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Advancing the Industrial Circular Economy: The Integrative Role of Machine Learning in Resource Optimization

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Abstract: In the face of escalating resource scarcity driven by the consumption of non-renewable resources, the industrial circular economy (ICE) emerges as a vital paradigm shift, pivotal for fostering resource-efficient societies and ensuring national resource security. This integrative review aims to critically assess the evolution and challenges inherent within the ICE over recent years, with a specific focus on the burgeoning role of machine learning (ML) in this domain. By synthesizing extant literature, this examination reveals several key findings. Firstly, the ICE significantly contributes to cost reduction through enhanced recycling and secondary utilization, underscoring its environmental stewardship. Secondly, it is evident that ML exhibits substantial promise in the manufacturing sector, not only augmenting production processes but also elevating product precision, reducing defect rates, and minimizing the likelihood of production mishaps. Most crucially, the application of ML within the ICE is identified as a potent catalyst, driving advancements across various facets - data analysis, model development, technological innovation, and equipment refinement. This analysis further elucidates the intrinsic value of ML in resource recycling and waste management, yielding improvements in resource recycling rates and methodologies, which in turn curtails production costs and amplifies output efficiency. Despite the strides made in replacing traditional industrial models with more sustainable ICE practices, challenges persist, particularly regarding the suboptimal levels of resource recycling and the continued generation of industrial waste. The integration of ML within ICE frameworks is posited as a transformative approach, offering not only enhanced resource recycling capabilities and superior product quality but also a sustainable trajectory for future industrial development. This study, therefore, contributes to the growing discourse on sustainable industrial practices, underscoring the synergistic potential of ML in revolutionizing the ICE, thereby aligning with the broader objectives of sustainable economic development.

Keywords: Industrial circular economy; Recycling; Machine learning; Sustainability; Industrial production

1 Introduction

Industry has long been recognized as the primary catalyst for economic growth. The escalation of industrial production correlates strongly with rapid national economic development and the enhancement of a country's economic prowess. However, the sustainability of this growth is increasingly challenged by the pressing issue of resource limitations. In the context of escalating resource scarcity, the imperative to optimize product life cycles has emerged as a critical concern, as delineated by Burggraf et al. [1]. The circular economy, as a novel paradigm encompassing the social, environmental, and economic facets of sustainable development, presents a viable solution to mitigate the resource constraints and socio-environmental ramifications inherent in the prevailing linear economic model. This is substantiated by Guarnieri et al. [2], who highlight the circular economy's effectiveness in addressing resource scarcity. A key characteristic of this model is waste recycling, a practice facing significant challenges across various global economies, both in developing and developed nations, as identified by Ansar et al. [3]. The ICE, forming the nucleus of this broader circular paradigm, exerts a direct influence on a nation's overall development trajectory. This is particularly evident in energy-intensive industries such as steel, electricity, and cement. In these sectors, even marginal enhancements in resource utilization efficiency and recycling levels can yield substantial improvements in economic benefits and the lifecycle of production processes.

The role of circular economy in the transformation of industrial production has been extensively examined across various sectors. In the textile industry, the paradigm shift towards a circular model is documented by Jia et al. [4], while similar transitions in the leather industry are explored by Bai et al. [5]. The automobile sector, as detailed by Zhao [6], and the steel industry, investigated by Liu et al. [7], also reflect significant strides in integrating circular economy principles. Furthermore, the adoption of these practices within the field of chemical materials is articulated by Yang et al. [8]. Parallel to these industry-specific studies, critical challenges in industrial production have also been identified. These include continuous manufacturing processes, as discussed by Lim et al. [9], and concerns surrounding economic security, highlighted by Lu et al. [10]. Energy transformation, a pivotal aspect in the current ecological landscape, is analyzed by Xie et al. [11], while the enhancement of resource efficiency is scrutinized by Chen et al. [12]. The pursuit of cleaner production methods is another area of focus, investigated by Lim et al. [13], and the intricate processes of waste treatment are detailed by Yao et al. [14].

The utilization of ML presents a promising avenue for the future evolution of the ICE. One can envision an ideal manufacturing scenario as a self-contained system equipped with assembly robots, IoT sensors, and a suite of automated machinery. In this model, raw materials are introduced at one end, and finished products emerge seamlessly at the other. The only human intervention required would be routine maintenance of the equipment. ML stands as a pivotal tool in realizing this vision, offering insights into optimizing such a system. Given the burgeoning growth and expansive potential of ML within industrial production, this study aims to conduct a thorough review of its application in enhancing the ICE. This investigation not only outlines the development and current implementations of ML in this context but also probes into prospective future directions and possibilities in the industrial realm. While this study delineates the attributes of the ICE, elucidating the myriad strategies proposed by researchers to optimize it remains a complex challenge. Through a comprehensive review of pertinent research in the field, this analysis seeks to refine the understanding of the ICE. By engaging with the literature at its forefront, this study contributes to deepening the knowledge base, thereby facilitating future advancements and optimization in the sector.

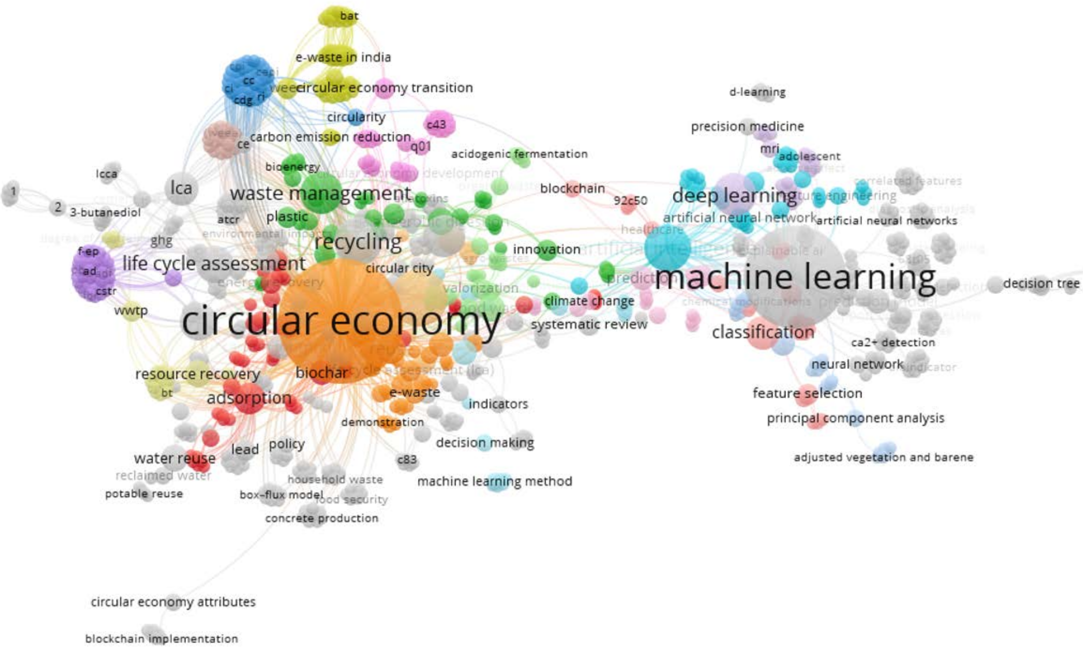

Figure 1. Keywords and combination of circular economy and ML in recent years

Figure 1 illustrates that, despite significant advancements within their respective domains, the intersection between circular economy and ML remains relatively unexplored. The evolution of the circular economy is not only a fundamental requirement for the establishment of a modern economic system but also plays a crucial role in shifting development paradigms. It emerges as an inevitable strategy for reducing pollution and carbon emissions, fostering green growth, and is a critical component in addressing climate change.

In an endeavor to delve deeper into this subject, this study has collated journal articles pertaining to circular economy and ML published over the past two years. The search parameters included key terms such as "circular economy + machine learning", "industrial circular economy", "intelligent manufacturing", "industry 4.0", and "industry 5.0". Post the exclusion of duplicate articles, news reports, conference proceedings, and work reports, a total of 353 articles were selected for analysis. This investigation primarily focuses on high-frequency keywords, employing the keyword co-occurrence method to identify and examine the focal areas and interconnections between

ICE and ML. Table 1 shows the high-frequency keywords in the literature related to ICE and ML. The aim is to clarify existing research trajectories, offer insights for advancing relevant studies, and assist in charting viable future directions for the development of the ICE.

