2019

TRANSFORMING A CIRCULAR ECONOMY INTO A HELICAL ECONOMY FOR ADVANCING SUSTAINABLE MANUFACTURING

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Digital Object Identifier: https://doi.org/10.13023/etd.2019.132

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TRANSFORMING A CIRCULAR ECONOMY INTO A HELICAL ECONOMY FOR ADVANCING SUSTAINABLE MANUFACTURING

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Engineering
at the University of Kentucky

By
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2019

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ABSTRACT OF DISSERTATION

TRANSFORMING A CIRCULAR ECONOMY INTO A HELICAL ECONOMY FOR ADVANCING SUSTAINABLE MANUFACTURING

The U.N. projects the world population to reach nearly 10 billion people by 2050, which will cause demand for manufactured goods to reach unforeseen levels. In order for us to produce the goods to support an equitable future, the methods in which we manufacture those goods must radically change. The emerging Circular Economy (CE) concept for production systems has promised to drastically increase economic/business value by significantly reducing the world's resource consumption and negative environmental impacts. However, CE is inherently limited because of its emphasis on recycling and reuse of materials. CE does not address the holistic changes needed across all of the fundamental elements of manufacturing: products, processes, and systems. Therefore, a paradigm shift is required for moving *from sustainment to sustainability* to "produce more with less" through smart, innovative and transformative convergent manufacturing approaches rooted in redesigning next generation manufacturing infrastructure. This PhD research proposes the Helical Economy (HE) concept as a novel extension to CE. The proposed HE concepts shift the CE's status quo paradigm away from post-use recovery for recycling and reuse and towards redesigning manufacturing infrastructure at product, process, and system levels, while leveraging IoT-enabled data infrastructures and an upskilled workforce.

This research starts with the conceptual overview and a framework for implementing HE in the discrete product manufacturing domain by establishing the future state vision of the Helical Economy Manufacturing Method (HEMM). The work then analyzes two components of the framework in detail: designing next-generation products and next-generation IoT-enabled data infrastructures. The major research problems that need to be solved in these subcomponents are identified in order to make near-term progress towards the HEMM. The work then proceeds with the development and discussion of initial methods for addressing these challenges. Each method is demonstrated using an illustrative industry example. Collectively, this initial work establishes the foundational body of knowledge for the HE and the HEMM, provides implementation methods at the product and IoT-enabled data infrastructure levels, and it shows a great potential for HE's ability to create and maximize sustainable value, optimize resource consumption, and ensure continued technological progress with significant economic growth and innovation. This research work then presents an outlook on the future work needed, as well as calls for industry to support the continued refinement and development of the HEMM through relevant prototype development and subsequent applications.

KEYWORDS: Sustainable Manufacturing, Helical Economy, Product Design, Modeling and Optimization, Smart Manufacturing

Ryan T. Bradley

[04/15/2019]
Date

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To Caroline

ACKNOWLEDGMENTS

This dissertation would not have been possible without the technical and moral support of many, and I wish to thank them all with the upmost sincerity and gratitude. First, I want to thank Dr. Jawahir for the continuous academic guidance and encouragement. Over the years, Dr. Jawahir has become a mentor and a friend, and I am forever thankful for the initial passion he instilled in me for the field. I hope that we will continue brainstorming big ideas far into the future and continue progressing Sustainable Manufacturing to great heights.

Next, I want to offer a personal thanks to Dr. Badurdeen. She has been a cornerstone of my education in and out of the classroom. I look forward to future collaborations.

I also want to offer a sincere thanks to Dr. Rouch and Dr. Holloway for agreeing to be a part of my committee. Their insight in the field has been inspiring. I also want to offer a special thanks to Dr. Dadi for serving as the outside examiner.

My time spent at the Institute for Sustainable Manufacturing (ISM) and the University of Kentucky has been incredibly rewarding. I have met incredible colleagues, friends, and mentors along the way; and although there are too many to name individually, I thank them all. One day, I hope to give back to the place that has offered me so much.

In addition to the technical and academic support, I wish to thank my family and friends for offering their never-ending moral support. I thank my dad for always teaching me to give my all and to never give up. I thank my mom for teaching me to be humble in my successes and to always offer a lending hand. I thank Julie Whitney and Niko Murrell for being great mentors. I thank my friends for taking the time out of their days to offer their friendship and laughter. This wouldn't have happened without you all. And lastly, I want to thank my best friend and loving wife, Caroline, for being there for me since the beginning. She and our dog, Reags, continually bring joy to my life.

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CHAPTER 1 INTRODUCTION AND MOTIVATION

1.1 Motivation

1.1.1 *Manufacturing's Vital Role*

The U.N. projects the world population to reach ~10 billion people by 2050 [1]. In addition, in 2011, 71% of the global population was living on less than 10 dollars per day [2]. This 71% wants a path towards the middle class, so this sought-after upward mobility in the developing world combined with a surging population will cause the demand for manufactured goods to reach unforeseen levels. This demand will translate into an unprecedented consumption of materials. Based on the Organization for Economic Co-operation and Development's (OECD) *Global Material Resources Outlook to 2060* [3] study, if materials use were to keep up with the economic growth, the total global materials use would increase by 458%. Not only is the direct materials use alarming, but this increase in manufactured goods will also result in unparalleled energy consumption and associated greenhouse gas emissions. The manufacturing sector already contributes significantly to both of these, directly consuming more than 35% of the global energy supply [4] and directly contributing more than 25% of global greenhouse gas emissions [5]. These numbers increase further when accounting for the indirect contributions through the transportation, agriculture, and other economic sectors. Therefore, the broader, outsized impact that the global manufacturing sector has on the overall sustainability of the environment, economy, and society cannot be ignored. For the global manufacturing sector to support an equitable and sustainable future, the methods in which we manufacture goods must radically change with significant novelty and innovation.

1.1.2 *Lean to Green to Sustainable Manufacturing*

Lean manufacturing focused efforts on *Reducing* waste throughout production systems. Great industrial leaders such as Henry Ford and Taiichi Ohno greatly transformed the face of manufacturing and ushered in monumental waste elimination across various industries [6,7]. However, up until the late 1900s, all focus was on the economic value of waste. It was not until the "Green" movement when consumers, industrial leaders, and politicians became interested in the environmental and societal impacts that were directly associated with manufacturing. It was at this time when the concept of *Reusing* and *Recycling* started to take hold across many manufacturing operations [8]. However, the flaw in this concept was that it was inherently limited by recycling and reuse applications, and it was dismissive in the economics around settling for sacrificing cost for an environmental and societal benefit.

The 21st century economy demanded further innovation and it showed that achieving sustainable value in manufacturing required yet another transformation from a 3R [9] to a 6R foundation; a transformation where the emphasis is not singularly on economics or on environmental and societal aspects, but where it is on the "Triple-Bottom-Line", or the combination of the economy, environment, and society in one. By extending the original 3Rs of *Reduce, Reuse,* and *Recycle* to a 6R concept [10], with the addition of widespread *Recovery* of material resources, *Redesigning* legacy technology and next-generation products and processes, and the subsequent *Remanufacturing* of products, there arises a defined rapidly emerging methodology known as Sustainable Manufacturing. The progression from Lean to Green to Sustainable Manufacturing can be seen in Figure 1.1 [11]. This 6R-based closed-loop approach, which was originally introduces in 2006 by

Jawahir et al. [10], not only targets the growing problem with depleting resources, but also reimagines what was once considered waste into a recoverable, reusable, and remanufacturable economic asset for the future.

1.1.3 *Linear to Circular to Helical Economy*

The consumerism-driven linear economy, the underlying basis that has driven the global

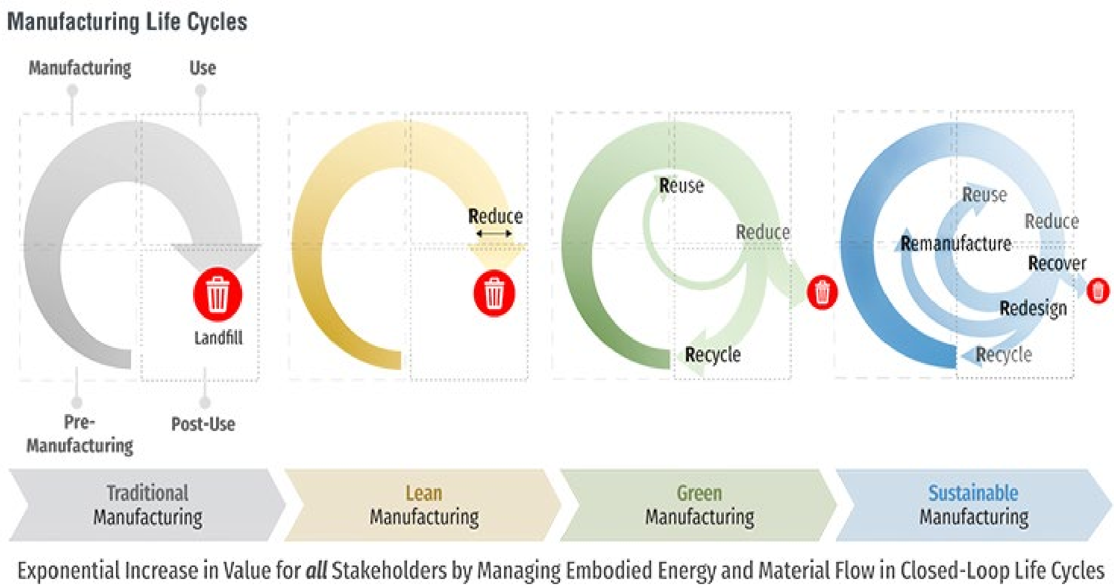


Figure 1.1: Progression from Lean to Green to Sustainable Manufacturing [11]

economy since the Industrial Revolution, is inherently flawed and poses significant economic, environmental, and societal risk to current and future generations. Looking back to early civilizations, the foundation for modern-day consumerism originated as a solution for eliminating scarcity and inequality in hierarchical societies [12,13]. This rise of consumerist thought was embedded in the idea that consuming more would blur the lines in an archetypal classed-based civilization. It would soon be latched on to as the sole solution for driving political, economic, and technological progress. Consequently, humanity would be plagued with the lingering perception of "Consumption = Progress".

Industrial leaders would exploit this speculation even further and with the aid of the Industrial Revolution and globalization, a global economic system would be formed based on a linear model of rapidly taking resources, creating goods, selling those goods to consumers, and the consumers disposing of those goods. All manufacturing infrastructure over the next century would be created for this linear economy, from product design tools and techniques, to manufacturing processes and tooling, to factories and complex supply chains.

As awareness of sustainability and the role of manufacturing began to grow, the Circular Economy (CE) concept surfaced. The Circular Economy has roots across many other topics, but the general premise is keeping resources in use for as long as possible, and then capturing them and reutilizing them in new products in order to reduce overall resource and energy consumption. The 6Rs serve as the technological elements of the Circular Economy (CE) concept [14], and this 6R concept can be coupled with the new waved with the "Circular Economy" concept is making in the sociopolitical space to offer a technical foundation for manufacturing implementation [14]. This coupling is illustrated in Figure 1.2 [14].

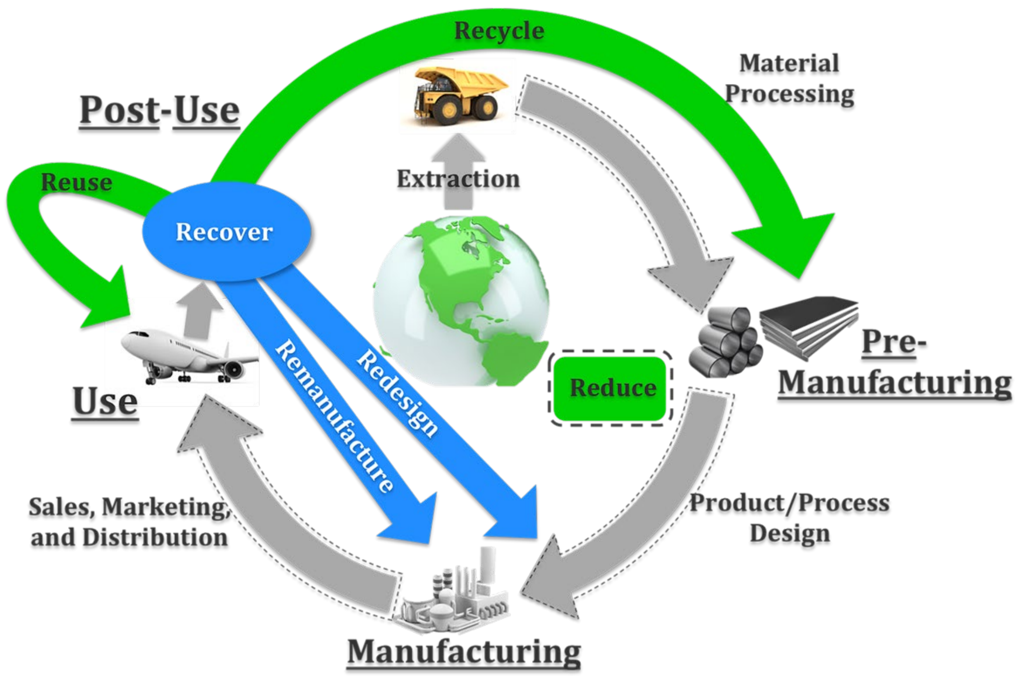


Figure 1.2: Circular Economy and the 6R foundational elements [14]

The Circular Economy promises to simultaneously reduce anthropogenic emissions while generating business value [15]. However, CE mainly lives in ambiguity in the manufacturing domain because CE does not explicitly address the changes needed at the product, process, and system levels. Also, due to the market differentiation CE establishes, industry has seen many misrepresentations of the implementation strategies of CE. Numerous manufacturers are relabeling business practices as being a new implementation of CE, when in reality; the practice was already in existence. Even for the new CE applications, the CE approach taken is more aligned with a waste management strategy than with a manufacturing framework [16–19]. CE is inherently limited because of its strong emphasis on recycling and reuse and the sustainment of earthly resources. CE does not address the changes needed across all of the fundamental elements of manufacturing:

products, processes, and systems. Therefore, a paradigm shift is required for moving from sustainment to sustainability to “produce more with less” through innovative and transformative convergent manufacturing approaches rooted in redesigning next generation products and processes. This dissertation proposes the Helical Economy concept. Helical Economy shifts the paradigm away from waste management and to redesigning manufacturing infrastructure at the product, process, and system levels. Shown

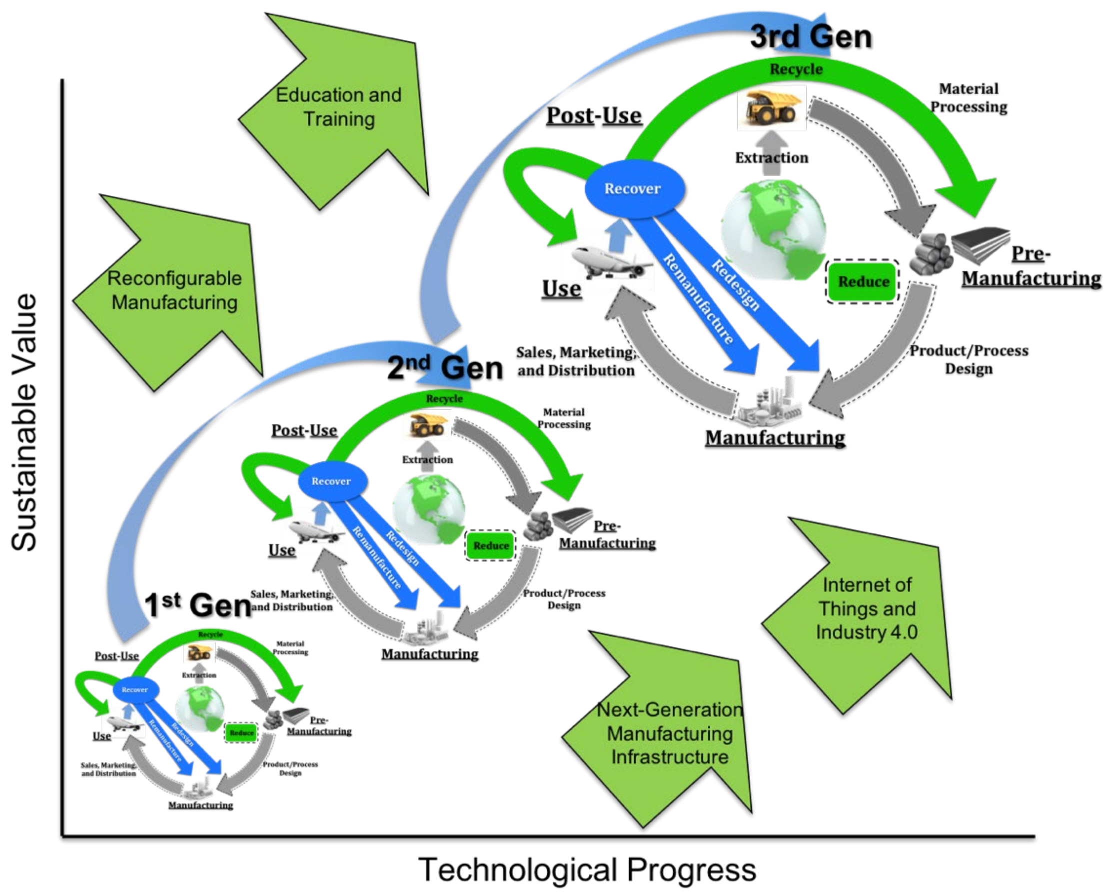


Figure 1.3: Transforming Circular Economy to Helical Economy and the Driving Elements shown in green.

in Figure 1.3, to achieve this, the Helical Economy takes advantage of multiple concepts across multiple manufacturing technological elements: internet of things and Industry 4.0, redesigning manufacturing infrastructure, leveraging reconfigurable manufacturing systems, and upskilling a next-generation workforce through education and training. The scope of work is shown to be interdisciplinary and systems-focused.

1.2 Research Objectives

The major research objectives of this dissertation are to:

1. *Propose the Helical Economy as a novel extension to the Circular Economy, and develop the framework for the Helical Economy Manufacturing Method (HEMM)*

With the alarmingly rising global population, atmospheric carbon dioxide levels and other toxic gases from manufacturing activities, and an unprecedented consumption of natural resources, the impetus for defining an alternative manufacturing paradigm is easily understood. This dissertation abstracts the current state of the linear economy and circular economy and tries to establish a future state that can improve sustainable value, reduce resource consumption, and maintain technological progress.

Once established at an abstract level, the Helical Economy concept must be tied into the manufacturing domain. Therefore, the dissertation aims to develop a framework for the Helical Economy Manufacturing Method (HEMM) that is deeply rooted in the redesigning of manufacturing infrastructure at product, process, and system levels. This framework includes the definition of key performance indicators for driving increased sustainable value, a reduction in resource consumption, and maintaining technological progress.

The second and third objectives focus on two components of the HEMM: designing next-generation products and IoT-enabled data infrastructures:

2. *Identify the major research problems that need to be solved in designing next-generation products and develop initial methods in order to make near-term progress towards the HEMM.*

3. *Identify the major research problems that need to be solved in designing next-generation IoT-enabled data infrastructures and develop initial methods in order to make near-term progress towards the HEMM.*

This dissertation does not aim to solve every aspect of defining the HEMM. It is well understood that successful implementation of the HEMM will take many years of research and innovation. However, the dissertation does aim to identify the major research problems that can be solved for designing next-generation products and IoT-enabled data infrastructures in order to make near-term progress towards the HEMM.

This dissertation could also not conceivably define the entire set of tools and methodologies needed to realize the HEMM vision. Tool and methodologies for the existing manufacturing paradigms have been being developed over decades and nearly centuries. However, this dissertation does establish a few initial methods for designing next-generation products and IoT-enabled data infrastructures that can be used for near-term industry implementation.

1.3 Dissertation Outline

This dissertation is outlined as follows:

Chapter 2 reviews the relevant literature in order to provide a foundation for the dissertation. Topics reviewed are sustainable manufacturing, circular economy, manufacturing methods, and the internet of things (IoT) and manufacturing. The chapter then highlights the research gap that this dissertation aims to address and outlines the approach taken.

Chapter 3 proposes the methodology for the Helical Economy concept through an abstraction that compares its benefits in relation to the Circular and Linear Economy alternatives. Three key performance indicators (KPIs) are then proposed: sustainable value creation, resource consumption, and technological progress. The framework for the Helical Economy Manufacturing Method is then presented which focuses on redesigning manufacturing infrastructure at product, process, and system levels with a strong emphasis on utilizing an IoT data infrastructure and upskilled workforce.

Chapter 4 examines designing next-generation products, as a core component of the HEMM. A motivation is presented and the relevant literature around product design is reviewed. The major research problems and challenges for designing products are then identified. Initial methods for industry implementation are then presented for two classes of product design: 1) new product design, and 2) adaptive product design and redesign. For new product design, a new set of Design for Helical Economy (DfHE) guidelines is presented. For adaptive product design and redesign, an initial framework for a toolkit is developed, the Helical Optimization and Prediction Engine (HOPE). HOPE is comprised of three product-level modules: 1) predicting product life cycle performance during design (HOPE-Design), and 2) predictively and proactively maintaining a modular product (HOPE-Maintain), and 3) selecting optimal product configuration and reconfiguration (HOPE-Configure) which is planned as future work.

In Chapter 5, the topic of designing an IoT data infrastructure is examined. A motivation is presented, and the relevant literature surrounding smart manufacturing is reviewed. The major design challenges related to establishing an IoT-enabled data infrastructure for the HEMM are identified. An integration plan for two initial methods of industry implementation are then presented: 1) A scalable method for reducing the overall sensor infrastructure needed through the use of machine-learning (ML) and concurrent engineering, and 2) A method for reducing the training set needed in deploying machine-learning based sensor systems in a smart-manufacturing infrastructure.

In Chapter 6, the contributions of the dissertation are summarized. Future work for examining the process and systems level manufacturing infrastructure as it pertains to the HEMM is previewed along with a look at the next-generation workforce. The dissertation closes with initial plans for industry application and prototype developments.

CHAPTER 2 LITERATURE REVIEW

2.1 The 6Rs of Sustainable Manufacturing

The traditional 3R [9] of Reduce, Reuse, Recycle follows a cradle-to-grave approach, but it fails to recognize the post-use stage and the existence of multiple generations of use. The sustainable manufacturing approach focuses on a broader, innovation-based 6R methodology for products over multiple life-cycles [10]. In the 6R methodology, *Reduce* mainly focuses on the first three stages of the product life-cycle, and focuses on reducing overall resource and energy consumption. *Reuse* refers to the reuse of the product, its assemblies, or its individual components after its first life-cycle, for subsequent life-cycles, in an effort to reduce total resource and energy consumption. *Recycle* involves the process of taking the materials of a used product and converting them through mechanical or chemical processes into raw materials that can be used by the same or different products. The process of collecting products at the end of the use stage, disassembling, sorting and cleaning for utilization in subsequent life-cycles of the product is referred to as *Recover*. The *Redesign* activity involves the act of redesigning of next generation products, processes and systems to better utilize components, materials and resources recovered from the previous generation. *Remanufacture* involves the re-processing of already used products for restoration to their original state or a like-new form through the reuse of as many parts as possible without degradation of quality. This 6R approach offers a manufacturer-centric, closed-loop, multi-generational life-cycle system as the basis for sustainable manufacturing (Fig. 2.1) [20].

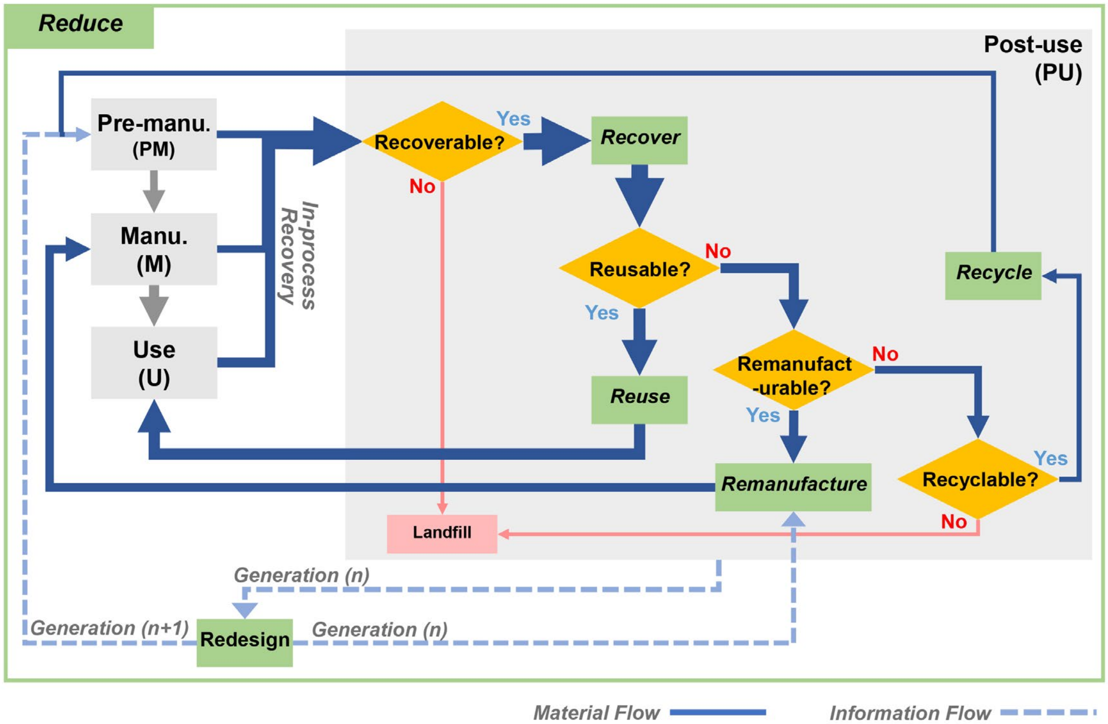


Figure 2.1:Overall framework of the 6R elements of sustainable manufacturing [20]

Since the formation of the 6R concept, there has been considerable research on its application to product design and manufacturing. Liew et al. [21] used aluminum beverage cans as a case study to apply the 6R concepts for enhanced sustainability. The work showed great promise in improving the recycling process. Ungureanu et al. [22] took the 6R elements and applied them to automotive components. Aluminum and steel bodies were reviewed and compared against each other. The result showed that aluminum should be further reviewed as a potential replacement for steel in the future. De Silva et al. [23] utilized the 6R elements in the development of several key metrics that evaluated the sustainability of a product at the design and development stage. The work showed great application in a case study involving consumer electronic products. Gupta et al. [24] also showed the development of a set of metrics that evaluated a product based on total life cycle considerations. The paper identified the 4 stages of a manufactured product: Pre-Manufacturing, Manufacturing, Use, and Post-Use. The work showed that the consideration of the total life cycle holds an advantage over the 3R approach. Zhang et al. [25] expanded on the work by De Silva et al. [23] to establish a product sustainability index. This mathematical and quantitative method showed the ability to apply the 6R concept to the assessment of an array of manufactured products. Overall, the 6R concept has passed the viability stage, but there is a need for it to be built into a practical manufacturing framework to bring the closed-loop concept into reality.

2.2 The Circular Economy Concept and its Limitations

2.2.1 *Circular Economy Origins*

It is hard to track the origin of the concept of circular economy, because the general premise has roots across many concepts, and it holds many definitions which can be generalized to the Figure 2.2 [26]. Economists such as Skene and Murray [27] have mapped the progression of the circular economy to previous concepts such as biomimicry [28], industrial symbiosis [29], industrial ecology [30], cradle-to-cradle [31], etc.

Figure 2.2: Generalization of CE [26]

Biomimicry is the idea that nature can be used as a source for technological innovation [32]. For example, the honeycomb geometry of a bee has been utilized in many engineering applications as the means for minimizing resources, costs, and overall weight while still achieving high performance mechanical properties.

Industrial Symbiosis refers to the collaboration of distinct industries in the exchange of materials, energy, water, and/or byproducts in order to minimize overall resource consumption [29]. An example of this in action is microbreweries that create spent grain and then supply this grain to local farms.

Industrial Ecology builds an analogy between the biological ecosystem and the industrial ecosystem where the products, processes and systems function to minimize resource and energy consumption [33]. Jelinski et al. [34] defined three system types in the industrial ecology domain: Type 1 (linear), Type 2 (semi-cyclical), and Type 3 (completely cyclical) systems. The work goes on to say that the biological system as evolved over million years to produce all of the entities needed for a Type 3 system, but in order for the industrial ecosystem to move to Type 3 entities, it will require the creation of the missing entities, which can also be interpreted as the necessary infrastructure.

Cradle-to-Cradle is the concept of going beyond the cradle to grave manufacturing model, and designing products that can be used as biological or technical nutrients once after their useful life [31]. McDonough and Braungart both recognized that infrastructure needed to change in order to realize their vision.

The Circular Economy concept also has roots in China. The concept was first introduced in China by Zhu [35] in 1998 in a proposal that would be later adopted by the Chinese government in 2002 as a viable plan to alleviate growing resource depletion and pollution concerns [36]. Yuan et al. [36] also noted that the conventional linear approach to economic development was unsustainable in China. The work reviewed the idea of CE and its implementation at three levels: the individual firm level, the regional level, and the province level. At the individual firm level, the firms are usually required to perform auditing to their manufacturing practices. As a part of this, local environmental agencies label the firms according to their environmental performance. At the regional level, developing an eco-friendly network of production systems is the primary objective. In fact, China has created eco-industrial parks where infrastructure and equipment is shared in order to implement CE at this level (See the example in Figure 2.3 [37]). At the third level, the focus shifts from a pure production standpoint and is refocused on both production and consumption.

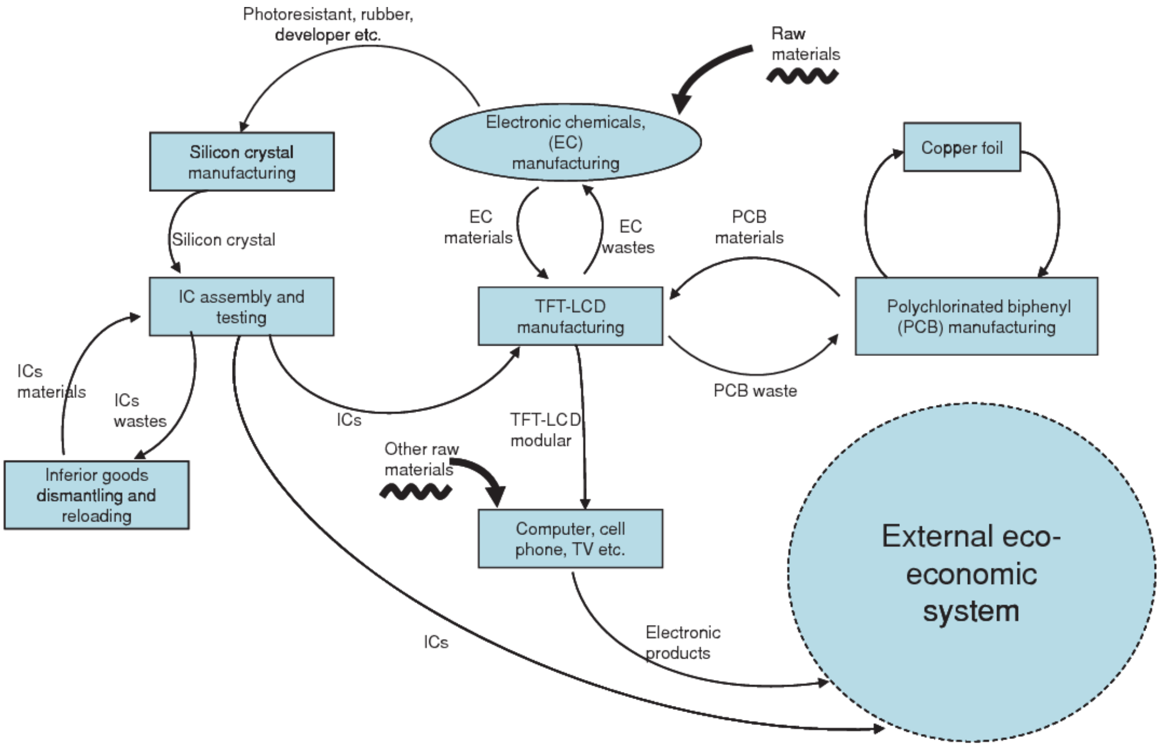


Figure 2.3: Example of an Eco-Industrial Park in Guigang City [37] License Number: 4576281379218

Although CE tends to be used in explaining materials and energy flows, CE is gaining interest as an economic paradigm. Under that umbrella, the CE concept has close ties to the degrowth and steady state economic theories of Georgescu-Roegen and Daly [38,39]. In steady-state economics, the economy must shrink or go through a period of degrowth to arrive at a state that is within ecological limits. CE's ideal case aligns with this strategy by keeping materials in a perpetual loop of utilization and eliminating the need for virgin resources. However, the steady-state theory is not without its flaws. It assumes that the population is economically equal when entering into the steady state and that no material fluctuations will occur in population or economic growth.

2.2.2 *The Modern Resurgence*

The Circular Economy (CE) concept has been most recently championed by the Ellen MacArthur Foundation (EMF) [40–42], and is defined as being "restorative and regenerative by design, and aims to keep products, components, and materials at their highest utility and value at all times." Figure 2.4 shows the system diagram championed by the EMF.

