57727.

[227] Fowler, J. E., 2001, Systems Integration for Manufacturing Applications, biennial report fiscal years 1999-2000, National Institute of Standards and Technology, Gaithersburg, MD, doi:10.6028/NIST.IR.6721.

[228] Feng, S. C., and Song, E. Y., 2003, “A Manufacturing Process Information Model for Design and Process Planning Integration,” Journal of Manufacturing Systems, 22(1), pp. 1–15, doi:10.1016/S0278-6125(03)90001-X.

[229] PRé Sustainability, 2020, SimaPro 9.0 LCA Software, Amersfoort, The Netherlands.

[230] Sphera, 2020, "GaBi Software - Version GaBi ts 9.5."

[231] ASTM, 2020, "Standard Terminology for Sustainable Manufacturing (ASTM E2987/E2987M-20)," doi:10.1520/E2987_E2987M-20.

[232] ASTM, 2018, "Standard Guide for Definition, Selection, and Organization of Key Performance Indicators for Environmental Aspects of Manufacturing Processes," doi:10.1520/E3096-18.

[233] Yang, B., Qiao, L., Zhu, Z., and Wulan, M., 2016, "A Metamodel for the Manufacturing Process Information Modeling," Procedia CIRP, 56, pp. 332–337, doi:10.1016/j.procir.2016.10.032.

[234] Chen, G., 1998, Fuzzy logic in data modeling: semantics, constraints, and database design, Springer, Boston, MA.

[235] Cox, B. J., and Novobilski, A. J., 1991, Object-oriented programming: an evolutionary approach, Addison-Wesley Pub. Co, Reading, Mass.

[236] Hanrahan, R. P., 1995, "The IDEF process modeling methodology," Journal of Defence Software Engineering, 8, pp. 1–8.

[237] Mayer, R. J., 1990, A Reconstruction of the Original Air Force Wright Aeronautical Laboratory, Knowledge-Based System Inc, College Station, TX.

[238] Kacprzak, M., and Kaczmarczyk, A., 2006, "Verification of integrated IDEF models," J Intell Manuf, 17(5), pp. 585–596, doi:10.1007/s10845-006-0024-2.

[239] Kalla, D., Corcoran, S., Twomey, J., and Overcash, M., 2011, "Energy Consumption in Discrete Part Production," ASME 2011 International Manufacturing Science and Engineering Conference, pp. 669–675, doi:10.1115/MSEC2011-50163.

[240] Abeykoon, C., Kelly, A. L., Vera-Sorroche, J., Brown, E. C., and Coates, P. D., 2014, "Monitoring and modelling of the energy consumption in polymer extrusion," 2014 European Control Conference (ECC), pp. 1030–1035, doi:10.1109/ECC.2014.6862154.

[241] Energy, Mines and Resources Canada, 1992, Energy Management Series for Industry Commerce and Institutions: Process Furnaces, Dryers and Kilns.

[242] Kaminski, D., and Jensen, M., 2011, Introduction to Thermal and Fluids Engineering, Wiley, Hoboken NJ.

[243] Kelly, A. L., Sorroche, J. V., Brown, E. C., and Coates, P. D., 2012, "Improving thermal efficiency of single screw extrusion," SPE ANTEC Tech. Papers, pp. 1080–1088.

[244] Yang, J., Wang, H., xia Song, L., Gao, Y., and Wei, E., 2012, "Model Establishing and Analyzing of Energy Consumption in the Process of Aquatic Feed Extrusion," 2012 Dallas, Texas, July 29-August 1, 2012, American Society of Agricultural and Biological Engineers, p. 1.

[245] BEE, "Energy Performance Assessment of Furnaces."

[246] Kang, J., Rong, Y., and W. Wang, 2004, Numerical Simulation of Heat Transfer in Loaded Heat Treatment Furnaces, Journal de Physique IV.

[247] Kang, J., and Rong, Y., 2006, "Modeling and simulation of load heating in heat treatment furnaces," Journal of Materials Processing Technology, 174(1–3), pp. 109–114, doi:10.1016/j.jmatprotec.2005.03.037.

[248] Orlowski, K. A., Ochrymiuk, T., Hlaskova, L., Chuchala, D., and Kopecky, Z., 2020, "Revisiting the estimation of cutting power with different energetic

methods while sawing soft and hard woods on the circular sawing machine: a Central European case," Wood Sci Technol, 54(2), pp. 457–477, doi:10.1007/s00226-020-01162-9.

[249] Chuchala, D., Orlowski, K. A., Sandak, A., Sandak, J., Pauliny, D., and Barański, J., 2014, "The Effect of Wood Provenance and Density on Cutting Forces While Sawing Scots Pine (Pinus sylvestris L.)," BioResources, 9(3), pp. 5349–5361, doi:10.15376/biores.9.3.5349-5361.

[250] Kirschstein, T., and Meisel, F., 2015, "GHG-emission models for assessing the eco-friendliness of road and rail freight transports," Transportation Research Part B: Methodological, 73, pp. 13–33, doi:10.1016/j.trb.2014.12.004.

[251] Smullin, M. M., Garretson, I. C., and Haapala, K. R., 2016, "Composability of Unit Manufacturing Process Models for Manufacturing Systems Analysis," Proceedings of the ASME 2016 Manufacturing Science and Engineering, ASME, Blacksburg, Virginia, USA, doi:10.1115/MSEC2016-8804.

[252] Nagarajan, H. P. N., Haapala, K. R., and Raman, A. S., 2018, "A Sustainability Assessment Framework for Dynamic Cloud-based Distributed Manufacturing," Procedia CIRP, 69, pp. 136–141, doi:10.1016/j.procir.2017.11.120.

[253] Mourtzis, D., and Doukas, M., 2012, "Decentralized manufacturing systems review: challenges and outlook," Logistics Research, 5(3–4), pp. 113–121.

[254] Rauch, E., Dallinger, M., Dallasega, P., and Matt, D. T., 2015, "Sustainability in Manufacturing through Distributed Manufacturing Systems (DMS)," Procedia CIRP, 29, pp. 544–549, doi:10.1016/j.procir.2015.01.069.

[255] Haapala, K. R., Kim, K.-Y., Kremer, G. E. O., Kubat, R., Shilkrot, R., and Sciammarella, F. M., 2020, "An Open Online Product Marketplace to Overcome Supply and Demand Chain Inefficiencies in Times of Crisis," 4(3), pp. 299–302, doi:10.1520/SSMS20200055.

[256] Lajevardi, B., Leith, S., King, D., and Paul, B., 2011, "Arrayed Microchannel Manufacturing Costs for an Auxiliary Power Unit Heat Exchanger," Proceedings of the 2011 Industrial Engineering Research Conference, Reno, NV.

[257] Leith, S. D., King, D. A., and Paul, B., 2010, "Toward Low-Cost Fabrication of Microchannel Process Technologies - Cost Modeling for Manufacturing Development," Proceedings of the 2010 AIChE Annual Meeting, Pacific Northwest National Laboratory (PNNL), Richland, WA (US), Salt Lake City, Utah.

[258] ASM International, 1990, "ASM Handbook Volume 2: Introduction to Aluminum and Aluminum Alloys," Properties and Selection: Nonferrous Alloys and Special-Purpose Materials, ASM International, Materials Park, Ohio, pp. 3–14, doi:10.31399/asm.hb.v02.a0001057.

[259] Hatch, J. E., Aluminum Association, and American Society for Metals, eds., 1984, Aluminum: properties and physical metallurgy, American Society for Metals, Metals Park, Ohio.

[260] J. R. Davis & Associates, and ASM International, eds., 1993, Aluminum and aluminum alloys, ASM International, Materials Park, OH.

[261] Arif, A. F. M., Sheikh, A. K., Qamar, S. Z., and Al-Fuhaid, K. M., 2001, "Variation of Pressure with Ram Speed and Die Profile in Hot Extrusion of

Aluminum-6063," Materials and Manufacturing Processes, 16(5), pp. 701–716, doi:10.1081/AMP-100108630.

[262] Ko, D.-H., Kang, B.-H., Ko, D.-C., and Kim, B.-M., 2013, "Improvement of mechanical properties of Al6061 extrudate by die cooling with N2 gas during hot extrusion," J Mech Sci Technol, 27(1), pp. 153–161, doi:10.1007/s12206-012-1213-x.

[263] ASM International, 1989, "ASM Handbook Volume 16: Machining of Aluminum and Aluminum Alloys," Machining, ASM International, Materials Park, Ohio, pp. 761–804, doi:10.31399/asm.hb.v16.a0002184.

[264] Ioras, H., Nicholls, T., Perkins, M. C., Münz, U. V., and Larmann, A., 2002, "A review for cutting forces and stresses in circular saws," Holz als Roh- und Werkstoff, 60(1), pp. 55–59, doi:10.1007/s001070100220.

[265] Fontecchio, M., Maniruzzaman, M., and Sisson Jr., R., 2004, Quench Factor Analysis and Heat Transfer Coefficient Calculations for 6061 Aluminum Alloy Probes Quenched in Distilled Water, Center for Heat Treating Excellence Materials Science and Engineering Program, Worcester Polytechnic Institute (WPI), Worcester, MA.

[266] Totten, G. E., ed., 2016, "Quenching of Aluminum Alloys," Heat Treating of Nonferrous Alloys, ASM International, pp. 148–178, doi:10.31399/asm.hb.v04e.a0006260.

[267] ASM International, ed., 1990, ASM handbook Volume 4E: Heat Treating of Nonferrous Alloys, ASM International, Materials Park, Ohio.

[268] Energy Information Administration (EIA), 2021, “Electric Power Monthly - U.S. Energy Information Administration (EIA),” Electric Power Monthly.

[269] USEPA, 2020, eGRID Summary Tables 2018, U.S. Environmental Protection Agency, Washington D.C.

[270] BLS, 2020, May 2020 National Occupational Employment and Wage Estimates, Bureau of Labor Statistics, Washington D.C.

[271] Saaty, T. L., 1986, “Axiomatic Foundation of the Analytic Hierarchy Process,” Management Science, 32(7), pp. 841–855, doi:10.1287/mnsc.32.7.841.

[272] Ramlan, R., and Qiang, L. W., 2014, “An Analytic Hierarchy Process Approach for Supplier Selection: A Case Study,” Proceedings of the 3rd International Conference on Global Optimization and Its Application, Indonesia, pp. 150–160.

[273] DOE, 2016, Sustainable Manufacturing Workshop - Workshop Summary report, DOE Office of Energy Efficiency and Renewable Energy (EERE), Portland, OR.

[274] Rachuri, S., Sriram, R. D., Narayanan, A., Sarkar, P., Lee, J. H., Lyons, K. W., and Kemmerer, S. J., 2010, Sustainable manufacturing program workshop report :: metrics, standards, and infrastructure-NIST workshop report, National Institute of Standards and Technology, Gaithersburg, MD, doi:10.6028/NIST.IR.7683.

[275] Nujoom, R., Mohammed, A., and Wang, Q., 2019, “Drafting a cost-effective approach towards a sustainable manufacturing system design,” Computers & Industrial Engineering, 133, pp. 317–330, doi:10.1016/j.cie.2019.05.007.

[276] Yien, J. T., and Tseng, M. M., 1997, “Manufacturing systems design: a review of state-of- the-art methodologies,” Integrated Product, Process and Enterprise

Design, B. Wang, ed., Springer US, Boston, MA, pp. 392–434, doi:10.1007/978-1-4615-6383-9_13.

[277] Alves, A. C., and Silva, S. C., 2009, “A review of design methodologies for manufacturing systems,” 1ST International Conference on Innovations, Recent Trends and Challenges in Mechatronics, Mechanical Engineering and New High-Tech Products Development, Bucharest, pp. 183–200.

[278] US EPA, O., 2015, “Sustainable Manufacturing.”

[279] Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X., and Liu, C., 2020, “Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey,” Renewable and Sustainable Energy Reviews, 132, p. 110112, doi:10.1016/j.rser.2020.110112.

[280] Bueno, C., Pereira, L. M., and Fabricio, M. M., 2018, “Life cycle assessment and environmental-based choices at the early design stages: an application using building information modelling,” Architectural Engineering and Design Management, 14(5), pp. 332–346, doi:10.1080/17452007.2018.1458593.

[281] 1994, “Guidelines for Life-Cycle Assessment:: A ‘Code of Practice’ from the workshop held at Sesimbra, Portugal, 31 March – 3 April 1993 Society of Environmental Toxicology and Chemistry (SETAC),” Environ. Sci. & Pollut. Res., 1(1), pp. 55–55, doi:10.1007/BF02986927.

[282] Umeda, Y., Takata, S., Kimura, F., Tomiyama, T., Sutherland, J. W., Kara, S., Herrmann, C., and Duflou, J. R., 2012, “Toward integrated product and process life cycle planning—an environmental perspective,” CIRP Annals -

Manufacturing Technology, 61(2), pp. 681–702, doi:10.1016/j.cirp.2012.05.004.

[283] Yang, Y., and Heijungs, R., 2019, "Moving from completing system boundaries to more realistic modeling of the economy in life cycle assessment," Int J Life Cycle Assess, 24(2), pp. 211–218, doi:10.1007/s11367-018-1532-y.

