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Enabling Sustainable Manufacturing Through AI-Optimized Supply Chains

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Abstract: Rapid digital transformations in every aspect of life, work, and society are aided by quickly developing technologies like artificial intelligence (AI) and the Internet of Things (IoT). The sophisticated data-driven decision-making environment that they inspire enables the implementation of smart manufacturing, in which every aspect of manufacturing is monitored using sensors that continuously record and analyze data streams in real-time. The focus is on monitoring the real-time state of affairs within the ecosystem of machines, processes, and resources. This shift in paradigm can increase productivity, efficiency, and profitability in a significantly disruptive manner by enhancing the transparency of operations and automating data-driven decision-making processes. This transformation needs to embrace many technological and systematic alterations that require aligned collective efforts from stakeholders. The design, development, and interoperation are essential for the successful implementation of smart manufacturing systems. Mass customization, lower energy consumption, retrofitting and reusability of assets, lower environmental impact, and a more sustainable production process are desirable manufacturing efficiencies that will drive up the acceptance of smart manufacturing systems.

A supply chain (SC) must be designed to allow for efficient management of all aspects of supply chain planning, analysis, modeling, monitoring, and control with the support of data-driven business intelligence (BI) systems. The smart manufacturing system architecture that is detailed in this context. Singularity of the suggested system architecture shields processes, operations, systems, subsystems, and their interactions from external environment factors that have an effect on them, to provide a high-quality working mode in the time of overflowing demand. The core of the AI-assisted BI system centered around prediction includes (i) a HW/SW architectural setup, and (ii) and AI algorithms with differing depths for data cleansing and feature engineering that enables the existence of such a smart manufacturing system architecture. Alternative AI algorithms are employed with fusing/conjunction of numerous learning algorithms for more efficient training of models with superior forecast accuracy to predict production, delivery, and external demand. The AI-assisted BI system is scalable and adaptable to more than 2 massive datasets for expectant production planning and control through training of models that can provide estimates of machine UT, jobs carried out in time, and the number of finished products. Contemplating on the trade-off between profitability and sustainability with model operationalization that considers data governance, data utilization, and data development costs alongside carbon- and energy-aware manufacturing are possible.

Keywords: Sustainable Manufacturing, Artificial Intelligence, Supply Chain Optimization, Green Manufacturing, Predictive Analytics, Smart Logistics, Resource Efficiency, Carbon Footprint Reduction, AI-Driven Decision Making, Circular Economy, Environmental Impact, Machine Learning, Real-Time Monitoring, Energy Efficiency, Data-Driven Manufacturing.

I. INTRODUCTION

As a result of dwindling natural resources and a growing global population, the manufacturing sector faces increasing pressure to produce high-quality goods sustainably in response to rising demand. Increased sustainability regulations, customer awareness, and industrial initiatives are forcing companies to review their core business model and operations. To attain the overarching objective of sustainability, manufacturing companies must identify the sustainability indicators that yield the highest benefits for upstream supply chain structures, such as suppliers, before implementing changes in manufacturing process capabilities.

Sustainable manufacturing methods bolster product quality, decrease energy intensity, and boost productivity while fostering environmentally friendly product characteristics, waste reduction, and employee safety. Sustainability concerns must be considered in sourcing, design, and production processes due to the long-lasting effects of decisions made by the supply chain's upstream structures. Managing sustainability indicators upstream in the supply chain is a highly intricate decision-making issue that is presently not addressed in the literature.

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Artificial intelligence (AI) is a series of technologies that allow machines and algorithms to replicate human languages and actions, making decisions for themselves without explicit programming. The emergence of AI and enhanced optimization methods enables the detailed modeling of these complex decision-making problems. AI-generated insights and optimizations can also be used to enable the continued use of the achieved decision-making processes in operative decision-making systems.

To foster digitalization, profitability, and sustainability paradigms, manufacturing companies must become competitive in an oscillating economic environment. Supply chains are fundamentally changing due to competition and disruptions, making methodological advancements for data-driven optimization approaches for supply chains vital. Companies face challenges such as complex structures across corporate boundaries, high item and supply chain complexity, ever-tougher global competition, increasing customer expectations and demand volatility, and scarce resources, leading to unexploited response rules and dimensions for proactive decision-making in manufacturing and supply chain management.

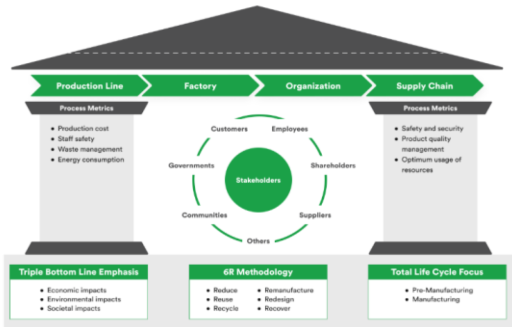

Fig 1: AI-Driven Optimization for Sustainable Manufacturing

1.1. Background And Significance

Manufacturing is one of the most significant contributors to global GDP, accounting for $16.4 trillion in 2019, and illicitly contaminating the environment through denser pollution. The sector consumes 54% of energy use and contributes 61% of greenhouse gas (GHG) emissions. Manufacturing plays a vital part in fulfilling Sustainable Development Goals (SDG) by 2030. However, without intervention, emissions could increase by 60% by 2030. The manufacturing sector has many seemingly solitary components. A systemic approach to achieving transparency across the supply chain infrastructure, sourcing, logistics, production, waste treatment, and recycling, can identify opportunities for waste reduction and energy efficiency, as well as automate relevant information collection. To estimate the potential of utilizing AI to systemic sustainability, a narrower analysis of AI aspects in addressing the supply chain's impact on the sustainability of the manufactured product is conducted. Supply chains address the vast majority of sustainability burdens, with sourcing and logistics impacting heavily on Economic and Social impacts, while production can individually source 19.6% of environmental impacts depending on production factors and circumstances. Few efforts have focused on the systemic aspects of AI and their potential to improve sustainability.

A one-stage product's life cycle can feel like the end of the impact. This systematic approach includes all components of manufacturing and thus can help identify the potential for improvement. Addressing only one part of manufacturing can redirect attention and responsibility without reducing impact. A set of widely applicable AI techniques are investigated for their possible contribution to improved sustainability and understand the challenges that might hinder implementation. Predictive maintenance is a well-studied field that can reduce the economic impact of production and increase reliability. Most approaches utilize Asset Condition Monitoring (ACM), which consists of signals such as vibration, temperature, and stress that can be turned into health monitoring signals. This tracking of working parameters helps maintenance departments prepare for maintenance events and avoid halts. A system with ACM alone can lower production reliability due to additional uncertainty.

Equ 1: Total Cost Function

$$C_{\text{total}} = \sum_{i=1}^{n} (C_{p,i} + C_{t,i} + C_{h,i})$$

Where:

- $C_{p,i}$: Production cost at node i
- $C_{t,i}$: Transportation cost from node i
- $C_{h,i}$: Inventory holding cost at node i

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II. THE IMPORTANCE OF SUSTAINABILITY IN MANUFACTURING

For the optimization of unit processes, proper control of process parameters is essential. The term sustainable manufacturing is the creation of manufactured products that minimize negative environmental impacts, conserve energy and natural resources, and are safe for employees and communities. Sustainable manufacturing is the manufacturing of economic, social, and environmentally friendly products. The need for a sustainable manufactured product escalates due to the increasing consumption of non-renewable resources and generation of wastes and pollution.

