

Review

A Comprehensive Review of Theories, Methods, and Techniques for Bottleneck Identification and Management in Manufacturing Systems

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Abstract: With the advancement in global market integration, manufacturing enterprises face increasingly fierce competition, making the development of intelligent manufacturing systems a key factor in enhancing market competitiveness. However, manufacturing systems are characterized by varying characteristics of manufacturing resources and strong interdependencies, which make production control more complex. A bottleneck refers to the issue where the manufacturing system's actual production capacity is less than or equal to the demand placed on a resource. After extensive research, scholars have concluded that the definition, identification methods, and related studies on bottlenecks are not fixed but depend on the specific research subject and the type of bottleneck. Therefore, scholars suggest that only by accurately defining the bottlenecks within a system can appropriate models be employed for prediction, thereby avoiding issues such as inefficient resource allocation and delivery delays, or implementing measures to minimize these negative impacts. Particularly under unstable production conditions, dynamic bottlenecks are likely to occur, making the prediction and identification of bottlenecks under dynamic environmental conditions crucial. Currently, there is still a lack of research in real-time state sensing and integration, as well as a lack of systematic review of related research. To fill this research gap, this review comprehensively introduces the current state and achievements in bottleneck research within manufacturing systems, focusing on bottleneck categories, identification, shifting, and management. It also provides an outlook on future research trends and directions in the study of manufacturing system bottlenecks.

Keywords: bottleneck identification; shifting bottleneck; bottleneck prediction; manufacturing system



Citation: Tang, J.; Dai, Z.; Jiang, W.; Wu, X.; Zhuravkov, M.A.; Xue, Z.; Wang, J. A Comprehensive Review of Theories, Methods, and Techniques for Bottleneck Identification and Management in Manufacturing Systems. *Appl. Sci.* **2024**, *14*, 7712. <https://doi.org/10.3390/app14177712>

Academic Editor: Abílio M. P. De Jesus

Received: 15 July 2024

Revised: 13 August 2024

Accepted: 15 August 2024

Published: 31 August 2024



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1. Introduction

In today's digital era, the predictability of manufacturing output and the repeatability of production processes are key indicators that measure the manufacturing system's stability and efficiency. The bottleneck is a limiting factor for the manufacturing system to meet the production demand behavior. The type of bottleneck may vary depending on the research subject. Only by accurately defining and predicting bottlenecks can companies effectively control processes. Therefore, accurately identifying and effectively managing bottlenecks has become an important topic in current manufacturing research.

Goldratt first proposed the term “bottleneck” of the manufacturing system in the publication *The Goal: A Process of Ongoing Improvement* in 1984 [1]. He defines any resource whose capacity is equal to or less than the demand placed upon it as the bottleneck. The theory he created is called the theory of constraints (TOC), laying the foundation for the

research of bottleneck identification, bottleneck drift, and bottleneck prediction, along with lean production and Six Sigma, and is known as the world's three major management theories. As awareness of the impact of bottlenecks on manufacturing system performance has increased; more scholars have joined the research in this field. Consequently, studies and theories on bottlenecks have become increasingly refined. Lim and Biller proposed that static manufacturing bottlenecks are defined based on stable system parameters and environments [2,3]. Guide, Laan, and Gundogar proposed that dynamic manufacturing bottlenecks and bottleneck shifting involve uncertainties within the system and in the production environment [4–6]. However, most of the past studies on bottlenecks in manufacturing systems are based on the assumption that bottlenecks are static; this assumption does not necessarily hold in the actual production process. Some scholars proved that many uncertainties in an enterprise's manufacturing system cause bottlenecks to be dynamic [7–10]. Therefore, in recent years, more and more scholars have been devoted to the study of dynamic bottleneck prediction and identification to provide insights of more practical value. By reading the previous research literature, it can be concluded that most of the scholars' research mainly focuses on the definition of the bottleneck concept and explores how to transform the bottleneck problem into a more fundamental theoretical problem to promote the theoretical development of the field. Some experts believe that when bottleneck technology and TOC are applied to industries with different production conditions, the bottleneck identification and prediction methods will be different [11–14]. For the identification of single and multiple bottleneck problems, the bottleneck identification is transformed into a state feedback control problem based on a control theory approach. By identifying the operations that affect the performance of the system, the bottleneck problem can be identified and solved more accurately. Liu, Guo, and Huang have already made bottleneck predictions with the help of statistics, time series analyses, and deep learning. The bottlenecks have also been solved by employing process redesign, resource reallocation, and technology upgrades [15]. Many experts have also applied bottlenecks to different subject areas such as supply chain management [16], transportation systems [17], and computer networks [18] to explore solutions to bottlenecks in specific areas. Along with the rise in Industry 4.0, the integration and application of advanced manufacturing technologies such as Digital Twins, deep learning, and interpretable artificial intelligence have revolutionized bottleneck identification and prediction in systems [19,20]. In the presence of increasingly diverse production structures, existing bottleneck research methods have made it difficult to satisfy the needs of modern manufacturing systems. Therefore, it is necessary to review the current status of bottleneck research to further clarify the research trends, explore new research paths, promote the development of bottleneck identification and prediction techniques, and provide more forward-looking technical guidance for manufacturing enterprises.

