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The Role of Computational Intelligence in Modern Manufacturing: A Review of Models and Industrial Applications

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ABSTRACT

The rapid evolution of manufacturing systems under Industry 4.0 has introduced increased complexity, high variability, and vast data generation, necessitating intelligent and adaptive decision-making tools. Computational Intelligence (CI) models—encompassing artificial neural networks, fuzzy logic systems, genetic algorithms, and hybrid approaches—offer powerful capabilities for addressing these challenges. This review examines the theoretical foundations, capabilities, and limitations of CI techniques and explores their industrial applications across key manufacturing functions, including cost estimation, process optimization, predictive maintenance, and quality control. Emphasis is placed on how these models contribute to improved efficiency, accuracy, and responsiveness in dynamic production environments. While CI models have shown substantial promise, their implementation still faces challenges related to data integration, interpretability, and scalability. The review highlights emerging trends, such as the integration of CI with real-time analytics and IoT systems, and identifies research gaps that hinder broader industrial adoption. By synthesizing current developments, this study provides a comprehensive resource for researchers and practitioners seeking to harness CI for smarter, data-driven manufacturing. Ultimately, the review underscores the strategic value of CI in shaping the future of intelligent manufacturing systems and calls for continued innovation and interdisciplinary collaboration to realize its full potential.

Keywords: Computational Intelligence, Modern Manufacturing, Models, Industrial Applications, Industry 4.0

Introduction

Computational Intelligence (CI) refers to a set of nature-inspired computational methodologies and approaches, including artificial neural networks (ANNs), fuzzy logic systems, evolutionary algorithms such as genetic algorithms (GAs), and hybrid models that combine these techniques. These models are particularly suited to solving complex, nonlinear, and ill-structured problems where conventional analytical approaches fall short (Zadeh, 2008; Haykin, 2009). CI models possess the ability to learn from data, adapt to changing conditions, and generalize solutions, making them highly effective for real-world applications across diverse domains. In the manufacturing sector, CI has found utility in process control, predictive maintenance, quality assurance, and, increasingly, in cost estimation and control (Jain et al., 2018).

Manufacturing costing is a critical function that involves estimating and allocating the direct and indirect costs associated with production activities. Accurate costing is essential for pricing strategies, budgeting, profitability analysis, and strategic decision-making. Traditional costing methods, such as standard costing and activity-based costing, often struggle to keep pace with the complexity and dynamism of modern manufacturing systems (Gunasekaran et al., 2004). These traditional methods may oversimplify cost drivers and fail to account for real-time changes in production environments, leading to inefficiencies and misinformed decisions.

The advent of Industry 4.0 technologies—such as the Internet of Things (IoT), big data analytics, and cyber-physical systems—has further transformed manufacturing operations, generating vast amounts of real-time data (Zhou et al., 2020). CI models, with their ability to handle high-dimensional data and model complex relationships, are well-positioned to address the limitations of conventional costing techniques. For example, ANNs have been used for forecasting manufacturing costs based on historical data, while fuzzy logic systems can incorporate expert knowledge and uncertainty in cost estimation processes (Nguyen & Aiello, 2021).

Despite their potential, the application of CI in manufacturing costing is still in a nascent stage, with existing literature offering fragmented insights and inconsistent methodologies. Many studies focus on specific use cases without providing a comprehensive framework or comparative analysis of different CI models. Moreover, practical implementation challenges, such as model interpretability, data integration, and scalability, often hinder their industrial adoption (Rani et al., 2022). Therefore, there is a pressing need for a systematic review of CI models specifically in the context of manufacturing costing to evaluate their effectiveness, identify research gaps, and provide guidance for future development and deployment in industrial settings.

Computational intelligence techniques are a subset of artificial intelligence (AI) that focus on developing intelligent algorithms and models to solve complex problems (Okwu *et al.,* 2019). These techniques are particularly relevant in manufacturing operations, where data-driven decision-making and optimization are crucial. Some commonly used computational intelligence techniques in manufacturing include:

1. **Fuzzy Logic Systems (FLS)**

Fuzzy Logic System, **(FLS)** is a mathematical framework specifically tailored to address uncertainty and imprecision encountered in decision-making processes. It provides a structured approach for dealing with situations where information is vague, subjective, or qualitative in nature (Akbari *et al.*, 2019). By employing FLS, it becomes possible to reason effectively using information that might be expressed in terms like "very good" or "very poor." In the system of manufacturing, FLS has found application in various tasks such as control systems, process optimization, and decision support systems. This enables industries to harness the benefits of fuzzy reasoning to enhance their operations and outcomes (Akbari *et al*., 2019). However, it's important to note that in certain contexts like logistics systems, the preference for quantitative data arises from the need to maintain consistency, reduce uncertainty, and ensure a higher degree of precision and quality (Akbari M. *et al*., 2019). Homayouni & Tang (2018) took on the challenge of optimizing the scheduling of Quay Cranes (QC) and Automated Guided Vehicles (AGV) using a genetic algorithm. To enhance the efficiency of their genetic algorithm, they incorporated a heuristic method to assign AGVs to tasks. The algorithm's performance was evaluated based on factors like total traveling time of vehicles and delays in final tasks. This approach demonstrated effectiveness through numerical testing and the development of a fuzzy logic controller (FLC) and fuzzy genetic algorithm (FGA) in the MATLAB® toolbox.

Another application area is the management of complex decision-making problems involving multiple criteria. Balendra (2017) proposed a fuzzy logic decision-making approach for selecting transportation processes with multiple objectives and intricate interdependencies. He applied fuzzy logic to tackle both qualitative and quantitative attributes, effectively handling the complexity of the problem. Sayed *et al.*, (2015) extended the use of FLS and genetic algorithms to the scheduling of handling and storage equipment in container terminals. Their innovative contribution was the integration of a fuzzy logic controller (FLC) with a genetic algorithm to optimize scheduling. By dynamically controlling the genetic algorithm's parameters through fuzzy logic, the solution quality was enhanced, yielding outcomes approximately 2.5% better than those obtained using the genetic algorithm alone (Sayed *et al.*, 2015). In summary, the applications of Fuzzy Logic System encompass a wide range of fields, from manufacturing to logistics, decision-making, and optimization. The integration of fuzzy logic with other techniques, such as genetic algorithms, demonstrates the potential to improve solution quality and address complex real-world problems.