The following factors must be targeted for sustainable manufacturing: energy consumption, material wastage and emissions, and less use of non-renewable resources. The manufacturing performance is the primary determinant of the growth of any organization. Manufacturing participation has great importance in the development of an organization as it directly affects the productivity and profit of the organization. As either a producing organization or a consuming organization, the product manufacturers are critical in economic growth. Additionally, the organizations are under the pressure to minimize the detrimental impact of their manufacturing activities on the environment while maintaining the social and economic aspect in gaining competitive advantage. The organizations are under the pressure to adapt themselves to sustainable manufacturing processes due to internal and external pressures from legislation and regulation and changes in consumer behaviors and societal values. However, the need for implementing sustainable manufacturing initiatives escalates due to the increasing consumption of non-renewable resources and the generation of wastes and pollution.

Due to the large magnitude of the scientific and technological advances in many industries, there is considerable potential to improve economic, social, and environmental performance. The manufacturing sector is identifying and eliminating barriers to the implementation of sustainable framework and tools. Significant improvement in the economic benefit and environmental performance can be attained if proper implementation of these frameworks and tools is introduced. Energy, CO2 emission, and material wastages are important indicators considered for sustainability performance evaluation. Better sustainability performance can be attained through improvements in energy, CO2 emission, and material productivity.

2.1. Environmental Impact

Manufacturing is the basis for many industries and is key for modernization and value creation in many societies. Still around three-quarters of the world's annual energy consumption comes from fossil fuels, of which around one-fifth is used for energy-intensive processes such as manufacturing. Therefore, enabling sustainable manufacturing, that is, maximizing product value while minimizing the consumption of the world's limited social, environmental, and economic resources, is a key challenge for all stakeholders.

To enable sustainable manufacturing, manufacturing systems need to be synchronized across multiple sites for product supply chains. Such multi-site manufacturing typically involves manufacturing operations in multiple, geographically distributed locations. Synchronizing production of associated parts for assembly, sub-management of individual factories, schedule make/buy from multiple factories, and multi-criteria selection of new suppliers are just some examples of such problems. To efficiently calculate optimal solutions for these NP-hard problems, full understanding of combinatorial optimizations and mathematical programming tools is often insufficient. However, these problems have been successfully solved with relatively simple, computationally efficient, heuristic-based meta-optimization methods, such as Genetic Algorithm. AI techniques have significantly improved product supply chain performance by reducing manufacturing time and downtime costs, improving lead time, and minimizing the risk of unscheduled downtime and idle time in machines. The development of AI-based methods for optimizing multi-site manufacturing has intensified in the last decade, driven by the tremendous growth of data from the Internet of Things and machine vision and the improvements of computational capacity. Nonetheless, few works have been reported that targeted solely at minimizing the carbon footprints of such manufacturing systems.

To the authors' knowledge, no academic works have directly addressed the AI-enabled supply chain optimized for environmental sustainability. This is an important research area that deserves greater attention and more novel methods. Historical case studies have concluded that optimizing energy consumption impacts on scheduling performance by around 40%. The significant impact of AI-enabled supply chain and scheduling optimization on manufacturing efficiency and sustainability may thus be expected in a similar order of magnitude. A hybrid system combining simulation with meta-optimization has been developed to demonstrate the potential improvements in product supply chain performance with AI-enabled methods. One of the model factories at the site is a stamping workshop, where a dozen robots and industrial presses that should be strategically scheduled within a short time frame are deployed.

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2.2. Economic Benefits

Intelligent Supply Chains (iSC), as the most modern iteration of SCM, involve intelligent, digitalized, and networked connection between stakeholders and systems. Various definitions and characteristics of iSC exist, however, low maturity in any of these components may hinder the realisation of the vision of an end-to-end supply chain. SCM is pointed as a discipline that would become more complex with increasing product customization and technology integration. For example, the trend of intelligent manufacturing solutions being directly integrated to supply influences supply chain producing goods or services which are networked, customizable, and even produced through the use of 3-D printers. The globalisation or internationalisation of business, as well as the internationally connected supply requirement of manufacturers, lead SCs to become more complex in terms of their participants, territories, and operating processes, however, information is not in line with the flow of products.

The research and investigation of SC has been a long historical path, such as in 1999 with increased complexity and IT application's role in SC, global SCM, SC architecture design, and design of its information system. A few classical SC definitions are shared. In terms of operation SCM is defined as the management of upstream and downstream relationships, generating, distributing, and consuming economic value of product, information and cash. The essence of SC is viewed as the interconnectedness of async process automations, however, it falls short of characterising complexity and control approach. Classic definitions are too loose to characterize demand, capacity, customer interaction with SC, products, information, and process types, whereas comprehensive SC constructs become too complicated to tame by any classical control approaches. Hence, innovations in both theoretical understanding and managerial practice of modern SC are demanded.

Applicable techniques, principles and methodologies from other disciplines of engineering and social-sciences, such as Internet, ATD, information theory, agent-based modelling, complex systems, game theory, control theory, etc. Big Data raises new opportunities and uncertainties in industries, but its characteristics have not been rigorously investigated and understood. This leads to tremendous benefits, but the current SC seeing is far like this. Data from different systems in a SC ship advertising, order being through, MRP generating plan, production information provided by experts etc, but it works individually. Humans are too illogical or lazy to handle the information well. SC planning and control level, which works on aggregated data, is served with rather poor visibility. As a result, SC tends to be overstocked, less responsive, more inefficient, lacking control room or model, more stubborn and polluted country-wide.

2.3. Social Responsibility

Research has shown that customer demand, social responsibility, and ethical issues have a significant impact on SCPs. Therefore, a socially responsible supply chain is vital for manufacturing companies, as it impacts brand image and company goodwill. Having good supplier relationships can improve brand loyalty as well as consumer acceptance of the company or brand. A survey conducted on various suppliers and the evaluation of their CSR practices and programs provided important recommendations. Communication systems among suppliers can enhance CSR programs of companies. Information might be vital for suppliers to learn about the CSR programs undertaken by companies. The supplier CSR performance rating database can serve as a guide for companies when sourcing suppliers in new geographic regions. The companies should allocate more effort toward suppliers in developing countries. The suppliers of companies in developed countries may be of higher maturity compared to suppliers of companies based in developing countries.

Saving works of art is creating a humanitarian organization with various professionals and requesting donations to create committees around the topic. Requesting the US Department of State to request technical advice to implement a risk assessment. In regard to other issues such as understanding school safety and threats, valuing vendor due diligence services, protecting diversity, and inclusivity: 1.3379% calculated as 50 divided by 3700, equals 170.063 5,917.503 – 24,15000% – 368.23216% – 59.726% of the audience surveyed have teachers union or lack adequate IT resources. There is no solution. Requesting the US Senate to have semi-public hearings on safety protocols, structures, and vulnerabilities, request interviews with administrators in various school systems, posting summaries of findings on the website. Supply chain social responsibility research scope and methodology provide a satisfactory examination of these topics, which were adapted to meet the needs of this research effort.

III. OVERVIEW OF AI IN SUPPLY CHAIN MANAGEMENT

This study focuses on the six generic components of the end-to-end supply chain, including planning, sourcing, manufacturing, warehousing, distribution, and customer interface. Broad applications of artificial intelligence (AI) in individual domains, such as the digitalization of Industry 4.0 applications for smart manufacturing, are taken as given.

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Applications that extend beyond the boundaries of a single supply chain component and encompass the end-to-end supply chain, such as network flow optimization in logistics systems, are excluded. A supply chain is the most natural system to apply AI, and considering the tremendous volume of data produced, AI applications must be relevant.

To assess the applicability of AI within supply chains, it is crucial to consider the conditions under which the technology proves beneficial. AI algorithms thrive by capitalizing on large datasets. Machines should be able to derive unique insights while having enough training data to perform such tasks better and more efficiently than human operators. Classic data types gathered by enterprise resource planning systems, such as master data, sales orders, inventory records, and timesheets, ideally fill this requirement, doubling or tripling in volume annually.