In this review, the first section briefly reviews the current stage of research on bottlenecks in manufacturing systems. The second section introduces the definitions of various types of bottlenecks in manufacturing systems and the bottleneck extended concepts. The third section focuses on methods for bottleneck identification, including static model-based, simulation-based, and data-driven-based approaches. This section also provides a detailed explanation of the causes of bottleneck shifting, the consequences of a bottleneck, and the bottleneck management strategies, with the current research stage and existing challenges of the above fields. The fourth section explores the integration of bottleneck issues with advanced technologies such as Digital Twins and neural networks, offering a perspective on future research trends in manufacturing system bottlenecks. The final section summarizes the future directions and trends in bottleneck research within manufacturing systems.

2. Categories of Manufacturing Bottlenecks

2.1. Definition of Bottlenecks in Manufacturing Systems

The bottleneck refers to the resource problem in that the actual production capacity is less than or equal to the load in the production process. However, such abstract definitions

are often difficult to apply effectively in actual production. Influenced by different production environments and assumptions of the systems, the definition of bottlenecks needs to depend on the specific research problem. Only by accurately defining the bottlenecks in a system can businesses optimize and control processes effectively. As scholars continue to study the concept of bottlenecks, they categorize bottlenecks into the following categories: bottleneck machines (processing units), logistics bottlenecks, bottleneck processes, bottleneck workpieces, human resource bottlenecks, and bottlenecks caused by maintenance and upkeep, as shown in Figure 1.

Categories of bottlenecks in the manufacturing system



Figure 1. Categories of bottlenecks in the manufacturing system.

2.1.1. Bottleneck Machines

Lawrence and Buss proposed that the machine with the largest number of parts or inventory in the pre-buffer should be regarded as the bottleneck machine [21]. Pollett defined the machine with the longest average waiting time as the bottleneck machine [22]. To be more relevant to actual production, Kuo and Lim proposed that when a machine has the worst processing capacity and seriously impedes the production process of the production line, it is regarded as a bottleneck machine [23]. Yan, Gu, and Xi defined the machine with the greatest workload or the least idle time as the bottleneck machine [24]. Roser and Nakano announced that the bottleneck machine refers to the machine with the highest average activity rate [25]. Aiming at short-term bottlenecks, Chang proposed that the machine with the most sensitive productivity to changes in the manufacturing system is the bottleneck machine [26].

2.1.2. Logistics Bottlenecks

Wang and Chen used the Petri network and Flexsim model to simulate actual production logistics, as well as analyzed and defined logistics bottlenecks [27]. Straka, Spirkova, and Filla define the logistics bottleneck as the part of the logistics with the most significant impact on output by adjusting the parameters of the logistics section [28]. Wang and Long used the simulation software AnyLogic to simulate the production and logistics system; they defined and analyzed the logistics bottlenecks for increasing production in mines [29].

2.1.3. Bottleneck Processes

Cordero-Lanzac analyzed the impacts of real environmental disturbances using a lifecycle assessment method to identify the primary bottleneck processes in manufacturing systems [30]. Li and his colleagues proposed first identifying the resources in a manufacturing system where the production load exceeds production capacity, designating these as bottleneck resources [31]. They then define the operations requiring support from these bottleneck resources as bottleneck processes. He and his research team members used the sensitivity of system performance indicators to changes in processing time as the criterion for identifying bottleneck processes [32].

2.1.4. Bottleneck Workpieces

Liu defined a bottleneck workpiece as the least able to meet the delivery deadline throughout the entire machining process [33]. Zhang and Wu propose that if a workpiece exhibits a significant delay under the current scheduling scheme and has a relatively small amount of slack time, and if the delayed weight of the workpiece is relatively large, then this workpiece is considered a bottleneck workpiece in the processes [34]. Wu considers that, during the grinding of hard alloys, the criterion for identifying a bottleneck workpiece is the degree of degradation of the workpiece's surface integrity [35].

2.1.5. Human Resource Bottlenecks

The work shifts and working hours of employees can also be factors contributing to bottlenecks in the production system. Urban and Rogowska proposed that if the employees are absent, like employees on vacation or sick leave, it cannot be ruled out that the associated process might not be a bottleneck [36]. Ovaskainen posits that even when utilizing identical equipment, the skill level of employees significantly impacts system throughput [37]. Peng proposed using Flexsim simulation to analyze human resources on the production line, using output as the performance metric. Based on this analysis, he gives proposals on staffing in the production line to avoid bottlenecks [38].

2.1.6. Bottlenecks Caused by Maintenance and Upkeep

To avoid bottlenecks, many manufacturing industries typically adopt a first-come, first-served policy. However, Langer and his team proposed a priority-based dynamic bottleneck scheduling strategy, through an extensive data analysis. This strategy assigns different priority levels to each bottleneck machine. When multiple service requests are received, maintenance personnel will prioritize servicing high-priority machines first. This strategy can significantly improve system throughput compared to the first-come, first-served approach [39]. Guillaume, Rémy, and Gilles integrated a production line simulator with a genetic algorithm optimizer to optimize the maintenance tasks for all machines on a production line to enhance overall throughput. This maintenance scheduling method was validated on an actual automotive engine production line [40].

2.2. Extensional Concept of Manufacturing Bottlenecks

The aforementioned definition of bottlenecks primarily focuses on the division of manufacturing processes, which has a relatively limited scope. Some scholars have proposed the concept of bottleneck extension from a global perspective of manufacturing and workshop configuration, thereby broadening the application of this theory.