2. **Fuzzy Linear Programming Model**

The Linear Programming Problem (LPP) serves as a valuable optimization technique, particularly well-suited for resolving issues characterized by linear relationships between decision variables, objective functions, and constraints. These constraints might take the form of equalities or inequalities, offering a versatile approach to problem-solving (Karthikeyan & Sampath 2018).

Over the course of the last twenty years, the system of fuzzy linear programming has witnessed widespread application in addressing an array of challenges within the manufacturing domain. These challenges span diverse areas such as scheduling, aggregate planning, material requirements planning, supplier selection, and outsourcing decisions (Karthikeyan & Sampath 2018). Moreover, the incorporation of fuzzy logic into transhipment modelling through mathematical programming has emerged as a novel and prominent topic. Delving into the landscape of fuzzy modelling reveals several notable facets, including the development of fuzzy evaluation systems to quantify the flow of products from source to destination, the utilization of fuzzy approaches for selecting sources and destinations, the management of inventory levels via fuzzy supply and demand considerations, the determination of stock policies using fuzzy inventory cost parameters, and the optimization of schedules and distributions. Fuzzy logic has also been harnessed to create intelligent agents for product distribution, and the application of fuzzy multi-objective methodologies has been pivotal in solving intricate production and distribution networks within network distribution systems (Wen & Rein 2010).

In essence, the evolution of fuzzy linear programming has brought about innovative ways to tackle intricate manufacturing challenges. This approach not only extends to conventional problem-solving areas but also ventures into advanced applications like transhipment modelling and multi-objective optimization, where the incorporation of fuzzy logic enables more robust and adaptable solutions.

Peidro & Zupta (2017) introduced an innovative approach to supply chain planning by presenting a fuzzy mathematical programming model. This model addresses the intricacies arising from uncertainties related to supply, demand, and processes. Their approach becomes particularly relevant in scenarios where data might lack certainty or historical records are unavailable. By leveraging fuzzy set theory, their model encompasses a broad search space, allowing it to effectively capture the nuanced interplay between certainties and uncertainties within supply chain dynamics. This framework offers a robust method to navigate the complexities of supply chain management (Peidro & Zupta 2017). Building on this foundation, Wen & Rein (2010) devised a game-based framework designed to probe the strategic interactions among supply chain partners. This unique framework harnesses fuzzy multi-objective programming in conjunction with the alliance or association matrix and the concept of achievement level or aspiration degree. The resulting model empowers a comprehensive analysis of the strategic behaviours adopted by different partners within the supply chain ecosystem. The inclusion of fuzzy elements enhances the ability to represent the multifaceted and often vague aspects of decision-making, thereby leading to a more insightful understanding of supply chain collaborations (Wen & Rein 2010). Furthermore, Gumus & Guneri (2019) contributed to the field by crafting an advanced multi-echelon inventory management framework. Their framework is tailored to handle the complexities brought about by stochastic and fuzzy supply chain design models. They also extended their efforts to construct a supply chain network for a well-established multinational corporation. This initiative showcases their commitment to addressing the challenges inherent in modern supply chain management. By incorporating both stochastic and fuzzy elements, their model is poised to address the intricacies of decision-making and inventory management within a dynamic supply chain environment (Gumus & Guneri 2019).

In summary, the works of Peidro & Zupta (2017), Wen & Rein (2010), and Gumus & Guneri (2019) , underscore the significance of integrating fuzzy set theory and mathematical programming into the system of supply chain management. Their contributions not only expand our understanding of supply chain dynamics but also provide practical methodologies for grappling with uncertainties, strategic behaviors, and inventory management, all of which are pivotal aspects of contemporary supply chain operations.

Peidro & Zupta (2017), embarked on an insightful journey by leveraging fuzzy set theory to encapsulate the intricate nature of uncertainties present within supply chain dynamics. In pursuit of enhanced tactical supply chain planning, they constructed a fuzzy linear programming model. This innovative model was tailored to address the complexities inherent in a multi-echelon, multi-product, multi-level, and multi-period supply chain network. By effectively integrating the inherent uncertainties through the lens of fuzzy sets, they offered a comprehensive framework that contributes to informed decision-making in the dynamic landscape of supply chain operations. Similarly, Bilgen (2010), delved into the world of supply chain intricacies with a focus on production and distribution planning. In a supply chain system where the allocation of production volumes among various production lines and the subsequent distribution of products to distribution centres are central concerns. Bilgen (2010), proposed an integrated optimization model that was meticulously designed to holistically address production and distribution planning, aiming to harmoniously synchronize and optimize the crucial interdependent logistics decisions within the intricate supply chain ecosystem. Continuing on this path of innovation, Gumus & Guneri (2019) devised a sophisticated inventory management framework catering to multi-echelon supply chains operating within stochastic and fuzzy environments. This framework encompassed deterministic as well as stochastic-neuro-fuzzy cost models. These models, intricately embedded within the overarching framework, demonstrated the authors' dedication to achieving effective inventory management solutions while accounting for the uncertainties inherent to modern supply chain operations. Adding to the rich tapestry of supply chain research, Zhou (2021) explored the system of fuzzy-operated supply chains. In this context, the fuzziness was attributed to customer demands and manufacturing costs. He presented two distinct game structures that guide the behaviour of supply chain participants. One structure fostered cooperation between the manufacturer and the retailer, amalgamating their efforts into an integrated entity. Alternatively, they examined scenarios where the manufacturer assumed a leadership role and exerted dominance within the supply chain, thereby influencing its trajectory.

