Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/WC02.20250179
Published: October 14, 2025

A Review of Bottleneck Management Strategies in Manufacturing Under Uncertainty for Sustainable Manufacturing

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Abstract

Uncertainty in the manufacturing environment can cause inefficient resource utilization and bottlenecks, leading to delays, increased costs, and energy consumption, which contradicts sustainable manufacturing practices. Minimal research has been done in exploring how different uncertainties leads to bottleneck in manufacturing and modelling them for system optimisation under uncertainty. This paper provides an extensive review of manufacturing bottlenecks, categorizing them into various types and examines the role of uncertainty—both internal and external—on the formation of bottlenecks. Moreover, the paper discussed the types of uncertainties found in manufacturing and the level to which they are categorized based on the information available. Various methods of modelling these uncertainties are discussed, including probability distributions, fuzzy logic, Bayesian networks, and grey system theory. The applicable approaches for uncertainty management are discussed with their strengths and limitations. Furthermore, the paper sheds light on state-of-the-art optimization approaches that are used in uncertain environments, their strengths and limitations. The paper also explores how Industry 4.0 technologies can help improve bottleneck management by introducing more resilient and adaptive solutions. Also, the role of Industry 4.0 technologies in modelling uncertain parameters and for optimization under uncertain manufacturing is discussed. It is concluded that managing these uncertainties effectively is critical for enhancing production efficiency and supporting sustainable practices in manufacturing. This paper can be used to select appropriate uncertainty modelling and optimization approaches to mitigate bottlenecks under uncertainty.

Keywords:
Sustainable manufacturing, Bottlenecks, Uncertainty Analysis, Uncertainty Modelling, Industry 4.0.

1. Introduction
Sustainability in manufacturing has become a critical focus for industries worldwide to minimize environmental impact while maintaining economic viability . Bottlenecks, or points of congestion in a production system, can lead to inefficiencies that increase energy use and higher emissions . By identifying and addressing these bottlenecks, manufacturers can streamline operations, reduce energy consumption, and improve overall sustainability. However, in practice, pinpointing and removing bottlenecks is challenging, often requiring practitioners to depend on their experience and intuition . The widely used traditional approaches such as simulation and optimization are effective

for planning under stable conditions and fall under the strategy of "predict and plan." However, the manufacturing environment is inherently dynamic and often subject to unexpected changes . These changes introduce a level of uncertainty that can make traditional methods less effective. For instance, variability in labour availability, material supply, and equipment performance can suddenly alter production dynamics, requiring a more flexible and adaptive response. This leads to the necessity for an "adapt and react" strategy . Unlike "predict and plan," in which simulation is used to predict the bottleneck and then optimization is used to find optimal solutions to mitigate those bottlenecks, "adapt and react" focuses on adjusting operations in real-time to effectively address emergent challenges. Traditional simulation and optimization methods may struggle due to their reliance on predefined parameters and their inability to quickly adapt to changes. These ongoing issues and the need for deeper exploration form the basis of the three pivotal literature questions addressed in this research: 1. What are bottlenecks in manufacturing, and what are their categories and types? 2. What types of uncertainties exist in manufacturing, and how do they impact bottleneck management? 3. What strategies and methodologies have been proposed to address bottlenecks under uncertainty? 4. How can Industry 4.0 help in bottleneck management under uncertainty? Section 2 outlines the methodology. Section 3 presents the results of the literature questions. Section 4 provides a discussion, and Section 5 concludes with future research directions**.**

2. Literature Review

The literature search was conducted using the Scopus and Google Scholar databases, selected for their extensive collections and wide coverage across different fields. Keywords such as "Manufacturing system challenges," "KPIs in manufacturing," "Digital Twin and manufacturing," "Digital Twin and KPI," "AI and Machine Learning in manufacturing", "Uncertainty modelling in manufacturing", "Optimization under uncertainty", "Uncertainty and bottlenecks in manufacturing" and related were used. Screening and Selection were chosen for detailed analysis based on their direct relevance to this research's scope, which include challenges in manufacturing systems, the strategic role of KPIs, advancements in Digital Twin and AI technologies in manufacturing, uncertainty modelling and optimization. Each article was carefully reviewed to determine its contribution to the research areas. A total of 132 papers were downloaded out of which 79 papers were selected for review. Papers were included if they addressed uncertainty in manufacturing using Industry 4.0 technologies (e.g., AI, IoT, digital twins); studies without this focus or lacking uncertainty modelling were excluded. Additional exclusions were applied to duplicates, non-English texts, and promotional content.