Konopka proposed a CUBES model for calculating production throughput and identifying efficiency loss points [41]. The CUBES model comprehensively considered factors such as the production scenario, equipment configuration, and process personnel coordination to further optimize production line bottlenecks. For assembly lines with Markov characteristics [42], researchers such as Kuo and Lim have defined and explored concepts including downtime bottlenecks, operational bottlenecks, system bottlenecks, downtime prevention bottlenecks, operation prevention bottlenecks, and delivery performance bottlenecks from multiple perspectives [23,43–45]. In research on flexible assembly lines, Pegels and Watrous defined a unit that fails to achieve the expected output level as a bottleneck and studied the performance of systems by analyzing bottleneck characteristics such as Work In Progress (WIP) levels of processing units, the starvation, and blocking states of upstream and downstream units [46]. Chen defined bottlenecks in the system based on the average processing time of each machine in a processing equipment group. He proposed a systemic concept for addressing the total bottleneck problem, and demonstrated the effectiveness and practicality of this concept in production management [47]. Wang et al. categorized bottlenecks into structural, planning, and execution bottlenecks, which are based on the time scope of production tasks, and further analyzed the characteristics of bottlenecks under different time ranges [48]. Su proposed that the current definition of manufacturing resources is not detailed enough, so it cannot meet the needs of dynamic bottleneck identification. They defined nine fine-grained states of manufacturing resources in the process. Then, they summarized them into effective and ineffective states, as shown in Table 1. Based on these classifications, they determined the dynamic bottlenecks [49].

Table 1. The definition and categories of nine fine-grained states.

	States	Definitions	Categories
1	Producing	The machine is processing products.	Effective machine states
2	Set up	Preparing a machine for its next run after completing the previous one.	
3	Tool change	Replacing the required tooling for the equipment.	
4	Repair	Checking, testing, and replacing worn parts on a planned and ongoing basis.	
5	Breakdown	Period during which equipment or machine is not functional or cannot work.	Ineffective machine states
6	Waiting for repair	Waiting time between machine breakdown and maintenance.	
7	Stop	Waiting beyond starvation and blockages that cannot increase system output.	
8	Blockage	The machine is idle because it cannot transport WIP downstream.	
9	Starvation	The machine is idle due to a lack of WIP from upstream.	

To sum up, with the continuous development of actual demand and the deepening of academic research, the definition of a bottleneck has become more and more clear, which has further promoted scholars' research on manufacturing bottleneck identification methods.

3. Manufacturing System Bottleneck Research

3.1. Bottleneck Identifications

In the field of bottleneck identification and prediction, researchers have explored various methods to address the challenges in manufacturing systems. Bottleneck identification methods are generally categorized into three main types: static model-based, simulation-based, and data-driven-based. Furthermore, due to the complexity of dynamic manufacturing system environments, bottlenecks may shift over time. Shifting bottlenecks introduce delays in production planning, leading to decreased resource utilization and production efficiency. Bottleneck prediction provides a strategic approach for the early identification of potential bottlenecks, helping manufacturing systems achieve long-term production efficiency goals.

3.1.1. Bottleneck Identification Based on Static Models

Li et al. and Meerkov developed a series of assumptions based on static models to analyze real production scenarios, which led to the creation of analytical tools such as the

Bernoulli model and queuing theory models for manufacturing systems [50]. This static model identifies bottlenecks by calculating the throughput of the system. Ching, Meerkov, and Zhang derived the throughput calculation formula based on the non-exponential machine manufacturing system, and further improved the bottleneck analysis method of the non-exponential machine assembly system [51]. Varga and Subramaniyan successfully identified short-term and long-term throughput bottlenecks in the production line by analyzing the higher-order statistical information on arrival time [52,53]. Qiao proposed a system bottleneck judgment method based on the system priority assignment and queuing theory analysis model [54,55]. Malkowski established an automatic bottleneck identification method based on a statistical intervention model through repeated experiments in various scenarios [56]. Gershwin and Zhai decomposed the manufacturing process based on the production process differentiation theory and optimized the multi-bottleneck prediction method [57–59]. Sengupta and Das proposed a method of ranking equipment fault cycles based on the manufacturing system's time interval and fault cycle data [60].

When dealing with complex manufacturing systems, static bottleneck identification methods have many limitations in analyses. Qiu proposed that the presence of interference and uncertainty in manufacturing systems can significantly reduce the efficiency of such methods in bottleneck identification [61]. In addition, Li and his colleagues believe that the bottleneck identification methods based on static models lack flexibility; it is limited to identifying system bottlenecks that are in a stable state for a long time. Also, when dealing with random models, it cannot respond to dynamic changes in the system eventually [62].

3.1.2. Bottleneck Identification Based on Simulations

In the face of complex manufacturing systems, traditional bottleneck identification methods often suffer from inaccuracies and inefficiencies. Therefore, Alden and Wedel have proposed using simulation software to model and identify bottlenecks in manufacturing systems [63,64]. This approach has been widely applied in engineering practice and has achieved significant results. Simulation-based identification methods possess the capability to quickly and accurately identify system bottlenecks, aiming to provide more efficient solutions for the design, analysis, and management of systems, thereby optimizing overall production performance. Li and Hofmann proposed simulation-based identification methods that use external characteristics of the production line, such as starvation time [65], equipment utilization [66], buffer capacity [67], load-to-capacity ratio [68], throughput [26], and waiting time [69], to identify bottlenecks in manufacturing systems [70,71]. Roser, Nakano, and Tanaka, who work in Toyota Central R&D Labs, were the first to propose using GAROPS Analyzer simulation software to model production scenarios in discrete manufacturing workshops [72]. Alden further developed this approach by utilizing the C-MORE system to concentrate on improving General Motors' manufacturing operations, achieving a more effective identification of bottlenecks in the manufacturing network [63]. The development of software technology has significantly advanced the in-depth research on bottleneck identification in simulation systems. Currently, simulation software such as AnyLogic, Arena, and Flexsim has become an important tool in bottleneck identification research. Su used the simulation software AnyLogic to construct a one-to-one mapping of discrete workshop production processes, integrating equipment status to identify dynamic bottlenecks in the workshop [49]. Zheng and Liu performed a detailed analysis of order duration and inventory levels based on AnyLogic, and they established a simulation-based model for identifying manufacturing system bottlenecks [73]. The AnyLogic software established by Khedri Liraviasl is developed with Java as the underlying logic and possesses powerful discrete event simulation capabilities, making it widely used for bottleneck identification and analyses in discrete manufacturing systems [74]. Gundogar, Sari, and Kokcam used Arena simulation software in conjunction with constraint theory to identify bottlenecks and validate the feasibility of simulation-based bottleneck identification methods. Tang and his research group members proposed the concept of a global system based on the simulation software Flexsim and introduced a combined optimization method for

