Increasing the Accessibility of Sustainability Modeling for Manufacturing Enterprises

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Abstract

Sustainability will be a significant characteristic of high tech, global, manufacturing enterprises in 2040. Successful enterprises will have sustainable practices in place for all phases of the product realization process. Achieving this level of sustainability by 2040 will be a challenge for today's manufacturing enterprises. While many enterprises today are concerned about sustainability, tools and methodologies for predictive modeling in the fields of sustainability are not accessible for industry wide use. This article illustrates how current research from the fields of product architecture (PA) and social impact predictive modeling can contribute to sustainability modeling in complex systems. As enterprises move from the present to the future, artificial intelligence (AI) and machine learning (ML) take the methodologies and processes currently being researched and transform them into accessible tools for industry wide practice. As AI and ML shoulder the technical or mathematical burden of using complicated engineering modeling methods, engineers and designers in the product realization process will be able to spend more time on iterative creative work, designing sustainable products and processes, and actively solving pressing issues that society faces today.

Introduction

Preparing a company for success as a high tech global enterprise in 2040 will entail many challenges. As engineers and designers look to the future of design and manufacturing, they will see great opportunities and great challenges. Some of these opportunities could be the benefits that advances in Artificial Intelligence (AI), Machine Learning (ML), cyber physical systems, and cloud computing have to offer the manufacturing community. However, great challenges will also persist. Some of these challenges are described in five megatrends [1]:

1. Rapid Urbanization
2. Climate Change and resource Scarcity
3. Shift in Global Economic Power
4. Demographic and Social Change
5. Technological Breakthroughs

Furthermore, the United Nations has defined 17 sustainable development goals to guide individuals, communities, corporations, and nations as they work towards a more sustainable future [2]. The US product realization industry has a large role to play in achieving the sustainability milestones outlined by these megatrends and UN sustainability goals.

Global, high tech product realization is a very complex system, where optimizing the system for overall performance characteristics, such as sustainability, is difficult. Research from the fields of product architecture (PA) and social impact modeling have produced valuable insights into how products and processes can be optimized for sustainability. However, these methods are not being readily adopted into industry because of the technical barriers and complexity involved in using them.

Artificial intelligence (AI) and Machine Learning (ML) could make complex modeling tools from PA and social impact predictive modeling more accessible for industry wide use. Currently, many people are seeing how AI is making complex graphic design tasks previously limited to graphic design professionals accessible to graphic designers without as much experience. Furthermore, experienced graphic designers are benefiting from sped up workflows, which lets them focus more on creative work. Similarly, as AI and ML make sustainability modeling more accessible to practitioners in the product realization industry, manufacturing enterprises will be better equipped to design meaningful products and processes sustainably.

The remainder of this article first reviews how AI and ML can affect manufacturing enterprises going into the future. Then, current research from PA and social impact modeling is reviewed, with an emphasis on how AI and ML can make this research more usable in industry. The article concludes by summarizing some of the characteristics high tech global manufacturing enterprises will display in 2040.

Artificial Intelligence and Machine Learning

Artificial Intelligence has become a household term in many homes across the United States, and refers to the effort to make programs, machines, and systems that demonstrate intelligent, self-learning behaviors. Machine Learning (ML) is a subset of AI defined as the capability of AI systems to "acquire their own knowledge by extracting patterns from raw data" [3]. ML is found in various creative fields, and it can be expected that ML will play an increasingly large role in product realization. In product realization, ML could speed up complicated or monotonous tasks, letting engineers and designers focus on creative or evaluative work.

The impact of AI and ML in graphic design could provide useful insight into the potential for AI and ML in product realization. Recent developments in AI and graphic design have resulted in artificial photo generators, photo and film editors, and graphic design packages. It should be noted that there are several concerns with using AI in graphic design and art. For example, many content creators worry about AI impersonating their work, or using their work in training models, and not receiving credit or recognition for their work. These concerns have motivated several market leading companies to collaborate on standards for the use of AI and ML in digital, creative work [4]. The Coalition for Content Provenance and Authenticity (C2PA) "addresses the prevalence of misleading information online through the development of technical standards for certifying the source and history (or provenance) of media content" [4]. The development of standards for tracking and proving original verses AI generated art would protect creator's rights when creating content.