Given the network-based architecture of modern supply chains, coupled with the tremendous volumes of data they produce, the scalability of AI is a natural fit for their architecture. Considerable technological advancements are expected, including substantial reductions in the need for pre-processing data, gathering new types of data, and improved training algorithms and models. In this sense, the big data hype is only beginning to unfold, and it is expected that the potential impact AI can have on logistics and supply chain management will be greater than in almost any other business area. It is estimated that by fully utilizing AI in supply chains, close to USD 7 trillion in economic value could be generated annually. Much of this value is currently left untapped because legacy supply chain management tools are overstrained by the ever-increasing volume, velocity, and variety of data generated.

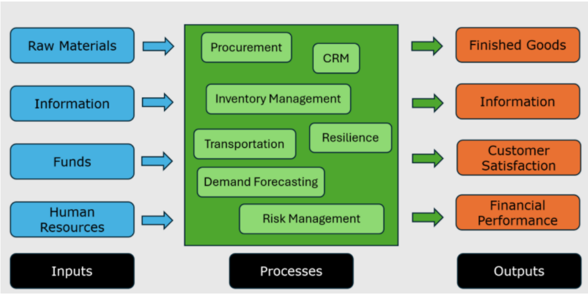

Fig 2: AI Applications in Supply Chain Management

3.1. Definition of AI in Supply Chains

Among various applications of AI techniques in non-manufacturing domains like Retail, Customer Service and Integration, Supply Chains (SC) is the most concentrated area of development. While supply chain managers have been grappling with uncertainties around customer demand and supplier deliveries, as well as with data integration issues, tech-savvy start-ups and established giants like IBM, SAP, Microsoft and Oracle have been disrupting this field. SC planning and control solutions suffer from high complexity and have proven difficult, if not impossible, to design with legacy technologies like Mathematical Optimization (MO) and Discrete Event Simulation (DES). Cloud-based Big Data and AI technologies bring the necessary elasticity, computational power, robustness, integration capacity and speed to enable SCs to continuously enhance their performance and cope with complexities from global sourcing, to new production methods, to Covid-19. The importance and breadth of SC AI applications have attracted enormous R&D investments over recent years and will be highlighted by several examples. It has been mentioned the increasing understanding among enterprises that data and AI will become key factors of competitiveness and survival. This is the reason to focus on SCs, which tend to be more mature regarding SC AI applications than other business areas. It is crucial to realize that merely deploying systems like improved forecasting or sourcing optimization solutions does not guarantee success. This can be attributed to supply chain managers' initial engagement or leadership, poor data availability and quality, inadequate or misaligned modelling approaches and objectives to name but a few. More importantly, in an internal, rather than fundamental, manufacturing-focused perspective, not enough attention has been devoted to indicators by which to assess or compare the applicability and impact of SC AI techniques across tools and implementations.

3.2. Current Trends in AI Technologies

Machine learning (ML) platforms are being utilized to monitor supply chain safety patterns, making detection possible for all extended supply chain stakeholders, rather than just a portion of them. Artificial intelligence (AI) technologies can be described as advanced analytics that are not limited purely to mathematics and statistics. Any method that relies on reasoning or data path lengths in a general sense can be classified as AI. A distinction is often made between the sphere of AI definitions and long-term AI aspirations of putting a reasoning machine at the same level as humans. Current AI applications still mainly rely on mathematical and statistical methods. Various techniques from multiple domains are currently being applied in a master/slave computer structure.

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Only recently, denser algorithms and exponential increase of computer power matched to deal with the vast databases stored, allowing for ever more advanced analytics to be used. Supply chain optimization efforts on the basis of brute data calculations often lead to suboptimal solutions that change continually. The match of an exponentially growing need for supply chain efficiency with analytics needed to approach that challenge led to the awakening of artificial intelligence as an umbrella covering many different methods. Nevertheless, this variety narrowed within the last five years by the focus on a few topics, namely ML methods where which technique, or optimal parameter set to apply, is learned based on enormous amounts of available data, rather than just to impose a set of rules. Supply chain task forces are increasingly exploring Long Short-Term Memory (LSTM) techniques to model supply chain risk propagation in a network, for probability calculations that should lead to earlier risk identification and mitigation. Another hot spot of research and software development is Reinforcement Learning (RL). It outperformed previously training methods for Atari games where a RL agent was able to simply watch the game and then, totally independent, learn strategies that penalized the worst actions and eventually guided itself to not only be as good as a professional player that trained for a long time, but simply outperforming all previous constraints. Here again, due to the exponential growth of real-time additional players acting on the game and storing just those actions that turned out to be good, new opportunities opened for SC as a game where applications such as finding FCFS rules that outperform all heuristics used can be envisaged.

IV. AI-DRIVEN OPTIMIZATION TECHNIQUES

The management of artificial intelligence is considered to undergo a great change in manufacturing. Large amounts of data collected within the scope of manufacturing and logistics offer a basis on which intelligent models influence production controls and process management for data-based resolutions. Thus, along with the collection of data, the consideration of AI-based models to provide resolutions for manufacturing processes as well as supply chain conditions is imperative. Artificial intelligence solves complex challenges via process automation, optimization techniques, and utilizing the already available data in greater detail. AI can aid in integrating systems and tools into more holistic solutions. AI comes with numerous impacts on lengths, development heights, and the perspective of AI on the business itself.

Regarding the processes, a variety of digitization means can be noticed on a spectrum of plausibility, involvement, and tightness. At the highest level, the complete automation of processes establishes a new level of intensity that rises above the generation of data within digitization regarding its impacts on single processes throughout the complete supply chain. The data is not merely collected passively and on a correspondent basis without any effect on supply chains' lives. Various facets can be recognized under the consideration of the availability of large amounts of data accumulated within a supply chain. On the one hand, the collection of data and the observation of processes come at trade-offs.

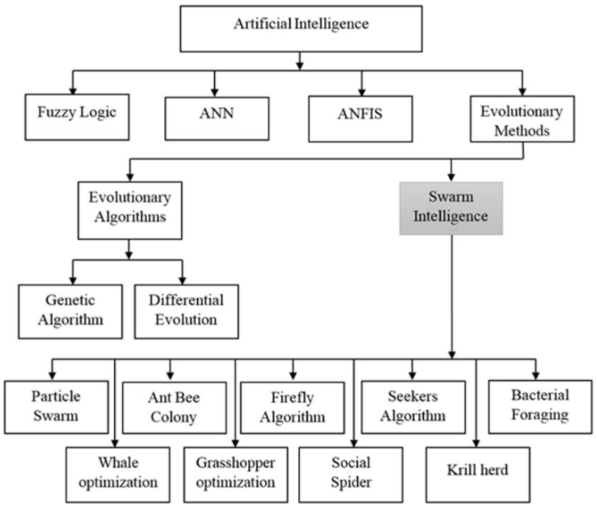

Fig 3: AI-based optimization technique

4.1. Predictive Analytics

Predictive analytics refers to estimating future outcomes, behavior, and trends based on historical data. For decades, companies have been amassing data, enabling them to make statistically sound estimates in decision-making. With AI's growth, predictive analytics has matured into diverse and advanced capabilities.