In summary, these research works collectively elevated the discourse surrounding supply chain management. By embracing fuzzy logic, intricate modelling, and strategic game structures, these scholars have enriched our understanding of supply chain complexities and offered practical methodologies for addressing uncertainties, optimizing decision-making, and fostering effective collaboration within the supply chain ecosystem. Chang (2020) introduced an innovative approach that harnessed the power of fuzzy sets to address the complex challenges of integrating manufacturing and distribution planning decisions (MDPD) within supply chains. Their approach extended to encompass multi-product and multi-time period scenarios. One of the noteworthy additions to their model was the incorporation of the time value of money, which allowed for a more comprehensive consideration of the operating cost categories. This holistic approach aimed to provide a more accurate representation of the dynamic nature of supply chain decision-making processes. Chang (2020) took this endeavour further by formulating a fuzzy multi-objective linear programming (FMOLP) model. This model employed a piecewise linear membership function to tackle intricate problems involving integrated multi-product and multi-time period production and distribution planning decisions (PDPD). The use of fuzzy objectives enabled the representation of the complex and uncertain nature of the decision-making process. By embracing this model, Chang aimed to enhance the ability to navigate the intricacies of supply chain dynamics while accounting for various product types and time horizon. Furthermore, Selim & Jang (2008) recognized the significance of collaborative planning issues within the supply chain context. To address this, they introduced decision makers' imprecise aspiration levels for goals into their model. Employing a fuzzy goal programming approach, they created a more realistic model structure that reflected the nuanced nature of decision makers' preferences and aspirations. This approach enriched the decision-making process by accommodating imprecision and variations in decision makers' goals, leading to more robust and adaptable solutions. In summary, the research contributions of Chang (2020)., Selim & Jang (2008) highlight the evolution of supply chain management methodologies by incorporating fuzzy logic and innovative modelling techniques. Their efforts not only enhance the accuracy and realism of decision-making processes but also pave the way for addressing multi-faceted challenges such as multi-product, multi-time period, and collaborative planning considerations within supply chains. Through their pioneering work, these scholars have significantly enriched our toolkit for tackling the complexities of modern supply chain operations. In 2019, Xu & Bai introduced an innovative strategy designed to effectively address the uncertainty inherent in demand fluctuations. Their approach was tailored to handle the ambiguous and uncertain nature of demand, offering an optimized technique that could contribute to more adept management of demand variability within supply chain operations. In a parallel line of research, Manzini &Gebennini (2018) embarked on developing a comprehensive framework for the assessment of supply chain partnership (SCP) performance. Their efforts extended beyond mere evaluation to encompass dynamic relationships within the SCP context. By meticulously constructing a framework rooted in the fundamental structure of the European Foundation for Quality Management (EFQM) model, the researchers aimed to establish a versatile methodology capable of evaluating and enhancing supply chain partnerships which relied on a novel modification to the S-curve membership function. Their methodology harnessed the power of fuzzy logic to address complex decision-making scenarios within supply chain operations. The integration of this modified membership function allowed for a more nuanced representation of uncertainties, leading to improved decision-making strategies. Delfani *et al.*, (2022) further advanced the field by introducing an interactive fuzzy multi-objective linear programming method. This innovative approach was specifically designed to tackle the intricate challenges posed by fuzzy multi-objective transportation problems. By employing a piecewise linear membership function, the aim was to enhance the modelling of these problems, allowing for more accurate and adaptable solutions that catered to the multifaceted aspects of transportation planning under fuzziness. In the same vein of addressing uncertainty within supply chain planning, Peidro & Zupta (2017) put forth a novel mathematical programming model grounded in fuzzy linear programming principles. Their approach was meticulously tailored to handle the intricacies of tactical supply chain planning in the face of uncertainties. By leveraging fuzzy logic-based techniques, the team aimed to create a robust and effective strategy for navigating the challenges of supply chain planning within an uncertain environment. By introducing optimal techniques for handling demand fuzziness, dynamic assessment frameworks for partnerships, modified membership functions, interactive approaches, and fuzzy-based tactical planning models, these researchers have significantly advanced our understanding and capabilities in addressing uncertainties and optimizing decision-making within the intricate dynamics of supply chains. Chang (2020) introduced a fresh perspective that revolutionized the formulation of binary piecewise linear membership functions. This novel idea challenged traditional approaches, presenting a new and innovative way to represent membership functions in a binary context. Chang's contribution opened doors to more nuanced and adaptable techniques for handling membership functions in complex scenarios. Building on this innovative spirit, Liu *et al.,* (2019) made significant strides by developing a multifaceted fuzzy multi-objective linear programming model. This model leveraged piecewise linear membership functions to address the intricate challenges posed by integrated multi-product and multi-time period production and distribution planning decisions. By utilizing these membership functions, Liu *et al.* (2019) aimed to capture the nuances of fuzzy objectives in a manner that aligned with the complexities of real-world decision-making scenarios. They proposed a ground-breaking mathematical programming model. Their model was uniquely designed to navigate the uncertainties stemming from supply, process, and demand fluctuations. By formulating these uncertainties as a fuzzy mixed-integer linear programming model, their technique addressed the inherent ill-knowledge of data through the utilization of triangular fuzzy numbers. This approach offered a comprehensive strategy for handling uncertainty in supply chain planning scenarios. Dinash & Ashok (2011) brought innovation to the forefront by devising a stochastic chance constrained mixed-integer nonlinear programming model. Their focus was on tackling the complex challenges associated with short-term crude oil scheduling in refinery operations. By incorporating stochastic and chance constraints, Dinash & Ashok (2011) aimed to create a robust and effective methodology for refining scheduling decisions in a volatile and uncertain environment. In a different avenue of research, Zandhessami *et al.,* Zubril (2011) introduced a hybrid approach that combined Analytic Network Process (ANP) with fuzzy goal programming to address supplier selection challenges. Their methodology provided a holistic framework for evaluating and selecting the best supplier within a supply chain context. By merging the strengths of ANP and fuzzy goal programming, Zandhessami and his team aimed to offer a more comprehensive and well-informed supplier selection strategy. These researchers introduced novel concepts, methodologies, and models that not only addressed challenges but also pushed the boundaries of knowledge. By embracing innovative approaches to handle membership functions, objectives, uncertainties, scheduling, and supplier selection, these scholars have significantly advanced our understanding and capabilities in navigating the intricate landscape of modern supply chains. Boucif *et al.,* (2020) embarked on a comprehensive exploration of an innovative concept—an adaptive neuro-fuzzy vehicle regulator developed through the implementation of the subtractive clustering method. Their research delved into the process of vehicle suspension control systems, with a keen focus on the efficacy and adaptability of neuro-fuzzy regulators under both normal and challenging operational conditions. By leveraging this novel approach, they aimed to enhance the performance of adaptive vehicle suspensions, contributing to more seamless functioning across varying contexts. Within their study, Boucif. *et al.,* (2020) not only examined the fundamental principles behind the adaptive neuro-fuzzy vehicle regulator but also extended their investigation to assess the regulator's practical applications. They conducted comprehensive analyses of how the regulator responded and performed under diverse circumstances, including regular operating conditions and more complex scenarios. This holistic evaluation enabled them to gauge the effectiveness of their proposed approach in achieving the desired control outcomes. One of the remarkable contributions of their research lay in the development and implementation of a hybrid methodology for diagnosing and predicting the technical state of transportation systems. This hybrid approach effectively combined diagnostics and predictive techniques, resulting in a sophisticated framework that offered both high efficiency and operational reliability. By integrating these diagnostic and predictive capabilities, Boucif and his team addressed a critical aspect of transportation facility management, maintaining and ensuring the reliability of the technical components that keep vehicles operational. Furthermore, the outcomes of their study have broader implications for the transportation industry as a whole. In an era where operational efficiency, safety, and reliability are of paramount importance, the introduction of an adaptive neuro-fuzzy vehicle regulator and a hybrid diagnostic-predictive methodology brings significant advancements. By enhancing the adaptability and control capabilities of vehicle suspension systems and concurrently providing a means for predicting and diagnosing technical issues, their work contributes to the evolution of transportation systems that are not only more efficient but also more robust and dependable.