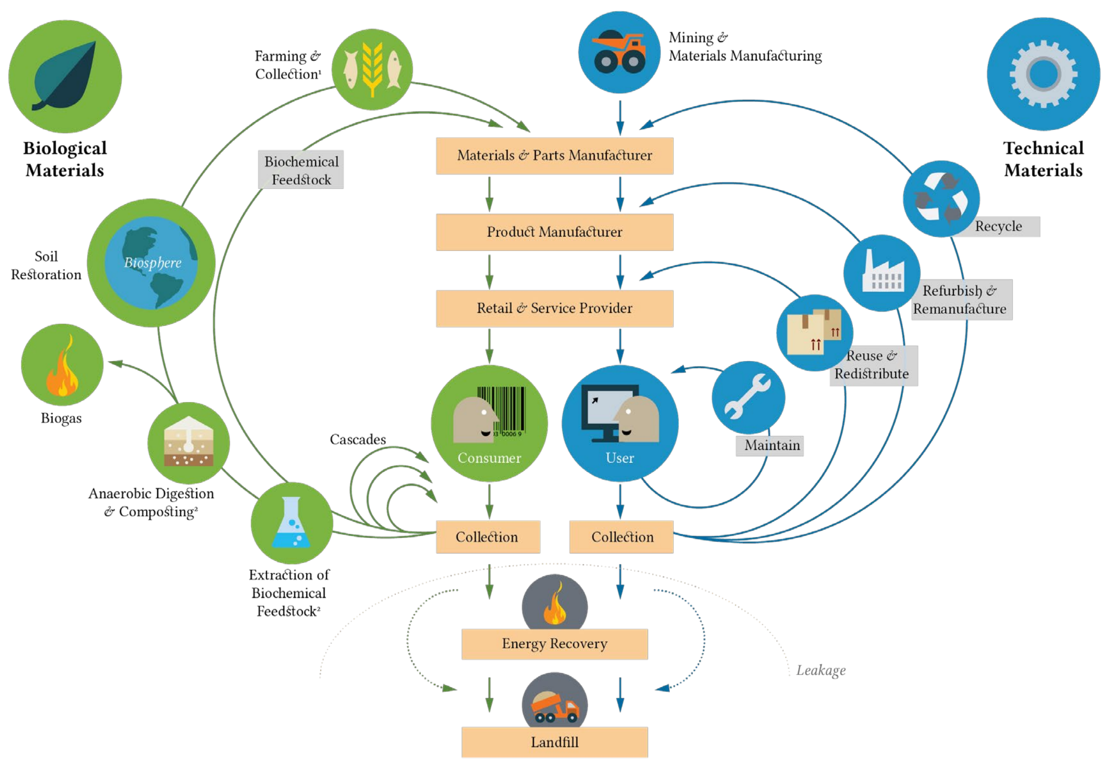


Figure 2.4: CE System Diagram Championed by the EMF [40], used with educational permission from the Ellen MacArthur Foundation

Although not novel, this conceptualization of CE seems to have gained the most traction and stakeholder support amongst all of its predecessors due to its appeal to both environmentally conscious and economically conscious agendas. That being said, a polarization of the concept has been observed across the research and industrial practice communities [43]. There is the school of thought that CE is a waste reduction strategy aimed at closing material loops via recycling and other end-of-life mechanisms [16–19]. There is also the school of thought, that is widely promoted through the EMF, that aims at a redesign across all life cycle stages of pre-manufacturing, manufacturing, use, and post-use [14,44,45]. In the former, CE is thought of as either a "band-aid" solution to the linear economic model or as a means to mine short-term economic value, both of which ignore finding the root cause. In the latter, the root cause is addressed with an understanding that there may or may not be a short-term economic gain. This chasm is due to the abstractness of the concept, and it has been why the CE has been slow in implementation. Due to the public relations advantage around corporate sustainability and the differentiation it establishes in business-to-business (B2B) markets, industry has seen a lot of "noise" in regard to true implementation of CE. Numerous manufacturers are relabeling certain business practices as being implementations of CE, when in reality; the practice was already in existence.

2.2.3 *6Rs and the Circular Economy*

The CE concept has also been linked to the 6R elements of sustainable manufacturing [14]. Looking across the "R" elements, Kirchherr et al. [46] analyzed 114 definitions of CE. A vast majority of the definitions had an overarching focus on the 3Rs (Reduce, Reuse, Recycle) with a 4th "R" (Recover) only mentioned on occasion. From this, the conclusion drawn is that most manufacturers are primarily leveraging CE as a waste management strategy rather than a manufacturing framework. CE implementations of this nature are attempting to mine short-term economic value rather than address the long-term problems through a system-level redesign. In fact, across the 114 CE definitions analyzed by

Kirchherr et al., a system shift is often not highlighted as part of the description. The waste management focused strategy also causes degradation in sustainable value because there are still constraints to operate in a linear infrastructure. To go beyond a waste management strategy, the "R" elements of Redesign and Remanufacturing must be considered in combination with the prevention of degradation. These together result in upgradability [47], which is a key element of overall sustainability.

2.2.4 *Key Limitations*

Circular economy has emphasized the need for closed-loop material flow and technology advancement, but the technological aspects of achieving the conceptual state have been largely unaddressed [26], leaving the implementation up to the synthesis of limited industry case studies. There has been a lack of analysis of the various technological elements and infrastructure changes that need to be developed and integrated into economic models to create sustainable value. Overall, the three gaps that exist in the current landscape of the CE concept are:

1. Manufacturers need a more practical conceptualization in the context of products, processes, and systems;
2. Degrowth and Steady State economics are not viable options for the significant portion of the world that lives in poverty. Economic growth needs to be decoupled from resource consumption through technological innovation;
3. A waste management focused strategy of recycling and reuse is not sufficient. The lack of consideration for the redesign of manufacturing infrastructure can result in adverse impacts on innovation and economic growth.

2.3 Internet of Things (IoT) and Manufacturing

2.3.1 *Industry 4.0 & Cyber-Physical Systems*

The manufacturing arena has seen the concepts of Industry 4.0 and the Cyber-Physical systems (CPS) gain interest in the last decade, and they both have a close connection to IoT (See Figure 2.5 [48]).

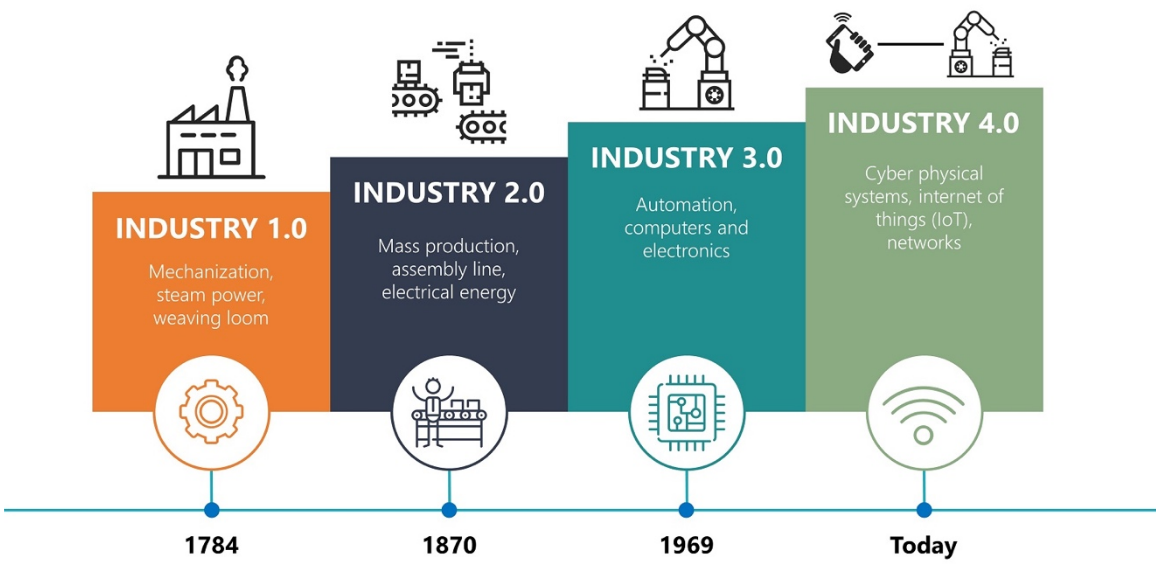


Figure 2.5: Showing Industry 4.0 evolution and integration with Cyber Physical Systems [48]

CPS are defined to be a harmonization of physical processes and the computational world through mechanisms such as embedded sensors and feedback control systems [49]. Industry 4.0 takes CPS and envisions a next-generation manufacturing industry where CPS are highly utilized on the factory floor [50]. In addition, the approach claims that high value data and analytics, collected from the CPS, are leveraged to make manufacturing more efficient, more customizable, and more resilient [51,52]. There has also been work that looks at extending CPS to Socio-Cyber-Physical Systems within production networks. In this work, the human element of creativity and problem solving are combined with the technological innovation of CPS [53].

In the Industry 4.0 context, the scope considered is usually within the walls of the manufacturer being considered, therefore missing the integration with the pre-manufacturing, use, and post-use phases. Although CPS has dominated areas such as industrial automation, home automation, green transportation, and smart cities [54], the application to sustainability and circular economy is newly forming, and presents a novel opportunity for establishing initial methodologies.

2.3.2 *Previous Case Studies*

There have been several case studies involving the use of IoT and BD in order to drive sustainable value creation. In Pan et al. [55], a framework is built surrounding the HVAC and building industry and the use of IoT systems to improve energy usage. The approach envisions creating significant economic benefits, as well as social and environmental benefits. Tao et al. [56] presents integration between an IoT system and a traditional PLM system. This work provides an idea for collecting environmental and life-cycle data throughout the entire life cycle. The work also proposes the idea of a big Bill of Material (BOM) that uses the integration interface with the IoT systems in order to exchange and transform information. The next case considers the idea of using cloud-based technologies in order to support product services [57]. In other words, a decision support system is built on top of the BD foundation. In other cases, these services are built to be proactive by building in predictive models and analytics into the decision support system [58].

Another case is seen in the food production sector where the application of BD to the supply chain can have implications for many industries. The work claims that analytics can translate customer requirements into an increase in sales, by being able to mine the rationale from metadata. In addition to the positives, the utilization of BD results in negatives as well. For example, tailored consumer level detail can result in the loss of purchasing options among other things [59].

Despite the abundant research, IoT is plagued with its own infancy. Many of the companies that have been banking on big data still do not have much to show for their efforts [60]. In fact, those same companies have not even cashed in on the information systems that that they put into place 10-15 years ago [60]. The current approach of creating these extensive IoT frameworks involves outfitting legacy products, processes, and systems with numerous sensor nodes and IT systems in order to collect a significantly large dataset, only to have a fraction of it filtered into a usable state. Although excellent in theory, this approach can lead to an astronomical initial investment that could hinder any practical implementation into a production environment. On the other hand, if this approach is implemented blindly, there is a great risk associated with managing the new overhead. This trap is caused by the idea that information is free. While information is free, the ability to access it and use it in a way that can be beneficial is far from free. Everything from collecting the data points, to processing, and then storing them has an associated cost. For example, if only one million data points out of the original one billion is actually usable in a way that they can see a return on investment, then there was a waste of 99.9% of the data collected. There is a critical need to connect the research behind IoT to a tractable common goal, that goal being an IoT-based sustainable manufacturing paradigm that is focused on reducing resource consumption and maximizing sustainable value.

2.4 Manufacturing Paradigms and Product, Process, and System Level Infrastructure

A manufacturing paradigm is as set of principles and philosophies that define the field of manufacturing. Since the Industrial Revolution, the manufacturing industry has evolved through multiple manufacturing paradigms (See Figure 2.6). This section reviews the most relevant and widely known paradigms.

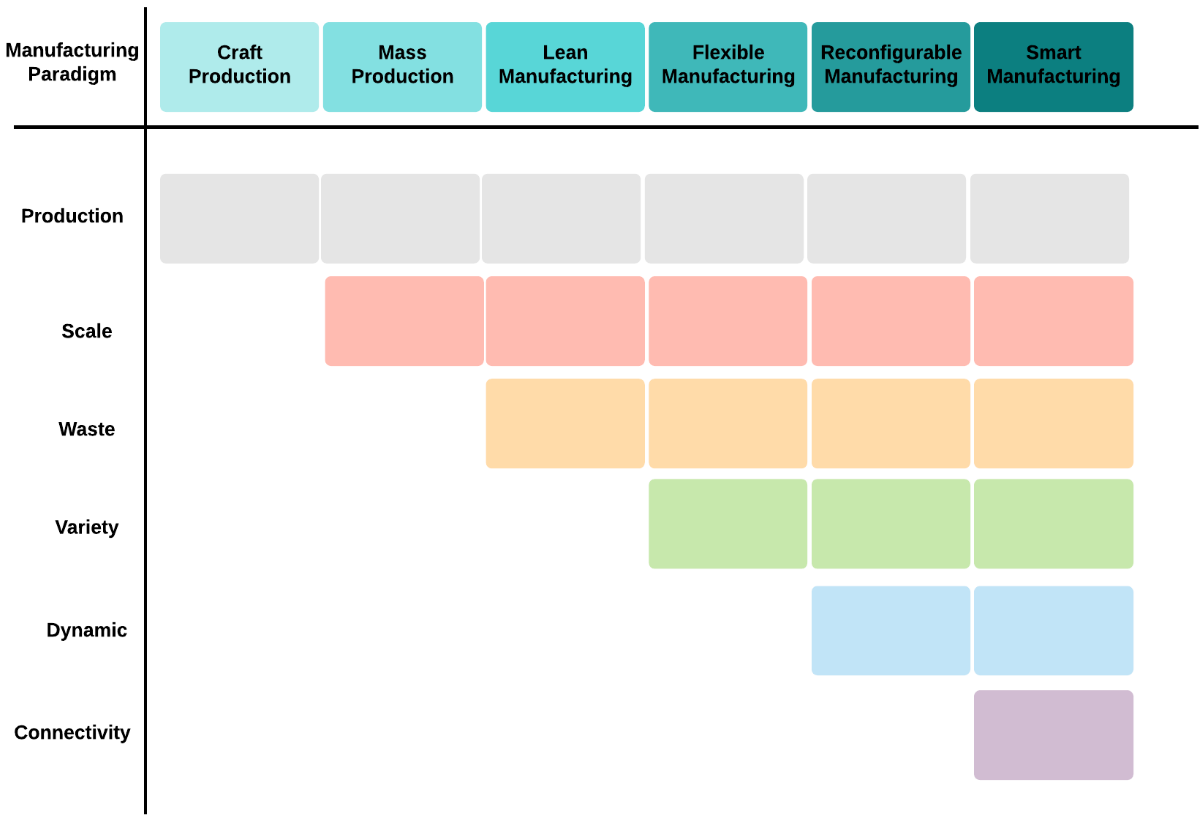


Figure 2.6: Evolution of Manufacturing Paradigms

2.4.1 *Craft Production, Mass Production, and Lean Manufacturing*

Craft Production refers to the paradigm that existed before the Industrial Revolution, where products where handcrafted, manufacturing tools were either hand tools or pre-automated, and no manufacturing systems existed. These products came at a high cost and the providers of these products were constrained geographically [61].

Mass Production is the resulting paradigm of the Industrial revolution that began with Henry Ford and brought along the interchangeability of parts in products, as well as the assembly line. Mass production did allow for the scalability of production at a low cost, but it has limitations.

Lean Manufacturing is the paradigm that began with the Toyota Production System when Toyota vehicles started to produce higher quality vehicles than American manufacturers. This paradigm is grounded in the primary goal to minimize "muda", or waste, without sacrificing production. The eight wastes are: 1) Defects, or mistakes in the manufactured product, 2) Overproduction,

or producing without a customer, 3) Waiting, or downtime in the process, 4) Not-Utilizing Talent, or underutilizing the workforce, 5) Transportation, 6) Inventory Excess, 7) Motion, and 8) Extra Processing.

2.4.2 *Flexible Manufacturing and Reconfigurable Manufacturing*

Flexible Manufacturing is a paradigm that targets defining a manufacturing system that can simultaneously process medium-sized volumes of a variety of part types [62]. Flexible Manufacturing Systems (FMS) are designed to produce a narrow set of products and can respond to market demand relatively quickly. However, these systems are relatively capital intensive and result in a high product cost [63].

Reconfigurable Manufacturing is a paradigm that is targeted at defining a manufacturing system that can adapt to unpredictable, high-frequency market changes [64] in a more cost-effective manner than FMS. Mehrabi, Ulsoy, and Koren [65] define a Reconfigurable Manufacturing System (RMS) as: *A reconfigurable manufacturing system is designed for rapid adjustment of production capacity and functionality, in response to new circumstances, by rearrangement or change of its components. Components may be machines and conveyors for entire production systems, mechanisms for individual machines, new sensors, and new controller algorithms. New circumstances may be changing product demand, producing a new product on an existing system, or integrating new process technology into existing manufacturing systems.* An example of a conceptual RMS-based assembly system is shown in Figure 2.7 [66].

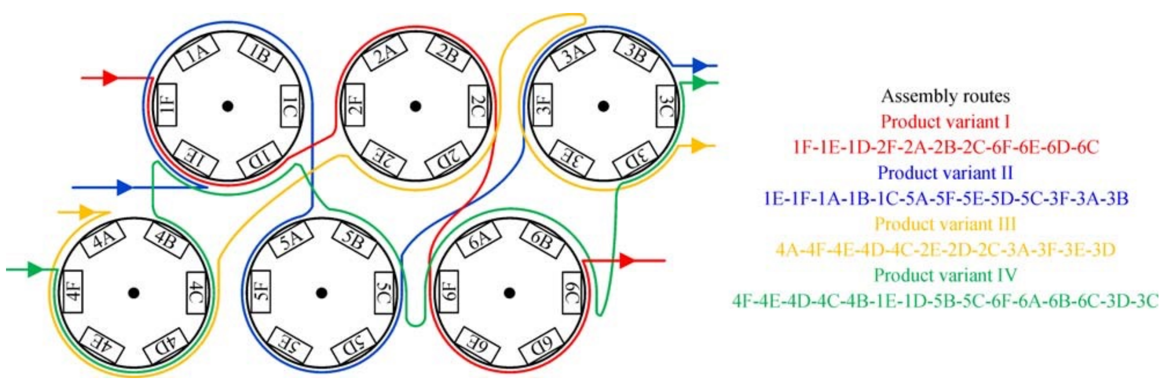


Figure 2.7: Example conceptual reconfigurable assembly system [66]

2.4.3 *Smart Manufacturing and Cloud Manufacturing*

NIST defined a Smart Manufacturing Systems as one that attempts to maximize a manufacturer's sustainable competitiveness with respect to cost, delivery, quality through the use of emerging information technologies and is enabled by combining features of earlier manufacturing paradigms [67].

Cloud Manufacturing (CMfg) falls under the Smart manufacturing umbrella, and is specific to using cloud computing resources in order to decentralize manufacturing services to be service oriented [68]. The premise behind CMfg is that any consumer would be able to access manufacturing resources via the cloud as easily as water, electricity, etc.

2.4.4 *Infrastructure Challenges Across Manufacturing Paradigms*

Manufacturing infrastructure is defined here as the tools, equipment, and physical structures that are needed in order to carry out manufacturing operations (see Figure 2.8).

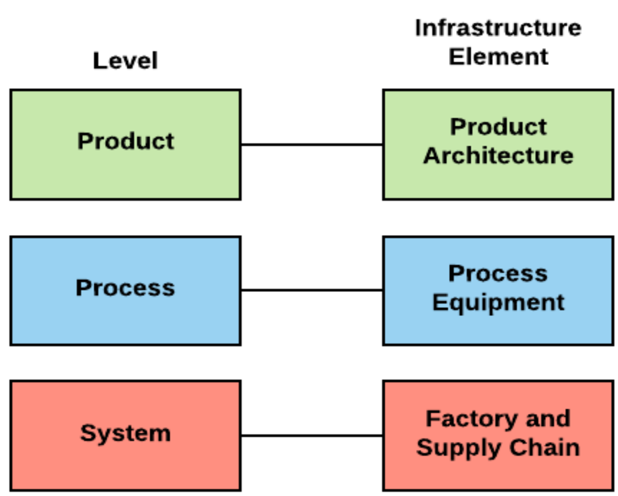


Figure 2.8: Manufacturing Infrastructure at Product, Process, and System Levels

All of the above manufacturing paradigms have influenced the product, process, and system level infrastructure elements. For example, the assembly line was the main contribution of the mass production paradigm. This infrastructure is also path dependent, and the infrastructure developed at all of these levels for each of the above manufacturing paradigms has been for the linear economy model. Like mentioned above, in order to maximize sustainable value, infrastructure has to be in place at all life cycle stages. As an example, for a modular product to be utilized, the system level infrastructure must be in place to take advantage of a reverse flow of products.

2.5 Summary of Research Gap and Dissertation Approach

2.5.1 *Summary of Research Gap*

The research gap can be summarized as follows:

1. The CE concept is inherently limited because it is leveraged almost exclusively as a waste management framework. A new extension to CE is needed that focuses on redesigning manufacturing infrastructure at product, process, and system levels.
2. CE is not equitable for the significant portion of the world that lives in poverty. Economic growth needs to be decoupled from resource consumption through technological innovation;
3. The traditional approach of IoT involving deploying extensive sensor networks is limited in practical implementation. The use of IoT in the manufacturing domain needs a new approach in order for manufacturers to realize sustainable value creation.

4. Manufacturing infrastructure at product, process, and system levels has all been developed for a linear economy. A new manufacturing paradigm is needed that joins elements of sustainable manufacturing and smart manufacturing together under one mission: maximizing sustainable value, reducing resource consumption, and maintaining technological progress.

2.5.2 *Dissertation Approach*

The dissertation addresses the gaps by introducing the Helical Economy (HE) concept as a novel extension to the CE concept. An overview of the approach is shown in Figure 2.9. In Chapter 3, An overview and conceptual representation of the concept is formed, and then key performance indicators (KPIs) are developed based on that representation. The approach is then to define the future state vision of a Helical Economy Manufacturing Method (HEMM) by reimagining infrastructure elements at the product, process, and system levels. This satisfies research objective one:

4. *Propose the Helical Economy as a novel extension to the Circular Economy, and develop the framework for the Helical Economy Manufacturing Method (HEMM)*

The goal is then to work backwards from that future state vision in order to define methods for industry implementation that will allow near-term progress towards the HEMM vision. The approach here is to dive deep into two components of the HEMM: next-generation products and IoT-enabled data infrastructures.

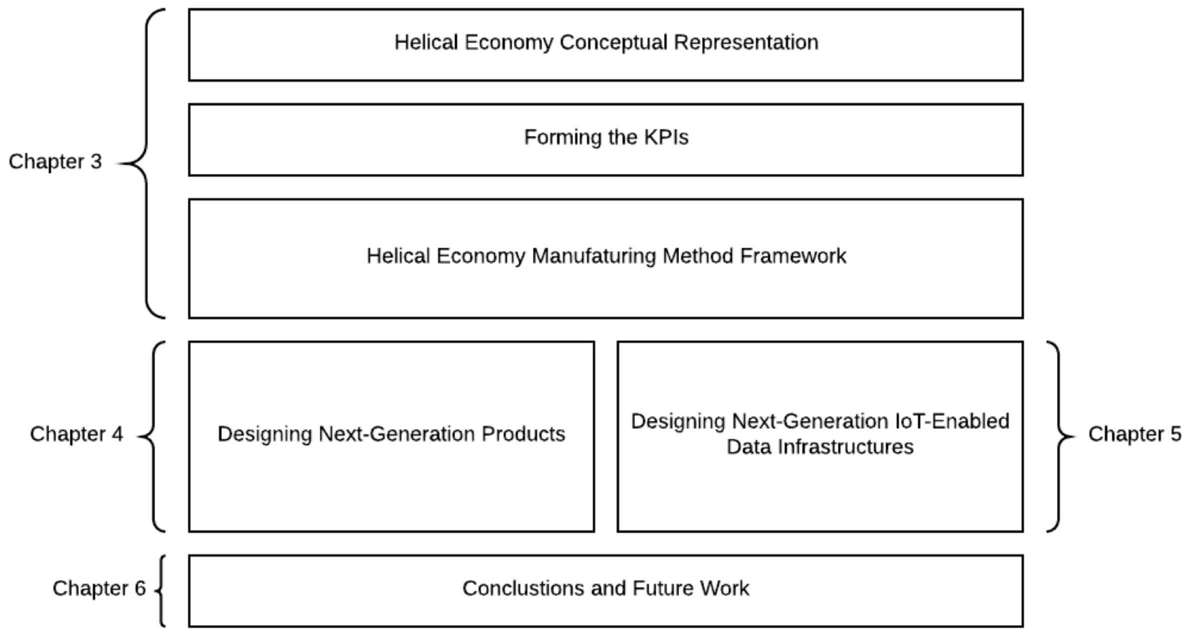


Figure 2.9: Overall Approach of Dissertation

Chapters 4 and 5 satisfy research objectives two and three:

2. *Identify the major research problems that need to be solved in designing next-generation products and develop initial methods in order to make near-term progress towards the HEMM.*

3. *Identify the major research problems that need to be solved in designing next-generation IoT-enabled data infrastructures and develop initial methods in order to make near-term progress towards the HEMM.*

The dissertation closes with defining the future work that needs to be done across next-generation process equipment and planning, next-generation factory and supply chain design, and next-generation workforce training.

CHAPTER 3 HELICAL ECONOMY MANUFACTURING FRAMEWORK

3.1 Introduction to Helical Economy

In the 1970s, the $I = PAT$ equation [69,70] was proposed as a macro-level estimate for overall environmental impact as a function of global population (P, number of people), affluence (A, units of technology per person), and Technology (T, impact per unit of technology). Considering the fact that the U.N. projects the world population to reach ~10 billion people by 2050 [1], and the fact that 71% of the global population in 2011 was living on less than 10 dollars per day [2], the only equitable way to address environmental impact is through technology. The manufacturing sector plays a key role in enabling technology, and in order for the manufacturing sector to support lower impact technology, the sector needs a framework that aims to decouple technological progress and economic growth from resource consumption. The Circular Economy (CE) has claimed to be a framework for achieving this, but CE is inherently limited because of its emphasis on waste management and the recycling and reuse of materials. Therefore, the Helical Economy (HE) concept is proposed as a novel advancement of CE—shifting the CE's status quo paradigm away from post-use recovery for recycling and reuse and towards redesigning manufacturing infrastructure at product, process, and system levels, along with leveraging IoT-enabled data infrastructures and an upskilled workforce.

In this chapter, the HE concept is first presented through an abstraction that allows the reader to compare and contrast the differences between Helical Economy, Circular Economy, and Linear Economy. Through this abstraction, three key performance indicators (KPIs) are identified and established as the measurement foundation for HE: sustainable value creation, resource consumption, and technological progress. The Helical

Economy concept is then extended into the manufacturing domain in order to form the framework and establish the future state vision of the Helical Economy Manufacturing Method (HEMM). The HEMM is intended to shift the paradigm of sustainable manufacturing away from the waste reduction and diversion concentration of CE and to redesigning the fundamental infrastructure elements at product, process, and system levels. This framework provides the foundational body of knowledge for developing HEMM implementation tools for manufacturing stakeholders. Following this chapter, the reader will have a clear understanding of HE, how to measure it, and how it can be applied to the manufacturing domain.

In order to understand the value proposition behind Helical Economy (HE) and how it relates to Circular Economy (CE) and the Linear Economy (LE), an abstraction is presented in Figure 3.1 [71] that visualizes each in a three-dimensional cylindrical space where, $r = SVC(R_{1-6})$ is the sustainable value creation achieved as a function of the 6Rs of Sustainable Manufacturing (*Reduce, Reuse, Recycle, Recover, Redesign, and Remanufacture)*, $\theta = f(t)$ is time, and z is the technological progress achieved*:*

$$r = SVC(Reduce, Reuse, Recycle, Recover, Redesign, Reman.) : [0, \Psi] \quad (3.1)$$

$$\theta = f(t) : [\phi_k, \phi_{k+1}] \quad (3.2)$$

$$z = Technological\ Progress: [\mu, \mathrm{M}] \quad (3.3)$$

r is bounded by 0, representing no value creation, and Ψ, the theoretical maximum sustainable value. θ is finite and bounded by the k-th generation time interval, ϕ_k, and the k+1 generation time interval ϕ_{k+1}. z has a lower bound, μ, and an upper bound, M. The gray plane, μ, is the ecological limit of technological progress under circular economy conditions and M is the theoretical maximum limit while maintaining Ψ sustainable value. From Figure 3.1, LE can be seen to deliver technological progress, but at the expense of

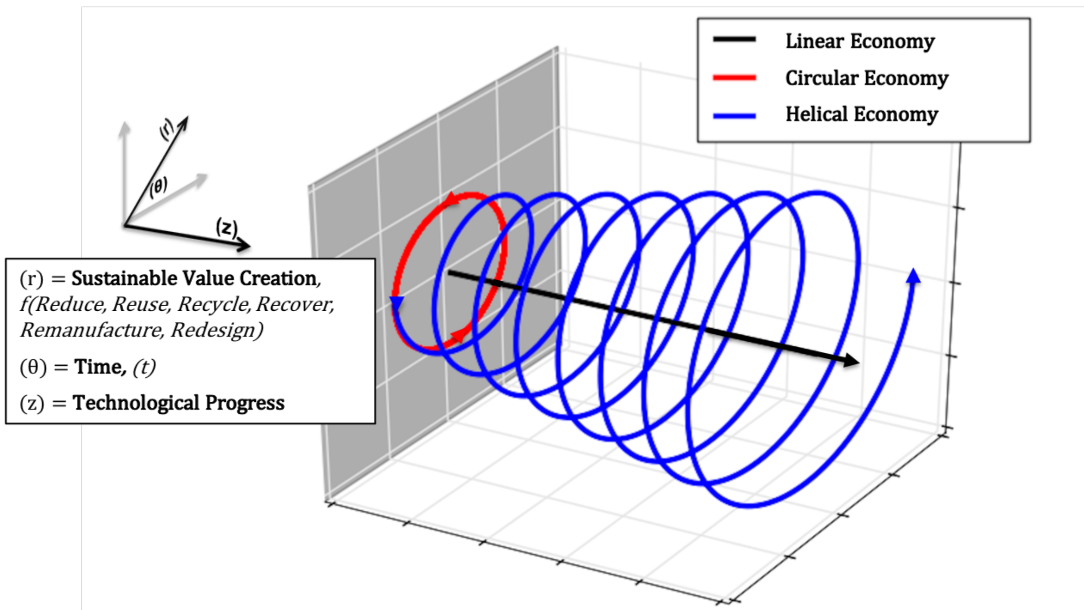


Figure 3.1: Abstract Representation of the Helical Economy in reference to the Linear and Circular Economies [71]

sustainable value. While society can function under these conditions for a short period, this will result in long-term harm to the economy, society, and the environment. That being said, the untapped sustainable value present in a linear economy should be viewed as an opportunity to manufacturing stakeholders.

CE aims to extract some of this untapped sustainable value with an improvement to the LE. However, this is at the expense of technological progress, as it is shown to not move past the two-dimensional plane at μ, which is the CE's theoretical maximum. This maximum is a function of the use of the 4R elements of Reduce, Reuse, and Recycle, and Recover, and it reflects that the omission of Redesign and Remanufacture. This reflects the current “waste management focused” implementations of CE. This causes degradation in sustainable value and promotes technological stasis because there are still constraints to operate in a linear manufacturing infrastructure. To go beyond a waste management strategy, the “R” elements of Redesign and Remanufacturing must be considered in combination with the prevention of degradation.

HE is shown to advance the improvements made by CE by shifting the paradigm of sustainable manufacturing away from a waste management strategy and to a holistic redesign of manufacturing infrastructure at product, process, and system levels. By utilizing all 6R elements, HE eliminates the linear infrastructure constraint and enables stakeholders to extract more of the untapped sustainable value while maintaining high levels of technological progress.

3.2 Key Performance Indicators for Helical Economy

With the HE concepts formed, key performance indicators (KPIs) must be developed that allow manufacturers to measure the performance and success of their HE activities. These KPIs must be easily calculated with available information, they must be easily understood by both business leaders and shop floor practitioners, and they must easily allow for tracking improvements over time. The three proposed KPIs that meet these criteria are: sustainable value creation, resource consumption, and technological progress. The following sub-sections will establish the frameworks for each of these KPIs.

3.2.1 *Sustainable Value Creation*

Bilge et al. [72] states that value creation in the manufacturing context is achieved through changing the ratio between input and output in terms of raw materials and resources for manufacturing acvitities. In that context, tbe assumption is that manufacturers exist to create maximum value in order to be compensated by customers. However, indirect impacts that don't directly affect the manufacturer or the customer are not factored into that transactional view of manufacturing, and therefore these externalities are not considered in deciding what activities to undertake in order to create the value. Therefore, the concept of sustainable value arises, or the total life cycle economic, societal, and environmental impacts [73] of manufacturing activities requires an alternative framework and value creation mechanisms. There has been a lot of previous work in this space. Chandler [74] looks at sustainable value creation from the perspective of how can a manufacturer create the most value for each stakeholder involved. In other words, different stakeholders demand different definitions of value from a firm. The goal then becomes synthesizing all of these definitions of value into a common value creation assessment in order to drive the entire firm in the direction of maximizing sustainable value. Ueda et al. [73] reflects some of this thought through the emergent synthesis decision-making approach that takes multiple agents with their own purpose, and thhis collective interaction results in an effective solution for the whole system. Nils et al, Jovane et al, Seliger et al., and Stock and Seliger [75–78] have advocated for value creation networks that co-create value for all stakeholders. The premise is that manufacturers own their core competency and cooperate together on tackling the sustainability challenges. This is becoming more prevalent today as global partnerships form around complex, cross-cutting sustainability topics such as Circular Economy, Plastics. That being said, these global corporate partnerships are starting to face scrutiny because they lack transparency, leaving the perception as being too qualitative.

