Computers & Industrial Engineering 165 (2022) 107964

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

# Artificial neural network-based decision support systems in manufacturing processes: A systematic literature review

Fredrick Mumali

*Institute of Management and Information Systems, Faculty of Engineering Management, Poznań University of Technology, 60-965 Poznań, Poland*

A R T I C L E  I N F O

*Keywords:*
Decision support systems
Intelligent decision support
Artificial neural networks
Manufacturing
Systematic literature review

A B S T R A C T

The use of artificial neural network models to enrich the analytical and predictive capabilities of decision support systems in manufacturing has increased. The growing complexity and uncertainty in the manufacturing sector demand improved decision-making to ensure low operations costs, high productivity, and sustainable use of resources. Artificial neural networks have the inherent capacity to analyze the most uncertain and complex patterns in unstructured decision problems. This review aims to synthesize and provide a comprehensive summary of recent studies on artificial neural network-based decision support systems as applied in manufacturing processes. First, the specific processes in manufacturing where artificial neural network-based decision support systems are used are analyzed. A total of 99 multi-disciplinary publications on artificial neural network-based decision support systems published between 2011 and 2021 are retrieved and processed following a rigorous execution of the designated acceptance criteria and quality assessment. A review of the selected studies indicates a growing interest in applying artificial neural networks in decision support systems. Product and process design, performance evaluation, and predictive maintenance are the main application areas identified. A growing tendency to combine artificial neural network models with other intelligent tools, notably fuzzy logic, and genetic algorithm, is noted to overcome drawbacks such as slow convergence when training the algorithms. Further research should extend to other tools for enriching the performance of artificial neural networks in manufacturing processes.

## 1. Introduction

Decision support systems (DSS) continue to evolve as manufacturing companies strive to remain adaptive in the face of an increasingly dynamic business environment. In recent years, manufacturing firms have seen an increase in complexity and uncertainty, necessitating more complex nonlinear model-based and data-based decision support systems. Artificial neural networks (ANN) are increasingly utilized in DSS, particularly model-based and data-driven approaches to enrich the analytical and predictive capabilities. Fonseca & Navaresse (2002) observed that ANN-based simulation models integrated into DSS significantly improve decision-making in complex scenarios requiring quick responses. ANNs are among the intelligent systems driving the performance of DSSs due to inherent algorithmic learning, fault tolerance, prototyping, and parallel processing capabilities, among other features. ANN has demonstrated its ability to be an effective tool in DSS in manufacturing, especially for classification and pattern recognition problems. Despite the plethora of research on ANN-based DSS in manufacturing environments, the ever-increasing uncertainty and complexity in unstructured decision problems necessitate a comprehensive understanding of the current state of ANN in DSS.

A DSS describes a piece of computer technology that provides substantial support to decision-makers in complex decision problems. DSSs help decision-makers use data, models, and computerized knowledge bases (Liao et al., 2012). The concepts of DSS proliferated in the 1970s with advances in computer technologies and information systems. Manufacturing is among the key areas where DSS is adopted due to complex decision-making processes associated with the sustainable production of products and services across industries. Several methods for DSS involving ANN have been developed to build robust and intelligent DSS (IDSS). As pointed, IDSS incorporates problem-solving tools of artificial intelligence with data, models, and expert knowledge to support decision-makers (Sarma, 1994). Artificial Intelligence techniques commonly used in creating IDSSs include ANN, fuzzy logic, genetic algorithms, and natural language processing.

This systematic literature review focuses on ANN-based DSS. ANNs are computer algorithms inspired by biological human brain structure and processes (Liao et al., 2012). As such, ANN can mimic the brain's

*E-mail addresses:* fredrick.m.mumali@doctorate.put.poznan.pl, frederickmumali@gmail.com.

https://doi.org/10.1016/j.cie.2022.107964
Received 7 October 2021; Received in revised form 10 January 2022; Accepted 15 January 2022
Available online 21 January 2022

process of accomplishing a particular function Fonseca et al., 2003). ANN can be described as interconnected neurons with great parallel computation power (Basheer & Hajmeer, 2000). ANN-based models can provide accurate solutions for poorly understood structured and unstructured decision problems (Basheer & Hajmeer, 2000). ANN provides a robust tool capable of handling the uncertainty and complexity of large datasets in manufacturing. ANN is divided into three layers: input, hidden, and output. The input layer receives normalized data from external sources. The data is passed on to the hidden layer comprising neurons that perform the processing and the output produced by its layer. The essential element of ANN is the neuron, which forms a connection distinguished by weights (Efendigil et al., 2009). The weights are adjusted during learning, either supervised or unsupervised.

Manufacturing is one of the critical sectors that is significantly impacted by rapid technological advancements. Integrating intelligent digital technologies with manufacturing is rapidly powering industry 4.0 innovations and implementations. Oztemel & Gursev (2020) noted that artificial intelligence is projected to be a dominant research field featuring applications such as intelligent DSS. ANN-based decision systems are frequently mentioned in the context of industry 4.0 (Oztemel & Gursev, 2020; Ramezani & Jassbi, 2017b; Sipsas et al., 2016). In addition, product ranges constantly evolve due to technological advances, highly competitive markets, and rapidly changing consumer needs (Francalanza et al., 2017). The authors further note that manufacturers need to build capabilities to produce different products (Francalanza et al., 2017). Given the complexity involved, decision-making processes remain crucial in achieving the specified manufacturing goals. Designing manufacturing systems must consider the current parameters and their evolution over time (Francalanza et al., 2017). New products, demand dynamics, and technological changes pressure companies to respond instantly and efficiently (Renna, 2017). As such, the ability of ANN to enhance both data-driven and model-based DSS seems to hold great potential in decision-making processes.

Despite the importance of robust and intelligent decision systems in manufacturing, recent research fails to comprehensively analyze ANN-based DSS trends, challenges, and implications. This paper presents a systematic review of empirical studies on ANN in DSS between 2011 and 2021. With the increasing interest in incorporating artificial intelligence techniques such as ANN in DSS, a systematic review of recent developments, challenges, and implications of ANN-based DSS in manufacturing. This study aims first to analyze the specific manufacturing processes that use ANN-based DSS. Second, the study seeks to evaluate and trends and identify research gaps in the use of ANN-based DSS in manufacturing.

The main objective of this systematic literature review is to identify, synthesize and provide a comprehensive summary of recent studies on artificial neural network-based decision support systems as applied in manufacturing processes. The specific objectives are to identify the leading areas in manufacturing where artificial neural network-based decision support systems have been used and to evaluate trends in the design and development of artificial neural network-based decision support systems in manufacturing.

## 2. Background and rationale

Manufacturing enterprises face a growing need to improve production processes from the highly dynamic business environments and customer needs. To become sustainable in the prevailing turbulent conditions, manufacturing enterprises must continuously look for ways to optimize operations. Research reveals that manufacturing entities must lead innovations to withstand unprecedented global competition in the wake of intelligent manufacturing (Jardim-Goncalves et al., 2017). Critical managerial functions such as planning, implementing, and controlling manufacturing processes involve a great deal of decision-making, featuring a wide range of parameters and data. The objective of decision-making processes is to identify the optimal course of action from a pool of different possibilities that would guarantee high performance and sustainability. Jardim-Goncalves et al. (2017) noted that manufacturers must embrace digital technologies to create high-quality and intelligent manufacturing systems capable of optimizing performance. The authors further pointed out that sustainable manufacturing concepts must be adopted to ensure cost-efficiency and management of complex product assembling (Jardim-Goncalves et al., 2017). Similar research argues that innovation around manufacturing processes and product design remains crucial to industrial evolution (Abdulhameed et al., 2019). Given the growing uncertainty and complexity, DSS remains central to the rapid development of digital manufacturing as a new paradigm.

A plethora of research on different designs of intelligent DSS in manufacturing and their application in specific processes exists. DSS is developed for machine tool selection that uses ANN to analyze performance and machine characteristics for prediction (Alberti et al., 2011). Canz & Jagdale (1995) describe the adoption of machine learning in the decision-making process as part of a study on intelligent machining. The authors focus on using the predictive capabilities of ANN to predict process parameters for specific machine tools from the evaluation criteria (Canz & Jagdale, 1995). Similarly, Bergmann et al. (2014) suggest using neural networks and traditional simulation techniques to improve decision-making if certain choices are limited by insufficient fundamental system knowledge. The authors introduce a novel approach to decision support that entails emulating the system's dynamic behavior using ANN to approximate decision rules. Mawson and Hughes (2021) argue for the use of ANNs in the energy sector because of their ability to process large amounts of data and analyze complex relationships between variables. The authors propose a decision support tool that monitors and predicts energy consumption in a building using ANN. Energy spikes identified from the predicted energy consumption helps managers to develop and maintain optimized manufacturing schedules.

Although ANN remains a powerful tool, it is also combined with other intelligent techniques such as fuzzy logic to create model based DSS. For instance, the one proposed for a decision involving the residual weld stress by Edwin Raja Dhas & Kumanan (2011). (Sadeghian & Sadeghian, 2016) also proposed a decision support system that combines ANN and fuzzy logic to guide decision-makers in machine tools selection. Yu-gang & Shi-chao (2019) point out the complex decision problem resulting from environmental impact assessments in manufacturing. Competition and highly dynamic changes in customer needs across manufacturing industries are primarily influenced by environmental awareness and sustainability. Yu-gang & Shi-chao (2019) explore intelligent systems to analyze the environmental implications of cutting processes in manufacturing. A decision support tool for choosing the most optimal environmental alternative using artificial intelligence is proposed (Yu-gang & Shi-chao, 2019). Other manufacturing technologies such as 3D printing benefit from ANN (Mahmood et al., 2021). The authors acknowlegde that ANN is the most widely utilized model in machine learning due to its ability to solve large datasets inbuilt computational supremacy and highlight the usage in 3D printing (Mahmood et al., 2021). ANN is showcased as having high prediction accuracy for better performance in optimization cases involving cloud manufacturing (Chen et al., 2020). The study showcases the critical role played by ANN in the development of industry 4.0 and cloud manufacturing.

ANN remains an essential component in the DSS evolution and the creation of intelligent manufacturing systems. The need to increase the potential of ANN adoption in manufacturing decision-making processes necessitates a clear and comprehensive view of recent developments in terms of challenges, trends, and implications. This paper presents a systematic literature review (SLR) through a comprehensive analysis of empirical studies on ANN-based DSS in manufacturing processes. Systematic reviews provide a logically, analytically, and transparently analyzed and synthesized body of literature (Pigott & Polanin, 2020).

SLR originates from evidence-based research developed in medicine (Kitchenham et al., 2009). SLR synthesizes high-quality studies on a specific research domain, providing rigorously reviewed results (Kitchenham et al., 2009). SRL adheres to a structured and predefined process (Munn et al., 2018), which acts as the protocol and involves rigorous methods to ensure quality, credible, and reliable results.

## 3. Methodology

This study is conducted as a systematic literature review. The 10-stage review process suggested by (Brereton et al., 2007) is preferred. The processes are divided into three phases: planning, conducting the review, and reporting. The three phases together entail ten procedures. First, the processes included in the planning stage are specifying research questions, developing a review protocol, and validating the developed protocol (Brereton et al., 2007). Second, the conducting phase involves identifying relevant research, selecting primary studies, studying quality assessment, data extraction, and analyzing extracted data (Brereton et al., 2007). The last step entails two processes: documenting and validating the SRL report (Brereton et al., 2007). The purpose of this SLR is to understand current and new practices, reported challenges, and areas of future research on the application of ANN-based DSS in manufacturing processes.

### 3.1. Research questions

RQ1: In what specific processes are artificial neural network-based decision support systems are applied in manufacturing?

RQ2: what trends in artificial neural network-based decision support systems are presented?

### 3.2. Developing review protocol

Conducting a rigorous and reliable systematic literature review requires a proper set of rules and standards that governs the process. As pointed out, establishing a protocol is a critical element in conducting systematic literature reviews (Brereton et al., 2007). The authors highlight minimizing bias in the research by predefining the structure of conducting the review as a vital objective of developing a protocol (Brereton et al., 2007). The protocol for this systematic literature review involves all processes outlined in the three adopted phases as outlined in the methodology section.

### 3.3. Validating review protocol

The review protocol is rigorously reviewed through a preliminary review. Identification of relevant research and selection of primary studies processes were performed to provide an insight into the protocol's reliability. Initially, the search strategy involved five databases; Web of Science, JSTOR, Scopus, and IEEE Explore. In addition, only articles published in the last ten years (2011 – 2021) were included. However, during the validation of the review protocol, most studies obtained from IEEE Explore were conference papers without citations. Out of a total of 52 publications retrieved, eight had been cited precisely two times, while only nine had been cited at least thrice. As a result, the protocol was revised, with the number of search databases limited to Scopus and web of science.

### 3.4. Identification of relevant research

Identifying relevant research entailed formulating search terms from the research questions based on the adopted review protocol. The keywords identified were decision support, intelligent decision, artificial neural networks, and manufacturing. Next, the keywords artificial neural network, decision support, and manufacturing were selected and used with ANN to form a search string. Finally, the search string was customized for each searched database as follows:

a) Scopus:

(({artificial neural network}) AND ({ANN}) AND ({decision support}) AND (manufacturing)) AND (LIMIT-TO (PUBSTAGE,“final”)) AND (LIMIT-TO (LANGUAGE,“English”))

b) Web of Science:

((TS=(artificial neural network)) AND TS=(decision support)) AND TS=(manufacturing)

### 3.5. Selection of primary studies

A 6-step selection criterion as defined in the review protocol was applied to the relevant research. The purpose of using the selection criteria was to ensure that only primary research involving artificial neural networks in decision systems or intelligent support systems in manufacturing are reviewed.

Step 1: The initial relevant research results published in the English language were filtered to exclude editorials, books, book chapters, and reviews. The purpose of this step was to ensure that only rigorously evaluated and peer-reviewed primary journal and conference publications were selected.

Step 2: The resulting studies from step 2 were filtered based on the publication date. Studies published more than ten years ago were excluded. Based on the stated purpose of this systematic review, studies published within the past ten years were deemed well suited to provide comprehensive synthesized evidence in the relevant applications of artificial neural networks-based intelligent decision support in manufacturing with minimal out-of-date information.

Step 3: The included studies were filtered based on the number of citations. Articles not cited at least three times were excluded. Publications with 0 – 2 citations are left out because they are not cited could be poor content or failure to address the subject matter effectively.

Step 4: The result from step 3 were checked for correctness of the publication details and relevance to the purpose of the current SLR. The publication results missing any details such as abstracts, source titles, and author information were excluded. The included papers were analyzed, and only those involving the use of ANN in manufacturing processes either directly or indirectly are included.

Step 6: The resulting publications from each database, Scopus, and Web of Science, were combined and the duplicates eliminated.

### 3.6. Quality assessment

Only publications in the most reputable and high-ranking scientific journals are considered to ensure the result is based on the best quality evidence. As such, the quality assessment checklist included, first and foremost publication search database renowned for high-quality and peer-reviewed articles. Secondly, poor-quality publications are rarely cited. For this reason, the quality checklist included the number of citations. Only publications with at least three citations were included. Thirdly, the coherence between the study design and its appropriateness to outlined research objectives. Fourthly, risk of bias and choice of outcome measure, finally, the overall reporting quality. The quality assessment was included to exclude low rate, weakly written, and incoherent publications.

### 3.7. Data extraction

Data extraction was performed on the resulting publications from selection steps described earlier and quality assessment. The data types extracted included publication date, number of times cited, conference details, source journal information, research titles, the field of study, the purpose of the study, and the research questions if highlighted. In addition, the study findings and challenges observed were also extracted for analysis.

### 3.8. Data synthesis and analysis

The extracted data were tabulated or represented graphically to show the number of publications in the past ten years and their distribution, the source journal titles, citations, and publication type. Finally, further analysis was done on the findings to answer the research questions for this SLR as outlined.

## 4. Results

A total of 863 and 121 papers published in the English language were retrieved from Scopus and Web of Science respectfully. As per the protocol for this review, the publications were not combined on retrieval. Instead, each of the two sets underwent further processing independently. First, the resulting publications sets were separately subjected to another filter, whereby all books, book chapters, editorials, and reviews were excluded. The goal of the process was to retain only journal publications and conference proceedings. From this exercise, the result was 694 and 104 publications from Scopus and the Web of Science, respectively. Next, a publication date filter was applied to ensure that only studies published between 2011 and 2021 were included. The process resulted in 584 studies from Scopus and 104 from the Web of Science published in 10 years. The resulting papers were filtered by the number of citations received. As per the review protocol, only publications cited at least three times are considered to be of good quality. Based on the citation criteria, a total of 355 and 42 papers were included from Scopus and Web of Science, respectively.