Table 1. High-frequency keywords of circular economy and ML

Serial Number	Keyword	Frequency of Occurrence
1	Sustainable resource management	54
2	Recovery management	53
3	Predictive analysis	51
4	Regression model	50
5	Big data	48
6	Sustainable	47
7	Utilization of resources	41
8	Quality management	39
9	Supply-chain	38
10	Production efficiency	35

The structure of this paper is outlined as follows. Following the introduction, Section 2 presents a comprehensive overview of the circular economy. This includes its origins, evolution, and defining characteristics, along with an examination of specific aspects pertinent to the ICE. Section 3 is dedicated to a critical review and synthesis of the applications of ML within the ICE. In Section 4, the focus shifts to a discussion on the prospective future applications of ML in enhancing the ICE. Section 5 anticipates potential future scenarios and challenges, based on the results and application prospects discussed previously. The paper concludes with Section 6, which synthesizes the findings to provide strategic guidance for future research and practical applications in this field.

2 Overview of Circular Economy

2.1 The Origin of Circular Economy

The concept of a circular economy encompasses an economic production model that emphasizes the reuse and regeneration of resources to extract value, facilitate recycling, and minimize waste. This concept traces its origins to the mid-1960s, with American economist Kenneth Polding pioneering the notion in his seminal work, "The Economics of the Coming Spaceship Earth," Polding's metaphorical comparison of Earth to a spacecraft encapsulates the essence of the circular economy. In his analogy, Polding posits that a spacecraft, constrained by limitations such as distance, velocity, and human lifespan, is not capable of extensive universe exploration. However, by constructing a significantly large spaceship equipped with a self-sufficient, closed-loop ecosystem, continuous processing and utilization of all onboard resources, including astronauts' waste, would be possible. This setup would enable astronauts to live and explore the cosmos across generations. Similarly, Earth is likened to a vast spacecraft with finite resources and a prolonged, but ultimately limited, lifespan. Polding cautions that without judicious use of these resources, Earth's reserves will inevitably deplete. Furthermore, Polding draws parallels between the relationship of humans with the environment and that of a "spaceship" with its "crew", underlining the intertwined fate within an ecological economy. The finite resources and production capacity of Earth necessitate the establishment of a circular production system, geared towards sustainability and resource conservation. The metaphor underscores the imminent risks of unsustainable resource exploitation and environmental degradation, likening them to a spacecraft's eventual crash. In this context, the pursuit of a circular economy is presented not only as a sustainable development strategy but as an imperative for human survival.

2.2 Characteristics of Circular Economy

The circular economy, as an emergent model of economic development, is distinguished by its unique characteristics, which manifest in several key aspects. Firstly, the circular economy introduces a novel systemic perspective. This system encompasses humans, natural resources, and science and technology, forming an integrated whole. Within this framework, individuals are encouraged to perceive production and consumption not as external activities, but as integral components of this larger system, aligning economic principles with objective natural laws. Secondly, the circular economy adopts a fresh economic paradigm. Rooted in ecological principles, this approach advocates for economic development that respects and operates within the ecological carrying capacity, ensuring that resource utilization does not exceed nature's regenerative capabilities. Thirdly, the circular economy is underpinned by new value systems. These values call for the preservation of a healthy ecosystem cycle, considering the role of science and technology in ecosystem restoration, and promoting human development in harmony with nature. This holistic approach aims to foster a balanced coexistence between human progress and the natural world. Fourthly, the circular economy redefines the concept of production. Production processes are reimagined to prioritize the conservation of natural resources, enhancement of resource utilization efficiency, and promotion of resource recycling. The effectiveness of these practices is measured through various indicators, including final disposal rates, actual recycling rates, waste energy recovery rates, resource recycling rates, and resource productivity. This approach seeks to achieve a sustainable and rational utilization of resources [15]. Finally, the circular economy revolutionizes consumption concepts. Advocating for moderate and tiered material consumption, this model emphasizes the importance of integrating waste recycling into consumption processes, thus establishing a comprehensive cycle of production and consumption that is both sustainable and efficient.

2.3 Circular Economy and Industrial Production

The ICE, pivotal for the inclusive and sustainable development of nations and regions, embodies a vital condition for progress. It synergizes economic growth with environmental stewardship, thereby emerging as a focal point in development strategies across numerous countries and regions. This prioritization reflects a global recognition of the necessity to balance economic advancement with ecological sustainability.

2.3.1 The operation mode of ICE

Contrasting markedly with the linear economy's unidirectional 'resource-product-waste' flow, the ICE eschews the inefficiencies where unutilized resources transition to waste, consequently consuming vast resources and precipitating environmental pollution. In this alternative model, the emphasis is placed on maximizing reuse across resources, products, and waste, striving to unearth their potential for repeated utility [16]. As delineated in Figure 2, the ICE commences with resource extraction from nature for product fabrication. These products, once their lifecycle culminates in scrapping or disposal by consumers, are not relegated to waste. Instead, they undergo classification and decomposition, reentering the cycle as resources, or are treated to revert back to natural resources.

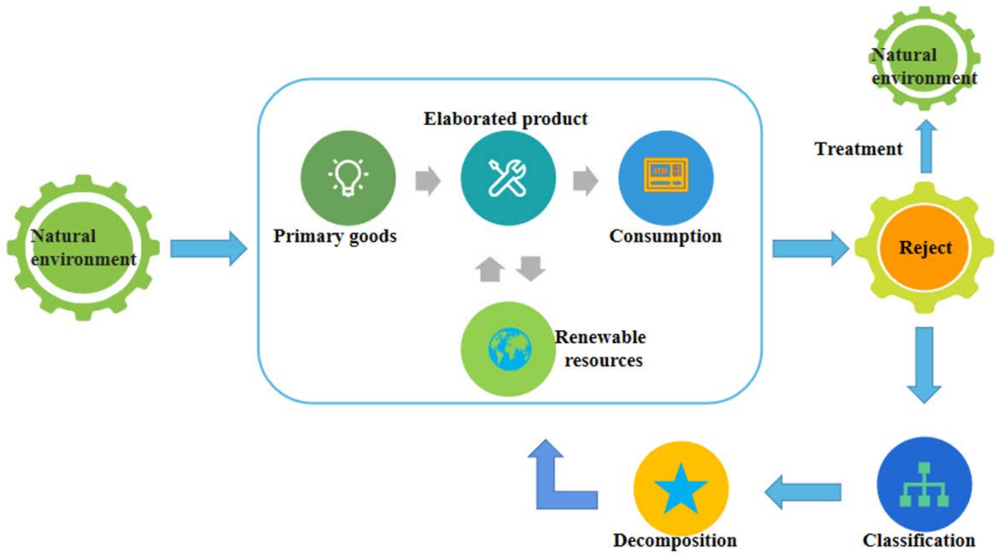

Figure 2. Process of ICE

2.3.2 Technical basis of ICE

The technological underpinnings of the ICE can be primarily categorized into three domains: cleaner production technology, waste utilization technology, and pollution treatment technology. Cleaner production technology encompasses methods that substantially reduce or even eradicate the generation of pollution and its toxicity. Waste utilization technology entails processes that facilitate the recycling and reuse of materials within the production cycle. Meanwhile, pollution treatment technology is concerned with methods addressing pollution generated throughout the entire production process [17]. It is imperative, however, that the technologies underpinning the ICE continue to evolve and progress. Future developments in this realm ought to focus more intensely on addressing challenges and overcoming existing limitations. This includes advancements in areas such as new energy and separation technology [18], and the enhancement of intelligent manufacturing technology alongside refined production modes [19]. The sustained evolution and breakthroughs in these technological spheres are essential for ensuring the viability and continued progression of the ICE.

3 ICE and ML

As industrial digitization advances, the prevalence of machine-assisted production in industrial manufacturing is increasing markedly. This shift plays a pivotal role in enhancing the productivity of manufacturing enterprises and in shaping future production strategies. This section delves into the critical function of ML in bolstering industrial production, with a specific focus on its contribution to the advancement of the ICE. Pertinent literature on this subject is also reviewed, offering a comprehensive understanding of the interplay between ML and industrial practices.

3.1 Data Analysis

ML possesses the capability to swiftly process extensive datasets, extracting trends, rules, and patterns critical for informing enterprise decision-making. Leveraging data support, businesses can craft production strategies aligned with emerging trends, dynamically adjust outputs, and mitigate losses stemming from either overproduction or supply shortfalls. A prerequisite for ensuring predictive accuracy involves identifying key variables influencing production, such as meteorological conditions, environmental factors, policy shifts, or fluctuations in resource availability. Employing ML to analyze substantial datasets facilitates the derivation of relevant predictive models. Production plans calibrated based on these models can lead to significant resource conservation [20]. Nonetheless, the efficacy of these models necessitates validation, particularly in assessing the impact of the identified variables and the accuracy of the predictive outcomes. Addressing these challenges remains a pertinent area for future research, which this discussion does not explore in depth.