[284] Suppipat, S., Teachavorasinskun, K., and Hu, A. H., 2021, "Challenges of Applying Simplified LCA Tools in Sustainable Design Pedagogy," Sustainability, 13(4), p. 2406, doi:10.3390/su13042406.

[285] Dias, L. C., Passeira, C., Malça, J., and Freire, F., 2016, "Integrating life-cycle assessment and multi-criteria decision analysis to compare alternative biodiesel chains," Ann Oper Res, doi:10.1007/s10479-016-2329-7.

[286] Linke, B. S., Corman, G. J., Dornfeld, D. A., and Tönissen, S., 2013, "Sustainability Indicators for Discrete Manufacturing Processes Applied to Grinding Technology," Journal of Manufacturing Systems, 32(4), pp. 556–563, doi:10.1016/j.jmsy.2013.05.005.

[287] Madan, J., Mani, M., and Lyons, K. W., 2013, "Characterizing Energy Consumption of the Injection Molding Process," American Society of Mechanical Engineers Digital Collection, doi:10.1115/MSEC2013-1222.

[288] Valivullah, L., Mani, M., Lyons, K. W., and Gupta, S. K., 2014, "Manufacturing Process Information Models for Sustainable Manufacturing," Volume 1: Materials; Micro and Nano Technologies; Properties, Applications and Systems; Sustainable Manufacturing, American Society of Mechanical Engineers, Detroit, Michigan, USA, p. V001T05A005, doi:10.1115/MSEC2014-4105.

[289] Kishawy, H., Hegab, H., and Saad, E., 2018, "Design for Sustainable Manufacturing: Approach, Implementation, and Assessment," Sustainability, 10(10), p. 3604, doi:10.3390/su10103604.

[290] Naegler, T., Becker, L., Buchgeister, J., Hauser, W., Hottenroth, H., Junne, T., Lehr, U., Scheel, O., Schmidt-Scheele, R., Simon, S., Sutardhio, C., Tietze, I., Ulrich, P., Viere, T., and Weidlich, A., 2021, "Integrated Multidimensional Sustainability Assessment of Energy System Transformation Pathways," Sustainability, 13(9), p. 5217, doi:10.3390/su13095217.

[291] Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., and Bansal, R. C., 2017, "A review of multi criteria decision making (MCDM) towards sustainable renewable energy development," Renewable and Sustainable Energy Reviews, 69, pp. 596–609, doi:10.1016/j.rser.2016.11.191.

[292] Cegan, J. C., Filion, A. M., Keisler, J. M., and Linkov, I., 2017, "Trends and applications of multi-criteria decision analysis in environmental sciences: literature review," Environ Syst Decis, 37(2), pp. 123–133, doi:10.1007/s10669-017-9642-9.

[293] Kurth, M. H., Larkin, S., Keisler, J. M., and Linkov, I., 2017, "Trends and applications of multi-criteria decision analysis: use in government agencies," Environ Syst Decis, 37(2), pp. 134–143, doi:10.1007/s10669-017-9644-7.

[294] Gao, Q., Lizarazo-Adarme, J., Paul, B. K., and Haapala, K. R., 2016, "An Economic and Environmental Assessment Model for Microchannel Device Manufacturing: Part 2 – Application," Journal of Cleaner Production, 120, pp. 146–156, doi:10.1016/j.jclepro.2015.04.141.

[295] Stoycheva, S., Marchese, D., Paul, C., Padoan, S., Juhmani, A., and Linkov, I., 2018, "Multi-criteria decision analysis framework for sustainable manufacturing in automotive industry," Journal of Cleaner Production, 187, pp. 257–272, doi:10.1016/j.jclepro.2018.03.133.

[296] Li, Y., and Mathiyazhagan, K., 2018, "Application of DEMATEL approach to identify the influential indicators towards sustainable supply chain adoption in the auto components manufacturing sector," Journal of Cleaner Production, 172, pp. 2931–2941, doi:10.1016/j.jclepro.2017.11.120.

[297] Mokhtari, H., and Hasani, A., 2017, "A multi-objective model for cleaner production-transportation planning in manufacturing plants via fuzzy goal programming," Journal of Manufacturing Systems, 44, pp. 230–242, doi:10.1016/j.jmsy.2017.06.002.

[298] Feng, S. C., and Song, E. Y., 2000, "Information Modeling of Conceptual Design Integrated With Process Planning," Recent Advances in Design for Manufacture (DFM), American Society of Mechanical Engineers, Orlando, Florida, USA, pp. 123–130, doi:10.1115/IMECE2000-1058.

[299] International Organization for Standardization [ISO], 2003, "ISO 16100-2:2003 - Industrial automation systems and integration — Manufacturing software capability profiling for interoperability — Part 2: Profiling methodology."

[300] OPC Foundation, 2022, "What is OPC?," OPC Foundation.

[301] PRé Sustainability, 2020, SimaPro Database Manual: Methods Library, PRé Sustainability B.V.

[302] International Organization for Standardization, ISO 20140:2019.

[303] Komoto, H., Bernstein, W. Z., Kwon, S., and Kimura, F., 2020, “Standardizing environmental performance evaluation of manufacturing systems through ISO 20140,” Procedia CIRP, 90, pp. 528–533, doi:10.1016/j.procir.2020.02.043.

[304] Ghita, M., Siham, B., Hicham, M., and Griguer, H., 2021, “Digital Twins Based LCA and ISO 20140 for Smart and Sustainable Manufacturing Systems,” Sustainable Intelligent Systems, A. Joshi, A.K. Nagar, and G. Marín-Raventós, eds., Springer Singapore, Singapore, pp. 101–145, doi:10.1007/978-981-33-4901-8_8.

[305] Bernstein, W. Z., Tamayo, C. D., Lechevalier, D., and Brundage, M. P., 2019, “Incorporating unit manufacturing process models into life cycle assessment workflows,” Procedia CIRP, pp. 364–369, doi:10.1016/j.procir.2019.01.019.

[306] Ziout, A., Azab, A., Altarazi, S., and ElMaraghy, W. H., 2012, “Multi-criteria decision support for sustainability assessment of manufacturing system reuse,” CIRP Journal of Manufacturing Science and Technology, 6(1), pp. 59–69, doi:10.1016/j.cirpj.2012.10.006.

[307] Shankar Raman, A., Morris, K. C., and Haapala, K. R., “Composition of Unit Manufacturing Process Models for Characterizing Sustainability Performance of Manufacturing Systems,” To be submitted to Journal of Manufacturing Science & Engineering.

[308] Fowler, M., 2004, UML distilled: a brief guide to the standard object modeling language, Addison-Wesley, Boston.

[309] Strahan, D. and Centre for Low Carbon Futures, 2013, Liquid air in the energy and transport systems opportunities for industry and innovation in the UK ; full report, Centre for Low Carbon Futures, York.

[310] Oni, A. O., Anaya, K., Giwa, T., Di Lullo, G., and Kumar, A., 2022, “Comparative assessment of blue hydrogen from steam methane reforming, autothermal reforming, and natural gas decomposition technologies for natural gas-producing regions,” Energy Conversion and Management, 254, p. 115245, doi:10.1016/j.enconman.2022.115245.

[311] Brown, T., 2014, “Ammonia Capacity in North America,” Ammonia Industry.

[312] Peters, M. S., Timmerhaus, K. D., and West, R. E., 2004, Plant Design and Economics for Chemical Engineers, McGraw-Hill, Boston.

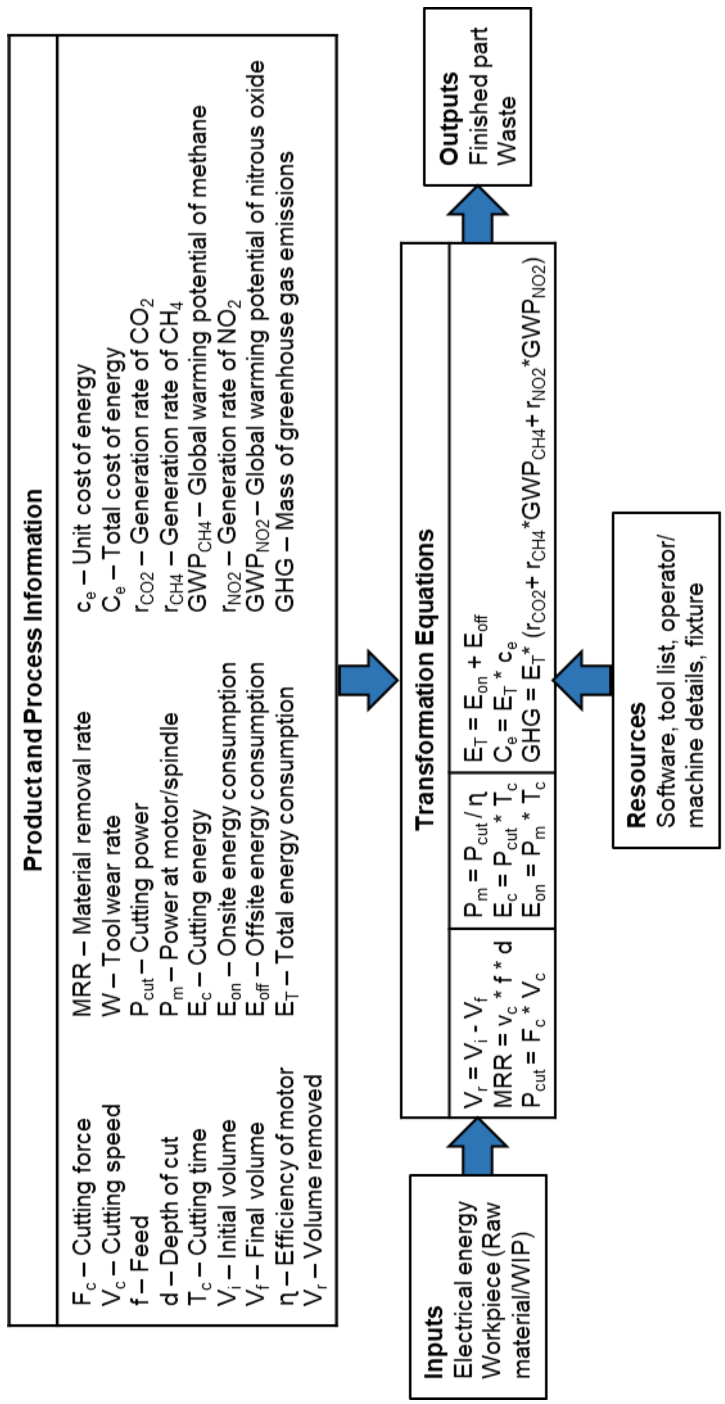
[313] Green, D. W., and Southard, M. Z., eds., 2019, Perry’s chemical engineers’ handbook, McGraw Hill Education, New York.

[314] Tribe, M. A., and Alpine, R. L. W., 1986, “Scale Economies and the ‘0.6 Rule,’” Engineering Costs and Production Economics, 10(4), pp. 271–278, doi:10.1016/S0167-188X(86)80025-8.

[315] Lang, H. J., 1948, “Simplified approach to preliminary cost estimates,” Chemical Engineering, 55(6), pp. 112–113.

[316] Andersson, J., and Lundgren, J., 2014, “Techno-economic analysis of ammonia production via integrated biomass gasification,” Applied Energy, 130, pp. 484–490, doi:10.1016/j.apenergy.2014.02.029.