3. Results

3.1 What are bottlenecks in manufacturing, and what are their categories and types?

A bottleneck is a constraint in the production process that limits overall efficiency and slows down operations. It restricts throughput and impacts the efficiency and productivity of manufacturing operations . Bottlenecks lead to an accumulation of work-in-progress (WIP) inventory upstream, while downstream processes face shortages, reducing overall system efficiency. Bottlenecks can be dynamic and shift between different resources over time. The variability in production processes and interdependencies of resources further complicate accurate bottleneck identification. Generally, bottlenecks can be classified into three types based on their timing: momentary bottlenecks, average bottlenecks and shifting bottlenecks . Momentary throughput bottlenecks occur when a workstation temporarily becomes a bottleneck due to unexpected disruptions, such as a sudden machine breakdown or a brief shortage of materials. Average throughput bottlenecks involve equipment that consistently slows down the production process over a longer duration, indicating an ongoing issue, for example, an older press machine that operates slower than other machines consistently creates a backlog in the production line. Shifting throughput bottlenecks occur when the bottleneck alternates between different machines at various times due to changes in production speed or workflow variations. If one production phase occasionally speeds up or slows down, the bottleneck may shift between adjacent machines. Both machines involved are considered part of the bottleneck during these transitions.

3.1.1 Bottleneck identification approaches

Popular approaches to detect bottlenecks are Gemba walk and discrete event simulation . Gemba walks is an approach that relies on human observations on the shop floor. During the bottleneck walk, two types of observations are collected: machine activities and queue information. These observations are then used to identify momentary and shifting throughput bottlenecks . Bottlenecks can be detected using simulation models, with discrete event simulation being the most commonly used approach in academic research for bottleneck detection

3.1.2 Bottleneck categories
Resource limitation bottleneck
Resource bottlenecks can include the shortage of human resources, material, or machinery unavailability. Resource reliability is essential for maintaining a continuous production flow in manufacturing. Equipment failures can cause unexpected production stoppages, leading to immediate bottlenecks . Likewise, if a station lacks the required materials to continue a task, it can create a queue of unfinished jobs, leading to significant production delays. Similarly, human resources are crucial for maintaining a smooth manufacturing process . If attendance is low, fewer workers are available to operate machines and complete tasks, causing delays and slowing down in production. This can lead to bottlenecks as tasks pile up at certain stages. Additionally, overworked employees may make more errors, increasing the risk of quality issues. A shortage of raw materials in manufacturing can cause disruptions. Material shortages can create significant bottlenecks in the manufacturing plant , as delays in material arrival can halt or slow down the entire production process. These shortages can arise from various external factors, such as regulatory changes, supplier changes, transportation delays, and fluctuations in demand.

Process Bottlenecks due to inefficiencies
Process bottlenecks in manufacturing result from workflow inefficiencies such as poor scheduling, reconfiguration delays, and quality variation. Inefficient job shop scheduling can cause machine idle time and resource underutilization .Inefficient line balancing can lead to idle time at workstations and reducing overall productivity . Manufacturing reconfiguration can slow down production system, as it often involves interruptions to production activities, leading to production loss and increased ramp-up time . Variation in quality can lead to extra rework time which slows down entire manufacturing system and also can limit resources in some cases because extra workers are often needed for rework, which is moved from other stations.

Facility bottleneck
Inefficient layout designs and logistics flow in manufacturing facilities can disrupt production efficiency, leading to increased costs both in the short and long term . A poorly designed facility layout can create bottlenecks by increasing material travel distances and causing inefficient workflows . If storage areas are located far from production lines or if workstations are not sequenced properly, it can lead to delays and interrupt the production flow. Several approaches can be employed to improve factory layout design and efficiency, such as CORE, ALDeP, AI and so on.