3.2 Prediction and Planning

ML offers strategic planning and decision-making support for the ICE, with decision trees being one of the most prevalent methods employed. A decision tree is a tool for risk assessment and feasibility evaluation of projects. It is constructed to calculate the probability that the expected net present value will exceed zero, based on known probabilities of various scenarios. The decision tree methodology encompasses three core steps: feature selection, decision tree construction, and pruning of the decision tree. This approach identifies information that maximally reduces uncertainty by analyzing the variability of random variables under specific conditions, thereby aiding decision-makers in formulating informed decisions and plans [21]. ML, in tandem with decision trees, enables manufacturers to navigate complex and dynamic environments, making informed decisions to minimize resource use and reduce costs. The features and applications of the decision tree are illustrated in Figure 3.

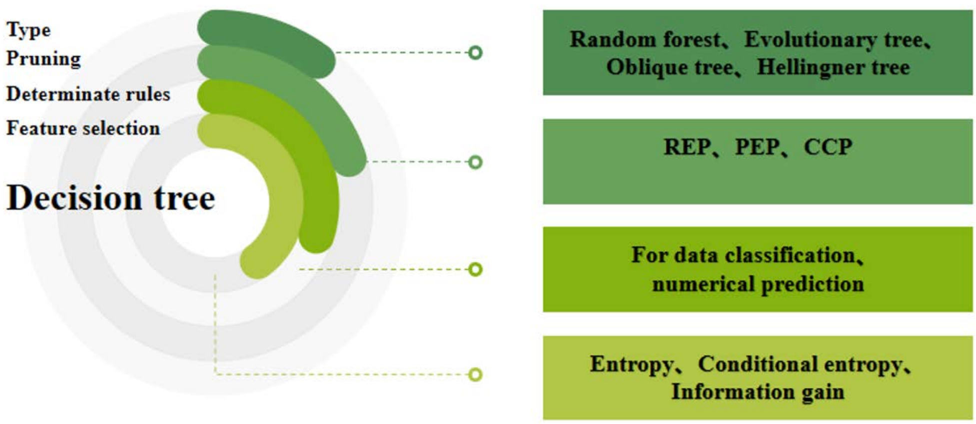

Figure 3. Features and applications of decision tree

3.3 Automation

ML enables enterprises to automate their production processes, enhancing efficiency, minimizing resource consumption and waste, and fostering the development of a circular economy. In the context of an escalating consumer economy globally, there is a growing demand for higher production efficiency in workshops [22]. However, many factories continue to rely on a blend of outdated equipment and manual labor. This mode of production is not only less efficient, but as production technology advances and the demand for precision in products increases, the drawbacks of manual labor become increasingly evident. Automation, powered by ML, addresses these shortcomings effectively. It offers workers intuitive human-computer interaction and can adapt to various production processes with agility. Moreover, automated production can mitigate issues such as low efficiency, high defect rates, and safety risks in manufacturing [23]. Consequently, this shift not only boosts production efficiency and safety but also reduces losses and pollution, playing a significant role in the economic advancement of businesses.

3.4 Intelligent Manufacturing

ML plays a pivotal role in realizing intelligent manufacturing, a process that significantly reduces resource waste and enhances resource utilization through automated and intelligent production methods. Intelligent manufacturing represents a new generation of industrial technology, globally acknowledged as a key driver in transforming and upgrading industrial systems. In response to the rapid evolution of emerging technologies, several countries have initiated strategic plans to foster and develop intelligent manufacturing. Notable examples include the 'Re-industrialization' initiative of the United States, Japan's 'New Robot Strategy', Germany's 'Industry 4.0', and 'Made in China 2025'. At the heart of intelligent manufacturing lies the product life cycle value chain. This approach leads to the establishment of intelligent factories characterized by dynamic sensing, real-time analysis, autonomous decision-making, and precise execution capabilities. These factories are designed for intelligent production, aiming to achieve efficient, high-quality, low-consumption, environmentally friendly, and safe manufacturing and services. This approach significantly contributes to the advancement of the ICE [24, 25]. The impact of intelligent manufacturing on the ICE is illustrated in Figure 4. Additionally, Table 2 presents a review of literature focusing on the key roles of ML within the ICE.

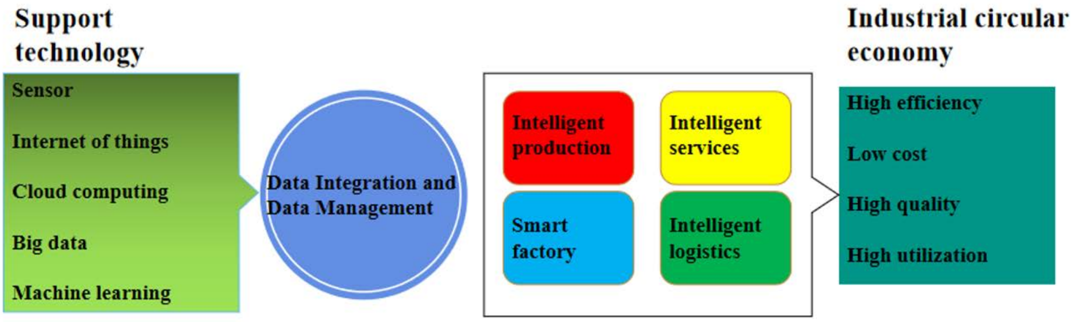

Figure 4. Intelligent manufacturing and ICE

Table 2. The application of ML in ICE

Researchers	Application Domain	Effects	Pros
Data Analysis			
Ahmed et al. [26]	Petroleum and gas	Ensure production safety, reduce costs	Automate the processing of targeted survey data
Li et al. [27]	Aircraft fuel-system	Guide maintenance through data analysis	Avoid the loss caused by untimely maintenance
Li et al. [28]	Blast furnace-ironmaking	Processing huge and complex	Adjust the mode of production, save costs
Saco et al. [29]	Energy development	Provides the best-solution to-explore hidden knowledge-from the generated data	Improve the utilization efficiency of -alternative -energy sources and reduce costs
Mowbray et al. [30]	Industrial process detection	Monitoring product quality	Reduce production defect rate
Forecaste and Plan			
Deffrennes et al. [31]	Metal-liquidus	Provide a general framework for predicting binary liquidus	Optimizing the design and processing of materials
Osei et al. [32]	shear-critical RC beams and slabs	Provide well-informed-decisions for RC -damage assessment	Accurately predict critical values and reduce waste
Yang et al. [33]	Biodiesel production	Leverage the accuracy and-credibility of machine-learning to make informed decisions	Improve the conversion rate and utilization of resources

Researchers	Application Domain	Effects	Pros
Amini et al. [34]	Wind turbine	Predicts the probability of failure and reduces troubleshooting and diagnostic time	Prolong machine life and reduce scrapping
Gahm et al. [35]	Metal-working industr	Adjust the upper and lower decision-making in the - hierarchical plan	Plan ahead and verify credibility
Automation			
Kamm et al. [25]	Industrial automation	Processing heterogeneous data	Provide promising solutions and methods
Gloeser-Chahoud et al. [36]	Electric vehicle battery	Accelerate the industrial cycle of waste batteries with automation	Accelerate the recovery and utilization of resources, while- reducing environmental- pollution.
Kumar et al. [37]	Waste recovery	Solve the possible hazards when recycling waste through automation	Accurately classify the recovered materials to increase the recovery cost
Alejandrino et al. [38]	Economic transition	Automation is the most ecological and efficient solution for economic transformation.	Provides a reference for the transformation of industrial- linear economy to circular economy
Al Shahrani et al. [39]	Industrial automation	Improve industry's ability to control and monitor the- industrial environment with machine learning and - automation	Reduce major risk management and inefficiency of traditional processes
Li et al. [40]	Industrial automation	Design a reliable, efficient and automated defect- detection system to achieve- full automation	Automatic defect detection and reduced material loss
Intelligent Manufacturing			
Poschmann et al. [41]	Intelligent robot	Using intelligent robots to participate in production	Robots will make optimal decisions according to different situations to maximize the use of resources
Xu et al. [42]	Cement production	Adjust production capacity to save costs and reduce emissions	Intelligent adjustment combined with data, while optimizing the production process
Chand and Ravi [43]	Disassembly sequence planning	Optimal disassembly sequence is obtained by machine planning	Reducing the ecological and economic impact of products in the remanufacturing industry
Turner et al. [44]	production process optimization	Using machines to provide- workers with decision- making or physical activities	Rapid decision-making while improving the sustainable reuse of resources

4 Application Prospect

4.1 Product Design and Production

ML offers transformative solutions for designing greener and more sustainable products in the circular economy, achieved by accurately predicting market demands and optimizing production processes.

The strength of ML lies in its capability to assimilate vast amounts of historical data through sophisticated algorithms, subsequently developing empirical models that can guide production. A prime example is demand forecasting. Zhao et al. [45] utilized extensive user data from home appliance manufacturers to create ML models. These models predict future customer demands and consumption behaviors. Through these predictive insights, manufacturers are empowered not only to fine-tune their production plans but also to grasp customer behavior. This understanding enables them to design highly personalized products, optimizing resource utilization. It also facilitates anticipating product use, thereby enabling timely product recycling and accelerating resource circulation. Another critical application of ML in the ICE is the optimization of production processes. Modern products often entail complex production steps with varied standards and requirements. ML utilizes previous production experiences to gain a holistic view of the industry. It meticulously controls factors such as production temperature, duration, and environmental humidity, thereby pinpointing optimal process conditions. This approach ensures maximum resource utilization while enhancing product quality and production rates [46].