The resulting publications were checked for correctness. The exercise was performed to ensure that only publications with relevant details such as author(s), source title, and abstracts were considered for this SLR. The check for correctness was followed by a check for relevance. The inclusion criteria at this stage were intended to ensure only publications with correct details and related to manufacturing processes are included. A total of 73 papers from Scopus and 33 from Web of Science were included, combined, and duplicates removed. The final list comprised 99 publications. The SLR execution process is summarized in Fig. 1 below.

The reviewed publications were first analyzed based on the year of publication. The number of selected papers per the year of publication ranges from 5 to 13. Publication years 2014, 2015, and 2018 have the

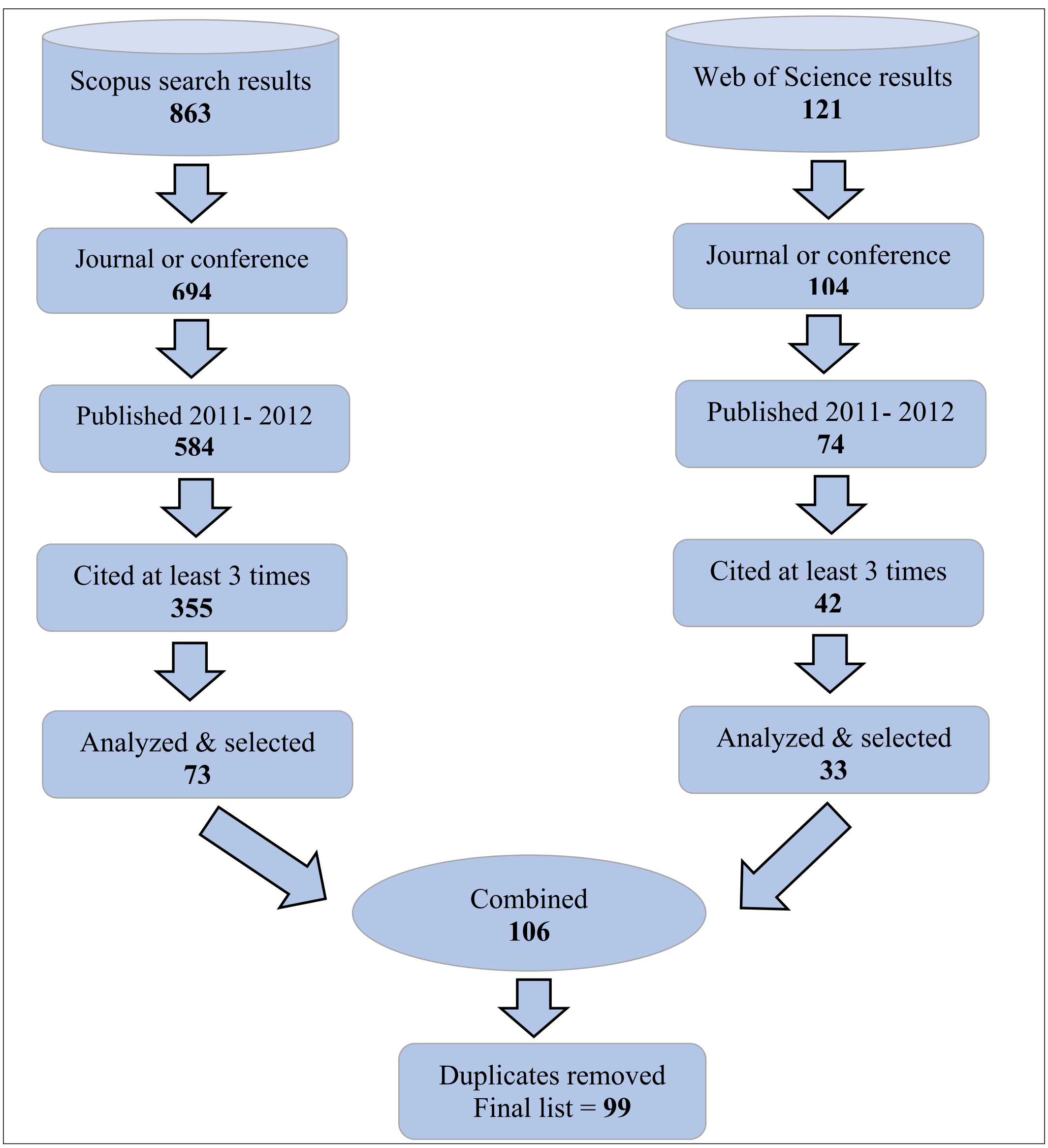


**Fig. 1.** SLR execution flow.

lowest number of selected papers at 5, 6, and 6, respectively. Publication years 2012, 2017, and 2019 have 11 papers. The year 2013 has 8 papers, while the years 2020 and 2021 have 10 papers each. Given the increased interest in sustainable manufacturing and artificial intelligence, the number of publications for the last years should be higher were it not for the significant disruptions in the education sector and research activities by the COVID-19 pandemic (Aucejo et al., 2020). The fight against the pandemic involves measures such as restricted travel and quarantine, which adversely affect research activities, especially in the manufacturing sector. A summary of publications on artificial neural networks-based decision support systems in manufacturing in the past ten years is shown in Fig. 2 below.

Out of the 99 studies selected for review, only 4 are conference papers, while 94 are studies are journal articles as shown in Fig. 3. Type of selected publication below. This outcome aligns with the quality assessment strategy of selecting high-quality studies. In addition, while journal papers are rigorous peer-reviewed and re-written multiple times before publication, conference papers often involve general instead of specific feedback. Besides, most conference papers report ongoing studies and provide the authors with a platform to interact with audiences from similar fields for their feedback. Thus, the significantly higher number of journal papers indicates the quality of the studies selected for review (see Fig. 4).

The number of times a study is cited as an essential quality assessment check. High-quality papers published in reputable journals are likely to be cited compared to inferior studies. As such, only papers cited at least three times are selected. The highest number of citations is observed in articles published in 2012, while the least cited studies were published in 2014. There is no correlation between the number of citations and the publication year. This outcome is expected, given that the quality of the paper is not correlated to the publication year in which it was published. For instance, there 5 papers selected in 2014, whose total number of citations is 42. By contrast, 6 papers selected in 2015 have a total of 255 citations. Nevertheless, the significantly higher number of citations in 2012 can be attributed to the explosive growth in internet and technological advances, which saw several publications on artificial neural networks-based decision support systems that would later be used as references in the subsequently published papers.

The selected studies are obtained from 75 unique sources, see Appendix B. Further details are extracted, such as the number of papers per source and the total number of citations received. Ranking the top 4 sources by the number of articles, the first spot is taken by Computers and Industrial Engineering with 9 studies. The second and third positions go to the International Journal of Advanced Manufacturing and

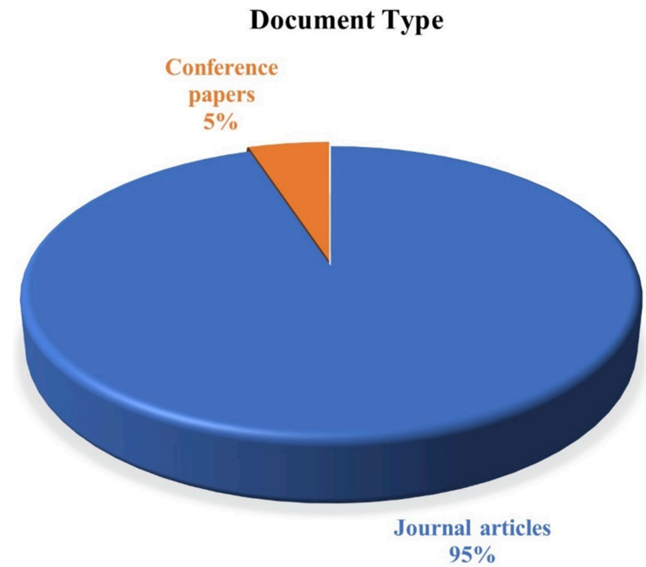


**Fig. 3.** Type of selected publication.

Journal of Intelligent Manufacturing with 6 and 4 papers. The fourth position is occupied by 8 sources, as shown in Table 1 below.

Breaking down the number of citations recorded for each publication source, the *Journal of Intelligent Manufacturing* emerges at the top, with a total of 263 citations. The next spot is taken by *Computers and Industrial Engineering* with 231. International *Journal of Advanced Manufacturing Technology* completes the list of the top 3 highly cited sources with 126 citations. Extending the list to the top 10, the 9th position is taken by *IEEE Transactions on Computer-Aided Design Of Integrated Circuits and Systems* with 62 citations, while the *International Journal of Engineering Research in Africa* concludes the list with 49 citations. Combining the 10th source with the remaining 65 into 'Others,' Fig. 5 below shows the distribution of the number of citations per the source title. See Appendix B for the entire list (see Fig. 6).

The extracted data on the field of study of the selected publications shows that a majority of the articles are multi-disciplinary as they have more than one listed field of study. There are 20 unique fields of studies in total as follows:

1) Agricultural and Biological Sciences
2) Biochemistry, Genetics and Molecular Biology

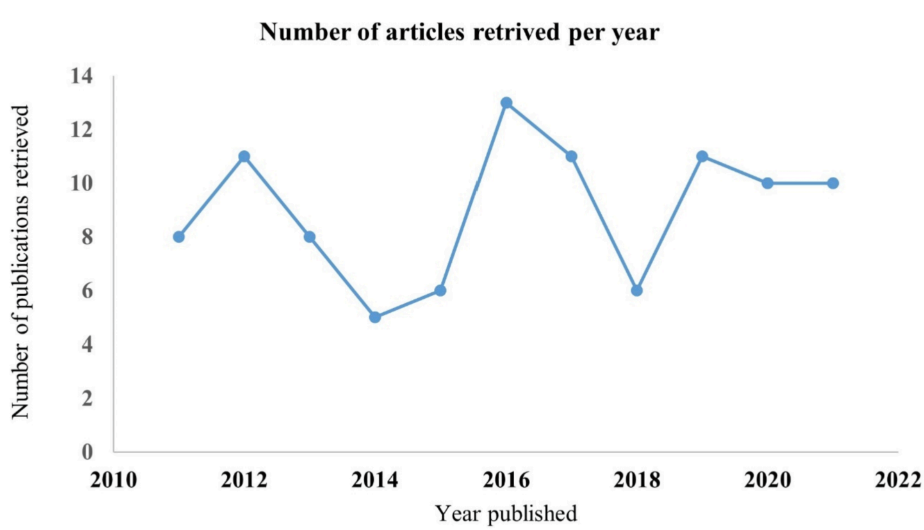


**Fig. 2.** Number of papers per year of publication.

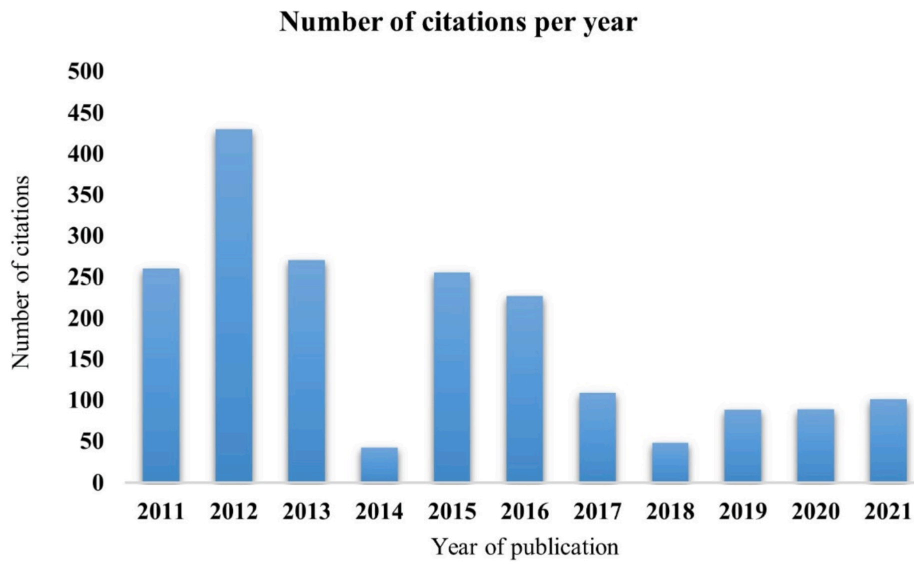


**Fig. 4.** Citations per year of publication.

**Table 1**
Sources and number of publications retrieved.

| Source title | Articles |
|---|---|
| Computers and Industrial Engineering | 9 |
| International Journal of Advanced Manufacturing Technology | 6 |
| Journal of Intelligent Manufacturing | 4 |
| Eksploatacja i Niezawodnosc | 2 |
| Advances in Mechanical Engineering | 2 |
| Materials | 2 |
| International Journal of Industrial and Systems Engineering | 2 |
| Applied Sciences (Switzerland) | 2 |
| Chemical Engineering Science | 2 |
| Neural Computing and Applications | 2 |
| Computational Intelligence and Neuroscience | 2 |

3) Business, Management, and Accounting
4) Chemical Engineering
5) Chemistry
6) Computer Science
7) Decision Sciences
8) Earth and Planetary Sciences
9) Economics, Econometrics, and Finance
10) Energy
11) Engineering
12) Environmental Science
13) Materials
14) Materials Science
15) Mathematics
16) Neural Computing and Applications
17) Neuroscience
18) Physics and Astronomy
19) Renewable Energy
20) Social Sciences

Although the total number of unique fields of studies is 20, only 5 of them are listed once in the publications. The remaining are listed in