Appendix A1: Manual milling model based on the ASTM E3012-20 standard

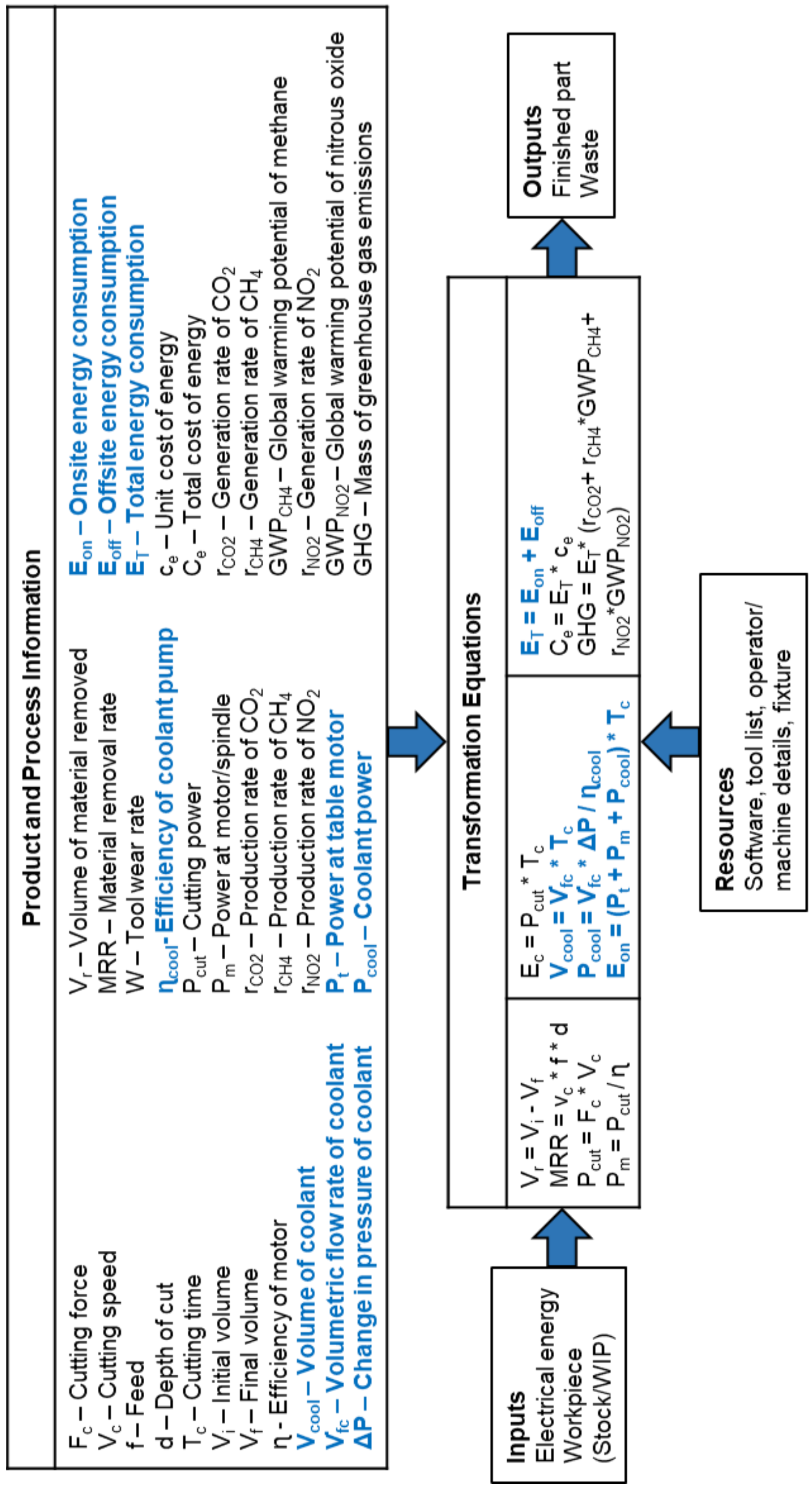


Appendix A2: XML representation of a manual milling model

```
<UMP name="Manual Milling" type="Material Removal" description="Manual milling model">

//INPUT SECTION

<Input name="Bar stock" description= "Type of workpiece input to the process"
category=""type="Workpiece" unit="" / >
<Input name="Electrical Energy" description="Input electrical energy to the process"
category=""type="Energy" unit="kWh" / >

//PRODUCT AND PROCESS INFORMATION SECTION

<ProductProcessInformation name="Cutting force" description="Force on the cutting tool"
category="Process" value="" unit="N" / >
<ProductProcessInformation name="Cutting speed" description="Tangential speed of cut"
category="Process" value="" unit="mm/s" / >
<ProductProcessInformation name="Feed" description="Input feed of tool" category="Process"
value="" unit="mm/s" / >
<ProductProcessInformation name="Depth of cut" description="Axial depth of cut per pass"
category="Process" value="" unit="mm" / >
<ProductProcessInformation name="Cutting time" description="Total cutting time"
category="Process" value="" unit="s" / >
<ProductProcessInformation name="Initial volume" description="Volume of workpiece before
operation" category="Product" value="" unit="mm^3" / >
<ProductProcessInformation name="Final volume" description="Volume of workpiece after
operation" category="Product" value="" unit="mm^3" / >
<ProductProcessInformation name="Efficiency of motor" description="Efficiency of motor"
category="Process" value="" unit="" / >
<ProductProcessInformation name="Volume removed" description="Total volume of material removed"
category="Product" value="" unit="mm^3" / >
<ProductProcessInformation name="Material removal rate" description="Rate of material removal"
category="Product" value="" unit="mm^3/s" / >
<ProductProcessInformation name="Tool wear rate" description="Rate of tool wear"
category="Process" value="" unit=" mm^3/s" / >
<ProductProcessInformation name="Cutting power" description="Power required to cut material"
category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Motor/spindle power" description="Power measured at the
motor/spindle" category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Generation rate of CO2" description="Mass of CO2 produced per
unit of energy use" category="Process" value="" unit="kg CO2/kWh" / >
<ProductProcessInformation name="Generation rate of CH4" description="CH4 produced in equivalent
mass of CO2 per unit of energy use" category="Process" value="" unit="kg CO2e/kWh" / >
<ProductProcessInformation name="Generation rate of NO2" description="NO2 produced in equivalent
mass of CO2 per unit of energy use" category="Process"value="" unit="kg CO2e/kWh" / >
<ProductProcessInformation name="Cutting energy" description="Energy required to cut the part"
category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Energy onsite" description="Consumed energy generated on site"
category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Energy offsite" description="Consumed energy generated on
site" category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Total energy consumption" description="Total energy
consumption" category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Unit cost of energy" description="Cost of 1kWh of energy"
category="Process" value="" unit="$/kWh" / >
<ProductProcessInformation name="Total cost of energy" description="Total cost of energy"
category="Process" value="" unit="$" / >
<ProductProcessInformation name="Mass of GHG emissions" description="Greenhouse gas emissions
in equivalent mass of CO2" category="Process" value=""unit="kg CO2e" / >

//TRANSFORMATION SECTION

<Transformation>
	<Equation description="Volume removed" set="">V_r = V_i - V_f</Equation>
	<Equation description="Material removal rate" set="">MRR = v_c * f * d</Equation>
	<Equation description="Cutting power" set="">P_cut= F_c * V_c</Equation>
```

```
        <Equation description=“Motor power” set=“”>P_m= P_cut / Eff</Equation>
        <Equation description=“Cutting energy” set=“”>E_c = P_cut * T_c</Equation>
        <Equation description=“Onsite energy” set=“”>E_on = P_m * T_c</Equation>
        <Equation description=“Total energy consumption” set=“”>E_T = E_on + E_off</Equation>
        <Equation description=“Total cost of energy” set=“”>C_e = E_T * c_e</Equation>
        <Equation description=“GHG emissions” set=“”>GHG = E_T * (rCO2 + rCH4 + rNO2)</Equation>
</Transformation>

//RESOURCE SECTION

<Resource name=“Software” description=“Software used for computer control” value=“Linux CNC” />
<Resource name=“Machine ID” description=“ID of the machine that is being used” value=“MM01” />
<Resource name=“Operator” description=“Name of operator” value=“John Doe” />

//OUTPUT SECTION

<Output name=“Finished parts” description=“Number of workpieces produced in an hour” category=“”
type=“workpiece” unit=“” / >
<Output name=“Waste” description=“Total waste – Machining chips” category=“Waste”
type=“workpiece” unit=“kg”/ >

</UMP>
```

Appendix A3: Model of a two-and-a-half axis mill with lubrication system extended from a manual milling model (extensions in bold blue text)

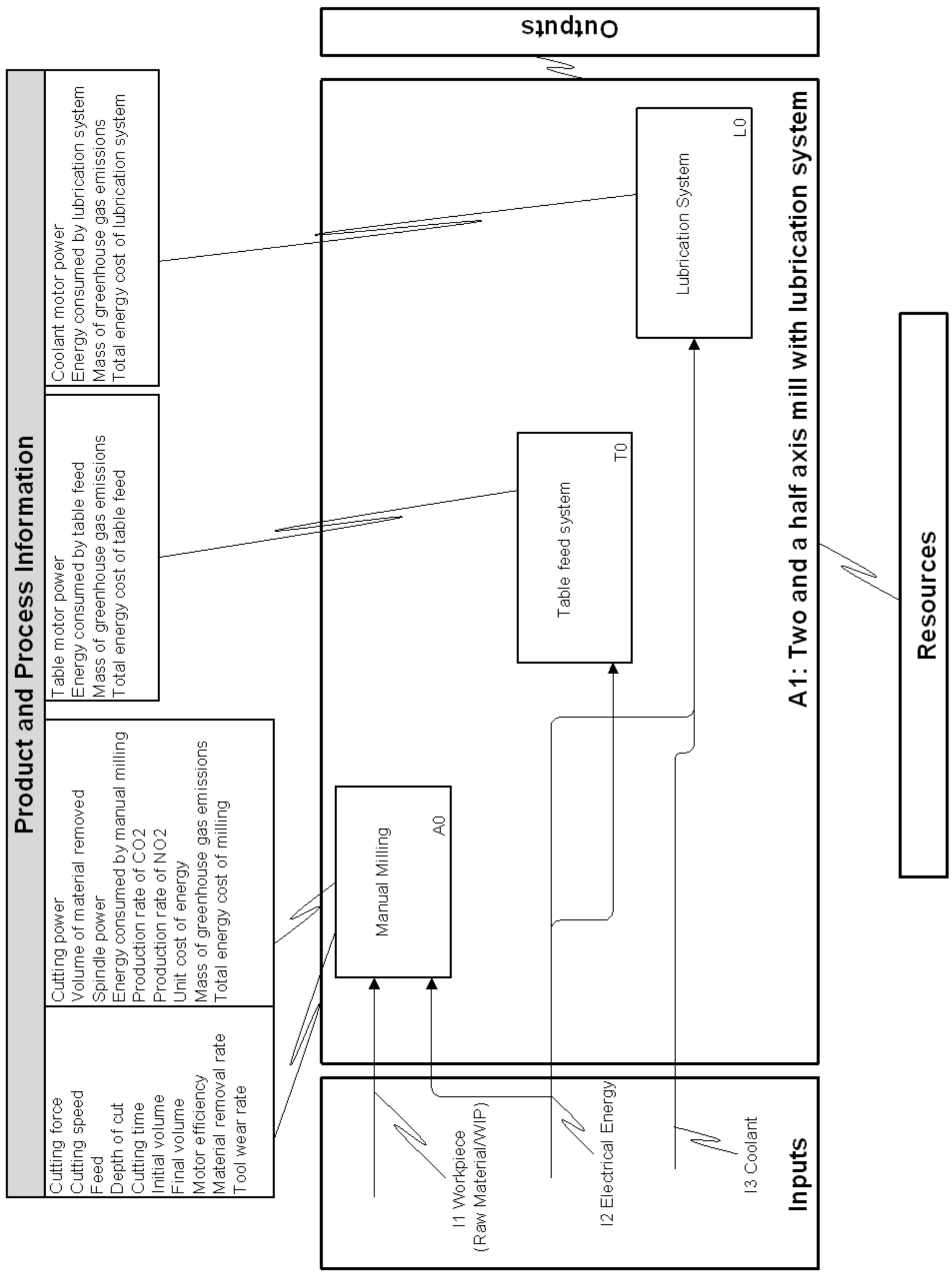


Appendix A4: XML representation of a two-and-a-half axis mill with lubrication system