While ML has the potential to significantly impact production and the ICE, many models face challenges due to the involvement of numerous variables, limiting their practical application. However, as more industries begin integrating ML into their production processes, we can anticipate further development and exploration of the ICE, propelled by ML innovations.

4.2 Energy Management

ML offers innovative solutions for intelligent energy management within the circular economy, achieving energy conservation and emission reduction by optimizing energy consumption and enhancing efficiency.

Energy is fundamental to modern society. In recent decades, the world has witnessed a rapid surge in energy consumption, fueled by population growth and increasing demands for comfort. Without effective energy-saving strategies, this trend could severely impact the environment and deplete resources. Grim et al. [47], Amasyali and El-Gohary [48] utilized ML to forecast energy consumption, providing valuable insights for energy utilization and planning. As the depth of study into ML expands, its methods are increasingly recognized as the most suitable for achieving accurate predictions. In this context, Olu-Ajayi et al. [49] employed ML techniques to develop efficient energy usage models. These models not only facilitate more effective energy use but also empower workers to make informed decisions. Further, numerous scholars have applied ML technologies to maximize the use of renewable energy sources, thereby substituting non-renewable options. This shift not only reduces production costs but also encourages resource recycling and sustainability [50].

4.3 Sustainable Supply Chain

ML can significantly enhance the sustainability of enterprise supply chains by optimizing and real-time monitoring of raw material usage, production processes, and product transportation.

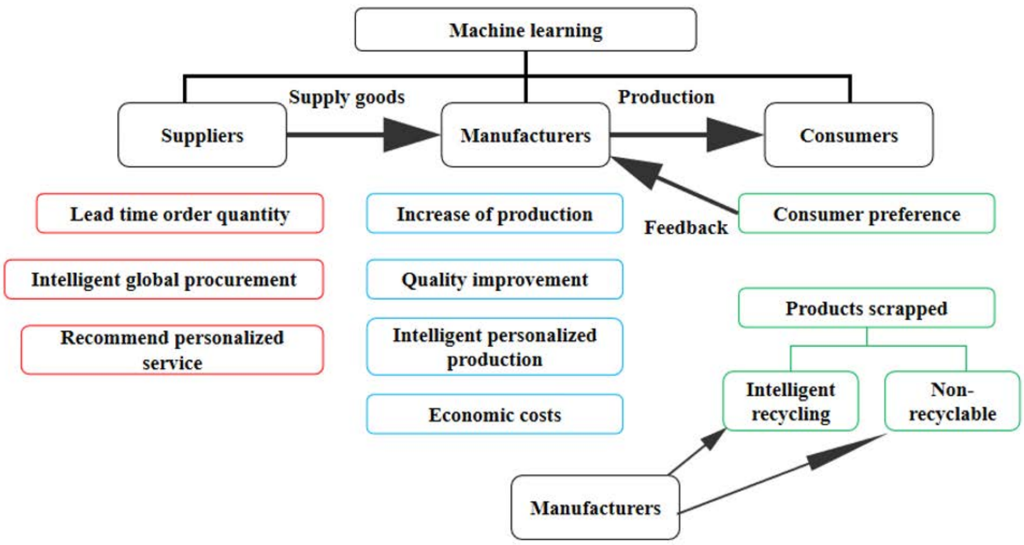

Figure 5. Application examples of ML in supply chain

In the rapidly evolving information age, the efficacy of supply chain ecosystems is increasingly critical for the manufacturing industry. However, many enterprises face challenges such as low operational efficiency in supply chains, high logistics costs, fragmented information across upstream and downstream channels, and a lack of coordination. Furthermore, decision-making processes in supply chains often lack intelligence, agility, and flexibility, making it difficult to manage sudden risks. Govindan and Hasanagic [51] emphasized the significance of supply chains in the circular economy of the manufacturing sector, exploring the driving forces, hurdles, and practices influencing circular economy implementation within supply chain contexts. Building on this, Nascimento et al. [52] developed a business model focused on reusing and recycling waste materials, leveraging ML and circular economy principles. ML is also instrumental in understanding causal relationships within circular supply chains and comprehensive resource management, leading to effective frameworks for a sustainable circular supply chain [53]. By harnessing rich qualitative data through ML, models can be established and validated to integrate network technology, reincorporate waste into the supply chain, manufacture products on demand, and enhance business sustainability. Moreover, ML facilitates the planning of multifaceted and cross-industrial supply chains, thereby extending sustainable practices across various sectors and promoting a global circular economy [54]. Figure 5 shows an application example of machine learning in supply chain.

While industrial production supply chains face numerous challenges, these also represent opportunities. Global economic integration and liberalization policies have enabled manufacturing enterprises worldwide to participate in constructing 'world factories' and global supply chain networks [55]. From a policy perspective, the efficiency and security of supply chains are increasingly central. For intelligent manufacturing industries, prioritizing supply chain management is essential. In the future, with the trend towards customized products, manufacturers must adapt to diverse customer needs, frequent production line changes, and small-scale, varied production. This presents a significant challenge in balancing production flexibility and cost – an enduring issue for supply chains. Addressing these challenges necessitates integrating supply chains with emerging technologies. Birkel and Muller [56] explored the convergence of industrial supply chains and emerging technologies, highlighting vast potential for the future. Their findings suggest that the integration of ML with supply chains still has significant untapped potential, offering promising avenues for aiding the ICE.

4.4 Social Value

ML can significantly contribute to the circular economy by providing relevant educational and training resources, enhancing environmental awareness and skills, and promoting circular economy development. It is also instrumental in evaluating the social impact of circular economy initiatives, thereby offering a scientific basis for decision-making by governments and enterprises. Merli et al. [57] conducted a comprehensive review of literature on the impact of the circular economy, observing that most studies only marginally consider the social and institutional impacts. ML can aid industries in developing a hierarchical framework for assessing management effectiveness, addressing policies related to reduction, reuse, and recycling, and ensuring the implementation of waste minimization and resource recovery plans. Furthermore, Negash et al. [58] have developed an assessment framework specifically for waste management in the construction industry. This framework continually provides standards for waste management, guided by expert evaluations. It is important to note that as science and technology advance, the complexity and number of challenges we face are increasing. Integrating ML into the circular economy to analyze and address these complex issues holds immense potential for fostering human development and advancing the circular economy.

5 Future Work

The potential of ML in the ICE for sustainable development is immense. As explored and summarized in the initial sections, numerous scholars have contributed significantly to the advancement of the ICE. They have identified existing issues and outlined areas for future research. Ren et al. [59] delved into the future prospects of the circular economy and discovered its profound interconnection with Industry 4.0 and sustainable development goals. In addressing the impending challenge of resource scarcity and the consequent resource demands of future production, there is a pressing need for an effective integration of ML with the ICE. This integration is vital to meet the stringent requirements posed by these challenges. Table 3 presents a summary of various applications of ML in the industrial sector, along with anticipated trends in its future development.

Table 3. The application of ML in the industrial field and its future development trend

Application Domain	In Use Today	Change over the Next Five Years	In Use in Five Years
Predictive maintenance	28%	+38%	66%
Big data driven process and quality optimization	30%	+35%	65%
Process visualization/automation	28%	+34%	62%
Connected factory	29%	+31%	60%
Integrated planning	32%	+29%	61%
Data-enabled resource optimization	52%	+25%	77%
Digital twin of the factory	19%	+25%	44%
Digital twin of the production asset	18%	+21%	39%
Digital twin of the product	23%	+20%	43%
Autonomous intra-plant logistics	17%	+18%	35%
Flexible production methods	18%	+16%	34%
Transfer of production parameters	16%	+16%	32%
Modular production assets	29%	+7%	36%
Fully autonomous digital factory	5%	+6%	11%

Several frontiers in the research of ML and its application in the ICE remain to be fully explored. Currently, the main focus is on the lawful use of data, enhancement of production processes, improvement of product quality, and the comprehensive recovery and utilization of materials. This section will concentrate on presenting significant cutting-edge advancements that address existing challenges, thereby enhancing the practical application of ML in manufacturing. Additionally, we will briefly introduce some promising avenues for future developments in this domain, highlighting directions that hold potential for significant advancements in the field.

5.1 Data Collection and Processing

The utilization of ML in the ICE critically hinges on the handling of large datasets. Consequently, the forthcoming challenges include the acquisition of extensive data for modeling, its reasonable use, and effective and correct data utilization [60].