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Manufacturing companies are renowned for being data-surveilling organizations that collect a wealth of information on their processes. Hence, the sector is well ahead in terms of the amount, quality, and discipline of its stored data, with SAP or Oracle being the common Enterprise Resource Planning systems utilized across a range of enterprises within the industry. As a result, manufacturers are in a prime position to benefit from AI-powered predictive analytics akin to what has been recently demonstrated for retail supply chains. Evidence is presented herein that high-profile manufacturing companies in the automotive, consumer goods, pharmaceuticals, consumer electronics, and high-tech industries are already employing AI to enhance supply chain performance surmount the recent pandemic and sustainability-related challenges. However, these companies are front-runners and not all manufacturers are in the same advantageous position.

4.2. Machine Learning Algorithms

The optimization of supply chain networks via machine learning revolves around the disentanglement of transportation and acreage costs. The latter comprises leasing costs for facilities stocked with goods, spoilage loss on invalid goods in inventory, and penalty costs for unfulfilled orders. Supply overstocking results from the former, in which goods flow over longer distances than required, raising customer costs. The focus of this optimization is on the transportation of goods, stock, and storage locations. To tackle this NP-hard combinatorial optimization problem, the methodology relies on the Chinese postman problem, which is approximated with a well-tested heuristic algorithm. A spreadsheet incorporating the essence of the methodology helps end-users of all statistical expertise levels. This spreadsheet was implemented as a self-coded program, and its potential advantages remain under review through experimentation.

The global supply chain is characterized by its complexity and high volume of information to be monitored. A multitude of components work in parallel, each containing several actions that have to be perceived with a given frequency, be continuously assessed, and be appropriately recorded to evaluate performance and build each component. It must be assured by the design that all actions are performed correctly and that no operation is left unattended either for bulk assessment or for unusual occurring conditions (events). The target of this application note is to assess, analyze, and discuss the power of Artificial Intelligence (AI) and Machine Learning (ML) applications from a global perspective concerning Supply Chain (SC) digital transformation. The selected approach is a descriptive bibliographic analysis based on the Database, which is the basis to present a recent vision of AI and ML development in the SC domain. The structure proposes the involvement of SC processes and AI-ML technologies, common methodologies, gaps and consequences, and future opportunities. The output is a dashboard tool to navigate through information on several components that characterize AI and ML development in SC.

Equ 2: Environmental Impact Function

$$E_{\text{total}} = \sum_{i=1}^{n} \left(\epsilon_{p,i} + \epsilon_{t,i} + \epsilon_{w,i}\right)$$

Where:

- $\epsilon_{p,i}$: Emissions from production
- $\epsilon_{t,i}$: Emissions from transport
- $\epsilon_{w,i}$: Waste generated

4.3. Automated Decision-Making

Machine Learning (ML) algorithms have the capability of learning patterns and associations within a given dataset utilizing only the data itself, thereby identifying concealed patterns without requiring any interpretation, establishment of hypothesis, or other human intervention. ML has gigantic commercial potential and has incrementally entered manufacturing domains. ML techniques constitute various tools that can be applied across all levels of manufacturing. ML enables advanced manufacturing systems allowing flexibility while preserving accuracy and productivity. These capabilities have made ML algorithms a center of research and significant investment bringing with it a multitude of potentials in Requirements Engineering (RE), design, processing, production, and other manufacturing domains, leading to a transformation of the manufacturing paradigm. AI is being recognized as a new paradigm by laying the foundation for the Fourth Industrial Revolution (Industry 4.0). The explosion of data and revolution of communication technology have enabled data exploration, and triggered the emergent development of big data, namely, the 4Vs characteristics of volume, velocity, variety, and veracity. The wide access of high computing power platforms has made data exploration possible. On the other side, the lack of discernibility of big data and lack of automation and intelligence for manufacturing systems hindered the exploration of the 4Vs of big data. Hence, the revolution of big data analytics and AI-enabled smart manufacturing systems are considered strategic keys to enabling sustainable manufacturing.

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V. CASE STUDIES OF AI IN SUSTAINABLE MANUFACTURING

Supply chains worldwide contributed significant economic value in 2017. In addition to the value they create, supply chains also have enormous environmental and social costs. Transportation is likely to remain a major contributor to climate change, air pollution, and human suffering. Using AI to optimize supply chains could drive efficiency improvements that yield reductions in emissions, pollution, and other undesirable outputs, all while lowering costs. A large body of literature about supply chains exists. A more recent subfield relates to optimization problems using machine learning algorithms. Furthermore, some industries are explored, for instance, the supply chains of fresher products or sustainable supply chains using AI methods. Still, a comprehensive overview of the potential applications of AI and its impact on sustainable manufacturing and supply chains from a descriptive view is lacking. Manufacturing operations planning, inventory routing, transportation, production, and warehousing are all crucial components of a supply chain. Their sustainability can be reached by reducing costs, emissions, or food waste, creating a win-win situation for the supply chain and the environment. The demand for optimizing the supply chain is high as it determines its efficiency next to the demand forecast, but the complexity of the subproblems is always difficult. Worldwide, the agricultural system delivers millions of tons of fruits, vegetables, and other fresh products daily, where multiple companies are involved in transporting and storing those products. The mathematical models and methods for different supply chains are discussed, showing how heuristic, exact, and custom-built optimization methods can be applied to sustainable supply chains.

Manufacturers worldwide also face the challenge of surviving in an increasingly volatile market with fast-changing customer needs. One potential solution is to implement smart factories, a new generation of smart manufacturing facilities aimed at optimizing productivity gains and reducing production costs through manufacturing process automation and integration of cyber-physically connected resources. Tighter consideration of customer dynamics, however, makes the resulting production scheduling problem more puzzling. AI-enabled technologies already employed at an advanced level in a few factories globally are surveyed. An AI-driven smart factory architecture is proposed for AI-powered intelligent manufacturing, where agents, Internet of Things, and cloud computing technologies equip stakeholders with flexible and adaptive tools to respond to real-time changes across the entire supply chain. The architecture is validated through simulation by addressing challenges arising from a case of an automotive supplier. Suggestions on information expansion and sharing, data centralization, and decision agreement under model deception for further implementation of the proposed architecture are discussed.

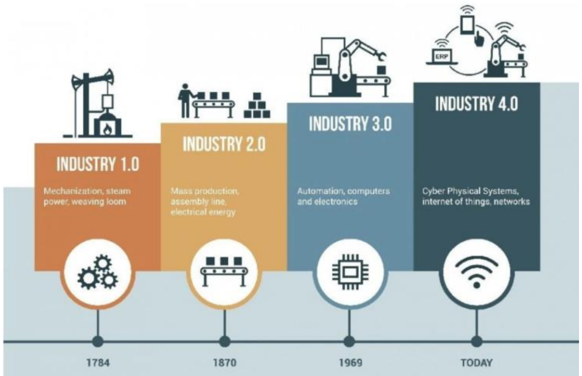

Fig 4: AI in the Manufacturing Industry

5.1. Case Study 1: Company A

Company A is a traditional manufacturer of CPW parking lot and traveling beverage vending equipment. It has created an integrated management information system (MIS) and product life cycle management (PLM) information system, which helps with enterprise resource planning (ERP) and customer relationship management (CRM) at the enterprise level. It has also introduced an information network comprising locally connected controlling units, dial modems, GSM, Internet, and centralized cloud computing. However, difficulties in system upgrading remain due to the use of self-developed electrical control components and software matching their own convention. It has also encountered challenges related to overstock levels of product parts inventory, labor input and productivity, manufacturing and transportation safety accumulator levels of which remain generally unmoved.

Company A is currently working on optimizing its material inventory management. An investigation on the overall situation of material inventory of the machine park sizing and function (MPSF) type vending equipment was conducted.