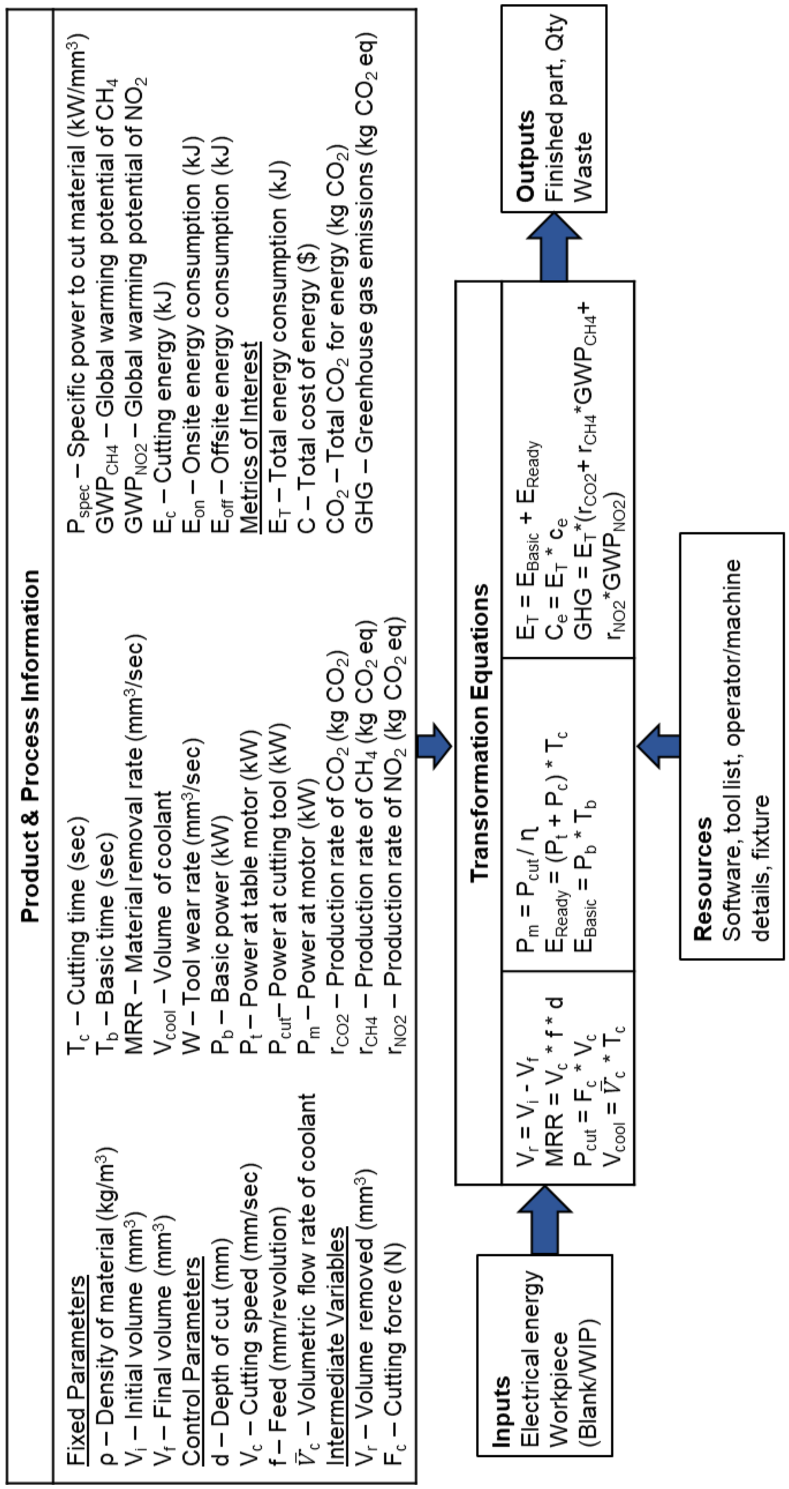
```
<UMP name="Two-Axis Milling with Lubrication System" type="Material Removal" description="Two
and a half axis milling with lubrication system">

//INPUT SECTION
<Input name="Bar stock" description= "Type of workpiece input to the process"
category=""type="Workpiece" unit="" / >
<Input name="Electrical energy" description="Input electrical energy to the process"
category=""type="Energy" unit="kWh" / >

//PRODUCT AND PROCESS INFORMATION SECTION
<ProductProcessInformation name="Cutting force" description="Force on the cutting tool"
category="Process" value="" unit="N" / >
<ProductProcessInformation name="Cutting speed" description="Tangential speed of cut"
category="Process" value="" unit="mm/s" / >
<ProductProcessInformation name="Feed" description="Input feed of tool" category="Process"
value="" unit="mm/s" / >
<ProductProcessInformation name="Depth of cut" description="Axial depth of cut per pass"
category="Process" value="" unit="mm" / >
<ProductProcessInformation name="Cutting time" description="Total cutting time"
category="Process" value="" unit="s" / >
<ProductProcessInformation name="Initial volume" description="Volume of workpiece before
operation" category="Product" value="" unit="mm^3" / >
<ProductProcessInformation name="Final volume" description="Volume of workpiece after
operation" category="Product" value="" unit="mm^3" / >
<ProductProcessInformation name="Efficiency of motor" description="Efficiency of motor"
category="Process" value="" unit="" / >
<ProductProcessInformation name="Volume removed" description="Total volume of material removed"
category="Product" value="" unit="mm^3" / >
<ProductProcessInformation name="Material removal rate" description="Rate of material removal"
category="Product" value="" unit="mm^3/s" / >
<ProductProcessInformation name="Tool wear rate" description="Rate of tool wear"
category="Process" value="" unit=" mm^3/s" / >
<ProductProcessInformation name="Cutting power" description="Power required to cut material"
category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Motor/spindle power" description="Power measured at the
motor/spindle" category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Generation rate of NO2" description="NO2 produced in equivalent
mass of CO2 per unit of energy use" category="Process"value="" unit="kg CO2e/kWh" / >
<ProductProcessInformation name="Cutting energy" description="Energy required to cut the part"
category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Energy onsite" description="Consumed energy generated on site"
category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Energy offsite" description="Consumed energy generated on
site" category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Total energy consumption" description="Total energy
consumption" category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Unit cost of energy" description="Cost of 1kWh of energy"
category="Process" value="" unit="$/kWh" / >
<ProductProcessInformation name="Total cost of energy" description="Total cost of energy"
category="Process" value="" unit="$" / >
<ProductProcessInformation name="Mass of GHG emissions" description="Greenhouse gas emissions
in equivalent mass of CO2" category="Process" value=""unit="kg CO2e" / >
<ProductProcessInformation name="Coolant flow rate" description="Volumetric flow rate of
coolant" category="Process" value="" unit="L/s" / >
<ProductProcessInformation name="Volume of coolant" description="Volume of coolant used"
category="Process" value="" unit="L" / >
<ProductProcessInformation name="Basic power" description="Power to setup and idle"
category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Basic time" description="Time to setup and idle"
category="Process" value="" unit="s" / >
```

```
<ProductProcessInformation name="Table motor power" description="Power to table motor" category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Coolant motor power" description="Coolant motor power" category="Process" value="" unit="kW" / >
<ProductProcessInformation name="Basic energy" description="Energy to setup and idle" category="Process" value="" unit="kJ" / >
<ProductProcessInformation name="Ready energy" description="Energy for cutting" category="Process" value="" unit="kJ" / >

//TRANSFORMATION SECTION
<Transformation>
    <Equation description="Volume removed" set="">V_r = V_i - V_f</Equation>
    <Equation description="Material removal rate" set="">MRR = v_c * f * d</Equation>
    <Equation description="Volume of coolant" set="">V_cool = V_flow_rate * T_c</Equation>
    <Equation description="Motor power" set="">P_m= P_cut / Eff</Equation>
    <Equation description="Basic energy" set="">E_Basic = P_b * T_b </Equation>
    <Equation description="Ready energy" set="">E_Ready = (P_t + P_c) * T_c </Equation>
    <Equation description="Volume of coolant" set="">V_cool = V̇_c * T_c</Equation>
    <Equation description="Onsite energy" set="">E_on = E_Basic + E_Ready</Equation>
    <Equation description="Total energy consumption" set="">E_T = E_on + E_off</Equation>
    <Equation description="Total cost of energy" set="">C_e = E_T * c_e</Equation>
    <Equation description="GHG emissions" set="">GHG = E_T * (rCO2 + rCH4 + rNO2)</Equation>

</Transformation>

//RESOURCE SECTION from TABLE 1
<Resource name="Software" description="Software used for computer control" value="Linux CNC" />
<Resource name="Machine ID" description="ID of the machine that is being used" value="MM01" />
<Resource name="Operator" description="Name of operator" value="John Doe" />

//OUTPUT SECTION
<Output name="Finished parts" description="Number of workpieces produced in an hour" category="" type="workpiece" unit="" / >
<Output name="Waste" description=" Total waste – Machining chips" category="Waste" type="workpiece" unit="kg" / >

</UMP>
```

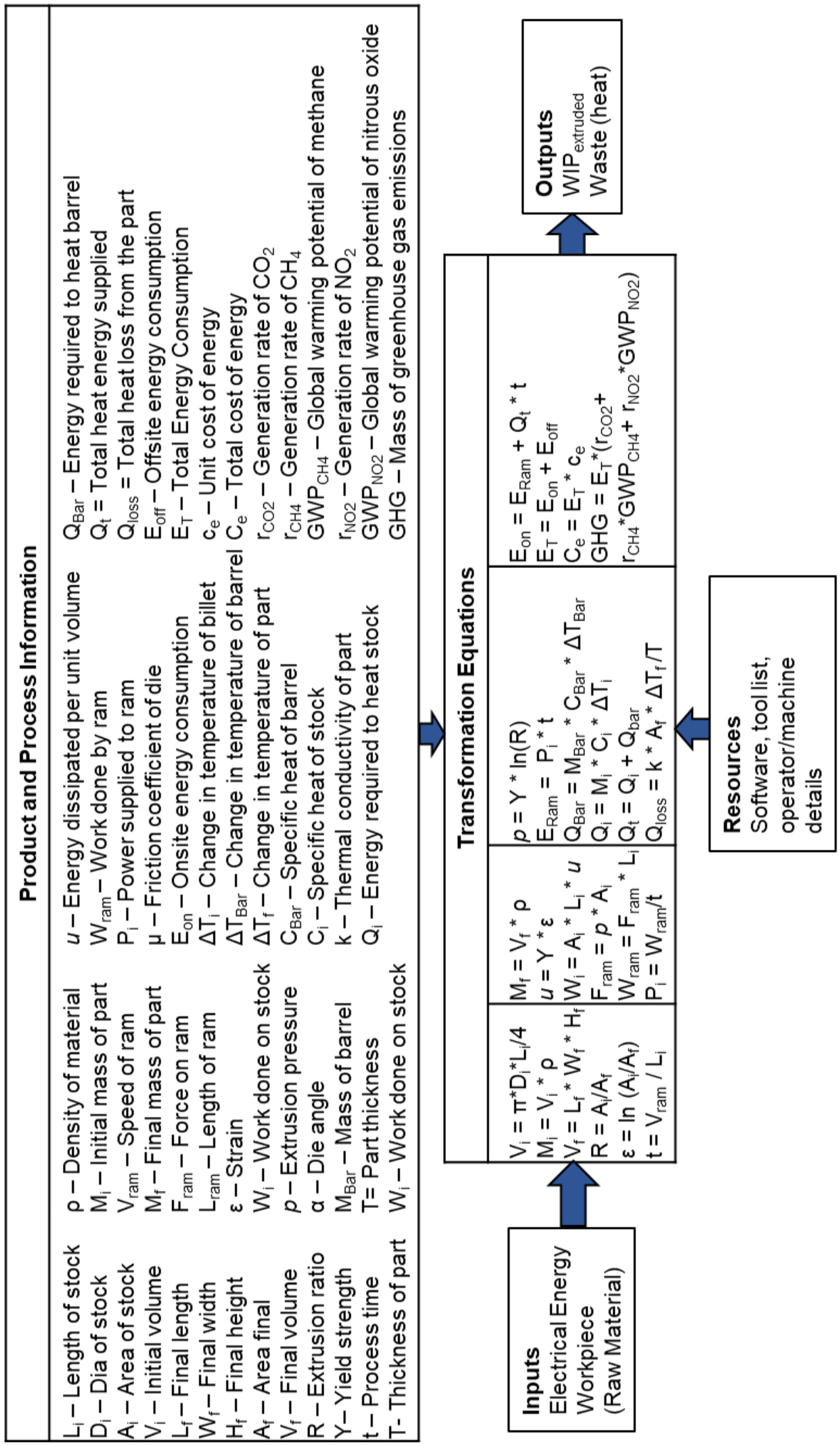
Appendix A5: IDEF0 representation of two and a half axis mill with lubrication system



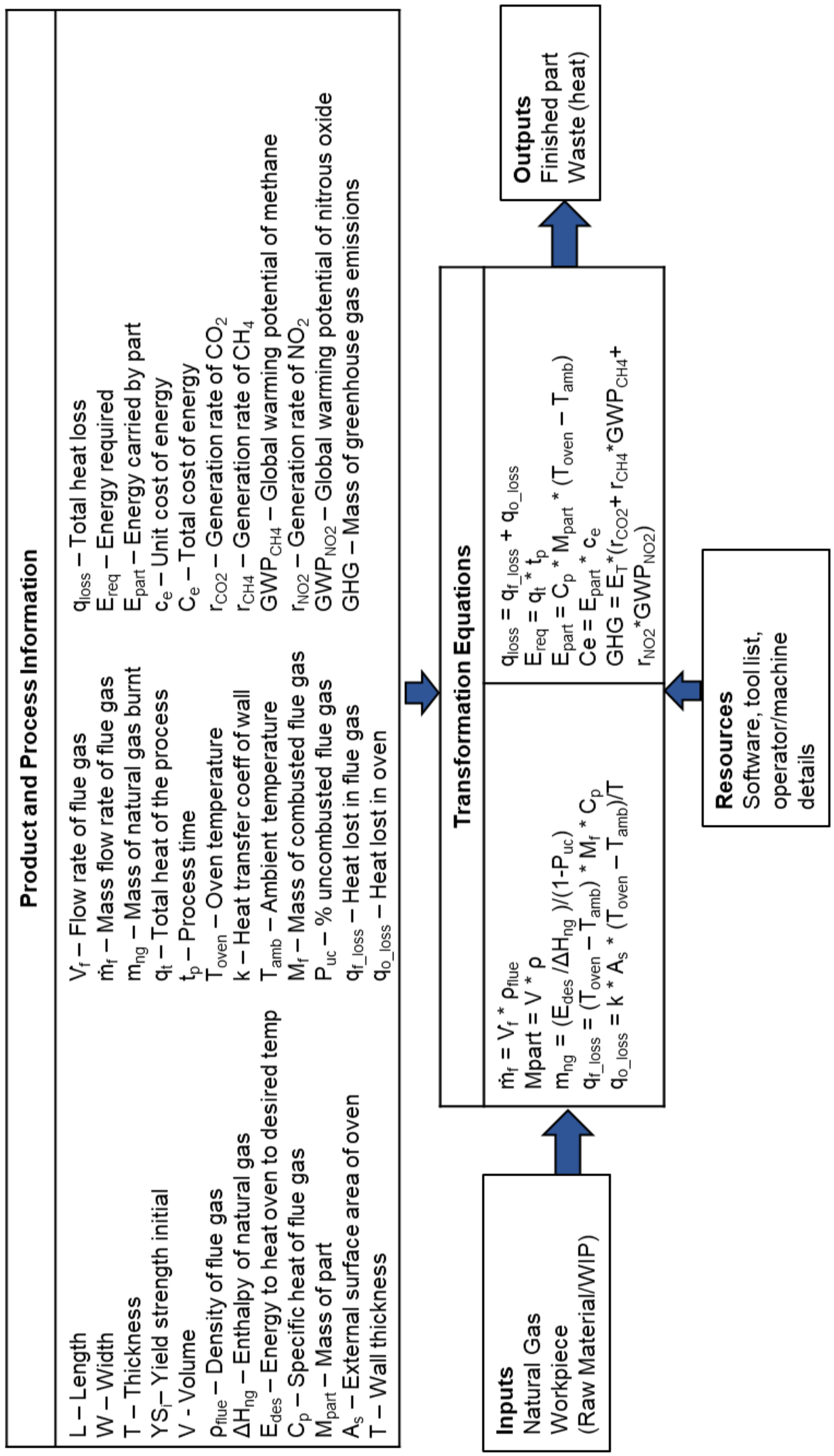
Appendix B1: Milling UMP model based on the ASTM E3012-20 standard