shifting bottleneck factors to determine the optimal bottleneck location to maximize system benefits [75].

Compared with the static model, the main advantage of simulation-based bottleneck identification is that it can solve the bottleneck identification problem in complex production lines to a certain extent. However, this approach still has limitations, because the accuracy of the results depends on the software performance and its degree of fit with the actual manufacturing system conditions. Khalid believes that in complex systems, the causes of bottlenecks are often the result of multiple interacting factors, and a singular simulation-based identification method may lead to erroneous simulation outcomes, thereby failing to accurately identify the bottlenecks [76].

3.1.3. Bottleneck Identification Based on Data-Driven Approaches

Researchers announced that the data-driven approaches are more effective in addressing the dynamic changes within systems. By leveraging real-time data feedback from online monitoring systems, dynamic bottlenecks within the system can be promptly identified [26,77]. Ungern-Sternberg and Teriete proposed a data-driven method for bottleneck identification and diagnoses based on priority ranking and active cycle methods [78]. Li proposed a data-driven, simulation-free method for identifying both short-term and long-term bottlenecks by collecting data such as buffer records and blocking records [79]. Roser proposed a dynamic bottleneck identification method based on the total runtime duration, which applies to unstable discrete manufacturing systems [80,81]. By monitoring real-time data from the system, this method can identify both static and transient bottlenecks. Gu, Jin, and Ni developed an indirect system bottleneck identification method based on historical data [82]. Furthermore, experts developed breakpoint methods and heuristic algorithms for dynamic bottleneck identification by collecting external characteristics of production lines such as buffer capacity, starvation time, and equipment utilization [67,83]. However, these identification methods are only applicable to systems with buffers and are susceptible to the capacity of the buffers, which may lead to misjudgment of bottlenecks.

This data-driven identification method can not only identify dynamic bottlenecks in real-time but also assist enterprises in dynamically adjusting production plans and decisions. However, it cannot provide a quantitative calculation method for dynamic bottlenecks or clarify the specific impact of dynamic bottlenecks on manufacturing system performance. Therefore, there are also limitations to data-driven bottleneck identification methods.

To make a more intuitive comparison of the above bottleneck identification methods, we drew up a table to list their strengths and limitations, as shown in Table 2.

Table 2. Bottleneck identification methods and their strengths and limitations.

Identification Methods	Strengths	Limitations
Based on static models	Easier to understand; it can be built and analyzed more quickly. Does not involve a time dimension, which means that less computing and resources are required.	Applies only to long-term stable systems and lacks flexibility. Fails to respond to dynamic changes promptly in random models.
Based on simulations	More flexible and has higher accuracy than the static model-based method. By simulating different scenarios and conditions, you can identify and take preventive measures in advance.	Accuracy relies on software performance and alignment with the actual system. Bottlenecks result from multifactor; simulations considering only a few factors may yield wrong results.
Based on data-driven approaches	Can identify real-time dynamic bottlenecks in the system. Helps dynamically adjust predictions and decisions in response to system changes.	Quantitative calculation of bottlenecks is not available. The impact of dynamic bottlenecks on system performance cannot be quantified. Requires lots of real-time data.

3.2. Shifting Bottlenecks

3.2.1. Causes of Bottleneck Shifting

Bottleneck shifting occurs because the manufacturing system is in a dynamic production environment. When the system is disturbed, the pre-sequence or post-sequence load of each machining unit may change, and these changes indirectly affect other non-bottleneck machining units, thus transforming them into new bottleneck units. This phenomenon makes the production plan based on “static bottleneck” lag, resulting in the plan deviating from the efficient production goal.

Thürer believes that when the system’s capacity is balanced, meaning that the non-bottleneck processing units have sufficient capacity, bottleneck shifting is less likely to occur [84,85]. This is because, in a balanced capacity state, the load among different manufacturing units and the differences in the upstream and downstream production environments are relatively small. On the contrary, when the system’s capacity is unbalanced, bottleneck shifting is more likely to occur in manufacturing systems. Additionally, research indicates that the closer the bottleneck processing unit is to the upstream, the easier it is to achieve better performance by implementing stricter controls. They also studied the impact of a shifting bottleneck on Drum–Buffer–Rope (DBR) system performance, focusing on the impact of a shifting bottleneck from its current location to its upstream and downstream location on the overall system performance. Meanwhile, Ling explored how transfer factors affect the location of bottlenecks in manufacturing systems regarding the phenomenon of bottleneck shifting [86]. Scholz-Reiter systematically defines the bottleneck shift in the production network based on Bottleneck-Oriented Logistic Analysis (BOLA), and visually processes the defined bottleneck through data. Finally, the validity of the logistics handling curve is verified [87]. Lawrence and Buss studied the bottleneck shift problem from the perspective of analyses. Based on the Jackson production network model, they quantified the tendency of processing units to become bottlenecks and defined the maximum queue length accordingly [88]. When shifting bottlenecks occur in the system, it is essential to predict which processing unit will become the next bottleneck promptly, so that new production plans can be effectively developed to restore efficient production in the system.

