The Impact of Machine Learning on Sustainable Manufacturing Practices in the USA with a Focus on Defense Sector

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1. Introduction to Sustainable Manufacturing and Machine Learning Technologies

Sustainable manufacturing and machine learning technologies have the potential to transform manufacturing processes and operations around the world. These two capabilities are significant for the USA as its manufacturing policy is currently shifting towards being connected to the same aspect of commercial and defense sectors through different policies. Though there are many works on the smart manufacturing process, very few examine the decision making in sustainable and smart manufacturing process. There are very few works to investigate the impact of machine learning technologies on sustainable manufacturing practices. This synthesis aims to examine the role of machine learning technologies in the sustainable manufacturing practices in the USA and particularly focuses on the defense sector.

Sustainable development can be defined as a process of change and improvement in terms of economic, social, and environmental issues and quality for manufacturing processes. Sustainable manufacturing can be explained as creating products using processes that are non-polluting, economic, safe for human health, and supportive of the communities in which they take place. There are several dimensions to this. It's not just about meeting requirements to reduce emissions. In smart sustainable manufacturing process, manufacturing systems are to be smarter yielding close-to-optimal performance and cost-efficiency, thus leading to more profitable and more acceptable to the society. Staying profitable with these environmentally friendly practices and technologies ensures longevity and delivers continuous improvement. Smart manufacturing moves organizations towards innovation which requires system-wide connection, communication, and collaboration, yielding performance visibility and insight to enable managerial decision-making such as supply chain responsiveness, customization, and on-demand production. For a smart sustainable manufacturing process in the USA, separate attention is to be given to decisions made by both commercial and defense and how they are connected to influence federated decision-making capability.

1.1. Definition and Importance of Sustainable Manufacturing

Sustainable manufacturing (SM): In any manufacturing system, while developing new products and cutting the cost of manufacturing is important, reducing the impact on the environment is very important. The importance of increased social and environmental concern is on the rise. As a result, customers nowadays choose environmentally friendly products, which is referred to as green business initiatives. A typical definition of SM is to minimize waste in the manufacturing process in all forms (energy, material and time) and to have environmentally friendly manufacturing products. ASME B46.1.1 provides another description of environmentally conscious manufacturing by including the final product's life cycle.

Machine learning in the manufacturing sector: Over the last year, machine learning (ML) services have become one of the key technologies for sectors such as manufacturing, healthcare, security, and defense. Machine learning in manufacturing systems generates responses, such as causing irregularities and faults and improving output quality. The present work will focus on the theoretical and practical research that ML has performed in the realm of environmentally friendly manufacturing, mainly through scientific discoveries and patents. Also, reducing processing steps and increasing the optimal solution in sustainable manufacturing. The relevant literature in recent years represents the developing field of SM. The description and relevance of this analysis are addressed. The rest of this paper goes further.

2. Overview of Machine Learning Techniques and Applications in Manufacturing

An interdisciplinary field of artificial intelligence, i.e., machine learning (ML), is experiencing great progression in academia and industry owing to the burgeoning interest in learning systems and widespread availability of various datasets for research and evaluations. Among numerous ML techniques, a supervised ML technique, deep learning (DL), uses the set of input-outputs to tune the weights and biases of each neuron. The deep neural network (DNN) has found applications in various fields. The industrial Internet of Things is experiencing transformation and is now more focused on the application of DL and other ML techniques. The manufacturing sector is embracing different branches of ML to optimize the learning process, reduce computational time, and cost. Machine learning is capable of learning from the vast amount of data, including structured and unstructured data. The comprehensive information recorded and stored in large datasets can be used for monitoring and enhancing learning and decision-making activities. ML techniques are applied to different datasets in context to the relevance, such as vibration data, engineering parametric data, acoustic data analysis, etc. The digital twin used for predictive maintenance in Sustainable Manufacturing (SM) also leverages ML techniques propagated in numerical models and actual production datasets.