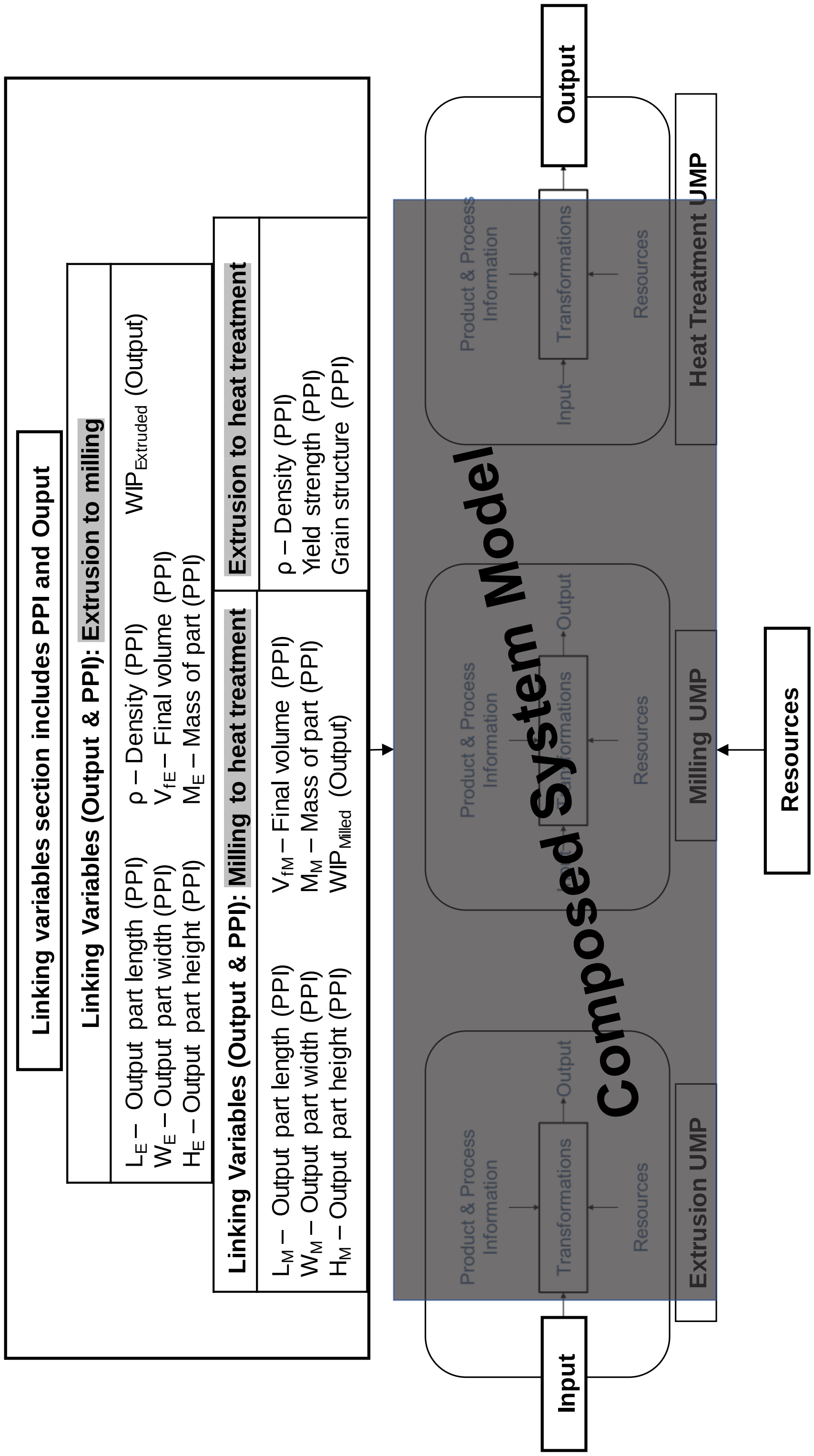
Appendix B2: Extrusion UMP model based on the ASTM E3012-20 standard



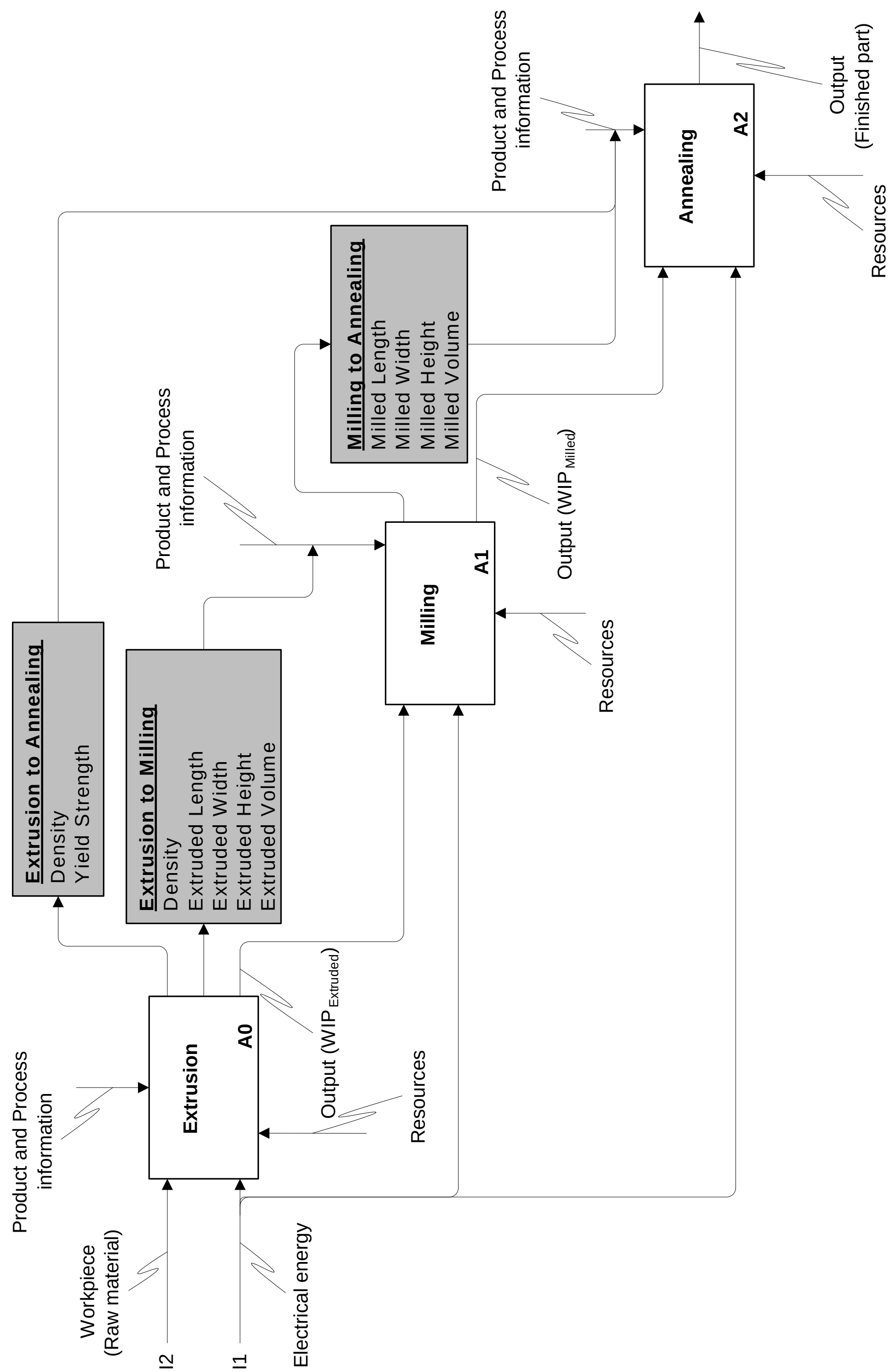
Appendix B3: Annealing UMP model based on the ASTM E3012-20 standard



Appendix B4: Graphical representation of a composed system (extrusion to milling to annealing)



Appendix B5: IDEF0 representation of a composed system (extrusion to milling to annealing)

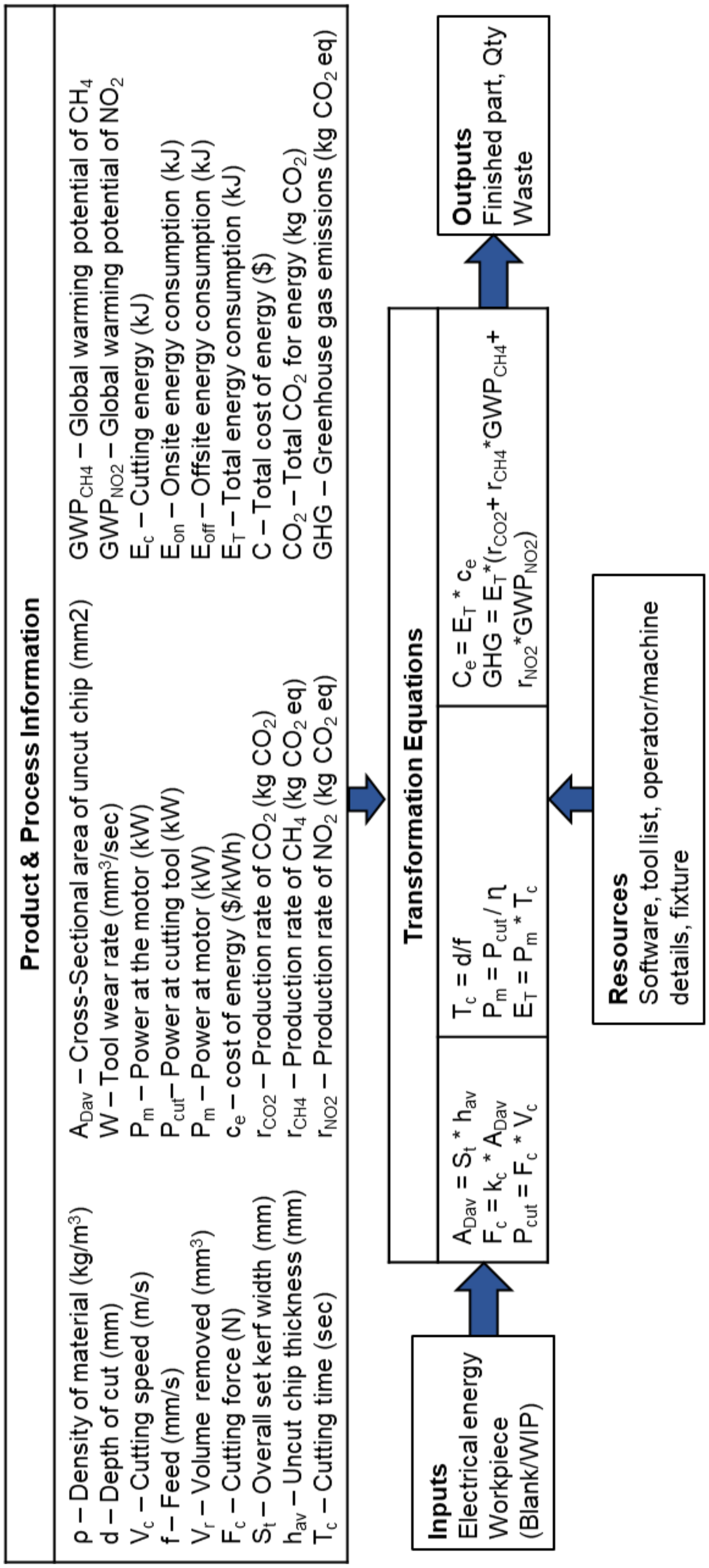


Appendix B6: XML representation of a composed system (extrusion-milling-annealing)

