Integration of Artificial Intelligence in Sustainable Manufacturing: Current Status and Future Opportunities

Abstract

Manufacturing firms often struggle to attain the optimum balance of environmental, economic, and social goals. Sustainable Manufacturing (SM) is one of the ways to balance the aforesaid aspects. Many disruptive technologies such as Artificial Intelligence (AI), blockchain, machine learning, the Internet of Things, and Big Data, are contributing immensely to the digitalisation in SM. This article aims to explore the trends of AI applications in SM during the period of 2010-2021 by conducting a systematic literature review and bibliometric and network analyses. Prominent research themes, namely sustainable scheduling, smart manufacturing and remanufacturing, energy consumption, sustainable practices and performances, and smart disassembly and recovery have been identified through network analysis. Content analysis of extant literature reveals that Genetic Algorithm (GA), Artificial Neural Network (ANN), and Fuzzy Logic are the most widely used AI techniques in SM. Potential future research directions like amalgamation of AI with Industry 4.0, use of hybrid AI systems, focus on social sustainability and use of emerging AI techniques (Deep learning, CNN etc.) have also been proposed. The intellectual map of AI in SM delineated in this article will be helpful for the researchers as well as industry practitioners in their future endeavours.

Keywords Industry 4.0; Environment Sustainability; Strategic Integration; Artificial intelligence; Network analysis; Sustainable manufacturing

1 Introduction

The increasing population and high resource consumption required to support economic growth are the primary concerns in today's world (Malek and Desai 2020; Yu et al. 2021b). In the race of enhancing product quality, manufacturing industries worldwide have focussed primarily on economic benefits till the 1990s. It has led to high resource consumption, increased pollution, and unabated waste generation (Cassettari et al. 2017; Malek and Desai 2020). However, increased pressure from consumers, government, and social groups has forced many industries to tune their manufacturing strategy in the last two decades so that it aligns with environmental and social needs (Graafland and Smid 2017; Bangsa and Schlegelmilch 2020; Govindan et al. 2021). Therefore, manufacturing industries are striving hard to optimise their resource utilisation by better design, manufacturing practices, and minimising wastes. One of the ways to enhance resource utilisation is the adoption of Sustainable Manufacturing (SM) practices (Goyal et al. 2017; Karuppiah et al. 2021; Bai et al. 2022). According to The US Department of Commerce, the SM is defined as "The creation of manufactured products which use processes that minimise negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, consumers and are economically sound" (Chan et al. 2017). SM is an initiative to enhance resource utilisation, minimise harmful emissions, and improve human beings' livelihood. SM integrates the environmental, social, and economic aspects to sustain itself in a competitive market by fulfilling the Triple Bottom Line (TBL) (Naz et al. 2021). The definition of SM clearly outlines the concept; however, many challenges need to be overcome to adopt SM in the manufacturing sector (Xia et al. 2015). The major barriers to the adoption of SM practices are high production cost (Tura et al. 2019), limited available technologies, and lack of infrastructure (Govindan and Hasanagic 2018). Some of these challenges can be addressed by adopting AI technologies. There are positive outcomes of SM in various industries (Song and Young 2017; Golini and Gualandris 2018).

The demand for high-volume, high-quality, and faster production, while minimising the cost, environmental burden, and social implications, has necessitated the manufacturers to embrace digital technologies (Ferrari et al. 2022). Many digital technologies and platforms such as Artificial Intelligence (AI), blockchain, Big Data Analytics (BDA), Machine Learning (ML), Cloud Computing (CC), and the Internet of Things (IoT) have led to the complete transformation of many existing business models (Amjad et al. 2021; Konur et al. 2021; Nara et al. 2021; Akbari and Hopkins 2022). AI utilises information processing capabilities of high-speed computers and helps in intelligent decision-making on its own to provide solutions to complex problems (Lee et al. 2018). It helps in developing intelligent systems which mimics human intelligence to analyse intricate problems (Leo Kumar 2017). AI systems can perform intelligent tasks such as learning, communicating, interpreting and decision-making making (Ahmad et al. 2021; Ali et al. 2021). Therefore, AI can help in analysing and solving critical issues associated with SM, such as product design, decision-making, optimising material and energy resources, waste management, and minimising emissions. The adoption of AI can eliminate human intervention in complex problems involving large and imprecise data and thus the bias in the decision process is also obviated. The growth and development of AI technologies have proliferated their applications in different sectors such as healthcare, manufacturing, aerospace, and banking. It is expected that AI will play a pivotal role in SM in the years to come. Many recent studies have also discussed the benefits of adopting AI in manufacturing to get sustainable benefits.

While there is a growing body of literature on the potential benefits of AI in SM, there are certain gaps in terms of practical implementation of AI in manufacturing industry. This can be attributed to several factors such as the lack of IT infrastructure, lack of technical knowhow, the complexity of integration of AI with the manufacturing systems, and the high costs of AI-based solutions. While AI has the potential to significantly improve the sustainability of manufacturing processes, there is a need to address the potential negative impacts of AI on employment, inequality, and the environment. Additionally, there is a lack of research on the integration of AI with other advanced technologies such as IoT. The integration of AI with IoT can improve the efficiency and sustainability of manufacturing processes by allowing real-time monitoring and control of machines and resources.

Therefore, it is important to analyse the various facets of the current status of AI applications in SM so that a future roadmap can be delineated. From the ongoing discussion, the following research questions have been formulated.

RQ1. *What are the present research trends in the area of AI in SM?*

RQ2. *What are the areas of SM which have been supported by AI?*

RQ3. *What are the possible future research scopes in the area of AI in SM?*

To answer the above research questions, this article presents a systematic review of published articles focusing on AI in SM. The novelty of this article is that it presents a bird's-eye view of current research trends of AI applications in SM. The article looks at AI applications in SM from a holistic perspective and discovers five prominent research themes of this domain. The article also clearly spells out four research propositions for the future.

The rest of the article is arranged as follows. Section 2 presents the methodology adopted in this review article. Section 3 and section 4 present the results of the bibliometric study and network analysis respectively. Section 5 presents the content analysis of selected articles. Discussion of findings, implications and unique contribution of the study are presented in section 6. Section 7 includes conclusions and future research directions.

2 Methodology

A literature review is an important reflection of any research domain (Dhiaf et al. 2021). It provides valuable insights of the selected topic and also outlines future research directions (Govindan et al. 2015; Sharma et al. 2020). Based on the literature review of an academic field, research gaps can also be identified (Tranfield et al. 2003). There are different types of literature review like narrative, descriptive, scoping, systematic etc. The systematic review starts with some specific research questions, and then attempts to answer those through the review of relevant articles following some well-defined steps. The flowchart of the adopted methodology is presented in Figure 1.