Their investigation into the adaptive neuro-fuzzy vehicle regulator, coupled with the development of a hybrid diagnostic-predictive methodology, presents an innovative and practical approach to enhancing the performance, reliability, and efficiency of transportation systems, all while ensuring their seamless operation in various conditions. Ata & Kocyigit (2014) devised an innovative and comprehensive approach to address the intricate challenge of designing and planning closed-loop supply chains. Their methodology consisted of two distinct but interconnected phases, offering a holistic solution to this complex problem. In the initial phase, the researchers introduced an Adaptive Network Based Fuzzy Inference System (ANFIS) as a cornerstone of their methodology. This phase was dedicated to handling the inherent uncertainties associated with the quantities of return products, a critical aspect of closed-loop supply chains. By utilizing ANFIS, the researchers aimed to effectively predict and forecast return rates, thereby enhancing the decision-making process in designing the supply chain. This phase was crucial in setting the stage for the subsequent optimization process. Moving on to the second phase, the researchers leveraged the insights gained from the ANFIS-based forecasting to establish an optimized closed-loop supply chain network. This network was characterized by multiple echelons, diverse products, and extended periods, making it a complex optimization challenge. To ensure the attainment of the global optimum, general exact solvers were employed. This phase represented the culmination of their integrated methodology, resulting in a finely tuned closed-loop supply chain network designed for optimal performance. To assess the effectiveness of their methodology, Thresh et al. conducted a comprehensive evaluation over a span of 25 periods, employing a numerical example. The results obtained from this evaluation provided valuable insights into the performance of their proposed two-phase optimization method. The outcomes demonstrated that the methodology yielded acceptable performance in addressing the challenges associated with closed-loop supply chain design and planning. This research contribution by Thresh and his team holds significant implications for the field of supply chain management. By introducing a two-phase methodology that combines accurate forecasting with optimization techniques, they provide a comprehensive framework for tackling the complexities of closed-loop supply chains. The integration of ANFIS-based forecasting and rigorous optimization not only enhances decision-making but also promotes efficiency and effectiveness in the design and planning of closed-loop supply chains. In conclusion, Ata & Kocyigit (2014) mark a pivotal advancement in the field of closed-loop supply chain management. Their integrated two-phase methodology, encompassing forecasting and optimization, represents a holistic approach to address uncertainties, design intricacies, and operational challenges within closed-loop supply chains. Through meticulous evaluation and meaningful results, their work provides a valuable contribution to the enhancement of supply chain design and planning strategies.

Bilgen (2010) conducted a study that shed light on the remarkable capabilities of a fuzzy inference system (FIS) when applied to the evaluation of suppliers within a supply chain context. Their research encompassed a comprehensive framework that factored in both qualitative and quantitative considerations, while also considering the influence of gradual coverage distance, a novel dimension. The primary objective of the study was to explore the potential of various measures and metrics in the domain of supply chain network design, specifically pertaining to the selection of suppliers. The researcher delved into the intricacies of supplier evaluation, recognizing the intricate interplay between qualitative and quantitative factors that contribute to supplier selection decisions. The work recognized that the conventional methods used for supplier evaluation might fall short in capturing the nuanced nuances of supplier quality and performance. To address this, they introduced the concept of a fuzzy inference system, a technique known for its adaptability and capability to incorporate multiple variables and dimensions. Their study emphasized the comprehensive nature of the FIS approach. It showcased the system's ability to accommodate diverse criteria in evaluating suppliers within a single cohesive framework. This approach not only enhanced the accuracy of supplier evaluations but also provided a more holistic view of supplier performance across various dimensions. One of the most notable contributions of their research was the introduction of the concept of gradual coverage distance into the supplier evaluation process. This dimension accounted for the varying degrees of influence and reach that suppliers might have across different aspects of the supply chain. By incorporating gradual coverage distance, Muhammed and Salman introduced a dynamic and adaptive element to supplier evaluation, making their approach more realistic and aligned with the complexities of real-world supply chain dynamics. In conclusion, the study conducted by Bilgen (2010) presents a significant advancement in the domain of supplier evaluation within supply chain management. By showcasing the expressive power of a fuzzy inference system, their research offers a fresh perspective on how to comprehensively assess suppliers while considering both qualitative and quantitative factors. Moreover, their introduction of gradual coverage distance as a crucial dimension highlights their innovative approach to addressing the intricate dynamics of supplier evaluation. Through this work, the researchers contribute to the enhancement of supplier selection processes and pave the way for more informed decision-making within supply chain networks.