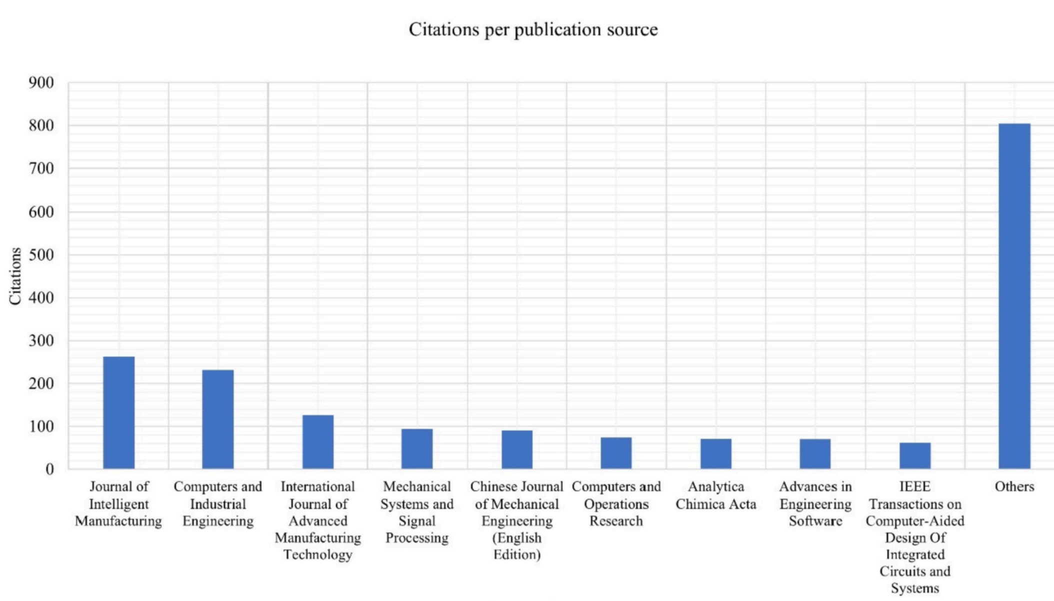


**Fig. 5.** Citations per publication source.

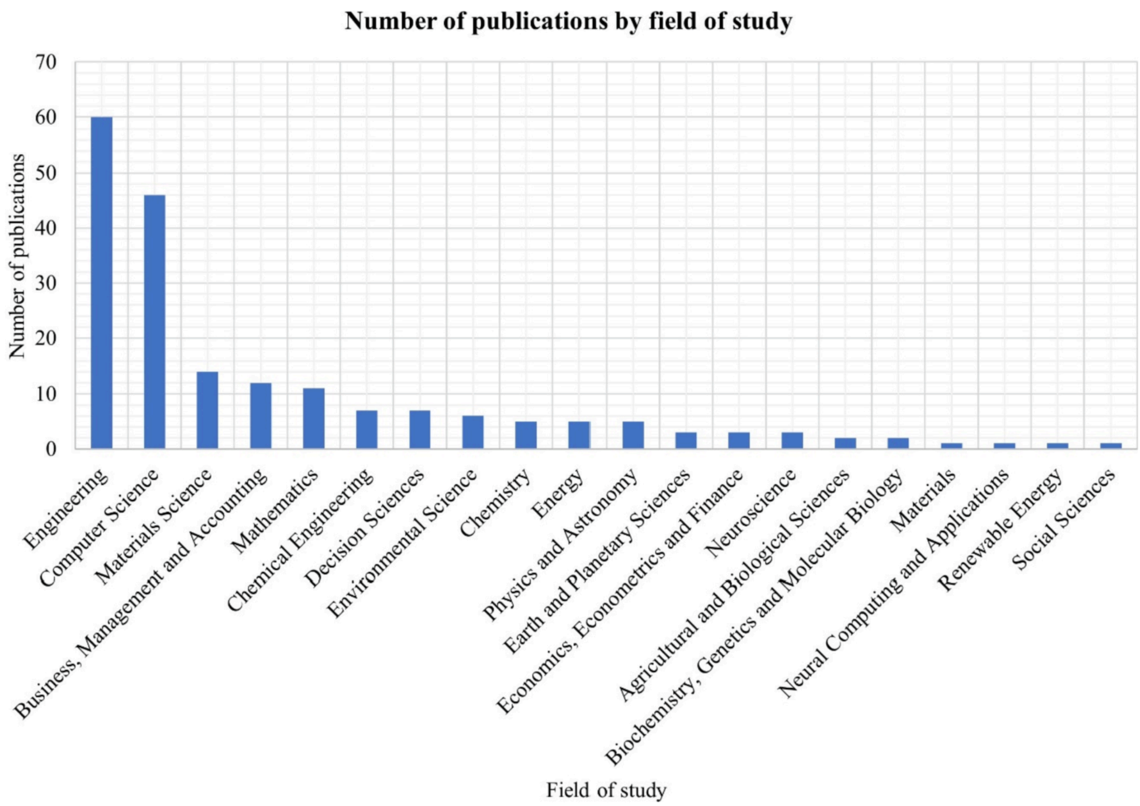


**Fig. 6.** Distribution of publications per field of study.

different 40 combinations, bringing the total number of fields of study, both single and multiple, to 45. However, out of the 45, only 13 combinations have 2 or more selected papers, as shown in Table 2 below. For the complete list, see Appendix C.

To better present the distribution of recent research on the application of ANN in the decision support systems in manufacturing, the extracted data on the field of study is further processed to show the number of publications per field irrespective of the initial occurrence in combination with the combination of these others. That is, the number of times a field of study is listed in publication details, whether single or in combination with other fields of study. The results show Engineering, Computer Science, Material Science, Business Management and Accounting, and Mathematics as the top 5 featured fields. By contrast, Neural Computing and Applications, Renewable Energy and Social Sciences have the least number of publications, each having just one.

To answer research question 1, the top three areas where artificial neural networks-based decision support systems are applied are identified as performance evaluation and or prediction, product or process design, and predictive maintenance. A total of 55 studies involve the use of ANN in either product or process design and management. 32 studies involve performance evaluation or prediction using ANN, while 22 involve the use of ANN in predictive maintenance.

Recent patterns in artificial neural networks in the selected studies are analyzed to answer the second research question. A common trend noted is the combination of ANN models with other intelligent techniques. The observed trends are identified as the combination of ANN with fuzzy logic and genetic algorithm (GA). A total of 13 studies combines ANN with at least fuzzy logic to enhance the predictive or analytical capacity. On the other hand, 8 studies involve combining ANN with GA to improve the overall quality of the studied model. Table 3 below shows the identified use cases, trends, and sources for the corresponding selected studies. Further information is available in Appendix D.

**Table 2**
Top 4 field of studies by the number of articles.

| | Field of science | Publications |
|---|---|---|
| 1 | Computer Science/Engineering | 26 |
| 2 | Engineering | 12 |
| 3 | Computer Science | 6 |
| 4 | Engineering/Material Science | 4 |
| 5 | Materials Science | 3 |
| 6 | Mathematics | 2 |
| 7 | Computer Science/Mathematics/Neuroscience | 2 |
| 8 | Computer Science/Mathematics | 2 |
| 9 | Computer Science/Engineering/Mathematics | 2 |
| 10 | Chemical Engineering/Computer Science/Engineering/ Materials Science/Physics and Astronomy | 2 |
| 11 | Chemical Engineering/Chemistry/Engineering | 2 |
| 12 | Business, Management and Accounting/Decision Sciences | 2 |
| 13 | Business, Management and Accounting | 2 |

## 5. Discussion

Decision support systems have evolved, integrating intelligent capabilities to support decision-making processes. The transformation of DSS into IDSS was made inevitable by the unprecedented global industrial development. The increasing complexity and uncertainty resulting from the rapid development of manufacturing industries (Liang et al., 2018) have led to significant growth in semi-structured and structured decision parameters. Today, manufacturing enterprises must navigate uncertainty caused by dynamic customer needs, turbulent markets, and increasing calls for sustainability. The review presents recent trends in applying artificial neural networks based DSS in manufacturing. The reviewed literature reveals performance evaluation, product or process design, and predictive maintenance as the trending specific processes applied by ANN-based DSS. The reviewed paper further shows the combination of ANN and other intelligent systems and techniques, including fuzzy logic, GA, DEA, and SEM, as another leading

**Table 3**
ANN use case and trends and the selected sources.

| RQ1 | Sources |
|---|---|
| Performance evaluation/ Prediction | (Sakthivel et al., 2017), (Ramezani & Jassbi, 2017), (Hawryluk & Mrzygłód, 2017; Hawryluk & Mrzygłów, 2017) (Tsadiras et al., 2013), (Y. Yu et al., 2012), (Dębska & Guzowska-Świder, 2011), (Yucesan, Gul, & Celik, 2017), (Ju et al., 2016), (Kwon, Lee, et al., 2016; Kwon, Roh, et al., 2016), (Badkar et al., 2013), (Al-Chalabi et al., 2014a), (D. Li et al., 2020), (Farizhandi et al., 2020), (Susac & Stan, 2020), (Hosseini Nasab et al., 2012), (Karaoglan & Karademir, 2016), (Ushada et al., 2017), (Han et al., 2019), (Dietrich et al., 2020), (Rojek et al., 2016), (Dasgupta et al., 2017), (Khalaj et al., 2013), (Barletta et al., 2014), (Lima-Junior & Carpinetti, 2019), (Asadi et al., 2012), (Mrzygłód et al., 2020), (Edwin Raja Dhas & Kumanan, 2011), (Martinek & Krammer, 2019), (Kheirkhah et al., 2013), (Mehrpouya et al., 2021) and (Suresh et al., 2021) |
| Product or process design | (Sakthivel et al., 2017), (Tsadiras et al., 2013), (Yucesan, Gul, & Erkan, 2017), (Badkar et al., 2012), (Karaoglan & Karademir, 2016), (Dietrich et al., 2020), (Barletta et al., 2014), (Asadi et al., 2012), (Kheirkhah et al., 2013), (Mehrpouya et al., 2021), (Suresh et al., 2021), (Can & Heavey, 2012), (Sadeghian & Sadeghian, 2016a), (Taha & Rostam, 2011), (Y. Yu et al., 2011), (Wen et al., 2019), (Aktepe & Ersoz, 2012), (Hachicha, 2011), (Mohammad Nezhad & Mahlooji, 2014), (Kartal et al., 2016), (Xu et al., 2016), (Vimal & Vinodh, 2013), (Klintong et al., 2012), (Almonti et al., 2019), (Egilmez et al., 2016), (Solarte-Pardo et al., 2019), (Alberti et al., 2011), (Mitra, 2013), (Chang et al., 2010), (Khan et al., 2021), (Gegovska et al., 2020), (Simeunovic et al., 2017), (Nallusamy et al., 2015), (Chakraborty et al., 2019), (Nuñez-Piña et al., 2018), (Saberi & Yusuff, 2010), (Fallahpour et al., 2017), (Bergmann et al., 2014), (Huang et al., 2012), (Ahmarofi et al., 2017), (Souza et al., 2019), (Farsi & Masood Hosseini, 2019), (Wong et al., 2012), (Mitra & Majumder, 2011), (J.-B. Yu et al., 2014), (Gonzalez-Carrasco et al., 2012), (Sila & Walczak, 2017), (Güven & Şimşir, 2020), (Kocamaz et al., 2016), (Wang et al., 2015), (Doan et al., 2021), (Zhan & Li, 2021), (Gupta et al., 2021), (Zhu et al., 2021) and (Ushada et al., 2015) |
| Predictive maintenance | (Saberi & Yusuff, 2010), (Hawryluk & Mrzygłód, 2017), (Liu & Guo, 2017), (Tian, 2012), (Özcan et al., 2020), (Bhargava et al., 2018), (Krenek et al., 2016), (Ye et al., 2013), (Zhang et al., 2019), (Mrzygłód et al., 2018), (Ribeiro Junior et al., 2020), (Kaya et al., 2011), (K. Wang & Wang, 2018), (Ahmadzadeh & Lundberg, 2013), (Badkar et al., 2012), (Azadeh et al., 2015), (Hage et al., 2019), (Özden et al., 2019), (Roshani et al., 2021), (Xie et al., 2021), (Barghash, 2015), (Gao et al., 2014), (W. Li et al., 2015) |
| **RQ2** | **Sources** |
| Fuzzy logic | (Bhargava et al., 2018), (Zhang et al., 2019), (Sadeghian & Sadeghian, 2015; Taha & Rostam, 2011) (Taha & Rostam, 2011), (Y. Yu et al., 2011), (Xu et al., 2015), (Vimal & Vinodh, 2013), (Klintong et al., 2012), (Khan et al., 2021), (Gegovska et al., 2020), (Zhan & Li, 2021), and (Edwin Raja Dhas & Kumanan, 2011) |
| Genetic Algorithm | (Xu et al., 2015), (Klintong et al., 2012), (Sakthivel et al., 2017), (Can & Heavey, 2012; Egilmez et al., 2016), (Solarte-Pardo et al., 2019), (Chakraborty et al., 2019), (J.-B. Yu et al., 2014), (Dasgupta et al., 2017 |

trend.

### 5.1. Performance analysis

Overall, performance evaluation is used to make important decisions about products and processes in manufacturing environments. ANN-based DSS models are increasingly designed to simplify decision-making involving processes and products. A total of 32 selected papers present ANN models or DSS based on ANN and other techniques models designed using other algorithms to analyze the performance of processes and products. For instance, ANN is used in a model set up by combining Gene Expression Programming and Artificial Neuro-Fuzzy Interface to evaluate the performance of fly ash-based geopolymer concrete (Khan et al., 2021b). The ANN predictive model analyses the product's performance in different setups and, as such, allows managers to take significant steps to ensure high-quality manufacturing. Similar studies deploy an ANN-based model to estimate the performance of ground granulated furnace concrete by analyzing its compressive strength (Han et al., 2019). The model also evaluates 35 performance degradation parameters in ball bearing in time, frequency, and time–frequency domains (Liu & Guo, 2018). Product or process performance evaluation is critical to the survival of a manufacturing enterprise. The outcome of performance evaluation forms the essential basis of product or process design decisions. ANN-based DSS provides a cheaper way of performance analysis through simulation using parameters and measures in different combinations.

### 5.2. Product and process design

Product and process design remain vital for the success of all business activities. Undoubtedly, poorly designed products perform poorly on the global market due to performance and quality issues (Ahmad et al., 2018). Similarly, poorly designed manufacturing processes lead to low quality and increased costs due to the high volume of re-work and wastes. Therefore, product and process design emerge as the general application of ANN-based DSS. A total of 18 reviewed articles uses ANN directly in product and process design either as standalone models or in combination with other intelligent technologies such as genetic algorithm and fuzzy logic. Designing products and processes depends on the specifics of various products, used technology, consumer needs, and enterprise capacity. Still, the entire end-to-end process of designing products and processes should be thoroughly reviewed and quality decisions made to avoid risks such as poor quality, high costs, and high failure rates during manufacturing (Ahmad et al., 2018). One of the reviewed studies presents an ANN model based DSS developed to optimize machining parameters in thermoplastic polymers (Susac & Stan, 2020). The authors use the ANN algorithm to establish the optimum cutting conditions and predict the quality of the processed materials (Susac & Stan, 2020). Only the designed cutting processes that yield optimum value is selected among the alternatives. ANN algorithm is trained and deployed to aid the design of wind turbines by predicting lift coefficient and the maximum lift-drag ratio (Wen et al., 2019b). As observed, predicting parameters such as the life coefficient of airfoil helps designers of the wind turbines make appropriate decisions that would lead to optimum value creation. Prediction of optimal design parameters only requires a few samples to train the ANN algorithm to avoid re-work and sub-standard products. The training dataset can be expanded using simulation.

More product and process design problems are described and solved using ANN model DSSs in the reviewed studies. For instance, buffer allocation problems in production line design (Tsadiras et al., 2013). Decisions on buffer allocation are simplified by eliminating tedious and complex mathematical analyses (Tsadiras et al., 2013). Thus, the high cost of manufacturing samples for testing is considerably cut as ANN models can learn from a training dataset and simulate different scenarios. Several other reviewed papers present results of ANN models designed to help decision-makers design processes such as sales, costing, and inventory management. For instance, a feed-forward back-propagation ANN is used to predict time-series events of a power transformer (Ahmarofi et al., 2017). The authors recognize the importance of prediction in deciding on better cost estimation models (Ahmarofi et al., 2017). Manufacturing completion time is predicted with the help of ANN, using historical data. The future forecast takes into consideration underlying related and complex variables. A flexible manufacturing system is selected using a DSS that combines ANN and fuzzy logic. The designed model considers several parameters, including manufacturing rate, accuracy, and energy consumption, to select a flexible manufacturing system (Sadeghian & Sadeghian, 2016). GA is deployed in cell loading and shipment optimization problems, with ANN used as a support tool to analyze solution quality (Egilmez et al., 2016). As showcased, DSSs based on ANN are increasingly playing a leading role in designing various processes, focusing on optimization and cost reduction.

### 5.3. Predictive maintenance

Predictive maintenance remains a critical component of manufacturing systems. The advent of industry 4.0 has led to unprecedented growth in the complexity and uncertainty in manufacturing processes. The interconnection and integration of several systems to drive manufacturing efficiency rapidly increase the amount of data that can be collected and analyzed. Predictive maintenance has gained prominence in multidisciplinary research fields (Zonta et al., 2020). With industries relying on complex machines and tools (Aivaliotis et al., 2019), monitoring and maintaining the same is crucial to facilitate sustainable operations. Twelve out of the selected studies for review are dedicated to predictive maintenance using ANN algorithms. Intelligent support systems in predictive maintenance are studied using ANN and fuzzy logic (Edwin Raja Dhas & Kumanan, 2011). Using simulated datasets, the residual weld stress is predicted using ANN and fuzzy logic models. Prediction of the useful life of the equipment is reported in several studies (Ahmadzadeh & Lundberg, 2013; Al-Chalabi et al., 2014; Tian, 2012) while the analysis of wear and tear of tools using ANN is described by Mrzygłód et al., (2018). Maintenance activities are designed with the help of the ANN algorithm in combination with data envelopment analysis (DEA) and principal component analysis (PCA) (Azadeh et al., 2016). Decisions on the maintenance schedule are significant in ensuring an uninterrupted flow of activities. The use of ANN models to analyze and predict fault is studied in power plants, highlighting the importance of such prediction to the process of planning maintenance works (Özcan et al., 2020). Classification of defects in predictive maintenance using ANN is presented (Ribeiro Junior et al., 2020). The classified and predicted flaws, including their impact, allow fast decision-making.