Other approaches around sustainable value creation have leaned quantitative, especially in the field of economics. Figge and Hahn [79] establish a measure for sustainable value added that adjusts economic growth based on environmental and societal impacts. This is done by pricing externalities, and this can be applied from the perspective of bottom line cost or top line revenue, depending on the end goal. However, the inherent assumption in this approach for sustainable value added is that a firm will forego short term profits if they will be compenesated for that avoided harm in the long-term. Although are limitations with this thinking, it is best aligned with the price-based transactions already being used by firms, and because of this, it could be adopted easier than an attempt to change the entire definition of value.

Therefore, we propose a similar approach as Figge and Hahn, but explicity from the perspective of the total life cycle cost (TLCC) to all stakeholders (See Figure 3.2). From this Figure, the TLCC takes into consideration the societal and environmental externalities. In addition, it is shown that TLCC + Value Creation is equal to the hypothetical total life cycle market value. Therefore, by minimizing TLCC, total life cycle value creation can be maximized. This allows manufacturing stakeholders to uncover untapped potential in their value chains. The cost model should capture life cycle activities from material extraction, manufacturing, transportation, use, reverse logistics, post-use activities (recycling, remanufacturing, reuse), as well as account for the externalities associated with each of these activities. These externalities can be pollution, climate change, etc. In practice, a life cycle cost model will be highly dependent upon the particular application being evaluated and the data available to a particular stakeholder, but to offer a starting point, this section presents the generic total life cycle cost model (TLCCM) for HE.

The TLCCM for HE can be formulated into a hierarchy of mathematical relationships. The

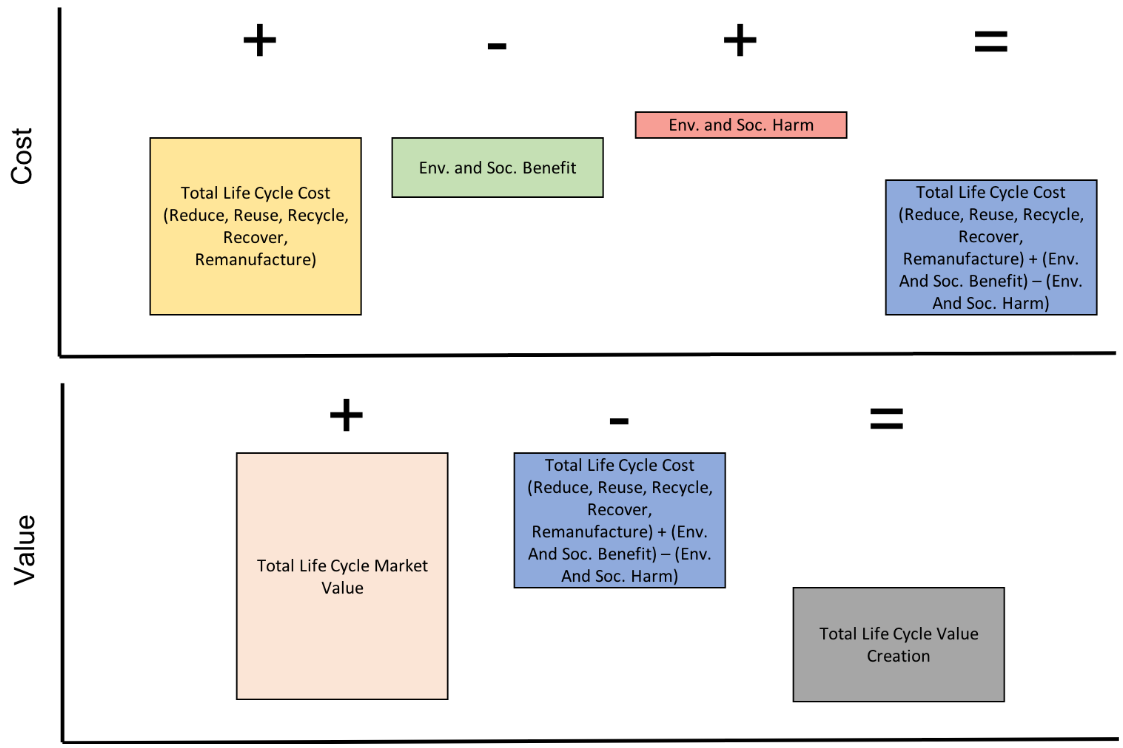


Figure 3.2: TLCC's connection to value creation

goal of this model is aimed at maximizing sustainable value creation for all stakeholders; therefore, the total life cycle must be considered. The first tier of the hierarchy can be seen in Equation (3.4).

$$TLCC = C_{MFG} + C_{CUST} \tag{3.4}$$

This top-level hierarchy distinguishes between cost to manufacturer (C_{MFG}) and the cost to the customer (C_{CUST}), in the sense that although these two different costs are very different in nature, they both make-up the total cost of a particular manufacturing activity. This important distinction provides a significant advantage because it illustrates the reality of the manufacturer and customer relationship. As seen in Rivera et al. [80] although they are independent actors, their decisions significantly affect one another. By considering the cost to the customer, a manufacturer can control the costs to the customer and even choose to make an investment on behalf of the customer in order to lower their overall cost. Each of these two costs are expanded to much more detail in the second tier of the hierarchical cost model that can be seen in Equations (3.5-3.8).

$$C_{MFG} = C_{F,MFG} + C_{V,MFG} \tag{3.5}$$

$$C_{CUST} = C_{F,CUST} + C_{V,CUST} \tag{3.6}$$

$$C_{MFG} = C_{F,MFG} + \sum_{t=0}^{n} \frac{1}{(1+i)^t} \left[C_{MFG,VIR,t} + C_{MFG,RU,t} + C_{MFG,RM,t} + \ C_{MFG,REC,t}\right]_t \tag{3.7}$$

$$C_{CUST} = N_T \left[\left(C_{MFG/U} \cdot K\right) + \sum_{t=0}^{n} \frac{1}{(1+i)^t} \left[C_{CUST,U,t}\right]_t\right] \tag{3.8}$$

In this level of hierarchy, the manufacturer and customer costs are both segmented into fixed ($C_{F,MFG}$, $C_{F,CUST}$) and variable costs ($C_{V,MFG}$, $C_{V,CUST}$). For HE, this distinction is important because it advocates for a redesign of manufacturing infrastructure, and therefore a common analysis in the HE domain may be assessing whether investing in new infrastructure will result in a return. In Equation (3.7), the variable costs to the manufacturer are allocated across four channels of production: virgin ($C_{MFG,VIR,t}$), reuse ($C_{MFG,RU,t}$), remanufacturing ($C_{MFG,RM,t}$), and recycling ($C_{MFG,REC,t}$) in year, t . Customer variable costs in year, t, are represented by ($C_{CUST,U,t}$). Both manufacturer and customer variable costs are discounted at the i discount rate to net present value (NPV).

In Equation (3.8) customer fixed costs are affixed to the total manufacturer costs per unit scaled by a profit margin, K. Total fixed and variable costs are scaled by the total number of units, N_T, to calculate the total cost to customers.

A more granular view of the costs to the manufacturer are shown in Equations (3.9-3.13):

$$C_{F,MFG} = C_{EQ} + C_{INFRA} \tag{3.9}$$

$$C_{MFG,VIR} = N_{VIR}\left[C_{RM} + C_{MP} + C_T + C_{ES} + C_{OTH,VIR}\right] \tag{3.10}$$

$$C_{MFG,RU} = N_{RU}\left[C_{RL} + C_T + C_{ES} + C_{OTH,RU}\right] \tag{3.11}$$

$$C_{MFG,RM} = N_{RM}\left[C_{RL} + C_{MP} + C_T + C_{ES} + C_{OTH,RM}\right] \tag{3.12}$$

$$C_{MFG,REC} = N_{REC}\left[C_{RL} + C_R + C_{MP} + C_T + C_{ES} + C_{OTH,REC}\right] \tag{3.13}$$

Manufacturer fixed costs are segmented into the cost of equipment (C_{EQ}) and the cost of infrastructure (C_{INFRA}). Equipment costs may include machines, tooling, and/or line changes and infrastructure costs would include facilities.

The variable costs from virgin production are the cost of raw materials (C_{RM}), cost of manufacturing processes (C_{MP}), cost of transportation (C_T), costs of environmental and societal externalities (C_{ES}), and case-specific costs ($C_{OTH,VIR}$). Externalities are costs that indirectly impact the system (Ex. ecotoxicity, human health, climate change, etc.)

The variable costs from reuse production are the cost of reverse logistics (C_{RL}), cost of transportation (C_T), the costs of environmental and societal externalities (C_{ES}), and case-specific costs ($C_{OTH,RU}$).

The variable costs from remanufacturing production are the cost of reverse logistics (C_{RL}), cost of manufacturing processes (C_{MP}), cost of transportation (C_T), the costs of environmental and societal externalities (C_{ES}), and case-specific costs ($C_{OTH,RM}$).

The variable costs from recycling production are the cost of reverse logistics (C_{RL}), cost of recycling (C_R), cost of manufacturing processes (C_{MP}), cost of transportation (C_T), the costs of environmental and societal externalities (C_{ES}), and case-specific costs ($C_{OTH,REC}$).

In an ideal case, all of the variable costs associated with environmental and societal externalities across each channel of production should be included. In practice, all of the externalities will likely not be known, but all that are known should be included. As an example, for climate change, the social cost of carbon (SCC) emissions can be included [81]. The SCC measures the economic harm, in dollars, of emitting one ton of carbon dioxide into the atmosphere. The EPA has currently calculated this to be $42/ton [82]. Accounting for SCC in the cost model would allow a manufacturer to account for the indirect impact that their manufacturing activities and decisions have on climate change. This approach affords the manufacturer to include the externalities that its stakeholders really care about, as well as set their own price on externalities. Some manufacturers may set the price higher than others, because their stakeholders may have a stronger response than others.

The generic TLCCM model shown here is intended to be the starting point for a manufacturer trying to measure their total sustainable value creation in relation to adopting the Helical Economy. For implementation in practice, it is expected that this generic model will need to be adapted to industry specific cases.

3.2.2 *Resource Consumption*

While the TLCCM does account for the material value in its model, this value can be dwarfed by all of their value-add activities throughout a manufacturer's value chain. Because of this, in order to ensure resource consumption is minimized, this has to be measured independently. KPIs that already exist around resource consumption are often focused on measuring the mass of all resources utilized by an economy. For example, the material consumption metric used by the EU [83], looks at the mass flow of all materials through the economy. This number is often compared to the GDP of an economy in order to estimate the resource efficiency. While good in practice, these types of KPIs treat all materials equally, and do not account for the differing footprints that materials have. For example, 1 kg of sand is not equivalent to 1 kg of aluminum. Therefore, mass-based KPIs are not sufficient. Instead, a value per kilogram of material needs to be assigned in order to prioritize and assess different resources. Because the TLCCM is already proposed as a metric, the value chosen should represent environmental or societal impact. Therefore, life cycle assessment's (LCA) most robust indicator is proposed: Global Warming Potential (GWP). GWP not only quantifies a materials impact to climate change, but it also is representative of a physical view. The GWP value represents the energy and mass of material, which allows us to distinguish the importance of our starting example: 1 kg of sand vs. 1 kg of aluminum. The GWP of 1kg of sand is equivalent 0.01 kg CO2eq, while 1 kg of aluminum is equivalent to 8.14 kg CO2eq, or 814 more than that of sand [84]. The metric proposed for resource consumption is shown in Equation (3.14).

$$RC = \frac{\sum_{i=0}^{W} ef_i \cdot M_i}{N_T} \tag{3.14}$$

Where, M_i is the i-th material in kilograms and ef_i is the GWP value of the i-th material. The sum of all W materials being utilized across a manufacturer is then normalized to the total number of units, N_T, produced. This metric gives manufacturers the ability to track their resource consumption performance overtime and assess the tradeoffs of implementing helical economy initiatives.

3.2.3 *Technological Progress*

HE's core value proposition is that it aims to maintain technological progress while maximizing sustainable value and minimizing resource consumption. A metric for technological progress is therefore vital for validating the core benefit of HE. However, technological progress is hard to measure and quantify. Often, it relies on the R&D dollars spent by a firm or by the number of patents granted to the firm in relation to the number of new products released. Neither of these KPIs are an actual measure of technological progress, but instead are only proxies. To move beyond a proxy, it requires an understanding of what technological progress actual is. For the sake of simplicity, let's assume the definition of technological progress is interchangeable with innovation. Innovation can be defined in many ways: product innovation, process innovation, and business model innovation. To quantify innovation, one must look to the field of TRIZ, or the theory of inventive problem solving [85]. TRIZ defines five levels of innovation as seen in Table 3.1:

Table 3-1: Levels of Innovation [85]

Level	Description
Level 1	Apparent design change to an existing technical system
Level 2	Improvement to an existing technical system
Level 3	Elements of an existing system are completely replaced with knowledge obtained from outside the original domain.
Level 4	Novel system that contains a breakthrough from other fields of science.
Level 5	Pioneering discovery or breakthrough for a radically new system.

To develop the metric for technological progress, an innovation factor (IF) is defined in Table 3.2 based on the relative percentage of each innovation level as determined in Genrich Altshuller's *The Innovation Algorithm* [86].

Table 3-2: Innovation Factor (IF)

Level	IF Value
Level 1	0
Level 2	1
Level 3	2.3
Level 4	10.5
Level 5	140

Level 1 is set to 0, considering it to be incremental change and not innovation. Level 2 is set to 1, and levels 3-5 are inversely calculated based on the relative percentage of patents classified as each in comparison to Level 2. Now, that innovation factors are determined, these must be applied across the products being produced by a manufacturer. Equation (3.15) scales the IF by the total revenue P_i from the j-th product. These values are summed across all of the products (Z) produced by a manufacturer and then normalized by the total number of units produced, N_T, to obtain the technological progress metric.

$$TP = \frac{\sum_{i=1}^{Z} IF_i \cdot P_i}{N_T} \quad (3.15)$$

This KPI gives manufacturers the ability to track their technological progress over time and assess the tradeoffs of implementing helical economy initiatives.

Overall, this section has proposed three KPIs for measuring HE performance across the core value proposition of maximizing sustainable value, minimizing resource consumption, and maintaining high levels of technological progress. These are intended to be the foundational KPIs and are intended to be iterative overtime and tweaked to account for special considerations in certain industries.

3.3 The Helical Economy Manufacturing Method

Now that the overall HE concept has been established, and the KPIs for measuring success have been identified, this section addresses how HE can be implemented in the manufacturing domain. It provides the conceptual level foundation for the future state vision of the Helical Economy Manufacturing Method (HEMM), which proposes redesigning manufacturing infrastructure at the product, process, and system levels. (Infrastructure in this context is defined as the physical structure, supporting equipment, and facilities needed to support manufacturing operations.)

The HEMM framework consists of five core components: next-generation products, next-generation processes and process equipment, next-generation factories and supply chains, next-generation IoT-enabled data infrastructures, and a next-generation workforce. The overview of the HEMM is shown in Figure 3.3. The following sub-sections will provide the conceptual level foundation for each of these core components.

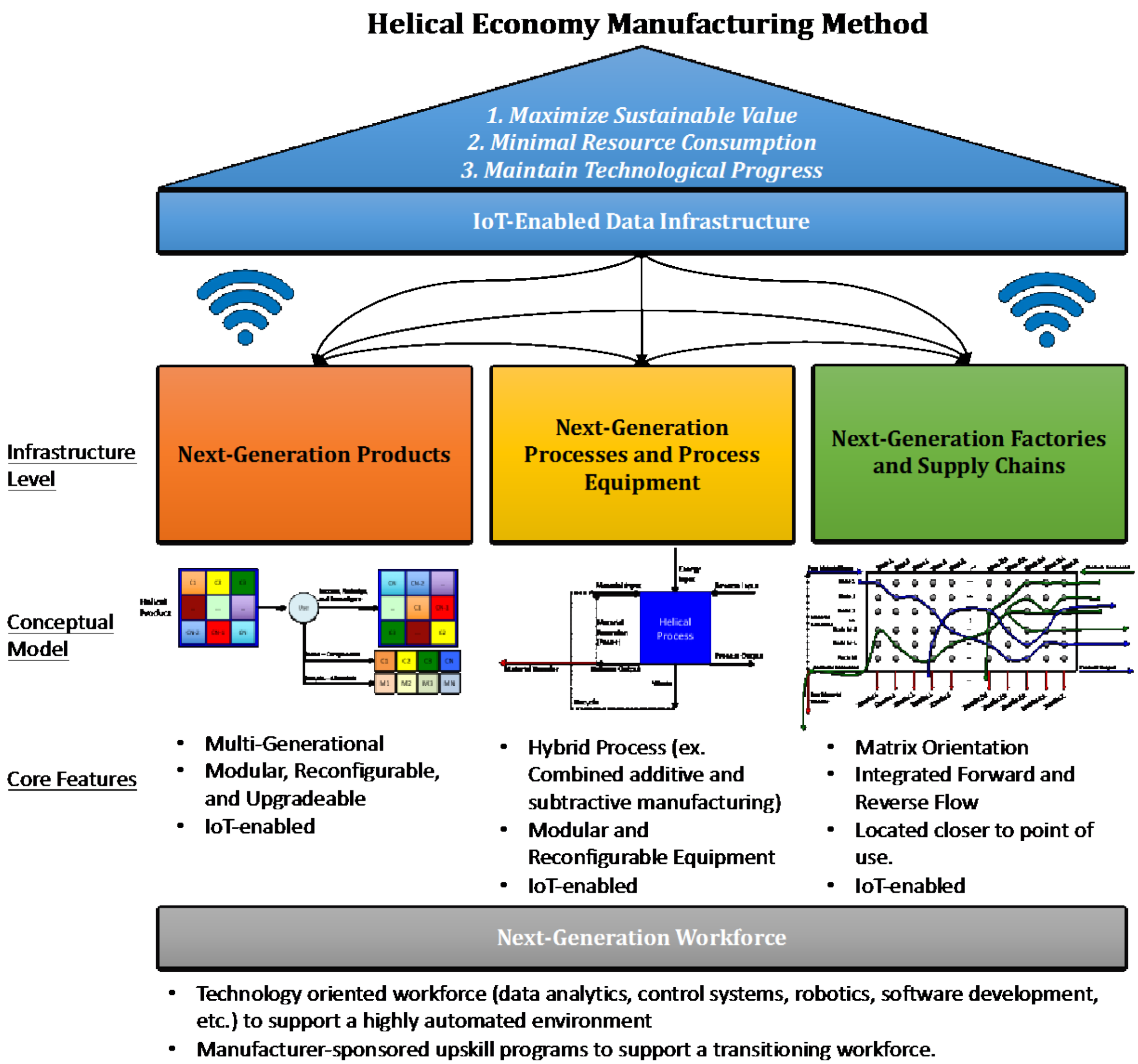


Figure 3.3: Overview of the Helical Economy Manufacturing Method

3.3.1 *Next-Generation Products*

At the product level, the linear economy has defined everything from the conceptual understanding of products; the design tools and processes that have been created to develop products; and the way the system boundary is defined when approaching the design of a product. Therefore, delivering on the HEMM vision requires a total redesign of what fundamentally defines a product. Looking at Figure 3.4 [71], the linear product is composed of an assembly of $C_1, C_2, \ldots, C_N$ components. The product is then used and disposed of resulting in zero sustainable value creation.

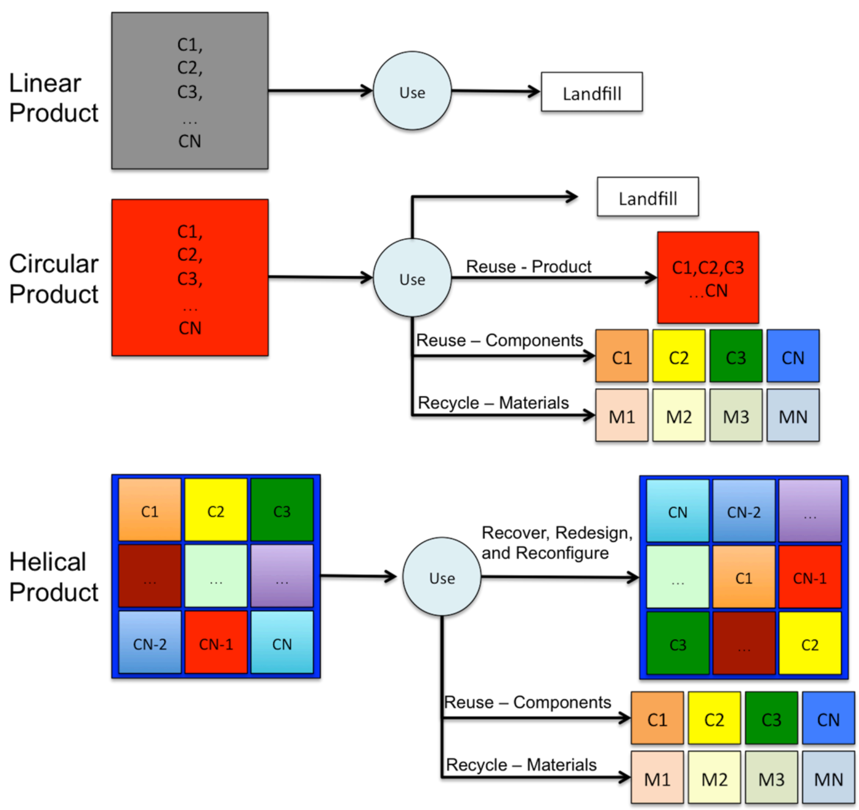


Figure 3.4: Conceptual Representation of Linear, Circular, and Helical Products [71]

The circular product is still composed of the same $C_1, C_2, \ldots, C_N$ components because it is still locked into being manufactured by the infrastructure that was designed for the linear economy environment. The linear tools and technologies of today's manufacturing environment inherently limit the circular economy waste management centric approach of using recycled materials and ensuring recycling. Sustainable value is extracted through recycling of $M_1, M_2, \ldots, M_N$materials, and through the limited the reuse of products and components, but because the circular product is still locked into a linear infrastructure, there is an inherent degradation of value that occurs.

HE goes beyond CE to include a redesign and reconfiguration effort. The helical product is comprised of modular components that are reconfigurable to the market demand. Post-use, the product can be reconfigured into a new product, or the material can be transferred out of the product life cycle in the form of components via parts harvesting and/or materials via recycling.

In practice, the product is IoT-enabled, and the collected data is fed into a new suite of design tools that are developed specifically for HE. The helical product must also be reconfigurable and use common components and materials. Using manual or automated processes, components must be able to be rearranged into new products to meet immediate demand. The product must also be designed in parallel to the process plan and process equipment in order to ensure the infrastructure is in place to take advantage of the modular and upgradeable product structure. The product must also prevent degradation of value and have the ability to be upgraded through reconfiguration and remanufacturing.

3.3.2 *Next-Generation Processes and Process Equipment*

At the manufacturing process level, the linear economy has dramatically defined the existing technologies that are in use today. Since the Industrial Revolution, development and investment from manufacturers have supported a one-way flow of products, from getting raw materials at their gate to delivering a finished product to their end customers. As such, the current manufacturing process level infrastructure and technology caters to this linear economy derived one-way flow of inputs and outputs. To achieve the HEMM vision, helical manufacturing processes and process equipment must become multi-dimensional, enabling a hybrid manufacturing and remanufacturing process that can continue to meet the current market demand. As shown in Figure 3.5 [71], helical manufacturing processes have a reverse capability built in parallel to that of the original manufacturing process. The material from the reverse manufacturing step is either transferred to a different process or retained and reprocessed.

Current technologies that would support the HEMM at the process level are for example, a combined additive and subtractive manufacturing process and machine, as well as a combined assembly and disassembly robot that can simultaneously handle new product assembly and return product disassembly.

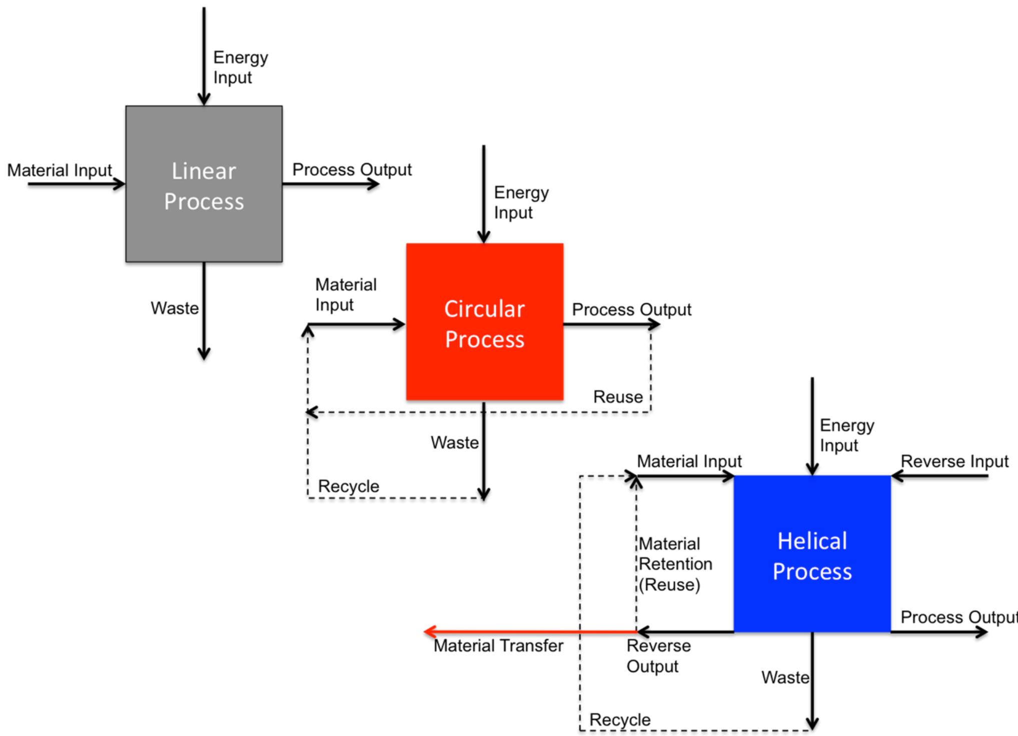


Figure 3.5: Conceptual Representation of Linear, Circular, and Helical Manufacturing Processes [71]

In practice, the process equipment is IoT-enabled, and data is actively collected and used to execute decision on which inventory to pull from and operations that need to take place. These decisions are made in combination with current market conditions to determine which products meet current demand. Data from products in the field and other process equipment is also used to continuously improve product performance. Using the information gathered from products in the field, near real-time sustainability performance enhancements can be made on the manufacturing floor.

3.3.3 *Next-Generation Factories and Supply Chains*

At the system level, helical products and processes come together to form next-generation factories and supply chains. Production in the HEMM vision has to be able to respond to market demand instantaneously. With this consideration, a the HEMM system level infrastructure builds on the concept of reconfigurable manufacturing systems (RMS) [64,87], with the added premise of leveraging the same machines and lines for both manufacturing and remanufacturing. This creates a forward and reverse flow of products through the system that can move about the system in a nonlinear way (See Figure 3.6 [71]). Manufacturing "lines" in a HEMM become reconfigurable matrices of $S_1, S_2, \ldots, S_N$ process stages and $N_1, N_2, \ldots, N_M$ nodes interconnected through the IoT-enabled data infrastructure. Products in the forward manufacturing path take advantage of the reconfigurable and flexible manufacturing stage-node combinations to support many SKUs while achieving maximum throughput.

Return products that enter in reverse are deconstructed into components and materials that are then allocated to the next best stage-node combinations that keep the components and materials at the highest possible value. Materials and components can be transferred to or from another product line at any point in the process via transfer points $T_1, T_2, \ldots, T_P$. Because of the forward and reverse flow consolidation, this encourages the factory and supply chain levels to oriented close to the customer points of use.

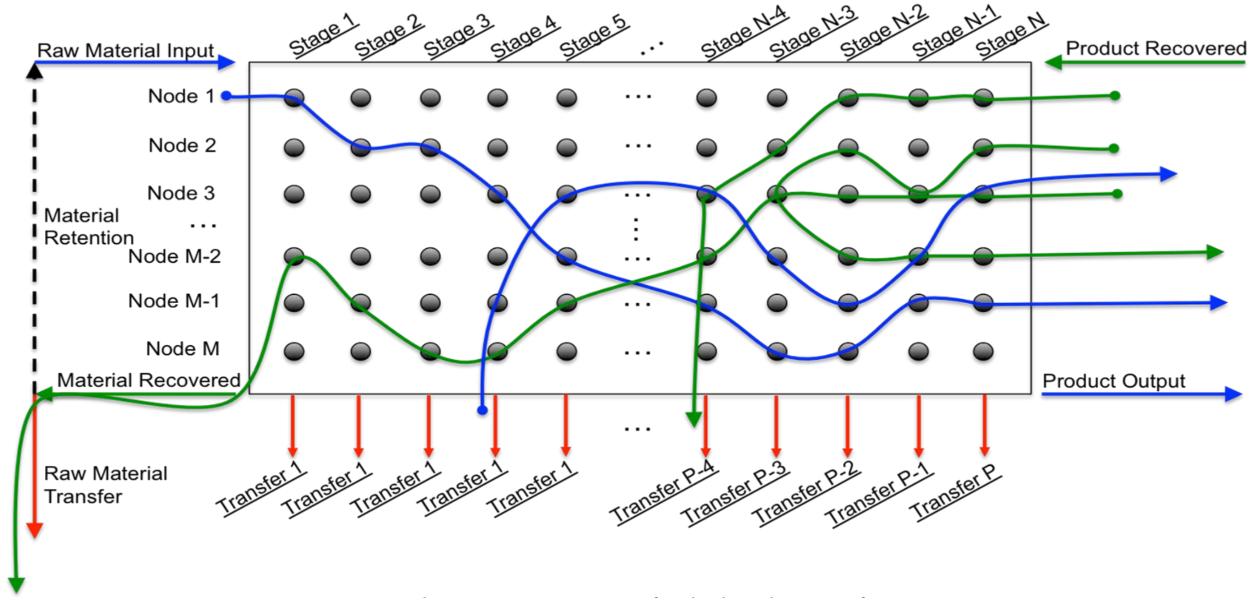


Figure 3.6:Conceptual representation of a helical manufacturing system. It is reconfigurable to support a forward and reverse material flow where the path is determined by the optimal combination of N stages, M nodes, and P transfer points. [71]

In practice, the system is IoT-enabled and consists of interconnected products, process equipment, and system-level equipment. The data collected across this sensor network is used in order to make the decisions to move from a stage, node, and/or transfer point. These decisions are made using the HE KPIs of sustainable value creation, resource consumption, and technological progress.

3.3.4 *Next-Generation IoT-Enabled Data Infrastructure*

The Internet of Things (IoT) has been referred to as a means for aligning physical and information life cycles [88]. This vision suggests that this intimate connection and the information itself present a major source of value to manufacturers [88,89]. However, to extract this value, the IoT-enabled data infrastructure (Figure 3.7 [71]) has to be leveraged in a framework that presents an opportunity at realizing this value.

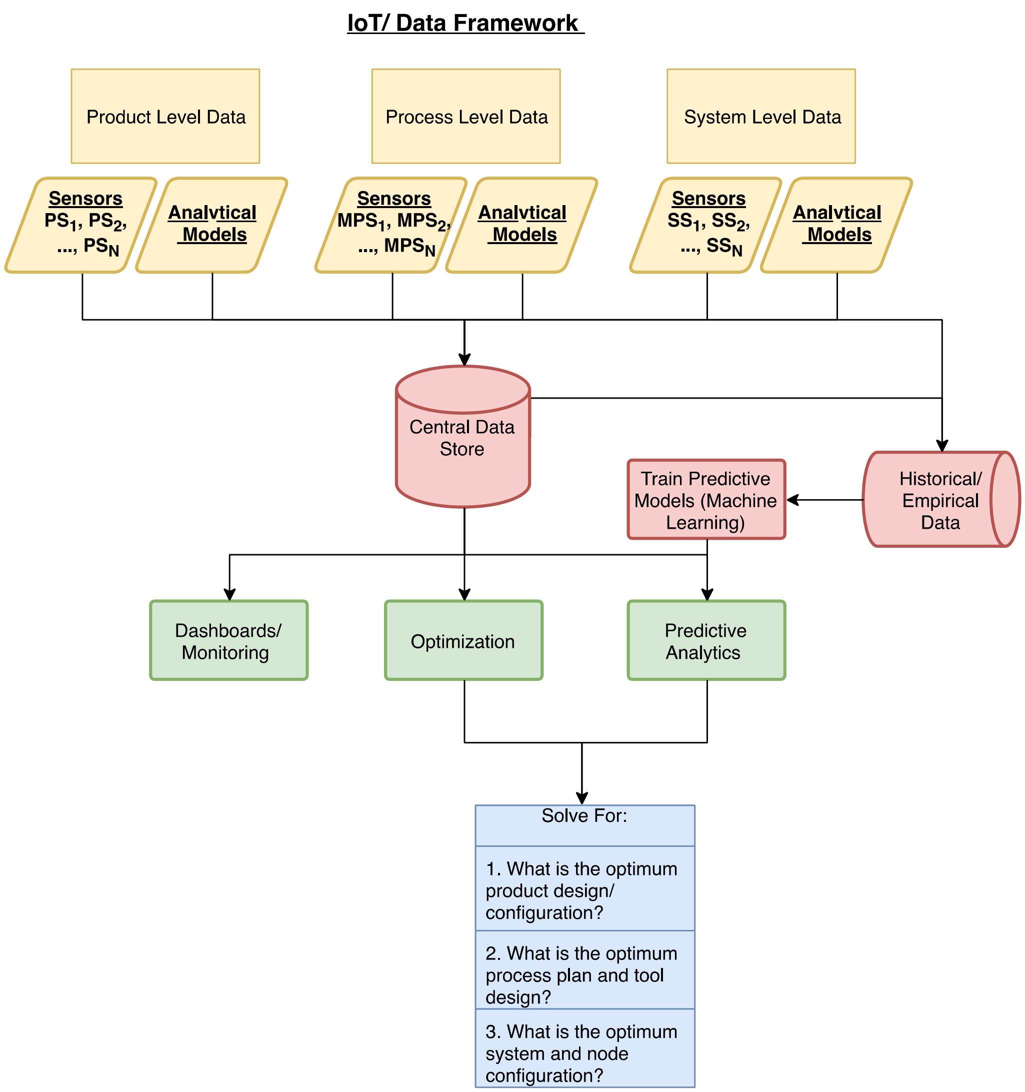


Figure 3.7: Conceptual Representation of the IoT-Enabled Data Infrastructure [71]

In context of the HEMM framework, the IoT-enabled data infrastructure can be leveraged to widen the helix to maximum point of sustainable value creation. It achieves this by increasing the amount of life cycle information available to manufacturers through the use of dynamic data collection system, where data is collected via sensors and analytical models at product, process and system levels. This data allows one to construct a virtual system view of the complete manufacturing life cycle. This total life cycle-oriented data can then be used to train predictive models in solving for the optimum product design/configuration, the optimum process plan and equipment/tool design, and the optimum system and node matrix configuration, based on the three KPIs of sustainable value creating, resource consumption, and technological progress. However, this highly leveraged sensor network can come with a serious investment. To keep costs low, special attention should be paid to minimizing sensors deployed through the use of the domain expert knowledge of the physical system [90], as well as ensuring that every piece of data being collected and stored has a business purpose.