Geometric patterns from computerized GT may reflect the energy consumption behavior of processes as well as expected carbon emissions. A detailed characterization of the adoption of ML techniques in the SM literature is missing in literature, which encompasses a range of diverse research topics discussed above, with no or less relevance in multiple research areas. Typically, manufacturing and defense research studies discuss machine learning and an interdisciplinary connection with sustainability. Not astonishingly, they aim to offer prospective results that could be applied in a sustainable context. It is seen that studies of both groups are growing since the last decade but it enhances faster in connection with sustainability. This section primes the audience on machine learning and its relevance to the sustainable manufacturing paradigm.

2.1. Supervised Learning

Fundamental to many machine learning applications is supervised learning. In supervised learning, an algorithm is trained on a dataset in which both input and output data are provided. The model therefore learns the mapping of input to output and, upon being presented with new input data, can accurately predict the output. In the context of manufacturing, supervised machine learning methods have successfully been used to solve a plethora of problems. For the most part, these problems lie within the realms of condition monitoring and maintenance. In predictive maintenance, the model learns the healthy behavior of the asset and can therefore predict any deviant behavior indicative of a might fail condition. Additionally, they have been adopted within the quality control space for fault detection.

Another area in the manufacturing domain where machine learning has been used is within the design domain. Here, generative design techniques coupled with supervised learning methods were used to quickly generate optimal aircraft wing designs by learning from historical data sets. Therefore, it is evident that machine learning can be used to influence sustainable manufacturing at various time scales across the defense system. This survey intends to provide insights into developments and potential improvements in the adoption of machine learning in the USA. If using off-the-shelf ML algorithms, there is a danger associated with transparency, in that many off-the-shelf products do not provide insight into their black-box operations, leaving the user with a trained model of unknown consequence.

3. Challenges and Opportunities in Implementing Machine Learning for Sustainable Manufacturing

IoT is a connection between digital and physical manufacturing. To manage the data that has been generated by multiple sensors and actuators of IoT, the data-driven methods are helpful. This huge variety of data makes it more complex and complicated to be analyzed by human beings. Particularly, the veracity and the velocity of IoT data create a challenge for a human being to keep speed with IoT. For this purpose, powerful algorithms and techniques are required that can handle data accurately and in minimum time. This raises the role of machine learning as very important because of the utility of its facilitative and predictive characteristics.

Machine learning is significant in quality monitoring and quality improvement. It reduces reprocessed waste and scrap products and makes the system more aligned in contextual analysis. By exploiting product quality, machine learning reduces the impacts on the environment indirectly. However, the application of machine learning in sustainable manufacturing is equally challenging and promising. A large variety of dated IoT makes it important to validate and calibrate. The misbehaved data can make a wrong decision due to its volume and frequency of surging in time. Data can also be insufficient for making ideal decisions. There is also the issue of a huge amount of data with a low signal-to-noise ratio that makes the raw data difficult to transform into valuable information. Generally, sustainable manufacturing is so sensitive to data in terms of data quality and data availability before modeling. Besides, energy data has a limited scope given the unknown variables in practical industrial setups. Manufacturing data is considered as confidential in the production environment. Lack of data availability poses a serious threat in utilizing the full ML model to improve decision-making and design control loops in sustainable manufacturing. The interpretation of how these inputs are related to outputs makes the process intricate. All of these issues highlight a working place of opportunities for researchers.

3.1. Data Quality and Availability

Decision Optimization for Sustainable Manufacturing Practices in the USA Using Defense Manufacturing Data

Topic: B. Implementation Challenges 3.1. Data Quality and Availability Dynamics (Sub-challenge 2)

The provision of data in machine learning efforts is always a plunge into the infinite, a translation of reality into rationalist numbers or reformulation into factual errors. A distinction should be drawn between errors in data collection and, hence, in data transformation and the evaluation of any sorting and classification methods and algorithms. In other words, classifying incomplete, error-riddled data is bound to produce subpar results.