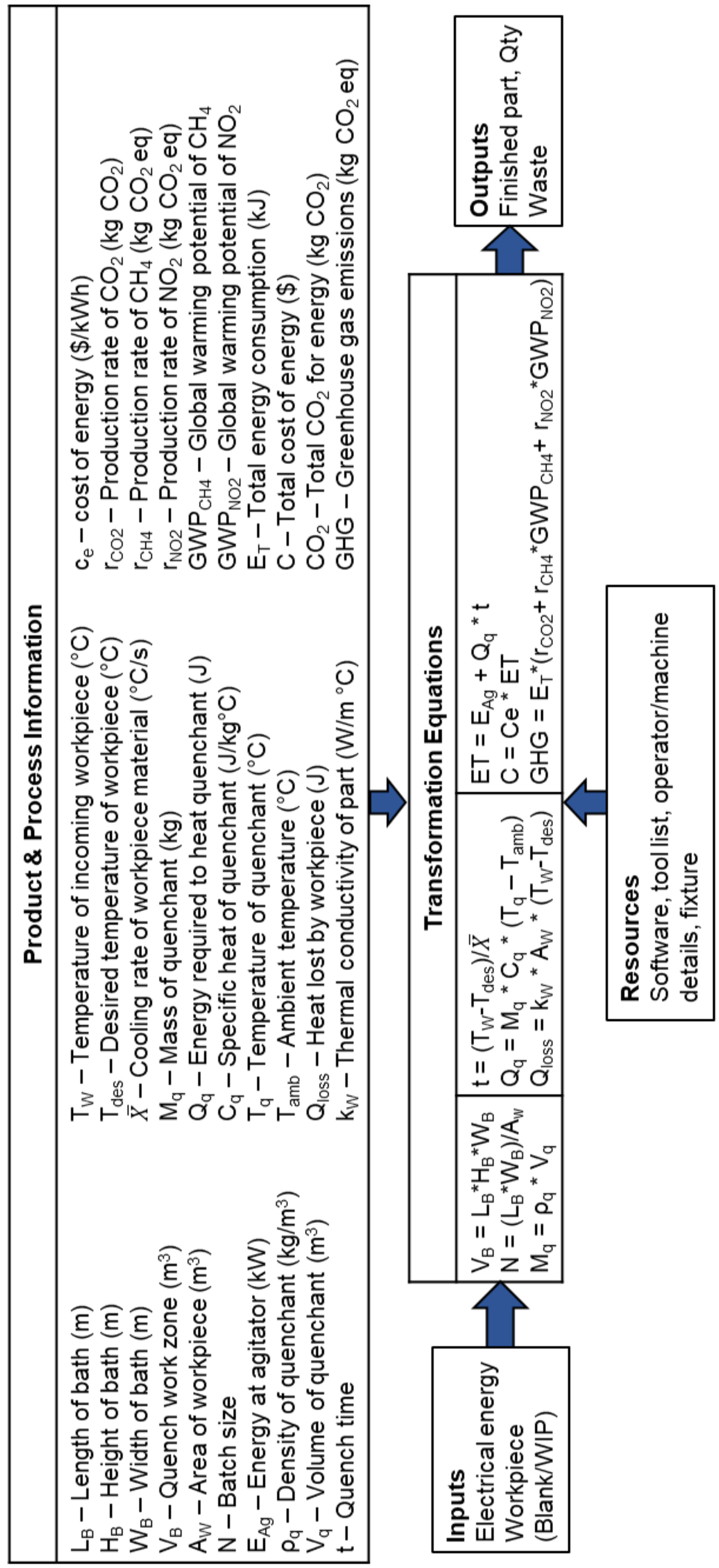

```
<UMP name=“Composed System” type=“Composition” description=“Extrusion_Milling_Annealing”>

//INPUT SECTION
<Input name=“Raw Material” description= “Type of workpiece input to the system”
category=“”type=“Workpiece” unit=“”/>
<Input name=“Electrical Energy_extrusion” description=“Input electrical energy for extrusion”
category=“”type=“Energy” unit=“kWh”/>
<Input name=“Electrical Energy_milling” description=“Input electrical energy for milling”
category=“”type=“Energy” unit=“kWh”/>
<Input name=“Electrical Energy_Annealing” description=“Input electrical energy for extrusion”
category=“”type=“Energy” unit=“kWh”/>
<Input name=“Natural gas” description=“Natural gas” category=“”type=“Energy” unit=“kg”/>

//LINKING VARIABLES SECTION

<Extrusion to Annealing>
<LinkingVariable name=“Density” description=“Material Density” category=“Process”value=“”
unit=“kg.mm^3”/>
<Linking variable name=“Yield Strength” description=“Yield Strength final”
category=“Process”value=“” unit=“N/m^3”/>
</Extrusion to Annealing>

<Extrusion to Milling>
<LinkingVariable name=“Density” description=“Material Density” category=“Process”value=“”
unit=“kg.mm^3”/>
<Linking variable name=“Extruded Length” description=“Yield Strength final”
category=“Process”value=“” unit=“N/m^3”/>
<Linking variable name=“Extruded Width” description=“Yield Strength final”
category=“Process”value=“” unit=“N/m^3”/>
<Linking variable name=“Extruded Height” description=“Yield Strength final”
category=“Process”value=“” unit=“N/m^3”/>
</Extrusion to Milling>

<Milling to Annealing>
<LinkingVariable name=“Density” description=“Material Density” category=“Process”value=“”
unit=“kg.mm^3”/>
<Linking variable name=“Milled Length” description=“Yield Strength final”
category=“Process”value=“” unit=“m”/>
<Linking variable name=“Milled Width” description=“Yield Strength final”
category=“Process”value=“” unit=“m”/>
<Linking variable name=“Milled Height” description=“Yield Strength final”
category=“Process”value=“” unit=“m”/>
</Milling to Annealing>

//PRODUCT AND PROCESS INFORMATION SECTION
//THIS SECTION WILL CONTAIN ALL THE PRODUCT AND PROCESS INFORMATION (PPI) OF EACH INDIVIDUAL
UMP
<Extrusion PPI>
</Extrusion PPI>
<Milling PPI>
</Milling PPI>
<Annealing PPI>
</Annealing PPI>

//TRANSFORMATION SECTION

//THIS SECTION WILL CONTAIN ALL THE TRANSFORMATION OF EACH INDIVIDUAL UMP
<Extrusion Transformation>
</Extrusion Transformation>
<Milling Transformation>
</Milling Transformation>
<Annealing Transformation>
</Annealing Transformation>
```

```
//RESOURCE SECTION

//THIS SECTION WILL CONTAIN ALL THE RESOURCE OF EACH INDIVIDUAL UMP
<Extrusion Resource>
</Extrusion Resource>
<Milling Resource>
</Milling Resource>
<Annealing Resource>
</Annealing Resource>

//OUTPUT SECTION

//THIS SECTION WILL CONTAIN ALL THE OUTPUT OF EACH INDIVIDUAL UMP
<Output name="Finished Part" description="Number of workpieces produced in an hour" category=""type="workpiece" unit=""/>
<Output name="Waste" description="Total waste of the system" category="Waste"type="workpiece" unit="kg"/>
</UMP>
```

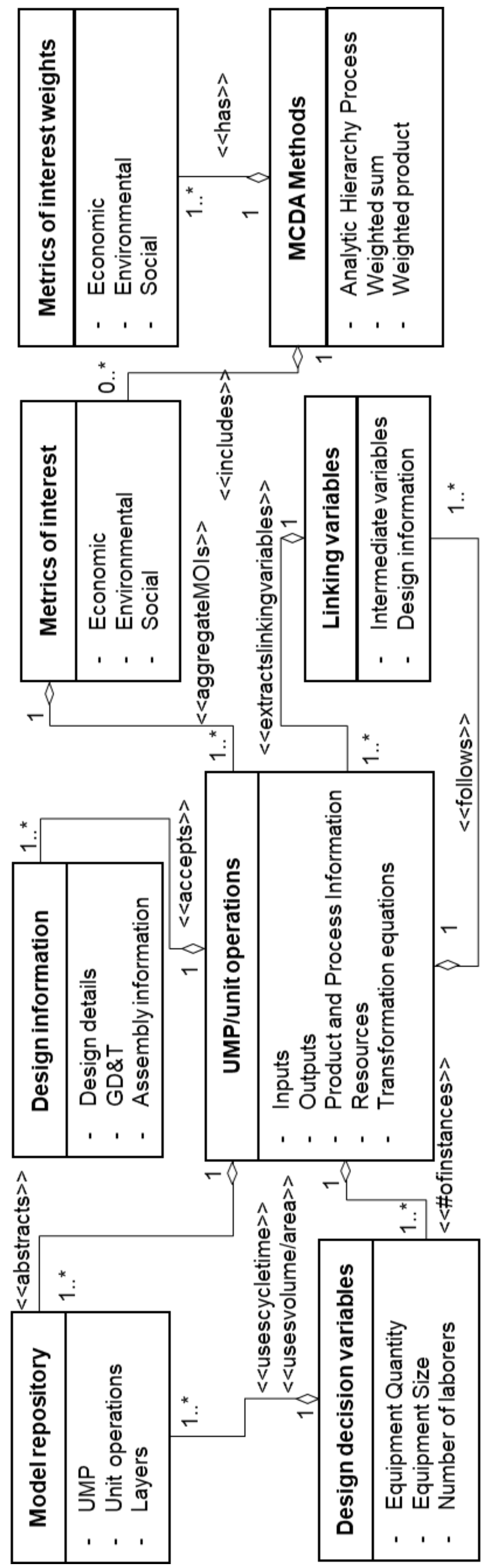
Appendix B7: Saw cutting UMP model based on the ASTM E3012-20 standard



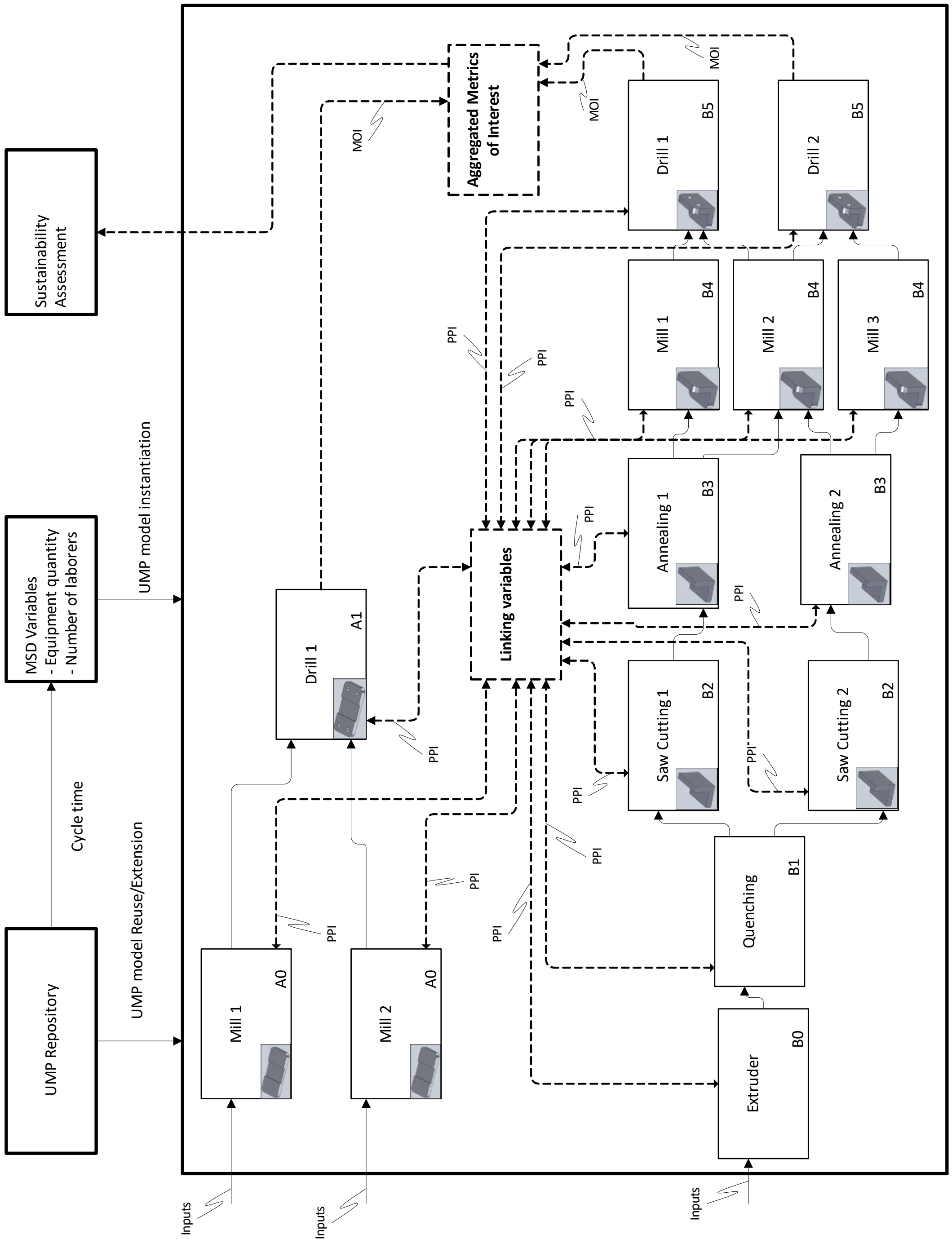
Appendix B8: Quenching UMP model based on the ASTM E3012-20 standard