3.2 What types of uncertainties exist in manufacturing, and how do they impact bottleneck management?
As per Normative Decision Theory, uncertainty can be defined as lack of knowledge about probability of future state of events . Uncertainty can be categorised as known, unknown and unknowable uncertainties . **Known Uncertainty** refers to situations where the variables and their impacts are well-understood. The range of possible outcomes is predictable and can often be modelled using historical data. **Unknown Uncertainty** involves scenarios where the variables may be identifiable, but their outcomes or impacts are unpredictable due to a lack of historical data or complex interdependencies. **Unknowable Uncertainty** pertains to situations that are unforeseeable and cannot be planned for, as they emerge from entirely new or unprecedented circumstances where neither the variables nor their potential impacts are understood in advance. Deep uncertainty is part of unknowable uncertainty and falls under level 4 and level 5 as can be seen in Figure1. Deep uncertainty refers to conditions where decision-makers cannot determine (1) the appropriate models to describe the interactions among a system's variables, (2) probability distributions to represent uncertainty about key variables and parameters in those models, and/or (3) how to value desirability of alternative outcomes. This type of uncertainty is characterized by three main types: model uncertainty, which pertains to the inadequacy of models; parameter uncertainty, which involves unknown or imprecise values of parameters within the models; and objective uncertainty, which relates to the ambiguity regarding the desirability of different outcomes. All these levels can be seen in Figure 1.

The types of uncertainty mentioned in the literature often overlap. There are further ways to describe uncertainty as well based on the nature of the information. Two of these ways include epistemic, aleatory, ambiguity and pragmatic uncertainty . Epistemic Uncertainty is the kind of uncertainty that arises from the lack of knowledge due to various reasons which include incomplete knowledge regarding the situation, phenomena, and evaluation of related characteristics . Aleatory uncertainty is stochastic, which means the outcome cannot be predicted. This is opposite to epistemic uncertainty because aleatory uncertainty cannot be reduced .

			LEVEL					
			Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	
LOCATION	**Context**	**Complete Certainty**	A clear enough future	Alternate futures (with probabilities)	Alternate futures with ranking	A multiplicity of plausible futures	An unknown future	**Total ignorance**
	System model		A single (deterministic) system model	A single (stochastic) system model	Several system models, one of which is most likely	Several system models, with different structures	Unknown system model; know we don't know	
	System outcomes		A point estimate for each outcome	A confidence interval for each outcome	Several sets of point estimates, ranked according to their perceived likelihood	A known range of outcomes	Unknown outcomes ;know we don't know	
	Weights on outcomes		A single set of weights	Several sets of weights, with a probability attached to each set	Several sets of weights, ranked according to their perceived likelihood	A known rage of weights	Unknown weights;know we don't know	

Figure 1. Different levels of uncertainty

However, two more types of uncertainties have been addressed as part of the uncertainty types. Ambiguity uncertainty arises when the situation can be interpreted in various ways by the decision-makers. This uncertainty arises when different stakeholders have different views regarding the same situation . For example, a production manager informs three supervisors from the day, afternoon, and night shifts that five workers will be absent tomorrow. However, the manager does not specify which shifts the absent workers are from. Without this specific information, each supervisor might assume that the absences will occur during their respective shifts. This incomplete information could lead each supervisor to make pre-emptive decisions on resource allocation, potentially causing an imbalance within their shifts and leading to bottlenecks in production. Pragmatic uncertainty occurs when stakeholders struggle to agree on a situation or find it challenging to implement policies effectively due to complex circumstances. Similar to ambiguity uncertainty, where data or situations can be interpreted in multiple ways, pragmatic uncertainty also involves the difficulty of putting decisions into action. Even when a decision is reached, the real-world complexities makes its implementation problematic. This type of uncertainty highlights the gap between decision-making and practical execution in dynamic environments . Traditional decision-making approaches may fail in the face of deep uncertainty, necessitating the development of robust and adaptive plans**.**

3.2.1 Uncertainties in manufacturing and bottleneck

This section synthesizes key findings on how financial, supply chain, environmental, equipment performance, and resource availability uncertainties lead to bottlenecks, as shown in Fig. 2. The text highlighted in red shows the category of bottleneck while the other circles leading towards these bottlenecks are different uncertainties leading to constraints in the plant. For example, supply chain uncertainty can lead to material shortage which can create a bottleneck because resources can be limited, slowing down the process.

Equipment performance uncertainty

If the equipment is unreliable and fails, it can cause disruptions, causing delays, and potentially leading to bottlenecks .