### 5.4. Integration with other intelligent tools

The reviewed studies indicate a rise in the combination of ANN models with analytical and predictive tools. As observed, the commonly used combination in developing intelligent DSSs involves ANN and GA. Although ANN remains one of the most used techniques for various problems such as pattern recognition, classification, and prediction, restrictions exist, especially in training the algorithm. Learning algorithms are typically initialized with random data, and as such, slow converging is a common issue. From the reviewed papers, getting trapped in the local lamina and slow learning rate hinder the performance of ANNs. The authors point out that such drawbacks can be alleviated and improved by combining ANNs and GA (Sakthivel et al., 2019). Further studies reviewed present the use of GA in different to incorporate adequate data when training the ANN model. Thus, GA is utilized to improve the training of ANN, which enhances the overall performance of the ANN models.

ANN and fuzzy logic models are another notable trend in the reviewed studies. There are inherent differences between fuzzy logic and ANN. Fuzzy logic is more straightforward than ANN, performs better in pattern recognition, and easily extracts knowledge. However, it requires an explicit definition of all variables. On the other hand, ANN can learn from sample datasets and excels at performing predictions. Combining fuzzy logic and ANN leads to a more capable model with increased performance. Although ANN is highly significant in resolving complex problems, its performance is much better when combined with fuzzy logic (Khan et al., 2021). Like GA, fuzzy logic enhances the potential of ANN models in intelligent DSSs.

## 6. Conclusion

Although it is generally accepted that DSS is rapidly evolving and incorporating intelligent knowledge engineering tools, many reviews synthesizing the exact trends are scarce. This SLR provides a detailed view of trends in ANN-based DSSs. The SLR identified a total of 99 papers after rigorous quality assessment and acceptance criteria as outlined in the protocol. 95% of the selected papers are journals articles, while only 5% are conference proceedings. While conference papers contribute significantly to scientific research and knowledge expansion, they are less rigorously peer-reviewed and revised compared to journal articles. The Journal of Intelligent Manufacturing, Computers and Industrial Engineering, and the International Journal of Advanced Manufacturing Technology are the major sources of cited work on ANN-based decision support systems for manufacturing processes, having 10%, 9%, and 5% of the total number of citations for the selected papers. A majority of the selected studies are drawn from Engineering as a field of study, followed by Computer Science. The literature review on individual processes is abundant, as showcased by the significantly high number of retrieved works before acceptance criteria and quality assessment steps. The review isolates studies involving different approaches to utilizing ANN in manufacturing environments and provides a clear view of recent trends. The results show that ANN-based DSS are commonly used in performance evaluation, product and process design, and predictive maintenance. 56% of the reviewed papers focus on product or process design as the main use case for ANN models. Performance evaluation and predictive maintenance take 32% and 22% of all the reviewed papers, respectively. The observation is in line with the demands of the contemporary business environment, characterized by highly dynamic customer needs, increased competition, and rapid modernization and digitalization of the economies. Manufacturers are constantly looking for ways to optimize their products and processes, including designing, attaining, and maintaining a competitive edge while operating sustainably. ANN models will continue to revolutionize the way products and business processes are designed. Performance evaluation and predictive maintenance remain key areas where critical decisions are made. Given the complexity and uncertainty in manufacturing today, the need for intelligent tools will only grow further. Therefore, understanding the current trends, such as the combination of ANN with GA and fuzzy logic to resolve emerging issues such as training the models, is crucial for the future of intelligent support systems in manufacturing.

## 7. Future work

The focus of this SLR was on analyzing the specific processes in manufacturing that uses ANN-based DSS and evaluating trends to identify research gaps. Based on the reviewed empirical works, the challenges and limitations of combing ANN with other intelligent tools are not investigated across the manufacturing industries. There are, however, mentions of increasing the performance of ANN-based DSS. As such, a thorough investigation of the challenges and limitations of different combinations of intelligent tools and ANN-based DSS presents an area for future research. In addition, there is a need to study the implications of combining various predictive and analytical tools with ANN-based models on the future of decision-making in the context of increasing uncertainty and complexity in manufacturing.

### CRediT authorship contribution statement

**Fredrick Mumali:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Resources, Writing – original draft, Writing – review & editing, Visualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Selected studies

| *Authors citation* | *Year* | *Title* | *Source title* |
|---|---|---|---|
| (Can & Heavey, 2012) | 2012 | A comparison of genetic programming and artificial neural networks in metamodeling of discrete-event simulation models | Computers and Operations Research |
| (Sadeghian & Sadeghian, 2015) | 2016 | A decision support system based on artificial neural network and fuzzy analytic network process for selection of machine tools in a flexible manufacturing system | International Journal of Advanced Manufacturing Technology |
| (Hawryluk & Mrzygłów, 2017) | 2017 | A durability analysis of forging tools for different operating conditions with application of a decision support system based on artificial neural networks (ANN) | Eksploatacja i Niezawodnosc |
| (Taha & Rostam, 2011) | 2011 | A fuzzy AHP-ANN-based decision support system for machine tool selection in a flexible manufacturing cell | International Journal of Advanced Manufacturing Technology |
| (Sakthivel et al., 2017) | 2019 | A genetic algorithm-based artificial neural network model with TOPSIS approach to optimize the engine performance | Biofuels |
| (Raut et al., 2017) | 2017 | A hybrid approach using data envelopment analysis and artificial neural network for optimising 3PL supplier selection | International Journal of Logistics Systems and Management |
| (Ramezani & Jassbi, 2017) | 2017 | A hybrid expert decision support system based on artificial neural networks in process control of plaster production – An industry 4.0 perspective | IFIP Advances in Information and Communication Technology |
| (Liu & Guo, 2017) | 2018 | A neural network approach for prediction of bearing performance degradation tendency | 9th International Conference On Modelling, Identification and Control |
| (Yu et al., 2011) | 2011 | A new and efficient intelligent collaboration scheme for fashion design | IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans |
| (Wen et al., 2019) | 2019 | A new optimization method of wind turbine airfoil performance based on Bessel equation and GABP artificial neural network | Energy |
| (Aktepe & Ersoz, 2012) | 2012 | A quantitative performance evaluation model based on a job satisfaction-performance matrix and application in a manufacturing company | International Journal of Industrial Engineering : Theory Applications and Practice |
| (Hachicha, 2011) | 2011 | A simulation metamodelling based neural networks for lot-sizing problem in MTO sector | International Journal of Simulation Modelling |
| (Hawryluk & Mrzyglod, 2018) | 2018 | A system of analysis and prediction of the loss of forging tool material applying artificial neural networks | Journal of Mining and Metallurgy, Section B: Metallurgy |
| (Tsadiras et al., 2013) | 2013 | An artificial neural network-based decision support system for solving the buffer allocation problem in reliable production lines | Computers and Industrial Engineering |
| (Mohammad Nezhad & Mahlooji, 2014) | 2014 | An artificial neural network meta-model for constrained simulation optimization | Journal of the Operational Research Society |
| (Tian, 2012) | 2012 | An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring | Journal of Intelligent Manufacturing |
| (Özcan et al., 2020) | 2020 | An artificial neural network model supported with multi criteria decision making approaches for maintenance planning in hydroelectric power plants | Eksploatacja i Niezawodnosc |
| (Kartal et al., 2016) | 2016 | An integrated decision analytic framework of machine learning with multi-criteria decision making for multi-attribute inventory classification | Computers and Industrial Engineering |
| (Xu et al., 2015) | 2016 | An integrated solution—KAGFM for mass customization in customer-oriented product design under cloud manufacturing environment | International Journal of Advanced Manufacturing Technology |
| (Bhargava et al., 2018) | 2018 | An intelligent prognostic model for electrolytic capacitors health monitoring: A design of experiments approach | Advances In Mechanical Engineering |
| (Yu et al., 2012) | 2012 | An intelligent quick prediction algorithm with applications in industrial control and loading problems | IEEE Transactions on Automation Science and Engineering |
| (Vimal & Vinodh, 2013) | 2013 | Application of artificial neural network for fuzzy logic-based leanness assessment | Journal of Manufacturing Technology Management |
| (Dębska & Guzowska-Świder, 2011) | 2011 | Application of artificial neural network in food classification | Analytica Chimica Acta |
| (Krenek et al., 2016) | 2016 | Application of artificial neural networks in condition based predictive maintenance | Studies in Computational Intelligence |
| (Yucesan et al., 2017) | 2017 | Application of artificial neural networks using bayesian training rule in sales forecasting for furniture industry | Drvna Industrija |
| (Klintong et al., 2012) | 2012 | Artificial intelligence and successful factors for selecting product innovation development | 3rd International Conference on Intelligent Systems Modelling and Simulation |
| (Ju et al., 2016) | 2016 | Artificial intelligence metamodel comparison and application to wind turbine airfoil uncertainty analysis | Advances in Mechanical Engineering |
| (Almonti et al., 2019) | 2019 | Artificial neural network in fibres length prediction for high precision control of cellulose refining | Materials |
| (Kwon et al., 2016) | 2016 | Best performance modeling using complementary DEA-ANN approach Application to Japanese electronics manufacturing firms | Benchmarking-An International Journal |
| (Kwon, Roh, et al., 2016) | 2016 | Better practice prediction using neural networks: an application to the smartphone industry | Benchmarking |
| (Ye et al., 2013) | 2013 | Board-Level Functional Fault Diagnosis Using Artificial Neural Networks, Support-Vector Machines, and Weighted-Majority Voting | IEEE Transactions On Computer-Aided Design Of Integrated Circuits And Systems |
| (Egilmez et al., 2016) | 2016 | Cell loading and shipment optimisation in a cellular manufacturing system: An integrated genetic algorithms and neural network approach | International Journal of Industrial and Systems Engineering |
| (Solarte-Pardo et al., 2019) | 2019 | Cutting insert and parameter optimization for turning based on artificial neural networks and a genetic algorithm | Applied Sciences (Switzerland) |
| (Zhang et al., 2019) | 2020 | Deep Fuzzy Echo State Networks for Machinery Fault Diagnosis | IEEE Transactions on Fuzzy Systems |
| (Alberti et al., 2011) | 2011 | Design of a decision support system for machine tool selection based on machine characteristics and performance tests | Journal of Intelligent Manufacturing |
| (Badkar et al., 2012) | 2013 | | |

(*continued on next page*)

(*continued*)

| Authors citation | Year | Title | Source title |
|---|---|---|---|
| | | Development of RSM- and ANN-based models to predict and analyze the effects of process parameters of laser-hardened commercially pure titanium on heat input and tensile strength | International Journal of Advanced Manufacturing Technology |
| (Mrzygłód et al., 2018) | 2018 | Durability analysis of forging tools after different variants of surface treatment using a decision-support system based on artificial neural networks | Archives of Civil and Mechanical Engineering |
| (Al-Chalabi et al., 2014) | 2014 | Economic lifetime prediction of a mining drilling machine using an artificial neural network | International Journal of Mining, Reclamation and Environment |
| (Li et al., 2020) | 2020 | Development of a group method of data handling technique to forecast iron ore price | Applied Sciences (Switzerland) |
| (Farizhandi et al., 2020) | 2020 | Evaluation of material properties using planetary ball milling for modeling the change of particle size distribution in a gas–solid fluidized bed using a hybrid artificial neural network-genetic algorithm approach | Chemical Engineering Science |
| (Mitra, 2013) | 2013 | Evolutionary Surrogate Optimization of an Industrial Sintering Process | Materials and Manufacturing Processes |
| (Susac & Stan, 2020) | 2020 | Experimental investigation, modeling and optimization of circularity, cylindricity and surface roughness in drilling of PMMA using ANN and ANOVA | Materiale Plastice |
| (Ribeiro Junior et al., 2020) | 2020 | Fault classification in three-phase motors based on vibration signal analysis and artificial neural networks | Neural Computing and Applications |
| (Hosseini Nasab et al., 2012) | 2012 | Finding a probabilistic approach to analyze lean manufacturing | Journal of Cleaner Production |
| (Karaoglan & Karademir, 2016) | 2017 | Flow time and product cost estimation by using an artificial neural network (ANN): A case study for transformer orders | Engineering Economist |
| (Kaya et al., 2011) | 2011 | Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks | Advances in Engineering Software |
| (Chang et al., 2010) | 2012 | Forecasting of manufacturing cost in mobile phone products by case-based reasoning and artificial neural network models | Journal of Intelligent Manufacturing |
| (Khan et al., 2021) | 2021 | Geopolymer Concrete Compressive Strength via Artificial Neural Network, Adaptive Neuro Fuzzy Interface System, and Gene Expression Programming With K-Fold Cross Validation | Frontiers in Materials |
| (Gegovska et al., 2020) | 2020 | Green Supplier Selection Using Fuzzy Multiple-Criteria Decision-Making Methods and Artificial Neural Networks | Computational Intelligence and Neuroscience |
| (Wang & Wang, 2018) | 2018 | How AI Affects the Future Predictive Maintenance: A Primer of Deep Learning | Lecture Notes in Electrical Engineering |
| (Simeunovic et al., 2017) | 2017 | Improving workforce scheduling using artificial neural networks model | Advances in Production Engineering And Management |
| (Ushada et al., 2017) | 2017 | Kansei engineering-based artificial neural network model to evaluate worker performance in small-medium scale food production system | International Journal of Industrial and Systems Engineering |
| (Han et al., 2019) | 2019 | Learned prediction of compressive strength of GGBFS concrete using hybrid artificial neural network models | Materials |
| (Dietrich et al., 2020) | 2020 | Machine learning based very short-term load forecasting of machine tools | APPLIED ENERGY |
| (Nallusamy et al., 2015) | 2016 | MCDM tools application for selection of suppliers in manufacturing industries using AHP, fuzzy logic and ANN | International Journal of Engineering Research in Africa |
| (Chakraborty et al., 2019) | 2019 | MCDM towards knowledge incorporation in ANN models for phase transformation in continuous cooling of steel | Multidiscipline Modeling in Materials and Structures |
| (Rojek et al., 2016) | 2016 | Methods of Computational Intelligence in the Context of Quality Assurance in Foundry Products | Archives of Foundry Engineering |
| (Dasgupta et al., 2017) | 2017 | Modeling and optimization of polymer enhanced ultrafiltration using hybrid neural-genetic algorithm based evolutionary approach | Applied Soft Computing Journal |
| (Nuñez-Piña et al., 2018) | 2018 | Modeling of Throughput in Production Lines Using Response Surface Methodology and Artificial Neural Networks | Complexity |
| (Khalaj et al., 2013) | 2013 | Modeling the Correlation Between Heat Treatment, Chemical Composition and Bainite Fraction of Pipeline Steels by Means of Artificial Neural Networks | Neural Network World |
| (Barletta et al., 2014) | 2014 | Modelling the Electrostatic Fluidised Bed (EFB) coating process using Support Vector Machines (SVMs) | Powder Technology |
| (Saberi & Yusuff, 2010) | 2012 | Neural network application in predicting advanced manufacturing technology implementation performance | Neural Computing and Applications |
| (Fallahpour et al., 2017) | 2017 | Nonlinear genetic-based model for supplier selection: a comparative study | Technological and Economic Development of Economy |
| (Bergmann et al., 2014) | 2014 | On the use of artificial neural networks in simulation-based manufacturing control | Journal of Simulation |
| (Huang et al., 2012) | 2012 | Optimization of data mining in dynamic environments based on a component search neural network algorithm | Journal of Convergence Information Technology |
| (Ahmarofi et al., 2017) | 2017 | Predicting completion time for production line in a supply chain system through artificial neural networks | International Journal of Supply Chain Management |
| (Lima-Junior & Carpinetti, 2019) | 2019 | Predicting supply chain performance based on SCOR ® metrics and multilayer perceptron neural networks | International Journal of Production Economics |
| (Asadi et al., 2012) | 2012 | Predicting the grain size and hardness of AZ91/SiC nanocomposite by artificial neural networks | International Journal of Advanced Manufacturing Technology |
| (Ahmadzadeh & Lundberg, 2013) | 2013 | Remaining useful life prediction of grinding mill liners using an artificial neural network | Minerals Engineering |
| (Badkar et al., 2012) | 2016 | Selecting optimum maintenance activity plans by a unique simulation-multivariate approach | International Journal of Computer Integrated Manufacturing |
| (Mrzygłód et al., 2020) | 2020 | Sensitivity analysis of the artificial neural networks in a system for durability prediction of forging tools to forgings made of C45 steel | International Journal of Advanced Manufacturing Technology |
| (Souza et al., 2019) | 2019 | Soft sensors in the primary aluminum production process based on neural networks using clustering methods | Sensors (Switzerland) |
| (Souza et al., 2019) | 2019 | Statistical distributions comparison for remaining useful life prediction of components via ANN | International Journal of Systems Assurance Engineering and Management |
| (Wong et al., 2012) | 2012 | Stochastic dynamic lot-sizing problem using bi-level programming base on artificial intelligence techniques | Applied Mathematical Modelling |
| (Mitra & Majumder, 2011) | 2011 | Successive approximate model based multi-objective optimization for an industrial straight grate iron ore induration process using evolutionary algorithm | Chemical Engineering Science |