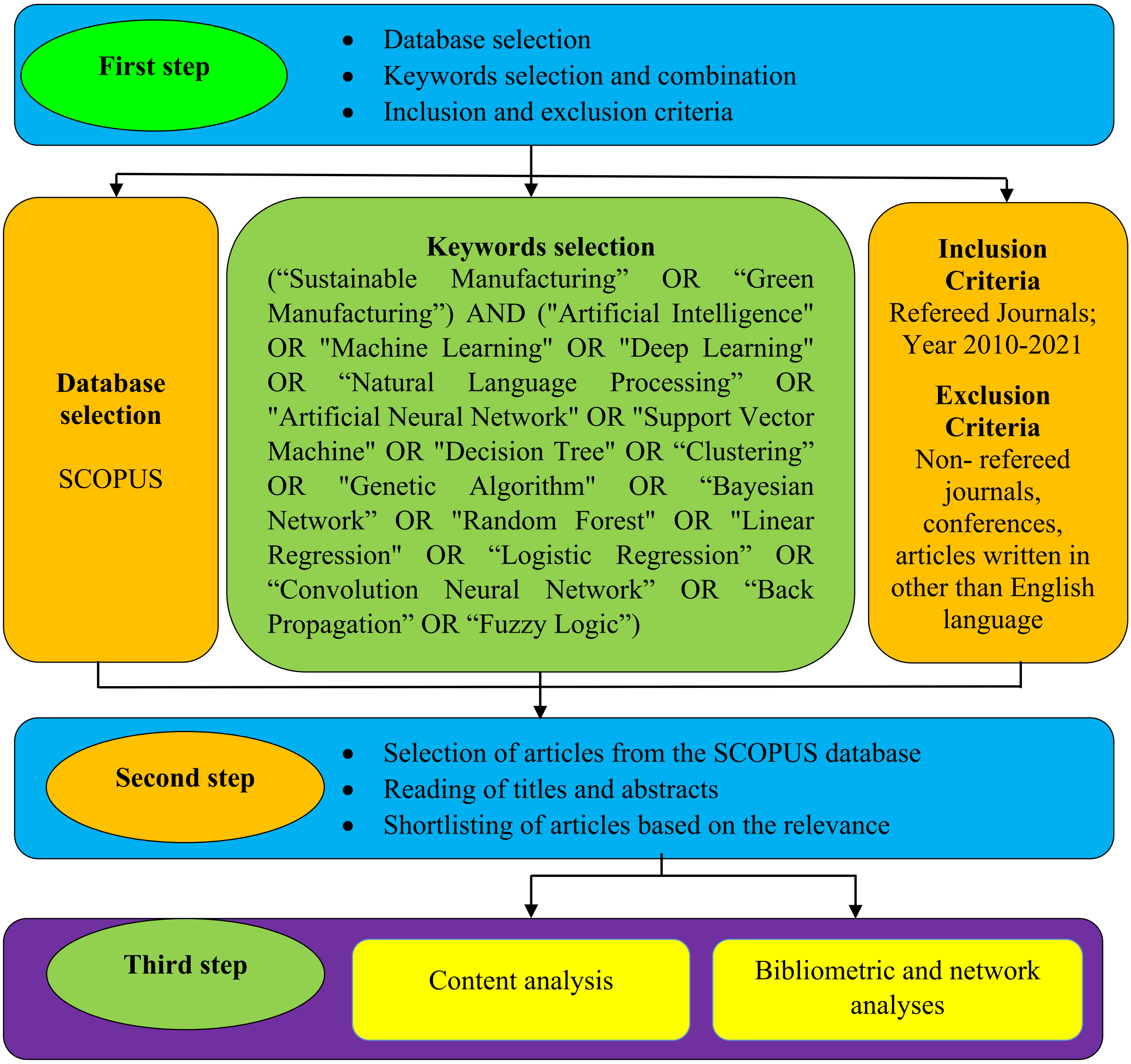

Fig. 1 The flowchart of methodology

2.1 Database Selection

In this study, relevant sources of publications were analysed in the field of AI in SM. SCOPUS database has been used in the study to identify the articles in the field of AI in SM. SCOPUS database is considered as it is one of the largest databases of articles from reputed publishers such as Elsevier, Emerald Insights, Springer, IEEE, Wiley, Tailor and Francis, and Inderscience (Sharma et al. 2020). It is considered to be more comprehensive as compared to other databases like Web of Science or Google scholar (Mongeon and Paul-Hus 2016). While Web of Science covers 24952 journals, SCOPUS encompasses 39237 journals (Majumdar et al. 2022).

2.2 Keywords Selection

This study explores the integration of two emerging research areas (artificial intelligence and sustainable manufacturing). For the identification of relevant articles, one of the critical aspects is the selection of keywords. It ensures that only relevant articles are selected while eliminating irrelevant ones. The selected keyword combinations used in this research are shown below:
("Sustainable Manufacturing" OR "Green Manufacturing") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Natural Language Processing" OR "Artificial Neural Network" OR "Support Vector Machine" OR "Decision Tree" OR "Clustering" OR "Genetic Algorithm" OR "Bayesian Network" OR "Random Forest" OR "Linear Regression" OR "Logistic Regression" OR "Convolution Neural Network" OR "Back Propagation" OR "Fuzzy Logic")

2.3 Inclusion and Exclusion Criteria

Only peer-reviewed journals published in the English language have been included in this study. The duration of the study spans from 2010-2021. Non-refereed journals, conference papers, and magazine articles were excluded from the study as they may not always go through the stringent peer-review process. Initially, 368 articles were collected from the SCOPUS database by using the selected keyword combinations. Then by using inclusion and exclusion criteria, 240 articles were shortlisted. Further refinement of articles was done by reading the titles and abstracts to ensure that the selected articles matched the focus of this study. Finally, 196 articles were considered for content analysis.

3 Bibliometric Analysis

3.1 Publication Trends

Bibliometric analysis is a well-defined study used to collect the research articles' statistical information in a particular field (Fahimnia et al. 2015). Many researchers have used the bibliometric study to analyse the trend of research and to get insights into the topic (Sharma et al. 2020). The bibliometric study includes analysis of data related to authors, authors' affiliation, country collaboration, keywords, publication trends, and so on (Firdaus et al. 2019). There are many packages available to perform the bibliometric study, namely SATI, CiteSpace, BibExcel, HistCite, and R package (Firdaus et al. 2019). R package is an open-source software that provides excellent web-interface to perform bibliometric studies (Agrawal et al. 2021). So, in this study, the R package was used for bibliometric analysis. Various statistics related to authors, journals, countries, and keywords have been analysed. The year-wise publications of articles in the field of AI in SM are presented in Figure 2. It is observed that the interest in this area has grown over the years and more rapidly after 2015 which coincides with the adoption of sustainable development goals (SDG) by the United Nations. Between 2016 and 2021, the number of publications increased by 281% (from 16 to 61).

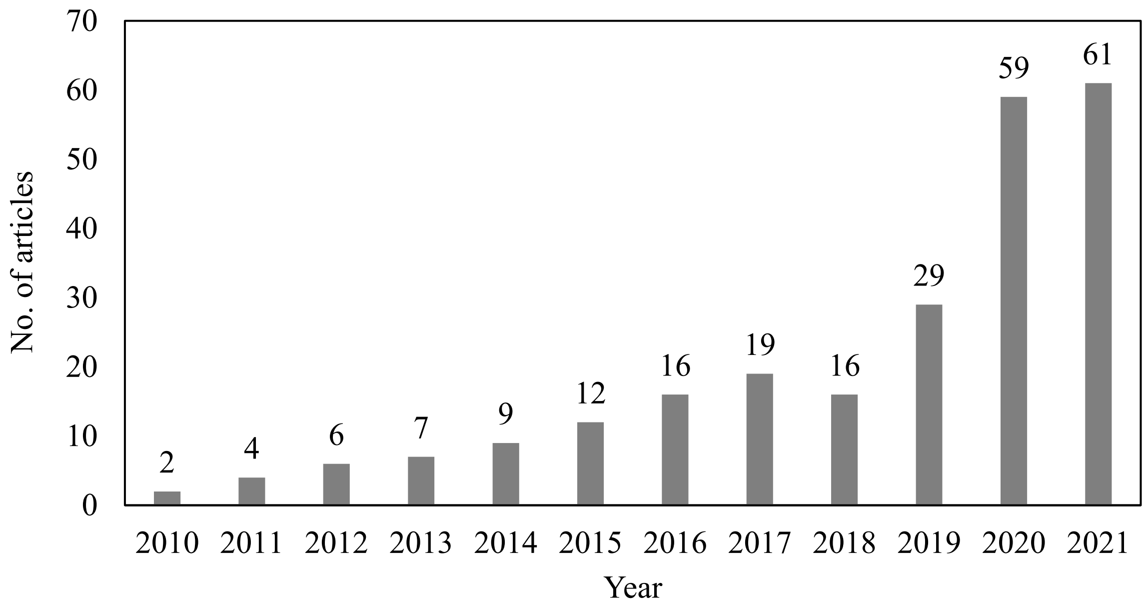

Fig. 2 Year-wise trend of article publication in the field of AI in SM

3.2 Citations Statistics of Articles

The top ten articles that received the highest citations are presented in Table 1. It is observed that Kusiak (2018) received the highest number of citations (304) for his pioneer paper on 'smart manufacturing', followed by Luo et al. (2013) and Liu et al. (2014) with 237 and 182 citations respectively. Kusiak (2018) discussed the origin, current status, and future development possibilities in smart manufacturing. The author critically examined the smart manufacturing concept as a growing form of production that integrates manufacturing resources with computing platforms, sensors, control, simulation, predictive engineering, data-intensive modelling, and communication technology. Luo et al. (2013) presented a metaheuristic-based ant colony optimisation algorithm that not only enhanced production efficiency but also reduced electricity costs in a job shop. Liu et al. (2014) proposed a multi-objective scheduling approach, using a genetic algorithm, which reduced the energy consumption of processes and minimised the total tardiness of the job.