With the enactment of the General Data Protection Regulations, users have gained unequivocal ownership of their data. This regulation stipulates that any institution or organization cannot use a user's data without explicit consent [61]. Furthermore, in the processes of data formation, analysis, and utilization, issues such as data silos arise. These are often caused by asymmetry, redundancy, and other factors leading to closed or semi-closed data environments. These challenges result from a mix of subjective initiative, technological limitations, policy environment, and system construction, impeding data communication within and between enterprises, confining the data to their respective databases.

Federated learning represents a novel approach in ML, designed to address the challenges of data silos while safeguarding data privacy. It involves a decentralized framework where multiple clients (such as mobile devices, institutions, organizations, etc.) collaborate with one or more central servers. Hatzivasilis et al. [62] introduced a green blockchain model utilizing a federated learning framework to foster a circular economy. Similarly, Li et al. [63] examined the feasibility and application prospects of federated learning in various manufacturing industries. The potential synergy of federated learning with the ICE can enhance data privacy and utilization while fostering a vast data-sharing network. However, challenges remain, such as the high energy consumption associated with federated learning, which can adversely affect device battery life and risk sensitive information leakage. Therefore, systems based on federated learning urgently require mechanisms to protect sensitive information effectively while improving energy efficiency [64]. Another concern is the potential for participants with specific motivations to engage briefly in the training process, gaining access to the global model while contributing minimally. This situation creates a fairness issue, disadvantaging participants who have been involved more extensively in federated learning. Future developments must thoroughly consider the performance, fairness, and security aspects of federated learning to optimize data collection and utilization [65].

5.2 Model Improvement and Supply Chain Improvement

ML models, primarily built on existing data, face the challenge of enhancing their effectiveness and generating additional value. Incorporating expert knowledge and advice is a promising approach for model improvement. For instance, Moktadir et al. [66] identified and assessed the key success factors for a circular economy, later validating these with expert insights. Similarly, Hofmann and Jaeger-Erben [67] consulted numerous experts on various circular economy issues to develop a conceptual model.

In recent years, the intersection of Big Data and Industry 4.0 is poised to revolutionize traditional supply chains. However, in the context of a circular economy, the sustainability of digital supply chains has not been adequately addressed. Patil et al. [68] employed the fuzzy best-worst method to evaluate multiple factors impacting sustainable supply chains, as determined by an expert group, ultimately identifying key elements crucial for sustainable supply chain development. These findings aid stakeholders in strategizing and planning for digital supply chain transitions. Nevertheless, due to the complex nature of these factors and challenges in precise assessments, the results are somewhat region-specific. Kumar et al. [69] utilized grey correlation theory in evaluation laboratories to minimize uncertainties and ambiguities in expert judgments. Tseng et al. [70] introduced and applied a hybrid methodology combining FDM and FDEMATEL, balancing subjective and objective considerations, and converting qualitative data into fuzzy values for processing, thereby enhancing supply chain management. However, this research is not without limitations. Firstly, the selection of criteria based on previous studies might not encompass all relevant factors, necessitating the inclusion of additional variables. Secondly, the knowledge, familiarity, and judgment biases of experts can somewhat skew conclusions, indicating the need for supplementary methods.

The insights and recommendations from experts are invaluable. In the future, refining ML models with expert opinions and merging data analysis with expert knowledge can mitigate the subjectivity of conclusions, addressing more challenges within the circular economy domain effectively.

5.3 Resource Utilization and Waste Management

The application of ML in the ICE primarily aims to enhance actual production processes. Lu et al. [71] proposed a practical approach to recycle industrial products using ML. Baduge et al. [72] integrated ML to improve the entire production lifecycle. In a similar vein, Rakhshan et al. [73] utilized supervised ML to facilitate the recycling of materials in industry, showcasing ML's ability to fully leverage resources for the development of an ICE. Additionally, ML can identify alternative materials to replace non-renewable resources, thereby reducing resource consumption in production. However, these models and methods are still in their infancy, and the resource issues can be further addressed by combining scientific research outcomes with ML.

Beyond resource utilization, ML also holds promise in waste management. Liang et al. [74] applied ML to predict waste generation and characteristics, optimize waste collection and transportation, and simulate waste-to-energy processes. Velis et al. [75] employed ML techniques, such as multivariate random forests and univariate nonlinear regression, to enhance urban waste management. However, without new policies promoting decoupling, per capita waste production could increase substantially. While prediction algorithms based on ML, diversified waste management frameworks, and data-driven waste management systems can significantly advance the ICE, several limitations exist. Firstly, many waste management frameworks are incomplete and could benefit from incorporating more comprehensive models for improvement. Secondly, numerous knowledge frameworks applied to the circular economy often overlook the full industrial process, impacts on other stakeholders and society, and interactions with the ICE, limiting their ability to identify waste reduction and resource efficiency opportunities. In the future, a more holistic approach, integrating ML and artificial intelligence, is necessary for comprehensive consideration in this field.

5.4 Equipment Upgrade

ML's role in the ICE extends beyond process improvement, offering significant contributions to production equipment. Khan et al. [76] provide a value-added alternative to conventional equipment upgrades. Utilizing a resource-based perspective, their approach enhances device performance to align with evolving customer preferences. Zacharaki et al. [77] introduced a novel concept for refurbishing and remanufacturing industrial equipment using ML and other advanced technologies. This approach revitalizes older equipment, reintegrating it into the production system and considerably reducing the opportunity costs of retaining such equipment in terms of both finances and resources. Additionally, Mercadillo et al. [78] employed classic ML for product feature identification, showcasing how computer vision can be applied for rapid and accurate quality control on the factory floor. A critical future consideration is how manufacturers can effectively discern and cater to consumer preferences. Furthermore, some older equipment might not be compatible with emerging technologies, necessitating manual intervention or equipment replacement to ensure uninterrupted production.

Machine tools are pivotal in the manufacturing industry, as their performance directly impacts product quality and production efficiency. In the context of Industry 4.0, these tools are expected to achieve higher levels of accessibility, connectivity, intelligence, adaptability, and autonomy. Liu et al. [79] highlighted future development directions for machine tools in terms of digitalization and servitization, encompassing data acquisition, digital twin modeling, intricate human-machine interactions, and service-oriented development methods. The incorporation and application of ML are crucial to address these aspects effectively.

The advent of Industry 4.0 has brought manufacturing, particularly sectors with a large inventory of old equipment, into sharp focus. Industry 4.0 elevates manufacturing automation by integrating customization and intelligent production technologies, as discussed by Möller et al. [80]. However, looking towards Industry 5.0, there is a growing need to further merge ML with the ICE. This integration will enhance existing equipment, optimize resource usage, and advance the development of personalized, custom production and services in the future.

5.5 Digital Twin Technology

Digital twin technology effectively simulates the entire production process in a digital format, creating a digital "clone" of a device or system. This "clone," or digital twin, is integral to all phases of a product's life cycle, including the simulation, monitoring, diagnosis, prediction, and control of physical products' formation and behavior in real-world settings. Through ongoing information exchange between digital twins and their physical counterparts, enhancements in product maintenance, upgrades, control, and optimization are achieved. Mügge et al. [81] leveraged digital twin technology to devise solutions for the circular economy, addressing issues related to information loss in end-of-life products. This approach enhances efficiency, sustainability, and the implementation of circular economy practices. Furthermore, digital twin technology has been shown to extend product lifespans. Kerin et al. [82] implemented digital twin models throughout product life cycles, utilizing data from various instances for optimization, remanufacturing, and predicting products' remaining service lives. They also posited that if the intelligent tools in digital twin technology could access current product states and reliable remanufacturing process information, it would significantly aid in product decision-making. In this context, the fusion of ML with digital twin technology across the entire product life cycle offers substantial benefits. It enables the replacement of actual R&D processes with digital twins, which conserves materials, elevates product quality, and extends product lifespan.

As a pioneering technology grounded in simulation, digital twinning plays a pivotal role in advancing industrial production. By integrating digital twin technology with ML, and substituting digital production for practical research, new product possibilities emerge while conserving resources. The digital twin concept not only inspires future work but also broadens the horizons for the future of the ICE.

6 Conclusion

This study has provided a comprehensive review and synthesis of the current integration and progression of ML within the ICE. It has also proposed several prospective directions for the future enhancement of ML in the industrial and manufacturing sectors. These include the promotion of greater data sharing, enhanced resource and equipment utilization, the acceleration of sustainable supply chain development, and more efficient waste recycling methodologies. The findings of this research contribute to a summative understanding of ML applications in the ICE and offer reference points for future developmental trajectories. The continuous evolution of ML in this realm is anticipated to yield substantial economic value-additions and foster the sustainable management of natural resources and environmental protection.