Application of Fuzzy Logic in Other Area of Engineering

Binary (2013) embarked on a pioneering exploration by harnessing the potential of fuzzy logic to overcome the shortcomings of Boolean logic in addressing the intricacies of assessing health impacts related to transportation problem. The study aimed to tackle the challenges posed by ambiguity and uncertainty inherent in the evaluation of the effects of distribution on public health. Binary's research unfolded in two main phases, involving the development of a fuzzy logic Geographic Information System (GIS) system within the ArcGIS platform, followed by the practical application of this novel decision support system in assessing transportation's influence on public health. The initial phase of the research was dedicated to the creation of a fuzzy logic GIS system. This system was specifically designed to address the limitations of Boolean logic, which struggles to accommodate the nuanced nuances and uncertainties present in health impact assessments. By integrating fuzzy logic into the GIS system, Binary sought to provide a more adaptive and realistic framework that could effectively model the complexities of health-related effects stemming from transportation. The subsequent phase of the study involved the practical application of the developed fuzzy logic GIS system. This step was instrumental in showcasing the utility and effectiveness of the decision support system in real-world scenarios. By employing the system to assess the impact of transportation on public health, Binary demonstrated the tangible benefits of employing fuzzy logic to capture the inherent uncertainties and ambiguities within the assessment process. The outcomes of Binary's research presented a compelling argument in favor of fuzzy logic's capabilities. The study revealed that fuzzy logic offers a notable advantage over Boolean logic by seamlessly accommodating the intricate dynamics of uncertainty and ambiguity that characterize health impact assessments in transportation scenarios. However, it's important to note that the effectiveness of fuzzy logic is closely linked to the availability of detailed data. Robust and comprehensive data enable fuzzy logic to perform optimally, enhancing its capacity to accurately model the complex relationships between transportation and public health (Liang 2008). Binary's research represents a significant contribution to the fields of transportation, public health, and decision support systems. By introducing fuzzy logic into the evaluation process, the study offers a novel and adaptive approach to addressing the challenges posed by uncertainty and ambiguity in assessing the health impacts of transportation. This approach not only enriches our understanding of the interplay between transportation and public health but also provides a practical tool for making more informed decisions in urban planning and policy development. Delfani *et al.,* (2022), introduced a series of mathematical programming models designed to tackle intricate challenges within supply chain production and transport planning. Their research extended to the development of a multi-criteria decision-making model that catered to the needs of both manufacturers and distributors. They constructed a stochastic planning model tailored to a two-echelon distribution system operating within the space of a petroleum company. The significance of their work was further underscored by Ray (2005) who emphasized the importance of addressing supply and demand uncertainties collectively in distribution contexts. The field of supply management has witnessed the emergence of various methods to grapple with the complexities introduced by uncertainties. Researchers have fervently pursued approaches such as scenario programming, stochastic programming, fuzzy logic, computer simulation, and intelligent algorithms, each method catering to specific scenarios and dimensions of uncertainty. This diverse array of methodologies, as highlighted by Liang (2008), underscores the need for tailored solutions that align with the specific context and nature of the problem at hand. While each method carries its own set of strengths and advantages, decision makers face the task of judiciously selecting the most appropriate approach for addressing uncertainties within their supply chain management scenarios. The complexity of the challenge at hand, the nature of the uncertainties, the availability of data, and the desired level of precision all play a role in shaping the decision-making process. In conclusion, the research landscape within out-bound operations management has witnessed a proliferation of methodologies aimed at addressing uncertainties. As scholars continue to advance these methodologies, decision makers must carefully assess the specific context and requirements of their supply chain scenarios in order to choose the most appropriate approach for effectively navigating the challenges posed by uncertainties.