(*continued on next page*)

(*continued*)

| *Authors citation* | *Year* | *Title* | *Source title* |
|---|---|---|---|
| (Yu et al., 2014) | 2016 | The knowledge modeling system of ready-mixed concrete enterprise and artificial intelligence with ANN-GA for manufacturing production | Journal of Intelligent Manufacturing |
| (Gonzalez-Carrasco et al., 2012) | 2014 | Towards a framework for multiple artificial neural network topologies validation by means of statistics | Expert Systems |
| (Sila & Walczak, 2017) | 2017 | Universal versus contextual effects on TQM: a triangulation study using neural networks | Production Planning and Control |
| (Edwin Raja Dhas & Kumanan, 2011) | 2011 | Weld residual stress prediction using artificial neural network and Fuzzy logic modeling | Indian Journal of Engineering And Materials Sciences |
| (Güven & Şimşir, 2020) | 2020 | Demand forecasting with color parameter in retail apparel industry using artificial neural networks (ANN) and support vector machines (SVM) methods | Computers and Industrial Engineering |
| (Hage et al., 2019) | 2019 | Optimized tabu search estimation of wear characteristics and cutting forces in compact core drilling of basalt rock using PCD tool inserts | Computers and Industrial Engineering |
| (Martinek & Krammer, 2019) | 2019 | Analysing machine learning techniques for predicting the hole-filling in pin-in-paste technology | Computers and Industrial Engineering |
| (Kocamaz et al., 2016) | 2016 | Control and synchronization of chaotic supply chains using intelligent approaches | Computers and Industrial Engineering |
| (Trappey et al., 2015) | 2015 | Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions | Computers and Industrial Engineering |
| (Wang et al., 2015) | 2015 | A data mining approach for training evaluation in simulation-based training | Computers and Industrial Engineering |
| (Kheirkhah et al., 2013) | 2013 | Improved estimation of electricity demand function by using of artificial neural network, principal component analysis and data envelopment analysis | Computers and Industrial Engineering |
| (Doan et al., 2021) | 2021 | Optimization strategies of neural networks for impact damage classification of RC panels in a small dataset | Applied Soft Computing |
| (Zhan & Li, 2021) | 2021 | Machine learning based fatigue life prediction with effects of additive manufacturing process parameters for printed SS 316L | International Journal of Fatigue |
| (Gupta et al., 2021) | 2021 | Artificial intelligence to deep learning: machine intelligence approach for drug discovery | Molecular Diversity |
| (Mehrpouya et al., 2021) | 2021 | The prediction model for additively manufacturing of NiTiHf high-temperature shape memory alloy | Materials Today Communications |
| (Özden et al., 2019) | 2021 | Artificial neural network modeling for prediction of cutting forces in turning unreinforced and reinforced polyamide | Journal of Thermoplastic Composite Materials |
| (Roshani et al., 2021) | 2021 | Predicting the effect of fly ash on concrete's mechanical properties by ANN | Sustainability (Switzerland) |
| (Zhu et al., 2021) | 2021 | Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks | Computational Mechanics |
| (Suresh et al., 2021) | 2021 | Enhanced ultrasonic assisted biodiesel production from meat industry waste (pig tallow) using green copper oxide nanocatalyst: Comparison of response surface and neural network modelling | Renewable Energy |
| (Xie et al., 2021) | 2021 | Online prediction of mechanical properties of hot rolled steel plate using machine learning | Materials and Design |
| (Ushada et al., 2015) | 2015 | Development of Kansei Engineering-based watchdog model to assess worker capacity in Indonesian small-medium food industry | Engineering in Agriculture, Environment and Food |
| (Barghash, 2015) | 2015 | An effective and novel neural network ensemble for shift pattern detection in control charts | Computational Intelligence and Neuroscience |
| (Gao et al., 2014) | 2015 | Feature extraction and recognition for rolling element bearing fault utilizing short time fourier transform and non-negative matrix factorization | Chinese Journal of Mechanical Engineering (English Edition) |
| (Li et al., 2015) | 2015 | Fault diagnosis of rotating machinery with a novel statistical feature extraction and evaluation method | Mechanical Systems and Signal Processing |

## Appendix B. Publication source and number of retrieved articles and citations

| **Nr** | **Source title** | **Total citations** | **Number of articles** |
|---|---|---|---|
| 1 | Journal of Intelligent Manufacturing | 263 | 4 |
| 2 | Computers and Industrial Engineering | 231 | 9 |
| 3 | International Journal of Advanced Manufacturing Technology | 126 | 6 |
| 4 | Mechanical Systems and Signal Processing | 94 | 1 |
| 5 | Chinese Journal of Mechanical Engineering (English Edition) | 91 | 1 |
| 6 | Computers and Operations Research | 74 | 1 |
| 7 | Analytica Chimica Acta | 71 | 1 |
| 8 | Advances in Engineering Software | 70 | 1 |
| 9 | IEEE Transactions on Computer-Aided Design Of Integrated Circuits and Systems | 62 | 1 |
| 10 | International Journal of Engineering Research in Africa | 49 | 1 |
| 11 | Minerals Engineering | 43 | 1 |
| 12 | Journal of Manufacturing Technology Management | 35 | 1 |
| 13 | IEEE Transactions on Automation Science and Engineering | 29 | 1 |
| 14 | IEEE Transactions on Fuzzy Systems | 26 | 1 |
| 15 | International Journal of Production Economics | 26 | 1 |
| 16 | International Journal of Fatigue | 25 | 1 |
| 17 | Journal of Clean Production | 23 | 1 |
| 18 | Neural Computing and Applications | 22 | 2 |
| 19 | Chemical Engineering Science | 21 | 2 |
| 20 | Eksploatacja i Niezawodnosc | 18 | 2 |
| 21 | Advances in Mechanical Engineering | 18 | 2 |
| 22 | International Journal of Simulation Modelling | 17 | 1 |
| 23 | Materials | 17 | 2 |
| 24 | Applied Sciences (Switzerland) | 17 | 2 |
| 25 | Lecture Notes in Electrical Engineering | 17 | 1 |
| 26 | Technological and Economic Development of Economy | 17 | 1 |

(*continued on next page*)

(*continued*)

| Nr | Source title | Total citations | Number of articles |
|---|---|---|---|
| 27 | Applied Soft Computing Journal | 16 | 1 |
| 28 | Neural Network Work | 16 | 1 |
| 29 | Molecular Diversity | 15 | 1 |
| 30 | IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans | 14 | 1 |
| 31 | Engineering in Agriculture, Environment and Food | 12 | 1 |
| 32 | Benchmarking-An International Journal | 11 | 1 |
| 33 | Journal of Simulation | 11 | 1 |
| 34 | Production Planning and Control | 11 | 1 |
| 35 | Sustainability (Switzerland) | 11 | 1 |
| 36 | Computational Mechanics | 11 | 1 |
| 37 | International Journal of Industrial Engineering : Theory Applications and Practice | 10 | 1 |
| 38 | Journal of the Operational Research Society | 10 | 1 |
| 39 | Studies in Computational Intelligence | 10 | 1 |
| 40 | International Journal of Industrial and Systems Engineering | 10 | 2 |
| 41 | Archives of Civil and Mechanical Engineering | 10 | 1 |
| 42 | Advances in Production Engineering And Management | 10 | 1 |
| 43 | Applied Energy | 10 | 1 |
| 44 | Applied Mathematical Modelling | 10 | 1 |
| 45 | Renewable Energy | 10 | 1 |
| 46 | International Journal of Logistics Systems and Management | 9 | 1 |
| 47 | Computational Intelligence and Neuroscience | 9 | 2 |
| 48 | Drvna Industrija | 8 | 1 |
| 49 | International Journal of Mining, Reclamation and Environment | 8 | 1 |
| 50 | Engineering Economist | 8 | 1 |
| 51 | Powder Technology | 8 | 1 |
| 52 | Materials and Manufacturing Processes | 7 | 1 |
| 53 | Complexity | 7 | 1 |
| 54 | Applied Soft Computing | 7 | 1 |
| 55 | Journal of Thermoplastic Composite Materials | 7 | 1 |
| 56 | Materials and Design | 7 | 1 |
| 57 | IFIP Advances in Information and Communication Technology | 6 | 1 |
| 58 | Energy | 6 | 1 |
| 59 | Sensors (Switzerland) | 6 | 1 |
| 60 | 9th International Conference On Modelling, Identification and Control | 5 | 1 |
| 61 | 3rd International Conference on Intelligent Systems Modelling and Simulation | 5 | 1 |
| 62 | Archives of Foundry Engineering | 5 | 1 |
| 63 | Expert Systems | 5 | 1 |
| 64 | Indian Journal of Engineering and Materials Sciences | 5 | 1 |
| 65 | Biofuels | 4 | 1 |
| 66 | Benchmarking | 4 | 1 |
| 67 | Frontiers in Materials | 4 | 1 |
| 68 | Journal of Convergence Information Technology | 4 | 1 |
| 69 | International Journal of Supply Chain Management | 4 | 1 |
| 70 | Materials Today Communications | 4 | 1 |
| 71 | Journal of Mining and Metallurgy, Section B: Metallurgy | 3 | 1 |
| 72 | Materiale Plastice | 3 | 1 |
| 73 | Multidiscipline Modeling in Materials and Structures | 3 | 1 |
| 74 | International Journal of Computer Integrated Manufacturing | 3 | 1 |
| 75 | International Journal of Systems Assurance Engineering and Management | 3 | 1 |

## Appendix C. Field of science dataset

| Field of science | Articles |
|---|---|
| Computer Science/Engineering | 26 |
| Engineering | 12 |
| Computer Science | 6 |
| Engineering/Material Science | 4 |
| Materials Science | 3 |
| Mathematics | 2 |
| Computer Science/Mathematics/Neuroscience | 2 |
| Computer Science/Mathematics | 2 |
| Computer Science/Engineering/Mathematics | 2 |
| Chemical Engineering/Computer Science/Engineering/Materials Science/Physics and Astronomy | 2 |
| Chemical Engineering/Chemistry/Engineering | 2 |
| Business, Management and Accounting/Decision Sciences | 2 |
| Business, Management and Accounting | 2 |
| Renewable Energy | 1 |
| Neural Computing And Applications | 1 |
| Materials Science/Physics and Astronomy | 1 |
| Engineering/Materials/Mathematics | 1 |
| Engineering/Materials Science/Mathematics | 1 |
| Engineering/Materials Science | 1 |

(*continued on next page*)

(*continued*)

| Field of science | Articles |
|---|---|
| Engineering/Environmental Science | 1 |
| Energy/Environmental Science | 1 |
| Energy/Engineering/Mathematics | 1 |
| Energy/Engineering/Environmental Science | 1 |
| Energy, Environmental Science | 1 |
| Economics, Econometrics and Finance/Engineering/Social Sciences | 1 |
| Economics, Econometrics and Finance | 1 |
| Earth and Planetary Sciences/Engineering/Materials Science | 1 |
| Computer Science/Neuroscience | 1 |
| Computer Science/Chemical Engineering | 1 |
| Computer Science/ Decision Science | 1 |
| Chemistry/Engineering/Material Science | 1 |
| Chemistry/Earth and Planetary Sciences/Engineering | 1 |
| Chemical Engineering | 1 |
| Business, Management and Accounting/Engineering | 1 |
| Business, Management and Accounting/Energy/Engineering/Environmental Science | 1 |
| Business, Management and Accounting/Earth and Planetary Sciences | 1 |
| Business, Management and Accounting/Decision Sciences/Engineering/Physics and Astronomy | 1 |
| Business, Management and Accounting/Decision Sciences/Economics, Econometrics and Finance/Engineering | 1 |
| Business, Management and Accounting/Computer Science/Engineering | 1 |
| Business, Management and Accounting/Computer Science/Decision Sciences/Engineering | 1 |
| Business, Management and Accounting/Computer Science/Decision Science | 1 |
| Biochemistry, Genetics and Molecular Biology/Chemistry/Environmental Science | 1 |
| Biochemistry, Genetics and Molecular Biology/Chemistry/Computer Science/Engineering/Physics and Astronomy | 1 |
| Agricultural and Biological Sciences/Chemical Engineering/Engineering | 1 |
| Agricultural and Biological Sciences | 1 |

## Appendix D. ANN-based DSS use cases and other tools mentioned

| *Authors citation* | *Title* | *Performance evaluation* | *Product or process design* | *Predictive Maintenance* | *Fuzzy logic* | *GA* |
|---|---|---|---|---|---|---|
| (Can & Heavey, 2012) | A comparison of genetic programming and artificial neural networks in metamodeling of discrete-event simulation models | | ✓ | | | ✓ |
| (Sadeghian & Sadeghian, 2015) | A decision support system based on artificial neural network and fuzzy analytic network process for selection of machine tools in a flexible manufacturing system | | ✓ | | ✓ | |
| (Hawryluk & Mrzygłów, 2017) | A durability analysis of forging tools for different operating conditions with application of a decision support system based on artificial neural networks (ANN) | | | ✓ | | |
| (Taha & Rostam, 2011) | A fuzzy AHP-ANN-based decision support system for machine tool selection in a flexible manufacturing cell | | ✓ | | ✓ | |
| (Sakthivel et al., 2017) | A genetic algorithm-based artificial neural network model with TOPSIS approach to optimize the engine performance | ✓ | ✓ | | | ✓ |
| (Raut et al., 2017) | A hybrid approach using data envelopment analysis and artificial neural network for optimising 3PL supplier selection | | | | | |
| (Ramezani & Jassbi, 2017) | A hybrid expert decision support system based on artificial neural networks in process control of plaster production – An industry 4.0 perspective | ✓ | | | | |
| (Liu & Guo, 2017) | A neural network approach for prediction of bearing performance degradation tendency | | | ✓ | | |
| (Yu et al., 2011) | A new and efficient intelligent collaboration scheme for fashion design | | ✓ | | ✓ | |
| (Wen et al., 2019) | A new optimization method of wind turbine airfoil performance based on Bessel equation and GABP artificial neural network | | ✓ | | | |
| (Aktepe & Ersoz, 2012) | A quantitative performance evaluation model based on a job satisfaction-performance matrix and application in a manufacturing company | | ✓ | | | |
| (Hachicha, 2011) | A simulation metamodelling based neural networks for lot-sizing problem in MTO sector | | ✓ | | | |
| (Hawryluk & Mrzyglod, 2018) | A system of analysis and prediction of the loss of forging tool material applying artificial neural networks | ✓ | | | | |
| (Tsadiras et al., 2013) | An artificial neural network-based decision support system for solving the buffer allocation problem in reliable production lines | ✓ | ✓ | | | |
| (Mohammad Nezhad & Mahlooji, 2014) | An artificial neural network meta-model for constrained simulation optimization | | ✓ | | | |
| (Tian, 2012) | An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring | | | ✓ | | |
| (Özcan et al., 2020) | An artificial neural network model supported with multi criteria decision making approaches for maintenance planning in hydroelectric power plants | | | ✓ | | |
| (Kartal et al., 2016) | An integrated decision analytic framework of machine learning with multi-criteria decision making for multi-attribute inventory classification | | ✓ | | | |
| (Xu et al., 2015) | An integrated solution—KAGFM for mass customization in customer-oriented product design under cloud manufacturing environment | | ✓ | | ✓ | ✓ |
| (Bhargava et al., 2018) | An intelligent prognostic model for electrolytic capacitors health monitoring: A design of experiments approach | | | ✓ | ✓ | |

(*continued on next page*)