Table 1 Top ten globally cited documents in the area of AI in SM

Author	**Title of the paper**	**Total citations**	**Citations per Year**
Kusiak (2018)	"Smart manufacturing"	304	76.00
Luo et al. (2013)	"Hybrid flow shop scheduling considering machine electricity consumption cost"	237	26.33
Liu et al. (2014)	"An investigation into minimising total energy consumption and total weighted tardiness in job shops"	182	22.75
May et al. (2015)	"Multi-objective genetic algorithm for energy-efficient job shop scheduling"	126	18.00
Vikhorev et al. (2013)	"An advanced energy management framework to promote energy awareness"	125	13.89
Yildirim and Mouzon (2012)	"Single-machine sustainable production planning to minimise total energy consumption and total completion time using a multiple objective genetic algorithm"	122	12.20
Tuptuk and Hailes (2018)	"Security of smart manufacturing systems"	90	9.00
Ghadimi et al. (2012)	"A weighted fuzzy approach for product sustainability assessment: a case study in automotive industry"	90	22.50
Panetto et al. (2019)	"Challenges for the cyber-physical manufacturing enterprises of the future"	82	27.33
Wang et al. (2015a)	"A systematic approach of process planning and scheduling optimisation for sustainable machining"	78	11.14

3.3 Keyword Statistics

The keyword statistics aims to identify the important keywords used by researchers in the field of AI in SM. The top twenty keywords used by researchers are presented in Table 2. From Table 2, it is noted that the most frequently used keywords are basically covering three facets, namely sustainability dimensions, operation management functions, and AI techniques. Green manufacturing, sustainable manufacturing, sustainable development, energy utilisation, energy efficiency, and environmental impact are the major aspects of sustainability dimensions covered in the literature. Green manufacturing and sustainable manufacturing are the two most prevalent keywords with a frequency of 74 and 65 respectively. Forecasting, decision-making, scheduling, optimisation, and decision support are the major operations management functions that have found a lot of applications of AI. The major techniques of AI are found to be genetic algorithm, Artificial Neural Network (ANN), and fuzzy logic. It is noteworthy that any keyword related to social sustainability does not find its place in the list of top 20 keywords. This implies that SM research aided by AI has helped primarily augmented the environmental dimension of sustainability. Further, a word cloud has been formed to see the most frequent words as depicted in Figure 3.

Table 2 Top twenty keywords used by the researchers

Words	Occurrences	Words	Occurrences
Green manufacturing	74	Multi-objective optimisation	19
Sustainable manufacturing	65	Optimisation	19
Genetic algorithms	53	Environmental impact	16
Sustainable development	50	Artificial neural networks	15
Energy utilisation	48	Manufacturing	14
Manufacture	45	Forecasting	13
Artificial intelligence	30	Industrial research	13
Energy efficiency	30	Fuzzy logic	12
Decision making	23	Learning systems	12
Scheduling	21	Decision support systems	11

Fig. 3 Word cloud of most frequently used keywords

4 Network Analysis

The aim of network analysis is to evaluate the association and associative strength between keywords and articles. The association between articles is evaluated through a co-citation network and bibliometric coupling network. The analysis of clusters formed by the network analysis helps to identify research themes within the domain of interest.

4.1 Keyword Co-occurrence

In this study, only those keywords having a minimum occurrence of 2 were considered and thus the number of keywords was reduced from 2230 to 85. The Keyword overlay network is presented in Figure 4 which shows the chronological changes in the use of different keywords. From the network diagram, it is found that 4 clusters were formed. Cluster 1, the biggest one, contains 23 keywords while cluster 2, cluster 3, and cluster 4 have 22, 22, and 18 keywords respectively. The keyword co-occurrence network reveals that sustainable manufacturing, green manufacturing, sustainable development, and artificial intelligence are the most networked keywords with 78, 78, 78, and 56 links with other keywords and total link strength are 471, 345, 312, 173. From the keyword overlay network, it is found that the keyword product design, production planning, production control, clustering algorithms, machining centres etc. were popular in 2016-2017, whereas sustainable manufacturing, green manufacturing, energy utilisation, artificial neural network, NSGA-II, and sustainable development were emerging in 2018-2019. Finally, keywords related to digitalisation like Industry 4.0, Big Data, ML, and Deep Learning are emerging in recent years (2019-2021) showing the new directions of AI in SM.

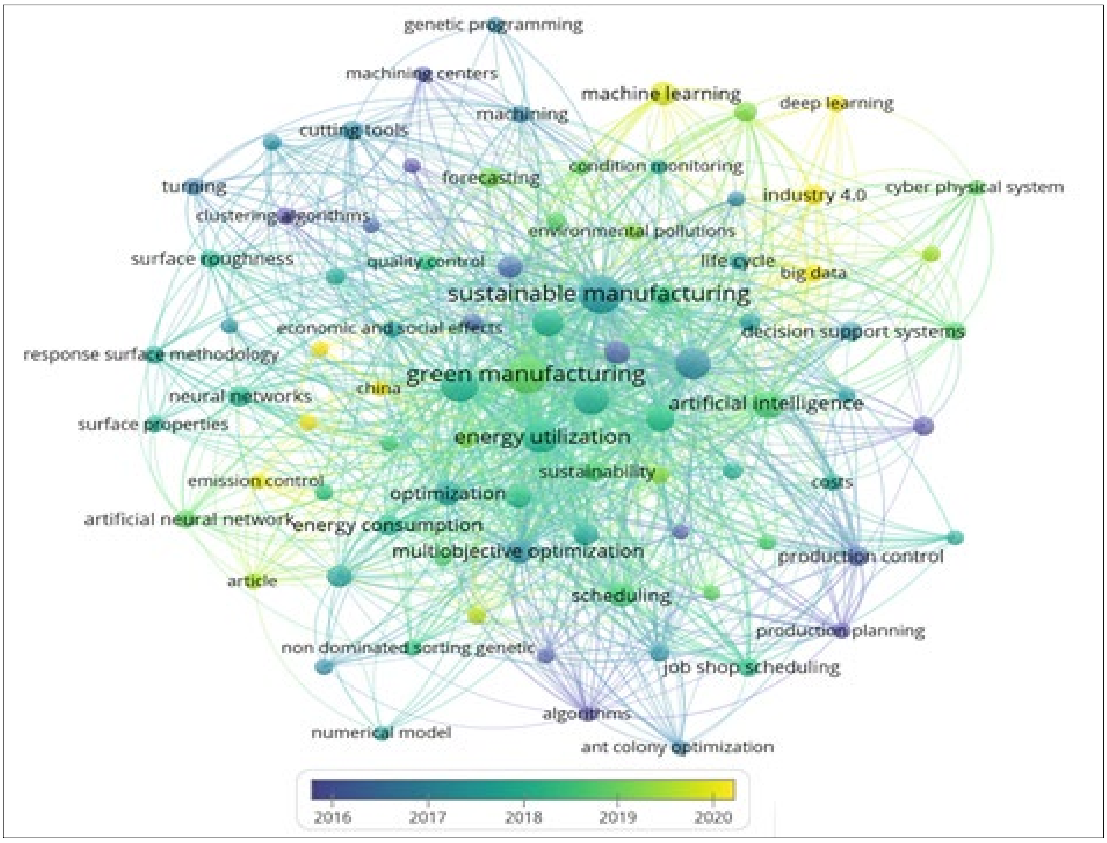

Fig. 4 Keyword overlay network

4.2 Co-citation Analysis of Authors

Co-citation of authors occurs when the two authors are cited together in another article. As articles connected through co-citation are expected to have some commonality, co-citation helps to identify sub-themes within a research domain. In 196 articles considered in this research, there are 9450 cited references and 17437 cited authors. We considered only those authors who received at least 15 citations and thus the count of cited authors was reduced to 120. Figure 5 presents the co-citation network of the authors. It is found that there are 4 clusters with a total of 5357 links between the cited authors. Cluster 1 (red) is the biggest cluster with 38 authors while cluster 2 (green), cluster 3 (blue), and cluster 4 (yellow) have 34, 28, and 20 authors respectively. The red cluster belongs mainly to Chinese authors, and they focused primarily on energy consumption, environmental impact, and process parameter optimisation. The top authors in the red clusters are Liu H, Zhang H, and Zhang Y with 117, 114, and 114 links and 1935, 1691, and 1660 total link strength. The top authors in cluster 2 (green) are Li X and Zhang C with 114 and 112 links and 2405 and 1586 total link strength and they focussed mainly on process planning and scheduling. Deb K., who developed the non-dominated sorting genetic algorithm II (NSGA-II), is also present in cluster 2. The top authors in cluster 3 (blue) are Gunasekaran A., Govindan K., and Jabbour C. J. C. with 81, 76, and 70 links and 902, 602, and 625 total link strength. The other important authors in this cluster are Dubey R., Diabat A., and Bag S. It is interesting to note that these authors in cluster 3 are leading and well-known contributors in the field of sustainable supply chain management. In the last cluster 4 (Yellow), the top authors are Zhang L, Tiwari M. K., and Dolgui A. with 110, 74, and 54 links and 1839, 240, and 328 total link strength and they focused mainly on sustainable routing, Industry 4.0, and mathematical modelling.