As a nascent technology, ML is garnering increasing attention. The insights presented herein aim to assist researchers in addressing the challenges currently faced in the manufacturing domain. Nevertheless, this study acknowledges certain limitations. The future developmental pathways delineated herein represent a selection of possible directions, without exhaustive exploration of other significant application prospects. Furthermore, it is observed that the intersection of ML and the circular economy predominantly resides within industrial and manufacturing spheres. Future research is encouraged to extend this integration across diverse sectors and industries, catalyzing a transition to sustainable and high-quality societal development. Additionally, both ML and the circular economy serve humanity at their core. With the evolution of lifestyle aspirations, individual needs are becoming increasingly nuanced. It is therefore hoped that future research in ML will increasingly cater to these individualized human requirements.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] P. Burggraf, T. Adlon, K. Müller, N. Föhlisch, J. Dackweiler, and C. Fölling, "Adaptive remanufacturing – Methodology towards an intelligent maintenance strategy for production resources," *Proc. CIRP*, vol. 98, pp. 330–335, 2021. https://doi.org/10.1016/j.procir.2021.01.112

[2] P. Guarnieri, A. Bianchini, J. Rossi, L. Câmara e Silva, F. Trojan, M. Lizot, and B. de Oliveira Vieira, "Transitioning towards a circular economy under a multicriteria and the new institutional theory perspective: A comparison between Italy and Brazil," *J. Clean. Prod.*, vol. 409, p. 137094, 2023. https://doi.org/10.1016/J.JCLEPRO.2023.137094

[3] M. A. Ansar, M. Assawadithalerd, D. Tipmanee, L. Laokiat, P. Khamdahsag, and S. Kittipongvises, "Occupational exposure to hazards and volatile organic compounds in small-scale plastic recycling plants in Thailand by integrating risk and life cycle assessment concepts," *J. Clean. Prod.*, vol. 329, p. 129582, 2021. https://doi.org/10.1016/j.jclepro.2021.129582

[4] F. Jia, S. Y. Yin, L. Chen, and X. W. Chen, "Circular economy in textile and apparel industry: A systematic literature review," *J. Clean. Prod.*, vol. 259, p. 120728, 2020. https://doi.org/10.1016/j.jclepro.2020.120728

[5] C. Bai, H. B. Ahmadi, M. A. Moktadir, S. Kusi-Sarpong, and J. J. H. Liou, "Analyzing the interactions among the challenges to circular economy practices," *IEEE Access*, vol. 9, pp. 63 199–63 212, 2021. https://doi.org/10.1109/ACCESS.2021.3074931

[6] X. M. Zhao, "The development Jilin Province's automobile industry artificial intelligence and LC economy," *J. Phys.: Conf. Ser.*, vol. 1852, p. 022035, 2021. https://doi.org/10.1088/1742-6596/1852/2/022035

[7] Y. Liu, H. Li, H. An, R. Santagata, X. Liu, and S. Ulgiati, "Environmental and economic sustainability of key sectors in China's steel industry chain: An application of the emergy accounting approach," *Ecol. Indic.*, vol. 129, p. 108011, 2021. https://doi.org/10.1016/j.ecolind.2021.108011

[8] Y. Yang, E. G. Okonkwo, G. Huang, S. Xu, W. Sun, and Y. He, "On the sustainability of lithium ion battery industry - A review and perspective," *Energy Storage Mater.*, vol. 36, pp. 186–212, 2021. https://doi.org/10.1016/j.ensm.2020.12.019

[9] M. K. Lim, M. Lai, C. Wang, and S. Y. Lee, "Circular economy to ensure production operational sustainability: A green-lean approach," *Sustainable Prod. Consump.*, vol. 30, pp. 130–144, 2022. https://doi.org/10.1016/j.spc.2021.12.001

[10] S. Lu, X. Guan, F. Qin, X. Liu, and D. Zhang, "The assessment of forest ecological security and its determining indicators: A case study of the Yangtze River Economic Belt in China," *J. Environ. Manage.*, vol. 258, p. 110048, 2020. https://doi.org/10.1016/j.jenvman.2019.110048

[11] W. Xie, T. Li, A. Tiraferri, E. Drioli, A. Figoli, J. C. Crittenden, and B. Liu, "Toward the next generation of sustainable membranes from green chemistry principles," *ACS Sustainable Chem. Eng.*, vol. 9, no. 1, pp. 50–75, 2021. https://doi.org/10.1021/acssuschemeng.0c07119

[12] H. Chen, K. Wan, Y. Zhang, and Y. Wang, "Waste to wealth: Chemical recycling and chemical upcycling of waste plastics for a great future," *Chem. Sus. Chem.*, vol. 14, no. 19, pp. 4123–4136, 2021. https://doi.org/10.1002/cssc.202100652

[13] J. S. Lim, C. Li, Y. V. Fan, and J. J. Klemes, "How circular economy and green technology can address sustainable development goals?" *J. Clean. Prod.*, vol. 333, p. 130161, 2022. https://doi.org/10.1016/j.jclepro.2021.130161

[14] C. Yao, G. Liu, X. Hao, and Y. Liu, "Symbiotic integration of waste disposal capability within a city cluster: The case of the Yangtze River Delta," *J. Environ. Manage.*, vol. 330, p. 117166, 2023. https://doi.org/10.1016/j.jenvman.2022.117166

[15] S. Yi, "Evaluation and development of Korea's national plan for resource circulation towards a circular economy," *Energy Environ.*, vol. 31, no. 7, 2019. https://doi.org/10.1177/0958305X19876055

[16] R. Iagaru, A. Sipos, and P. Iagaru, "Strategic thinking and its role in accelerating the transition from the linear to the circular economic model—Case study of the agri-food sector in the Sibiu Depression microregion, Romania," *Sustainability*, vol. 15, no. 4, 2023. https://doi.org/10.3390/su15043109

[17] A. Starodubova, D. Iskhakova, and C. Misbakhova, "The role of eco-industrial parks in promoting circular economy technologies in the regions," in *BIO Web of Conferences*, vol. 48. Les Ulis, France: EDP Sciences, 2022, p. 01024. https://doi.org/10.1051/bioconf/20224801024

[18] S. Sharma, S. R. Asolekar, V. K. Thakur, and P. Asokan, "Valorization of cellulosic fiber derived from waste biomass of constructed wetland as a potential reinforcement in polymeric composites: A technological approach to achieve circular economy," *J. Environ. Manage.*, vol. 340, p. 117850, 2023. https://doi.org/10.1016/j.jenvman.2023.117850

[19] D. Powell, M. C. Magnanini, M. Colledani, and O. Myklebust, "Advancing zero defect manufacturing: A state-of-the-art perspective and future research directions," *Comput. Ind.*, vol. 136, p. 103596, 2022. https://doi.org/10.1016/j.compind.2021.103596

[20] A. Joshi, B. Pradhan, S. Chakraborty, and M. D. Behera, "Winter wheat yield prediction in the conterminous United States using solar-induced chlorophyll fluorescence data and XGBoost and random forest algorithm," *Ecol. Inform.*, vol. 77, p. 102194, 2023. https://doi.org/10.1016/j.ecolinf.2023.102194

[21] S. Park, "Identification of overall innovation behavior by using a decision tree: The case of a Korean manufacturer," *Sustainability*, vol. 11, no. 22, p. 6207, 2019. https://doi.org/10.3390/su11226207

[22] Y. Zhang, "Layout design and optimization of industrial robot automated production line based on genetic algorithm," *J. Comput. Methods Sci. Eng.*, vol. 23, no. 1, pp. 469–484, 2023. https://doi.org/10.3390/su11226207

[23] S. Dembski, T. Schwarz, M. Oppmann, S. T. Bandesha, J. Schmid, S. Wenderoth, K. Mandel, and J. Hansmann, "Establishing and testing a robot-based platform to enable the automated production of nanoparticles in a flexible and modular way," *Sci. Rep.*, vol. 13, p. 11440, 2023. https://doi.org/10.1038/s41598-023-38535-6

[24] C. Mejía-Moncayo, J. P. Kenné, and L. A. Hof, "On the development of a smart architecture for a sustainable manufacturing-remanufacturing system: A literature review approach," *Comput. Ind. Eng.*, vol. 180, p. 109282, 2023. https://doi.org/10.1016/j.cie.2023.109282

[25] S. Kamm, S. S. Veekati, T. Müller, N. Jazdi, and M. Weyrich, "A survey on machine learning based analysis of heterogeneous data in industrial automation," *Comput. Ind.*, vol. 149, p. 103930, 2023. https://doi.org/10.1016/j.compind.2023.103930

[26] M. I. Ahmed, R. A. Zaghdoud, M. S. Ahmed *et al.*, "Intelligent directional survey data analysis to improve directional data

acquisition," *Math. Model. Eng. Probl.*, vol. 10, no. 2, pp. 482–490, 2023. https://doi.org/10.18280/mmep.100214

[27] J. Li, S. King, and I. Jennions, "Intelligent fault diagnosis of an aircraft fuel system using machine learning—A literature review," *Machines*, vol. 11, no. 4, p. 481, 2023. https://doi.org/10.3390/machines11040481