3. Artificial Neural Network

Artificial Neural Networks (ANN) represent a machine learning methodology inspired by the intricate design and operation of biological neural networks. Comprising interconnected nodes, also referred to as neurons, this technique simulates the information processing and transmission capabilities observed in living organisms (Okwu *et al.,* 2022). In the system of manufacturing, ANN has found substantial application across various domains including quality control, fault detection, predictive maintenance, and production forecasting. Albert Einstein's timeless wisdom, as echoed in the quote "Look deep into nature then you will understand everything better," serves as a testament to the profound insights that can be drawn from nature's mechanisms. Indeed, the inherent principles underlying natural brain functioning have guided the development of intelligent systems that mirror these intricate processes. Much like the way neurons in the natural brain process information from the external environment and encode it into electrical signals, ANN functions in a similar manner, where electrical signals serving as input are transmitted to neurons, effectively resembling the input data provided to solve a problem (Dostal 2008). When the electrical input surpasses a specific threshold, it triggers neurons to send signals to other interconnected neurons, akin to a cascade effect. The perceptron, a fundamental component of ANN, takes in this input and combines the weighted values associated with each input. If the cumulative sum of these weighted inputs surpasses a predefined threshold, the perceptron undertakes a process of iterative training, ultimately resulting in the activation of the optimal output. This iterative training ensures that the perceptron adapts to refine its outputs and align them with desired outcomes (Okwu *et al.,* 2022). By emulating the fundamental dynamics of biological neural networks, ANN introduces a versatile and adaptable approach to machine learning. Its applications across various manufacturing domains showcase its potential to revolutionize decision-making and enhance processes in industry. The profound words of Albert Einstein serve as a reminder that the natural world holds the key to understanding and designing intricate systems. In this vein, ANN's ability to mimic neural operations serves as a testament to the ingenuity of translating natural processes into intelligent, data-driven solutions that can power advancements across industries. Neural network approaches have emerged as compelling alternatives to traditional methods, offering a distinct computational and learning paradigm that introduces a fresh modeling perspective for addressing complex challenges (Dostal 2008). These approaches have proven their mettle by successfully addressing intricate real-world problems across a diverse array of fields including engineering, medicine, business, manufacturing, and military applications, as noted by Tereza (2016). In essence, neural networks emulate the information processing mechanisms observed in the human brain, presenting a sophisticated network of interconnected processing units—neurons—that operate in parallel to tackle specific problem-solving tasks. The distinctive feature of neural networks lies in their departure from the conventional problem-solving methodologies. Unlike the algorithmic methods that adhere to a predetermined sequence of steps to arrive at solutions, neural networks adopt a different trajectory. They embody a learning process, whereby the network is trained to grasp patterns, relationships, and complexities within data without the need for explicitly programmed instructions. This capacity to adapt and evolve based on training sets them apart from rigid algorithmic approaches (Ahmed *et al.,* 2016). By emulating the parallel processing and pattern recognition inherent in the human brain, neural networks not only provide a novel approach to problem-solving but also broaden the scope of what can be achieved. These constraints can potentially hinder their effectiveness in addressing complex and nuanced problems that may not conform to a predefined set of instructions. In contrast, the strength of neural networks lies in their ability to learn from data, adapt to evolving situations, and extrapolate knowledge beyond what is explicitly provided (Ahmed *et al.,* 2016). This adaptability enables them to grasp underlying patterns and relationships that may be obscured by noise or complexities. Neural networks, by their very nature, encourage the development of intelligent systems that possess the capability to discern insights from data that might otherwise elude conventional methods. In essence, the emergence of neural networks as an alternative approach signifies a shift toward more flexible and data-driven problem-solving methodologies. Their capacity to mimic the human brain's information processing mechanisms not only amplifies their potential but also marks a significant stride in shaping the landscape of modern problem-solving techniques. The fascination with artificial neural networks has persisted since their inception, driven by the realization that the human brain operates in a fundamentally distinct manner compared to traditional digital computers (Shie-Jue & Chen-Sen 2013). The human brain stands as a remarkable example of a highly intricate and parallel system for processing information. Its collection of interconnected neurons is capable of orchestrating computations at a pace that often surpasses the capabilities of even the most advanced digital computers today. This remarkable efficiency allows the brain to swiftly accomplish tasks like perceptual recognition, such as identifying a familiar face amidst an unfamiliar setting, in an astonishingly short span of time—typically around 100-200 milliseconds. This speed is in stark contrast to less complex tasks that might require days to be completed using traditional computer methods. Central to this understanding is the concept of a neural network, a machine designed to replicate the cognitive processes of the brain in tackling specific tasks (Tereza 2016). This network is either physically realized using electronic components or simulated in software on a digital computer. At its core, a neural network operates as a massive ensemble of interconnected processing units. These units, while relatively simple in isolation, collectively demonstrate a profound capacity for swiftly assimilating experiential knowledge and making it readily accessible for application. This remarkable attribute resonates with the functioning of the brain, as it also possesses a natural aptitude for efficiently storing and utilizing experiential information. ANN models have been used successfully to solve the demand forecasting and production scheduling problems. In their work, Gaafar & Choueiki (2010) applied a Neural Network model to a lot-sizing problem which is part of Material Requirements Planning (MRP) for the case of deterministic time-varying demand over a fixed planning horizon. Aburto &Weber (2007) in their research made available a hybrid intelligent system combining Autoregressive Integrated Moving Average models and Neural Network for demand forecasting. The study showed an improvement in forecasting accuracy and proposed a replenishment system for a Chilean supermarket which leads simultaneously to fewer failures as well as lower inventory levels. Artificial Neural Network structure was used and compared with the traditional statistical techniques by Hamzacebi (2008). The results from the modeled ANN made use of time-series forecasting proved that the proposed ANN model comes with a lower prediction error than other approaches. Paper introduced by Hachicha (2011) also used ANN and deals with material distribution problem by application of metamodeling simulation. The out-bound operations operate in a make-to-order environment and it is characterized by multi-product, multi-location production planning with capacity constraints and stochastic parameters such as material arrival order, transit time etc. The results confirm the effectiveness, flexibility and usability of the ANN method applied practically. Notably, ANN-based model was proposed by Paul & Azaeem (2011) which determines the optimum level of finished goods inventory as a function of product demand, holding, and material costs. The technique was tested with a manufacturing organization data and the results indicated that the approach can forecast finished goods inventory level in response to the parameters of the model. The model can be applied for optimization of finished goods inventory for any manufacturing enterprise. A fast convergent BP Artificial Neural Network model for predicting inventory level is described in the work of He (2013). The work also applies the BP ANN model to predict the inventory level of an automotive parts company. In their findings, improved algorithm not only exceeds the standard algorithm significantly but outperforms some other improved BP related algorithms in prediction accuracy. **ANN**s have been widely utilized in several fields due to its ability to learn as well as model complex relationships between input variables. Some of the methodologies include Multi-layer Perceptron (MLP), a widely used ANN architecture for complex relationship modeling (Hornik 2016), Backpropagation which is a common training algorithm utilized in optimizing ANN weights and biases (Rumelhart 2015), and Hybrid Approaches combining ANNs with other techniques such as fuzzy logic or genetic algorithms, to improve accuracy in modeling (Wang 2013). In manufacturing, ANNs have been utilized to predict quality control measures, production processes optimization and complex relationship modeling between operational parameters. Kumar (2016), in their research titled ANN based modelling and optimization of machining processes, optimized production processes using ANNs technique. In the energy sector, Kalogirou (2019) applied ANNs to predict energy consumption, optimize energy efficiency as well as model relationships between energy inputs and outputs. Due to the versatility of ANNs, Hassan, (2017) applied ANN to predict stock prices. The researcher was able to model credit risk and optimizes portfolio management. However, ANNs face challenges and limitations such as overfitting and interpretability. ANNs can suffer from overfitting especially when dealing with complex relationships and limited data (Srivastava 2018). Another challenge is interpretability. ANNs can be difficult to interpret, making it challenging to understand the relationships between input variables (Lipton 2018).

The future directions for ANNs include Explainable AI. This implies developing techniques to improve the interpretability of ANNs and understand the existing relationships between input variables (Adadi 2018). Another important direction is Transfer Learning. This has to do with applying pre-trained ANNs to new domains or problems, reducing the need for extensive training data (Tan 2018).

4. Genetic Algorithms (GA)

GA is an optimization technique inspired by natural selection and genetics. It involves using evolutionary principles such as selection, crossover, and mutation to iteratively search for the best solution to a problem. GA has been applied in manufacturing for various tasks, such as production scheduling, facility layout optimization, and supply chain optimization (Altiparmark *et al.,* 2006). Genetic Algorithm (GA) was introduced by John Holland in 1975 with the help of his colleagues and students. Genetic algorithm is a type of optimization algorithm which is often categorized as a global search heuristic. Being a branch of the field of study called evolutionary computation; they are known to mimic the natural selection of biological processes of reproduction and to solve the 'fittest' solutions (Simon 2013). It is often known to be an optimizer of vector feature weights in either a linear or a nonlinear fashion. The selection and quality of each pattern feature have an influence on the pattern classification of subsequent success and this pattern classification requires that for a set of measurable features (Raymer *et al.,* 2010). This process or algorithm is used in minimizing or maximizing an objective function by mimicking the process of natural evolution. Genetic algorithm as an optimization technique takes its root from nature and the terminologies often used or associated with it are biological. The basic components of GA include; Fitness function used for optimization, population of chromosomes, selection of chromosomes which reproduce, production of next generation of chromosomes by crossover, mutation of chromosomes in new generation in a random manner (Raymer *et al.,* 2010). Fitness function is the function that is to be optimized by the solution produced by the GA, the fitness function is one of the most important part of the algorithm hence it is done carefully. Selection operator selects based on probability of the chromosomes to be used for reproduction. The fitter a chromosome, the more likely it is to be selected (Altiparmak *et al.,* 2006). GAs are principally used to search for optimal solutions in complex-multidimensional spaces. Genetic Algorithms have been applied to optimize functions in different areas such as economics, engineering and computer science (Goldberg 2018). Gas have been extensively applied to scheduling problems such as job shop scheduling as well as resource allocation (Davis L 2015). Another area of application of GAs is in machine learning. Here, GAs are used to optimize model parameters and select features (Holland 2012). Advantages of GAs include global optimization, robustness and flexibility.