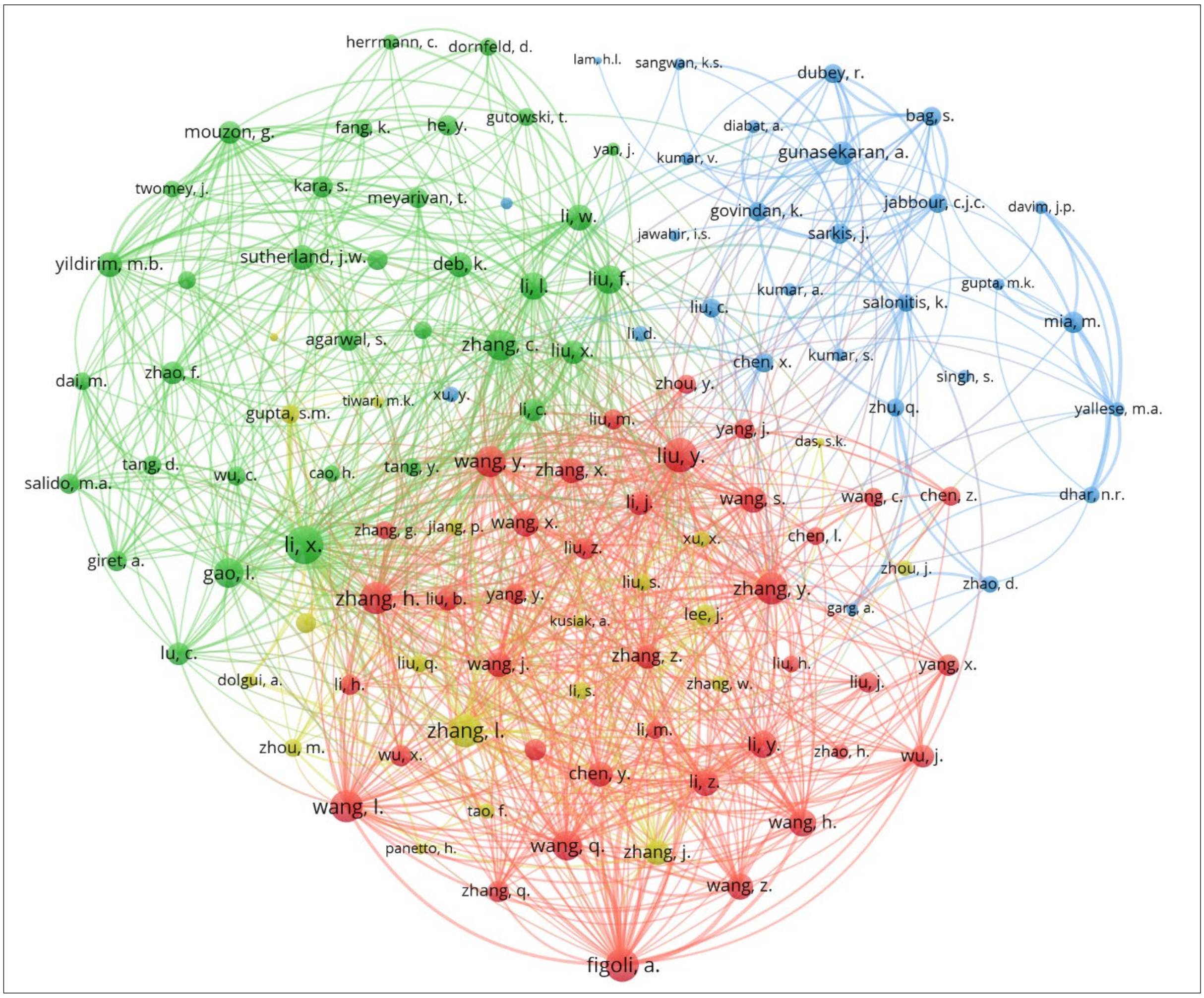

Fig. 5 Co-citation of cited authors

4.3 Prominent Research Themes

Bibliographic coupling of articles was considered to identify prominent research themes. Bibliographic coupling occurs when two articles cite a common article in their reference (Pirri et al. 2020). Bibliographic coupling measures the similarity relationship among considered documents. Out of 196 articles, only those articles which have at least five citations were considered and thus the number of articles was reduced to 94. After clustering, five clusters include 73 articles while the rest of the articles were removed due to a lack of connectivity with other articles. The clustered were named after reading the articles of each cluster and finding the common thread among them. These are sustainable scheduling, smart manufacturing and remanufacturing, energy consumption, sustainable practices and performances, and smart disassembly and recovery. Cluster 1 (red) is the biggest one containing 20 articles while cluster 2 (green), cluster 3 (blue), cluster 4 (yellow), and cluster 5 (Violet) have 17, 13, 13, and 10 articles respectively. Figure 6 shows the thematic clusters and the leading articles. The five leading articles, based on the link strength, of each cluster, are presented in Annexure (Table A1.)

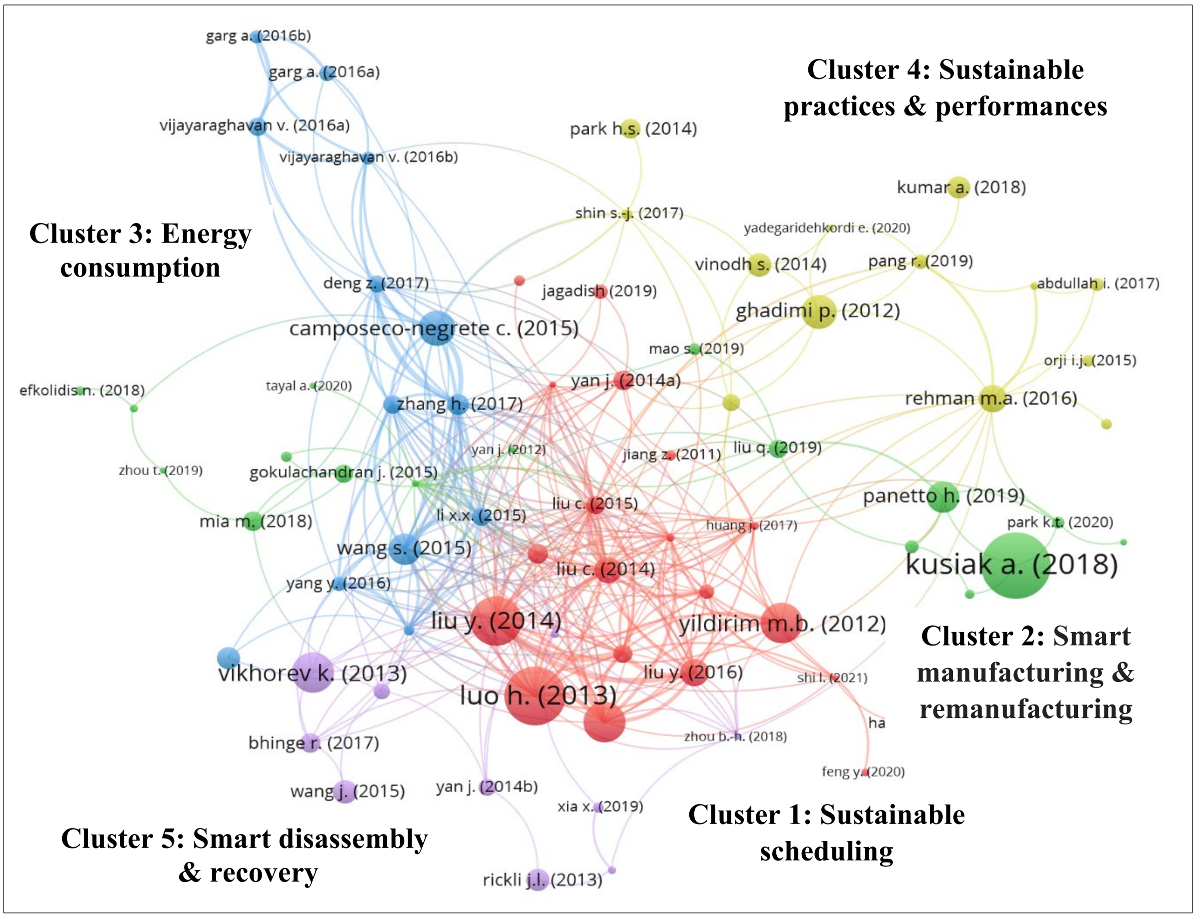

Fig. 6 Clustering of articles based on prominent research themes

5 Content Analysis

This section presents the content analysis of published articles in the field of AI in SM. This section is divided into various subareas such as AI techniques, smart product design, process scheduling, green manufacturing, smart manufacturing, decision support system, energy management, smart maintenance, emissions in smart manufacturing, smart disassembly and recovery of product, and performance assessment of AI in SM.

5.1 AI Techniques

Figure 7 shows the distribution of applications of different AI techniques in SM. GA (23%) is the most widely used technique followed by ANN (21%) and fuzzy logic (15%). NSGA-II, clustering, regression, and SVM have been used in 11%, 8%, 8%, and 6% of research papers respectively. However, CNN, Deep Learning, decision tree, Tabu search, etc. have been used in a very limited way.