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The result shows that a single order usually needs about 140 product parts, about 160 orders (about 8000 product parts) are expected per month based on current sales records, and about 48 on-average production lines are needed (or often panned/over planned). According to the average statistics, 2800 orders may be produced at the maximum, so a larger number of product parts in one well-functioned class may cause massive excessive stocking, inefficient production control, and frequent warehousing problems. Participating in the maintenance schedule, estimating the stock levels, and dealing with supply personnel/making orders are almost exclusively fallen on the owners' shoulders or the joinered staff's or leave them unattended in a circumstantial way.

5.2. Case Study 2: Company B

Company B is considered a "champion" organization with extensive sustainable manufacturing practices already in place. Therefore, AI solutions considered for Company B are anticipated to be complementary to existing approaches that may be enhanced with AI-enabled decision-support PSDs. The considered AI-PSDs as inputs for sustainable manufacturing in a supply chain context are "sustainable alternatives" and "circular economy." For each PSD, an assessment of the general and Industry 4.0 factors is conducted to guide debate on the issues that should be addressed in the accompanying innovation and deployment, use and evolution. The single impact of AI in this application area has been assessed as substantial to economy and environmental, moderate to social, and negligible to the remaining impact categories. The net impact of AI has been assessed as negligible to all impact categories.

Company B "sustainable alternatives" assists in the identification and determination of materials, processes, and suppliers that support a circular economy and reduce potential environmental impacts. This PSD is examined for eight classes of input factors. General dimension factors supported five classes of factors: applicability, instructions, robustness, user experience, and touch interface. Industry 4.0dimension factors supported three classes: IoT, CPS, and big data technologies. The estimated readiness level is three, indicating that all input factors are below needed levels for a putative level of innovation and investment.

Company B "circular economy" assists companies at a daily decision-support level in analyzing waste flows for secondary material valorization. This PSD is examined for the eight classes of input factors. Analysis via the general dimension factors operated as a "what-if" dialogue brochure to assist early-stage discussions on the application of AI in CE within the corporation. Industry 4.0dimension discussions held the cognitive load of many variations, adding to workshop preparations and efforts. Individual long-term specific considerations concerning this PSD highlighted excellent technical literacy but low data quality readiness. Automated test regimes for future software updates were also anticipated. The estimated readiness level is three, indicating that all input factors are below needed levels for a putative level of innovation and investment.

5.3. Case Study 3: Company C

Company C is a global green technology manufacturer headquartered in San Jose and operating across major continents. Its product portfolio comprises advanced technology solutions ranging from wireless communication equipment and semiconductor manufacturing tools to file storage solutions. With customers in several sectors, including high-tech equipment, computer networking, telecommunications, consumer electronics, and financial services, fulfillment of Company C's market-specific needs requires a mix of automation and custom manufacturing. Customer base shifts lead to cyclical fluctuations, resulting in relatively stable order patterns within each cycle. However, product evolution makes these cycles increasingly intricate, with rapid demand increase or decline across geographical sites. Analyses reveal order pattern shifts and their correlation with cycle behaviours, leading to contentions with production capacity.

The operation and manufacturing strategy of Company C focuses on producing most of its products in-house, with the aim to manufacture and supply products with less than 4.5% of its product cost. However, as raw material prices, labour cost, and energy expenses are all increasing due to the expansion of local production capabilities in Southeast Asian countries, Company C's margins are gradually shrinking. The COVID-19 pandemic has compounded the complications, further driving up transport and logistics expenses while delaying raw materials supplies due to ground and port congestions. As lead time-based contracts play an important role in Company C's client relations, the minimization of its order backlog becomes significant to Company C's longer-term business performance.

VI. CHALLENGES IN IMPLEMENTING AI SOLUTIONS

The sheer complexity of contemporary supply chain networks poses a challenge to AI fabrics. Traditional accounting architectures are inadequate for visualizing data flows, and network encapsulation is only slowly emerging.

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As a result, properly encapsulating data sources, creating AI fabrics based on these encapsulations, and then feeding data into the fabrics represents a major technical challenge. IT architectures dedicated to these tasks can help but also take significant time to implement, especially in very large supply chains. Moreover, as both technical and organizational governance are absent, organizations must be careful not to create new silos at the AI level.

Impact-based quantification of the value that AI fabrics could unleash generally incurs a prohibitive effort. AI will only increase the importance of robust data governance, which management seriously underestimated on previous waves of IT. The societal expectations of AI currently necessitate fundamental decisions. Large pre-trained visual language models are expected to democratize AI. The high costs and efforts that come with training new models on new datasets necessitate a global pooling of intellectual effort. The convergence of this effort on specialized, possibly proprietary models constitutes a serious risk to competition and social systems. Accordingly, responsible AI comes with high societal responsibility.

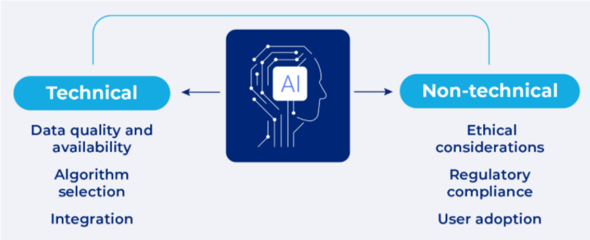

Fig 5: Top Challenges in Artificial Intelligence

6.1. Data Privacy Concerns

"The rise of Artificial Intelligence (AI) has raised several concerns relating to data privacy. The first step for companies to embrace AI and its potential for enhanced supply chain and logistics is for them to understand how AI works, its benefits, and its potential impact". Several well-publicized incidents such as leaks of confidential user data targeted by hackers at large organizations have taken place in recent years. Due to these data privacy concerns, users of AI need a clear understanding of which data are being used, how that data is used, which algorithms are used in AI, and where that data is sourced from. These concerns apply both to companies using AI and to customers, and data users across the supply chain are encouraged to adopt an analytics-driven strategy, as those utilizing data and AI will receive a substantial competitive advantage. Competition based on efficiency will become highly difficult. Consequently, data became a key asset, and due to high switching costs, companies have become locked-in to analytic models and cloud providers.

"Additionally, data sharing in the supply chain can hurt industrial IoT companies significantly, as knowledge about systems being used and trade secrets of processes and algorithms being employed could be leaked". Based on these concerns, concerns regarding the use of AI optimization for supply chain processes edge on four fronts: user data privacy, proprietary algorithm preservation, leveraging of existing data infrastructure, and trust of simulation datasets. Explainability of AI optimization models is also analyzed based on a considered data security model, since high reliability systems in safety-critical domains require detailed understandability of models underpinning states being made.

Lastly, it should be noted that the aforementioned concerns apply to AI in general, but not necessarily on a direct technological level. Regarding the existing current state of regulation, the EU is leading the way and has imposed the GDPR regulation on its member states. This regulation revolves around user data accessibility, in order to protect users from data misuse, it is not focusing on the soundness of AI algorithms being used or of the data being generated or obtained.

6.2. Integration with Existing Systems

Manufacturing Global Value Chains (GVCs) are critical to an economy's international competitiveness, productivity, job creation, and wage growth. However, the pandemic and Ukraine conflict exposed the vulnerability of PPP GVCs. Restrictions on raw material/parts supply, export control of technology goods, and rising freight costs impeded their operation. This triggered a widening multilateral crisis of energy, food, and materials prices. Factors such as supplier lockdowns intensified the differentiated impact of the crisis across industries. High logistic costs decreased profit margins, threatening to collapse industries reliant on China or only offshore production. Concerns over the over-concentration of sourcing and manufacturing capacities culminated in calls for reshoring, nearshoring, and re-regionalization. How to securely integrate the IT, OT, and IoT environments of manufacturers, suppliers, and customers has become a pressing issue for policymakers.