3.3.5 *Next-Generation Workforce*

While automation was been predicted to kill manufacturing jobs, Deloitte has shown this to be the opposite, but the increase in jobs are signaling a critical skills gap in between the talent pool and the jobs that are needed [91]. They predict that over 2 million US manufacturing jobs are will go empty between 2018 and 2028 [91]. In the context of HE and HEMM, the proposed framework reflects a highly automated manufacturing environment. However, even in a highly automated manufacturing environment, people will remain as a core foundational element of the HEMM, That being said, the HEMM will continue to shift the skills in demand for the manufacturing sector away from low-skilled laborers and towards higher skilled technology-focused skills (data analytics, software development, simulation, robotics, mechatronics, etc.) [92]. This shift in demanded skills may cause a deeper skills gaps than already exists for the manufacturing sector, because it will require new skills across product design, process and process equipment design, as well as industrial and manufacturing engineering. In order to bridge this gap, industry-sponsored upskilling programs will need to grow rapidly, and education systems across the globe will need to invest heavily in technical schools with manufacturing-oriented training programs. Transitioning the current workforce into a next-generation workforce prepared to support the HEMM will take time since requires a fundamental change in the core infrastructure around manufacturing education and training. Because of the time lag, there is a critical need to start this investment as soon as possible.

3.4 Chapter Summary and Discussion

In this chapter, the Helical Economy (HE) framework was presented, key performance indicators for measuring its success were identified, and the conceptual form of the Helical Economy Manufacturing Method was presented. In developing the concept, HE was shown to be a novel advancement of CE that enables maximizing sustainable value, minimizing resource consumption, while maintaining technological progress. A visual representation highlighted the advances made by HE: 1) shifting the paradigm of sustainable manufacturing away from a waste management strategy and to a holistic redesign of manufacturing infrastructure at product, process, and system levels, and 2) By utilizing all 6R elements, HE eliminates the linear infrastructure constraint and enables stakeholders to extract more of the untapped sustainable value while maintaining high levels of technological progress. These advances enable HE to support economic mobility of the developing world and global population growth.

Three KPIs were then proposed: sustainable value creation (*TLCC*), resource consumption *(RC),* and technological progress *(TP).* These KPIs will allow manufacturers to deploy helical economy solutions and track their success over time.

The Helical Economy Manufacturing Method (HEMM) was then presented as the conceptual framework for implementing HE into the manufacturing domain. The HEMM consists of five core components: next-generation products, next-generation processes and process equipment, next-generation factories and supply chains, next-generation IoT-enabled data infrastructures, and a next-generation workforce. Although largely conceptual, this work provided the critical foundational level of knowledge for how manufacturers may go about overhauling their linear economy manufacturing infrastructure. Without addressing the redesign aspect of manufacturing infrastructure, manufacturers will inherently be limited in the ability to create sustainable value or reduce resource consumption.

Overall, this chapter provides the foundation for the Helical Economy and its application to the manufacturing domain. The following chapters will address the redesigning of manufacturing infrastructure at the product level, followed by designing the IoT and Data infrastructure.

CHAPTER 4 DESIGNING NEXT-GENERATION PRODUCTS FOR A HELICAL ECONOMY

4.1 Introduction and Literature Review

4.1.1 *Motivation*

Product design has an outsized impact on sustainable value creation, resource consumption, and technological progress, and the Helical Economy vision cannot be realized without fundamentally changing the way products are designed. In a Helical Economy, product designers and engineers must expand their design scope beyond a single product, or even a single product line. Designers have to simultaneously design the product, the manufacturing process plan, the supply chain, the business model, and design in the capability to take advantage of all post-use activities (recovery, reuse, remanufacturing, recycling, and redesign/reconfiguration).

It is well-known that product design is largely an iterative process. During the early design stages of a product, designers tend to know very little about their design problem, yet this is when they have the most design freedom and control in order to meet design constraints. The costs to manufacture and life cycle impacts are already defined by the time the designer receives initial feedback. This is known as the designer's paradox (Figure 4.1 [93]).

Because of this paradox, initial product designs are rarely optimal. This paradox, however, may be a result of the linear economy's influence on the past several decades of product design tools, methodologies, and assessment frameworks. Products have been designed for

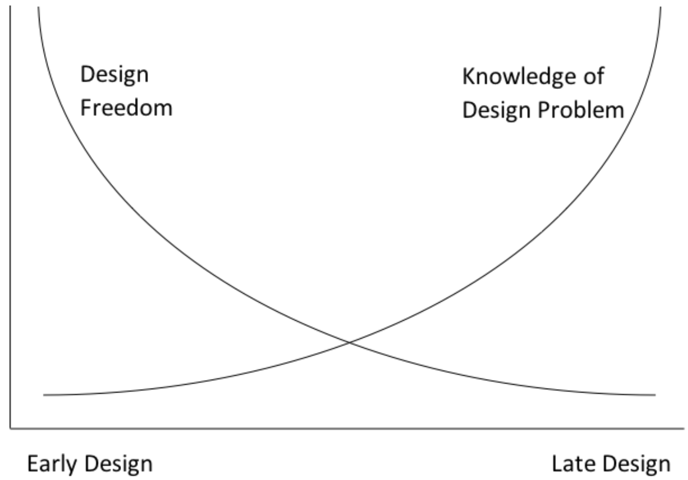


Figure 4.1:Designer's Paradox (Adapted from Dieter [93])

a linear economy for several years, with manufacturers iterating on their internal product development processes in order to continuously improve their ability to beat their competitors on price and time to market. Arming product designers with information on the life cycle performance of their product has not been a priority, even when this benefits the bottom line. The two traditional methodologies used in measuring the life cycle environmental and economic impact of a product, Life Cycle Assessment (LCA)[94] and Life Cycle Costing (LCC)[95], both require detailed design-level and system-level data. The timely collection of this data limits the design changes that can be made to a product without greatly affecting a manufacturer's cost or schedule.

To truly move the manufacturing sector towards the HEMM future vision, product level architecture needs to be redesigned, which will require new design tools and methods. This chapter begins with reviewing the literature in the field of product design as it applies to manufacturing, by summarizing the typical design process and the current state of the art on sustainable design tools. From this review, the product design challenges for realizing the near-term vision of the HEMM are identified. The chapter then presents four initial methods to address these design challenges. The methods are segmented into two classes of product design: 1) new product design, and 2) adaptive product design and redesign. For new products, a Design for Helical Economy (DfHE) set of guidelines is proposed that aims to aid new product design towards an improved “near-net design” that is suitable for the HEMM. For adaptive product design and redesign, an initial toolkit is developed, the Helical Optimization and Prediction Engine (HOPE). HOPE is comprised of three product-level methods: 1) predicting product life cycle performance during design (HOPE-Design), 2) predictively and proactively maintaining a modular product (HOPE-Maintain), and 3) selecting optimal product configuration and reconfiguration (HOPE-Configure)

4.1.2 *Literature Review*

4.1.2.1 The Design Process

Product design sits at a complex nexus between the fields of science, art, and psychology/sociology [96]. From a science perspective, a product requires a conglomeration of elements from the hard sciences that are put into action in a specific application. From an art perspective, a product must encompass creative elements that are novel and aesthetically appeasing. From a psychology/sociology standpoint, the design has to resonate with its customers and society. There are also many types of design: original design, adaptive design, and redesign [93]. Original design or new product design is a product that is striving to meet a new need or meet an existing need in an innovative way. This is the rarest form of design, and often has a low success rate. Adaptive design consists of taking elements of a known solution and applying them to meet a different need. Redesign is improving on an existing design, and this type of design is the most frequent.

With each of these types of design, there are numerous variables and competing elements at play, and because of the complexity required, there is not a "one-size-fits-all" solution for designing products.

However, in order to streamline designing a product, a structured design process is often used. This structure allows designers and engineers the ability to apply a quantitative structure to design elements and the given constraints. The design can then be iterated and improved upon in order to meet the requirements of the market demand. The most frequently cited design process [93,96] is comprised of four core stages: planning, concept design, embodiment design, and detail design.

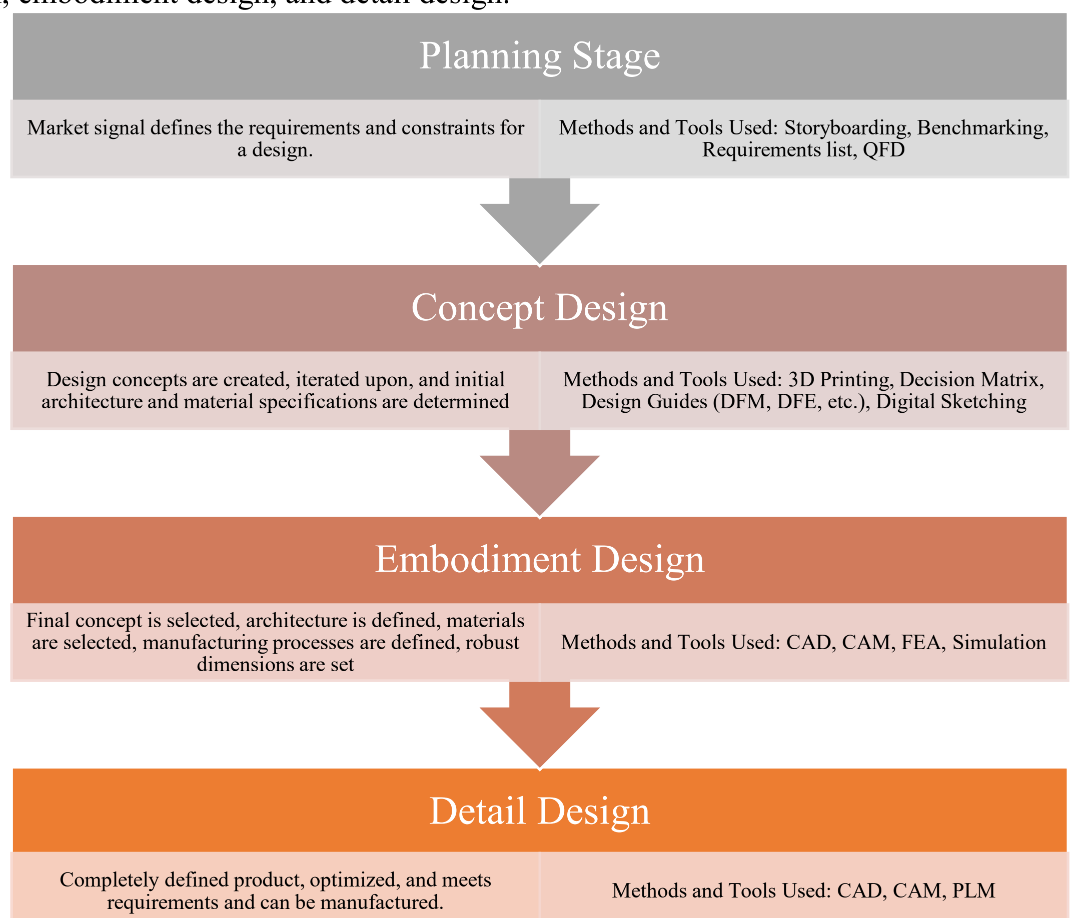


Figure 4.2: Design Process Overview

During the planning stage, the customer need is defined, a requirements list is created that specifies how the product will function and identifies the major constraints. The preliminary look of the product is also defined during the planning stage.

In the concept design stage, a spectrum of design concepts is generated and iterated upon using digital sketching and other tools. These concepts are down selected and non-functional prototypes are created using rapid prototyping or 3D printing. In this phase, designers and engineers rely on high-level design guides for manufacturability, environmental impact, etc. The aim is to rapidly get to a prototype of a “near-net design”, or a design that is close to the desired final product. Initial architecture and materials are specified.

In the embodiment design stage, the final concept is determined, the product architecture is finalized, materials are selected, and the manufacturing process plan is defined. The design is iterated upon in order to improve manufacturability and costs. Features that are not critical to the product requirements are removed. Computer-aided engineering and design (CAE, CAD) tools are used in order to create 2D and 3D models of the intended product. The design undergoes virtual simulation using FEA and other simulation tools in order to test the critical functional requirements and failure modes. This limits how many physical prototype builds must be done. However, multiple prototype builds will be completed in order to validate the design, product architecture, and the manufacturing process.

In the detailed design phase, the product will be completely defined, and it will have been tested for functional performance and manufacturability. Computer-aided manufacturing (CAM) tools will be used in order to optimize the manufacturing process of the product and components. The final Bill of Material (BoM) will be completed in the Product Lifecycle Management (PLM) system.

This is a generic overview of the product design process, and it will differ from organization to organization. However, it highlights the linear nature of the design process, and the impact that this has on the ability to design a product that takes into account total life cycle impacts. Since product design determines the majority of the embodied and downstream life cycle impacts, tools and methods are needed that can be used to predict the sustainability impacts of design decisions early on in the design process. The next section reviews the current methods and tools used in sustainable product design.

4.1.2.2 Design Tools and Methods

There has been significant research in developing sustainable product design tools and methods, or tools/methods that balance the triple-bottom-line (TBL), or the environmental, economic, and societal aspects of a product's design. That being said, a number of "sustainable design tools" only consider one component of the TBL because these three elements can often be in tension. This makes it extremely difficult to synthesize the data of these three elements into one common metric or result. Because of that fact, a hybrid set of qualitative and quantitative tools are needed in order to support the development of sustainable products. In this section, the current sustainable product design tools and methods are reviewed and summarized.

In doing the review, both academic and industry available tools were combined into a list. The search terms used were "sustainable product design tools"; "sustainable design tools"; "life cycle assessment design tools"; "life cycle costing design tools"; "product sustainability assessment tools"; "product design for circular economy"; and "circular economy design tools". Several tools from the search were compiled and analyzed across the following criteria (Shown in Table 4.1):

1. Economic Consideration? Is this tool/method/approach using a cost element as a design decision variable?
2. Environmental Consideration? Is this tool/method/approach using environmental impact as a design decision variable?
3. Societal Consideration? Is this tool/method/approach using societal impact as a design decision variable?
4. Which Design Stage (Planning, Concept, Embodiment, Detail) is the tool/method/approach used for, or what stage of data is required?

Table 4-1: Summary of Reviewed Sustainable Product Design Tools

Name	Description	Comments	Design Stage	Econ?	Env?	Soc?	Reference
GaBi, EcoInvent, openLCA, SimaPro, etc.	Commercially available life cycle assessment databases and software that can calculate the environmental performance of a product across multiple environmental performance indicators.	All of the commercial LCA tools require detailed data that is not readily available in a timely manner. They also lack in the connectivity of being able to be integrated into other design tools and manufacturing systems.	Detail		Yes		Commercial
ProdSI	Quantitative approach for evaluating a product normalizes, aggregates to determine a ProdSI score across all three dimensions.	ProdSi is very comprehensive, but the data required makes it less useful in the early design stages. However, using predictive modeling techniques may enable ProdSI to become an early design tool	Detail	Yes	Yes	Yes	Zhang et al. (2012)[97]
Granta	Commercially available CAD, CAE, PLM integrated materials database that allows engineers to select, iterate on, and track materials during product design.	Granta is limited to one component of design - materials.	Embodiment, Detail	Yes	Yes		Commercial
ResCOM Platform	Several quantitative and qualitative tools that look at economic and environmental impacts with a focus on circular economy	Partly funded by the European Commission, ResCOM is a good attempt at providing a toolkit for a designer looking to transition to Circular Economy.	Planning, Concept, Embodiment	Yes	Yes		Rashid et al. (2013)[98]
Multi-Objective Multiple Life Cycle Sustainable Product Configuration Design	Quantitative approach that optimizes product configuration design using economic and environmental data and a genetic algorithm	This method provides a good framework for configuration design optimization, and it can be a good foundational component of the HE transition.	Embodiment, Detail	Yes	Yes		Badurdeen et al. (2018) [99]
SolidWorks Sustainability	Commercially available CAD, CAE, PLM integrated environmental impact assessment that uses screening life cycle assessment.	Solidworks aims to bring LCA closer to the designer, but the same level of data is required, making it less applicable than it intends.	Embodiment, Detail		Yes		Commercial

Ford's PSI	Quantitative method using life cycle assessment and life cycle costing approaches that does not reduce the different indicators down to a single score	This is a good example of deploying LCA and LCC in an industry setting, but it is still limited by the data collection required.	Detail	Yes	Yes		Schmidt and Taylor (2006) [100]
Integrated ECQFD, AHP, and TRIZ	Quantitative model that uses environmentally conscious QFD in order to establish design alternatives and use TRIZ to define innovation.	Using TRIZ to consider the innovation is the contribution of this work, and this provides insight in how to leverage TRIZ for HE.	Planning, Concept	Yes	Yes		Vinodh et al. (2014) [101]
Multi-Objective Material Selection for Product Design	Quantitative approach that narrows the focus to material selection and uses environmental and economic factors in the selection criteria.	This approach is limited in that it only considers the material selection activity within product design.	Embodiment, Detail	Yes	Yes		Zhou et al. (2009) [102]
Combination of LCA and Virtual Development	Combining LCA and SLCA and leveraging CAD and CAE tools to develop a prototype-free design	Although this approach considers societal impacts, the data quality is questionable to be used in practice.	Concept, Embodiment, Detail		Yes	Yes	Luthe et al. (2013) [103]
Integrated Eco-Design Decision Making (IEDM)	Combines life cycle assessment, eco-process model, and eco-enhanced QFD process. Also uses an ecodesign house of Quality	This approach ignores economic and social impacts.	Detail		Yes		Romli et al. (2015) [104]
Normative Decision Analysis Method for the Sustainability-based Design of Products (NASDOP)	Combines LCC and LCA and uses normative decision-making methods to deal with conflicting criteria	Because this uses LCA and LCC data, this is still limited in the data collection required. Although they say this conceptual design stage, it seems to fit better under the embodiment design stage.	Embodiment	Yes	Yes		Eddy et al. (2013) [105]
Design for Multiple Life Cycles	A set of design thinking guidelines aimed at new product design that incorporates Design for Upgrade, Design for Assembly, Design for Disassembly, Design for Modularity, and others	This qualitative set of guidelines presents a composite structure of other DfX guidelines and this provides insight into how to structure a DfHE set of guidelines.	Planning, Concept	Yes	Yes	Yes	Go et al (2015) [106]

Based on the tools reviewed, the research is still very nascent along a few dimensions. In particular data collection is still an issue with most of the methods and tools reviewed. In addition, for HE and HEMM implementation, none of the existing tools incorporate the reconfiguration element into their methodologies. Lastly, most of the methods are siloed without the connectivity being demonstrated to already existing enterprise-level manufacturing data and systems. The next section will use the literature view as a starting point in order to highlight the product-level design challenges that face the HE and HEMM vision.

4.2 Product Design Challenges for a Helical Economy

From Chapter 3, we know that Helical Products (HPs) are defined as:

> *A product that must be reconfigurable and use common components and materials. Using manual or automated processes, components must be able to be rearranged into new products to meet immediate demand. The product must also be designed in parallel to manufacturing and remanufacturing/configuration process plans. The product must prevent degradation of value and have the ability to be upgraded through reconfiguration and remanufacturing.*

In order to achieve a truly helical product, the paradigm of the "Designer's Paradox" must be shifted. New tools and methods have to be developed to bend and move the knowledge curve up into the early design process. Designers need tools that allow them to know the life cycle impacts and implications of their design decisions on the overall product life cycle. This has to systematically be addressed across new product design, adaptive design, and redesign activities.

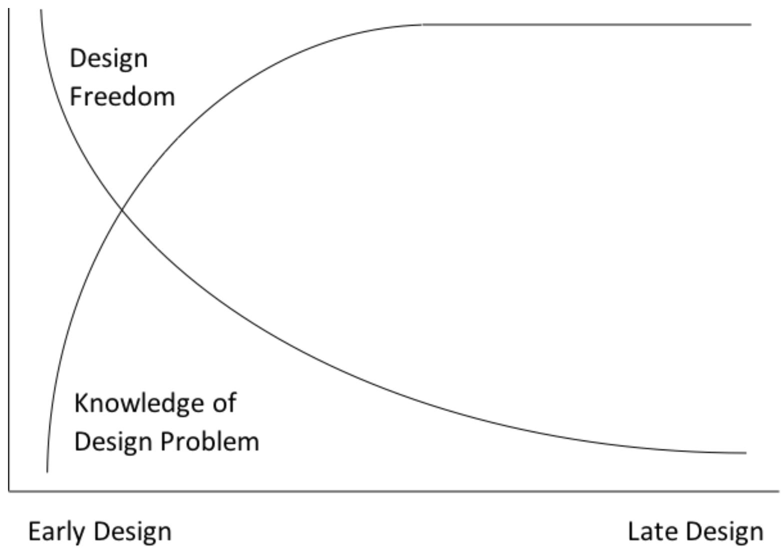


Figure 4.3: Shifted Paradigm of Designer's Paradox in order to achieve Helical Products

Based on the previous section's review of product design and the existing design tools and methods available, four near-term product design challenges are highlighted for being able to bend the knowledge curve and realize the HEMM vision:

1) For new product design, a new qualitative design guide is needed that brings to light the elements of helical economy that must be addressed at the earliest part of the design process.

2) For adaptive product design and redesign, the ability to predict life cycle performance from historical or IoT sensor information must be developed.

3) For modular products with multiple lifecycles, a method must exist for proactively predicting when a module requires maintenance or failure is imminent.

4) For designing modular products for multiple lifecycles, there must be process in place to systematically use historical information and predictive data in order to optimize a product's initial configuration and each life cycle reconfiguration.

For new product development, no prior knowledge of a particular design configuration exists. No historical data exists to be mined, and therefore, a designer has to use qualitative frameworks which consist of design guidelines, industry standards, and other experience-driven rules to design a "near-net" initial design. For HPs, we define a "near-net" design as a product that utilizes the benefits of the HE but may not be optimal. A set of guidelines must be created that allows a designer to get to a "near-net" helical design in a timely manner. These sorts of guidelines exist for other design goals, but one must be created specifically for HE.

Predicting life cycle performance is also a grand challenge for realizing a helical product, because the designer ideally has to design a product that is multi-generational and can stand the test of time. This is a highly complex and dynamic system level problem that requires an understanding of multiple fields of study and the interrelationships between them. For HPs, the life cycle performance that is of interest is based on the metrics described in Chapter 3: sustainable value creation, resource consumption, and technological progress.

At the core of HE is the concept of modular and reconfigurable products that can be configured and reconfigured at the time of manufacturing and remanufacturing in order to satisfy the product demand of that particular time. In addition, these products must be able to be maintained across multiple life cycles. In order to make this a reality, one must be able to optimize the product configuration at a given moment in time in order to maximize sustainable value creation, minimize resource consumption, and maximize technological progress. One must also be able to predict needed maintenance or imminent failure of a product module. This challenge is also highly complex, and it also must be broken down into something that is tractable and can be improved upon. Therefore, the initial target should be to assume that a modular product architecture is designed.

4.3 Initial Methods for Industry Implementation

4.3.1 *New Product Design: Design for Helical Economy (DfHE) Guidelines*

The first design challenge addressed is the challenge that focuses on the class of design problems surrounding new product design. For new product design problems, the goal is to get the designer to a "near-net" helical design in a timely manner. Therefore, we present a qualitative Design for Helical Economy (DfHE) set of guidelines (Figure 4.4):

Design for Helical Economy (DfHE) Guidelines
Design for Multiple Life Cycles Description: Helical products are designed in tandem with defining the manufacturing process plans, the supply chain designs, and corresponding business models. Reverse logistics should be incorporated in the design process, and the level of durability should be optimized for multiple product lifetimes.
Design for Interconnectivity Description: Helical products use IoT-networked or embedded sensor data obtained throughout the manufacturing, use, and use phases in order to best optimize the downstream activities of reuse, remanufacturing, and recycling. This enables life cycle performance data to be collected and validated.
Designing for Assembly, Disassembly, and Reassembly Description: Helical Products need to not only be designed for easily assembly, but they also must be able to be disassembled easily in order to be reconfigured via manual or automated processes.
Designing for Modularity and Upgradeability Description: Helical products are designed using modular components that have standard mechanical and electrical interfaces. Components that are upgradeable are decoupled with static modules.

Figure 4.4: DfHE Guidelines

Design for Multiple Life Cycles

When designing HPs, the scope has to expand to include the manufacturing process, system, and even business model. In other words, designing a product with snap-fits or screws is not sufficient for a HP. There has to be a process in place that can take advantage of these features. In fact, this expanded scope increases the types of features that can be implemented. As long the as the downstream process is in place in order to take advantage of the connection feature, the options are limitless. The following list is a set of guidelines that a designer can use to incorporate multiple life cycle design thinking into their product:

1. Reduce the technological, emotional, and regulation obsolescence of the product. Define a product architecture that can feasibly support new technology, changes in customer demand, and forthcoming legislation.
2. Use base materials in the design that are common and in demand across multiple applications. Proprietary materials for a single application may limit the full potential of the HEMM.
3. Concurrently design the manufacturing process plan, design the factory and supply chain, and the corresponding business models. This ensures the downstream infrastructure is aligned with the product features.
4. If reverse logistics costs are not sunk costs, ensure the embedded value of the product exceeds the planned for reverse logistics costs.

Design for Interconnectivity

HPs must advantage of smart manufacturing paradigms in which the product leverages an IoT network across all manufacturing stages. This data gives adds value to a given product, as all of the information regarding the manufacturing, use, and post-use lives with the product. Not all products that are designed for interconnectivity have to leverage active sensing measures. For example, a cost-conscious product may leverage passive sensing at only a set number of touchpoints across the life cycle. The following list is a specific set of guidelines for designing for interconnectivity in order for a designer to take this into consideration when designing a product:

1. Ensure total life cycle and multi-generational coverage: manufacturing, use, and post-use. Designing the connectivity of a product in a HEMM has a long-standing impact on the data that can be used in order to improve and optimize the system overtime, so ensuring total coverage upfront is vital.

2. Hardware used must be minimized in order to control costs and long-term maintenance of the data collection infrastructure.

3. Enable two-way communication in order for the product to report life cycle information and also allow for information to be pushed to the product in-field. This also can allow for communication to the customer on when the optimal use of a product has been met.

Designing for Assembly, Disassembly, and Reassembly

HPs must take advantage of assembly, disassembly, and reassembly. Since the value proposition of HPs is reconfiguration, upgradeability and minimized resource consumption, a designer must take into account the required assembly, disassembly, and reassembly activities that are directly associated with their design decision. For example, designing a mobile consumer electronic product without a replaceable battery is instantly a no-go, as the battery will degrade overtime and the product will be rendered useless. In addition, this will make recycling and remanufacturing extremely difficult and unsafe. The following list is a set of guidelines that a product designer should follow in order to design for assembly, disassembly, and reassembly:

1. Design the interfaces and connections that are easy to handle and reuse, and, if needed, design the tools and equipment necessary.
2. Limit the components that are not durable in the design. This prevents damage during assembly, disassembly, and reassembly processes.
3. Wear components should not be nested in the design and should be easily able to be removed and replaced.
4. Design the assembly, disassembly, and reassembly sequences concurrently with defining the product architecture.

Designing for Modularity and Upgradeability

The core value proposition of HPs relies on a modular and upgradeable product architecture that can stand the test of time. For example, if a designer architects a core assembly of a product's maintenance schedule to be a one-piece architecture, then the entire assembly must be replaced at the time of maintenance. The result is a sub-optimized module that prevents the product from maximizing its potential along the HEMM dimensions of sustainable value, resource consumption, and technological progress. To avoid this, the following list of guidelines allows a designer to incorporate elements of modularity and upgradeability into their product:

1. Modules should be defined based on components with similar materials and expected lifetimes. A Design Structure Matrix (DSM) can be used in order to support module selection.

2. Design with common components when possible, in order to ensure demand at the component level, reducing the number of components that have to be deconstructed into raw materials.

3. Modules and components that are subject to technological or emotional obsolescence should be decoupled from the ones that are not.

4. Hardware components and modules should be designed in order to support software updates across multiple life cycles.

4.3.2 *Adaptive Product Design and Redesign: Helical Optimization and Prediction Engine (HOPE)*

For adaptive product design and redesign, it is assumed that a modular product architecture and infrastructure has been realized. The goal is then to put quantifiable bounds on the decision space in order to make predictions and optimization decisions. To achieve this and to address the second, third, and fourth design challenges in 4.2, an initial framework for a toolkit is developed, the Helical Optimization and Prediction Engine (HOPE) (Figure 4.5). HOPE is comprised of three product-level modules: 1) predicting product life cycle

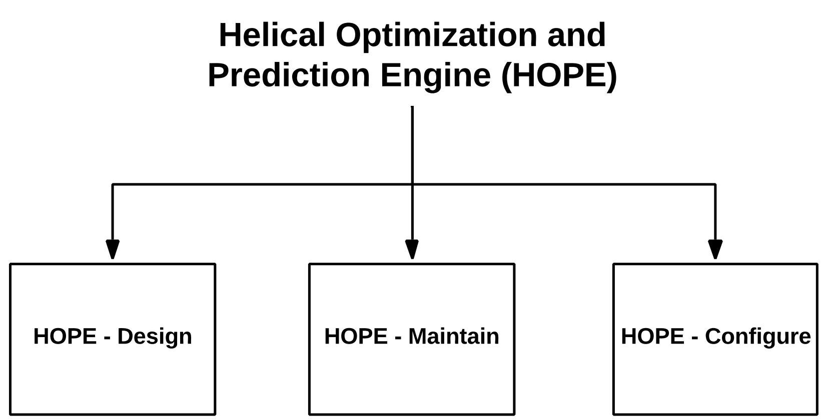


Figure 4.5: HOPE Framework

performance during design (HOPE-Design), and 2) predictively and proactively maintaining a modular product (HOPE-Maintain), and 3) selecting optimal product configuration and reconfiguration (HOPE-Configure) which is planned as future work.

4.3.2.1 HOPE-Design, Predicting Life Cycle Performance

Product designers face increasing demand to design sustainable products, yet they have no knowledge of the sustainability impacts of the design until the product is already in production. This is due to the fact that the two traditional methodologies used in measuring the life cycle environmental and economic impact of a product, Life Cycle Assessment (LCA) and Life Cycle Costing (LCC), both require detailed design-level and system-level definition. This timely input prevents the results of these methods from being used to inform design improvements.

Product manufacturers tend to perform environmental assessments of their products as a compliance-oriented strategy in the latter design stages of the product's design cycle. Since production has already begun at this point, this information provides little value to enhancing the overall sustainability of the product. Instead, a method is needed that can be used to predict the impacts of design decisions in the early design stages. This bends the knowledge curve in the direction of the product designer, moving towards the HE vision at the product-level. This first HOPE component is HOPE-Design Figure 4.6, which looks into developing a predictive performance relationship of a product in order to gain early insight into the life cycle performance across the helical economy dimensions of sustainable value, resource consumption, and technological progress. Instead of requiring a full life cycle assessment (LCA) or life cycle cost (LCC) analysis, this approach uses pre-existing LCA and LCCs and extracts out a finite number of design features that are major cost and impact drivers using machine-learning techniques, and then uses them to estimate the life cycle performance of a product. The goal is to provide a designer or engineer with directionally correct heuristics instead of first requiring detailed life cycle information that is timely to collect. The methodology is then put into action in a case study of the consumer electronics printing industry.