[28] H. Li, X. Li, X. Liu, X. Bu, H. Li, and Q. Lyu, "Industrial internet platforms: Applications in BF ironmaking," *Ironmak. Steelmak.*, vol. 49, no. 9, pp. 905–916, 2022. https://doi.org/10.1080/03019233.2022.2069990

[29] A. Saco, P. S. Sundari, and A. Paul, "An optimized data analysis on a real-time application of PEM fuel cell design by using machine learning algorithms," *Algorithms*, vol. 15, no. 10, p. 346, 2022. https://doi.org/10.3390/a15100346

[30] M. Mowbray, H. Kay, S. Kay, P. C. Caetano, A. Hicks, C. Mendoza, A. Lane, P. Martin, and D. Zhang, "Probabilistic machine learning based soft-sensors for product quality prediction in batch processes," *Chemom. Intell. Lab. Syst.*, vol. 228, p. 104616, 2022. https://doi.org/10.1016/j.chemolab.2022.104616

[31] G. Deffrennes, K. Terayama, T. Abe, E. Ogamino, and R. Tamura, "A framework to predict binary liquidus by combining machine learning and CALPHAD assessments," *Mater. Des.*, vol. 232, p. 112111, 2023. https://doi.org/10.1016/j.matdes.2023.112111

[32] J. B. Osei, M. Adom-Asamoah, J. O. Twumasi, P. Andras, and H. Zhang, "A machine learning-based structural load estimation model for shear-critical RC beams and slabs using multifractal analysis," *Constr. Build. Mater.*, vol. 394, p. 132250, 2023. https://doi.org/10.1016/j.conbuildmat.2023.132250

[33] Y. Yang, L. Gao, M. Abbas, D. H. Elkamchouchi, T. Alkhalifah, F. Alturise, and J. J. Ponnore, "Innovative composite machine learning approach for biodiesel production in public vehicles," *Adv. Eng. Softw.*, vol. 184, p. 103501, 2023. https://doi.org/10.1016/j.advengsoft.2023.103501

[34] A. Amini, J. Kanfoud, and T. H. Gan, "An artificial intelligence neural network predictive model for anomaly detection and monitoring of wind turbines using SCADA data," *Appl. Artif. Intell.*, vol. 36, no. 1, p. 2034718, 2022. https://doi.org/10.1080/08839514.2022.2034718

[35] C. Gahm, A. Uzunoglu, S. Wahl, C. Ganschinietz, and A. Tuma, "Applying machine learning for the anticipation of complex nesting solutions in hierarchical production planning," *Eur. J. Oper. Res.*, vol. 296, no. 3, pp. 819–836, 2022. https://doi.org/10.1016/j.ejor.2021.04.006

[36] S. Glöser-Chahoud, S. Huster, S. Rosenberg, S. Baazouzi, S. Kiemel, S. Singh, C. Schneider, M. Weeber, R. Miehe, and F. Schultmann, "Industrial disassembling as a key enabler of circular economy solutions for obsolete electric vehicle battery systems," *Resour. Conserv. Recycl.*, vol. 174, p. 105735, 2021. https://doi.org/10.1016/j.resconrec.2021.105735

[37] N. M. Kumar, M. A. Mohammed, K. H. Abdulkareem, R. Damasevicius, S. A. Mostafa, M. S. Maashi, and S. S. Chopra, "Artificial intelligence-based solution for sorting COVID related medical waste streams and supporting data-driven decisions for smart circular economy practice," *Process Saf. Environ. Prot.*, vol. 152, pp. 482–494, 2021. https://doi.org/10.1016/j.psep.2021.06.026

[38] C. Alejandrino, I. T. Mercante, and M. D. Bovea, "Combining O-LCA and O-LCC to support circular economy strategies in organizations: Methodology and case study," *J. Clean. Prod.*, vol. 336, p. 130365, 2022. https://doi.org/10.1016/j.jclepro.2022.130365

[39] A. M. Al Shahrani, M. A. Alomar, K. N. Alqahtani, M. S. Basingab, B. Sharma, and A. Rizwan, "Machine learning-enabled smart industrial automation systems using internet of things," *Sensors*, vol. 23, no. 1, p. 324, 2022. https://doi.org/10.3390/s23010324

[40] W. Li, H. Zhang, G. Wang, G. Xiong, M. Zhao, G. Li, and R. Li, "Deep learning based online metallic surface defect detection method for wire and arc additive manufacturing," *Robot. Comput.-Integr. Manuf.*, vol. 80, p. 102470, 2023. https://doi.org/10.1016/j.rcim.2023.102470

[41] H. Poschmann, H. Brüggemann, and D. Goldmann, "Fostering end-of-life utilization by information-driven robotic disassembly," *Procedia CIRP*, vol. 98, pp. 282–287, 2021. https://doi.org/10.1016/j.procir.2021.01.104

[42] G. Xu, D. Xue, and H. Rehman, "Dynamic scenario analysis of CO_2 emission in China's cement industry by 2100 under the context of cutting overcapacity," *Mitig. Adapt. Strateg. Glob. Change*, vol. 27, no. 8, p. 53, 2022. https://doi.org/10.1007/s11027-022-10028-3

[43] M. Chand and C. Ravi, "A state-of-the-art literature survey on artificial intelligence techniques for disassembly sequence planning," *CIRP J. Manuf. Sci. Technol.*, vol. 41, pp. 292–310, 2023. https://doi.org/10.1016/j.cirpj.2022.11.017

[44] C. Turner, J. Oyekan, W. Garn, C. Duggan, and K. Abdou, "Industry 5.0 and the circular economy: Utilizing LCA with intelligent products," *Sustainability*, vol. 14, no. 22, p. 14847, 2022. https://doi.org/10.3390/su142214847

[45] Y. Zhao, J. Zhao, L. Jiang, R. Tan, D. Niyato, Z. Li, L. Lyu, and Y. Liu, "Privacy-preserving blockchain-based federated learning for IoT devices," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 1817–1829, 2021. https://doi.org/10.1109/JIOT.2020.3017377

[46] O. Dogu, M. Pelucchi, R. Van de Vijver, P. H. Van Steenberge, D. R. D'hooge, A. Cuoci, M. Mehl, A. Frassoldati, T. Faravelli, and K. M. Van Geem, "The chemistry of chemical recycling of solid plastic waste via pyrolysis and gasification: State-of-the-art, challenges, and future directions," *Prog. Energy Combust. Sci.*, vol. 84, p. 100901, 2021. https://doi.org/10.1016/j.pecs.2020.100901

[47] R. G. Grim, Z. Huang, M. T. Guarnieri, J. R. Ferrell, L. Tao, and J. A. Schaidle, "Transforming the carbon economy: Challenges and opportunities in the convergence of low-cost electricity and reductive CO_2 utilization," *Energy Environ. Sci.*, vol. 13, no. 2, pp. 472–494, 2020. https://doi.org/10.1039/C9EE02410G

[48] K. Amasyali and N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1192–1205, 2018. https://doi.org/10.1016/j.rser.2017.04.095

[49] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, and S. Ajayi, "Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques," *J. Build. Eng.*, vol. 45, p. 103406, 2022. https://doi.org/10.1016/j.jobe.2021.103406

[50] S. Li, P. Zhao, C. Gu, J. Li, S. Cheng, and M. Xu, "Battery protective electric vehicle charging management in renewable energy system," *IEEE Trans. Ind. Inf.*, vol. 19, no. 2, pp. 1312–1321, 2022. https://doi.org/10.1109/TII.2022.3184398

[51] K. Govindan and M. Hasanagic, "A systematic review on drivers, barriers, and practices towards circular economy: A supply chain perspective," *Int. J. Prod. Res.*, vol. 56, no. 1-2, pp. 278–311, 2018. https://doi.org/10.1080/00207543.2017.1402141

[52] D. L. Nascimento, V. Alencastro, O. L. Quelhas, R. G. Caiado, J. A. Garza-Reyes, L. Rocha-Lona, and G. Tortorella, "Exploring industry 4.0 technologies to enable circular economy practices in a manufacturing context: A business model proposal," *J. Manuf. Technol. Manag.*, vol. 30, no. 3, pp. 607–627, 2019.