Despite these challenges, people in the graphic design industry are also positive about the opportunity to use AI tools in their design work. Many consumers are interested in using AI to speed up their workflow, spend less time on monotonous tasks, and spend more time rapidly iterating through ideas. These AI tools make graphic design more accessible to beginners and people without design experience or experience learning to use complicated software. Adobe advertises that their creative AI tools “unlock your creative superpowers” and “enhance the creative process” [5]. Images or scenes that used to take a long time creating can now be created or edited in seconds, which reduces the time between iterations of art pieces. The creator can spend less time on the creation of the artifact, and can spend more time ideating, evaluating, and iterating.

Similarly, AI tools can speed up or facilitate product realization activities. Product development tasks that were typically time intensive and error prone could be replaced with quicker alternatives – such as using AI tools to create mechanical drawings, process diagram sheets, or 3D models. One ML researcher wrote, “to make good use of ML tools it is instrumental to understand its underlying principles at the appropriate level of detail. It is typically not necessary to understand the mathematical details of advanced optimization methods to successfully apply deep learning methods” [6]. As the mathematical details of product realization work get allocated to AI systems, new engineers and designers will only need to understand what the fundamental principles of the design and manufacturing work are to make meaningful contributions in product realization.

Removing the requirement to understand deep mathematical or technical details to engineering activities will remove barriers to participating in product realization. As more people begin participating in product realization, safeguards will need to be enacted to ensure the quality of the artifacts being produced and that safety, ethical, and technical standards are being reviewed. In this capacity, expert review will always be required at some level. It must also be decided which “underlying principles,” and at what “appropriate level of detail,” are required before someone engages in AI assisted product realization activities. Determining these safeguards and principles would be important research areas for the manufacturing enterprise to consider before incorporating AI and ML into their regular workflow.

Allowing greater access to every stage of product realization gives manufacturing enterprises of the future a greater ability to develop human capital and harness ideas. As stated, societies are grappling with the effects of megatrends. Diverse ideas and perspectives are needed for a greater variety of novel, quality ideas in the pursuit of sustainable solutions. AI and ML tools would let more people contribute to engineering design as they strive for more sustainable products and processes. Successful enterprises will use technological advances in machine learning and artificial intelligence to leverage the full creative capacity of all their employees.

Research Opportunities

With a brief introduction into how AI and ML learning can benefit manufacturing enterprises in the future, the article will now turn to two areas of research that could be of interest to the manufacturing enterprise. First, product architecture (PA) will be reviewed, followed by social impact modeling. Both areas are complex fields of study that benefit from knowledge of systems engineering. ML has the potential to take knowledge and data from PA and social impact modeling and become transformative additions to product realization work.

Product Architecture and Systems Engineering

PA is the allotment of product functions to physical components [7]. PA research can inform designers, engineers, and researchers on good design practices for their products and systems. Furthermore, PA decisions have large impacts on the downstream design process, such as in manufacturing. As transportation, supply chain, and communications technologies improve, manufacturing enterprises will be better equipped to work with an increasing number of partners around the world. Enterprises will have more decisions to make regarding designers, suppliers, and manufacturers to work with – especially considering products with numerous components, when components could be produced all around the world. Insights from the field of Product Architecture (PA) could provide strategies for managing these complex opportunities.

One popular architecture strategy is product modularization, or modularity. Modular products have a one-to-one mapping of functions to components [7]. Modularization has been demonstrated as an effective way to manage complexity because large problems can be broken down into simpler components or modules [7,8]. Of particular interest to global enterprises is that modular designs facilitate the outsourcing of designs and production to out of house partners [7,8,9]. Another advantage of modular architectures is that they facilitate the parallel development and production, which lowers new product development time [7,8,9].

Differing from modular architectures, integral architectures have multiple functions assigned to any given component [7]. One key advantage of integral architectures is that they can be optimized for global performance characteristics. Here, global performance refers to optimization for performance over all of the product's modules or components. Modularity, on the other hand, is advantageous for optimizing specific functions but may fail to reach the same global optimum that integral architectures achieve [7]. Other advantages of integral architectures include decreasing the overall number of components through a process called function sharing, where multiple functions are assigned to the same component [10].