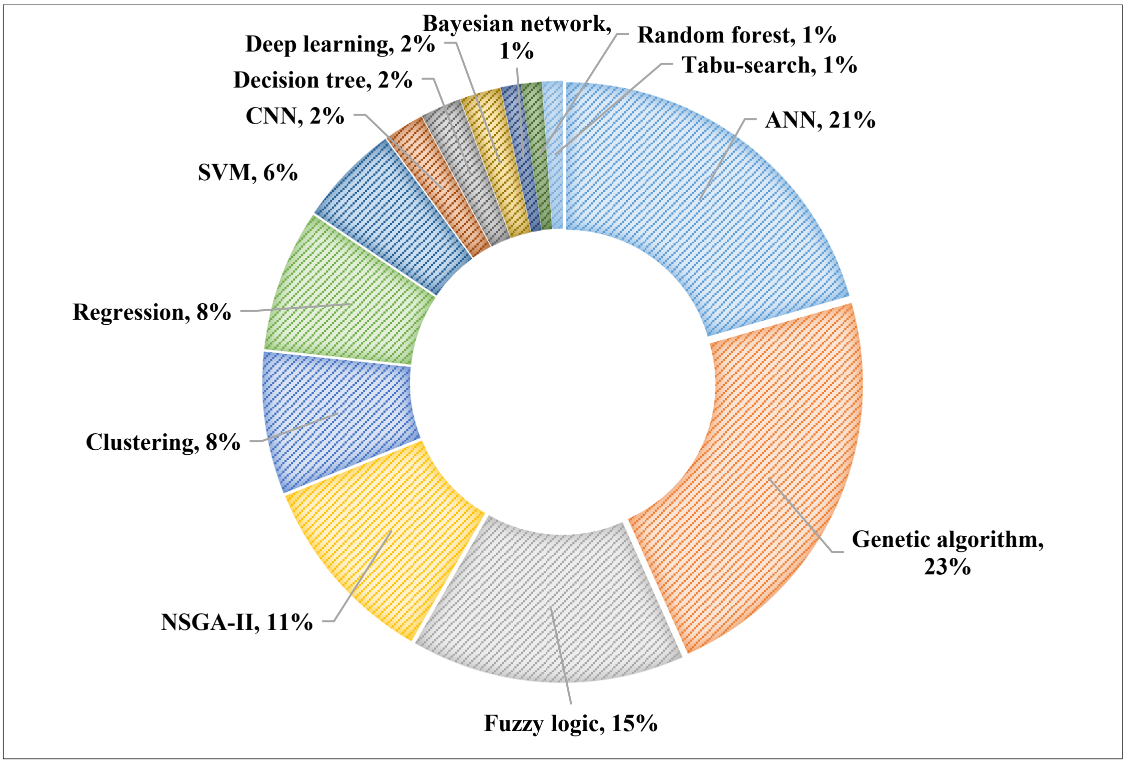

Fig. 7 Applications of various AI techniques in sustainable manufacturing

GA, which takes inspiration from the natural evolution process, can overcome the problem of gradient-based traditional optimisation algorithms which may often get stuck in local minima. GA and its variant NSGA-II (Deb et al. 2002) have been used in diverse optimisation problems related to routing and scheduling (Mokhtarinejad et al. 2015), supplier performance (Fallahpour et al. 2017), and decision support system for vendor-managed inventory (Borade and Sweeney 2015). ANN mimics the behaviour of biological neurons, and the connecting weights are optimised by supervised, unsupervised, or reinforcement learning (Lotter et al. 2020). ANN is a very potent tool for data modelling or classification. ANN has been used for demand forecasting (Bala 2012), and supplier performance prediction (Vahdani et al. 2012). Fuzzy logic has the capability of imprecision handling as it uses fuzzy sets which do not have clearly defined boundaries (Jagadish et al. 2019). The powerful learning capability of ANN and the excellent imprecision handling ability of fuzzy logic are combined in neuro-fuzzy systems (Jang 1993) which have been used to predict cutting tool life (Gokulachandran and Mohandas 2015). SVM has been used in many fields of SM including analysis of demand distortion (Carbonneau et al. 2007), and decision model for risk management (Rajesh 2020). In recent years, the application of deep neural networks and convolution neural networks is slowly gaining momentum to handle image processing-related problems (Traore et al. 2018). Decision tree has been applied to develop a decision support system to select strategies to minimise supply chain risk (Mogre et al. 2016). Hybrid AI techniques which amalgamate multiple techniques have often been used to take the complementary benefits of individual components. Some key applications of AI in SM have been presented in Table 3.

Table 3 AI techniques in SM

Article	**Research focus**	**AI technique**	**Results**
Leong et al. (2019)	The backpropagation ANN was used in effective decision-making to adopt lean and green concepts in smart manufacturing	ANN	The proposed ANN model is expected to enhance the firm's performance and enable lean and green production.
Yildirim and Mouzon (2012)	Energy consumption	GA	Optimal schedule which minimises energy consumption
Jagadish et al. (2019)	Development of a decision support system to predict and optimise machining process parameters	Fuzzy logic	The proposed model shows more than 95% accuracy and helps in identifying the most optimal process parameters to enhance the performance of green manufacturing processes.
Gokulachandran and Mohandas (2015)	Prediction of cutting tool life	Neuro-fuzzy logic and support vector regression	High accuracy of prediction of cutting tool life
Liu et al. (2015)	Production scheduling considering electricity	NSGA-II	4.4% reduction in carbon emissions

	consumption and tardiness		
Jia et al. (2017)	Production scheduling considering makespan and electricity cost	Ant colony optimisation	Better results are obtained compared to those with NSGA-II.
Rubaiee and Yildirim (2019)	Sustainable scheduling considering completion time and energy cost	Ant colony optimisation	Outperforms NSGA-II
Zhou et al. (2021)	Milling tool condition monitoring to support SM	Support vector machine	The proposed SVM model achieves an 85% classification rate and is effective in guiding tool replacement.
Jo et al. (2020)	Intelligent rework process to minimise defect rate and operational cost	Decision tree	An improved decision model for smart rework processing
Leng et al. (2021)	Order acceptance decision in PCB manufacturing considering cost, makespan, and carbon consumption	Deep reinforcement learning	Higher prediction accuracy with an eco-friendly order acceptance rate
Xin et al. (2021)	Sustainable scheduling considering makespan and total energy consumption	Whale swarm optimisation	9% reduction in average energy consumption and a 69% reduction in computational time.
Fertig et al. (2022)	Quality prediction for milling processes using machine tool data	Deep learning	92.45% accuracy in quality prediction with a precision of 93.14%

5.2 Smart Product Design

Product design for SM is a critical concept to manage the end life of a product effectively. Technologies like AI can help in developing smart products. Smart products are embedded with sensor technologies that allow data creation over time at any place for real-time monitoring. The data-driven smart product design using intelligent manufacturing has found its place in recent literature (Feng et al. 2020). The usage of AI can be an effective strategy in smart product design as well as its assessment. The decision tree approach of AI is an effective way of analysing alternate product design (Wang and Tseng 2011). Fuzzy logic is also seen as a useful technique in analysing the life cycle of a product (Recchioni et al. 2009). The green design of the product is an essential aspect of green manufacturing. In this regard, an AI based framework was developed by Zhang (2010) to analyse the performance of green product design. A weighted fuzzy assessment method is also an effective tool to analyse the sustainability of a product (Ghadimi et al. 2012). One of the ways in which AI can be used in product design is through the use of computer-aided design (CAD) software (Bonino et al. 2023). This software can be used to simulate and analyze the performance of a product in different environments and under different conditions. This allows designers to optimise the design of a product to minimise its environmental impact while still meeting the needs of the user. Another way of sustainable product design could be the use of machine learning algorithms which can be trained using large data sets to identify patterns and trends (Wang et al. 2023). This can help designers to create products that are more efficient, more durable, and more sustainable.

5.3 Process Scheduling

Scheduling is one of the most important operations management functions that attempt to minimise lateness, tardiness, and makespan. The intelligent monitoring of the system with the help of IoT sensors helps in the effective scheduling of machines. Wang et al. (2015a) used ANN to handle nonlinear relationships of process parameters with power consumption and surface quality for scheduling optimisation in the milling process. Industrial internet of things-based smart green resource allocation mechanism under 5G heterogenous networks showed an energy-efficient resource allocation model that was solved using deep reinforcement learning algorithms (Yu et al. 2022). Scheduling and an order acceptance problem were analysed by Kong et al. (2020) to maximise the total revenue using a modified variable neighbourhood search algorithm. Another study dealt with the sustainability criteria in manufacturing layout and presented a combined mathematical formulation for sustainable facility layout problems (Tayal et al. 2020). An integrated approach for edge computing-based smart green scheduling of the flexible workshop, under an uncertain machine state, optimised the energy consumption, processing quality, processing cost, and makespan (Feng et al. 2020). AI can also be used in process scheduling through the use of optimisation algorithms. These algorithms can be used to find the best schedule for a set of processes, taking into account factors such as system resources, process priorities, and deadlines (Chaaban 2023).