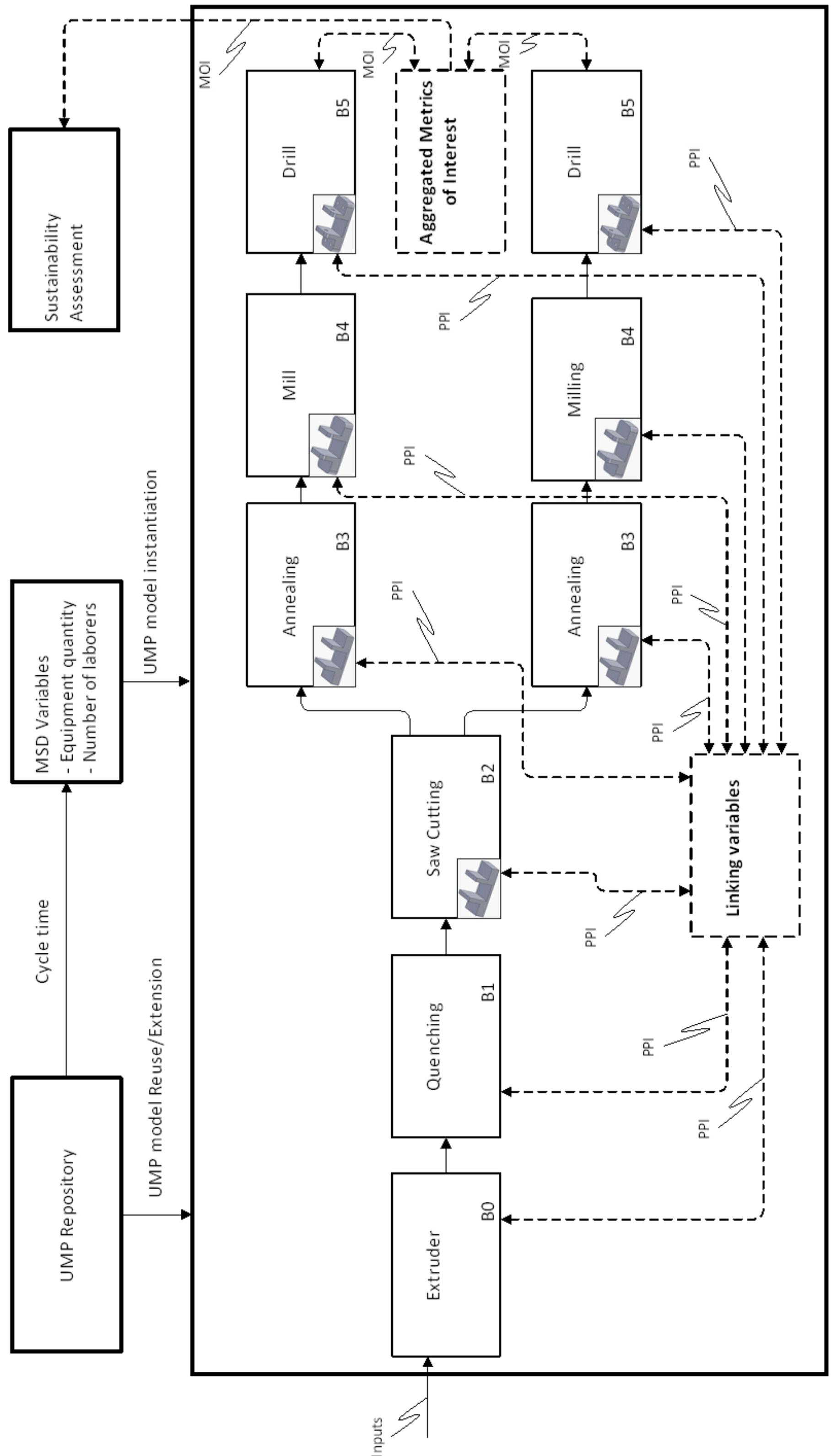
Appendix C1: Conceptual definition of the integrated framework using UML



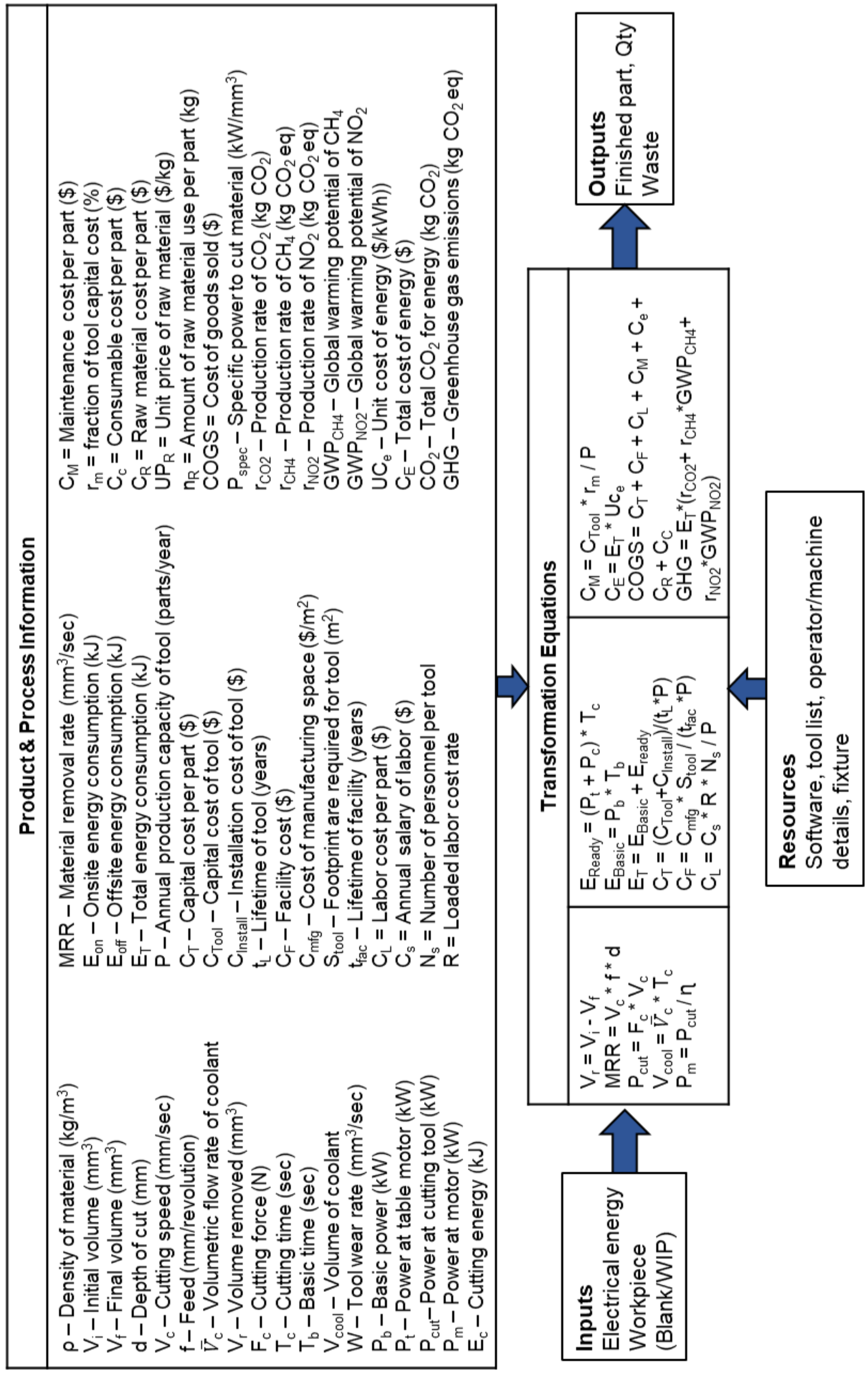
Appendix C2: Functional model of manufacturing system design alternative 1



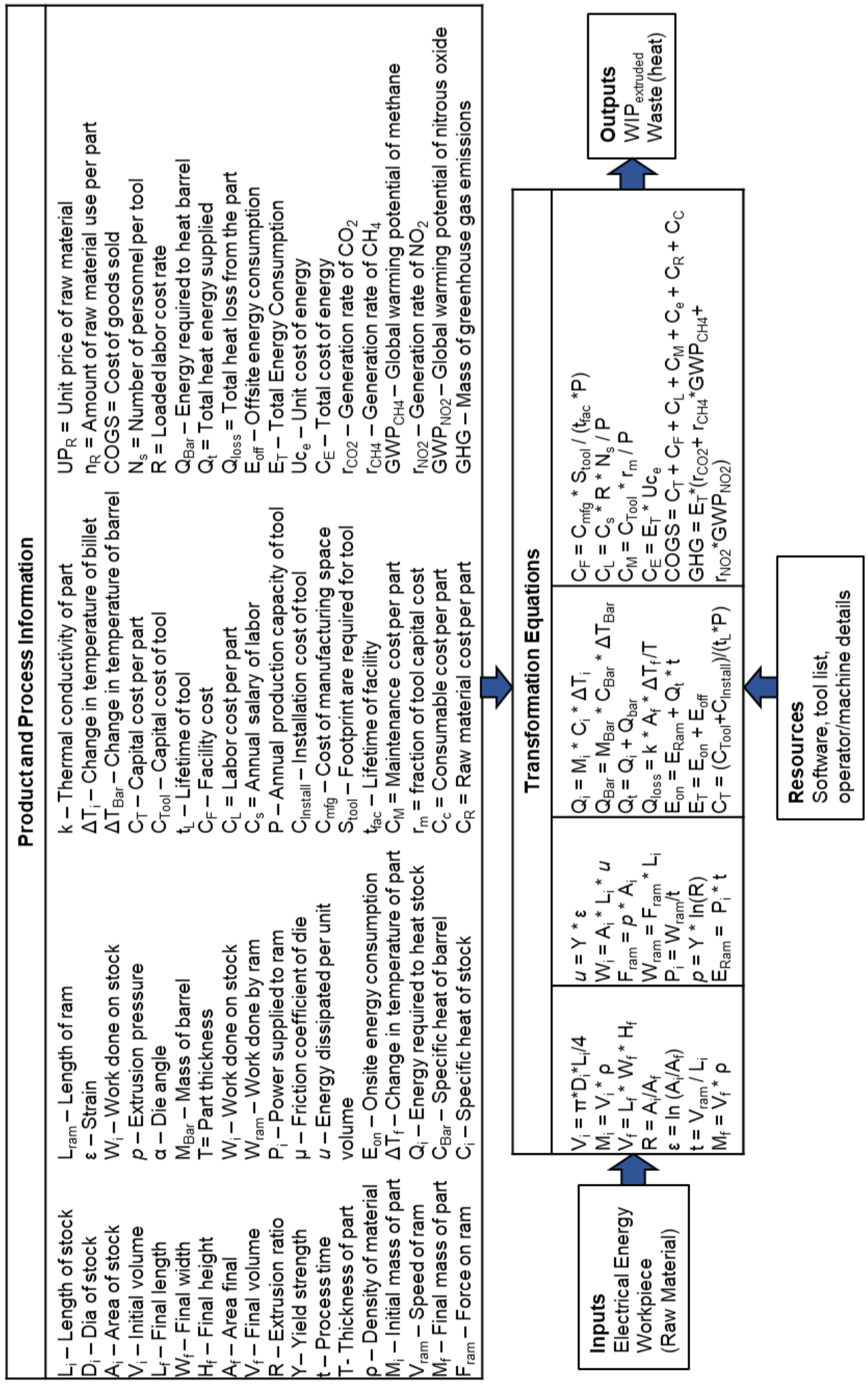
Appendix C3: Functional model of manufacturing system design alternative 2



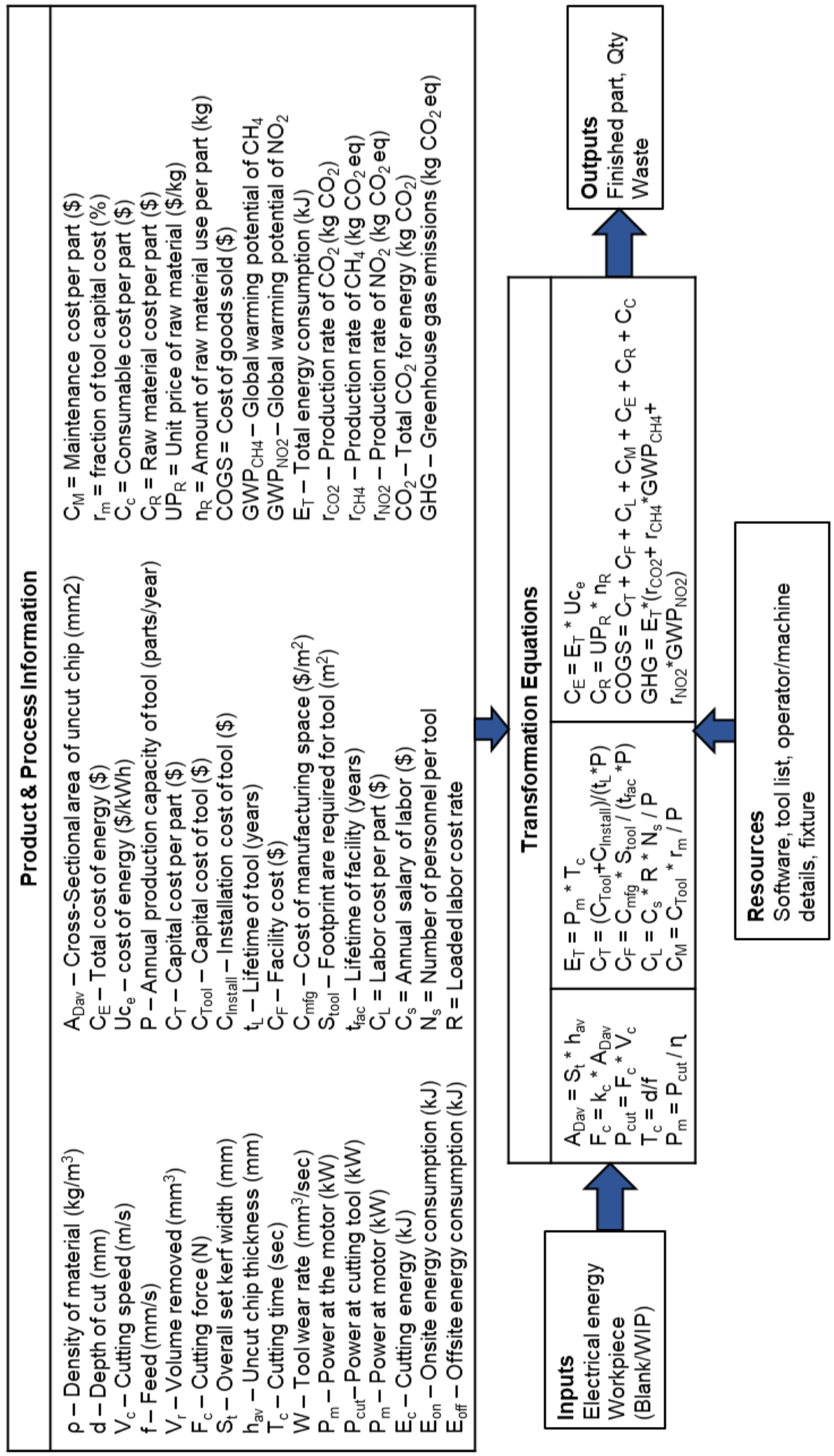
Appendix C4: Milling UMP model based on ASTM E3012-20 standard