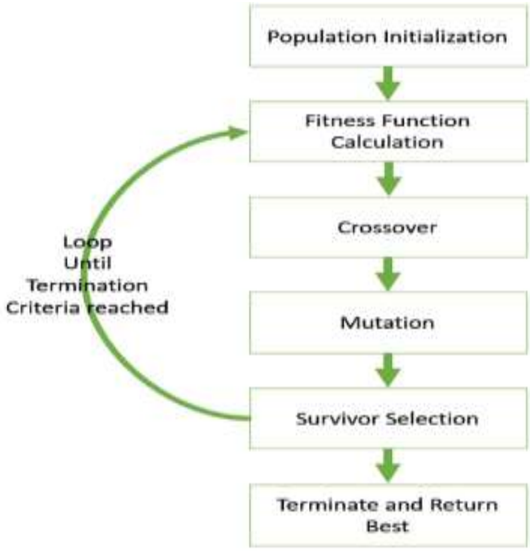

Figure 1: Structure of Genetic Algorithm

5. Particle Swarm Optimization (PSO):

PSO is an optimization technique inspired by the collective behavior of bird flocking or fish schooling. It involves iteratively adjusting a population of candidate solutions to find the optimal solution. PSO has been applied in manufacturing for tasks such as production scheduling, facility layout optimization, and inventory management (Ahmed 2022). It has been in the literature beyond any doubt that meta-heuristic optimization algorithm performs well by optimally handling several versatile real-world optimization tasks ranging from job shop scheduling, to classification, costing, supply chain and training of Artificial Neural Network (Ahmed 2022). The performance of PSO in engineering applications is significantly affected by topology selection and each problem has its appropriate optimal topology. Topology selection for PSO can be better guided by taking into account factors affecting the optimality of algorithm parameters with the aim of selecting a proper class of deterministic regular topologies (Liu *et al.,* 2016). Moayedi *et al.,* (2018) proposed PSO-optimized ANN model to solve the prediction problem of Landslide Susceptibility Mapping (LSM). The focus of this study was the prediction of landslide hazardous susceptibility mapping by applying a hybrid model of PSO and ANN. In a related research, Junior & Yen (2018) introduced a novel algorithm based on PSO and Convolutional Neural Network (CNN) called PSO-CNN. The proposed optimization algorithm is capable of fast convergence during search. In 2019, Lopez *et al.,* proposed Fuzzy Logic Controller (FLC) modified by PSO namely Fuzzy-PSO to elongate the lifetime of power electronics with a faster response of drive's speed in brushless DC electric motor. Maiyar & Thakkar (2019), employed multi objective hybrid particle swarm optimization in solving food grain transportation cost problem in their work. The result was courageous compared to the existing traditional techniques. Lopez *et al.,* (2018) adopted PSO in minimizing the industrial production cost with respect to the total cost per product. Better quality solution was realized although hybrid algorithm employed here used small datasets and failed to evaluate the computational time frame. Jiao *et al.,* (2019) commercially applied hybrid PSO technique in solving optimal location problem for an electric business center. The research work showed social benefits, low and high transportation convenience. It lacked multi-objective concept. Their proposed location estimation model was a welcome development in hybrid algorithm. Zhong *et al.,* (2018) proposed a PSO centered algorithm in solving their travelling salesman problem. The work showed strength in high balance between intensification and diversification. They were able to recommend the most optimal distribution cost for their organization of interest.

6. Ant Colony Optimization (ACO).

ACO is an optimization technique inspired by the foraging behavior of ants. It involves simulating the pheromone trail laying and following behavior of ants to find optimal paths or solutions. ACO has been applied in manufacturing for tasks such as routing optimization, job shop scheduling, and supply chain optimization (Afenogor 2022).

Ant Colony Optimization Algorithm

Ant algorithm which is also called ant colony optimization is a Meta-heuristic optimization process that is probabilistic in nature. It models the real-life movement or behavior of ants in order to solve optimization problem (Gong *et al.,* 2008). Since ants are blind, they move randomly from one place to another i.e. they choose a path based on probability.

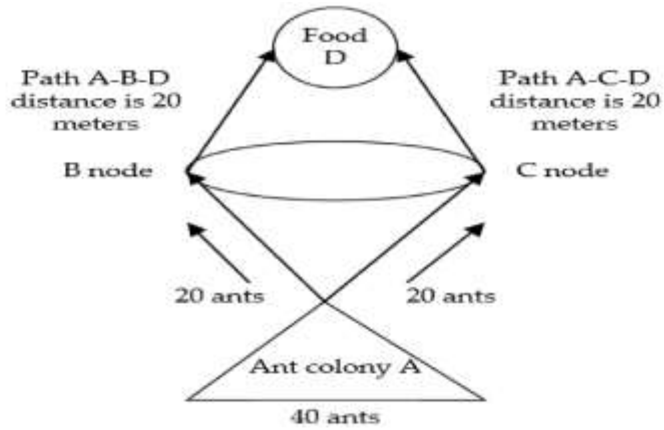

Figure 2: Ant choosing path based on probability

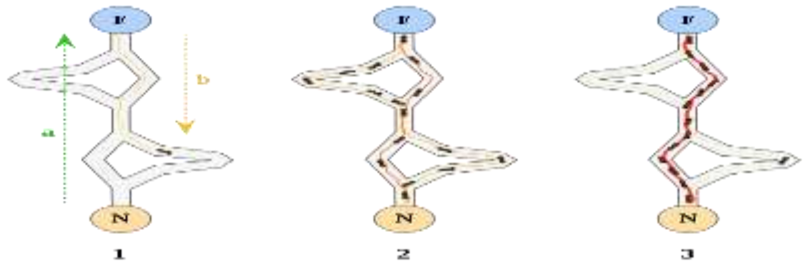

Figure 3: Ant movement seeking shortest path

Mathematical Model of ACO

This approach is in an attempt of proving that ants will converge along an optimal tour path which yields the minimum distance coverage. The pheromone secretion for iterations and the choice of next cities which is purely based on probability will be determined using the iterations carried out. In bid to optimize the problem, the most suitable ACO problem solving method will be adopted using the FMCG as a case study In a study by Afenogor (2022), the application of ACO was demonstrated.