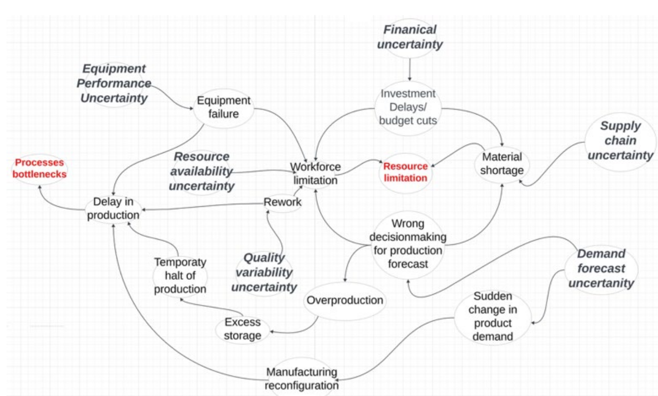

Figure 2. Uncertainties leading to Bottleneck in Manufacturing

Equipment uncertainty can stem from various factors, such as inadequate maintenance, aging machinery, or unforeseen wear and tear. Uncertainty in equipment performance can be modelled in various ways (Figure 2). For example, , uniform distribution, in Weibull distribution and Poisson distribution and in , normal distribution, were used to model different aspects of machine time failure. Fuzzy logic was used in . It is also important to identify which time interval in the plant a machine failure might occur. For example, , used Markov chains to model the uncertainty of the shift in which machine failure could happen. In , Bayesian networks were used for fault root cause analysis.

Resource availability uncertainty
Human resources can be unavailable in the manufacturing plant due to various reasons. For example, during pandemic, manufacturing industries faced challenges in managing human resources . There has been very minimal research found where the availability of human resources has been modelled in the manufacturing environment.

Demand forecast uncertainty
Inaccurate customer demand forecasting can result in poor production scheduling, leading to material or human resource shortages, as illustrated in Fig. 2, and creating a bottleneck. Several approaches can be used to model demand uncertainty, including probability distribution, grey system theory, and fuzzy logic. For instance , normal distribution, in uniform distribution was used. In , a fuzzy approach with triangular membership functions was applied to represent customer demand uncertainty.

Quality variability uncertainty
Variability in product quality can directly lead to bottlenecks in the manufacturing plant by causing the need for rework, and consequently consuming more resources from the system as shown in Fig. 2. Quality uncertainty arises from various factors, such as poor material quality from suppliers, insufficient worker training, or a lack of expertise, all of which can result in the production of defective parts. The uncertainty in defective parts was modelled using different approaches. For example, in , uniform and triangular distribution, and beta distribution were used. For the root cause analysis of the defective items, Bayesian networks were used in . In , grey numbers were used to model defective times and in to model the rework time. Fuzzy triangular membership, function was used for defective item rates. In , Markov chains was used to determine the probability of whether a defective part would go for rework or be scrapped if rejected during quality inspection.

Financial uncertainty
In some cases, uncertainty can arise from financial factors. These factors can be fluctuating revenues, higher operating costs, or delays in customer payments. Various approaches, such as probability distribution and fuzzy logic, are used to model production cost uncertainties. For instance, uniform distribution was applied in , to model production cost, holding cost, and lost sales, while fuzzy triangular numbers were used in for production cost uncertainty.

Supply chain uncertainty
Supply chain disruption can lead to material shortage and limiting the resources available for production and causing bottleneck. In , Bayesian Network was used to model supply uncertainty, improving forecasting and decision-making in dynamic manufacturing environments.

3.3 What strategies and methodologies have been proposed to address bottlenecks under uncertainty?
Optimization using simulation
Optimisation based on simulation can be used to mitigate the bottleneck in the manufacturing plant. For example in , simulation was used to optimize the process layout to reduce the travel time between the stations so that the process can be efficient. Siemens Tecnomatix was used to create a layout of the manufacturing plant and then a bottleneck analyzer was used to identify the bottleneck. However, the model did not incorporate any uncertainty factor. Despite its advantages, robust modeling of DT presents challenges such as synchronization , which is crucial to achieving an accurate representation of the manufacturing system's true state. Thus, discrepancies between simulation model and actual system can lead to suboptimal or misleading simulation outcomes. Uncertainty, such as equipment failures, unexpected worker absences, or supply chain disruptions, can alter production conditions. Since optimization using simulation assumes stable or predictable conditions, it struggles to adapt to these dynamic changes, unless the uncertainty has been incorporated in the simulation model. Consequently, the optimized plan can becomes ineffective, leading to unexpected bottlenecks and reduced productivity.