3.2.2. Consequence of System Bottlenecks

The emergence of bottlenecks in a manufacturing system can trigger a cascade of negative consequences. These may include delays in delivery schedules, reduced production efficiency, a decline in product quality, and a subsequent drop in customer satisfaction. Such bottlenecks can disrupt the entire production process, leading to harm to both the system’s output and its ability to meet market demands. Ultimately, the persistence of these bottlenecks can erode the competitive advantage of the manufacturing operation, resulting in potential financial losses and damage to the company’s reputation.

One of the most immediate impacts of bottlenecks is delayed deliveries. Gu, Lu, and Zhan argue that the excessive production tasks requested by the customer require more machine processing time within the delivery deadline than the actual capacity of the production line can handle, resulting in an inability to deliver on time [89]. Moreover, factors such as urgent orders, process changes, fluctuations in supply and demand, batch rework, and machine failures can all contribute to the emergence of bottlenecks, which in turn can significantly impact the overall system throughput. Another common negative impact of bottlenecks is the deterioration in product quality. Liu identified the removal of surface sand from 3D-printed sand cores as a time-consuming and labor-intensive process, representing a bottleneck process in the casting manufacturing system. When this step accrues a bottleneck, residual sand particles on the core surface can lead to defects such as porosity and cracks in the castings, severely compromising product quality [90]. Moreover, in large-scale production, a bottleneck at this stage can significantly impact delivery schedules. Another common impact is the reduction in production efficiency on the production line and the inefficient allocation of resources. Tadesse used overall equipment effectiveness (OEE) as a metric to compare simulations of the existing and

optimized production lines using Arena Simulation software. The comparison results demonstrated that the bottleneck's appearance in the manufacturing system will reduce production efficiency [91].

3.3. Bottleneck Management

Bottleneck management in manufacturing systems primarily focuses on two aspects: proactive bottleneck prediction and reactive mitigation strategies. The former aims to anticipate and prevent bottlenecks before they occur, while the latter focuses on minimizing the negative impacts once a bottleneck has already emerged. The following sections will elaborate on both approaches to bottleneck management.

3.3.1. Proactive Bottleneck Prediction

Bottleneck prediction holds significant strategic importance in the optimization of manufacturing systems. By accurately identifying potential bottlenecks in the production process, companies can proactively formulate improvement measures, thereby enhancing overall production efficiency and resource utilization. Bottleneck prediction is essentially a process of preemptively identifying potential bottlenecks, aiming to recognize parts of the system that have not yet become bottlenecks but may develop into them in the future.

Cao and his group studied the effects of product type, processing time, machine utilization, and buffer capacity on bottlenecks, and proposed a method based on adaptive network fuzzy inference to predict bottleneck issues in the system [92]. Roser utilized system buffer data, combining active state methods and buffer data to predict production bottlenecks [93]. Zhou developed a bottleneck index based on the workload and variability of wafer manufacturing systems. He proposed a new method for predicting bottleneck machines during system transient processes [94]. Those above bottleneck prediction methods still have certain limitations, and most models rely on static analysis assumptions, failing to adequately account for the changes in and evolution of bottlenecks in dynamic environments. Consequently, these prediction methods lack flexibility and accuracy when applied to dynamic models and fail to predict bottlenecks promptly.

However, the prediction of bottlenecks based on dynamic models enables a more accurate and timely identification of potential bottlenecks within a system. Chang utilized an online monitoring system to collect and process real-time production data from manufacturing enterprises for bottleneck prediction, aiming to achieve production line balance [26]. Subramaniyan proposed a data-driven algorithm for bottleneck activity cycles, which has the advantage of utilizing real-time production data for forecasting [95]. Xue and his team members used real-time data captured by Arena software and employed a data-driven approach to predict bottlenecks under multivariable uncertainty in remanufacturing systems [96]. Compared to static bottleneck prediction methods that apply only to long-term stable systems, this data-driven approach can predict system bottlenecks in real-time and with higher flexibility. However, the accuracy of this method often depends on the availability of large volumes of real-time data and the performance of the software.

3.3.2. Reactive Mitigation Strategies

In modern manufacturing processes, numerous uncertainties frequently cause bottleneck shifts in the production system. These dynamic bottlenecks lead to deviations in production planning and control decisions from the actual production process. After a bottleneck occurs in a manufacturing system, it is essential to quickly minimize its negative impacts.

The initial step in reactive mitigation strategies is to pinpoint the source of the constraint and find the bottleneck root cause. Current research predominantly employs retrospective control to optimize production processes, passively adapting to changes in bottlenecks. Wang suggests to use the root cause method to locate the bottleneck of the host. This method, based on the loop-back test, uses host performance bottlenecks as path state features to accurately identify the root causes of bottlenecks [97]. Qi proposed a novel

method for a fine-grained discrete root cause analysis using machine learning, and they found and uncovered a little-known cause of lagging tasks [98]. This approach offers a new perspective for identifying and understanding parallel data processing programs.