While the effects of various architecture strategies are well documented in the literature, tools or methods to assist designers in the selection of architecture strategies are lacking. With large amounts of ML algorithms have the potential to assist enterprises of the future. ML could assist enterprises of the future as they try to optimize modular benefits (such as facilitating parallel work or out of house design and manufacturing), and integral performance benefits. This would prove quite valuable when it comes to sustainable design. Sustainability is likely to be a global performance characteristic that is achieved over all of the components.

ML algorithms are designed to explore a large space of hypotheses (the hypospace) and experiment with which relationships or correlations are the best [6]. Using ML to find and select optimal PA strategies for enterprises in the future is an important research topic that can enable enterprises to select the best strategies for what they are trying to accomplish.

Sustainability Modeling

Great research potential also exists in sustainability analysis. Moving forward, research can focus on sustainability for the triple bottom line. This will entail new predictive methods and analysis tools. Previously, one of the greatest difficulties in performing sustainability modeling has been a lack of training data and not being able to sort through everything in a meaningful way. ML could also be used to synthesize results from various analyses and compare global outcomes.

In environmental analysis, Life Cycle Assessments (LCA) are an insightful tool that looks at a product's environmental impact over its entire life (manufacture, use, and disposal) [11]. These impacts are then described in terms of damage to health, damage to ecosystem, and damage to resource extraction. Agent Based Modeling (ABM) is a stochastic computational tool that can model complex systems, such as society. ABM has been used to scale the effects of LCA of individual products to larger levels of society [11]. Coupling together LCA and ABM methods would let manufacturing enterprises design products and processes for minimal environmental impact.

Social impact modeling tools are not as developed, available, or integrated into current business practice as other forms of impact modeling [12, 13]. When social impacts are considered, it is often limited to public health and safety. Successful enterprises of 2040 could benefit from further tools and methods for modeling a more comprehensive set of social impacts. Rainock et al described a set of 11 impact categories in the following areas [14]:

1. Health and Safety
2. Education
3. Paid Work
4. Conflict and Crime
5. Family
6. Gender
7. Human Rights
8. Stratification
9. Social Networks and Communication
10. Population Change
11. Cultural Identity and Heritage

A social impacts inspired failure methods element analysis has been proposed that takes this broad set of social impacts into consideration [15]. Taking the next step forward, enterprises in 2040 would greatly benefit from predictive modeling software packages that estimate social impacts and outcomes. Engineers have contributed greatly to other predictive modeling fields, such has been seen in Finite Element Analysis (FEA) programs available for mechanical systems, such as structural, thermal, or fluid dynamics. Future research could work towards a sociotechnical FEA program that enables designers to consider a product's social impact on various levels of society.

In order to support this research, engineers would need to know mathematical relationships between technological elements and societal elements. ML can assist researchers in this endeavor by deriving the relationships between products and their social impacts. Data to derive these relationships would need to be from technical databases that describe features of products, and social databases that describe characteristics of people. A challenging research question for enterprises in the future would be how to link technical and social data to reveal product impacts. ML could assist researchers in this endeavor by exploring the hypospace of all possible relationships between products and society.

Conclusion

PA and social impacts modeling are complicated subjects of study that have previously been out of reach of industry use and practice. However, these fields of study also hold valuable insights that would enable manufacturing enterprises to put renewed focus on economic, environmental, and social sustainability. Much research could be done to make these findings more accessible and usable for practitioners in industry settings. AI and ML are presented as a technology which could revolutionize how manufacturing enterprises design sustainable products and processes. Applying AI and ML to current research topics will enable manufacturing enterprises to engage in product realization work with a greater focus on creating products and processes that are sustainable. ML can shoulder the technical burden of sustainable, efficient, or profitable design. With this burden taken off the employees, employees will be able to spend more time on creative work and looking for ideas for society's most pressing concerns, as they are encapsulated by megatrends or UN sustainable development goals.

Sources

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