Stochastic programming

Stochastic programming is an optimization approach incorporates random variables to model uncertainties in parameters. It uses algorithms such as Benders decomposition and Lagrangean decomposition to solve optimization problems, commonly with linear constraints and continuous recourse . While Stochastic Programming (SP) is effective for small-scale problems with a limited number of predefined scenarios, it faces challenges when applied to more complex problems, because when the number of scenarios increases, the computational complexity grows exponentially, making it difficult to solve within a reasonable time frame . SP relies on two key elements: predefined scenarios and the probabilities associated with them. However, this dependence on fixed scenarios and probabilities poses challenges in dynamic contexts, where changing conditions require frequent updates to the scenarios. For example in , SP was used for optimal lot sizing under rework uncertainty because the probability of the defective items was known. SP struggles to adapt to these changes since all scenarios and their probabilities are fixed in advance. Consequently, it becomes inefficient and impractical for large-scale or dynamic optimisation problems. Also, in the situations of deep uncertainty, the probability of the events and its likelihood is unknown . This makes the use of SP highly challenging for optimization under deep uncertainty.

Robust optimization

Robust optimization is one of the two main paradigms, alongside stochastic optimization, for dealing with the uncertainty . Robust optimization does not require knowledge of probability distributions. Instead, it assumes that the uncertain data lies within a defined uncertainty set . The core principle of robust optimization is the introduction of parameterized families of constraints, enforced for all realizations of the uncertainty parameters belonging the uncertainty set. Using tools from convex optimization theory, these complicated semi-infinite constraints can often be reformulated into finitely many convex constraints, so that the resulting optimization problem can be solved using standard convex optimization procedure . For example in , robust optimization was used for yield uncertainty but all the scenarios were defined in the uncertainty set. When formulating an uncertainty set, it is assumed that the set, which represents a range of possible parameter realizations, is predefined and provided as input. However, recent studies highlight that determining the most appropriate uncertainty set is a challenge . This issue arises because worst-case scenarios are chosen based on the predefined uncertainty set. If the first-stage decision changes, it can create new scenarios outside this set. Traditional algorithms cannot handle these new scenarios, leading to convergence failures . These limitations indicate that Robust Optimization is not ideal for situations involving completely new scenarios, outside the predefined uncertainty set.

Genetic Algorithm

The genetic algorithm is a search method for optimization that uses natural selection and genetic rules . In manufacturing, GA is mostly used for scheduling problem optimization, such as job shop scheduling to find the best sequence and timing for tasks . For example, in , GA was proposed to optimize the production schedule, enabling the jobs to be efficiently assigned to a single machine. In , GA was used for optimization because it effectively handles the uncertainty in processing times in flexible job shop scheduling. By integrating GA with a fuzzy scheduling model, the approach optimizes the schedule despite variations in processing time, ensuring a more reliable and efficient production plan. In , was used because it effectively solves uncertainty job shop scheduling problems with interval grey processing time. By using an elitism strategy, the GA optimises the schedule to minimize the interval grey makespan, ensuring efficient job allocation despite inaccurate time quotas. In , GA was used because it optimises the flow shop scheduling after the uncertainties were represented using Grey Chance Constrained Programming and Grey Simulation. The GA finds the best scheduling solution based on the simulated grey uncertainties, ensuring optimal waiting-time flow shop scheduling. GA was used in because it optimizes the integrated processing and assembly scheduling under uncertainty, represented using triangular and trapezoidal fuzzy numbers for operation and delivery times. GA performs fuzzy integrated optimization, achieving high customer satisfaction in delivery periods. The authors in used GA and an improved Immune Genetic Algorithm to optimize the flexible job-shop scheduling problem (FJSP) under uncertainty, represented by fuzzy delivery times and dynamic machine failures. The algorithms aimed to minimize energy consumption, makespan, and consumer dissatisfaction, demonstrating effective scheduling under dynamic and uncertain production conditions.

Evolutionary algorithms face challenges when applied to optimization problems. First, the fitness function can be variable, introducing uncertainty in the evaluation of solutions. Second, design variables and/or environmental parameters may change after optimization, requiring the solution to remain robust against these changes. Third, the fitness function is often approximated, leading to potential approximation errors. Finally, the optimum of the problem can change over time, necessitating that the optimizer continuously tracks the evolving optimum .