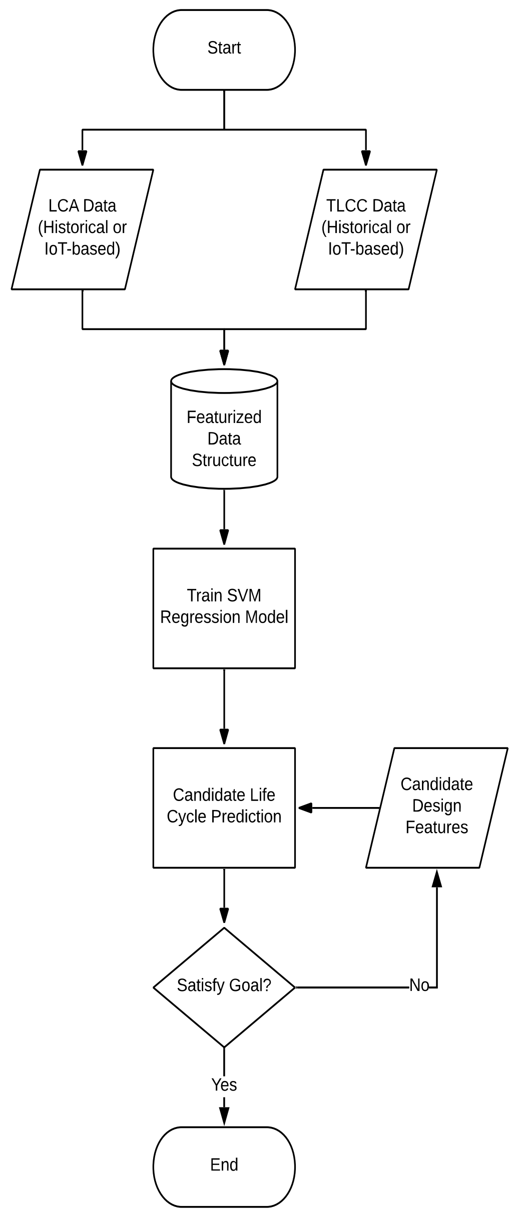


Figure 4.6: HOPE-Design Framework

At a high level, HOPE-Design uses previously recorded detailed life cycle assessment data and life cycle costing data is recorded for M variations or generations of a product line. An N number of features are then selected that are under the control of the stakeholder involved. Machine learning (ML) techniques can then be used in order to train a model that can uses the finite number of design features in order to get directionally correct estimates of life cycle performance in the early stages of the design and development process. The set of features that are fed to the model may vary with different stakeholders, and therefore, with this framework multiple models can be produced for various stakeholders across the organization without them having to be knowledgeable of life cycle assessment or life cycle costing. In a general case, the training data is of the form in Table 4.2, where there are M rows of product variants with N selected design features that have corresponding values for sustainable value, resource consumption, and technological progress.

Table 4-2: Generic Data Structure of the Training Set

	Design Feature 1	**Design Feature 2**	**Design Feature 3**	**..**	**Design Feature N**	**SV**	**RC**	**TP**
Product 1	x_{11}	x_{12}	x_{13}	…	x_{1n}	y_{11}	y_{12}	y_{13}
Product 2	x_{21}	x_{22}	x_{23}	…	x_{2n}	y_{21}	y_{22}	y_{23}
Product 3	x_{31}	x_{32}	x_{33}	…	x_{3n}	y_{31}	y_{32}	y_{33}
…	…	…	…	…	…	…	…	…
Product M	x_{m1}	x_{m2}	x_{m3}	…	x_{mn}	y_{n1}	y_{n2}	y_{n3}

This training set is then used to train a n-th dimensional, linear regression model to determine a predictive life cycle performance relationship. While some machine learning models use more complex computation methods, the mathematical model can be described using linear algebra and simplifying to the first order general case:

Let Equation 4.1 represent the predictor matrix, A:

$$A = \begin{vmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1n} \\ 1 & x_{21} & x_{22} & \cdots & x_{2n} \\ 1 & x_{31} & x_{32} & \cdots & x_{3n} \\ & \vdots & \vdots & & \vdots \\ 1 & x_{m1} & x_{m2} & \cdots & x_{mn} \end{vmatrix} \tag{4.1}$$

Let Equation 4.2 represent the response matrix, C, where the columns represent the HE KPIs of sustainable value, resource consumption, and technological progress:

$$C = \begin{vmatrix} y_{11} & y_{12} & y_{13} \\ y_{21} & y_{22} & y_{23} \\ y_{31} & y_{32} & y_{33} \\ \vdots & \vdots & \vdots \\ y_{n1} & y_{n2} & y_{n3} \end{vmatrix} \tag{4.2}$$

Let Equation 4.3 represent the parameters matrix, B:

$$B = \begin{vmatrix} c_{01} & c_{02} & c_{03} \\ c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \\ \vdots & \vdots & \vdots \\ c_{n1} & c_{n2} & c_{n3} \end{vmatrix} \tag{4.3}$$

Finally, let Equation 4.4 represent the residuals matrix, D:

$$D = \begin{vmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \\ \vdots & \vdots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \sigma_{n3} \end{vmatrix} \tag{4.4}$$

With these matrices defined, the regression function is known to be of form $C = \mathrm{AB} + \mathrm{D}$, where A and C are known, B must be solved for while minimizing D. To find the least-squares parameters, B, it is known the following equation must be solved:

$$B = (A'A)^{-1}A'C \tag{4.5}$$

From solving this, three least squares predictive models for sustainable value, resource consumption, and technological progress can be defined in Equations 4.6-4.8:

$$SV = c_{01} + c_{11}X_1 + c_{21}X_2 \cdots c_{N1}X_3 \tag{4.6}$$

$$RC = c_{02} + c_{12}X_1 + c_{22}X_2 \cdots c_{N2}X_3 \tag{4.7}$$

$$TP = c_{03} + c_{13}X_1 + c_{23}X_2 \cdots c_{N3}X_3 \tag{4.8}$$

These resulting equations are a function of the selected design features. These design features may change across stakeholders, allowing multiple predictive models to be generated for various stakeholders.

To test the framework, the case study is limited to resource consumption, and utilizes already existing Life Cycle Assessment results. Publicly available Life Cycle Assessment results were collected from 20 laser printers. This previously calculated LCA data is treated as a small training set to build a regression model that can predict resource consumption, as it is defined in Chapter 3. Although, this dataset is very small, this dataset is used to simulate the framework. 23 different design were identified were selected for the set of printers, and a random set of six design parameters were selected as the features to train the model.

Using the method as described above, the LCA results served as the response value, and each of the identified design features across the models represent the predictor matrix. This training set was then imported into Python, and a Support Vector Regression kernel from the sklearn library was used in order to generate a regression model for the six randomly selected design variables. The code used for this included in Appendix A. This was repeated 100 times in order to come up with 100 unique models with distinct feature sets. This serves the premise that different stakeholders across an organization care and have the control over a different set of features, and this is done to simulate the creation of multiple models for various stakeholders involved. The percent error is used as a metric for determining how many of these models can be used as directionally correct assessments. The most accurate model in the set is shown in Equation 4.9:

$$RC = 981 + 5.65X_9 + 0.94X_3 - 4.64X_{16} + 16.1X_{12} - 0.13X_{15} - 1.82X_2 \quad (4.9)$$

All of the models generated showed a percent error from the true value in the test models of less than 25%. All of the generated models and results are shown in Appendix B. Table 4.3 shows the summarized performance for the most accurate model that is depicted in Equation 4.9:

Table 4-3: Summary of Performance for Most Accurate Model

Set	Model	% Error
Train	MODEL 1	-12.829831
Test	MODEL 2	-2.485586
Train	MODEL 3	0.621047
Train	MODEL 4	2.51939
Train	MODEL 5	-15.348195
Train	MODEL 6	-2.619115
Train	MODEL 7	3.275619
Train	MODEL 8	-3.378509
Test	MODEL 9	0.174654
Train	MODEL 10	11.205968
Train	MODEL 11	0.570782
Train	MODEL 12	-9.076212
Train	MODEL 13	-1.996009
Train	MODEL 14	-6.86197
Train	MODEL 15	2.404463
Train	MODEL 16	-5.03862
Train	MODEL 17	-12.485986
Train	MODEL 18	1.983489
Test	MODEL 19	0.649684
Test	MODEL 20	0.635855

Overall, through the creation of multiple models for different stakeholders across an organization, life cycle performance information can be decentralized and democratized to where all stakeholders are united under the same KPIs. Limitations should be noted for this framework:

1) This method assumes that a manufacturer has completed multiple detailed LCA and LCC studies across their product portfolio. With the interconnected IoT/Data Infrastructure of a Helical Economy Manufacturing Method, the data collection for these deep studies is intended to be easier and less costly. Each product manufactured in the HEMM will have near real time results for all three HE KPIs. Instead of using previously done studies, the training set can be acquired at the very beginning of a production ramp. This framework is forward looking and intends to accompany this alternate future.

2) This framework is more relevant for highly complex products. For a simplified product, for example a plastic cup, this framework would be overkill in that it is easy to define a parameterized LCA model. That being said, this framework is most useful for products that have thousands of components and complex life cycles that are not easily understood without applying computation.

Although this initial proof-of-concept shows promise, there is significant improvement that can be made by fully characterizing necessary input features, surveying other mathematical methods for composing the predictor equations, and expanding to the other two HE KPIs of sustainable value and technological progress.

4.3.2.2 HOPE-Maintain, Predictive Maintenance for a Modular Product

Scheduled maintenance or planned preventive maintenance has been well established in industries for many years. The automobile industry is the best example of this, with schedule oil changes, part replacement, etc. in order to keep the automobile working in its best condition. However, scheduled maintenance introduces a lot of waste, as it reduces each condition down to its statistical probability. Therefore, many components are replaced well before the end of their useful life. That being said, in the context of IoT, there exists the ability to monitor products in real-time, and only repairing, maintaining, and replacing modules within that product as the data stream indicates it. Various approaches can be used, from simplified knowledge-engineered rules to embedded machine learning algorithms. This approach has the ability to extend the life of products, maximize sustainable value and reduce overall resources.

The second component of HOPE, HOPE-Maintain, assumes an IoT-enabled modular product, and then predicts the remaining life of that particular module. At a high level, the HOPE-Maintain framework is shown in Figure 4.7.

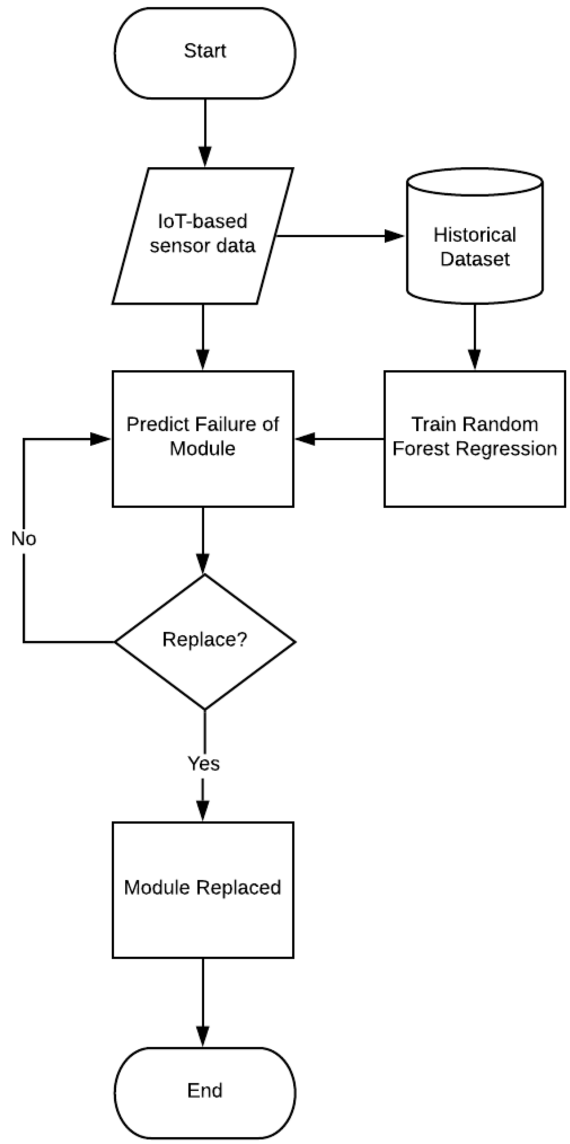


Figure 4.7: HOPE-Maintain Framework

HOPE-Maintain relies on IoT-based sensor data that returns sensor readings about the module's health. These sensors are designed concurrently with the product and distinctly capture the likely failure mode of a module. This sensor data is then aggregated into a historical database form and used to train a random forest regression machine learning model that predicts the remaining life of the module. Once the prediction is made, the module can be replaced based on a set of criteria.

To test the framework, a case study takes sample data from 1882 modules of a mass-produced product. Over 400,000 observed instances and seven million distinct data points were used to train a random forest regression ML model. The code used for this is included in Appendix C. In Figure 4.8, the distribution of the test set prediction is shown. Figure 4.9 shows the prediction of a single module throughout its lifetime.

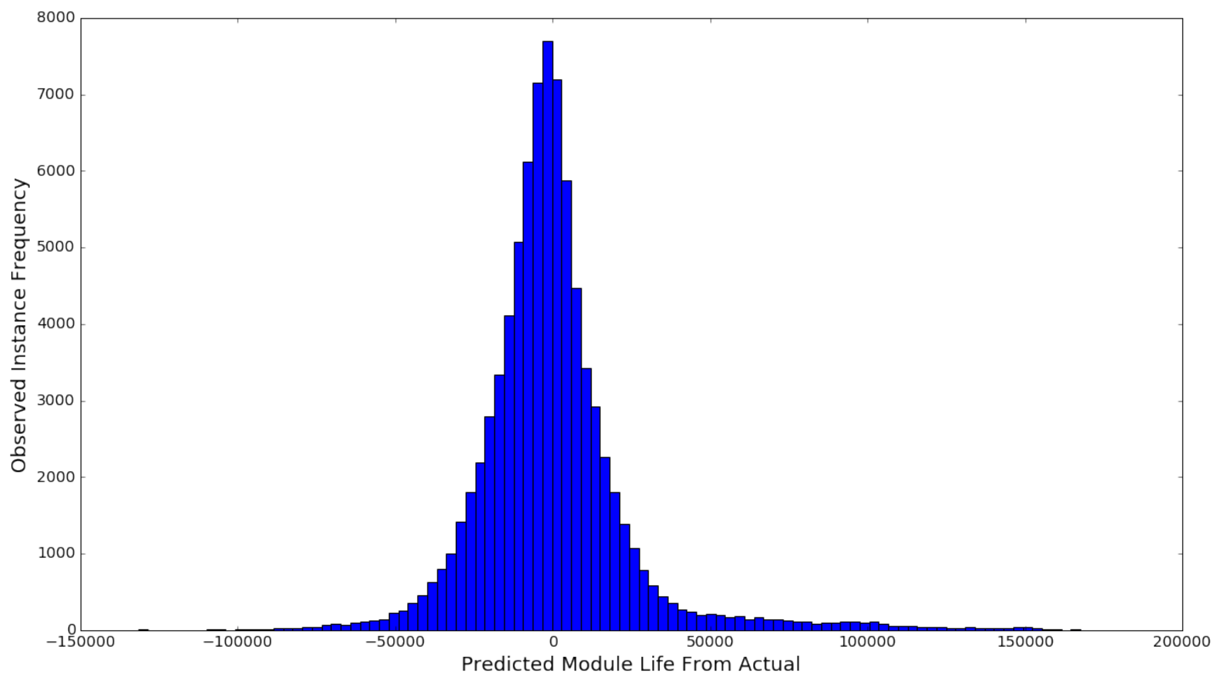


Figure 4.8:Distribution of Test Set Predictions

With this prediction, the module can be replaced based on a set of conditions. These conditions ideally would be tied to the KPIs of the HEMM, which are sustainable value, resource consumption, and technological progress. That being said, this part has not yet been developed, and is a current limitation of HOME-Maintain.

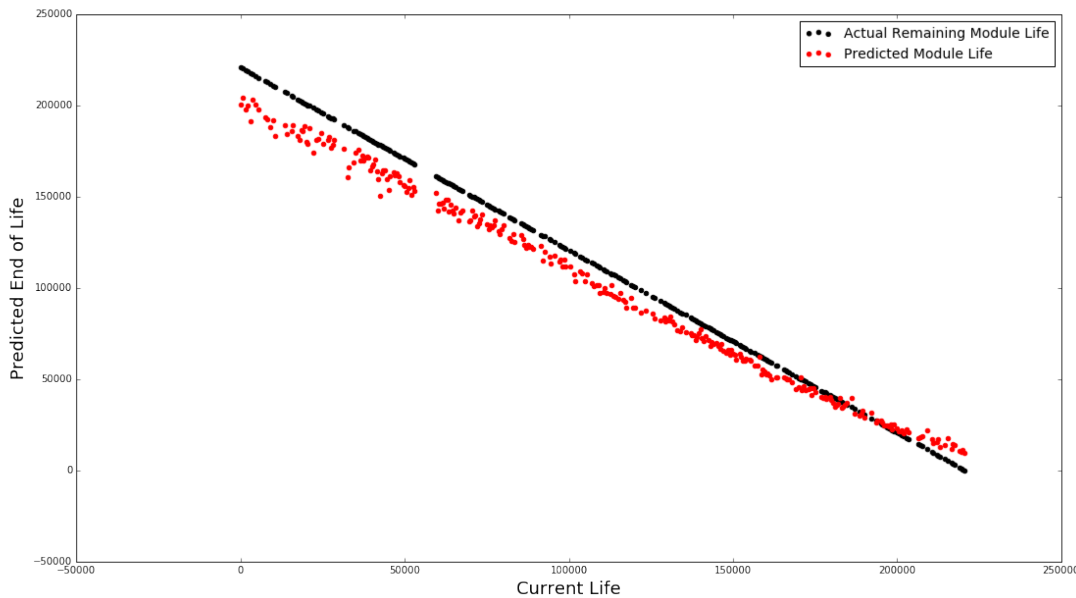


Figure 4.9: Comparison of Actual Remaining Module and Predicted Module Life

4.3.2.3 Future Work, HOPE-Configure, Optimizing Modular Product Configuration and Reconfiguration

The value proposition of HE and the HEMM is grounded in redesigning manufacturing infrastructure at product, process, and system levels. At the product-level, the infrastructure referred to is the product architecture itself. Product architecture must be redesigned to be modular and reconfigurable in order to maximize sustainable value, minimize resource consumption, while maintaining technological progress. The previous sections have outlined potential methods in order to arrive at a modular product architecture, but if it assumed that a modular architecture can be defined, then there must be a process in place for systematically determining initial product configurations and reconfigurations to ensure they are optimized for the HE KPIs of sustainable value, resource consumption, and technological progress. Therefore, in this section the third component of HOPE, HOPE-Configure, is framed and outlined as a future addition to the HOPE framework.

HOPE-Configure assumes a modular product with a finite number of configurations, and then selects an optimal initial configuration and reconfiguration according the HE KPIs. At a high level, the HOPE-Configure framework is shown in Figure 4.10.

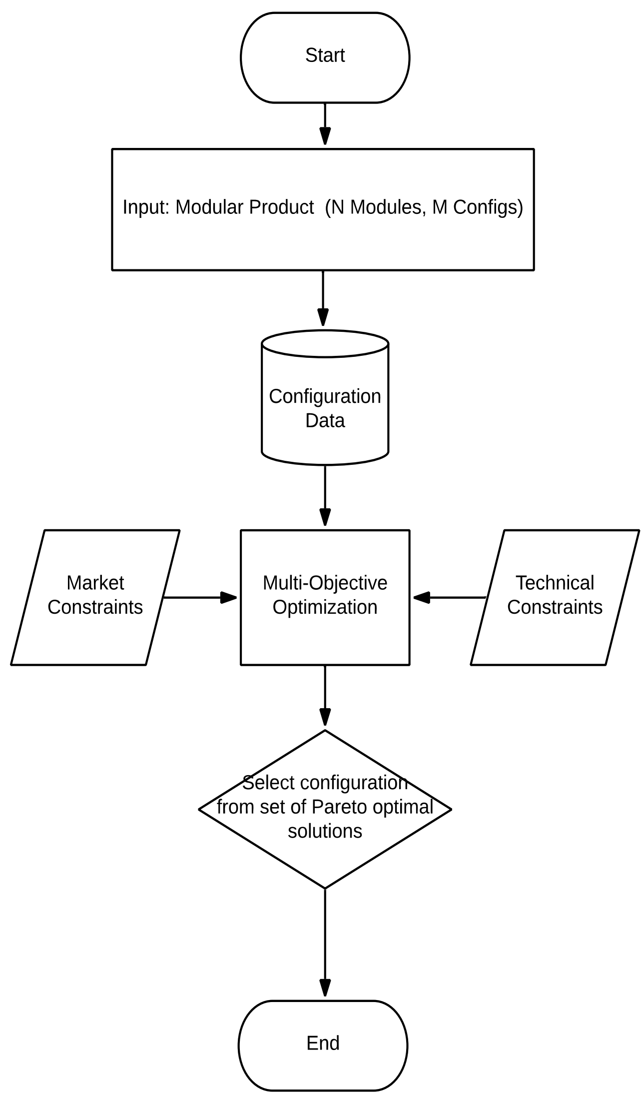


Figure 4.10: Overview of HOPE-Configure Framework

In practice, HOPE-Configure is used to determine when a modular product should be reconfigured based on market demand and technical constraints in order to optimize for sustainable value and resource consumption. Technological progress is omitted here as it is assumed that this has been taken into account during early design of the product modules and associated architecture. Mathematically, HOPE – Configure can be generally formulated as a standard multi-objective optimization problem:

$$Min\ W(x) = \big(SV(x), RC(x)\big), subject\ to \tag{4.10}$$

$$g_a(x) \geq 0, a = 1, 2, \dots, m \tag{4.11}$$

$$h_b(x) = 0, b = 1, 2, \dots, n \tag{4.12}$$

$$x = (N_1, N_2, \dots, N_N) \tag{4.13}$$

$W(x)$ is the objective function, and $SV(x)$ is the minimum objective function for the total life cycle cost, and $RC(x)$ is the minimum objective function for resource consumption. $g_a(x)$ are the inequality constraints and $h_b(x)$ are the equality constraints that reflect market or technical constraints. The x is the binary decision vector of which N modules will be configured in the product or not. The result of the optimization will be the pareto optimal set of configurations. Doing this for the initial configuration is less novel, and similar approaches have been taken before [99,107].

However, for product reconfiguration, the problem then becomes a modular product made up of a finite number of modules, along with a set number of modules that can be added to the product in order to upgrade the function and/or add/change functionality of the product. The question then becomes is it optimal for the product to remain in the current configuration or switch into another configuration subject to the technical and market constraints. HOPE-Configure is in progress as a future addition to HOPE, so no case study is provided, but the overall framework outlines the approach.

4.4 Chapter Summary and Discussion

This chapter addressed designing next generation products for a Helical Economy by first motivating and defining the problem, then reviewing the state of the art, and then identifying the primary challenges, and then finally presenting the DfHE guidelines for new product design and the Helical Optimization and Prediction Engine (HOPE) for adaptive design and redesign. These two elements aim to move manufacturers towards the HE and HEMM future vision.

In defining the problem, it was stated that product design has an outsized impact on the sustainable value and resource consumption obtained by manufacturing. Because of this, product designers in a HE need to be able to concurrently design the product, the manufacturing process, the supply chain, and simultaneously design for a multi-generational life cycle.

The four primary challenges identified for designing next-generation products for a HE include: 1) For new product design, a new qualitative design guide is needed that brings to light the elements of helical economy that must be addressed at the earliest part of the design process, 2) For adaptive product design and redesign, the ability to predict life cycle performance from historical or IoT sensor information must be developed, 3) For modular products with multiple lifecycles, a method must exist for proactively predicting when a module requires maintenance or failure is imminent, and 4) For designing modular products for multiple lifecycles, there must be process in place to systematically use historical information and predictive data in order to optimize a product's initial configuration and each life cycle reconfiguration.

The chapter then presents two components for industry implementation that take aim at the above design challenges: 1) Design for Helical Economy (DfHE) set of guidelines for new product design that aims for product designers to get to a near-net HE design, and 2) the Helical Optimization and Prediction Engine (HOPE), a quantitative framework for redesigning next-gen products. The DfHE guidelines are rooted in four themes:

1. Designing for Multiple Life Cycles
2. Designing for Interconnectivity
3. Designing for Assembly, Disassembly, and Reassembly
4. Designing for Modularity and Upgradeability

The set of 15 guidelines is intended to give a designer a set of guardrails or design constraints at the earliest of design stages, while not being overly prescriptive or quantitative in an effort to not hinder creativity.

The proposed Helical Optimization and Prediction Engine (HOPE) framework is a set of three modules, two of which are presented with case studies, and a third which is presented as a future addition. HOPE is aimed at being the quantitative driving structure for adaptive product design and redesign. The first module, HOPE-Design, aims at predicting life cycle performance, performance in this case being referred to as the HE KPIs. The module takes existing LCA or LCC data from an historical database or an IoT collected sensor system and uses a support vector machine regression model to train predictive models for various stakeholders. For a highly complex product, multiple models can be produced and only the driving parameters controlled by the stakeholder are surfaced to them. This collectively unites stakeholders across the organization under the same quantitative structure and common goals. The second module HOPE-Maintain, takes a modular product that is IoT-enabled and predicts the remaining life of that module. Sensors capture the health of the module and this data is aggregated and stored in a centralized database. A random forest regression model is trained and then used to predict the remaining life of modules in the field. These modules can then be replaced based on a set of criteria. The third component of HOPE, HOPE-Configure, is framed as a future addition to HOPE. This module is intended to optimize a modular product's configuration and reconfiguration based on the HE KPIs. The initial configuration problem is quite easy to frame, but the reconfiguration problem ideally takes a modular product made up of a finite number of modules, along with a set number of modules that can be added to the product in order to upgrade the function or add/change functionality of the product. The problem then becomes is it optimal for the product to remain in the current configuration or switch into another configuration subject to the technical and market constraints. Once this is solved, HOPE will span multiple life cycles stages and offer a multi-generational view of a product.

Overall, this chapter provides the initial foundation for designing next-generation products for the Helical Economy and HEMM. By addressing multiple facets of design and design stages, manufacturers will be able to use the DfHE or HOPE to take a first step towards the HEMM future vision.

CHAPTER 5 DESIGNING AN IOT-ENABLED DATA INFRASTRUCTURE FOR A HELICAL ECONOMY

5.1 Introduction and State of the Art

5.1.1 *Motivation*

With the race to monetize data, manufacturers are going "all in" on big data. The International Data Corporation predicts global Internet of Things (IoT) spend to top $1.29 trillion by 2020 [108], with the manufacturing sector being the dominant contributor. Manufacturers across the globe are investing hundreds of billions of dollars in Industrial Internet of Things (IIoT) and Industry 4.0 infrastructures and the necessary skilled personnel to support them. This level of investment reflects the opportunity at stake. The manufacturing industry generates more data than any other sector [109]. That unstructured, semi-structured, and structured data can ideally be processed and then used to achieve significant improvement in product design, manufacturing efficiency, cost reductions, scalability, resiliency, and environmental sustainability [110,111]. However, with the current approach (Figure 5.1), these manufacturers may be looking for diamonds (i.e., efficiencies and cost savings) in the rough (billions of unstructured data points) in order to justify the initial investment and ongoing costs.

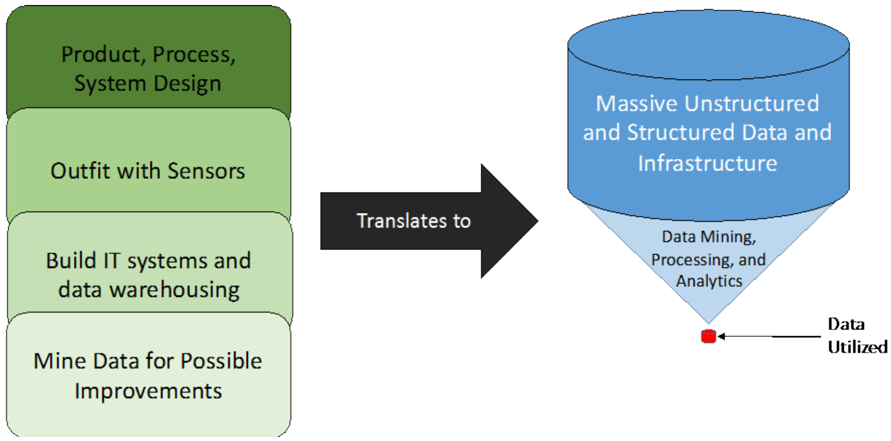


Figure 5.1: An overview of the traditional approach to designing IoT systems

The data seems to agree that the current approach is flawed. In 2017, Cisco produced survey results that indicated ~75% of IoT initiatives have been failures [112]. Gartner has also reported that 60% of IoT and big data projects fail to go beyond a pilot and predicts that by 2022, only 20% of IoT data insights will drive business outcomes [113]. Based on the lack of results in industry, there is fundamental problem with the current approach to IIoT and Industry 4.0 initiatives. The current approach of creating these extensive IoT frameworks involves outfitting legacy products, manufacturing equipment, and manufacturing systems with numerous sensor nodes and IT systems in order to collect a significantly large dataset, only to have a fraction of the dataset return business value. Although excellent in theory, this approach can lead to an astronomical initial investment that could hinder any practical implementation in a cost-constrained production environment. In addition, if this approach is implemented blindly, there is a great risk associated with managing the new overhead. This trap is caused by the idea that information is free. While information is free, the ability to access it and use it in a way that can be beneficial is far from free. Everything from collecting the data points, to processing, and then storing them has an associated cost. If only one million data points out of the original one billion is actually usable in a way that they can see a return on investment, then 99.9% of the data collected was wasted, and it directly impacts the bottom line.

With that in mind, there is a need for a counter approach to implementing IIoT and Industry 4.0 projects. This must begin with defining the key business outcomes that are desired, and although many companies are going after cost reductions, those reductions will inevitably give way to the law of diminishing returns. Instead manufacturers can apply the Helical Economy and HEMM framework to their IIoT and Industry 4.0 implementations in order to achieve a holistic result of maximizing sustainable value creation, minimizing resource consumption, and ensuring continued technological progress. This chapter begins with reviewing the current state of the art in designing IoT and data infrastructures for the manufacturing sector. From this review, the primary challenges for designing an IoT and data infrastructure for the HEMM are summarized. The chapter then presents an alternative implementation of an IoT infrastructure using two initial methods: 1) a method for reducing sensor hardware, and 2) a method for reducing the size of the data set needed. The chapter is then concluded with a summary and relevant discussion. This chapter includes work that was done when the author was on an industry research team at Lexmark International that resulted in: two published US patents ([114], [115]), one co-authored journal publication [116], and one co-authored submitted journal paper. The author was a lead contributor to the foundational work shown in this chapter, and the integration plan of this foundational work into the overarching theory and strategy for designing IoT-enabled data infrastructures for HE in the manufacturing domain was the author's sole contribution.

5.1.2 *State of the Art and Previous Case Studies*

For years, the vision of the IoT and its impact on product design and manufacturing has been molded for future implementation. It can be said that the IoT is a means for aligning the physical and information life cycles [88]. This vision suggests that this intimate connection and the information itself present a major source of value [88,89]. Dubey et al. [58] suggest that Big Data (BD) is one of the emerging research areas that are considered "game changers" in the manufacturing sector, with the claim that the use of big data can see a 15-20% increase in return on investment and surplus cash for customers [58]. Because of the well-documented opportunity, the manufacturing arena has seen an array of concepts arise and gain significant interest in the last decade (See Figure 5.2): Industry 4.0, Cyber-Physical Systems (CPS), Industrial Internet of Things (IIoT), Smart Manufacturing, Factories of the Future, and Digital Thread and Digital Twin.

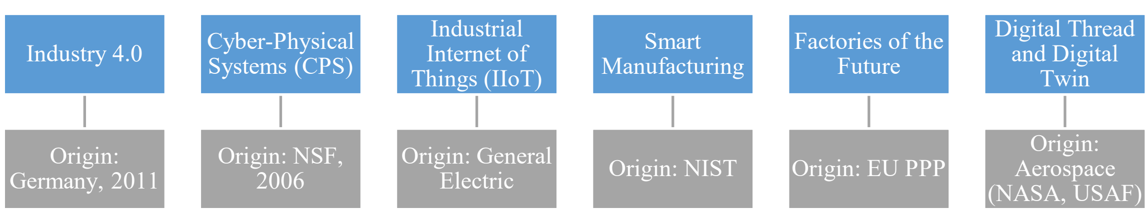


Figure 5.2: Overview and Origin of concepts in the IoT domain for the manufacturing industry

The "Industry 4.0" concept came out of Germany and was first published in 2011 by Kagermann [117]. The underlying premise is that the first industrial revolution (Industry

1.0) was the product of the rise of steam power, the second industrial revolution (Industry 2.0) was the product of the rise of the assembly line and mass production, the third industrial revolution (Industry 3.0) was the product of the rise of computers and automation, and claims that the fourth industrial revolution (Industry 4.0) will be the product of the rise of the Industrial Internet of Things and Cyber-Physical Systems (CPS).

Cyber-Physical Systems (CPS), said to have been coined around 2006 by Helen Gill (National Science Foundation) [118], are defined to be a harmonization of physical processes and the computational world through mechanisms such as embedded sensors and feedback control systems [49]. Industry 4.0 takes CPS and envisions a next-generation manufacturing industry where CPS are highly utilized on the factory floor [50]. In addition, the approach claims that high value data and analytics, collected from the CPS, are leveraged to make manufacturing more efficient, more customizable, and more resilient [51,52]. There has also been previous work that looks at extending CPS to Socio-Cyber-Physical Systems within production networks. In this work, the human element of creativity and problem solving are combined with the technological innovation of CPS [53].

The Industrial Internet of Things (IIoT) which refers to the Industrial Internet, said to have been first coined by General Electric [119], is rooted in IoT applications that are targeted at industrial and manufacturing environments. IIoT applications are underpinned by the interconnectivity of products and machine-to-machine communication in combination with cloud computing and sensor-based data collection.

Smart Manufacturing is defined by NIST as: "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 [120]."

Factories of the Future is a public-private partnership in EU that is focused on advancing manufacturing research and innovation, with partial focus on two relevant research initiatives: adaptive and smart manufacturing, as well as digital, virtual and resource-efficient factories.

The Digital Twin and the Digital Thread concepts were first established in the aerospace industry [121,122], and respectively refer to the digital replication of a physical asset, and the interconnectivity and data flow of that asset throughout its lifecycle. Both of these concepts have found their way into Industry 4.0 and IIoT conceptualizations, with NIST forming a research program around Digital Thread for Manufacturing Systems.