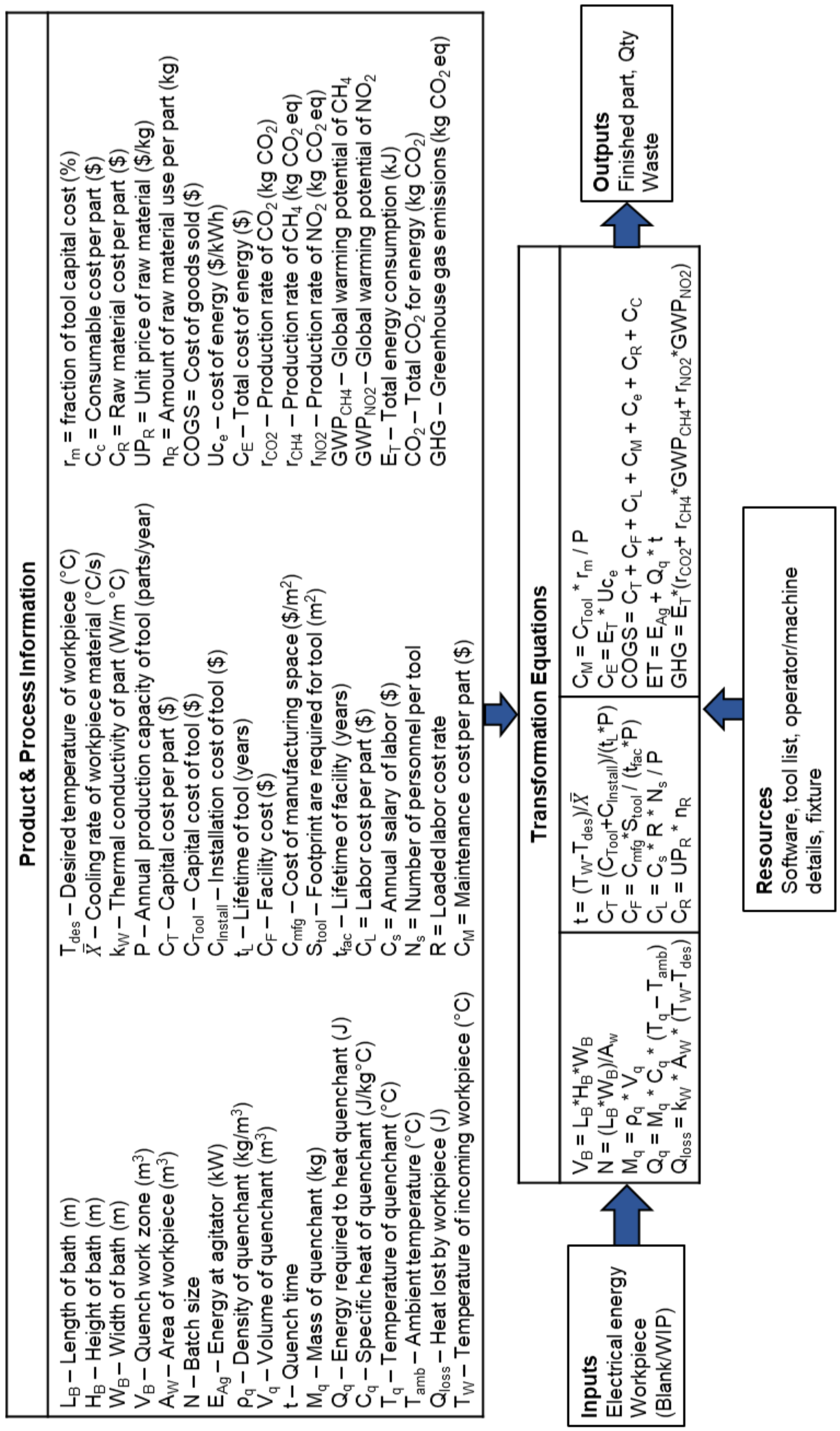
Appendix C5: Extrusion UMP model based on ASTM E3012-20 standard



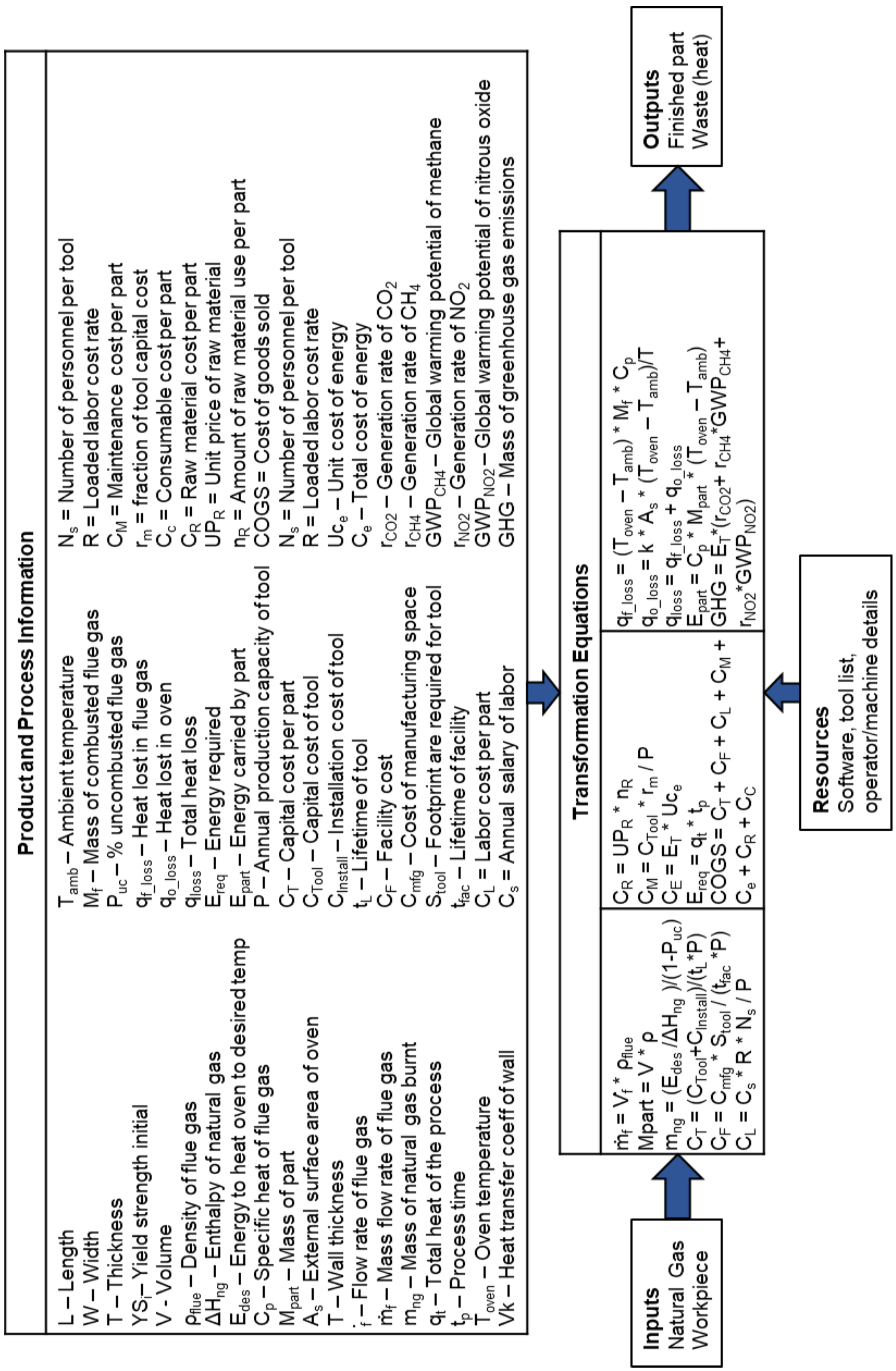
Appendix C6: Saw Cutting UMP model based on ASTM E3012-20 standard



Appendix C7: Quenching UMP model based on ASTM E3012-20 standard



Appendix C8: Annealing UMP model based on ASTM E3012-20 standard



Appendix C9: Drilling UMP model based on ASTM E3012-20 standard

Product & Process Information

ρ – Density of material (kg/m^3)
V_i – Initial volume (mm^3)
V_f – Final volume (mm^3)
d – Depth of hole (mm)
V_c – Cutting speed (mm/sec)
f – Feed (mm/revolution)
$\bar{V}_c$ – Volumetric flow rate of coolant
V_r – Volume removed (mm^3)
F_c – Cutting force (N)
T_c – Cutting time (sec)
T_b – Basic time (sec)
V_{cool} – Volume of coolant
W – Tool wear rate (mm^3/sec)
P_b – Basic power (kW)
P_t – Power at table motor (kW)
P_{cut} – Power at cutting tool (kW)
P_m – Power at motor (kW)
E_c – Cutting energy (kJ)

MRR – Material removal rate (mm^3/sec)
E_{on} – Onsite energy consumption (kJ)
E_{off} – Offsite energy consumption (kJ)
E_T – Total energy consumption (kJ)
P – Annual production capacity of tool (parts/year)
C_T – Capital cost per part ($)
C_{Tool} – Capital cost of tool ($)
$C_{Install}$ – Installation cost of tool ($)
t_L – Lifetime of tool (years)
C_F – Facility cost ($)
C_{mfg} – Cost of manufacturing space ($/m^2)
S_{tool} – Footprint are required for tool (m^2)
t_{fac} – Lifetime of facility (years)
C_L = Labor cost per part ($)
C_s = Annual salary of labor ($)
N_s = Number of personnel per tool
R = Loaded labor cost rate

C_M = Maintenance cost per part ($)
r_m = fraction of tool capital cost (%)
C_c = Consumable cost per part ($)
C_R = Raw material cost per part ($)
UP_R = Unit price of raw material ($/kg)
n_R = Amount of raw material use per part (kg)
COGS = Cost of goods sold ($)
P_{spec} – Specific power to cut material (kW/mm^3)
r_{CO2} – Production rate of CO_2 (kg CO_2)
r_{CH4} – Production rate of CH_4 (kg CO_2 eq)
r_{NO2} – Production rate of NO_2 (kg CO_2 eq)
GWP_{CH4} – Global warming potential of CH_4
GWP_{NO2} – Global warming potential of NO_2
UC_e – Unit cost of energy ($/kWh))
C_E – Total cost of energy ($)
CO_2 – Total CO_2 for energy (kg CO_2)
GHG – Greenhouse gas emissions (kg CO_2 eq)

Inputs
Electrical energy
Workpiece
(Blank/WIP)

Transformation Equations

$V_r = V_i - V_f$
$MRR = V_c * f * d$
$P_{cut} = F_c * V_c$
$V_{cool} = \bar{V}_c * T_c$
$P_m = P_{cut} / \eta$
$E_{Basic} = P_b * T_b$

$E_{Ready} = (P_t + P_c) * T_c$
$E_T = E_{Basic} + E_{ready}$
$C_T = (C_{Tool}+C_{Install})/(t_L*P)$
$C_F = C_{mfg} * S_{tool} / (t_{fac} *P)$
$C_L = C_s * R * N_s / P$
$C_R = UP_R * n_R$

$C_M = C_{Tool} * r_m / P$
$C_E = E_T * Uc_e$
$COGS = C_T + C_F + C_L + C_M + C_e + C_R + C_C$
$GHG = E_T*(r_{CO2}+ r_{CH4}*GWP_{CH4}+ r_{NO2}*GWP_{NO2})$

Outputs
Finished part, Qty
Waste

Resources
Software, tool list, operator/machine details, fixture

Appendix C10: Functional model of Haber Bosch Process (1 MT/day capacity)