Ant Colony Optimization

Ant Colony Optimization (ACO) is a swarm intelligence approach that is effective in solving various types of discrete and continuous optimization problems . In , study models the Job Shop Scheduling Problem (JSSP) to optimize the sequence of jobs on machines, aiming to minimize makespan and reduce idle time. ACO algorithm has disadvantage of slow convergence and a tendency to get stuck in local optima .

Particle swarm optimization

Particle Swarm Optimization (PSO) is a metaheuristic global optimization technique that has gained popularity over the past two decades due to its simplicity and effectiveness in solving complex, multidimensional problems. It is particularly suitable when traditional deterministic algorithms are ineffective . To minimize cycle time and maximize workload smoothness in a single-model assembly line balancing problem, PSO was proposed . PSO was used in this study to optimize a four-objective intelligent food logistics system, aiming to minimize total expense, CO2 emissions, and delivery lead time while maximizing average food quality. The modified multi-objective PSO algorithm (MO-GLNPSO) was applied to achieve sustainable and efficient food logistics operations. The PSO algorithm has proven to be an effective method for solving static function optimization problems. While extensions of the PSO algorithm designed for dynamic environments have improved its performance, optimizing in dynamic environments remains a challenging issue due to noise in the fitness function, which can be caused by uncertain information .

Reinforcement learning

Reinforcement learning (RL) is a subset of machine learning that sets itself apart from supervised and unsupervised learning through its trial-and-error approach, where the model learns by interacting directly with its environment . RL is regarded as a promising approached for robust decision-making, enabling production managers to engage with a complex manufacturing environment, learn from past experiences, and make optimal decisions. RL involves an agent interacting with an environment by performing actions and perceiving states, learning the optimal behavior (policy) based on a feedback signal. Unlike a static database, the environment has its own internal state, which the agent influences through its actions. In RL, agents pursue specific goals and improve their decision-making by interacting with the environment to achieve these objectives. In manufacturing, RL is used to optimize with different parameters. For example in , RL was applied to optimize the process time of an assembly case in an Industry 4.0 environment. The RL agent interacted with machine sensors and controlled machine parameters using Q-learning, resulting in reduced process time while maintaining product quality within acceptable limits. RL was applied to optimize decision-making in a degrading manufacturing system in . The approach combined RL with lean green manufacturing to reduce material consumption and improve sustainability. RL in was applied to solve the job-shop scheduling problem (JSSP) in dynamic manufacturing environments. It enabled the smart scheduler to autonomously optimize scheduling decisions in real-time, handle unexpected events like urgent orders or machine failures, and balance efficiency and profits.

The selection of an appropriate method depends on several factors, including the type of bottleneck, the nature and availability of data, the form of uncertainty involved (e.g. probabilistic, fuzzy, unknown), and the specific goal such as minimizing cycle time, improving scheduling, or ensuring robustness. Understanding these factors allows practitioners to choose optimization strategies that are both technically suitable and practically effective for managing bottlenecks under uncertainty.

3.4 How Industry 4.0 technologies can help in bottleneck management under uncertainty?

Industry 4.0 represents a paradigm shift in manufacturing through the integration of advanced digital technologies, automating and data analysis . A key concept within Industry 4.0 is the Digital Twin (DT), which is the virtual representation of a physical system in the cyber domain . DT serves as an model of a physical system, allowing for continuous synchronization between the digital and physical worlds. DES and simulation approaches can be used for scenario analysis and identifying bottlenecks as well. However, DT provides a more accurate analysis by offering a current and up-to-date representation of the manufacturing plant, helping to capture real-time variations and uncertainties. One of the key advantages of DT in manufacturing is its ability to predict bottlenecks by simulating real-world conditions in the manufacturing plant .