It can be seen that across all the various concepts across manufacturing, there is significant overlap of the core concepts and intended outcomes. Also, these concepts usually limit the scope to within the metaphorical walls of the manufacturer being considered, therefore missing the integration with the pre-manufacturing, use, and post-use phases of the life cycle. Also, although CPS has dominated areas such as industrial automation, home automation, green transportation, and smart cities [54], the application to sustainability-focused outcomes is newly forming and presents a novel opportunity for establishing initial methodologies. The sought-after gain from such an implementation mainly aims at reducing energy and resource consumption, but it is suggested that improvements to sustainability can also come in the form of combining multi-source information, and then making a calculated decision from that information using cloud computing and web services [123].

There have been several case studies involving the use of IoT and BD in order to drive sustainable value creation. In Pan et al. [55], a framework is built surrounding the HVAC and building industry and the use of IoT systems to improve energy usage. The approach envisions creating significant economic benefits, as well as social and environmental benefits. Tao et al. [56] presents integration between an IoT system and a traditional PLM system. This work provides an idea for collecting environmental and life-cycle data throughout the entire life cycle. The work also proposes the idea of a big Bill of Material (BOM) that uses the integration interface with the IoT systems in order to exchange and transform information. The next case considers the idea of using cloud-based technologies in order to support product services [57]. In other words, a decision support system is built on top of the BD foundation. In other cases, these services are built to be proactive by building in predictive models and analytics into the decision support system [58].

Another case is seen in the food production sector where the application of BD to the supply chain can have implications for many industries. The work claims that analytics can translate customer sustainability requirements into an increase in sales, by being able to mine the rationale from metadata. In addition to the positives, the utilization of BD results in negatives as well. For example, tailored consumer level detail can result in the loss of purchasing options [59]. The Ellen MacArthur Foundation has also done initial work outlining the role that “intelligent assets” will have in their Circular Economy vision [124].

There are also case studies where IoT has been deployed in combination with machine learning in order to realize operational efficiencies and cost reductions. Wu et al. [125]

established a data-driven smart manufacturing application for tool wear prediction using machine learning algorithms. Shin et al. [126] developed a BD infrastructure driven analytics model for predicting manufacturing power consumption using MTConnect [127] and a neural network. Kumar et al. [128] uses a MapReduce-based BD framework for fault-detection in a steel plate manufacturing application.

The next section will use the learnings from the problem definition and prior art to identify the primary challenges for designing an IoT and data infrastructure for HE and the HEMM vision.

5.2 IoT and Data Infrastructure Design Challenges for a Helical Economy

In order to achieve a HE and HEMM, the IoT and data system must act as the “glue” of the HEMM. Data must be collected at the product level, the process level, and at the system level using networked sensors that send data to a centralized data store. In addition, data must be collected across all life cycle phases: design, manufacturing, use, and post-use. The data collected must be compiled and analyzed in order to make decisions such as: reconfiguring the product, determining the optimized process plan, and/or but not limited to determining the optimal system level configuration. An application layer can sit on top of this data infrastructure layer to operate as the overall control system. This system will be comprised of dashboards and monitoring control, optimization functions, and machine learning derived predictive analytics to support decision making at every life cycle stage.

Based on the industry success rate of IoT projects, current research approaches are either not being successfully spun out of academic domains or not being adopted, and therefore, a counter approach must be defined for designing an IoT and data infrastructure for a HE.

More attention needs to be given to minimizing the required infrastructure in order to reduce initial and reoccurring expense. For a HE and HEMM specifically, the IoT and Data infrastructure must also span beyond the manufacturer's physical domain and to all other life cycle stages: pre-manufacturing, use, and post-use. The size of and breadth of this level of data coverage will require unprecedented challenges with data security. Therefore, three primary challenges can be highlighted for designing an IoT and data infrastructure for the HE and HEMM vision:

1) Reducing the number of sensors required by designing and selecting the hardware specifically based on the end-use application, which will reduce the overall cost of the infrastructure required.
2) Reducing the amount of data required for end-use applications, such as machine-learning based analytics.
3) Ensuring secure harmonization of data across products, manufacturing equipment, and manufacturing systems, logistics providers, and customers.

The first and second challenge must address the issues present in the traditional approach of implementing an IIoT, which is to retrofit existing infrastructure with numerous sensor nodes and collect as much data as possible, with the hope to convert a fraction of this data into business value. This approach balloons the cost of the system and creates unnecessary waste. Instead, a counter approach would be to deploy only the number of sensors required and to collect only the data that provides business value. This approach can give the IoT and data infrastructure a lean overall cost structure and higher chance of success.

The third challenge must ensure data harmonization across products, processes, and systems, as well as across multiple life cycles at the pre-manufacturing, manufacturing use, and post-use stages. Although highly conceptual, this challenge would result in the overall control system for the HEMM, knowing what products to manufacture, what products to reconfigure, the optimal disposition of a product, managing the overall flow throughout the system to constantly ensure maximized sustainable value creation, minimized resource consumption, and continued technological progress. This end goal is difficult to achieve in that multiple sub-problems have to be solved at the product, process, and system level in order for this to be able to put into production. There is no "silver bullet" solution that will make this a reality overnight. In addition, the security challenge that this level of interconnectivity requires, in itself, requires significant research and development investment.

5.3 Initial Methods for Industry Implementation

In this section, the first two primary challenges that were identified in 5.2 are addressed: 1) reducing sensor count and 2) data set reduction for machine-learning based applications. The first method discussed is a method for reducing the number of sensors required for a supervised machine learning classification system and the second method discussed is a method for reducing the data set required for machine-learning applications in cost conscious domains. These methods were created as part of an industry team, and the general cases of both methods have high relevance to HE and the manufacturing domain.

5.3.1 *Scalable Method for Reducing Sensor Infrastructure in Machine Learning IoT Applications*

5.3.1.1 Introduction

Many manufacturers have incorporated IIoT sensor-based control schemes across their products and their manufacturing infrastructure. Recently, these manufacturers have begun using machine learning algorithms to leverage this trend to enable new functionality. IIoT-based multi-sensor information may be used to generate input features for algorithms the span all stages of the manufacturing life cycle. Concerns arise with the rising use of sensor hardware to gain new pieces of information.

This section discusses a method to reduce the number of sensors required for an IoT-based supervised machine learning classification system. Expert knowledge of a sensor's interaction within the system allowed more information to be distilled from a measurement. The system hardware and control system were concurrently developed, and a temporal data stream was leveraged in order to capture more distinct information. The time series data was discretized into several distinct zones of interest corresponding to the sensor's response to different events happening in the system. A difference method allowed the extraction of additional features that would aid the learning algorithm's performance. This methodology is validated by a case study of a media classification system developed for a commercial laser printer, which was manufactured and deployed at a large volume. The results from this method exceeds that of embodiments using multiple sensors. Finally, the HE implications of this design methodology and advantages over a traditional multi-sensor approaches are discussed.

5.3.1.2 Methodology

In concurrently developed IoT infrastructures, the designer has access to significantly more information about the situation than is often available with analyzing time series data in a general case. Time series data output by a single sensor may contain information about multiple physical quantities due to system dynamic behavior. Therefore, multiple physical quantities do not always need to be measured by the same number of physical sensors. The designer has an opportunity to tune the hardware to produce a time series output from a single sensor and then discretize the output with domain expert knowledge to produce multiple features while preserving uniqueness. This results in a system with fewer sensor nodes and a lower associated cost.

The traditional approach to IoT machine learning based systems is shown in Figure 5.3, and it places the burden of the system on the sensor nodes themselves. The physical system is outfitted with a complex network of sensor nodes in order to collect a large amount of data coinciding with various attributes of the system. In this figure it can clearly be seen that there are four nodes that are collecting data and storing that data in the cloud. There

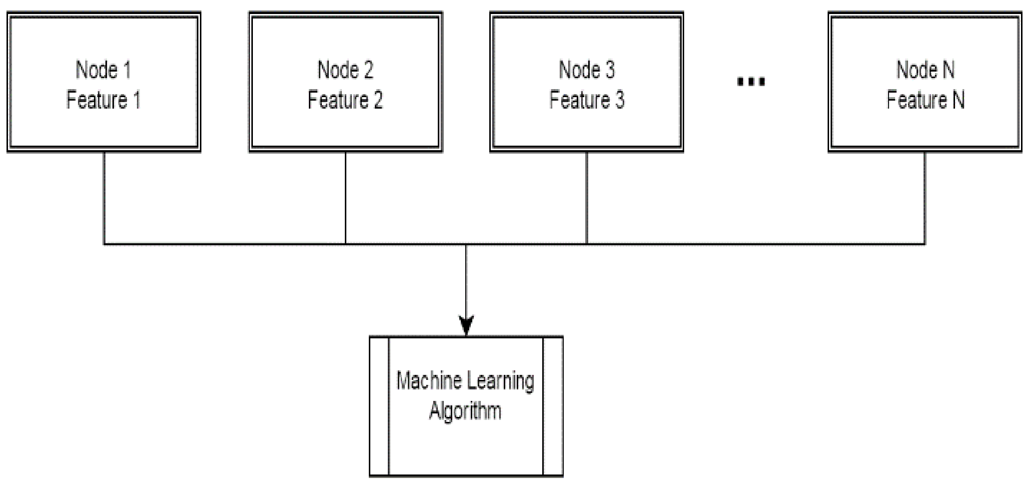


Figure 5.3: Traditional IoT Approach with Extensive Sensor Nodes

are two issues with this setup: 1) It requires hardware for each node, 2) The data is stored in the cloud and must sifted through to come up with the needed subset. This results in an inflated system with considerable amount of resources and energy being required for the hardware, as well as a large amount of required processing in order to consume the data.

With that in consideration, this setup shows that there is much left to be desired in terms reducing the overall cost and footprint of the system.

The proposed alternative approach illustrated by Figure 5.4 puts the burden of the system on the domain expert knowledge and the temporal output of a single node. The domain

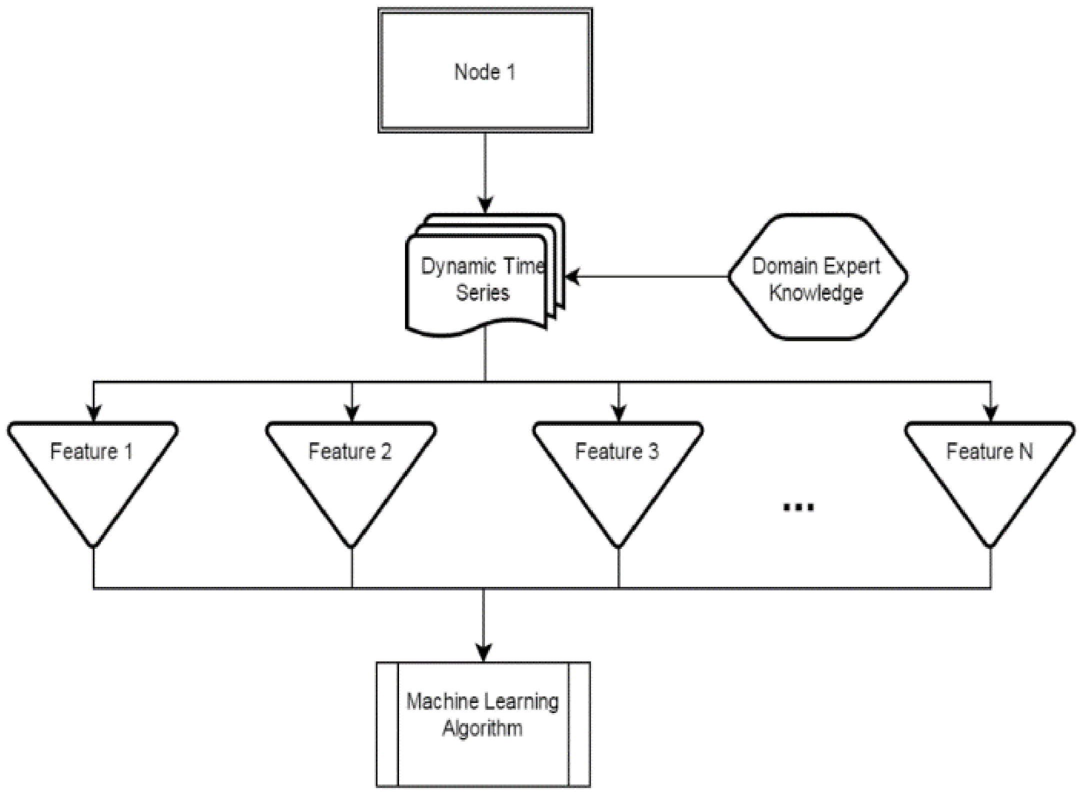


Figure 5.4: Proposed Method for Sensor Reduction

expertise is used to partition the measurement time series $m(t)$ into discrete intervals, such that:

$$m(t) = \begin{matrix} [x(t_1, t_2): & [\Psi_{t_1,t_2}], \\ x(t_2, t_3): & [\Psi_{t_2,t_3}], \\ \vdots & \\ x(t_{N-1}, t_N): & [\Psi_{t_{N-1},t_N}]] \end{matrix} \tag{6.14}$$

Here, the time intervals $[(t_1, t_2), (t_2, t_3), \ldots, (t_{N-1}, t_N)]$ correspond to known physical events in the system and $[x(t_1, t_2), x(t_2, t_3), \ldots, x(t_{N-1}, t_N)]$ is the set of discrete measurement intervals. Ψ is a set of statistical measures (mean, variance, skewness, range, minimum, maximum, etc.) taken within the corresponding measurement interval to describe the interval under inspection.

The classifier is trained on collected data that is of the form (y_k, x_k). Ideally, $x_k = \phi_k$, where ϕ_k is the set of intrinsic physical properties in the system ($\phi_k = [\phi_1, \phi_2, \dots, \phi_{N1}]_k^T \in \mathbb{R}^{N1}$). $N1$ represents an ideal set of intrinsic properties, and $\Psi \subseteq \phi_k$. In other words, the sets to be classified are well separated by a measurement of some direct attribute. In the practical case, this is not so. Every measurement is a function of both the intrinsic property being measured and the properties of the physical system involved in that measurement. These properties include the structure of the system and its operation, which are controllable by the system designer, and known environmental factors which may not be controllable by the designer. Considering the form of the constructed intervals and corresponding statistical measures, the training data examples x_k are such that:

$$x_k = \begin{matrix} [f_1(\phi_k, Y_1, Z_k), \\ f_2(\phi_k, Y_2, Z_k), \\ \vdots \\ f_N(\phi_k, Y_N, Z_k)] \end{matrix} \tag{6.15}$$

Here, $(f_1, f_2, \dots, f_N)$ are nonlinear functions of the arguments: ϕ_k, the intrinsic physical properties; $Z_k \in \mathbb{R}^{N2}$ which are known, quantifiable extrinsic system properties that influence the measurement ($N2$ is the number of extrinsic properties affecting measurements); and $(Y_1, Y_2, \dots, Y_N)$, which are uncontrollable external factors that are a function of the hardware design.

In the case of systems where measurements taken in different intervals are coupled, taking the difference between two functions can help to train the classifier with independent information about system interactions and decouple external factors that influence the measurement. This can be justified with a brief expansion analysis [116]. Given two functions f_i and f_j, the Taylor series expansions can be taken about a nominal operating point as:

$$f_i(\phi_k, Y_i, Z_k) = \frac{\partial f_i}{\partial \phi_k}\Delta\phi_k + \frac{\partial f_i}{\partial Y_i}\Delta Y_i + \frac{\partial f_i}{\partial Z_k}\Delta Z_k + C_i \tag{6.16}$$

$$f_j(\phi_k, Y_j, Z_k) = \frac{\partial f_j}{\partial \phi_k}\Delta\phi_k + \frac{\partial f_j}{\partial Y_j}\Delta Y_j + \frac{\partial f_j}{\partial Z_k}\Delta Z_k + C_j \tag{6.17}$$

Taking the difference yields:

$$f_i(\phi_k, Y_i, Z_k) - f_j(\phi_k, Y_j, Z_k) = \tag{6.18}$$

$$\left(\frac{\partial f_i}{\partial \phi_k}\Delta\phi_k + \frac{\partial f_i}{\partial Y_i}\Delta Y_i + \frac{\partial f_i}{\partial Z_k}\Delta Z_k + C_i\right) - \left(\frac{\partial f_j}{\partial \phi_k}\Delta\phi_k + \frac{\partial f_j}{\partial Y_j}\Delta Y_j + \frac{\partial f_j}{\partial Z_k}\Delta Z_k + C_j\right) =$$

$$\Delta\phi_k\left(\frac{\partial f_i}{\partial \phi_k} - \frac{\partial f_j}{\partial \phi_k}\right) + \left(\frac{\partial f_i}{\partial Y_i}\Delta Y_i - \frac{\partial f_j}{\partial Y_j}\Delta Y_j\right) + \Delta Z_k\left(\frac{\partial f_i}{\partial Z_k} - \frac{\partial f_j}{\partial Z_k}\right) + C_i - C_j =$$

$$0 + \left(\frac{\partial f_i}{\partial Y_i}\Delta Y_i - \frac{\partial f_j}{\partial Y_j}\Delta Y_j\right) + 0 + C_i - C_j$$

For the same training example, $\Delta\phi_k = 0$. The same is true for ΔZ_k. Therefore, the only remaining terms are those that include ΔY_i and ΔY_j, the associated partial derivatives, and the difference of the offset constants. The new feature $f_i - f_j$, is solely a function of ΔY_i and ΔY_j, which are functions of certain fixed extrinsic system properties. With feature selection effectively decoupled from the number of nodes required, the result is a reduction of sensor nodes and associated cost. Every system measurement is a function of both the intrinsic property being measured and the properties of the physical system involved in that measurement. These physical properties include the structure of the system and its operation, which are controllable by the system designer, and environmental effects, which may not be controllable by the designer but are known. The resulting system consolidates the hardware required to a singular node, drastically reducing the overall footprint of the system from a cost, energy, and resources perspective.

5.3.1.3 Case Study

The case study applies the sensor reduction approach to a commercial laser printer intended for use in a managed print services environment. To address the issue of printer users not changing their media settings, an inexpensive sensor system and embedded machine learning algorithm were implemented to automatically determine the print media without any user input.

A low-cost LED/phototransistor pair was used as the single sensor, and by leveraging domain expert knowledge, this sensor output was discretized in a way that it would capture relevant information from different aspects of the printer's operation. These discretized features were configured as the training set to an embedded machine learning (ML) algorithm. The resulting ML model was embedded in the printer's firmware and used to control the relevant printer parameters in near real time.

A cross section of the printer media path is shown in Figure 5.5 [116]. The highlighted region contains a section view of the sensor positioned on opposite sides of the printer's media path between two media feed nips.

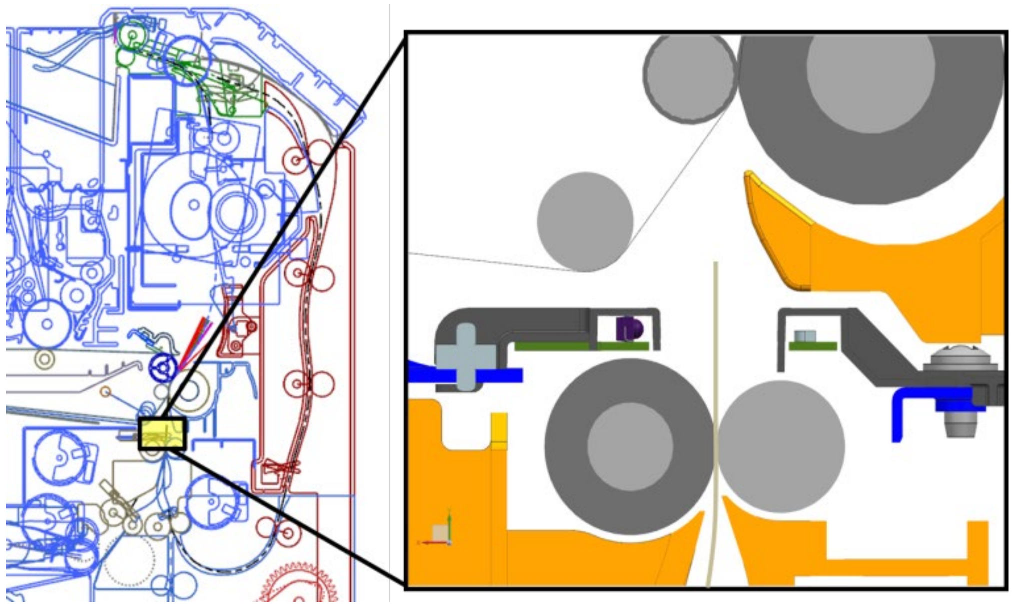
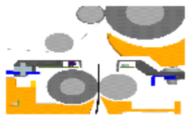
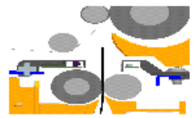
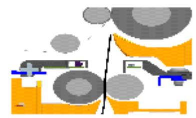
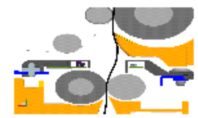
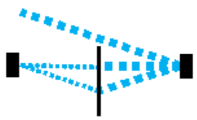
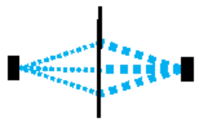
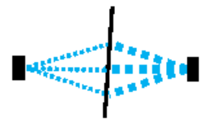
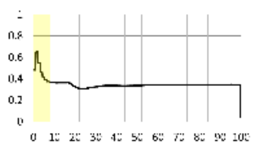
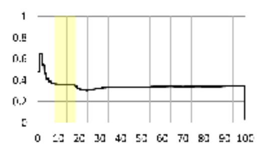
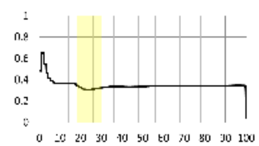
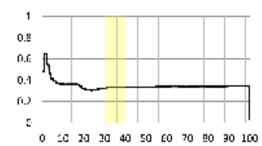
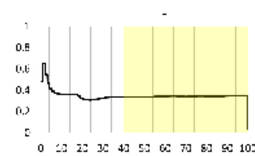


Figure 5.5: A cross section of the printer media path, with the highlighted region showing the sensor area [116]

Like mentioned above, the sensor's output was directly a function of the amount of light that was transmitted through the media. This corresponded to multiple physical elements of the media: media basis weight, media roughness, etc. Other properties extrinsic to the media under inspection also played a role: print speed, location of print media, etc.

This complex measurement was featurized in a way to obtain maximum information, while maintaining feature uniqueness. This was critical for the success of an ML implementation. This was achieved by breaking down the measurement according to Table 5.1 [116]. The resultant time series data was divided into zones that correspond to changes to the media and system interaction as the media moves throughout the printer.

Table 5-1: Simplified model of the sensing system [116]

	Zone 1	Zone 2	Null	Zone 3	Zone 4
Distance	0 - 8 mm	8 - 18 mm	18 - 30 mm	30 - 40 mm	40 - 100 mm
Media Path Cross Section					
Physical Description	Media enters the sensor and obscures the emitter.	Media is vertical and midway between the emitter and detector.	Media bends and interacts with downstream guides.	Media enters a second nip. Shock is possible. A bubble is created.	A velocity differential creates tension and removes the bubble.
Media Sensor Pictogram					
Characteristic Sensor Output					
Explanation of Time Series	Sensor intensity drops drastically when the detector is first obscured and increases as previously undetectable light is diffusely scattered by media moving downstream.	Mean sensor intensity remains steady. Sheet position is well controlled near the center of the sensor.	Sensor intensity increases as media bends closer to the emitter. Output variability due to drastic fluctuations in sheet position are typical.	Some variability due to fluctuation in sheet position is typical. Once controlled by the second nip, media position begins to stabilize and higher sensor intensities are typical.	Mean sensor intensity remains steady. Sheet position is well controlled. Media is slightly angled and closer to the emitter. Higher intensities are typical.

The features used for the machine learning algorithm are provided in Table 5.2 [116]. Features x_1, x_2, … x_5 are extrinsic system properties and uncontrollable external factors that are provided by the printer system's embedded firmware. Features x_6, x_7, … x_{18} contain information about the physical properties of the media, but each of these are coupled to the extrinsic factors and the external factors. Features x_{19}, x_{20}, x_{21}, and x_{22} represent the features that are the output of the differencing method used to decouple the features related to physical media properties.

Constructing the feature set in this manner allowed the use of a single sensor for maximized performance. Figure 5.6 [116] shows a set of features across media types. Feature 7 is predominantly a measure of the media opacity. Feature 18 is measure of the uniformity of the sheet and features 19 and 20 are difference features that decouple the opacity measurement from things like the interaction of the media and system. The features in Figure 5.6 demonstrate the unique information that each of these features provide the ML algorithm.

Table 5-2: List of Features Extracted from the Single Sensor [116]

Feature ID	Description	Predominant Measure Type	Intuition
X_1	Process Speed (Discrete)	Extrinsic	Feed rate influences dynamic media bubble formation and data sampling rate
X_2	Temperature (Continuous)	External	Thermal expansion impacts roller diameter (feed rate)
$X_{3\text{-}4}$	Relative Humidity & Grains Moisture (Continuous)	External	Moisture content influences media stiffness (media bubble formation)
X_5	Input Source (Discrete)	Extrinsic	Input source influences media position and curl (media bubble formation)
X_6	Zone 1 Opacity (Max)	Instrinsic	Media opacity*, coupled with feed rate
$X_{7\text{-}9}$	Zone 2 Opacity (Min, Mean, & Max)	Instrinsic	Media opacity*
X_{10}	Zone 2 Uniformity (Range)	Instrinsic	Media uniformity*
$X_{11\text{-}13}$	Zone 3 Opacity (Min, Mean, & Max)	Instrinsic	Media opacity*, coupled with bubble formation
X_{14}	Zone 3 Uniformity (Range)	Instrinsic	Media uniformity*, coupled with bubble formation
$X_{15\text{-}17}$	Zone 4 Opacity (Min, Mean, & Max)	Instrinsic	Media opacity*, coupled with media offset
X_{18}	Zone 4 Uniformity (Range)	Instrinsic	Media uniformity*, coupled with media offset
X_{19}	X_6 - X_7 (Difference)	Decoupling	Decouples media opacity in Zone 1 from feed rate
X_{20}	X_7 - X_{11} (Difference)	Decoupling	Decouples media opacity in Zone 2 from media bubble formation
X_{21}	X_7 - X_{15} (Difference)	Decoupling	Decouples media opacity in Zone 4 from media offset
X_{22}	X_{11}-X_{15} (Difference)	Decoupling	Helps decouple media bubble formation and media offset
*Function of media composition, thickness, roughness, etc.			

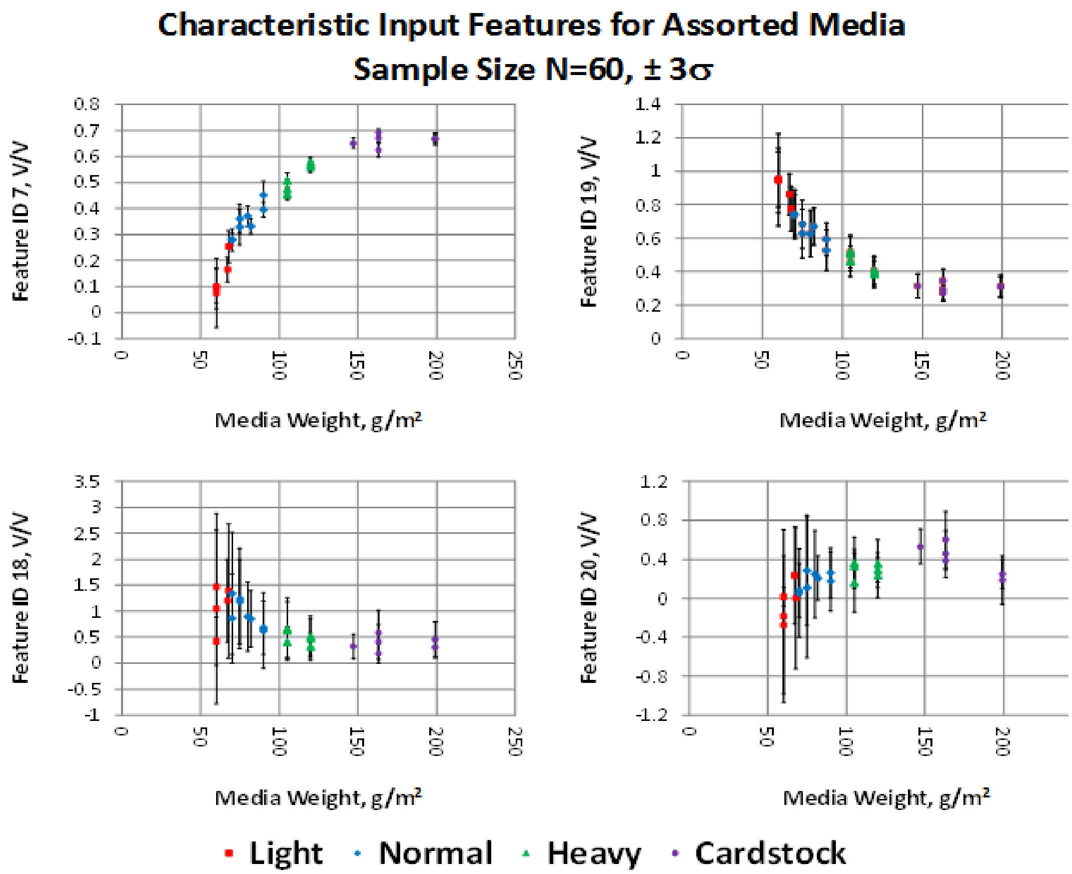


Figure 5.6: Representative Features after scaling [116]

After gathering a training set and training an ML algorithm, the algorithm was distilled into a set of decision polynomials that were able to be utilized by the printer's firmware to make rapid decisions.

The results of this sensor reduction approach are given in Table 5.3 [116], with the single node mean, which simulates a single sensor, and the domain expert knowledge which represents the method detailed here. The decision of the algorithm was then fed into a confisuion matrix that would dictate whether operating parameters would have to be changed or not. That being said, "% Acceptable" refers to boundary cases where no change is required and therefore inaccuracies are acceptable.

Table 5-3: Classification results showing a single node mean compared to the domain knowledge feature set [116]

				Single Node Mean		Domain Knowledge	
Media ID	**Class**	**Description**	**Basis Weight**	**% Correct**	**% Acceptable**	**% Correct**	**% Acceptable**
1	Light	Boise X9	60 g/m2	100.00%	100.00%	98.00%	99.00%
2		Clairmail Clairfontaine	60 g/m2	99.62%	100.00%	100.00%	100.00%
3		Hp EcoFFICIENT	60 g/m2	100.00%	100.00%	99.67%	100.00%
4		Ricoh My Paper	67 g/m2	100.00%	100.00%	96.33%	100.00%
5		Canon GFR-070	68 g/m2	66.15%	100.00%	4.67%	100.00%
6	Normal	Business ("C2")	70 g/m2	90.77%	90.77%	100.00%	100.00%
7		Sanyipaifuyinzhi	70 g/m2	86.92%	86.92%	100.00%	100.00%
8		Husky Xerocopy	75 g/m2	100.00%	100.00%	100.00%	100.00%
9		Hammermill Tidal	75 g/m2	100.00%	100.00%	100.00%	100.00%
10		Datacopy	80 g/m2	100.00%	100.00%	100.00%	100.00%
11		Premier "J"	82 g/m2	100.00%	100.00%	99.67%	100.00%
12		Domtar First Choice	90 g/m2	51.54%	51.54%	95.67%	99.67%
13		Hammermill Laser Print	90 g/m2	100.00%	100.00%	98.67%	100.00%
14	Heavy	Hammermill Laser Print	105 g/m2	0.00%	100.00%	31.00%	100.00%
15		Boise Cascade Presentation	105 g/m2	0.00%	100.00%	25.67%	100.00%
16		Via Satin Writing	105 g/m2	0.00%	100.00%	35.33%	100.00%
17		Fine Color Copy Writing	120 g/m2	0.00%	100.00%	72.67%	100.00%
18		Hammermill Laser Print	120 g/m2	0.00%	100.00%	80.00%	100.00%
19		Boise Cascade Presentation	120 g/m2	0.00%	100.00%	87.00%	100.00%
20	Cardstock	Exact Vellum Cover Bristol	147 g/m2	100.00%	100.00%	100.00%	100.00%
21		Accent Opaque Digital	163 g/m2	100.00%	100.00%	100.00%	100.00%
22		Hammermill Color Copy Cover	163 g/m2	100.00%	100.00%	100.00%	100.00%
23		Springhill Index	163 g/m2	100.00%	100.00%	95.67%	100.00%
24		Springhill Index	199 g/m2	100.00%	100.00%	100.00%	100.00%
25		Exact Index	199 g/m2	100.00%	100.00%	100.00%	100.00%
26	Transparency	Lexmark 70X7240	4.2 mil	0.00%	0.00%	100.00%	100.00%
		Total %		**69.02%**	**93.43%**	**85.38%**	**99.95%**

5.3.1.4 Conclusions

This method for reducing sensor hardware by leveraging domain expert knowledge and temporal data for the design of an IoT system resulted in a lower cost and complexity than more traditional approaches. This methodology was demonstrated in a case-study of a mass-produced electrophotographic printer in a system designed to classify media types. The proposed methodology increased classifier accuracy by 16% and classifier acceptability by 6.5% when compared with a more traditional method that did not leverage domain expert knowledge to enrich the dataset. The methodology used can be applied to

IoT applications seeking to benefit from a high computation tasks such as ML, while still meeting cost constraints.

The methodology described has significant cost advantages over the traditional approach. These advantages stem from several fundamental aspects of single sensor design. This includes a reduction in hardware and the associated non-recurring engineering expenses. This proposed approach can greatly benefit the manufacturing industry, and more specifically it can be a key component of designing an IoT and data infrastructure for a HE and a HEMM. The approach offers a lower cost implementation for driving maximizing sustainable value, minimizing resource consumption, and ensuring continued technological progress.