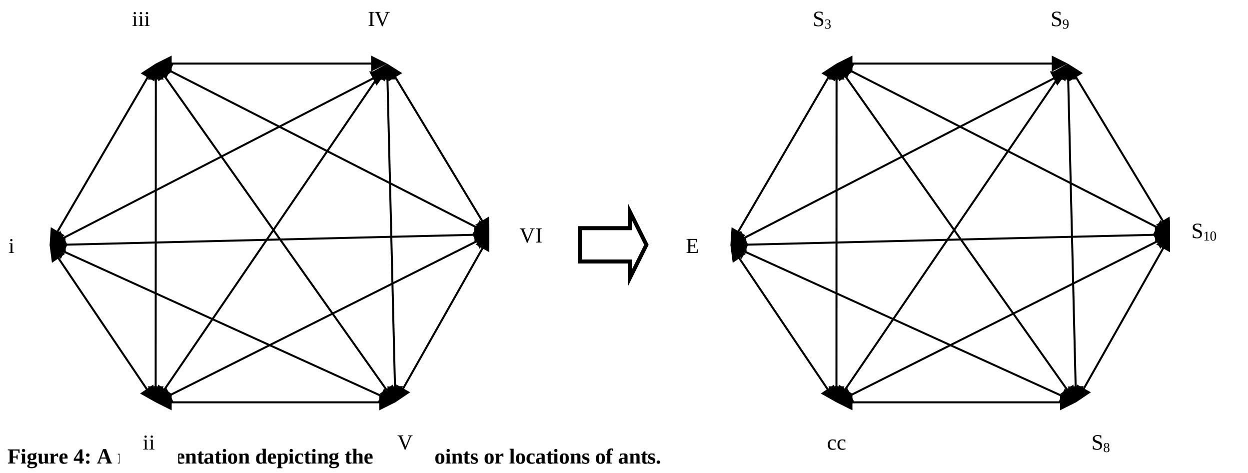

Figure 4: A **entation depicting the** **oints or locations of ants.**

The ACO model can be developed through the concept of bio-mimicry represented by nodes to be visited. It is equally important to implement this model by looking at the trails of the ACO during navigation (Gong *et al.,* 2008).This indicates the transformation of the nodes into actual locations. The nature of the experiment is heavily influenced by the dataset that is at hand. The specifics of the experiment are contingent upon the characteristics and contents of the available dataset. Depending on the underlying nature of the experiment, there's the potential to confine the scope of testing to a select few sections or components. This approach serves as a strategy to efficiently manage the experiment and tailor the investigation to the specific context it addresses. To enrich the diversity of outcomes, it is advantageous to adopt the Traveling Salesman Problem (TSP) principle. This principle entails envisioning a scenario where a salesman traverses each city just once before returning to their initial point of origin. By embracing this principle, the focus is placed on identifying the optimal sequence that ensures the salesman visits all cities while minimizing the overall route distance (Afenogor 2022). In the context of the experiment, a primary objective is to identify the shortest conceivable route for exiting the system after covering all designated locations. Drawing inspiration from nature, the TSP concept is imbued with an analogy to ant behavior. The analogy involves envisioning individuals as akin to ants embarking on journeys from their nests to food sources, guided by an unmarked trail. The underlying objective is to emulate the ants' natural behavior of seeking the shortest route from their nest to the source of sustenance.

In essence, the experiment's design hinges on the available dataset and is tailored to its unique characteristics. The adoption of the TSP principle brings forth a strategic approach to devising routes and sequences that minimize distances while maximizing efficiency. By employing the concept of ant movement and behavior, the experiment leverages nature's efficiency-driven strategies to inspire an intelligent approach that aims to identify the most optimized routes and sequences for the given context.

7. Feed-Forward Back-Propagation

Feed-Forward Back-Propagation (FFBP) algorithm is the most popular and the oldest supervised learning multilayer feed-forward neural network algorithm proposed by Rumelhart in 1986. It is built on high mathematical foundation and has very good application potential such as to pattern recognition, dynamic modeling. They studied three algorithms and different versions of backpropagation training for stable learning and robustness to oscillations. The new modification consists of a simple change in the error signal function. These algorithms have been tested on OR problem, encoding problem and character recognition as well as compared four cost functions in Three Term BP network. It has been tested on Balloon, Cancer, Diabetes and Pen-digits datasets. Through the experiments found out that MM cost function is the best cost function compared to BL (Bernoulli Function), Modified cost function (MM) and Improved cost function (IC). It is suitable for most of the real world problems that requires high accuracy but with a moderate speed. Zhen *et al.,* (2011) has done one of the comparison between genetic algorithm and back propagation learning algorithm over optimization cost problems such as Sin funciton, Iris plant and supply datasets and found that BPLA is faster than GA in terms of training speeds and also in terms of CPU time required, the BPLA yields better results than GA. Chukwuchekwa (2011) has proved using pattern recognition problem in operations management that BPA can be applied in manufacturing activities. On the other hand backpropagation was less to be used because of its time length needed to train the network to achieve the best result possible (Yeremia 2013).When faced against the larger datasets backpropagation still stuck into local minima problem but researcher like Bumghi *et al.,* (2008) has shown one of the novel idea and proposed the algorithm to avoid the local minima problem in complex problems and shown that there is still scope to fasten the BP Algorithm for larger and complex problems in cost optimizations.

The Back-propagation Neural Network (BPNN) Algorithm is widely used in solving many real time problems in world. It is highly suitable for the problems which involve large amount of data and there is no relationships found between the outputs and inputs. In 2009, Mitchell adjusted momentum-coefficient in a different way and was able to solve a distribution problem by considering all the weights in the Multi-layer perceptron (MLP). This technique was found much better than the previously proposed. In 2011, Rehman & Nawi adaptively changed the momentum for all nodes in the neural network which performed well for all classification operations problems.

Conclusion

Computational Intelligence significantly changes how manufacturing operates today by allowing smart decisions based on data in complicated processes. Techniques such as neural networks, fuzzy logic, and genetic algorithms improve cost predictions, optimize production, and support maintenance planning. This review underlines the increasing importance of CI methods, stressing the necessity for more studies and organized application to utilize their capabilities fully in fast-changing manufacturing settings influenced by Industry 4. 0.

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