After identifying the root cause of the bottleneck, managers need to develop and implement optimization strategies for the bottleneck resources. Duclos and Spencer proposed a DBR simulation model based on the TOC, which was applied to a diesel engine production line. The results demonstrated a significant improvement in system efficiency. The DBR scheduling method was employed by the company to control production rhythm, manage production inputs, and set buffers to achieve system balance or minimize the impact of bottlenecks [99]. Ma conducted a study focusing on automobile assembly lines, analyzing the balance of the production line [100]. They developed and implemented optimization strategies for resources like bottleneck processes, layout planning, and operator allocation, which ultimately led to the assembly line achieving optimal production efficiency.

After the reactive mitigation action is taken, it is essential to continuously monitor and periodically evaluate the manufacturing system to facilitate timely dynamic adjustments to production plans. Nakata established a JUSTICE/MORAL control system, which is capable of real-time monitoring of operational conditions by controlling the Work In Progress levels and managing bottleneck machines with random variations [101].

4. Bottleneck Research Trends in Manufacturing System

With the rapid development of digital and intelligent technologies, particularly the integration of advanced technologies such as Digital Twin (DT) and neural networks, a novel data-driven approach for bottleneck analyses in manufacturing systems has been opened up. As a bridge between the physical world and the virtual world, Digital Twin technology can not only map and predict the dynamic behavior of the system in real-time, but also provide forward-looking decision support for production control through simulation. With its powerful data processing and pattern recognition capabilities, neural networks show unique advantages in bottleneck identification and root cause analyses of complex systems [102].

4.1. Digital Twin Technology Promotes the Development of Data-Driven Bottleneck Analysis

Virtualization technology opens up a new prospect for data mining research in production control. Digital Twin (DT) technology is capable of responding to various disturbances during the execution of pre-scheduled operations in manufacturing systems.

Ragazzini proposed an innovative approach based on Digital Twin technology, to predict potential future production bottlenecks in manufacturing systems [20]. They developed a virtually integrated bottleneck prediction and analysis framework that provides feedback on order release and scheduling information through system information flow. By dynamically adjusting control decisions to adapt to the predictions provided by the Digital Twin (DT), the study demonstrated that using DT as a synchronous simulation model is feasible.

Kumbhar, Amos, and Bandaru proposed a Digital Twin for complex manufacturing systems (OME) [103]. It contains three components, data collection and system control, the core entity, and the user interface entity, as shown in Figure 2. The data collection and device control entity is responsible for integrating the information flow for enterprise planning, production execution, and process monitoring, as well as confirming the availability of raw materials and other resources. This resource demand is recorded as an order in the ERP, and the production line will execute orders from the ERP to produce each component, which is then assembled into the finished product with the help of the transportation system. Additionally, these above activities are recorded in the MES. Ultimately, equipment statuses and events are logged in SCADA for monitoring and documentation purposes. The core entity is responsible for integrating ERP and MES data to generate event logs, which can be used for product traceability. Additionally, it can create dynamic process maps based on process logs and perform data description and diagnostics to support analyses and

summarize real-time processes. The user entity uses log data in CSV format. It allows users to upload files from any period of data to analyze whether bottlenecks exist in the system during that time. This method effectively identifies both static and dynamic bottlenecks without relying on highly specialized knowledge to build the model. The feasibility and effectiveness of the proposed method were validated through experiments.