5.4 Green Manufacturing

Increasing pollution and high resource consumption are the major concerns in today's manufacturing scenario (Malek and Desai 2020). Green manufacturing is defined as “a system that integrates product and process design issues with issues of manufacturing planning and control in such a manner to identify, quantify, assess, and manage the flow of environmental waste with the goal of reducing and ultimately minimising environmental impact while trying to maximise resource efficiency” (Govindan et al. 2015). AI tools are nowadays being used for effective resource allocation along with waste minimisation to support green manufacturing. AI can be trained using historical data to predict equipment failures, energy consumption, and material usage (Mhlanga 2023). This information can be used to optimise the manufacturing process, reduce downtime, and improve energy efficiency. Use of text mining approach, employment of skilled workforce and government organisations' role were the important factors in improving the sustainable aspects of the manufacturing industries (Bhanot et al. 2016). AI have the ability to improve the efficiency of processes by 15-20% (Arnold et al. 2020). AI helps in task optimisation, and smart scheduling which helps in minimising the resource consumption (Abubakr et al. 2020). The adoption of latest technologies helps in enhancing the acceptance of green manufacturing in small-medium organisations also (Singh et al. 2020). Gholizadeh and Fazlollahtabar (2020) reported that genetic algorithm can be a useful technique to maximise the profit of manufacturing firms by considering environmental hazards.

5.5 Smart Manufacturing

The smart manufacturing concept integrates computing platforms, sensors, actuators, controllers, simulation, predictive engineering, data-intensive modelling, and communication technology (Kusiak 2018). AI has the potential to enable smart manufacturing by utilising intelligent algorithms which can mimic human intelligence. The growth and availability of AI technologies have made a significant revolution in manufacturing systems which are mostly operated and controlled with the help of computers rather than by a human. This has led to the emergence of smart manufacturing replacing the traditional manufacturing system. Literature shows several applications of AI and ML in smart manufacturing, such as decision-making, predicting accurate demand, and improving supply chain management (Cioffi et al. 2020). The impact of AI and ML in the current manufacturing environment was analysed by Cioffi et al. (2020). The backpropagation ANN was used in effective decision-making to adopt lean and green concepts in smart manufacturing (Leong et al. 2019). Senthiil et al. (2019) demonstrated that AI can optimise the process parameters which minimises the environmental impact associated with the manufacturing process. In recent work, a framework was established by integrating Industry 4.0 technologies with SM to analyse the research avenues in manufacturing sector (Bag and Pretorius 2020). AI can also be used in smart manufacturing through the use of automation and robotics. AI-powered robots and other automated systems can be used to perform tasks that are traditionally done by workers (Nagaty 2023). This can increase efficiency and productivity while reducing labour costs. Tuptuk and Hailes (2018) highlighted certain challenges such as cyber-attacks which need to be taken care while adopting AI in the manufacturing sector.

5.6 Smart Maintenance

Smart maintenance involves continuous monitoring of signals and parameters to be used by AI platforms. AI applications in smart maintenance primarily focus on condition monitoring of the machine and predictive maintenance. The use of Industry 4.0 technologies such as IoT, AI, ML, and Big Data analytics help in collecting and analyzing the real-time machine data, which enables proper monitoring of machine conditions. The use of Big Data analytics was explored to optimise the maintenance schedule with condition-based maintenance optimisation (Kumar et al. 2018). The condition monitoring and predictive analytics can help to improve the reliability of equipment which in turn reduces the maintenance cost (Murgia et al. 2023).

5.7 Decision Support Systems

The use of AI techniques facilitates effective decision-making in the manufacturing environment by eliminating human intervention. A Decision Support System (DSS) comprising of genetic algorithm was developed to analyse the ability to remanufacture a product with minimum calculation time over a set of end-of-life strategies (Yang et al. 2016). DSS utilising AI techniques also help to optimise the manufacturing process under constraints thereby improving the sustainable performance of manufacturing processes (Shin et al. 2017). According to Zarte et al. (2019), the focus should be given on the economic and social aspects of sustainability to enhance the control and planning operations using AI techniques. A fuzzy logic decision support system was used by Jagadish et al. (2019) to predict and optimise machining process parameters enhancing the performance of green manufacturing processes.

5.8 Disassembly of Product

Disassembly is an important stage of circular supply chain in which post-consumer products are disintegrated into sub-assembly and components. Implementation of intelligent technologies enables significant benefits in disassembly process. Usage of AI technologies enhances human-robot coordination which enables smart disassembly. The use of genetic algorithm has shown significant contribution in optimising the disassembly sequences depending on recovery reprocessing costs, revenues, disassembly operation costs, and environmental impacts (Rickli and Camelio 2013). The human-robot collaborative disassembly has made significant impact on environmental, social, and economic benefits (Liu et al. 2019). A process management system for intelligent rework was proposed by Jo et al. (2020) to overcome the defective items rework problems on the shopfloor. The proposed approach provided preventive rework measures with hidden defects using an intelligent rework policy. Some recent theories developed in the disassembly process enabled decision-makers to ensure the right way for disassembly sequence planning (Guo et al. 2021).

5.9 Energy Management

Analysis of energy consumption is of paramount importance to understand the sustainability level at different product manufacturing stages. The application of AI can easily provide insights into the energy management practices. The industries utilised AI techniques to monitor and manage energy consumption (Vikhorev et al. 2013). The application of AI techniques namely ANN and Gene Expression Programming was also seen in determining the best possible input parameters of the mass finishing process for minimising energy consumption and material removal rate (Vijayaraghavan and Castagne 2016). Furthermore, the chaos quantum group leader algorithm helped to analyse the material with minimum energy consumption for developing product with varied complexities (Tao et al. 2016). The genetic algorithm based bi-objective optimisation model can minimise non-productive energy consumption and make span of batch processing machine (Jia et al. 2017; Liu et al. 2016). Several other researchers have optimised the process parameters to minimise energy consumption using AI based optimisation tools (Deng et al. 2017; Nujoom et al. 2018). Varied customised orders with different specifications cause higher energy consumption and environmental pollution. Leng et al. (2021) used Deep Learning techniques to develop a decision-making model for order acceptance of PCBs, enhancing material utilisation, improving energy efficiency, and reducing carbon emissions. In another work, the scheduling problem considering setup time and conveyor speed control was addressed to determine the optimum sequence of job while minimising energy consumption (Xin et al. 2021).

5.10 Emissions in Manufacturing

One of the major concerns of SM is the generation of harmful emissions. To cope with this challenge, manufacturing sectors are striving hard to minimise their emissions. AI can help in analysing the harmful emissions and aid in decision-making to minimise them. A mathematical model was developed by Huang et al. (2017) to analyse the carbon emissions from manufacturing process. Usage of random forest modelling and sensor fusion was used by Nasir et al. (2020) to analyse sound, vibration, power, and acoustic emissions. Yang et al. (2020) demonstrated that genetic algorithm can be an effective approach to address a product configuration problem of carbon emissions.

5.11 Sustainability Performance Assessment

Manufacturing sector is considered to be one of the actors for sustainable development as it creates employment and improves social life of livelihood. The evaluation of sustainability in manufacturing firms is very crucial for their further development (Vinodh et al. 2011). Different models have been propounded in literature to analyse the sustainability of manufacturing sector such as fuzzy assessment model (Pirraglia and Saloni 2012), grey assessment model (Agrawal and Vinodh 2020). Various assessments were seen in literature to enhance the sustainability aspect of manufacturing sector such as assessment of supplier behaviour towards green manufacturing (Orji and Wei 2015), critical success factor of SM (Habidin et al. 2018), enablers of SM for low carbon performance (Ali et al. 2020) and indicators of SM (Yadegaridehkordi et al. 2020). Adoption of different strategies and technologies were seen in literature to enhance the sustainability of manufacturing firm such as integration of lean and green manufacturing (Leong et al. 2020), adoption of Industry 4.0 (Vinodh et al. 2021) and adoption of bigdata analytics (Bag et al. 2021).

6 Discussions

6.1 Discussion on the findings

The study presents a compendium of AI applications in SM through a systematic bibliometric and network analyses of 196 articles identified from the Scopus database. Various aspects of bibliometric and network analyses encompassing document type, author statistics, country statistics, keyword co-occurrence, co-citations, and bibliometric coupling have been performed. From the bibliometric analysis, important journals, leading authors and countries, and significant research trends were recognised. In this section, we attempt to answer the research questions

6.1.1 RQ1. What are the present research trends in the area of AI in SM?

While searching for the answer to the first research question, it is found that AI applications in SM is growing at an exponential rate and it has pervaded in every sphere of manufacturing. Three AI techniques, namely GA, ANN and fuzzy logic have been predominantly used in SM. GA has been used as an optimisation tool either with single or with multiple objectives (cost, time, energy etc.). In recent years, NSGA-II has emerged as a popular optimisation tool as it can provide multiple solutions in the form of Pareto optimal front. ANN has been used mostly for modelling and forecasting with backpropagation algorithm. Fuzzy logic has also been used in cases where the input data has imprecision or ambiguity. Deep learning and CNN have started to find their way in the last few years as evidenced by the overlay depiction of keywords. The former has the advantage that it can work with the raw data almost without any pre-processing. The data collected from the manufacturing environment is often noisy and it can be denoised using stacked encoders. On the other hand, CNN has immense potential in quality control and defect identification as it can efficiently deal with images. It has already been used in areas like surface roughness evaluation and detecting the thickness of coating on semiconductor devices (Henn et al. 2019) and their applications will definitely grow in the years to come. Another exciting application of CNN could be the human motion analysis for the human-robot collaboration.