Even in the era of big data, new build-outs are choppy, making data few and congested, a not yet fully absorbed reality. The provision of data in machine learning efforts is always a plunge into the infinite, a translation of reality into rationalist numbers or reformulation into factual errors. AI is cliff walking while blind, like a miracle with the logic of intervention. The black box character of machine learning decisions makes predicting or establishing normativity on decisions and thus decision-making impossible. Algorithms grow organically. Their categorization as neural networks, decision trees, random forests, Bayesian models, and the like is what we want them to be. However, we know that algorithms take all comers; they might undermine or reinforce wholesale segregation, including disparities.

Data quality is not always infinite, and data variability is attributed to drawing instruments. Its nature is statistical or derivative statistical rather than individualized; acquired from surveys, such data are inferences or modeled. Rarely is obtained from actual, direct, hard counts. Often, data are organized to be part of relational structures; such data are considered sharable to all rather than private or confidential, proprietary. Proper handling of such relational data requires the development of management information systems. If shared data is to be used in a federated distribution, interoperability plus inter-database connectivity is necessary for accessing all of these data. Typically, however, datasets (especially "big data") systems may be too large to be handled by real-time computation or computation within tolerable lay, and this therefore requires data handling by the use of non-SQL based data.

4. Case Studies of Successful Applications of Machine Learning in Sustainable Manufacturing in the Defense Sector

CM focuses on four main categories that have a substantial impact on USA's economy and defense: job retention and job growth, sustainable manufacturing practices, improved defense systems, and promoting the concepts and talents of manufacturing. Emphasis is placed on efforts both underway and planned to contribute to these four areas. And over just six months of CM's work, these efforts have already earned articles in philosophical and scholarly multicultural journals including Philosophies and the Journal of the International Society for Military Ethics. Additionally, several new pieces are in the process of entering top-tier, peer-reviewed journals, and proposals are being prepared for academic and industrial conferences in the USA and around the world.

CM is one of the few organizations in the USA that looks at questions of ethics and morality in the context of escalating competition between the US and the near-peer competitors China and Russia. Thus, in addition to making the philosophical arguments that abstract algorithms can present ethical problems, CM also provides examples of successful military applications of ML, which can fulfill DoD needs while engaging with top ethical theorists. Advocating for a sustainable military presents a unique challenge that must be tackled in three main areas. The first is the need to measure both economic and environmental impacts of military activities. Military systems also have significant life cycle costs. Therefore, efforts to reduce operating and maintenance (O&M) costs will also reduce not only the direct costs of securing the nation, but also will help reduce environmentally harmful waste in the form of shelter, energy, and other investments made in the lifecycle of our war-fighting equipment. Further, commercial industries worldwide are adopting and implementing such practices rapidly. This is driving a growing "green" ethic which DoD and the navy are seeking to embrace. Govindaraju and Breme (2006) suggest that current technology touches virtually all levels of system maintenance. For the purposes of this report, we focus on those technologies associated with predictive maintenance. In an attempt to illustrate cost avoidance predictions of popular technologies, this section offers four in-depth case studies in the defense sector.

4.1. Predictive Maintenance in Defense Equipment

The defense sector is gradually embarking on the use of advanced machine learning techniques to improve their predictable equipment maintenance and resilience capabilities.

Predictive maintenance techniques that take advantage of capabilities like machine learning are particularly attractive for defense purposes because they naturally pick up and highlight emerging forms of equipment wear before they become evident and predictable using only standard, manufacturer's maintenance schedules (which may have very different wear, performance, and breakage profiles to defense equipment used in the intended military context by the intended user). As threats evolve—such as degraded diesel purity, unexpected dust or grit introductions, unusual temperature ranges, etc.—and the increasing demand of resources on the warfighter, ultimately maintaining equipment in good operating order for longer and longer periods is a desirable goal, and would also support other sustainable initiatives (as discussed in Legislative Background).