(*continued*)

| *Authors citation* | *Title* | *Performance evaluation* | *Product or process design* | *Predictive Maintenance* | *Fuzzy logic* | *GA* |
|---|---|---|---|---|---|---|
| (Yu et al., 2012) | An intelligent quick prediction algorithm with applications in industrial control and loading problems | ✓ | | | | |
| (Vimal & Vinodh, 2013) | Application of artificial neural network for fuzzy logic-based leanness assessment | | ✓ | | ✓ | |
| (Dębska & Guzowska-Świder, 2011) | Application of artificial neural network in food classification | ✓ | | | | |
| (Krenek et al., 2016) | Application of artificial neural networks in condition based predictive maintenance | | | ✓ | | |
| (Yucesan et al., 2017) | Application of artificial neural networks using bayesian training rule in sales forecasting for furniture industry | ✓ | ✓ | | | |
| (Klintong et al., 2012) | Artificial intelligence and successful factors for selecting product innovation development | | ✓ | | ✓ | ✓ |
| (Ju et al., 2016) | Artificial intelligence metamodel comparison and application to wind turbine airfoil uncertainty analysis | ✓ | | | ✓ | |
| (Almonti et al., 2019) | Artificial neural network in fibres length prediction for high precision control of cellulose refining | | ✓ | | | |
| (Kwon et al., 2016) | Best performance modeling using complementary DEA-ANN approach Application to Japanese electronics manufacturing firms | ✓ | | | | |
| (Kwon, Roh, et al., 2016) | Better practice prediction using neural networks: an application to the smartphone industry | ✓ | | | | |
| (Ye et al., 2013) | Board-Level Functional Fault Diagnosis Using Artificial Neural Networks, Support-Vector Machines, and Weighted-Majority Voting | | | ✓ | | |
| (Egilmez et al., 2016) | Cell loading and shipment optimisation in a cellular manufacturing system: An integrated genetic algorithms and neural network approach | | ✓ | | | ✓ |
| (Solarte-Pardo et al., 2019) | Cutting insert and parameter optimization for turning based on artificial neural networks and a genetic algorithm | | ✓ | | | ✓ |
| (Zhang et al., 2019) | Deep Fuzzy Echo State Networks for Machinery Fault Diagnosis | | | ✓ | ✓ | |
| (Alberti et al., 2011) | Design of a decision support system for machine tool selection based on machine characteristics and performance tests | | ✓ | | | |
| (Badkar et al., 2012) | Development of RSM- and ANN-based models to predict and analyze the effects of process parameters of laser-hardened commercially pure titanium on heat input and tensile strength | ✓ | ✓ | | | |
| (Mrzygłód et al., 2018) | Durability analysis of forging tools after different variants of surface treatment using a decision-support system based on artificial neural networks | | | ✓ | | |
| (Al-Chalabi et al., 2014) | Economic lifetime prediction of a mining drilling machine using an artificial neural network | ✓ | | | | |
| (Li et al., 2020) | Development of a group method of data handling technique to forecast iron ore price | ✓ | | | | |
| (Farizhandi et al., 2020) | Evaluation of material properties using planetary ball milling for modeling the change of particle size distribution in a gas–solid fluidized bed using a hybrid artificial neural network-genetic algorithm approach | ✓ | | | | |
| (Mitra, 2013) | Evolutionary Surrogate Optimization of an Industrial Sintering Process | | ✓ | | | |
| (Susac & Stan, 2020) | Experimental investigation, modeling and optimization of circularity, cylindricity and surface roughness in drilling of PMMA using ANN and ANOVA | ✓ | | | | |
| (Ribeiro Junior et al., 2020) | Fault classification in three-phase motors based on vibration signal analysis and artificial neural networks | | | ✓ | | |
| (Hosseini Nasab et al., 2012) | Finding a probabilistic approach to analyze lean manufacturing | ✓ | | | | |
| (Karaoglan & Karademir, 2016) | Flow time and product cost estimation by using an artificial neural network (ANN): A case study for transformer orders | ✓ | ✓ | | | |
| (Kaya et al., 2011) | Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks | | | ✓ | | |
| (Chang et al., 2010) | Forecasting of manufacturing cost in mobile phone products by case-based reasoning and artificial neural network models | | ✓ | | | |
| (Khan et al., 2021) | Geopolymer Concrete Compressive Strength via Artificial Neural Network, Adaptive Neuro Fuzzy Interface System, and Gene Expression Programming With K-Fold Cross Validation | | ✓ | | ✓ | |
| (Gegovska et al., 2020) | Green Supplier Selection Using Fuzzy Multiple-Criteria Decision-Making Methods and Artificial Neural Networks | | ✓ | | ✓ | |
| (Wang & Wang, 2018) | How AI Affects the Future Predictive Maintenance: A Primer of Deep Learning | | | ✓ | | |
| (Simeunovic et al., 2017) | Improving workforce scheduling using artificial neural networks model | | ✓ | | | |
| (Ushada et al., 2017) | Kansei engineering-based artificial neural network model to evaluate worker performance in small-medium scale food production system | ✓ | | | | |
| (Han et al., 2019) | Learned prediction of compressive strength of GGBFS concrete using hybrid artificial neural network models | ✓ | | | | |
| (Dietrich et al., 2020) | Machine learning based very short-term load forecasting of machine tools | ✓ | ✓ | | | |
| (Nallusamy et al., 2015) | MCDM tools application for selection of suppliers in manufacturing industries using AHP, fuzzy logic and ANN | | ✓ | | | |
| (Chakraborty et al., 2019) | MCDM towards knowledge incorporation in ANN models for phase transformation in continuous cooling of steel | | ✓ | | | ✓ |
| (Rojek et al., 2016) | Methods of Computational Intelligence in the Context of Quality Assurance in Foundry Products | ✓ | | | | |
| (Dasgupta et al., 2017) | | ✓ | | | | ✓ |

(*continued on next page*)

(*continued*)

| *Authors citation* | *Title* | *Performance evaluation* | *Product or process design* | *Predictive Maintenance* | *Fuzzy logic* | *GA* |
|---|---|---|---|---|---|---|
| | Modeling and optimization of polymer enhanced ultrafiltration using hybrid neural-genetic algorithm based evolutionary approach | | | | | |
| (Nuñez-Piña et al., 2018) | Modeling of Throughput in Production Lines Using Response Surface Methodology and Artificial Neural Networks | | ✓ | | | |
| (Khalaj et al., 2013) | Modeling the Correlation Between Heat Treatment, Chemical Composition and Bainite Fraction of Pipeline Steels by Means of Artificial Neural Networks | ✓ | | | | |
| (Barletta et al., 2014) | Modelling the Electrostatic Fluidised Bed (EFB) coating process using Support Vector Machines (SVMs) | ✓ | ✓ | | | |
| (Saberi & Yusuff, 2010) | Neural network application in predicting advanced manufacturing technology implementation performance | | ✓ | ✓ | | |
| (Fallahpour et al., 2017) | Nonlinear genetic-based model for supplier selection: a comparative study | | ✓ | | | |
| (Bergmann et al., 2014) | On the use of artificial neural networks in simulation-based manufacturing control | | ✓ | | | |
| (Huang et al., 2012) | Optimization of data mining in dynamic environments based on a component search neural network algorithm | | ✓ | | | |
| (Ahmarofi et al., 2017) | Predicting completion time for production line in a supply chain system through artificial neural networks | | ✓ | | | |
| (Lima-Junior & Carpinetti, 2019) | Predicting supply chain performance based on SCOR ® metrics and multilayer perceptron neural networks | ✓ | | | | |
| (Asadi et al., 2012) | Predicting the grain size and hardness of AZ91/SiC nanocomposite by artificial neural networks | ✓ | ✓ | | | |
| (Ahmadzadeh & Lundberg, 2013) | Remaining useful life prediction of grinding mill liners using an artificial neural network | | | ✓ | | |
| (Badkar et al., 2012) | Selecting optimum maintenance activity plans by a unique simulation-multivariate approach | | | ✓ | | |
| (Mrzygłód et al., 2020) | Sensitivity analysis of the artificial neural networks in a system for durability prediction of forging tools to forgings made of C45 steel | ✓ | | | | |
| (Souza et al., 2019) | Soft sensors in the primary aluminum production process based on neural networks using clustering methods | | ✓ | | | |
| (Souza et al., 2019) | Statistical distributions comparison for remaining useful life prediction of components via ANN | | ✓ | | | |
| (Wong et al., 2012) | Stochastic dynamic lot-sizing problem using bi-level programming base on artificial intelligence techniques | | ✓ | | | |
| (Mitra & Majumder, 2011) | Successive approximate model based multi-objective optimization for an industrial straight grate iron ore induration process using evolutionary algorithm | | ✓ | | | |
| (Yu et al., 2014) | The knowledge modeling system of ready-mixed concrete enterprise and artificial intelligence with ANN-GA for manufacturing production | | ✓ | | | ✓ |
| (Gonzalez-Carrasco et al., 2012) | Towards a framework for multiple artificial neural network topologies validation by means of statistics | | ✓ | | | |
| (Sila & Walczak, 2017) | Universal versus contextual effects on TQM: a triangulation study using neural networks | | ✓ | | | |
| (Edwin Raja Dhas & Kumanan, 2011) | Weld residual stress prediction using artificial neural network and Fuzzy logic modeling | ✓ | | | ✓ | |
| (Güven & Şimşir, 2020) | Demand forecasting with color parameter in retail apparel industry using artificial neural networks (ANN) and support vector machines (SVM) methods | | ✓ | | | |
| (Hage et al., 2019) | Optimized tabu search estimation of wear characteristics and cutting forces in compact core drilling of basalt rock using PCD tool inserts | | | ✓ | | |
| (Martinek & Krammer, 2019) | Analysing machine learning techniques for predicting the hole-filling in pin-in-paste technology | ✓ | | | | |
| (Kocamaz et al., 2016) | Control and synchronization of chaotic supply chains using intelligent approaches | | ✓ | | | |
| (Trappey et al., 2015) | Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions | | | | | |
| (Wang et al., 2015) | A data mining approach for training evaluation in simulation-based training | | ✓ | | | |
| (Kheirkhah et al., 2013) | Improved estimation of electricity demand function by using of artificial neural network, principal component analysis and data envelopment analysis | ✓ | ✓ | | | |
| (Doan et al., 2021) | Optimization strategies of neural networks for impact damage classification of RC panels in a small dataset | | ✓ | | | |
| (Zhan & Li, 2021) | Machine learning based fatigue life prediction with effects of additive manufacturing process parameters for printed SS 316L | | ✓ | | ✓ | |
| (Gupta et al., 2021) | Artificial intelligence to deep learning: machine intelligence approach for drug discovery | | ✓ | | | |
| (Mehrpouya et al., 2021) | The prediction model for additively manufacturing of NiTiHf high-temperature shape memory alloy | ✓ | ✓ | | | |
| (Özden et al., 2019) | Artificial neural network modeling for prediction of cutting forces in turning unreinforced and reinforced polyamide | | | ✓ | | |
| (Roshani et al., 2021) | Predicting the effect of fly ash on concrete's mechanical properties by ann | | | ✓ | | |
| (Zhu et al., 2021) | Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks | | ✓ | | | |
| (Suresh et al., 2021) | Enhanced ultrasonic assisted biodiesel production from meat industry waste (pig tallow) using green copper oxide nanocatalyst: Comparison of response surface and neural network modelling | ✓ | ✓ | | | |
| (Xie et al., 2021) | | | | ✓ | | |

(*continued on next page*)

(*continued*)

| *Authors citation* | *Title* | *Performance evaluation* | *Product or process design* | *Predictive Maintenance* | *Fuzzy logic* | *GA* |
|---|---|---|---|---|---|---|
| | Online prediction of mechanical properties of hot rolled steel plate using machine learning | | | | | |
| (Ushada et al., 2015) | Development of Kansei Engineering-based watchdog model to assess worker capacity in Indonesian small-medium food industry | | ✓ | | | |
| (Barghash, 2015) | An effective and novel neural network ensemble for shift pattern detection in control charts | | | ✓ | | |
| (Gao et al., 2014) | Feature extraction and recognition for rolling element bearing fault utilizing short time fourier transform and non-negative matrix factorization | | | ✓ | | |
| (Li et al., 2015) | Fault diagnosis of rotating machinery with a novel statistical feature extraction and evaluation method | | | ✓ | | |
| | | **32** | **55** | **22** | **13** | **9** |

## References


Abdulhameed, O., Al-Ahmari, A., Ameen, W., & Mian, S. H. (2019). Additive manufacturing: Challenges, trends, and applications. *Advances in Mechanical Engineering, 11*(2). https://doi.org/10.1177/1687814018822880

Ahmad, M. F., Hoong, K. C., Hamid, N. A., Sarpin, N., Zainal, R., Ahmad, A. N. A., Hassan, M. F., & Nawi, M. N. M. (2018). The impact of product design and process design towards new product performance in manufacturing industry: A survey result in Malaysia. *International Journal of Supply Chain Management, 7*(2).

Ahmadzadeh, F., & Lundberg, J. (2013). Remaining useful life prediction of grinding mill liners using an artificial neural network. *Minerals Engineering, 53*, 1–8. https://doi.org/10.1016/j.mineng.2013.05.026

Ahmarofi, A. A., Ramli, R., & Abidin, N. Z. (2017). Predicting completion time for production line in a supply chain system through artificial neural networks. *International Journal of Supply Chain Management, 6*(3), 82–90.

Aivaliotis, P., Georgoulias, K., & Chryssolouris, G. (2019). The use of Digital Twin for predictive maintenance in manufacturing. *International Journal of Computer Integrated Manufacturing, 32*(11), 1067–1080. https://doi.org/10.1080/0951192X.2019.1686173

Aktepe, A., & Ersoz, S. (2012). A quantitative performance evaluation model based on a job satisfaction-performance matrix and application in a manufacturing company. *International Journal of Industrial Engineering : Theory Applications and Practice, 19*(6), 264–277.

Alberti, M., Ciurana, J., Rodríguez, C. A., & Özel, T. (2011). Design of a decision support system for machine tool selection based on machine characteristics and performance tests. *Journal of Intelligent Manufacturing, 22*(2), 263–277. https://doi.org/10.1007/s10845-009-0286-6

Al-Chalabi, H., Ahmadzadeh, F., Lundberg, J., & Ghodrati, B. (2014). Economic lifetime prediction of a mining drilling machine using an artificial neural network. *International Journal of Mining, Reclamation and Environment, 28*(5), 311–322. https://doi.org/10.1080/17480930.2014.942519

Almonti, D., Baiocco, G., Tagliaferri, V., & Ucciardello, N. (2019). Artificial neural network in fibres length prediction for high precision control of cellulose refining. *Materials, 12*(22). https://doi.org/10.3390/ma12223730

Asadi, P., Givi, M. K. B., Rastgoo, A., Akbari, M., Zakeri, V., & Rasouli, S. (2012). Predicting the grain size and hardness of AZ91/SiC nanocomposite by artificial neural networks. *International Journal of Advanced Manufacturing Technology, 63* (9–12), 1095–1107. https://doi.org/10.1007/s00170-012-3972-z

Aucejo, E. M., French, J., Ugalde Araya, M. P., & Zafar, B. (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *Journal of Public Economics, 191*. https://doi.org/10.1016/j.jpubeco.2020.104271

Azadeh, A., Sheikhalishahi, M., & Monshi, F. (2015). Selecting optimum maintenance activity plans by a unique simulation-multivariate approach. *International Journal of Computer Integrated Manufacturing, 1–15*. https://doi.org/10.1080/0951192x.2014.1003409

Azadeh, A., Sheikhalishahi, M., & Monshi, F. (2016). Selecting optimum maintenance activity plans by a unique simulation-multivariate approach. *International Journal of Computer Integrated Manufacturing, 29*(2), 222–236. https://doi.org/10.1080/0951192X.2014.1003409

Badkar, D. S., Pandey, K. S., & Buvanashekaran, G. (2012). Development of RSM- and ANN-based models to predict and analyze the effects of process parameters of laser-hardened commercially pure titanium on heat input and tensile strength. *The International Journal of Advanced Manufacturing Technology, 65*(9–12), 1319–1338. https://doi.org/10.1007/s00170-012-4259-0

Badkar, D. S., Pandey, K. S., & Buvanashekaran, G. (2013). Development of RSM- and ANN-based models to predict and analyze the effects of process parameters of laser-hardened commercially pure titanium on heat input and tensile strength. *International Journal of Advanced Manufacturing Technology, 65*(9–12), 1319–1338. https://doi.org/10.1007/s00170-012-4259-0

Barghash, M. (2015). An effective and novel neural network ensemble for shift pattern detection in control charts. *Computational Intelligence and Neuroscience, 2015*, 1–9. https://doi.org/10.1155/2015/939248