5.3.2 *Method for Reducing Data Set for Machine Learning IoT Applications*

5.3.2.1 Introduction

Production IoT-based systems utilizing high computational tasks such as ML usually requires a large amount of data in order to achieve the desired outcome. Unfortunately, this causes ML solutions to be impractical for low-cost sensor applications. This section discusses a new calibration method that results in the ability to use a low-cost hardware option and reduce the required training set within an IoT-based ML application. The method, Reference Calibration Mapping (RCM), creates a reference space from a single sensor and aims at transforming output from the remaining sensor population into that reference space. The training of the ML model is then performed on a featurized set of training data, and predictions are made after the sensor output is mapped to the reference space and featurized. This method was formed as the part of an industry team, and the relevance to HE is discussed in the conclusion.

5.3.2.2 Methodology

The following phases describe how a general system can apply the RCM method:

Phase 1: Characterize the sensing system (empirically or analytically) to gain an understanding of expected variation and how this variation would impact sensor output. Using this information, select a sensor as the reference standard.

Phase 2: Develop a reference calibration map to transform all sensor outputs within the sensor population back to the characterized reference standard.

Phase 3: Gather training data using the reference standard across all considered features and train the ML algorithm using this reduced data set.

Phase 4: In the final calibration step during manufacturing, adjust the system to continue to emulate the reference system. Apply the calibration map to transform the resulting outputs into the same space of the reference system.

5.3.2.3 Case Study

The deployed system was a media classification system in a laser printer product. The sensors chosen for this application were inexpensive and the mechanical tolerances for sensor placement from system to system and part to part sensor tolerances threatened to push the development expense in schedule and cost beyond the set constraints.

The simplified inexpensive design still had tolerance issues to overcome. Sensor to sensor variation, both in mechanical placement tolerance and in the sensor itself, was still requiring a data training set that exceeded existing resources. This is visualized in Figure 5.7 [129], where the yellow region indicates the variation part to part. To address this issue the team developed a process called “reference calibration mapping” in which all systems were measured during manufacturing and they were mapped to the space of a reference sensor in order to reduce the overall training set needed.

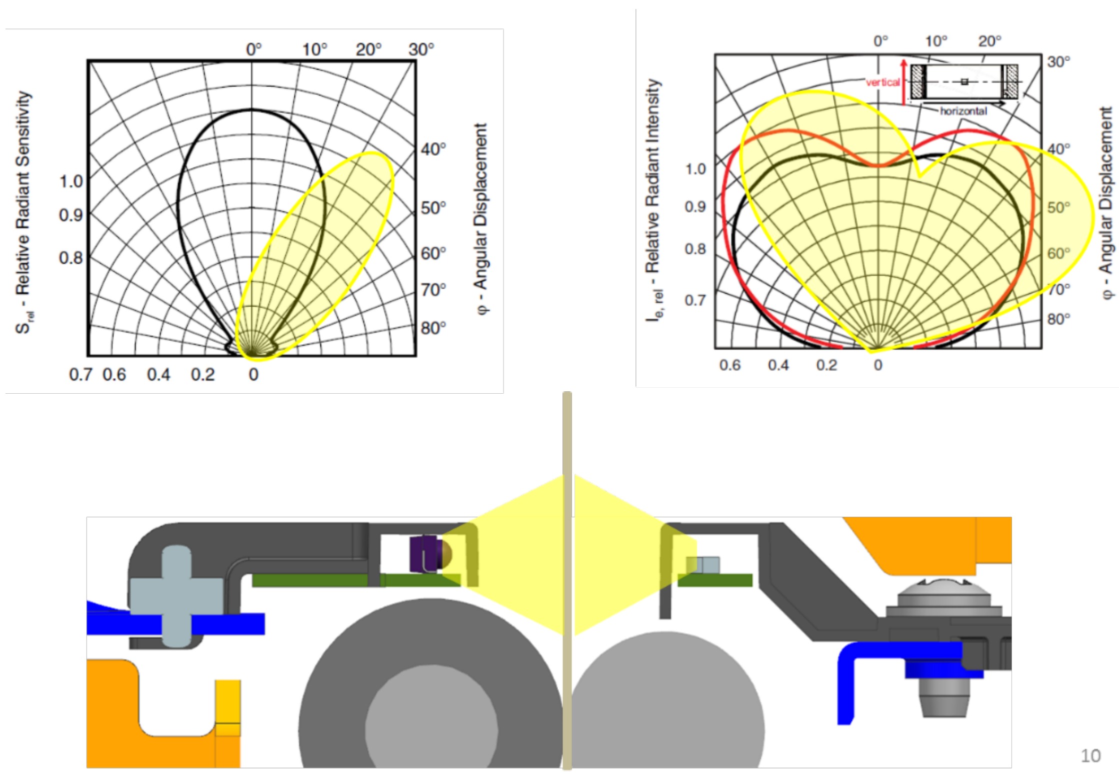


Figure 5.7: The physical system (bottom) and the angular displacement tolerances shown in yellow for the chosen sensor [129]

The first step in sensor reference calibration mapping was to select a “reference” sensor system, which would be used to collect all of the data for the SVM ML algorithm. The second step was to determine a mathematical relationship that would be used to drive all sensors to the same reference space as the golden reference. To do this a 'Performance Indicator' metric was developed which could be measured on the production line for each system by checking the sensor output with no media present, and with a "golden" standard present. That ratio is shown in the below equation:

$$PI = \frac{\frac{\sum(1024 - PC)}{N_{PC}}}{\frac{\sum(1024 - NPC)}{N_{NPC}}}$$

Where PI is the performance indicator, PC is the calibration value with paper present, NPC is the calibration value with no paper present, and N_{PC} is the number of trials with paper, and N_{NPC} is the number of trials without paper. PI was then used to determine a correction factor needed to bring the system being measured to that of the ideal system. That correction factor (CF) is given in the below equation:

$$CF = \frac{PI_{reference}}{PI_{calibrated}}$$

Where $PI_{reference}$ is the performance indicator of the reference sensor, and the $PI_{calibrated}$ is the performance indicator of the sensor being calibrated. When in use the sensor output (W_x) from the particular device is modified by the correction factor as shown in the following equation:

$$W_{calibrated} = (1 - K) + K(W_x)$$

This maps the sensor output under inspection to the space of the golden sample sensor. The mapped output is then used by the machine learning algorithm in order to classify the printer media.

Table 5.4 below shows the classification performance before and after the calibration method was applied. Without RCM, the algorithm was 57.5% accurate, and when acceptable misidentifications were included that accuracy rose to 76.9%. In the RCM corrected system, the printers tested identified the correct media 85.4% of the time and

Table 5-4: Performance Before and After RCM Method was applied [129]

		No Calibration		Two-Point Calibration	
Class	**Type**	**% Correct**	**% Acceptable**	**% Correct**	**% Acceptable**
Light	Boise X9	66.33%	100.00%	98.00%	99.00%
	Clairmail Clairfontaine	66.67%	100.00%	100.00%	100.00%
	Hp EcoFFICIENT	66.67%	100.00%	99.67%	100.00%
	Ricoh My Paper	66.67%	99.67%	96.33%	100.00%
	Canon GFR-070	38.00%	100.00%	4.67%	100.00%
Normal	Business ("C2")	58.67%	58.67%	100.00%	100.00%
	Sanyipaifuyinzhi	51.67%	51.67%	100.00%	100.00%
	Husky Xerocopy	35.33%	35.67%	100.00%	100.00%
	Hammermill Tidal	53.33%	53.67%	100.00%	100.00%
	Datacopy	33.33%	33.33%	100.00%	100.00%
	Premier "J"	33.00%	33.33%	99.67%	100.00%
	Domtar First Choice	30.67%	34.67%	95.67%	99.67%
	Hammermill Laser Print	32.33%	66.67%	98.67%	100.00%
Heavy	Hammermill Laser Print	20.33%	77.00%	31.00%	100.00%
	Boise Cascade Presentation	19.33%	70.67%	25.67%	100.00%
	Via Satin Writing	42.33%	93.00%	35.33%	100.00%
	Fine Color Copy Writing	63.67%	99.67%	72.67%	100.00%
	Hammermill Laser Print	23.33%	72.00%	80.00%	100.00%
	Boise Cascade Presentation	59.00%	97.33%	87.00%	100.00%
Cardstock	Exact Vellum Cover Bristol	75.67%	89.67%	100.00%	100.00%
	Accent Opaque Digital	100.00%	100.00%	100.00%	100.00%
	Hammermill Color Copy Cover	100.00%	100.00%	100.00%	100.00%
	Springhill Index	98.33%	100.00%	95.67%	100.00%
	Springhill Index	97.33%	100.00%	100.00%	100.00%
	Exact Index	98.67%	100.00%	100.00%	100.00%
Transparency	Lexmark 70X7240	66.67%	66.67%	100.00%	100.00%
	Total %	**57.59%**	**76.92%**	**85.38%**	**99.95%**

with allowable misclassifications that rose to 99.95%.

A similar optical sensor deployed in the same system had a bill of materials of ten times the resulting system. By lowering hardware performance requirements, the resulting system was able to take advantage of the cost savings by compensating with the presented calibration method. The method saved the generation of training data for system tolerances and based on the distribution of data seen with early prototype builds that is estimated to be 1/40 of the data that would have been needed for similar performance.

5.3.2.4 Conclusion

The case study validates RCM as a calibration method for implementing ML in low-cost IoT applications, which as high relevance to HE. RCM shifts the paradigm in implementing ML in production-scale systems. Traditional methods require multiple robust sensors, ongoing calibration, or ongoing ML. In addition to hardware, traditional methods require order of magnitude larger training sets. By lowering overall system hardware and development costs, RCM extends ML's feasible solution space to include cost-constrained applications such as embedded sensors in consumer electronics, predictive maintenance and cost-optimization solutions for manufacturing applications, and IoT-enabled agriculture management systems. RCM also has high relevance to use cases where sensors are not networked for data security and/or privacy reasons.

Applying the RCM approach to other manufacturing IoT system design, and more specifically for realizing the HE and HEMM vision, the following steps are required: first, the sensor system needs to be characterized empirically or analytically. Next, a reference sensor is selected. Then, a calibration map is generated to transform all sensor outputs within the expected sensor population back to the selected reference sensor. This calibration map will be device specific and will vary according to the system design. Training data can then be collected using the reference sensor system. Once trained, the ML algorithm and calibration map can be embedded in the control systems of the entire sensor population. The result will be a lower overall cost and reduced long-term maintenance.

5.4 Chapter Summary and Discussion

This chapter addressed designing an IoT-enabled data infrastructure for a Helical Economy by first motivating and defining the problem, then reviewing the state of the art, and then identifying the primary challenges, and then finally presenting two initial methods for industry implementation to move manufacturers' IIoT implementations towards the HE and HEMM future vision.

In defining the problem, it was stated that most IIoT and Industry 4.0 projects fail, revealing that there is fundamental problem with the current approach to IIoT and Industry 4.0 initiatives. The race to market has developed an approach that encourages the creation of extensive IoT sensor networks that involve retrofitting legacy products, manufacturing equipment, and manufacturing systems with numerous sensor nodes and IT systems in order to collect a significantly large dataset. This requires a significant investment in the sensor hardware and in the reoccurring cost to store and maintain the data. Therefore, it was noted that a counter approach is needed to increase the success rate of implementation, and it was proposed that the Helical Economy and HEMM framework could give the IIoT and Industry 4.0 implementations a holistic business outcome of maximizing sustainable value creation, minimizing resource consumption, and ensuring continued technological progress.

The state of the art was then reviewed across the concepts of Industry 4.0, Smart Manufacturing, Cyber-Physical Systems, Industrial Internet of Things, Factories of the Future, and Digital Twin and Digital Thread. Since the success of industry implementation is low, the state-of-the-art research concepts and approaches are missing a key element. In defining the primary challenges for designing the IoT and data infrastructure for the

HEMM vision, it was determined that the counter approach to the current IoT approach would be to minimize the required sensor infrastructure and associated data. In addition, for a HE and HEMM specifically, it was noted that the infrastructure must span all life cycle stages: pre-manufacturing, use, and post-use, and that the size and breadth of this data coverage would require an investment in data security. Along those dimensions, the three primary challenges we noted for designing an IoT and data infrastructure for a HE: 1) reducing the number of sensors required, 2) reducing the amount of data required, and 3) ensuring secure harmonization of data across products, processes, and systems, and all life cycle stages.

The chapter then discusses two initial methods for industry implementation of HE at the IoT-enabled data infrastructure level: 1) a method for reducing overall sensor count, and 2) a method for reducing the training data set needed for sensor-based machine-learning applications. The first method was a concurrent engineering approach where the sensor hardware and end-use analytics system was designed in parallel. The advantage from this approach is that in an IoT-based system, the number of sensors can be reduced without losing performance. Many industries can benefit from this method, especially the HEMM due to the unique use of unstructured and structured data to drive maximum sustainable value, minimized resource consumption, and continued technological progress. A case study was presented that looked at the consumer printing process and a sensor solution that aims at improving the field service issues. The case study validates the approach of concurrently designing a product, process, and/or system in parallel with the IoT framework in order to minimize costs and improve functionality. The combination of the domain/expert knowledge and the machine learning algorithm creates a robust framework for use in various applications.

The second method was a calibration method, Reference Calibration Mapping (RCM), that aims to reduce the data set size for IoT-based machine learning applications. Overall, RCM shifts the paradigm in implementing ML in production-scale IoT systems. Traditional methods would have required multiple sensors with tightly controlled static measurements, ongoing calibration or ongoing machine learning as opposed to an independent embedded algorithm. Additionally, traditional methods would have required a much larger training set for the machine learning algorithm, which would have been more expensive to develop and difficult to implement. The RCM method resulted in a robust yet inexpensive system which is now in production and performing well in the field.

Overall, this chapter provides the initial foundation for designing an IoT and data infrastructure for the Helical Economy and HEMM. By aligning the desired business outcomes of an Industry 4.0 or IIoT project with the desired outcomes of the HEMM, manufacturers will be able to take a first step towards maximizing sustainable value, minimizing resource consumption, while ensuring technological progress.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

6.1 Summary of Contributions

The contributions of this PhD work are threefold:

1. Presented a paradigm shift from *Circular Economy to Helical Economy* for advancing sustainable manufacturing through a novel framework for the Helical Economy Manufacturing Method (HEMM).
2. Identified the major research problems at the *product level* and developed initial methods to make near-term progress towards the HEMM.
3. Identified the major research problems in *designing next-generation IoT-enabled data infrastructures* and presented an integration plan with HEMM.

In Chapter 3, the Helical Economy (HE) concept was proposed through an abstraction that compares its benefits in relation to the Circular and Linear Economy alternatives. Three key performance indicators (KPIs) were then proposed: *sustainable value creation, resource consumption, and technological progress.* The framework for the Helical Economy Manufacturing Method was then presented focusing on redesigning manufacturing infrastructure at product, process, and system levels with a strong emphasis on utilizing an IoT data infrastructure and leveraging an upskilled workforce.

Chapter 4 examined the product component of the HEMM framework. The major research problems and challenges for designing products were then identified. Initial methods for industry implementation were then presented for two classes of product design: 1) new product design, and 2) adaptive product design and redesign. For new product design, a new set of Design for Helical Economy (DfHE) guidelines was presented. For adaptive product design and redesign, an initial framework for a toolkit was proposed, the Helical Optimization and Prediction Engine (HOPE), comprised of three product-level modules: 1) predicting product life cycle performance during design (HOPE-Design), 2) predictively and proactively maintaining a modular product (HOPE-Maintain), and 3) selecting optimal product configuration and reconfiguration (HOPE-Configure).

In Chapter 5, the IoT-enabled data infrastructure component of the HEMM framework was examined. The major design challenges related to establishing an IoT-enabled data infrastructure for the HEMM were identified, and two initial methods for industry implementation were presented: 1) A scalable method for reducing the overall sensor infrastructure needed through the use of machine-learning (ML) and concurrent engineering, and 2) A method for reducing the training set needed in deploying machine-learning-based sensor systems in a smart-manufacturing infrastructure.

Collectively, this initial work establishes the foundational body of knowledge for the HE and the HEMM, provides implementation methods at the product and IoT-enabled data infrastructure levels, and it shows a great potential for HE's ability to create and *maximize sustainable value, optimize resource consumption, and ensure continued technological progress with significant economic growth and innovation.*

6.2 Future Work

Although this work is foundational in proposing a paradigm shift away from the CE status quo of recycling and reuse of materials and to a more innovative perspective of redesigning manufacturing infrastructure at product, process, and system levels, the work only examined two components of the larger HEMM vision. Future work must address the three remaining components of the HEMM: 1) next-generation process equipment design and process planning, 2) next-generation factory and supply chain design, and 3) next-generation workforce training.

6.2.1 *Next-Generation Process Equipment and Planning for a Helical Economy*

It should be well understood that in order to achieve a change in an output, there are three options: change the output directly, change the input, or change the process. In the case of manufacturing for a Helical Economy, Chapter 3 made the case that changing of the output directly has limitations that hinder the ability to maximize sustainable value creation, minimize resource consumption, while ensuring technological progress; therefore, the chapter presented the Helical Economy Manufacturing Method (HEMM) as a fundamental paradigm shift. Chapter 4 addressed changing the input through designing a product for a Helical Economy. Although product design holds an outsized impact, this alone cannot realize the long-term HEMM vision without concurrently addressing the design and selection/planning of process level infrastructure (machines, tooling, automation equipment, and supporting equipment).

Today, the current process-level infrastructure (machines, tooling, material handling systems, automation equipment, etc.) has been, and is still being designed, for the linear economy model of *"take – make – use - dispose"*. The infrastructure has been optimized to cost efficiently go from input to output with maximum speed and quality. Machines and tooling have not been developed with the total life cycle of a product in mind, making it extremely difficult to close the loop on material flow and extract value in the post-use stage of a product.

At the same time, the process planning activities of selecting manufacturing processes, sequencing manufacturing operations, and selecting equipment are also being done in a linear nature. The product design is handed off, the process plan is created, and then the plan is executed. The current process planning does not take into consideration the total life cycle of a product, leaving the post-use activities such as remanufacturing, refurbishment, reconfiguration, and recycling undefined.

In order to achieve the long-term vision of the Helical Economy, manufacturers need to redesign process-level infrastructure, which will require new approaches to manufacturing equipment design and process planning. This work will require defining the equipment and process planning design challenges for realizing the near-term vision of the HEMM, and then developing initial methods and tools to address these challenges.

6.2.2 *Next-Generation Factory and Supply Chain Design for a Helical Economy*

A core component of the HEMM vision is the redesign of factories and supply chains in order to take advantage of a forward and reverse flow of product. The Helical Economy Manufacturing System (HEMS) is comprised of four major components: *Modular and Reconfigurable Products, Hybrid Manufacturing Processes and Tooling, Integrated Forward/Reverse Flow Production Systems, and IoT Data Infrastructures.*

1. Modular and Reconfigurable Products
    - A product that is upgradeable, disassemble, uses a set of common components, and is extremely durable.
2. Hybrid Manufacturing Processes and Tooling

- A process that is designed to accommodate a forward and reverse flow of inputs and outputs. These processes are multi-dimensional, combining subtractive and additive manufacturing processes or assembly and disassembly processes.

3. Two-Way Flow Production Systems
    - A production system designed for a forward and reverse flow of products. Manufacturing lines are reconfigurable matrices of multiple manufacturing stages, each with a distinct goal to minimize the total life cycle cost.
4. IoT Data Infrastructures
    - The IoT and data infrastructure is the software backbone of the helical system. Data is collected at the product level, the process level, and at the system level using networked sensors that send data to a central cloud.

Each of these four technologies have been proven technically viable in their respective domains, and although they haven't reached mainstream commercialization, the HEMS utilizes these technologies in defining a next-generation manufacturing system that aims to minimize resource consumption while serving a world of 10 billion people and beyond. To move from concept to implementation, manufacturing practitioners will need a decision support toolkit that helps them design and understand the value proposition of all four of the major components.

Because the HEMS calls for a new infrastructure installation or an overhaul of an existing manufacturing operation, the capital investment needed to even fully pilot the concept is quite high. Therefore, there is a need to estimate the potential benefit of HEMS from limited data. For the first tool, we propose an addition to HOPE (Helical Optimization and Prediction Engine), HOPE-System, an adaptive multi-method simulation model. HOPE-System takes a current product's Bill of Material (BoM) as the input, creates an abstraction of the product, and then simulates the product in a traditional manufacturing system, and in an adapted HEMS system. HOPE-System will provide outputs such as the potential total life cycle cost savings and the environmental benefits of transitioning to a HEMS. Since Industry partners are needed in order to pilot, validate, and iterate on HEMS, this tool provides a cost-effective and low-risk way to communicate the potential value of HEMS to industry stakeholders. Decision makers can compare these benefits to the estimated initial capital investment required for a pilot.

6.2.3 *Next-Generation Workforce Training for a Helical Economy*

The HEMM will continue to shift the skills in demand for the manufacturing sector away from low-skilled laborers and towards higher skilled technology-focused skills (data analytics, software development, simulation, robotics, mechatronics, etc.). In order to bridge this gap, industry-sponsored upskilling programs will need to be developed in collaboration with higher education systems. Transitioning the current workforce into a next-generation workforce prepared to support the HEMM will take time since it requires a fundamental change in the core infrastructure around manufacturing education and training.

Because of the time lag, there is a critical need to start this investment as soon as possible. To start, an industry partnership should be formed, and a pilot training program should be launched. This pilot can then be monitored, and it will provide a research testbed for the continued study of manufacturing workforce development for HE and the HEMM.

6.3 Industry Collaboration

The adoption of the Helical Economy (HE) and the Helical Economy Manufacturing Method (HEMM) is up to industry. The manufacturing sector must reinvent itself in order for it to support an equitable future for a world of 10 billion people. This reinvention will require multiple stakeholders from academia, government agencies, and industry to come together to support its continued refinement and development. A diverse consortium of stakeholders is critically needed in order to ensure the research work on HE and HEMM makes its way into the industrial domain.

For this continued future development, investment from a consortium of stakeholders would be directed into building a pilot facility that can serve as the testbed for HEMM development at product, process, and system levels. This pilot facility would enable a testbed for continued research in developing new product architecture designs, new manufacturing process equipment and tooling, new manufacturing systems, and new software and control systems. It is expected that a pilot facility of this nature would require a significant capital investment, and as such, it would require many avenues of financial support, and the incentive offered to industry partners would be that the IP being generated would be shared IP among the invested companies. The goal of the pilot would be to build an end-to-end proof-of-concept that can then be used to showcase the value proposition of the HEMM to manufacturing stakeholders, as well as serve as training opportunity for the next-generation workforce.

It is without a doubt that the future of the manufacturing sector is dependent on the reinvention of the status quo into a next-generation innovation hub centered around the

Helical Economy goals of maximizing sustainable value, minimizing resource consumption, and maintaining technological progress.

APPENDICES

Appendix A: HOPE-Design Code

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
import sklearn
from sklearn import svm
from sklearn.svm import SVR
import numpy as np
%matplotlib inline

Data=pd.read_csv('chapter_four_printer_data_obs.csv')
Features = Data.iloc[:,1:24]
#Going to Run through a 100 scenarios of features,
#in order to simulate creating different heuristics for different stakeholers.

ResultCols=[]
for i in range(0,100):

 #Need to downselect parameters
Subset = Features.sample(6, axis=1)
print(Subset)
print(Subset.columns)

#Split the Dataset into Test and training set, 80/20
xTrain, xTest, yTrain, yTest = sklearn.model_selection.train_test_split(Subset,
Data.o_gwp_total, test_size = 0.2, random_state = 0)

#Define the Model
   svr_poly = SVR(kernel='linear', degree=2, max_iter=10000)

   #Fit the Model
   model = svr_poly.fit(xTrain, yTrain)

   #Predictions
   yPred=model.predict(xTest)
   print(100*(yPred-yTest)/yTest)
   yPredTot=model.predict(Subset)
   print(100*(yPredTot-Data.o_gwp_total)/Data.o_gwp_total)

   #Collate Results
   ResultCols.append([Subset.columns.values, np.mean(abs((100*(yPred-
yTest))/yTest))])
   Results=pd.DataFrame(ResultCols, columns=['feature_set', 'percent_error'])
```

Results.to_csv('Results_chap4.csv')

Appendix B: HOPE-Design Complete Data

iteration	feature_set	percent_error
0	['feature_10' 'feature_4' 'feature_15' 'feature_11' 'feature_12' 'feature_14']	20.13243764
1	['feature_4' 'feature_21' 'feature_8' 'feature_12' 'feature_11' 'feature_17']	17.63331526
2	['feature_23' 'feature_17' 'feature_7' 'feature_5' 'feature_3' 'feature_9']	8.54689993
3	['feature_13' 'feature_4' 'feature_2' 'feature_23' 'feature_11' 'feature_16']	5.84460969
4	['feature_15' 'feature_4' 'feature_1' 'feature_18' 'feature_3' 'feature_7']	8.138966544
5	['feature_7' 'feature_1' 'feature_22' 'feature_10' 'feature_11' 'feature_14']	16.78727387
6	['feature_18' 'feature_19' 'feature_23' 'feature_12' 'feature_9' 'feature_21']	8.259092553
7	['feature_7' 'feature_21' 'feature_8' 'feature_9' 'feature_22' 'feature_15']	15.411699
8	['feature_3' 'feature_13' 'feature_2' 'feature_22' 'feature_6' 'feature_23']	5.888074451
9	['feature_8' 'feature_9' 'feature_1' 'feature_23' 'feature_11' 'feature_13']	10.56114525
10	['feature_6' 'feature_23' 'feature_22' 'feature_21' 'feature_1' 'feature_9']	6.549494991
11	['feature_2' 'feature_19' 'feature_13' 'feature_4' 'feature_17' 'feature_22']	6.023092477
12	['feature_17' 'feature_20' 'feature_13' 'feature_12' 'feature_15' 'feature_22']	15.91003849
13	['feature_18' 'feature_17' 'feature_9' 'feature_4' 'feature_12' 'feature_5']	20.02365249
14	['feature_19' 'feature_10' 'feature_9' 'feature_2' 'feature_7' 'feature_15']	5.032913393
15	['feature_11' 'feature_15' 'feature_23' 'feature_21' 'feature_4' 'feature_22']	11.22425786
16	['feature_1' 'feature_8' 'feature_18' 'feature_19' 'feature_2' 'feature_16']	2.572823017
17	['feature_23' 'feature_3' 'feature_22' 'feature_6' 'feature_12' 'feature_1']	6.801404671
18	['feature_14' 'feature_18' 'feature_3' 'feature_5' 'feature_17' 'feature_12']	2.170759613
19	['feature_10' 'feature_11' 'feature_17' 'feature_6' 'feature_2' 'feature_4']	5.682699405
20	['feature_1' 'feature_5' 'feature_4' 'feature_12' 'feature_11' 'feature_3']	4.159805229
21	['feature_11' 'feature_9' 'feature_6' 'feature_23' 'feature_12' 'feature_2']	8.718468572
22	['feature_5' 'feature_12' 'feature_1' 'feature_19' 'feature_22' 'feature_4']	20.64811107
23	['feature_16' 'feature_20' 'feature_11' 'feature_14' 'feature_5' 'feature_3']	3.693959486
24	['feature_10' 'feature_7' 'feature_16' 'feature_14' 'feature_18' 'feature_23']	7.534997654
25	['feature_23' 'feature_17' 'feature_10' 'feature_12' 'feature_18' 'feature_9']	7.079882445
26	['feature_12' 'feature_17' 'feature_5' 'feature_8' 'feature_6' 'feature_23']	10.79887002
27	['feature_23' 'feature_12' 'feature_11' 'feature_6' 'feature_1' 'feature_14']	10.61457981

28	['feature_1' 'feature_9' 'feature_13' 'feature_12' 'feature_3' 'feature_21']	1.661614042
29	['feature_18' 'feature_4' 'feature_9' 'feature_20' 'feature_1' 'feature_6']	21.08958979
30	['feature_7' 'feature_4' 'feature_22' 'feature_6' 'feature_16' 'feature_15']	18.17585328
31	['feature_21' 'feature_2' 'feature_15' 'feature_19' 'feature_16' 'feature_5']	6.498798838
32	['feature_22' 'feature_7' 'feature_4' 'feature_14' 'feature_1' 'feature_2']	5.330361779
33	['feature_9' 'feature_1' 'feature_14' 'feature_15' 'feature_20' 'feature_5']	20.23868598
34	['feature_14' 'feature_1' 'feature_19' 'feature_13' 'feature_7' 'feature_18']	9.95617851
35	['feature_13' 'feature_2' 'feature_19' 'feature_4' 'feature_17' 'feature_21']	3.97731027
36	['feature_23' 'feature_12' 'feature_16' 'feature_8' 'feature_7' 'feature_18']	6.833455028
37	['feature_14' 'feature_21' 'feature_8' 'feature_4' 'feature_9' 'feature_2']	3.094527388
38	['feature_7' 'feature_22' 'feature_12' 'feature_16' 'feature_19' 'feature_13']	17.82961256
39	['feature_16' 'feature_23' 'feature_10' 'feature_12' 'feature_21' 'feature_18']	4.153161171
40	['feature_1' 'feature_6' 'feature_20' 'feature_13' 'feature_23' 'feature_18']	6.358244034
41	['feature_20' 'feature_8' 'feature_12' 'feature_16' 'feature_22' 'feature_7']	17.35488007
42	['feature_20' 'feature_9' 'feature_15' 'feature_10' 'feature_7' 'feature_12']	19.00403102
43	['feature_3' 'feature_18' 'feature_13' 'feature_23' 'feature_1' 'feature_4']	6.187016454
44	['feature_23' 'feature_18' 'feature_11' 'feature_13' 'feature_19' 'feature_4']	9.127162866
45	['feature_20' 'feature_19' 'feature_9' 'feature_16' 'feature_3' 'feature_7']	4.406636985
46	['feature_22' 'feature_16' 'feature_23' 'feature_12' 'feature_7' 'feature_6']	8.021661927
47	['feature_20' 'feature_3' 'feature_2' 'feature_22' 'feature_6' 'feature_5']	9.629970596
48	['feature_19' 'feature_16' 'feature_21' 'feature_18' 'feature_6' 'feature_5']	12.56367952
49	['feature_5' 'feature_15' 'feature_23' 'feature_13' 'feature_21' 'feature_3']	4.120674399
50	['feature_19' 'feature_23' 'feature_10' 'feature_9' 'feature_8' 'feature_18']	6.914484294
51	['feature_13' 'feature_18' 'feature_9' 'feature_1' 'feature_23' 'feature_16']	7.413659989
52	['feature_18' 'feature_6' 'feature_21' 'feature_19' 'feature_2' 'feature_9']	3.147082516
53	['feature_5' 'feature_7' 'feature_10' 'feature_12' 'feature_2' 'feature_4']	5.307009266
54	['feature_9' 'feature_3' 'feature_16' 'feature_12' 'feature_15' 'feature_2']	1.573394568
55	['feature_17' 'feature_11' 'feature_2' 'feature_5' 'feature_8' 'feature_9']	6.517859469
56	['feature_1' 'feature_11' 'feature_12' 'feature_13' 'feature_16' 'feature_19']	18.43893383
57	['feature_9' 'feature_17' 'feature_3' 'feature_15' 'feature_23' 'feature_5']	8.586257286

58	['feature_15' 'feature_5' 'feature_1' 'feature_17' 'feature_18' 'feature_11']	17.26043931
59	['feature_18' 'feature_5' 'feature_2' 'feature_19' 'feature_10' 'feature_4']	9.061607722
60	['feature_4' 'feature_21' 'feature_7' 'feature_22' 'feature_9' 'feature_16']	17.99960924
61	['feature_12' 'feature_21' 'feature_13' 'feature_23' 'feature_2' 'feature_18']	5.581462882
62	['feature_22' 'feature_5' 'feature_17' 'feature_3' 'feature_21' 'feature_8']	13.65337468
63	['feature_18' 'feature_17' 'feature_14' 'feature_9' 'feature_23' 'feature_16']	5.814983297
64	['feature_20' 'feature_10' 'feature_12' 'feature_11' 'feature_9' 'feature_21']	19.42189095
65	['feature_23' 'feature_22' 'feature_16' 'feature_13' 'feature_10' 'feature_1']	8.373935044
66	['feature_21' 'feature_13' 'feature_2' 'feature_18' 'feature_9' 'feature_14']	3.548832439
67	['feature_7' 'feature_12' 'feature_21' 'feature_6' 'feature_3' 'feature_10']	2.058378992
68	['feature_5' 'feature_23' 'feature_10' 'feature_22' 'feature_13' 'feature_12']	10.70633251
69	['feature_5' 'feature_12' 'feature_21' 'feature_9' 'feature_16' 'feature_6']	17.27849052
70	['feature_19' 'feature_20' 'feature_4' 'feature_9' 'feature_10' 'feature_3']	4.961327309
71	['feature_4' 'feature_9' 'feature_20' 'feature_8' 'feature_12' 'feature_11']	20.23554288
72	['feature_10' 'feature_18' 'feature_17' 'feature_6' 'feature_2' 'feature_4']	8.665338352
73	['feature_19' 'feature_4' 'feature_15' 'feature_10' 'feature_18' 'feature_23']	9.001541771
74	['feature_11' 'feature_19' 'feature_14' 'feature_18' 'feature_5' 'feature_13']	17.82042009
75	['feature_9' 'feature_17' 'feature_11' 'feature_5' 'feature_19' 'feature_3']	4.080543004
76	['feature_1' 'feature_18' 'feature_4' 'feature_14' 'feature_5' 'feature_9']	21.08516999
77	['feature_18' 'feature_10' 'feature_6' 'feature_17' 'feature_7' 'feature_5']	9.539207613
78	['feature_9' 'feature_4' 'feature_5' 'feature_8' 'feature_22' 'feature_6']	19.9016492
79	['feature_9' 'feature_16' 'feature_8' 'feature_6' 'feature_14' 'feature_11']	17.91531454
80	['feature_23' 'feature_14' 'feature_6' 'feature_20' 'feature_12' 'feature_19']	10.69524811
81	['feature_10' 'feature_4' 'feature_18' 'feature_12' 'feature_6' 'feature_21']	21.21360889
82	['feature_1' 'feature_5' 'feature_21' 'feature_17' 'feature_12' 'feature_16']	16.28509326
83	['feature_8' 'feature_22' 'feature_11' 'feature_10' 'feature_3' 'feature_19']	5.96148573
84	['feature_11' 'feature_17' 'feature_13' 'feature_19' 'feature_9' 'feature_6']	17.85907959
85	['feature_20' 'feature_23' 'feature_13' 'feature_15' 'feature_6' 'feature_17']	6.57186724
86	['feature_5' 'feature_9' 'feature_3' 'feature_19' 'feature_20' 'feature_18']	4.262436494
87	['feature_12' 'feature_14' 'feature_8' 'feature_7' 'feature_22' 'feature_18']	20.92851944
88	['feature_5' 'feature_16' 'feature_11' 'feature_1' 'feature_7' 'feature_3']	3.993088221

89	['feature_7' 'feature_5' 'feature_21' 'feature_19' 'feature_17' 'feature_13']	10.16780605
90	['feature_12' 'feature_16' 'feature_4' 'feature_19' 'feature_9' 'feature_15']	18.43780484
91	['feature_8' 'feature_18' 'feature_1' 'feature_15' 'feature_17' 'feature_22']	9.440866217
92	['feature_5' 'feature_9' 'feature_3' 'feature_19' 'feature_21' 'feature_18']	5.396831287
93	['feature_12' 'feature_19' 'feature_23' 'feature_5' 'feature_1' 'feature_3']	6.574713278
94	['feature_22' 'feature_5' 'feature_17' 'feature_12' 'feature_4' 'feature_10']	16.98229496
95	['feature_11' 'feature_15' 'feature_21' 'feature_3' 'feature_22' 'feature_7']	3.001170812
96	['feature_9' 'feature_13' 'feature_18' 'feature_6' 'feature_12' 'feature_11']	21.27413141
97	['feature_14' 'feature_20' 'feature_15' 'feature_17' 'feature_18' 'feature_22']	9.434329479
98	['feature_21' 'feature_12' 'feature_5' 'feature_10' 'feature_1' 'feature_14']	18.59119095
99	['feature_2' 'feature_20' 'feature_6' 'feature_17' 'feature_5' 'feature_4']	5.66813044

Appendix C: HOPE-Maintain Code