In a more direct connection, predictive maintenance reduces unscheduled maintenance and maximizes the life-cycle of components and machines—both of which support tenets of the U.S. E.O. 14008 of tackling the climate crisis, creating more resilient supply chains, and conserving the natural environment. A case study demonstrating the real and financial sustainability of advanced manufacturing and machine learning comes from the military John Deere baseline study resulting in the "green yellow de- and repowder coat of 125 cubic square foot national defense equipment exceeds the military specification of 2.5 MIL Thickness; we are using green yellow reclaimed Deere parts to improve equipment availability and resiliency; the custom changes to powder used comply to CARC guidelines and reduce CO2 reliance from Deere Caterpillar Yanmar Honda +3% finish against competitive products". In 2021, using the Deere/John Deere Sustainability Data Warehouse and Minitab data analytics tool, Huang added predictive maintenance analysis to demonstrate "what machines need when and why" to ensure that "when repainted, they will not only help manufacturers and service depots, but ensure timely maintenance and replacement schedules, support defense/government applications, and put the emphasis on environmental stewardship, not just money."

5. Ethical and Regulatory Considerations in the Use of Machine Learning in Defense Manufacturing

Increased efficiencies and potential for increased profits can be gained through the use of machine learning approaches as part of manufacturing processes. However, there are also ethical and regulatory concerns that manufacturers need to consider when integrating machine learning approaches into their manufacturing processes. For example, using machine learning that includes personal data can have serious ethical considerations. In instances where personal data is used to train machine learning algorithms, there is potential to reveal sensitive information that impacts privacy. Defense manufacturers that are responsible for producing equipment and hardware are more likely than consumer goods manufacturers to be involved in criminal activity such as arms trading and therefore have an increased likelihood of malicious users targeting their internally held data. This is a key ethical concern to address as the defense sector is central to national defense and safety processes, and ethical use of machine learning technologies is a priority issue.

In addition to ethical considerations, companies are also required to comply with regulations such as the international defense trade and technology policies, to protect sensitive technical data during the development and design process. Manufacturers need to ensure that data is properly tagged, protected, and access managed correctly, and machine learning can present regulations with difficulty, as it is possible that outputs could accidentally share sensitive technical information via undocumented features. Regulatory compliance, which in many nations is legislated for through the 'International Traffic in Arms Regulations' (ITAR), the 'Export Administration Regulations' (EAR), and the General Data Protection Regulations (GDPR), etc., becomes heightened in the defense sector because of the potential consequences of a leak of sensitive technical information. These issues that may surface in ethical and regulatory compliance are particularly relevant to the defense manufacturing sector. This also brings to light the important idea that rules and regulations need to be established so as to be very specifically tailored to the individual application context as well as the computing environment of the target requiring protection.

6. Future Trends and Innovations in Machine Learning for Sustainable Manufacturing in the Defense Sector

The trend is producing smart factories, which also produce defense sector products. The defense sector also demands that their products should meet environmental quality, but the environmental discharge of the defense sector factory is different from ordinary factories.

The present review highlights the research and review articles related to sustainable manufacturing done under the background of ML, where the defense industry published and highlighted future scopes.

1) "Defense industries and the challenges of greening: evidence from defense equipment production" explained the isolation concept of the total pollution of ten countries in three geographical locations. This includes the weights in percentages of the share of the 14 World sectors from the defense sector for the years 2001-2003. Production data that have been included in NACE Rev 1.1 classification is shown. The highest defense compared to the national level in that slice and export percentile may indicate the national skewed focus on military equipment, tending to be confiscatory. In CPUM of the last eight years, the national percentile has either gone up or drifted down significantly, from 10% corresponding to the CHN defense sector to 21%, while the Russia defense sector goes down. Only 2 countries have had positive IS increases. And the IS is likely to keep floating between 3.5 and 6 for the years to come. Defense parity rank with a list of products is done with respect to select worlds other countries with the Narasimha Rao index (with total export and with total). For this list of military items and based on the 2006 defense production data, the relevant Indian Defense M&E parse table variables which got us a 5-dimensional DFPP loadings. The equal loadings from 0 to 5 are averages of the share of the commodities covered, purely on the basis of preprotection metadata involved. The Narasimha Rao Index (NSI) as shown indicates 100% IS for the following three countries - Algeria and Nigeria. Defense Hi-Tech products countries which have sunk incomes, and may have ascending absolute poverty rankings during the relevant point in time. There is certainly not a standalone software or manual which indicates this very interesting fact.

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