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Adapting supply chain structural and operational configurations can create a new economic and social landscape. Supply chain policymakers need measures to manage the unavoidable trade-offs between resilience and other achievements of economic and socio-environmental sustainability. Adoption of complementary measures to enhance traceability and transparency can reduce the sharp decline in profit margins. Enabling access to real-time supply chain data can also help policymakers understand economic impacts across industries and resolve disruptions or crises. Flexible data-sharing infrastructures and platforms need to be built to improve the accessibility and accuracy of supply chain data, promote data standardization, and enhance the willingness to share data. Providing legal/financial incentives can also help modulate data-sharing behaviors across various contexts and industries. Regulators ensuring accountability can also assist in developing solid regulations for data-sharing facilities, platforms, and infrastructures.

6.3. Workforce Adaptation

Artificial Intelligence (AI) is a transformative technology being widely adopted in the manufacturing sector due to the multi-faceted benefits it can deliver. The manufacturing and service sectors experience the 5th industrial revolution, experiencing rapid and fundamental transformation in manufacturing intelligence. The longstanding focus on ultra-efficient, large-batch production methods has resulted in high costs to society in the form of product damage. Concurrently, the demand for mass-customized products or services that can provide a high variety of unique products to satisfy idiosyncratic consumer needs arises. Aligning with sustainability goals, a paradigm shift of "green" is demanded towards sustainable manufacturing. The silver-bullet to such grand challenges is the paradigm of smart factories enabled by AI-optimized sustainable multi-level manufacturing (MLM). Stimulated by the AI Plan of the European Union, rapid advances of AI in manufacturing are witnessed with the rising interest areas of data-driven analytics, intelligent process control and scheduling, design for sustainability, and AI-based flexible and reconfigurable networks. Each facet introduces fresh challenges and opportunities in the post-pandemic and IoT-everything era. Eras of lost data and facts and the absence of design precision provide an unprecedented opportunity of AI-driven retrospection of the anatomy of manufacturing activities from a systems perspective. The far-reaching diversity of manufacturing activities threatens the one-size-fits-all view on sustainable manufacturing. There still lies a research void in industry-specific ontology and AI technologies behind. Crowdsourcing and social participation are ripe with past experience acquisition and bitter failure sharing. The authenticity and verifiability of such information are critical for the trust chain in accessing and utilizing crowd intelligence. The emergence of generative AI lays a toolkit for such a task, but the most pressing challenge is how to assess and control the inadvertently generated user-generated content that can deliberately or unintentionally mislead humans. AI will simultaneously challenge and support regulatory efforts as well as the quest for advanced knowledge, processes, and artifacts.

VII. FUTURE TRENDS IN AI AND SUSTAINABLE MANUFACTURING

AI-optimized supply chains are resource-efficient logistics ecosystems created to minimize environmentally harmful emissions while fulfilling the customer’s request. Sustainable supply chains are of paramount importance since product returns, waste, and rejected deliveries lead to significantly increased costs and loss of customer trust. Determining the supply processes in production and logistics is a well-known challenge. Complexity quickly becomes unmanageable, along with the importance of meeting customer requests in a timely manner. Reducing profit loss by a % of the unsold product quickly leads to a loss of millions or even billions of dollars per year. To counteract the rapidly increasing complexity and to remain competitive, machine learning must be used to extract insights and optimize the processes along large data volumes.

Data science and AI technologies can be effectively employed to visualize, forecast, and automate supply chain processes. The latest insights on AI technology and its potentially game-changing effect on supply chain management are discussed. First, it is discussed why AI technologies are suitable for this space and how they unlock substantial value. Then, it is highlighted how network-based architectures and visualization tools improve human cognition and cause a paradigm shift in decision-making. Forecasting disciplines and how these can be automated through machine learning algorithms are introduced. It is explained how a closed-loop control can be maintained through reinforcement learning in high-dimensional environments, with the supply chain as an example. Finally, it is pointed out where implementations are currently taking place and where further potential exists.

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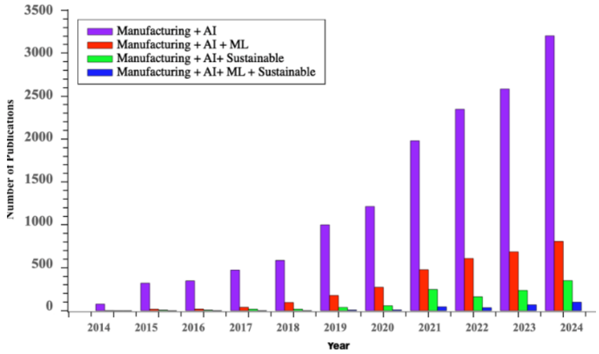

Fig 6: Machine Learning for Sustainable Manufacturing

AI-optimized supply chains can be a major catalyst for sustainability in the production and transport of goods. Making supply chains and their processes more efficient means fewer resources are used over the same period of time, which leads to fewer greenhouse gases and other emissions for the same output volume. Enabling sustainable manufacturing through AI-optimized supply chains requires involvement from every participant, but the first few steps can already have a big impact on efficiency and safety. The initiatives outlined above create room for improvement and the market incentives provide the opportunity to exploit this newly created capacity, which represents untapped profit potential.

7.1. Emerging Technologies

Sustainable manufacturing, a methodology that entails clean production processes, eco-design, life cycle assessment, and waste reduction, has emerged as a decisive priority across much of the manufacturing sector. To address growing concerns regarding the environmental ramifications of industrial processes, a growing number of manufacturers are transitioning to more sustainable manufacturing practices. Supply chains are assemblages of people, processes, and systems employed to distribute products or services. As they comprise all physical and virtual processes involved in the management and execution of connection for labor, capital, and goods among all corporations within the network, they have turned into a crucial locus of sustainability improvement opportunities for manufacturers.

Not only do AI-optimized supply chains have the ability to generate smart resource efficiency approaches for learner material flows, they also have the capability to considerably weaken the aggregate environmental impact on resource consumption and pollution, cap-and-trade financing, and design and manufacturing. Due to the wide resource consumption, waste emissions, service provision, and hazardous material disintegration of producing conventional machinery and power supply, manufacturers strive to migrate toward cleaner production processes, wherein products and production processes are designed in an environmental conscious manner starting from their conception, life cycle design analysis, and production process to the post-production stage, taking into account the entire life cycle assessment. On the other hand, as industry 4.0 concepts continue to mature, AI has begun to infiltrate supply chain operations, which can now be optimized holistically.

To assess the impact of artificial intelligence (AI) on supply chains, researchers adopted a broad definition of AI, focusing on the technology's use and applications in various closely allied subfields including fuzzy logic, neural networks, expert systems, and statistical machine learning. Machine learning (ML) techniques, a rapidly expanding subfield of AI, also have enormous market potential, as their capacity to learn from data and make predictions on new data makes them applicable in various quite different contexts. One such context that has thus attracted major attention recently is the SCM field, which academia has only just begun to address. AI is relevant throughout the SC from the planning to the customer interface, and its potential impact on SC analysis and design technologies and software solutions is particularly large.

Equ 3: Supply Chain Efficiency

$$\eta_{\text{SC}} = \frac{D_s}{D_t + L}$$

Where:

- D_s: Successfully delivered demand
- D_t: Total demand
- L: Average lead time

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7.2. Regulatory Impacts

The market entrance for many disruptive innovations such as electric cars and even self-driving cars is influenced by the development of private and public charging stations. In certain places legislation even requires a certain number of charging stations for a minimum number of electric cars. Similarly, there has to be a development of eco-friendly manufacturing facilities before many of the substantial ecologically beneficial technologies can penetrate the market. For example, producing steel from hydrogen is only being explored experimentally and just a few test plants exist. Other manufacturers deem investing in a hydrogen-producing steel plant as too risky given that their competitors will not invest in one. Consequently, additional laws and regulations are needed to jumpstart the switch to eco-friendly steel manufacturing to be beneficial for everyone.