```
import os
import pickle
import pandas as pd
import matplotlib
import numpy as np
import matplotlib.pyplot as plt
module.to_csv('ModuleLife.csv')
#Sort Data Properly
modulesort=module.sort_values(['moduleserialnumber', 'side_bin'], ascending=[True, True], inplace=False)
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
# change side_bin to sides for training
modulesort['side_bin']=modulesort['side_bin']*500
#Looks good
modulesort.head()
#Remove NaNs, if any
modulesort = modulesort.dropna()
#Module List
modulelist=pd.DataFrame()
modulelist=modulesort[['moduleserialnumber']].drop_duplicates()
#Split Into a Train/Test Set 80/20 by Modules for independent look
modulelist['is_train'] = np.random.uniform(0, 1, len(modulelist)) <= .80
#Capture train/test list of modules
```

```
trainfus, testfus = modulelist[modulelist['is_train']==True],
modulelist[modulelist['is_train']==False]
#Capture train/test datasets
train, test =
modulesort[modulesort['moduleserialnumber'].isin(trainmod['moduleserialnumber'])],
modulesort[modulesort['moduleserialnumber'].isin(testmod['moduleserialnumber'])]
print("Train Observations: " + str(len(train)))
print("Test Observations: " + str(len(test)))
modulesort['diff_int_value_coup']=(modulesort['average_int_value']-
modulesort['hist_average_int_value'])*modulesort['starting_bin']
#Drop Training Split Boolean
#features =
modulesort.columns[[4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,22,23,24,25,26,27,28,
29,30,31,32,33,34]]
features = modulesort.columns[[4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21]]
print(modulesort['starting_bin'].mean())
print("Features: ", features)
#Initialize RF
rfm = RandomForestRegressor(n_estimators=250, oob_score=True, n_jobs=-1,
max_features=2, verbose=4,)
#Fitting
rfm.fit(train[features], train['life remaining'])
rfm.predict(test[features])
rsq=rfm.score(test[features], test['life remaining'])
print("TRAIN R^2: ", rfm.oob_score_)
print("TEST R^2: ", rsq)
```

REFERENCES

[1] United Nations, World Population Prospects 2017 Revision, 2017. doi:10.1017/CBO9781107415324.004.

[2] R. Kochhar, A Global Middle Class is more Promise than Reality: From 2001 to 2011, Nearly 700 million Step out of Poverty, but Most Only Barely, 2015. http://www.pewglobal.org/files/2015/07/Global-Middle-Class-Report_FINAL_7-8-15.pdf.

[3] OECD, Global Material Resources Outlook to 2060, 2019. doi:https://doi.org/https://doi.org/10.1787/9789264307452-en.

[4] EIA, International Energy Outlook 2017 Overview, U.S. Energy Inf. Adm. (2017). doi:www.eia.gov/forecasts/ieo/pdf/0484(2016).pdf.

[5] EPA, Global Greenhouse Gas Emissions Data | Greenhouse Gas (GHG) Emissions | US EPA, United States Environ. Prot. Agency. (2014). doi:10.1038/sj.mp.4001545.

[6] H. Ford, S. Crowther, My Life and Work, Doubleday, Page, 1922. https://books.google.com/books?id=4K82efXzn10C.

[7] T. Ohno, Toyota Production System: Beyond Large-Scale Production, Product. Press. 1 (1978) 152. doi:10.1108/eb054703.

[8] R. Florida, Lean and green: The move to environmentally conscious manufacturing, Calif. Manage. Rev. 39 (1996) 80–105. doi:10.2307/41165877.

[9] UNEP, Reduce, Reuse and Recycle Concept (the “ 3Rs”) and Life-cycle Economy, 2005.

[10] I.S. Jawahir, K.E. Rouch, O.W. Dillon, K.J. Joshi, A. Venkatachalam, I.H. Jaafar, Total Life-Cycle Considerations in Product Design for Sustainability: A Framework for Comprehensive Evaluation, in: Proc. TMT 2006, Lloret de Mar. Barcelona, Spain., 2006: pp. 1–10.

[11] F. Badurdeen, I.S. Jawahir, Strategies for Value Creation Through Sustainable Manufacturing, Procedia Manuf. 8 (2017) 20–27. doi:10.1016/j.promfg.2017.02.002.

[12] P.N. Stearns, Consumerism in World History, 2006. http://books.google.com/books?id=3919AgAAQBAJ&pg=PR2&dq=intitle:Consumerism+in+World+History+(The+Global+Transformation+of+Desire+(AND+(AND)))&hl=&cd=1&source=gbs_api%5Cnpapers3://publication/uuid/B2594C69-761A-47FC-B0AD-9A276ACB9E58.

[13] P. Glennie, Consumption, Consumerism and Urban Form: Historical Perspectives, Urban Stud. 35 (1998) 927–951. doi:10.1080/0042098984628.

[14] I.S. Jawahir, R. Bradley, Technological Elements of Circular Economy and the Principles of 6R-Based Closed-loop Material Flow in Sustainable Manufacturing, Procedia CIRP. 40 (2016) 103–108. doi:10.1016/j.procir.2016.01.067.

[15] The Ellen MacArthur Foundation, Towards a Circular Economy - Economic and Business Rationale for an Accelerated Transition, Greener Manag. Int. (2012) 97. doi:2012-04-03.

[16] N.M.P. Bocken, C. Bakker, I. De Pauw, Product design and business model strategies for a circular economy, J. Ind. Prod. Eng. 1015 (2016) 20. doi:10.1080/21681015.2016.1172124.

[17] Dell Inc., Closed-Loop Recycled Content | Dell, (n.d.). http://www.dell.com/learn/us/en/uscorp1/corp-comm/closed-loop-recycled-content (accessed October 9, 2017).

[18] W. Haas, F. Krausmann, D. Wiedenhofer, M. Heinz, How circular is the global economy?: An assessment of material flows, waste production, and recycling in the European union and the world in 2005, J. Ind. Ecol. 19 (2015) 765–777. doi:10.1111/jiec.12244.

[19] P. ten Brink, J.-P. Schweitzer, E. Watkins, M. De Smet, H. Leslie, F. Galgani, Circular economy measures to keep plastics and their value in the economy, avoid waste and reduce marine litter, G20. (2017) 1–12.

[20] A. Jawahir I.S., Badurdeen F., Hapuwatte B.M., Aydin R., Bradley, R., Ali, The 6R principles of sustainable manufacturing for achieving Circular Economy, n.d.

[21] J. Liew, Innovative product design for sustainability enhancement in aluminum beverage cans based on design for sustainability concepts, University of Kentucky, 2005. http://uknowledge.uky.edu/gradschool_theses/371 (accessed October 7, 2017).

[22] C.A. Ungureanu, S. Das, I.S. Jawahir, Development of a sustainability scoring method for manufactured automotive products: A case study of auto body panels, in: Proc. ASME Int. Mech. Eng. Congr. Expo. 2007, VOL 15 - Sustain. Prod. Process. , 2008: pp. 309–314. doi:10.1115/IMECE2007-43818.

[23] N. De Silva, I.S. Jawahir, O. Dillon, M. Russell, A New Comprehensive Methodology for the Evaluation of Product Sustainability at the Design and Development Stage of Consumer Electronic Products, Russell J. Bertrand Russell

Arch. (2009) 335–340. doi:10.1504/IJSM.2009.023973.

[24] A. Gupta, A.D. Jayal, M. Chimienti, I.S. Jawahir, A total life-cycle approach towards developing product metrics for sustainable manufacturing, in: Glocalized Solut. Sustain. Manuf. - Proc. 18th CIRP Int. Conf. Life Cycle Eng., 2011: pp. 240–245. doi:10.1007/978-3-642-19692-8-42.

[25] X. Zhang, F. Badurdeen, I.S. Jawahir, On improving the product sustainability of metallic automotive components by using the total life-cycle approach and the 6R methodology, Glob. Conf. Sustain. Manuf. (2013) 194–199. https://www.depositonce.tu-berlin.de/bitstream/11303/5011/1/zhang_etal.pdf.

[26] UN Environment, Global Environment Outlook 6, 2019.

[27] K. Skene, A. Murray, Sustainable Economics: Context, Challenges and Opportunities for the 21st-Century Practitioner, Taylor & Francis, 2017. https://books.google.com/books?id=zqo0DwAAQBAJ.

[28] C.L. Merrill, Biomimicry of the Dioxygen Active Site in the Copper Proteins Hemocyanin and Cytochrome Oxidase: Part I: Copper (I) Complexes Which React Reversibly with Dioxygen and Serve to Mimic the Active Site Function of Hemocyanin. Part II: Mu-Imidazolato Binuclear, (1982).

[29] M.R. Chertow, Industrial symbiosis: literature and taxonomy, Annu. Rev. Energy Environ. 25 (2000) 313–337.

[30] B.R. Allenby, Achieving sustainable development through industrial ecology, Int. Environ. Aff. 4 (1992) 56–68.

[31] W. McDonough, M. Braungart, Cradle to Cradle: Remaking the Way We Make Things, Farrar, Straus and Giroux, 2010.

https://books.google.com/books?id=KFX5RprPGQ0C.

[32] J.M. Benyus, Biomimicry: Innovation Inspired by Nature, Quill. (1997). doi:10.2307/4450504.

[33] T. Graedel, W.R. Moomaw, Industrial Ecology: Definition and Implementation, in: Ind. Ecol. Glob. Chang., 1994. doi:10.1017/CBO9780511564550.005.

[34] L.W. Jelinski, T.E. Graedel, R.A. Laudise, D.W. McCall, C.K.N. Patel, Industrial ecology: Concepts and approaches., Proc. Natl. Acad. Sci. U. S. A. (1992).

[35] D.J. Zhu, Sustainable development calls for circular economy, Sci. Technol. Journal,(9). (1998) 39–42.

[36] Z. Yuan, J. Bi, Y. Moriguichi, The Circular Economy: A New Development Strategy in China, J. Ind. Ecol. (2006). doi:10.1162/108819806775545321.

[37] J.A. Mathews, H. Tan, Progress Toward a Circular Economy in China, 2011. doi:10.1111/j.1530-9290.2011.00332.x.

[38] N. Georgescu-Roegen, The Entropy Law and the Economic Process, 1971. doi:10.2307/2231206.

[39] H.E. Daly, Steady-state economics: with new essays, Island Press, 1991.

[40] Ellen MacArthur Foundation, McKinsey & Company, Towards the Circular Economy : Accelerating the scale-up across global supply chains, World Econ. Forum. (2014) 1–64. doi:10.1162/108819806775545321.

[41] The Ellen MacArthur Foundation, TOWARDS THE CIRCULAR ECONOMY VOL. 2 : Opportunities for the consumer goods sector, 2013.

[42] The Ellen MacArthur Foundation, TOWARDS THE CIRCULAR ECONOMY VOL. 3: Accelerating the scale-up across global supply chains, 2014.

[43] P. Ghisellini, C. Cialani, S. Ulgiati, A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems, J. Clean. Prod. 114 (2016) 11–32. doi:10.1016/j.jclepro.2015.09.007.

[44] Ellen MacArthur Foundation, Towards the Circular Economy, 2013. doi:10.1162/108819806775545321.

[45] W.R. Stahel, Circular economy: a new relationship with our goods and materials would save resources and energy and create local jobs, Nature. 531 (2016) 435–439.

[46] J. Kirchherr, D. Reike, M. Hekkert, Conceptualizing the circular economy: An analysis of 114 definitions, Resour. Conserv. Recycl. 127 (2017) 221–232. doi:10.1016/j.resconrec.2017.09.005.

[47] N.A. Aziz, D.A. Wahab, R. Ramli, C.H. Azhari, Modelling and optimisation of upgradability in the design of multiple life cycle products: A critical review, J. Clean. Prod. 112 (2016) 282–290. doi:10.1016/j.jclepro.2015.08.076.

[48] Trillium Manufacturing Network, THE RISE OF BIG DATA AND INDUSTRY 4.0, RISE BIG DATA Ind. 4.0. (2017).

[49] E.A. Lee, Cyber Physical Systems: Design Challenges, in: 2008 11th IEEE Int. Symp. Object Component-Oriented Real-Time Distrib. Comput., 2008: pp. 363–369. doi:10.1109/ISORC.2008.25.

[50] J. Lee, B. Bagheri, H.A. Kao, A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems, Manuf. Lett. 3 (2015) 18–23. doi:10.1016/j.mfglet.2014.12.001.

[51] M. Keller, M. Rosenberg, M. Brettel, N. Friederichsen, How Virtualization,

Decentrazliation and Network Building Change the Manufacturing Landscape: An Industry 4.0 Perspective, Int. J. Mech. Aerospace, Ind. Mechatron. Manuf. Eng. 8 (2014) 37–44. doi:10.1016/j.procir.2015.02.213.

[52] N. Jazdi, Cyber physical systems in the context of Industry 4.0, 2014 IEEE Autom. Qual. Testing, Robot. (2014) 2–4. doi:10.1109/AQTR.2014.6857843.

[53] E.M. Frazzon, J. Hartmann, T. Makuschewitz, B. Scholz-Reiter, Towards socio-cyber-physical systems in production networks, in: Procedia CIRP, 2013: pp. 49–54. doi:10.1016/j.procir.2013.05.009.

[54] A.W. Colombo, S. Karnouskos, T. Bangemann, Towards the next generation of industrial Cyber-Physical Systems, in: Ind. Cloud-Based Cyber-Physical Syst. IMC-AESOP Approach, 2014: pp. 1–22. doi:10.1007/978-3-319-05624-1_1.

[55] J. Pan, R. Jain, S. Paul, T. Vu, A. Saifullah, M. Sha, An Internet of Things Framework for Smart Energy in Buildings: Designs, Prototype, and Experiments, IEEE Internet Things J. 2 (2015) 527–537. doi:10.1109/JIOT.2015.2413397.

[56] F. Tao, Y. Zuo, L. Da Xu, L. Lv, L. Zhang, Internet of things and BOM-Based life cycle assessment of energy-saving and emission-reduction of products, IEEE Trans. Ind. Informatics. 10 (2014) 1252–1261. doi:10.1109/TII.2014.2306771.

[57] H. Demirkan, D. Delen, Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud, Decis. Support Syst. 55 (2013) 412–421. doi:10.1016/j.dss.2012.05.048.

[58] R. Dubey, A. Gunasekaran, S.J. Childe, S.F. Wamba, T. Papadopoulos, The impact of big data on world-class sustainable manufacturing, Int. J. Adv. Manuf. Technol. 84 (2016) 631–645. doi:10.1007/s00170-015-7674-1.

[59] M.C. Ahearn, W. Armbruster, R. Young, Big Data's Potential to Improve Food Supply Chain Environmental Sustainability and Food Safety., Int. Food Agribus. Manag. Rev. 19 (2016) 155–172. http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=116615772&lang=pt-br&site=ehost-live.

[60] J.W. Ross, C.M. Beath, A. Quaadgras, You may not need big data after all, Harv. Bus. Rev. (2013).

[61] S.J. Hu, Evolving paradigms of manufacturing: From mass production to mass customization and personalization, in: Procedia CIRP, 2013. doi:10.1016/j.procir.2013.05.002.

[62] J. Browne, D. Dubois, K. Rathmill, S.P. Sethi, K.E. Stecke, Classification of Flexible Manufacturing Systems, FMS Mag. (1984). doi:10.1080/00207548908942637.

[63] Y. Koren, M. Shpitalni, Design of reconfigurable manufacturing systems, J. Manuf. Syst. (2010). doi:10.1016/j.jmsy.2011.01.001.

[64] Y. Koren, U. Heisel, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, H. Van Brussel, Reconfigurable manufacturing systems, CIRP Ann. - Manuf. Technol. 48 (1999) 527–540. doi:10.1016/S0007-8506(07)63232-6.

[65] M.G. Mehrabi, A.G. Ulsoy, Y. Koren, Reconfigurable manufacturing systems: key to future manufacturing, J. Intell. Manuf. (2000). doi:10.1023/A:1008930403506.

[66] Y. Koren, X. Gu, W. Guo, Reconfigurable manufacturing systems: Principles, design, and future trends, Front. Mech. Eng. (2018). doi:10.1007/s11465-018-0483-0.

[67] Y. Lu, K. Morris, S. Frechette, Current Standards Landscape for Smart Manufacturing Systems, Natl. Inst. Stand. Technol. NISTIR,. (2016). doi:10.6028/NIST.IR.8107.

[68] F. Tao, L. Zhang, V.C. Venkatesh, Y. Luo, Y. Cheng, Cloud manufacturing: A computing and service-oriented manufacturing model, in: Proc. Inst. Mech. Eng. Part B J. Eng. Manuf., 2011. doi:10.1177/0954405411405575.

[69] P.R. Ehrlich, J.P. Holdren, Impact of population growth, Science (80-.). (1971). doi:10.1126/science.171.3977.1212.

[70] P.R. Ehrlich, J.P. Holdren, A Bulletin Dialogue on "The Closing Circle," Critique: One-Dimensional Ecology, Bull. At. Sci. 28 (1972) 16–27.

[71] R. Bradley, I.S. Jawahir, Designing and Redesigning Products, Processes, and Systems for a Helical Economy, in: 16th Glob. Conf. Sustain. Manuf., 2018.

[72] P. Bilge, F. Badurdeen, G. Seliger, I.S. Jawahir, Model-based approach for assessing value creation to enhance sustainability in manufacturing, in: Procedia CIRP, 2014: pp. 106–111. doi:10.1016/j.procir.2014.02.031.

[73] K. Ueda, T. Takenaka, J. Váncza, L. Monostori, Value creation and decision-making in sustainable society, CIRP Ann. - Manuf. Technol. (2009). doi:10.1016/j.cirp.2009.09.010.

[74] D. Chandler, Strategic corporate social responsibility: Sustainable value creation, Sage Publications, 2016.

[75] G. Weinert, Nils; Severengiz, Semih and Seliger, Sustainable Industrial Value Creation Networks, in: LCE 2008 15th CIRP Int. Conf. Life Cycle Eng. Conf. Proc., CIRP, 2008: pp. 70–75.

[76] F. Jovane, H. Yoshikawa, L. Alting, C.R. Boër, E. Westkamper, D. Williams, M. Tseng, G. Seliger, A.M. Paci, The incoming global technological and industrial revolution towards competitive sustainable manufacturing, CIRP Ann. - Manuf. Technol. (2008). doi:10.1016/j.cirp.2008.09.010.

[77] G. Seliger, Sustainable Manufacturing for Global Value Creation, in: Sustain. Manuf., 2012. doi:10.1007/978-3-642-27290-5_1.

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

[79] F. Figge, T. Hahn, Sustainable Value Added - Measuring corporate contributions to sustainability beyond eco-efficiency, Ecol. Econ. (2004). doi:10.1016/j.ecolecon.2003.08.005.

[80] P.J.C. Rivera, O.B. Hernandis, M.S. Cordeiro, O.O. Miranda, Immaterial Elements as Drivers of Sustainability in Products and Services, Procedia CIRP. 29 (2015) 615–620. doi:10.1016/j.procir.2015.02.205.

[81] R.S.J. Tol, The Social Cost of Carbon: Trends, Outliers and Catastrophes, 2010. doi:10.5018/economics-ejournal.ja.2008-25.

[82] Interagency Working Group on Social Cost of Greenhouse Gases, Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866, 2016. doi:10.1186/1472-6750-8-10.

[83] Eurostat, Material flow accounts and resource productivity, (2018). https://ec.europa.eu/eurostat/statistics-explained/index.php/Material_flow_accounts_and_resource_productivity.

[84] Winnipeg, Emission factors in kg CO2-equivalent per unit, (2012).

https://winnipeg.ca/finance/findata/matmgt/documents//2012/682-2012//682-2012_Appendix_H-WSTP_South_End_Plant_Process_Selection_Report/Appendix 7.pdf.

[85] G.S. Altshuller, L. Shulyak, S. Rodman, 40 Principles: TRIZ Keys to Technical Innovation, 1997. doi:10.1007/s00232-007-9039-7.

[86] G.S. Altshuller, The innovation algorithm: TRIZ, systematic innovation and technical creativity, Tech. Innov. Center, Inc. (2007). doi:10.1002/mrc.1918.

[87] Y. Koren, X. Gu, F. Badurdeen, I.S. Jawahir, Sustainable Living Factories for Next Generation Manufacturing, Procedia Manuf. 21 (2018) 26–36. doi:10.1016/j.promfg.2018.02.091.

[88] D. Uckelmann, M. Harrison, F. Michahelles, An Architectural Approach Towards the Future Internet of Things, in: Archit. Internet Things, 2011: pp. 97–129. doi:10/c88wkm.

[89] H. Sundmaeker, P. Guillemin, P. Friess, Vision and challenges for realising the Internet of Things, 2010. doi:10.2759/26127.

[90] R. Bradley, I.S. Jawahir, N. Murrell, J. Whitney, Parallel Design of a Product and Internet of Things (IoT) Architecture to Minimize the Cost of Utilizing Big Data (BD) for Sustainable Value Creation, in: Procedia CIRP, 2017: pp. 58–62. doi:10.1016/j.procir.2016.11.213.

[91] C.A. Giffi, P. Wellener, B. Dollar, H.A. Manolian, L. Monck, C. Moutray, 2018 Deloitte and The Manufacturing Institute skills gap and future of work study, Deloitte Insights. (2018).

[92] M. Rüßmann, M. Lorenz, P. Gerbert, M. Waldner, J. Justus, P. Engel, M.

Harnisch, Industry 4.0: The Future of Productivity and Growth in Manufacturing Industries, Bost. Consult. (2015). doi:10.1007/s12599-014-0334-4.

[93] G.E. Dieter, L.C. Schmidt, Engineering Design, 2013. doi:10.1016/0009-2614(94)00991-0.

[94] J. Guinée, Handbook on life cycle assessment — operational guide to the ISO standards, Int. J. Life Cycle Assess. 6 (2001) 255–255. doi:10.1007/BF02978784.

[95] Y. Asiedu, P. Gu, Product life cycle cost analysis: State of the art review, Int. J. Prod. Res. 36 (1998) 883–908. doi:10.1080/002075498193444.

[96] G. Pahl, W. Beitz, J. Feldhusen, K.H. Grote, Engineering design: A systematic approach, 2007. doi:10.1007/978-1-84628-319-2.

[97] X. Zhang, T. Lu, M. Shuaib, G. Rotella, A. Huang, S.C. Feng, K. Rouch, F. Badurdeen, I.S. Jawahir, A metrics-based methodology for establishing product sustainability index (ProdSI) for manufactured products, in: Leveraging Technol. a Sustain. World, Springer, 2012: pp. 435–441.

[98] A. Rashid, F.M.A. Asif, P. Krajnik, C.M. Nicolescu, Resource conservative manufacturing: An essential change in business and technology paradigm for sustainable manufacturing, J. Clean. Prod. (2013). doi:10.1016/j.jclepro.2013.06.012.

[99] F. Badurdeen, R. Aydin, A. Brown, A multiple lifecycle-based approach to sustainable product configuration design, J. Clean. Prod. 200 (2018) 756–769.

[100] W. Schmidt, Ford of Europe's Product Sustainability Index, in: LCE 2006, 2006.

[101] S. Vinodh, V. Kamala, K. Jayakrishna, Integration of ECQFD, TRIZ, and AHP for innovative and sustainable product development, Appl. Math. Model. (2014).

doi:10.1016/j.apm.2013.10.057.

[102] C.-C. Zhou, G.-F. Yin, X.-B. Hu, Multi-objective optimization of material selection for sustainable products: artificial neural networks and genetic algorithm approach, Mater. Des. 30 (2009) 1209–1215.

[103] T. Luthe, T. Kägi, J. Reger, A systems approach to sustainable technical product design: combining life cycle assessment and virtual development in the case of skis, J. Ind. Ecol. 17 (2013) 605–617.

[104] A. Romli, P. Prickett, R. Setchi, S. Soe, Integrated eco-design decision-making for sustainable product development, Int. J. Prod. Res. (2015). doi:10.1080/00207543.2014.958593.

[105] D.C. Eddy, S. Krishnamurty, I.R. Grosse, J.C. Wileden, K.E. Lewis, A normative decision analysis method for the sustainability-based design of products, J. Eng. Des. (2013). doi:10.1080/09544828.2012.745931.

[106] T.F. Go, D.A. Wahab, H. Hishamuddin, Multiple generation life-cycles for product sustainability: The way forward, J. Clean. Prod. (2015). doi:10.1016/j.jclepro.2015.02.065.

[107] W. Wei, W. Fan, Z. Li, Multi-objective optimization and evaluation method of modular product configuration design scheme, Int. J. Adv. Manuf. Technol. (2014). doi:10.1007/s00170-014-6240-6.

[108] International Data Corporation, Worldwide Semiannual Internet of Things Spending Guide, 2017.

[109] B. Hartmann, W.P. King, S. Narayanan, Digital Manufacturing: The Revolution Will be Virtualized, McKinsey Co. (2015).

[110] J. Bughin, M. Chui, J. Manyika, Clouds, big data, and smart assets: Ten tech-enabled business trends to watch, McKinsey Q. (2010) 75–86. doi:10.1109/MC.2012.358.

[111] D. Wu, D.W. Rosen, L. Wang, D. Schaefer, Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation, Comput. Des. 59 (2015) 1–14. doi:10.1016/j.cad.2014.07.006.

[112] C. Johansen, B. Culp, M. Mora, Cisco Survey Reveals Close to 3/4ths of IoT Projects Are Failing | The Network, Cisco Newsroom. (2017).

[113] Gartner, Predicts 2015: Big Data Challenges Move From Technology to the Organization, 2015.

[114] R.T. Bradley, J.L. Combs, N.J. Murrell, F.J. Palumbo, D. Steinberg, J.A.G. Whitney, Method of determining a media class in an imaging device using an optical translucence sensor, 2016. https://www.google.com/patents/US9451111.

[115] N. Murrell, J. Whitney, R. Bradley, Imaging device and method for determining operating parameters, US9367005 B2, 2014. https://www.google.com/patents/US9367005 (accessed October 7, 2017).

[116] N. Murrell, R. Bradley, N. Bajaj, J.G. Whitney, G.T.-C. Chiu, A method for sensor reduction in a supervised machine learning classification system, IEEE/ASME Trans. Mechatronics. 24 (2019) 197–206.

[117] H. Kagermann, L. Wolf-Dieter, W. Wolfgang, Industrie 4.0: Mit dem Internet der Dinge auf dem Weg zur 4. industriellen Revolution, VDI Nachrichten. (2011).

[118] E.A. Lee, The past, present and future of cyber-physical systems: A focus on models, Sensors (Switzerland). (2015). doi:10.3390/s150304837.

[119] A. Gilchrist, Industry 4.0: The Industrial Internet of Things, 2016. doi:10.1007/978-1-4842-2047-4.

[120] K.D. Thompson, Smart Manufacturing Operations Planning and Control Program, NIST. (2014).

[121] E. Glaessgen, D. Stargel, The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles, in: 2012. doi:10.2514/6.2012-1818.

[122] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering Aircraft Structural Life Prediction Using a Digital Twin, Int. J. Aerosp. Eng. (2011). doi:10.1155/2011/154798.

[123] S. Fang, L. Da Xu, Y. Zhu, J. Ahati, H. Pei, J. Yan, Z. Liu, An integrated system for regional environmental monitoring and management based on internet of things, IEEE Trans. Ind. Informatics. 10 (2014) 1596–1605. doi:10.1109/TII.2014.2302638.

[124] Ellen MacArthur Foundation, Intelligent Assets: Unlocking the Circular Economy Potential, Ellen MacArthur Found. (2016) 1–25. http://www.ellenmacarthurfoundation.org/assets/downloads/publications/EllenMacArthurFoundation_Intelligent_Assets_080216.pdf.

[125] R.X. Gao, D. Wu, J. Terpenny, S. Kumara, C. Jennings, A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests, J. Manuf. Sci. Eng. (2017). doi:10.1115/1.4036350.

[126] S.J. Shin, J. Woo, S. Rachuri, Predictive analytics model for power consumption in manufacturing, in: Procedia CIRP, 2014. doi:10.1016/j.procir.2014.06.036.

[127] A. Vijayaraghavan, W. Sobel, A. Fox, D. Dornfeld, P. Warndorf, Improving

Machine Tool Interoperability Using Standardized Interface Protocols : MT Connect, in: 2008 Int. Symp. Flex. Autom., 2008.

[128] A. Kumar, R. Shankar, A. Choudhary, L.S. Thakur, A big data MapReduce framework for fault diagnosis in cloud-based manufacturing, Int. J. Prod. Res. (2016). doi:10.1080/00207543.2016.1153166.

[129] N. Murrell, R. Bradley, N. Bajaj, J. Whitney, G.T. Chiu, New Calibration Method for Implementing Machine Learning (ML) in Low-Cost Sensor Applications, n.d.

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AWARDS AND HONORS

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Bradley, R., Jawahir, I.S., Badurdeen, F. (Preparing for Submission in 2019). A Conceptual Framework for Transforming a Circular Economy into a Helical Economy for Advancing Sustainable Manufacturing. *Journal of Manufacturing Systems*.

Jawahir I.S., Badurdeen F., Hapuwatte B.M., Aydin R., **Bradley, R**., Ali, A. (Being Prepared for Submission). The 6R principles of sustainable manufacturing for achieving Circular Economy

Murrell, N., **Bradley, R**., Bajaj, N., Whitney, J. G., & Chiu, G. T. C. (Submitted). New Calibration Method for Implementing Machine Learning (ML) in Low-Cost Sensor Applications. *IEEE Sensor Letters*.

Murrell, N., **Bradley, R**., Bajaj, N., Whitney, J. G., & Chiu, G. T. C. (2019). A method for sensor reduction in a supervised machine learning classification system. *IEEE/ASME Transactions on Mechatronics*, *24*(1), 197-206.

Bradley, Ryan and I.S. Jawahir. "Designing and Redesigning Products, Processes, and Systems for a Helical Economy." *GCSM 2018*.

Bradley, Ryan, et al. "A total life cycle cost model (TLCCM) for the circular economy and its application to post-recovery resource allocation." Resources, Conservation and Recycling (2018).

Bradley, Ryan, et al. " Parallel Design of a Product and Internet of Things (IoT) Architecture to Minimize the Cost of Utilizing Big Data (BD) for Sustainable Value Creation." *Procedia CIRP* 31 (2017): 58-62.

Bradley, Ryan, et al. "A Framework for Material Selection in Multi-Generational Components: Sustainable Value Creation for a Circular Economy." *Procedia CIRP* 48 (2016): 370-375.

Jawahir, I. S., and **Ryan Bradley**. "Technological Elements of Circular Economy and the Principles of 6R-Based Closed-loop Material Flow in Sustainable Manufacturing." *Procedia CIRP* 40 (2016): 103-108.

Bradley, Ryan T., "A Framework for Sustainable Material Selection for Multi-Generational Components" (2015). *Theses and Dissertations--Mechanical Engineering.* Paper 61.
http://uknowledge.uky.edu/me_etds/61

PATENTS AND PATENT APPLICATIONS:

Method of determining a media class in an imaging device using an optical translucence sensor- US 9451111

Imaging Device and Method for Sensing Media Type - US9367005

Imaging Device and Method for Determining Operating Parameters - US20160044195