Barletta, M., Gisario, A., Palagi, L., & Silvestri, L. (2014). Modelling the Electrostatic Fluidised Bed (EFB) coating process using Support Vector Machines (SVMs). *Powder Technology, 258*, 85–93. https://doi.org/10.1016/j.powtec.2014.03.017

Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks: Fundamentals, computing, design, and application. *Journal of Microbiological Methods, 43*(1), 3–31. https://doi.org/10.1016/S0167-7012(00)00201-3

Bergmann, S., Stelzer, S., & Strassburger, S. (2014). On the use of artificial neural networks in simulation-based manufacturing control. *Journal of Simulation, 8*(1), 76–90. https://doi.org/10.1057/jos.2013.6

Bhargava, C., Banga, V. K., & Singh, Y. (2018). An intelligent prognostic model for electrolytic capacitors health monitoring: A design of experiments approach. *Advances in Mechanical Engineering, 10*(10). https://doi.org/10.1177/1687814018781170

Brereton, P., Kitchenham, B. A., Budgen, D., Turner, M., & Khalil, M. (2007). Lessons from applying the systematic literature review process within the software engineering domain. *Journal of Systems and Software, 80*(4). https://doi.org/10.1016/j.jss.2006.07.009

Can, B., & Heavey, C. (2012). A comparison of genetic programming and artificial neural networks in metamodeling of discrete-event simulation models. *Computers and Operations Research, 39*(2), 424–436. https://doi.org/10.1016/j.cor.2011.05.004

Canz, T., & Jagdale, S. (1995). Decision support for manufacturing using artificial neural-networks. *Journal of Materials Processing Tech., 52*(1), 9–26. https://doi.org/10.1016/0924-0136(94)01439-8

Chakraborty, S., Das, P., Kaveti, N. K., Chattopadhyay, P. P., & Datta, S. (2019). MCDM towards knowledge incorporation in ANN models for phase transformation in continuous cooling of steel. *Multidiscipline Modeling in Materials and Structures, 15*(1), 170–186. https://doi.org/10.1108/MMMS-01-2018-0002

Chang, P.-C., Lin, J.-J., & Dzan, W.-Y. (2010). Forecasting of manufacturing cost in mobile phone products by case-based reasoning and artificial neural network models. *Journal of Intelligent Manufacturing, 23*(3), 517–531. https://doi.org/10.1007/s10845-010-0390-7

Chen, S., Fang, S., & Tang, R. (2020). An ANN-Based approach for real-time scheduling in cloud manufacturing. *Applied Sciences (Switzerland), 10*(7). https://doi.org/10.3390/app10072491

Dasgupta, J., Sikder, J., & Mandal, D. (2017). Modeling and optimization of polymer enhanced ultrafiltration using hybrid neural-genetic algorithm based evolutionary approach. *Applied Soft Computing Journal, 55*, 108–126. https://doi.org/10.1016/j.asoc.2017.02.002

Dębska, B., & Guzowska-Świder, B. (2011). Application of artificial neural network in food classification. *Analytica Chimica Acta, 705*(1–2), 283–291. https://doi.org/10.1016/j.aca.2011.06.033

Dietrich, B., Walther, J., Weigold, M., & Abele, E. (2020). Machine learning based very short term load forecasting of machine tools. *Applied Energy, 276*. https://doi.org/10.1016/j.apenergy.2020.115440

Doan, Q. H., Le, T., & Thai, D.-K. (2021). Optimization strategies of neural networks for impact damage classification of RC panels in a small dataset. *Applied Soft Computing, 102*, Article 107100. https://doi.org/10.1016/j.asoc.2021.107100

Edwin Raja Dhas, J., & Kumanan, S. (2011). Weld residual stress prediction using artificial neural network and fuzzy logic modeling. *Indian Journal of Engineering and Materials Sciences*, *18*(5), 351–360.

Efendigil, T., Önüt, S., & Kahraman, C. (2009). A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: A comparative analysis. *Expert Systems with Applications, 36*(3 PART 2), 6697–6707. https://doi.org/10.1016/j.eswa.2008.08.058

Egilmez, G., Celikbilek, C., Altun, M., & Süer, G. A. (2016). Cell loading and shipment optimisation in a cellular manufacturing system: An integrated genetic algorithms and neural network approach. *International Journal of Industrial and Systems Engineering, 24*(3), 302–332. https://doi.org/10.1504/IJISE.2016.079822

Fallahpour, A., Amindoust, A., Antuchevičienė, J., & Yazdani, M. (2017). Nonlinear genetic-based model for supplier selection: A comparative study. *Technological and Economic Development of Economy, 23*(1), 178–195. https://doi.org/10.3846/20294913.2016.1189461

Farizhandi, A. A. K., Zhao, H., Chen, T., & Lau, R. (2020). Evaluation of material properties using planetary ball milling for modeling the change of particle size distribution in a gas-solid fluidized bed using a hybrid artificial neural network-genetic algorithm approach. *Chemical Engineering Science, 215*. https://doi.org/10.1016/j.ces.2020.115469

Farsi, M. A., & Masood Hosseini, S. (2019). Statistical distributions comparison for remaining useful life prediction of components via ANN. *International Journal of Systems Assurance Engineering and Management, 10*(3), 429–436. https://doi.org/10.1007/s13198-019-00813-w

Fonseca, D. J., & Navaresse, D. (2002). Artificial neural networks for job shop simulation. *Advanced Engineering Informatics, 16*(4). https://doi.org/10.1016/S1474-0346(03)00005-3

Fonseca, D. J., Navaresse, D. O., & Moynihan, G. P. (2003). Simulation metamodeling through artificial neural networks. *Engineering Applications of Artificial Intelligence, 16*(3). https://doi.org/10.1016/S0952-1976(03)00043-5

Francalanza, E., Borg, J., & Constantinescu, C. (2017). Development and evaluation of a knowledge-based decision-making approach for designing changeable manufacturing systems. *CIRP Journal of Manufacturing Science and Technology, 16*, 81–101. https://doi.org/10.1016/j.cirpj.2016.06.001

Gao, H., Liang, L., Chen, X., & Xu, G. (2014). Feature extraction and recognition for rolling element bearing fault utilizing short-time Fourier transform and non-negative matrix factorization. *Chinese Journal of Mechanical Engineering, 28*(1), 96–105. https://doi.org/10.3901/cjme.2014.1103.166

Gegovska, T., Koker, R., & Cakar, T. (2020). Green supplier selection using fuzzy multiple-criteria decision-making methods and artificial neural networks. *Computational Intelligence and Neuroscience, 2020*. https://doi.org/10.1155/2020/8811834

Gonzalez-Carrasco, I., Garcia-Crespo, A., Ruiz-Mezcua, B., Lopez-Cuadrado, J. L., & Colomo-Palacios, R. (2012). Towards a framework for multiple artificial neural network topologies validation by means of statistics. *Expert Systems, 31*(1), 20–36. https://doi.org/10.1111/j.1468-0394.2012.00653.x

Gupta, R., Srivastava, D., Sahu, M., Tiwari, S., Ambasta, R. K., & Kumar, P. (2021). Artificial intelligence to deep learning: Machine intelligence approach for drug discovery. *Molecular Diversity, 1–46*. https://doi.org/10.1007/s11030-021-10217-3

Güven, İ., & Şimşir, F. (2020). Demand forecasting with color parameter in retail apparel industry using artificial neural networks (ANN) and support vector machines (SVM) methods. *Computers & Industrial Engineering, 147*, Article 106678. https://doi.org/10.1016/j.cie.2020.106678

Hachicha, W. (2011). A simulation metamodelling based neural networks for lot-sizing problem in MTO sector. *International Journal of Simulation Modelling, 10*(4), 191–203. https://doi.org/10.2507/IJSIMM10(4)3.188

Hage, R.-M., Hage, I., Ghnatios, C., Jawahir, I. S., & Hamade, R. (2019). Optimized tabu search estimation of wear characteristics and cutting forces in compact core drilling of basalt rock using PCD tool inserts. *Computers & Industrial Engineering, 136*, 477–493. https://doi.org/10.1016/j.cie.2019.07.049

Han, I.-J., Yuan, T.-F., Lee, J.-Y., Yoon, Y.-S., & Kim, J.-H. (2019). Learned prediction of compressive strength of GGBFS concrete using hybrid artificial neural network models. *Materials, 12*(22). https://doi.org/10.3390/ma12223708

Hawryluk, M., & Mrzygłód, B. (2017). A durability analysis of forging tools for different operating conditions with application of a decision support system based on artificial neural networks (ANN) | Analiza trwałości narzędzi kuźniczych dla różnych warunków eksploatacji z wykorzystaniem sy. *Eksploatacja i Niezawodnosc, 19*(3), 338–348. https://doi.org/10.17531/ein.2017.3.4

Hawryluk, M., & Mrzyglod, B. (2018). A system of analysis and prediction of the loss of forging tool material applying artificial neural networks. *Journal of Mining and Metallurgy, Section B: Metallurgy, 54*(3), 323–337. https://doi.org/10.2298/JMMB180417023H

Hawryluk, M., & Mrzygłów, B. (2017). A durability analysis of forging tools for different operating conditions with application of a decision support system based on artificial neural networks (ANN). *Eksploatacja i Niezawodnosc - Maintenance and Reliability, 19*(3), 338–348. https://doi.org/10.17531/ein.2017.3.4

Hosseini Nasab, H., Aliheidari Bioki, T., & Khademi Zare, H. (2012). Finding a probabilistic approach to analyze lean manufacturing. *Journal of Cleaner Production, 29–30*. https://doi.org/10.1016/j.jclepro.2012.02.017

Huang, C.-L., Chen, Y. H., & Wan, T.-L.-J. (2012). Optimization of data mining in dynamic environments based on a component search neural network algorithm. *Journal of Convergence Information Technology, 7*(7), 216–223. https://doi.org/10.4156/jcit.vol7.issue7.27

Jardim-Goncalves, R., Romero, D., & Grilo, A. (2017). Factories of the future: challenges and leading innovations in intelligent manufacturing. In *International Journal of Computer Integrated Manufacturing* (Vol. 30, Issue 1, pp. 4–14). Taylor and Francis Ltd. Doi: 10.1080/0951192X.2016.1258120.

Ju, Y., Zhang, C., & Ma, L. (2016). Artificial intelligence metamodel comparison and application to wind turbine airfoil uncertainty analysis. *Advances in Mechanical Engineering, 8*(5), 1–14. https://doi.org/10.1177/1687814016647317

Karaoglan, A. D., & Karademir, O. (2016). Flow time and product cost estimation by using an artificial neural network (ANN): A case study for transformer orders. *The Engineering Economist, 62*(3), 272–292. https://doi.org/10.1080/0013791x.2016.1185808

Kartal, H., Oztekin, A., Gunasekaran, A., & Cebi, F. (2016). An integrated decision analytic framework of machine learning with multi-criteria decision making for multi-attribute inventory classification. *Computers and Industrial Engineering, 101*, 599–613. https://doi.org/10.1016/j.cie.2016.06.004

Kaya, B., Oysu, C., & Ertunc, H. M. (2011). Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks. *Advances in Engineering Software, 42*(3), 76–84. https://doi.org/10.1016/j.advengsoft.2010.12.002

Khalaj, G., Pouraliakbar, H., Mamaghani, K. R., & Khalaj, M.-J. (2013). Modeling the correlation between heat treatment, chemical composition and bainite fraction of pipeline steels by means of artificial neural networks. *Neural Network World, 23*(4), 351–367. https://doi.org/10.14311/nnw.2013.23.022

Khan, M. A., Zafar, A., Farooq, F., Javed, M. F., Alyousef, R., Alabduljabbar, H., & Khan, M. I. (2021). Geopolymer concrete compressive strength via artificial neural network, adaptive neuro fuzzy interface system, and gene expression programming with K-fold cross validation. *Frontiers in Materials, 8*. https://doi.org/10.3389/fmats.2021.621163

Kheirkhah, A., Azadeh, A., Saberi, M., Azaron, A., & Shakouri, H. (2013). Improved estimation of electricity demand function by using of artificial neural network, principal component analysis and data envelopment analysis. *Computers & Industrial Engineering, 64*(1), 425–441. https://doi.org/10.1016/j.cie.2012.09.017

Kitchenham, B., Pearl Brereton, O., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering - A systematic literature review. *Information and Software Technology, 51*(1), 7–15. https://doi.org/10.1016/j.infsof.2008.09.009

Klintong, N., Vadhanasindhu, P., & Thawesaengskulthai, N. (2012). Artificial intelligence and successful factors for selecting product innovation development. *Proceedings - 3rd International Conference on Intelligent Systems Modelling and Simulation, ISMS 2012*, 397–402. Doi: 10.1109/ISMS.2012.86.

Kocamaz, U. E., Taşkın, H., Uyaroğlu, Y., & Göksu, A. (2016). Control and synchronization of chaotic supply chains using intelligent approaches. *Computers & Industrial Engineering, 102*, 476–487. https://doi.org/10.1016/j.cie.2016.03.014

Krenek, J., Kuca, K., Blazek, P., Krejcar, O., & Jun, D. (2016). Application of artificial neural networks in condition based predictive maintenance. In *Studies in Computational Intelligence* (Vol. 642). Doi: 10.1007/978-3-319-31277-4_7.

Kwon, H.-B., Lee, J., & Roh, J. J. (2016). Best performance modeling using complementary DEA-ANN approach: Application to Japanese electronics manufacturing firms. *Benchmarking, 23*(3), 704–721. https://doi.org/10.1108/BIJ-09-2014-0083

Kwon, H.-B., Roh, J. J., & Miceli, N. (2016). Better practice prediction using neural networks: An application to the smartphone industry. *Benchmarking, 23*(3), 519–539. https://doi.org/10.1108/BIJ-08-2013-0080

Li, D., Moghaddam, M. R., Monjezi, M., Armaghani, D. J., & Mehrdanesh, A. (2020). Development of a group method of data handling technique to forecast iron ore price. *Applied Sciences (Switzerland), 10*(7). https://doi.org/10.3390/app10072364

Li, W., Zhu, Z., Jiang, F., Zhou, G., & Chen, G. (2015). Fault diagnosis of rotating machinery with a novel statistical feature extraction and evaluation method. *Mechanical Systems and Signal Processing, 50–51*, 414–426. https://doi.org/10.1016/j.ymssp.2014.05.034

Liang, S., Rajora, M., Liu, X., Yue, C., Zou, P., & Wang, L. (2018). Intelligent manufacturing systems: A review. In *International Journal of Mechanical Engineering and Robotics Research* (Vol. 7, Issue 3, pp. 324–330). International Journal of Mechanical Engineering and Robotics Research. Doi: 10.18178/ijmerr.7.3.324-330.

Liao, Z., Wang, B., Xia, X., & Hannam, P. M. (2012). Environmental emergency decision support system based on Artificial Neural Network. *Safety Science, 50*(1), 150–163. https://doi.org/10.1016/j.ssci.2011.07.014

Lima-Junior, F. R., & Carpinetti, L. C. R. (2019). Predicting supply chain performance based on SCOR ® metrics and multilayer perceptron neural networks. *International Journal of Production Economics, 212*, 19–38. https://doi.org/10.1016/j.ijpe.2019.02.001

Liu, Z., & Guo, Y. (2017). A neural network approach for prediction of bearing performance degradation tendency. In *2017 9th International Conference on Modelling, Identification and Control (ICMIC)*. https://doi.org/10.1109/icmic.2017.8321639

Liu, Z., & Guo, Y. (2018). A neural network approach for prediction of bearing performance degradation tendency. *Proceedings of 2017 9th International Conference On Modelling, Identification and Control, ICMIC 2017, 2018-March*, 204–208. Doi: 10.1109/ICMIC.2017.8321639.

Mahmood, M. A., Visan, A. I., Ristoscu, C., & Mihailescu, I. N. (2021). Artificial neural network algorithms for 3D printing. *Materials, 14*(1), 1–29. https://doi.org/10.3390/ma14010163. MDPI AG.