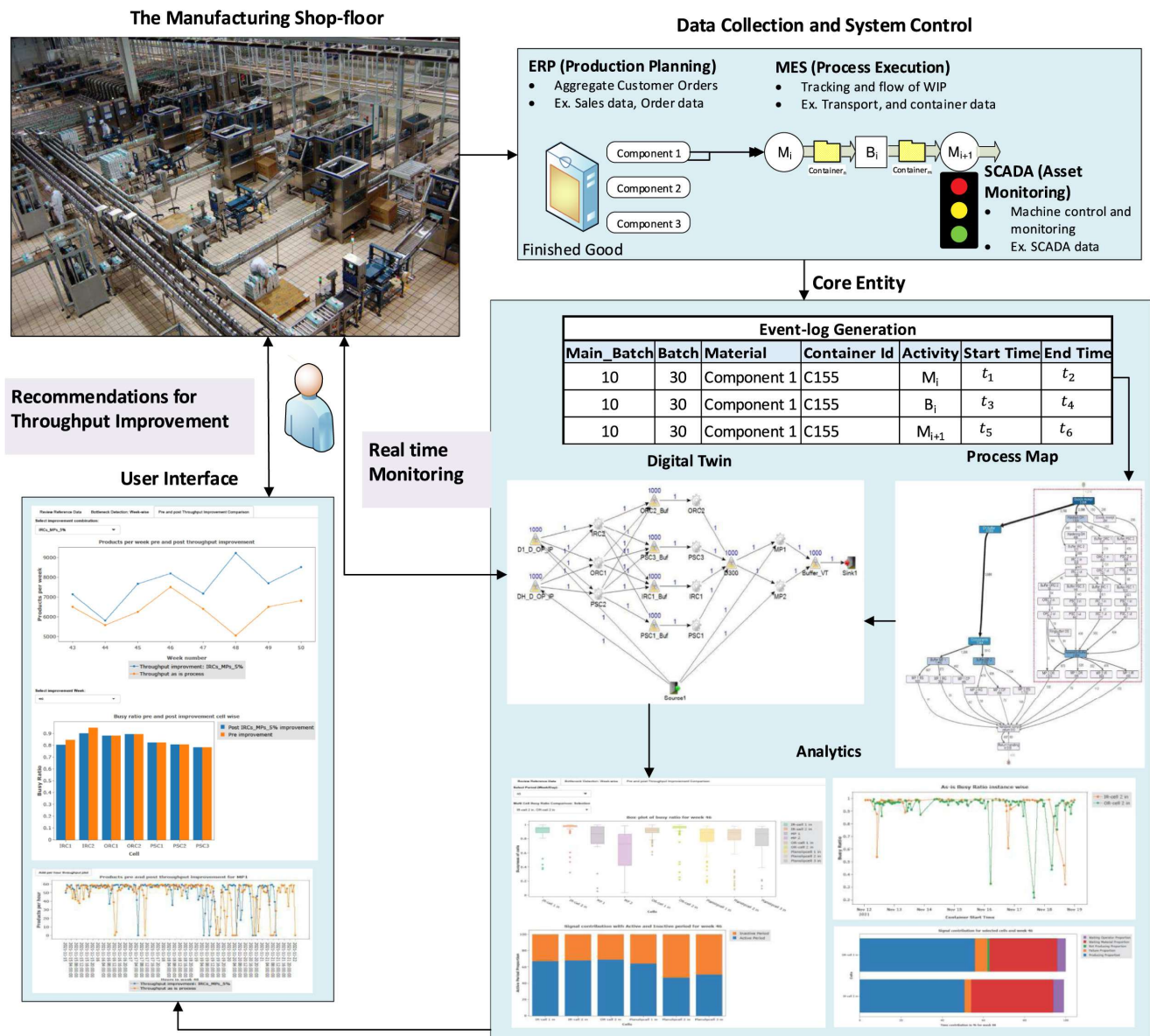


Figure 2. Digital Twin for complex manufacturing system (OME) consisting of data collection and system control, core entity, and user interface entity [103].

Latsou, Farsi, and Erkoyuncu proposed an Agent-based dynamic simulation control manufacturing system, which uses the Agent-based mode (ABM) to detect anomalies in sensor data and automatically identify and solve bottlenecks in the system [104]. This method employs a bottom-up ABM strategy to drive the Digital Twin (DT) and integrates ABM-discrete event simulation (ABM-DES) technology to enable the real-time simulation and decision control of complex manufacturing systems. It facilitates the automatic monitoring of these systems in an agile and efficient manner.

4.2. Use Neural Networks to Identify and Analyze Manufacturing System Bottlenecks

Using machine learning technology to automatically identify and extract key features in a process is becoming an effective research method for process management and its decision support. Bottleneck identification is an important step for process improvement, but traditional approaches based on quantitative measures, such as machine operations and resource requirements, have limitations in knowledge-intensive processes.

Lai and his research team proposed an interpretable modeling framework called the Bottleneck Spatial–Temporal Attention Network (BSTAN) to enhance bottleneck prediction in complex manufacturing systems [105]. In this framework, the first step involves extracting the network structure information of the production line. The second step involves using a graph neural network based on gated recurrent units to capture temporal trends and workstation interactions, enabling the prediction of blockages and starvation at each workstation. Finally, the bottlenecks are predicted by analyzing the distribution of blockages and starvation across the production line.

Si and his research group used fuzzy neural networks to study the bottleneck identification and bottleneck shifting prediction of automated production lines, and they proposed a new definition of a workshop bottleneck for precision forging blades [106]. By establishing a bottleneck recognition index system, the bottleneck recognition problem is transformed into a multi-attribute decision problem, and a fuzzy neural network can be used to train the bottleneck recognition and prediction.

The semiconductor manufacturing (SM) process involves both continuous dynamic changes and discrete event dynamics, making it one of the most complex models to analyze. Bottlenecks in this process can significantly impact system throughput, delivery times, and product quality. Cao and his research team proposed an improved Adaptive Neuro-Fuzzy Inference System (ANFIS) and the research team applied this predictive method to the SM system [92]. The SM product line has categorical inputs in addition to numerical inputs, but the standard ANFIS can only accept numerical inputs. However, the research team believes that this improved method adaptively integrates fuzzy inference systems with neural networks, capable of reflecting the contribution of categorical inputs to firing strength through a transformation matrix method. The improved ANFIS structure is shown in Figure 3; it consists of six layers of calculations. The first layer is the adaptive node function, which is the membership of the fuzzy set associated with the input; it belongs to the Gaussian function. The second layer is the firing strength of fuzzy rule calculating. The third layer of functions is responsible for normalizing all firing strength of the rule. The fourth layer is the calculation of the firing strength of the categorical input. The fifth layer of the linear function is responsible for the calculation of fuzzy rule output. The sixth layer's function is used to compute the overall output of the ANFIS. For numerical input, such as processing time, utilization rate, buffer length, mean time between failures (MTBF), mean time to repair (MTTR), and Work In Progress (WIP), we just need to follow the calculation sequence from layers one to six. For categorical input calculation, the research team used 1-out-of-n to encode categorical inputs S_1 (the job types) and S_2 (the releasing strategy), then input to the transformation matrix instead of following the first three layers of calculation. After that, the matrix turns those inputs into a five-dimensional vector, which will be used for layer 4–6 calculation. Finally, experimental results show that this method can accurately predict the bottleneck of the SM system.