6.1.2 RQ2. What are the areas of SM which have been supported by AI?

The current body of literature on AI applications in SM covers the entire domain of manufacturing including smart product design, process scheduling, green manufacturing, smart manufacturing, decision support systems, energy management, smart maintenance, emission control, disassembly of products, and sustainability performance assessment. In sustainable scheduling, the focus has revolved around the minimisation of resources and energy consumption along with minimisation of make span and tardiness (Yildirim and Mouzon 2012; Liu et al. 2014, 2016; Jia et al. 2017; Zhang 2017; Yu et al. 2021). Smart manufacturing and remanufacturing with the aid of AI has provided an impetus to the adoption of smart assembly and disassembly techniques along with reuse and remanufacturing activities to support sustainable development (Gokulachandran and Mohandas 2015; Mia et al. 2018; Panetto et al. 2019; Park et al. 2020; Zhang et al. 2020). A large number of complex decision-making in manufacturing environment has also been supplanted by AI based automated systems eliminating human judgement (Leong et al. 2019b; Meng et al. 2020). In energy consumption, a large number of articles have focused on minimising the energy consumption of the manufacturing processes (Wang et al. 2015a; Deng et al. 2017; Zhang 2017; Khan et al. 2019; Peng et al. 2019). Sustainable practices being adopted in the manufacturing sector has also received considerable attention from the researchers (Ghadimi et al. 2012; Vinodh et al. 2014; Shin et al. 2017; Kumar et al. 2018; Pang and Zhang 2019). In smart disassembly and recovery, adoption of smart disassembly techniques along with the reuse and remanufacturing activities to support sustainable development has received a lot of research focus (Rickli and Camelio 2013; Bhinge et al. 2017; Xia et al. 2019; Meng et al. 2020).

6.1.3 RQ3. What are the possible future research scopes in the area of AI in SM?

- ***Proposition 1:*** Sustainable scheduling, smart manufacturing and remanufacturing, energy consumption, sustainable practices and performances, and smart recovery and disassembly are the major themes that have seen predominant applications of AI techniques. Researchers should explore the integration of Industry 4.0 with these research themes so that further benefits of AI techniques can be achieved in SM.
- ***Proposition 2:*** GA, ANN, and fuzzy logic are the most popular AI techniques used in SM. There are ample opportunities to use hybrid AI techniques to get the synergistic benefits of multiple techniques. For example, ANN is a very powerful tool for function approximation, but it does not reveal any logical explanation about the underlying relationships. On the other hand, fuzzy logic provides linguistic rules which are easily comprehendible. However, it requires the knowledge of domain experts. Combining ANN with fuzzy logic, fuzzy rules can be developed using experimental data and this can be very useful for SM.
- ***Proposition 3:*** The research on SM using Big Data, CNN, Deep Learning, Decision Tree, Deep Learning, Bayesian network, and Random Forest are still at a nascent stage. Therefore, more emphasis should be given so that these emerging facets of AI can be successfully integrated with SM.
- ***Proposition 4:*** Almost all the research articles have revolved around the environmental sustainability while the application in the area of social sustainability has lagged behind. It is therefore important to pursue future research using AI techniques to improve health and safety aspects of workers, skill enhancement, community development etc. This could be a very strong research agendum for future.

6.2 Implications for Managers

AI in SM presents opportunities of some exciting applications in various facets of SM like smart product design, process scheduling, green manufacturing, smart manufacturing, decision support systems, energy management, smart maintenance, emission control, disassembly of product and sustainability performance assessment. The key insights developed from the previous studies will help practicing managers to assimilate the current status in this research field and also facilitate the adoption of some of the AI techniques in SM. Sustainable design of products will not only reduce the source consumption but also minimise the costs associated with disassembly and recycling paving the way of circularity. Managers can explore the immense potential of metaheuristics-based algorithms like GA, NSGA-II, ant colony optimisation etc. to optimise the job shop or flow shop scheduling minimising the energy consumption and make span. Another benefit that the managers could get from the adoption of AI is continuous health monitoring and predictive maintenance of machines utilising bigdata. There are myriad of decisions related to forecasting, production planning, materials requirement planning, inventory management etc. taken by the managers which consume significant time and effort. Some of these decisions can be made automated by integrating AI techniques in manufacturing. This will not only save enormous time but also eliminate the effect of human bias and monotony in decision making. At the same time, the managers should have open mind to embrace AI which will change at a rapid pace in the years to come. Therefore, they should be proactive to keep themselves abreast of changes in algorithms and technologies.

6.3 Implications for Researchers

Most of the research of AI in SM have relied on static and limited data. The emergence of bigdata, having volume, variety and velocity, has significantly increased the complexity of manufacturing decision making. From the perspective of energy management using AI, significant work has been done to monitor and manage the energy consumption in industries, however, the dedicated framework helping real-time monitoring, bigdata analytics and intelligent decision making require more translational research. Our study has highlighted that the application of bigdata for SM has attracted the attention of researchers only in last 2-3 years. Similarly, utilisation of AI for adoption of Industry 4.0 is another area where more research initiatives are needed. Use of hybrid AI techniques have a great potential to solve various problems of SM. While ANN can help in data modelling, fuzzy logic can aid in imprecision handling and GA and other metaheuristic algorithm can facilitate optimisation. However, most of the research has utilised AI techniques in disjointed manner, with neuro-fuzzy systems being the major exceptions. Therefore, researchers should couple ANN-GA, GA-fuzzy logic etc. to extract the synergistic benefit of these methods. Another promising area of AI that needs attention of researchers is application of convolutional neural network which can process the image files and thus has lot of potential in automated defect identification. Elimination of defects can help in reducing the wastage of materials and resources to a great extent.

6.4 Unique contribution of the study

This article presents a systematic review of articles to map the current trends of research of AI applications in SM and to develop a pathway future research. The study focusses on AI applications in SM from holistic perspectives. Prominent research themes of AI applications in SM have been identified along with the prevalence of various AI techniques. Thus, this article has created an intellectual map of the field that will help the academicians and practitioners to navigate through the subject. This study also identifies the research gaps in the field of implementation of AI techniques for sustainable manufacturing. The possibilities of future research that needs attention of research community have also been elucidated. Based on this study, four potential research propositions like amalgamation of AI with Industry 4.0, use of hybrid AI systems to yield synergistic benefits, focus on social sustainability and use of emerging techniques (Deep Learning, CNN, Decision Tree etc.) have been suggested. This will provide impetus to future research in the field of AI in SM and thus the academia as well as industry will be benefitted.

7 Conclusion

This article presents a holistic overview AI application in SM. Five major clusters or communities of research focussing on sustainable scheduling; smart manufacturing and remanufacturing; energy consumption; sustainable practices and performances; and smart disassembly and recovery have been identified.

The analysis of contents of selected papers show that AI has been used in all possible domains of SM though there are ample scopes to augment it further. In future, emerging AI techniques like CNN, Deep Learning, Random Forest etc. will require more attention form the researchers to solve specific research problems of SM. In this context, integration of Big Data, Industry 4.0, and AI deserves greater attention as it will pave the way for digital transformation of sustainable manufacturing with minimum human intervention. Application of hybrid AI techniques is another aspect that needs more attention from the researchers to elicit synergistic benefits of these powerful techniques. Another interesting research direction could be the role of AI in enhancing the social sustainability dimension in manufacturing industries.

This study possesses some limitations as it includes articles only from the SCOPUS database. The gamut of articles can further be extended by considering other databases such as Web of Science, Google scholar etc. Furthermore, this study includes only journal articles. This can be enriched by considering conference papers, book chapters, and reports. The present study looks at sustainable manufacturing through a holistic lens. This does not address industry-specific issues related to either sustainable manufacturing or AI techniques. Therefore, there is a scope to extend this review further with a specific analysis of select manufacturing sectors.

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Data availability statement

The data that support the findings of this study are openly available in the SCOPUS database and are available from the corresponding author on request.