Recently a bill was proposed in California for the state to set stricter safety and ethical guidelines for robots used in agriculture and supply chains. Legislating such guidelines will aid manufacturers in Ontario and the rest of North America with a clearer set of acceptable rules governing the use of AI at the facility level which, simply put, is the next evolving frontier in advanced manufacturing. Relatedly, as has been seen with autonomous vehicles, robots such as self-driving forklifts in factories and warehouses, and their manufacturers, will desire clearer regulation to aid target clients in feeling comfortable opting for such equipment without needing to redo the facility layout and train workers. In summary, regulators need to expand efforts to better define acceptable and safe usage of the larger-scale approaches to AI. During this refinement period the large computational resources used should also be supplanted with more private funding and publicly funded supercomputer access. Such resources are needed considering the generally informal and tacit understanding manufacturers typically have of AI and data science.

7.3. Global Collaboration Initiatives

Today, in a Globalized World, Goods are Manufactured Using Resources Located in Different Countries, and Transportation Systems Have Become Complex. The World Trade Organization (WTO) trade patterns connect distant agents (consumers' offer requirements) with suppliers. These patterns have a temporal component (lead time) that adds up to the process complexity. Systems for monitoring the trading links and transport units' location and status are needed. The advent of IoT (Internet of Things) technology is used to monitor transport systems and report their performance. This information can trigger new optimized production and transport configurations and produce new observatory decisions with the companies involved.

International decisions are made considering several conflicting objectives (e.g., cost, service level, and sustainability). These objectives are often formulated according to an Auto-Optimizing Stochastic Game Model. Decisions are made at various levels (increasing levels of Time, Scope, Complexity, and Cost). Depending on these levels, information is entered in a top-down or bottom-up manner (top-down information consists of requirements and schedules, and bottom-up information consists of performance reports). Decisions' objectives can be Local Optimal (narrowly defined, assuming fixed inputs) or Global Optimal (optimizing all companies' profits and vulnerability). For optimization purposes, multi-agent systems are proposed for cooperation and co-optimization (i.e., global optimization).

An Optimization Level is defined according to Cost-Effectiveness. Minimizing Costs = maximum profit = cost-effectiveness equilibria is a conventionally Local Optimal objective (individual optimization). Its focus is on producing nominees with nearby consumers in order to reduce logistics costs and a larger 'grouping area' (regional auto-production competences). Producing a range of different products locally is considered a Global Optimal objective (global maximization). Its focus is on a well-mapped Global Supply Chain, producing lower-cost nominees with prioritized sourcing of min-cost suppliers.

VIII. MEASURING SUCCESS IN AI-OPTIMIZED SUPPLY CHAINS

After mapping the processes that comprise the AI-optimized supply chain, the next step is to define the key metrics to evaluate success. To do this, it is helpful to classify metrics into different categories. Typically, these categories include financial, operational, and customer metrics. With respect to AI optimization, it is additionally critical to include metrics to measure the advanced level of AI optimization and separate various levels of AI optimization through the tailor-made metrics. Thus, five categories of metrics are used to evaluate the success of AI optimization.

Financial metrics typically include sales, profits, return-on-investment, total cost, etc. Operational metrics include operational movements and efforts, such as response time, lead time, booking time, handling time, waiting time, resources employed, etc. Customer metrics are defined as the measurable values used by firms to gauge how well the supply chain processes meet customers' needs. For example, availability of goods, completeness of orders, order production time, etc.

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Advanced metrics are defined to measure the extent of AI optimization implementation, such as AI-optimized decision, the amount of data used, availability of automated decision, etc.

Since quantitative metrics are used widely in practice to evaluate the possible improvement brought by AI optimization, it is important to develop corresponding metrics to separate different levels of AI solutions. As analog measures, AI optimization metrics can be used in sensitivity analysis to indicate the required degree of AI optimization to achieve a certain level of supply chain performance. For example, whether AI-optimized decisions are needed in some situations. Lastly, it is important to include qualitative metrics, such as AI understanding, the robustness of decisions, future forecasts, etc. These metrics can enrich the analysis of AI optimization to easily point out the defect of optimization without conflicting concerns. It will be worthwhile to perform empirical research to analyze whether the sorts of metrics differ across firms or industries.

8.1. Key Performance Indicators

With the increased awareness of sustainability issues and growing international competition, manufacturing companies are trying to modify their production systems towards a more sustainable manner in order to sustain their long-term growth. However, many of the existing weights in the decision variables of traditional optimization models are not suitable when the manufacturing objectives or expectations are updated to consider sustainability. Furthermore, the objectives of decision variables based on sustainability production systems are more difficult to measure. Understanding the sustainable manufacturing issues in the supply chain is fundamental to enabling sustainable manufacturing through optimal supply chain management decisions.

In literature dealing with the sustainable development issues of the supply chains, various sustainable key performance indicators (KPIs) were identified through comprehensive literature review. A general framework on how to measure and evaluate these sustainable KPIs was proposed and illustrated in an application case study. This work provided a comprehensive overview of some recent developments in the area of sustainable production planning and scheduling in the supply chains. Future research routes on addressing the related issues were delineated, which may motivate academic interests for advancing the field. Although some initial attempts have been made to develop some kinetic models in managing the green supply chains, much less attention has been paid to the biological approaches for the sustainable supply chain operation in the existing literature. No works were found to focus on the development of sustainable manufacturing systems by acquiring the domain knowledge of sustainable manufacturing issues from the experts in the industry and capturing the implicit knowledge in situ through implementing the bio-inspired models. Research opportunities should focus on developing: (i) bio-inspired hybrid modeling environment for sustainable supply chains; (ii) bio-inspired agent control mechanism for sustainable manufacturing decision making; (iii) multi-agent collaborative frameworks for sustainable supply chain operation decision making.

8.2. Feedback Loops

The feedback loops enable a firm to leverage supply chain data effectively from the engineering viewpoint. They can be grouped into two categories: data integration for improving model fitness and operational feedback loop learning for improving model usefulness. Complex problems often require complex models to quantify the interactions among the constituent factors of that problem comprehensively. The model fitness of a relatively simple model can be improved by integrating the relevant datasets of the problem from various sources. discussed the data integration by analyzing a real-world EV battery manufacturing system. Their proposed approach integrates data from battery inspection and equipment sensor data and increases the accuracy of the OHM prediction model.

The output of the improved model is still limited to manufacturing operations. These models can be adjusted to enable improved decision-making, considering the feedback data from the most relevant (4R principle) system-level measures. It is possible with SCbPM tools to quantify the relationships of sustainability-based measures, e.g., yield, scrap rate, and environmental impact, across the entities in the chain at design time. The trapping effect arises as firms optimize their capacity with decisions based on limited data, overshooting their sustainable goals and incurring unexpected costs. Continuous control via periodic operational feedback loop learning ensures that the sustainability targets are always met. This ensures that the implemented decision rules remain valid and effective over time. Algorithmic feedback loops are data-driven and leverage data from the implemented policies to adjust the supply chain parameters to maintain effective decisions. With forms available in the literature, the other algorithmic feedback loop types rely on transferring knowledge from one environment and domain to accelerate the learning process in another. Controlling massive supply chain networks is challenging due to massive decision variables and factors impacting the cost and operational performance. Cost and lead-time tradeoffs are mostly driven by a few higher-order factors and thus often exhibit chaotic dynamics.