[53] T. D. Bui, J. W. Tseng, H. Aminah, J. Sulistiawan, M. H. Ali, and M. L. Tseng, "Causality of total resource management in circular supply chain implementation under uncertainty: A context of textile industry in Indonesia," *Ann. Oper. Res.*, 2023. https://doi.org/10.1007/s10479-023-05200-0

[54] M. L. Tseng, R. R. Tan, A. S. Chiu, C. F. Chien, and T. C. Kuo, "Circular economy meets industry 4.0: Can big data drive industrial symbiosis?" *Resour. Conserv. Recycl.*, vol. 131, pp. 146–147, 2018. https://doi.org/10.1016/j.resconrec.2017.12.028

[55] G. Herczeg, R. Akkerman, and M. Z. Hauschild, "Supply chain collaboration in industrial symbiosis networks," *J. Clean. Prod.*, vol. 171, pp. 1058–1067, 2018. https://doi.org/10.1016/j.jclepro.2017.10.046

[56] H. Birkel and J. M. Muller, "Potentials of industry 4.0 for supply chain management within the triple bottom line of sustainability–A systematic literature review," *J. Clean. Prod.*, vol. 289, p. 125612, 2021. https://doi.org/10.1016/j.jclepro.2020.125612

[57] R. Merli, M. Preziosi, and A. Acampora, "How do scholars approach the circular economy? A systematic literature review," *J. Clean. Prod.*, vol. 178, pp. 703–722, 2018. https://doi.org/10.1016/j.jclepro.2017.12.112

[58] Y. T. Negash, A. M. Hassan, M. L. Tseng, M. H. Ali, and M. K. Lim, "Developing a hierarchical framework for assessing the strategic effectiveness of sustainable waste management in the Somaliland construction industry," *Environ. Sci. Pollut. Res.*, vol. 30, pp. 67 303–67 325, 2023. https://doi.org/10.1007/s11356-023-27060-8

[59] Y. Ren, R. Li, K. J. Wu, and M. L. Tseng, "Discovering the systematic interlinkages among the circular economy, supply chain, industry 4.0, and technology transfer: A bibliometric analysis," *Clean. Respons. Consum.*, vol. 9, p. 100123, 2023. https://doi.org/10.1016/j.clrc.2023.100123

[60] C. Chauhan, V. Parida, and A. Dhir, "Linking circular economy and digitalisation technologies: A systematic literature review of past achievements and future promises," *Technol. Forecast. Soc. Change*, vol. 177, p. 121508, 2022. https://doi.org/10.1016/j.techfore.2022.121508

[61] N. Z. Aitzhan and D. Svetinovic, "Security and privacy in decentralized energy trading through multi-signatures, blockchain and anonymous messaging streams," *IEEE Trans. Depend. Secure Comput.*, vol. 15, no. 5, pp. 840–852, 2016. https://doi.org/10.1109/TDSC.2016.2616861

[62] G. Hatzivasilis, S. Ioannidis, K. Fysarakis, G. Spanoudakis, and N. Papadakis, "The green blockchains of circular economy," *Electronics*, vol. 10, no. 16, 2021. https://doi.org/10.3390/electronics10162008

[63] L. Li, Y. Fan, M. Tse, and K. Y. Lin, "A review of applications in federated learning," *Comput. Ind. Eng.*, vol. 149, p. 106854, 2020. https://doi.org/10.1016/j.cie.2020.106854

[64] W. Zou, L. Li, Z. Xu, D. Wu, C. Xu, Y. Wang, H. Zhu, and X. Sun, "SmartDL: Energy-aware decremental learning in a mobile-based federation for geo-spatial system," *Neural Comput. Appl.*, vol. 35, no. 5, pp. 3677–3696, 2023.

[65] X. You, X. Liu, X. Lin, J. Cai, and S. Chen, "Accuracy degrading: Towards participation-fair federated learning," *IEEE Internet Things J.*, vol. 10, no. 12, pp. 10 291–10 306, 2023. https://doi.org/10.1109/JIOT.2023.3238038

[66] M. A. Moktadir, A. Kumar, S. M. Ali, S. K. Paul, R. Sultana, and J. Rezaei, "Critical success factors for a circular economy: Implications for business strategy and the environment," *Bus. Strat. Environ.*, vol. 29, no. 8, pp. 3611–3635, 2020. https://doi.org/10.1002/bse.2600

[67] F. Hofmann and M. Jaeger-Erben, "Organizational transition management of circular business model innovations," *Bus. Strat. Environ.*, vol. 29, no. 6, pp. 2770–2788, 2020. https://doi.org/10.1002/bse.2542

[68] A. Patil, A. Dwivedi, M. A. Moktadir, and Lakshay, "Big data-industry 4.0 readiness factors for sustainable supply chain management: Towards circularity," *Comput. Ind. Eng.*, vol. 178, p. 109109, 2023. https://doi.org/10.1016/j.cie.2023.109109

[69] M. Kumar, R. D. Raut, S. Jagtap, and V. K. Choubey, "Circular economy adoption challenges in the food supply chain for sustainable development," *Bus. Strat. Environ.*, vol. 32, no. 4, pp. 1334–1356, 2023. https://doi.org/10.1002/bse.3191

[70] M. L. Tseng, T. P. Tran, K. J. Wu, R. R. Tan, and T. D. Bui, "Exploring sustainable seafood supply chain management based on linguistic preferences: Collaboration in the supply chain and lean management drive economic benefits," *Int. J. Logist. Res. Appl.*, vol. 25, no. 4-5, pp. 410–432, 2022. https://doi.org/10.1080/13675567.2020.1800608

[71] H. Lu, D. J. Diaz, N. J. Czarnecki, C. Zhu, W. Kim, R. Shroff, D. J. Acosta, B. R. Alexander, H. O. Cole, Y. Zhang, and N. A. Lynd, "Machine learning-aided engineering of hydrolases for PET depolymerization," *Nature*, vol. 604, pp. 662–667, 2022.

[72] S. K. Baduge, S. Thilakarathna, J. S. Perera, M. Arashpour, P. Sharafi, B. Teodosio, A. Shringi, and P. Mendis, "Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications," *Autom. Constr.*, vol. 141, p. 104440, 2022. https://doi.org/10.1016/j.autcon.2022.104440

[73] K. Rakhshan, J. C. Morel, and A. Daneshkhah, "A probabilistic predictive model for assessing the economic reusability of load-bearing building components: Developing a circular economy framework," *Sustain. Prod. Consum.*, vol. 27, pp.

630–642, 2021. https://doi.org/10.1016/j.spc.2021.01.031

[74] R. Liang, C. Chen, A. Kumar, J. Tao, Y. Kang, D. Han, X. Jiang, P. Tang, B. Yan, and G. Chen, "State-of-the-art applications of machine learning in the life cycle of solid waste management," *Front. Environ. Sci. Eng.*, vol. 17, no. 4, p. 44, 2023.

[75] C. A. Velis, D. C. Wilson, Y. Gavish, S. M. Grimes, and A. Whiteman, "Socio-economic development drives solid waste management performance in cities: A global analysis using machine learning," *Sci. Total Environ.*, vol. 872, p. 161913, 2023. https://doi.org/10.1016/j.scitotenv.2023.161913

[76] M. A. Khan, O. Stoll, S. West, and T. Wuest, "Equipment upgrade service provision in the context of servitization: Drivers, capabilities, and resources," *Prod. Plan. Control*, 2022. https://doi.org/10.1080/09537287.2022.2063199

[77] A. Zacharaki, T. Vafeiadis, N. Kolokas, A. Vaxevani, Y. Xu, M. Peschl, D. Ioannidis, and D. Tzovaras, "RECLAIM: Toward a new era of refurbishment and remanufacturing of industrial equipment," *Front. Artif. Intell.*, vol. 3, p. 570562, 2021. https://doi.org/10.3389/frai.2020.570562

[78] V. O. Mercadillo, H. Ijije, L. Chaplin, I. A. Kinloch, and M. A. Bissett, "Novel techniques for characterising graphene nanoplatelets using Raman spectroscopy and machine learning," *2D Mater.*, vol. 10, no. 2, p. 025018, 2022. https://doi.org/10.1088/2053-1583/acc080

[79] C. Liu, P. Zheng, and X. Xu, "Digitalisation and servitisation of machine tools in the era of industry 4.0: A review," *Int. J. Prod. Res.*, vol. 61, no. 12, pp. 4069–4101, 2023. https://doi.org/10.1080/00207543.2021.1969462

[80] D. P. Möller, H. Vakilzadian, and R. E. Haas, "From industry 4.0 towards industry 5.0," in *2022 IEEE International Conference on Electro Information Technology (eIT)*, Mankato, MN, USA, 2022, pp. 61–68. https://doi.org/10.1109/eIT51626.2022.9815063

[81] J. Mügge, J. Grosse Erdmann, T. Riedelsheimer, M. M. Manoury, S. O. Smolka, S. Wichmann, and K. Lindow, "Empowering end-of-life vehicle decision making with cross-company data exchange and data sovereignty via Catena-X," *Sustainability*, vol. 15, no. 9, p. 7187, 2023. https://doi.org/10.3390/su15097187

[82] M. Kerin, N. Hartono, and D. T. Pham, "Optimising remanufacturing decision-making using the bees algorithm in product digital twins," *Sci. Rep.*, vol. 13, no. 1, p. 701, 2023. https://doi.org/10.1038/s41598-022-27048-0