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Table A1 Lead articles from the clusters

Authors	Title	Year	Journal	Citation	Main algorithm	Approach
Cluster 1 (Red): Sustainable scheduling						
Liu et al. (2016)	"A multi-objective GA for optimization of energy consumption and shop floor production performance"	2016	International Journal of Production Economics	65	GA	A multi-objective GA was deployed to minimise the total non-processing electricity consumption considering on job shop environment.
Liu et al. (2014)	"An investigation into minimizing total energy consumption and total weighted tardiness in job shops"	2014	Journal of Cleaner Production	182	NSGA-II	NSGA II was utilised to minimise the total weighted tardiness and total electricity consumption of classical job shop scenario.
Jia et al. (2017)	"Bi-criteria ant colony optimization algorithm for minimizing make span and energy consumption on parallel batch machines"	2017	Applied Soft Computing Journal	35	Pareto based colony optimisation (PACO), NSGA-II, SPEA2	PACO algorithm addressed the problem of reducing the total electric cost along with make span of a group of parallel identical batch processing machines.
Yildirim and Mouzon (2012)	"Single-machine sustainable production planning to minimize total energy consumption and total completion time using a multiple objective genetic algorithm"	2012	IEEE Transactions on Engineering Management	122	GA	Established a mathematical model to reduce the total completion time and energy consumption of a single machine. The multi-objective GA was used to achieve an approximate group of non-dominated alternatives.

Authors	Title	Year	Journal	Citation	Main algorithm	Approach
Zhang (2017)	"Sustainable scheduling of cloth production processes by multi-objective genetic algorithm with Tabu-enhanced local search"	2017	Sustainability (Switzerland)	7	GA, Tabu-enhanced local search	Constructed the three objective scheduling model including tardiness and environmental impact objectives. The problem was formulated using mixed integer programming technique and then multi-objective GA with Tabu local search was applied to investigate the computational time for sustainable cloth production scheduling.
Cluster 2 (Green): Smart manufacturing and remanufacturing						
Zhang et al. (2020)	"Analyzing sustainable performance on high precision molding process of 3D ultra-thin glass for smart phone"	2020	Journal of Cleaner Production	5	Quantum-behaved particle swarm optimisation (QPSO), and BPNN	Utilised the quantum-behaved particle swarm optimisation (QPSO) and back-propagation neural network (BPNN) to determine the carbon emissions and energy consumption of high-precision glass molding process.
Gokulachandran and Mohandas (2015)	"Comparative study of two soft computing techniques for the prediction of remaining useful life of cutting tools"	2015	Journal of Intelligent Manufacturing	31	Neuro fuzzy logic, Support vector machine (SVM), and regression technique	Experiments were carried out to obtain useful cutting tool life values using Taguchi approach. Further, efficacy of Neuro-fuzzy system and SVM regression was compared for the prediction of remaining useful life of cutting tools.
Park et al. (2020)	"Cyber Physical Energy System for Saving Energy of the Dyeing Process with Industrial Internet of Things	2020	International Journal of Precision Engineering	14	Synthetic minority over-sampling technique	Developed the cyber physical energy system for improving the energy efficiency of dyeing process using

Authors	Title	Year	Journal	Citation	Main algorithm	Approach
	and Manufacturing Big Data”		and Manufacturing - Green Technology		(SMOTE) and ANN	synthetic minority over-sampling technique (SMOTE) and ANN.
Mia et al. (2018)	“Prediction and optimization of surface roughness in minimum quantity coolant lubrication applied turning of high hardness steel”	2018	Measurement: Journal of the International Measurement Confederation	34	LS-SVM	Modelled the average surface roughness with respect to turning of hardness steel process parameters under minimum quantity coolant lubrication condition. Least square SVM (LS-SVM) was utilised to predict the roughness value at optimum process parameter.
Yan et al. (2012)	“Sustainable manufacturing-oriented prognosis for facility reuse combining ANN and reliability”	2012	Quality and Reliability Engineering International	5	ANN	Utilised ANN combined with reliability techniques to predict the remaining life of the reuse facilities.
Cluster 3 (Blue): Energy consumption						
Zhang et al. (2017)	“A process parameters optimization method of multi-pass dry milling for high efficiency, low energy and low carbon emissions”	2017	Journal of Cleaner Production	38	Principal component analysis (PCA), regression analysis GA	Identified the empirical model function coefficients by regression analysis and PCA using multi-pass dry milling experimental data. Further, GA was used to solve the optimisation model focusing on low carbon emissions, low energy, and high efficiency.
Wang et al. (2015a)	“A systematic approach of process planning and	2015	Journal of Cleaner Production	78	ANN	Systematic and innovative approach was developed for milling process planning and scheduling. The

Authors	Title	Year	Journal	Citation	Main algorithm	Approach
	scheduling optimization for sustainable machining”					relationship between the key parameters and surface quality and energy consumption was established using ANN.
Yang et al. (2016)	“Modeling and impact factors analyzing of energy consumption in CNC face milling using GRASP gene expression programming”	2016	International Journal of Advanced Manufacturing Technology	20	Greedy randomised adaptive search procedure (GGEP)	Utilised GRASP-based Gene Expression Programming (GGEP) learning algorithm to predict the energy consumption of CNC face milling process.
Khan et al. (2019)	“Multi-objective optimization of energy consumption and surface quality in nanofluid SQCL assisted face milling”	2019	Energies	31	Taguchi, Grey relational analysis and NSGA - II	A multi-objective optimisation of process parameters for CNC face milling was conducted using integrated Taguchi, grey relational analysis, and NSGA-II techniques. Further, the use of small quantity cooling lubrication was adopted to promote SM.
Peng et al. (2019)	“Towards energy and material efficient laser cladding process: Modelling and optimization using a hybrid TS-GEP algorithm and the NSGA-II”	2019	Journal of Cleaner Production	12	Gene expression programming (GEP), integrated Tabu search and GEP (TS-GEP)	Established a predictive model of metallic powder usage rate and specific energy consumption with respect to laser cladding process using GEP, response surface methodology and TS-GEP for appropriate parameters selection.

Cluster 4 (yellow): Sustainable practices and performance						
Kumar et al. (2018)	"A big data driven sustainable manufacturing framework for condition-based maintenance prediction"	2018	Journal of Computational Science	45	Fuzzy reasoning	Used big data analytics with fuzzy reasoning method to optimise maintenance schedule through condition-based monitoring with an accuracy of 97.61%.
Ghadimi et al. (2012)	"A weighted fuzzy approach for product sustainability assessment: A case study in automotive industry"	2012	Journal of Cleaner Production	90	Fuzzy Logic	A framework was developed to analyse sustainability of firm that was validated through a case of automotive industry
Pang and Zhang (2019)	"Achieving environmental sustainability in manufacture: A 28-year bibliometric cartography of green manufacturing research"	2019	Journal of Cleaner Production	21	Review	A review on environmental sustainability of manufacturing sector that suggested to adopt emerging technologies like AI, big data, and additive manufacturing to enhance the sustainable performance of manufacturing firm
Shin et al. (2017)	"Developing a decision support system for improving sustainability performance of manufacturing processes"	2017	Journal of Intelligent Manufacturing	13	Fuzzy logic in integration with decision support system (DSS)	A DSS based on fuzzy logic to optimise the process parameters for minimising energy consumption.
Vinodh et al. (2014)	"Development of decision support system for sustainability evaluation: A case study"	2014	Clean Technologies and Environmental Policy	47	Fuzzy logic	A computer based DSS was proposed by using fuzzy logic to analyse the sustainability of manufacturing firm

Cluster 5 (Violet): Smart recovery and disassembly						
Wang et al. (2015b)	“Enhanced particle filter for tool wear prediction”	2015	Journal of Manufacturing Systems	47	Bayesian network, autoregressive model and SVM	A model to predict tool wear which helps in ensuring machining quality and enables smart maintenance
Rickli and Camelio (2013)	“Multi-objective partial disassembly optimization based on sequence feasibility”	2013	Journal of Manufacturing Systems	45	Genetic algorithm	A GA based model to optimise disassembly sequence by considering operation cost, revenue, and environmental impacts.
Meng et al. (2020)	“Smart recovery decision-making of used industrial equipment for sustainable manufacturing: belt lifter case study”	2020	Journal of Intelligent Manufacturing	7	NSGA-II and cloud-based platform	A cloud-based conditioning monitoring was proposed with NSGA-II algorithm for effective decision making in recovery of equipment.
Bhinge et al. (2017)	“Toward a Generalized Energy Prediction Model for Machine Tools”	2017	Journal of Manufacturing Science and Engineering, Transactions of the ASME	35	Gaussian process regression machine-learning technique	Proposed a machine learning based prediction model to predict energy consumption of machine tools.
Xia et al. (2019)	“A balancing method of mixed-model disassembly line in random working environment”	2019	Sustainability (Switzerland)	11	Adaptive simulated annealing and GA	Proposed a mixed model for balancing disassembly line by using genetic algorithm