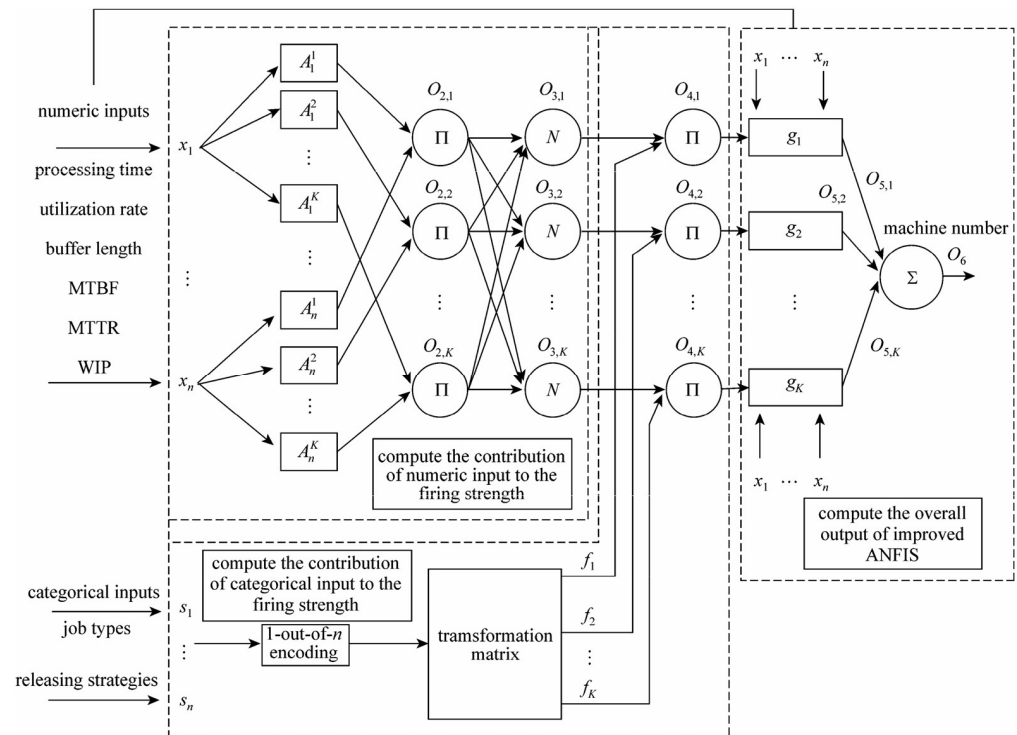


Figure 3. The logic of improved ANFIS [92].

5. Conclusions

Bottlenecks, as critical factors that constrain the overall throughput of manufacturing systems, have different definitions and classifications across various fields. Research indicates that the occurrence of bottlenecks in manufacturing systems often leads to significant drops in production efficiency, delays in delivery, and imbalanced resource utilization, all of which increase production costs and weaken market competitiveness. Therefore, an accurate identification and management of bottlenecks are essential to mitigate these negative impacts effectively. In this review, we have thoroughly examined the definitions of bottlenecks in manufacturing systems and systematically analyzed and compared static model-based, simulation-based, and data-driven-based bottleneck identification methods. Additionally, we have provided a detailed explanation of the causes of bottleneck shifting in manufacturing systems and discussed management strategies from both proactive bottleneck prediction and reactive bottleneck mitigation strategy. These analyses and discussions offer crucial theoretical support for the further research and optimization of manufacturing systems. Finally, we explored the research trends in integrating Digital Twin technology with neural networks for bottleneck analyses. These combinations show great potential in manufacturing systems, enabling a more precise and real-time simulation and prediction of bottleneck occurrences. By leveraging these advanced technologies, researchers can gain a more comprehensive understanding of bottleneck behavior in complex systems, leading to the development of more effective management and optimization strategies.

Nevertheless, current research still has several limitations, and we believe that future research will focus on the following aspects. Firstly, due to the varying research subjects and systems, there are significant differences in bottleneck identification and prediction methods. Whenever a new environment is encountered, it is necessary to redefine bottlenecks and prediction approaches, particularly when dealing with dynamic bottlenecks. This process is often cumbersome and computationally intensive. Therefore, it is imperative to develop several universally applicable bottleneck prediction algorithms that can help enterprises quickly and accurately identify bottlenecks in common manufacturing systems. Secondly, the causes of bottlenecks in complex manufacturing systems are often multifactorial. To correctly predict bottlenecks, it is crucial to fully identify all potential

contributing factors. However, given the current state of research, it is challenging to detect all the causative factors of bottlenecks, which may lead to inaccurate predictions. Consequently, improving the analysis of bottleneck causes to optimize simulation-based bottleneck identification methods is an inevitable trend in future research. Lastly, the computational complexity of bottleneck identification and monitoring is high in complex manufacturing systems. This process requires a large volume of high-quality real-time data. However, the current software's performance and data processing efficiency are inadequate, resulting in insufficient real-time bottleneck prediction, which in turn affects the timeliness and effectiveness of decision-making. Therefore, enhancing software data processing capabilities and optimizing algorithms are essential.

Author Contributions: Conceptualization, J.T. and Z.X.; methodology, J.T., W.J. and M.A.Z.; investigation, J.T. and Z.X.; resources, J.T. and Z.X.; writing—original draft preparation, J.T.; writing—review and editing, J.T. and Z.X.; visualization, J.T.; supervision, X.W. and J.W.; project administration, Z.D.; funding acquisition, W.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the Heilongjiang Major Scientific and Technological Achievements Transformation Project (grant number, CG21B010), Heilongjiang Province Key Research and Development Project (grant number: 2022ZX01A13), and Heilongjiang Provincial Nature Foundation research team project (grant number: TD2023E002).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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