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IX. POLICY RECOMMENDATIONS FOR SUSTAINABLE AI ADOPTION

Innovations that promote technological advancement offer potential pathways for countries and regions seeking a sustainable and just recovery from the COVID-19 pandemic. However, these innovations also present challenges and risks that governments must appropriately consider. Governments around the world are recognizing the importance of proactive policy interventions to promote responsible and beneficial AI outcomes across all sectors of the economy and society.

AI is a powerful set of new technologies with pervasive applications that can be adopted on economic scales in myriad sectors. Here, the challenge of AI governance is considered by determining what AI applications need to be governed in the manufacturing sector to promote sustainable societal outcomes. Research is based on a systematic review of manufacturing-focused scholarly writings on relevant applications and concerns regarding AI adoption. This review indicates that governments must govern the adoption of machine learning and robotics in manufacturing. AI security and bias are also seen as pertinent issues for governance. Moreover, there is a consensus on the importance of responsible AI. Despite pre-existing governances, standards and regulations may need to be reconsidered with an emphasis on AI and sustainability.

While some scholars call for the partnering of national policymakers and AI researchers to co-create sustainable research and innovation agendas, there are calls to reconsider the scope and target sectors of innovation support programs. Beyond the introduction of new manufacturing and service jobs, this tailored approach of matching R&D projects with supply chain programs may reduce disinformation risks and safeguard country priorities and information privacy. Such costs should be viewed as public and private investments over the long-run to enable AI applications in manufacturing that are not only economically viable, but which also promote social cohesiveness and inclusion and environmental sustainability.

9.1. Governmental Role

Israel currently has a once-in-a-generation opportunity to amplify its innovation impact globally and nationally through the exploitation of newly developed AI technologies. Receiving significant global and national attention are the many potential AI-based applications across all industries and service sectors, along with AI's anticipated impacts on jobs and employment dynamics. Also receiving significant attention are the anticipated societal implications of such applications, including ethical concerns, and potential impacts on economic inequality and human rights. Meanwhile, in many developed countries, including the UK, France, Canada, Japan, and the EU, governments are developing or finalizing plans and initiatives to bolster investments in AI R&D in response to the opportunities and challenges afforded these technologies. Israel's role as a key player in AI development is growing rapidly, with recent national initiatives similar to those in other countries. However, there is considerably less discourse and understood agreement on what societal implications matter most, or how best to promote the effective design and implementation of policies and regulations that enable AI applications.

Supply chains are a major focus in this context. AI applications to supply chains are currently underexploited in the general industry and service sectors. Simulations indicate that a consistent global exploitation of AI applications could increase manufacturing GDP by approximately 5% globally and 12% in Israel. However, the means to achieve this potential have not been sufficiently explored. To realize sustainable supply chains that have AI applications, manufacturing industry investments should be complemented with public-sector investment in two areas: education/training support and the convening and support of broad-based domain strategy-building efforts.

9.2. Industry Standards

With the exponential growth of global supply chains and current trends driving towards faster-than-ever delivery times, the transportation of goods and raw materials has quickly become an ever-growing concern in regard to climate change and sustainability. The EU Green Deal is the first step on the EU's path to becoming the world's first climate-neutral economy by 2050. With transportation accounting for nearly a quarter of total EU CO_2 emissions, a tremendous step towards this goal is a marked improvement of individual freight logistics footprints. AI and advanced heuristics methods can greatly improve routing decisions, accounting for last minute delays and offers.

Unique load unit bundling modelling allows for easy visualisation and quantification of how distribution trips can be consolidated. A generic integer programming formulation based on this modelling is introduced and results show it is a promising and versatile tool for businesses. Finally, a warehouse selection model is fitted based on real-world data in order to strengthen the backbone of the distribution network and improve the cost footprint.

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The increasing complexity of modern supply chains has made them susceptible to disruptions. Increasing resilience helps mitigate the impacts of disruptions and resumes business as usual. However, there is a trade-off between resilience and efficiency. Finding a suitable balance is challenging due to the complex interconnections and conflicting goals in supply chains. AI methods can assist decision makers in optimizing the trade-off between resilience and efficiency using data analytics. However, transferability is often neglected. Recent developments in robust AI suggest that the trade-offs should be optimized while ensuring the AI holds up to unforeseen changes in supply chains. This paper provides a proof of concept of such an approach by optimizing supplier diversification and transportation allocation decisions to decrease supplier dependency while selling the sustainability of operations. Results on a minor modification of an industrial case study show that after the reoptimization, resiliency and efficiency increase 61 and 151 percentage points respectively.

X. CONCLUSION

Supply chains play a pivotal role in the transition of manufacturing towards sustainability. However, these supply chains have grown incredibly complex, often resulting in inefficiency and inattention to the associated environmental and social challenges. With the advent of Industry 4.0, there are substantial opportunities for Big Data to be used for real-time supply chain predictions and optimization. Artificial Intelligence (AI) can incorporate real-time data from all partners along the supply chain to maximize the beneficial outcomes of actions taken by production companies. Generalized Predictive Dynamic Modeling (GPDM), a form of AI that can meet the data quality and quantity limitations of many manufacturing companies, can particularly drive this transformation. It can model supply chains so that predictive, prescriptive, and optimization analytics can be applied toward the sustainability goals of stakeholders along the supply chain and even at the system level. While AI has been discussed widely in the scientific literature concerning supply chains, papers that show a deeper focus on project setups and real industrial applications have been rare. Future research on the application of AI in sustainable manufacturing can thus focus on how to accelerate the implementation of AI in the production environment wherein it can affect the material flows.

With the increasing availability of data sources, predictive and prescriptive analytics will be adopted to enhance decision-making capability beyond traditional methods. Until then, efforts may be better invested in applying AI techniques with which current data sources can be exploited for greater benefits. AI-enhanced supply chains can facilitate the transition towards a circular economy by improving manufacturing flexibility, efficiency, and intelligence. Stakeholder-oriented decision support becomes possible on the path towards a sustainable manufacturing system.

10.1. Future Trends

AI technology is proven to be a major driver for paradigm shifts in industrial fields like financial services, health care, and sales. But most importantly, AI is seen as a game-changer for supply chains. Today's modern supply chains face an avalanche of information. The amount of relevant data from various sources that arrive at organizations today exceeds the processing capabilities of their legacy management systems. Big Data, i.e. data that is high in variety, volume, and velocity, requires a fundamental change in business processes, particularly in their management by tools and technologies. AI algorithms and applications promise to be part of that change.

Intelligent Supply Chains is a phrase that gets used in abundance by practitioners and academics alike. It refers to an endeavor of enhancing today's state-of-the-art supply chain management tooling, most prominently database management systems, ERP, APS, and BI, with sophisticated digital processing technologies, most prominently Internet of Things, Cloud Computing, Big Data, and AI. The idea is to operate SCs smarter by radically improving the IT-based capabilities of SCs, while keeping their industrial structures and processes. AI-optimized supply chains meanwhile also have a sustainability promise. As it is argued throughout this paper, AI technology can help by integrating and processing a plethora of information on sustainability and its impact on the whole supply chain. It can compare different sustainability impacts based on stakeholders' preferences, quantify and measure sustainability as a whole, optimize models to sustainably operate supply chains or their processes, discover alternative pathways based on historical data, and generally support sustainability-lared decision-making at all levels of abstraction and detail.

The sustainability challenges in focus at the moment can only be addressed if a long-term solution in the form of an AI-optimized supply chain set-up is established. Organizations are urged to amend their supply chains structures, processes, and management systems incrementally in the longer term. There is a vital need for a next generation of supply chain management systems that takes full advantage of the data processing capabilities of ALL available technologies in broad network-centric and information-driven environments. Both high insights and prediction capabilities, particularly on possible futures in terms of supply chain parasitism and sustainability, are regarded as top priorities.

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