This can help manufacturers understand how changes in variables such as resource availability, machine performance, and other variables impact the production . Scenario analysis allows manufacturers to make more informed decisions, optimizing operations under uncertain or variable conditions. To represent and model these uncertainties, Digital Twin can generate data such as Directed Acyclic Graphs (DAG), which can then be used for uncertainty modelling, such as with Bayesian Networks (BN) . These models help analyse complex relationships and quantify uncertainty in decision-making. Reinforcement Learning (RL) can be useful in addressing bottlenecks within manufacturing systems, as it continuously learns and adapts to dynamic environments. According to the Theory of Constraints, solving one bottleneck often reveals new constraints elsewhere in the system . RL, when integrated with a DT, can monitor and interact with the manufacturing system in real-time, identifying and responding to new bottlenecks as they emerge. This adaptability ensures that the system remains optimized even as new constraints are introduced, enabling efficient resource allocation and production scheduling. RL's ability to continuously update its decisions based on evolving conditions is key to maintaining system performance and addressing bottlenecks dynamically and sustainably. DT can also support optimization approaches in addressing uncertainty. For example, Reinforcement Learning (RL) can interact with Digital Twin as its environment, learning from the scenarios simulated within the DT . By feeding the RL agent various operational scenarios, the agent can adapt and improve decision-making strategies to optimize resource allocation, scheduling, and other aspects of production. RL uses DT to explore different policies and find the most effective ways to respond to uncertainty, helping manufacturers improve system performance and resilience in real-time.

4. Discussion

Manufacturing bottlenecks can significantly slow down the production process, affecting the entire operation. This not only prevents organizations from achieving their key performance indicators (KPIs) but also has a substantial impact on production costs, delays, and rework leading to excessive energy consumption, harming the environment and contradicting the principles of sustainable manufacturing. It is important to highlight that very minimal research has been found regarding human resource uncertainty modelling.

In the representation and modelling of uncertainty, it was observed that various approaches such as probability distributions, fuzzy logic, Bayesian networks, Markov chains, and Grey System Theory were used. It is important to note that these methods were not used interchangeably; rather, they were selected based on data availability and the specific purpose of modeling uncertainty. For instance, when sufficient data was available, probability distributions were used. In cases where expert opinion was available but not ample data, fuzzy logic was applied. When very limited data was available, typically only upper and lower bounds, Grey System Theory was utilized. Bayesian networks were employed for root cause analysis and to examine how one uncertain event could lead to multiple other uncertainties in a system, using conditional probabilities. Markov chains were used to model the probability of state changes. According to the review, probability distributions, fuzzy logic, and Grey System Theory can be used interchangeably depending on the available data. Various uncertainties, both external and internal, can lead to bottlenecks in a manufacturing plant. Numerous approaches have been proposed in research to model these uncertainties and mitigate their impact on production. However, most of the proposed work falls under the "predict and plan" approach, where uncertainties are modelled, and production plans are based on these predictions. Given the highly volatile nature of the manufacturing environment, there is a need for an "adaptive approach" that allows the system to adjust to the current situation and generate optimization plans based on real-time conditions. In the context of adaptive approaches to represent uncertainty, Bayesian networks have been widely used in research due to their ability to update beliefs and provide probabilities based on new incoming data. To generate optimization plans in an adaptive framework, reinforcement learning has been employed, as the agent can interact with the environment and generate optimized plans according to the real conditions of the plant. Furthermore, Industry 4.0 technologies, such as Digital Twin, can significantly support both of these adaptive approaches.

5. Conclusion

This paper provides a comprehensive review of the impact of bottlenecks on manufacturing plants, categorising the different types of bottlenecks and discussing the current methods for their identification. It also examines various uncertainties within the manufacturing environment and their role in creating different types of bottlenecks. The paper presents examples of modelling approaches used to address these uncertainties. Additionally, it discusses the strengths and limitations of current state-of-the-art optimisation approaches for managing bottlenecks under uncertainty. Finally, the paper highlights how Industry 4.0 technologies can provide more resilient solutions, improving existing approaches to bottleneck management in uncertain environments.

This paper provides valuable insights for the industry in effectively managing bottlenecks in manufacturing under uncertainty. It offers guidance on selecting the most suitable approaches for adaptive strategies, focusing on both uncertainty modelling and optimization. Future work should develop adaptive approaches for human resource allocation under deep uncertainty. A digital twin can act as a safe testbed to trial AI-driven human resource allocations before deploying them on the shop floor, helping maintain cycle time, throughput, and quality when demand, process times, or workforce availability change.

Acknowledgement

The authors acknowledge Australian Composites Manufacturing Cooperative Research Centre (ACM CRC) for supporting this research.

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