Martinek, P., & Krammer, O. (2019). Analysing machine learning techniques for predicting the hole-filling in pin-in-paste technology. *Computers & Industrial Engineering, 136*, 187–194. https://doi.org/10.1016/j.cie.2019.07.033

Mawson, V. J., & Hughes, B. R. (2021). Coupling simulation with artificial neural networks for the optimisation of HVAC controls in manufacturing environments. *Optimization and Engineering, 22*(1). https://doi.org/10.1007/s11081-020-09567-y

Mehrpouya, M., Gisario, A., Nematollahi, M., Rahimzadeh, A., Baghbaderani, K. S., & Elahinia, M. (2021). The prediction model for additively manufacturing of NiTiHf high-temperature shape memory alloy. *Materials Today Communications, 26*, Article 102022. https://doi.org/10.1016/j.mtcomm.2021.102022

Mitra, K. (2013). Evolutionary surrogate optimization of an industrial sintering process. *Materials and Manufacturing Processes, 28*(7), 768–775. https://doi.org/10.1080/10426914.2012.736668

Mitra, K., & Majumder, S. (2011). Successive approximate model based multi-objective optimization for an industrial straight grate iron ore induration process using evolutionary algorithm. *Chemical Engineering Science, 66*(15), 3471–3481. https://doi.org/10.1016/j.ces.2011.03.041

Mohammad Nezhad, A., & Mahlooji, H. (2014). An artificial neural network meta-model for constrained simulation optimization. *Journal of the Operational Research Society, 65*(8), 1232–1244. https://doi.org/10.1057/jors.2013.73

Mrzygłód, B., Hawryluk, M., Gronostajski, Z., Opaliński, A., Kaszuba, M., Polak, S., Widomski, P., Ziemba, J., & Zwierzchowski, M. (2018). Durability analysis of forging tools after different variants of surface treatment using a decision-support system based on artificial neural networks. *Archives of Civil and Mechanical Engineering, 18*(4), 1079–1091. https://doi.org/10.1016/j.acme.2018.02.010

Mrzygłód, B., Hawryluk, M., Janik, M., & Olejarczyk-Wożeńska, I. (2020). Sensitivity analysis of the artificial neural networks in a system for durability prediction of forging tools to forgings made of C45 steel. *International Journal of Advanced Manufacturing Technology, 109*(5–6), 1385–1395. https://doi.org/10.1007/s00170-020-05641-y

Munn, Z., Peters, M. D. J., Stern, C., Tufanaru, C., McArthur, A., & Aromataris, E. (2018). Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Medical Research Methodology, 18*(1). https://doi.org/10.1186/s12874-018-0611-x

Nallusamy, S., Sri Lakshmana Kumar, D., Balakannan, K., & Chakraborty, P. S. (2015). MCDM tools application for selection of suppliers in manufacturing industries using AHP, fuzzy logic and ANN. *International Journal of Engineering Research in Africa*, *19*, 130–137. Doi: 10.4028/www.scientific.net/jera.19.130.

Nuñez-Piña, F., Medina-Marin, J., Seck-Tuoh-Mora, J. C., Hernandez-Romero, N., & Hernandez-Gress, E. S. (2018). Modeling of throughput in production lines using response surface methodology and artificial neural networks. *Complexity, 2018*. https://doi.org/10.1155/2018/1254794

Özcan, E., Danışan, T., Yumuşak, R., & Eren, T. (2020a). An artificial neural network model supported with multi criteria decision making approaches for maintenance planning in hydroelectric power plants. *Eksploatacja i Niezawodnosc - Maintenance and Reliability, 22*(3), 400–418. https://doi.org/10.17531/ein.2020.3.3

Özcan, E., Danışan, T., Yumuşak, R., & Eren, T. (2020b). An artificial neural network model supported with multi criteria decision making approaches for maintenance planning in hydroelectric power plants | Planowanie utrzymania ruchu w elektrowniach wodnych w oparciu o model sztucznej sieci neuronowej wsparty w. *Eksploatacja i Niezawodnosc, 22*(3), 400–418. https://doi.org/10.17531/ein.2020.3.3

Özden, G., Mata, F., & Öteyaka, M.Ö. (2019). Artificial neural network modeling for prediction of cutting forces in turning unreinforced and reinforced polyamide. *Journal of Thermoplastic Composite Materials, 089270571984571*. https://doi.org/10.1177/0892705719845712

Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. In *Journal of Intelligent Manufacturing* (Vol. 31, Issue 1, pp. 127–182). Springer. Doi: 10.1007/s10845-018-1433-8.

Pigott, T. D., & Polanin, J. R. (2020). Methodological Guidance Paper: High-Quality Meta-Analysis in a Systematic Review. *Review of Educational Research, 90*(1), 24–46. https://doi.org/10.3102/0034654319877153. SAGE Publications Inc.

Ramezani, J., & Jassbi, J. (2017a). A hybrid expert decision support system based on artificial neural networks in process control of plaster production – An industry 4.0 perspective. In *IFIP Advances in Information and Communication Technology* (Vol. 499). Doi: 10.1007/978-3-319-56077-9_5.

Ramezani, J., & Jassbi, J. (2017). A hybrid expert decision support system based on artificial neural networks in process control of plaster production – An industry 4.0 perspective. *IFIP Advances in Information and Communication Technology, 499*. https://doi.org/10.1007/978-3-319-56077-9_5

Raut, R. D., Kamble, S. S., Kharat, M. G., Joshi, H., Singhal, C., & Kamble, S. J. (2017). A hybrid approach using data envelopment analysis and artificial neural network for optimising 3PL supplier selection. *International Journal of Logistics Systems and Management, 26*(2), 203–223. https://doi.org/10.1504/IJLSM.2017.081500

Renna, P. (2017). Decision-making method of reconfigurable manufacturing systems' reconfiguration by a Gale-Shapley model. *Journal of Manufacturing Systems, 45*, 149–158. https://doi.org/10.1016/j.jmsy.2017.09.005

Ribeiro Junior, R. F., de Almeida, F. A., & Gomes, G. F. (2020). Fault classification in three-phase motors based on vibration signal analysis and artificial neural networks. *Neural Computing and Applications, 32*(18), 15171–15189. https://doi.org/10.1007/s00521-020-04868-w

Rojek, G., Regulski, K., Wilk-Kołodziejczyk, D., Kluska-Nawarecka, S., Jaśkowiec, K., & Smolarek-Grzyb, A. (2016). Methods of computational intelligence in the context of quality assurance in foundry products. *Archives of Foundry Engineering, 16*(2), 11–16. https://doi.org/10.1515/afe-2016-0018

Roshani, M. M., Kargar, S. H., Farhangi, V., & Karakouzian, M. (2021). Predicting the effect of fly ash on concrete's mechanical properties by ANN. *Sustainability, 13*(3), 1469. https://doi.org/10.3390/su13031469

Saberi, S., & Yusuff, R. M. (2010). Neural network application in predicting advanced manufacturing technology implementation performance. *Neural Computing and Applications, 21*(6), 1191–1204. https://doi.org/10.1007/s00521-010-0507-0

Sadeghian, R., & Sadeghian, M. R. (2015). A decision support system based on artificial neural network and fuzzy analytic network process for selection of machine tools in a flexible manufacturing system. *The International Journal of Advanced Manufacturing Technology, 82*(9–12), 1795–1803. https://doi.org/10.1007/s00170-015-7440-4

Sadeghian, R., & Sadeghian, M. R. (2016). A decision support system based on artificial neural network and fuzzy analytic network process for selection of machine tools in a flexible manufacturing system. *International Journal of Advanced Manufacturing Technology, 82*(9–12), 1795–1803. https://doi.org/10.1007/s00170-015-7440-4

Sakthivel, G., Senthil Kumar, S., & Ilangkumaran, M. (2017). A genetic algorithm-based artificial neural network model with TOPSIS approach to optimize the engine performance. *Biofuels, 10*(6), 693–717. https://doi.org/10.1080/17597269.2017.1338123

Sakthivel, G., Senthil Kumar, S., & Ilangkumaran, M. (2019). A genetic algorithm-based artificial neural network model with TOPSIS approach to optimize the engine performance. *Biofuels, 10*(6), 693–717. https://doi.org/10.1080/17597269.2017.1338123

Sarma, V. V. S. (1994). Decision making in complex systems. *Systems Practice, 7*(4). https://doi.org/10.1007/BF02169361

Sila, I., & Walczak, S. (2017). Universal versus contextual effects on TQM: A triangulation study using neural networks. *Production Planning and Control, 28*(5), 367–386. https://doi.org/10.1080/09537287.2017.1296598

Simeunovic, N., Kamenko, I., Bugarski, V., Jovanovic, M., & Lalic, B. (2017). Improving workforce scheduling using artificial neural networks model. *Advances in Production Engineering & Management, 12*(4), 337–352. https://doi.org/10.14743/apem2017.4.262

Sipsas, K., Alexopoulos, K., Xanthakis, V., & Chryssolouris, G. (2016). Collaborative maintenance in flow-line manufacturing environments: An industry 4.0 approach. *Procedia CIRP, 55*. https://doi.org/10.1016/j.procir.2016.09.013

Solarte-Pardo, B., Hidalgo, D., & Yeh, S.-S. (2019). Cutting insert and parameter optimization for turning based on artificial neural networks and a genetic algorithm. *Applied Sciences (Switzerland), 9*(3). https://doi.org/10.3390/app9030479

Souza, A. M. F., Soares, F. M., Castro, M. A. G., Nagem, N. F., Bitencourt, A. H. J., Affonso, C. M., & Oliveira, R. C. L. (2019). Soft sensors in the primary aluminum production process based on neural networks using clustering methods. *Sensors (Switzerland), 19*(23). https://doi.org/10.3390/s19235255

Suresh, T., Sivarajasekar, N., & Balasubramani, K. (2021). Enhanced ultrasonic assisted biodiesel production from meat industry waste (pig tallow) using green copper oxide nanocatalyst: Comparison of response surface and neural network modelling. *Renewable Energy, 164*, 897–907. https://doi.org/10.1016/j.renene.2020.09.112

Susac, F., & Stan, F. (2020). Experimental investigation, modeling and optimization of circularity, cylindricity and surface roughness in drilling of PMMA using ANN and ANOVA. *Materiale Plastice, 57*(1), 57–68. https://doi.org/10.37358/MP.20.1.5312

Taha, Z., & Rostam, S. (2011). A fuzzy AHP-ANN-based decision support system for machine tool selection in a flexible manufacturing cell. *International Journal of Advanced Manufacturing Technology, 57*(5–8), 719–733. https://doi.org/10.1007/s00170-011-3323-5

Tian, Z. (2012). An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring. *Journal of Intelligent Manufacturing, 23* (2), 227–237. https://doi.org/10.1007/s10845-009-0356-9

Trappey, A. J. C., Trappeyv, C., Ma, L., & Chang, J. C. M. (2015). Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions. *Computers & Industrial Engineering, 84*, 3–11. https://doi.org/10.1016/j.cie.2014.12.033

Tsadiras, A. K., Papadopoulos, C. T., & O'Kelly, M. E. J. (2013). An artificial neural network based decision support system for solving the buffer allocation problem in reliable production lines. *Computers and Industrial Engineering, 66*(4), 1150–1162. https://doi.org/10.1016/j.cie.2013.07.024

Ushada, M., Okayama, T., & Murase, H. (2015). Development of Kansei Engineering-based watchdog model to assess worker capacity in Indonesian small-medium food industry. *Engineering in Agriculture, Environment and Food, 8*(4), 241–250. https://doi.org/10.1016/j.eaef.2015.03.004

Ushada, M., Okayama, T., Suyantohadi, A., Khuriyati, N., & Murase, H. (2017). Kansei engineering-based artificial neural network model to evaluate worker performance in small-medium scale food production system. *International Journal of Industrial and Systems Engineering, 27*(1), 28–47. https://doi.org/10.1504/IJISE.2017.085753

Vimal, K. E. K., & Vinodh, S. (2013). Application of artificial neural network for fuzzy logic based leanness assessment. *Journal of Manufacturing Technology Management, 24*(2), 274–292. https://doi.org/10.1108/17410381311292340

Wang, J., Lin, Y.-I., & Hou, S.-Y. (2015). A data mining approach for training evaluation in simulation-based training. *Computers & Industrial Engineering, 80*, 171–180. https://doi.org/10.1016/j.cie.2014.12.008

Wang, K., & Wang, Y. (2018). How AI affects the future predictive maintenance: A primer of deep learning. In *Lecture Notes in Electrical Engineering* (Vol. 451). Doi: 10.1007/978-981-10-5768-7_1.

Wen, H., Sang, S., Qiu, C., Du, X., Zhu, X., & Shi, Q. (2019). A new optimization method of wind turbine airfoil performance based on Bessel equation and GABP artificial neural network. *Energy, 187*. https://doi.org/10.1016/j.energy.2019.116106

Wong, J.-T., Su, C.-T., & Wang, C.-H. (2012). Stochastic dynamic lot-sizing problem using bi-level programming base on artificial intelligence techniques. *Applied Mathematical Modelling, 36*(5), 2003–2016. https://doi.org/10.1016/j.apm.2011.08.017

Xie, Q., Suvarna, M., Li, J., Zhu, X., Cai, J., & Wang, X. (2021). Online prediction of mechanical properties of hot rolled steel plate using machine learning. *Materials & Design, 197*, Article 109201. https://doi.org/10.1016/j.matdes.2020.109201

Xu, Y., Chen, G., & Zheng, J. (2015). An integrated solution—KAGFM for mass customization in customer-oriented product design under cloud manufacturing environment. *The International Journal of Advanced Manufacturing Technology, 84* (1–4), 85–101. https://doi.org/10.1007/s00170-015-8074-2

Xu, Y., Chen, G., & Zheng, J. (2016). An integrated solution—KAGFM for mass customization in customer-oriented product design under cloud manufacturing environment. *International Journal of Advanced Manufacturing Technology, 84*(1–4), 85–101. https://doi.org/10.1007/s00170-015-8074-2

Ye, F., Zhang, Z., Chakrabarty, K., & Gu, X. (2013). Board-level functional fault diagnosis using artificial neural networks, support-vector machines, and weighted-majority voting. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 32*(5), 723–736. https://doi.org/10.1109/tcad.2012.2234827

Yu, J.-B., Yu, Y., Wang, L.-N., Yuan, Z., & Ji, X. (2014). The knowledge modeling system of ready-mixed concrete enterprise and artificial intelligence with ANN-GA for manufacturing production. *Journal of Intelligent Manufacturing, 27*(4), 905–914. https://doi.org/10.1007/s10845-014-0923-6

Yu, Y., Choi, T.-M., & Hui, C.-L. (2012). An intelligent quick prediction algorithm with applications in industrial control and loading problems. *IEEE Transactions on Automation Science and Engineering, 9*(2), 276–287. https://doi.org/10.1109/TASE.2011.2173800

Yu, Y., Choi, T.-M., Hui, C.-L., & Ho, T.-K. (2011). A new and efficient intelligent collaboration scheme for fashion design. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, 41*(3), 463–475. https://doi.org/10.1109/TSMCA.2010.2089514

Yucesan, M., Gul, M., & Celik, E. (2017). Application of artificial neural networks using bayesian training rule in sales forecasting for furniture industry | Primjena umjetnih neuronskih mreža uz pomoć Bayesova pravila učenja u predviđanju prodaje za industriju namještaja. *Drvna Industrija, 68*(3), 219–228. https://doi.org/10.5552/drind.2017.1706

Yucesan, M., Gul, M., & Erkan, E. (2017). Application of artificial neural networks using Bayesian training rule in sales forecasting for furniture industry. *Drvna Industrija, 68*(3), 219–228. https://doi.org/10.5552/drind.2017.1706

Yu-gang, W., & Shi-chao, X. (2019). An intelligence evaluation method of the environmental impact for the cutting process. *Journal of Cleaner Production, 227*, 229–236. https://doi.org/10.1016/j.jclepro.2019.03.336

Zhan, Z., & Li, H. (2021). Machine learning based fatigue life prediction with effects of additive manufacturing process parameters for printed SS 316L. *International Journal of Fatigue, 142*. https://doi.org/10.1016/j.ijfatigue.2020.105941

Zhang, S., Sun, Z., Wang, M., Long, J., Bai, Y., & Li, C. (2019). Deep fuzzy echo state networks for machinery fault diagnosis. *IEEE Transactions on Fuzzy Systems, 1*. https://doi.org/10.1109/tfuzz.2019.2914617

Zhu, Q., Liu, Z., & Yan, J. (2021). Machine learning for metal additive manufacturing: Predicting temperature and melt pool fluid dynamics using physics-informed neural networks. *Computational Mechanics, 67*(2), 619–635. https://doi.org/10.1007/s00466-020-01952-9

Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers and Industrial Engineering, 150*. https://doi.org/10.1016/j.cie.2020.106889