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A framework for throughput bottleneck analysis using cloud-based cyber-physical systems in Industry 4.0 and smart manufacturing

Ehsan Mahmoodi [a,*], Masood Fathi[a,b], Morteza Ghobakhloo[b], Amos H.C. Ng [a,b]

[a] *Division of Intelligent Production Systems, School of Engineering Science, University of Skövde, 54128 Skövde, Sweden*
[b] *Division of Industrial Engineering and Management, Uppsala University, PO Box 534, Uppsala 75121, Sweden*

Abstract

The performance of a production system is primarily evaluated by its throughput, which is constrained by throughput bottlenecks. Thus, bottleneck analysis (BA), encompassing bottleneck identification, diagnosis, prediction, and prescription, is a crucial analytical process contributing to the success of manufacturing industries. Nevertheless, BA requires a substantial quantity of information from the manufacturing system, making it a data-intensive task. Based on the dynamic nature of bottlenecks, the optimal strategy for BA entails making well-informed decisions in real-time and executing necessary modifications accordingly. The efficient implementation of BA requires gathering, storing, analyzing, and illustrating data from the shop floor. Utilizing Industry 4.0 technologies, such as cyber-physical systems and cloud technology, facilitates the execution of data-intensive operations for the successful management of BA in real-world settings. The main objective of this study is to establish a framework for BA through the utilization of Cloud-Based Cyber-Physical Systems (CB-CPSs). First, a literature review was conducted to identify relevant research and current applications of CB-CPSs in BA. Using the results of the review, a CB-CPSs framework was subsequently introduced for BA. The application of the framework was assessed via simulation in a real-world manufacturer of marine engines. The findings indicate that the implementation of CB-CPSs can contribute significantly to throughput improvement.

Keywords: Bottleneck analysis; Cyber-physical systems; Industry 4.0; Simulation

* Corresponding author. Tel.: 0500-448526
E-mail address: Ehsan.mahmoodi@his.se

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1. Introduction

Manufacturing industries are constantly striving to improve the productivity of their processes [1]. Productivity improvement is mainly centered around increasing throughput, which can be defined as the pace at which parts pass through a production line [2,3]. The throughput of a production system is limited by one or more resources, referred to as "throughput bottleneck(s)." It is known that bottlenecks may account for up to 30% of throughput losses in manufacturing and production [4]. The impact of bottlenecks on the productivity of manufacturing systems has led to a notable interest in bottleneck analysis (BA) among scholars and practitioners.

The existing theories, including the theory of constraints (TOC) [5] and the theory of swift-even-flow [6], suggest that throughput may be continuously improved by frequently identifying bottlenecks and improving them. However, practitioners must depend on expertise and intuition while doing BA since it is difficult to detect and overcome bottlenecks in practice [7].

BA is divided into four stages: detection, diagnosis, prediction, and prescription [8]. Detection methods identify bottlenecks using analytical, simulation-based, and data-driven approaches [3]. It is worth mentioning that other bottleneck detection methods, including bottleneck walk and Go&See [9], are data-driven approaches, in nature. Diagnosis involves finding and prioritizing the root causes of bottlenecks, which are often due to process variabilities and disturbances in production [10]. Prediction methods assist decision-makers with predicting future bottlenecks and usually employ simulation modeling coupled with predictive analytics, network analysis, or neural networks [7]. Lastly, prescription offers recommendations for improvement based on descriptive and prescriptive analytics results, representing an emerging research area with potential for further exploration [11].

Among the existing approaches for BA, analytical and simulation models are limited in that they must be continuously updated to account for changes in the actual system. Maintaining analytical and simulation models is therefore quite challenging for practitioners. Thankfully, the ongoing digital transformation in manufacturing, known as Industry 4.0, seems to present significant implications for tackling the challenges related to BA [12]. Among many other implications, the real-time capability principle of Industry 4.0 might streamline continuous access to production data, boosting the capabilities of analytical and simulation models.

This study aims to investigate the application of Cloud-Based Cyber-Physical Systems (CB-CPSs) as one of the underlying technologies of Industry 4.0 that can contribute significantly to analyzing manufacturing bottlenecks. The present study followed a three-phase approach to investigate the potential benefits of CB-CPSs in sensing, monitoring, controlling, and manipulating manufacturing systems. While several researchers have predominantly reported on the application of CB-CPSs in production, with a focus on sensing, monitoring, and controlling aspects, the manipulation aspect has received comparatively less attention. This discrepancy can be attributed to the requirement of highly communicative and self-correcting robots and machines for CB-CPSs to be able to effectively manipulate the production line. However, this study specifically suggests and evaluates the application of CB-CPSs on highly flexible machines within production, namely Automated Mobile Robots (AMRs), that can be easily manipulated.

The first phase is a literature review to find the relevant and potential applications of CB-CPSs in BA. The second phase is to build a framework according to the results of the literature review. Finally, in the third phase, the proposed framework is examined in a real-world case from the marine engine manufacturing industry, in which the AMRs are allocated to machine calls using a bottleneck-oriented approach. The production line throughput is then compared with the current First-In-First-Out (FIFO) logic.

This paper is organized as follows: section 2 provides a literature review to find the applications of CB-CPSs in BA. Building upon the literature review results, section 3 elaborates on the proposed CB-CPSs framework for BA, in manufacturing industries. To show the implication and impact of the proposed framework, section 4 provides the application of the proposed framework in a real-world case study. Finally, section 5 provides the conclusion and future research directions.

2. Literature Review

In the first phase, a review of the literature was conducted to find and analyze the relevant research to this study. The main purpose of the performed literature review was to discover current and future CB-CPS applications in BA. To this aim, scientific publications were searched in two major scientific peer-reviewed databases, Scopus and Web of Science. The search string includes “bottleneck,” “cloud,” “CPS,” “cyber*physical,” and “manufacturing.” This resulted in 84 conference and journal articles. According to the low number of papers found, the only exclusion criterion was that the paper was not written in English. Afterward, the screening process started by reading the abstract and then the full text of the papers. This step resulted in only five relevant papers. Most papers were excluded because the above-mentioned keywords were only used in the abstract or keywords.

The literature review results revealed that CB-CPSs applications are sensing the physical system, performing BA, visualizing its results, and manipulating the physical systems. In the following sections, the results of the conducted literature review are presented in more detail.

2.1. Sensing the actual system

The performance of data-driven BA heavily depends upon the quality and timing of the data provided [13]. Therefore, providing high-quality and real-time data is vital for the success of data-driven BA. It is one of the applications of cloud technology in BA to provide real-time data, pre-process the data, store the data, and put the data from different parts of the line together. This data will be later used to perform data-driven bottleneck detection, diagnosis, prediction, and prescription.

In this regard, two studies were found in the literature focusing on the cloud-based BA. In Zhang et al. [7], the authors combined a discrete event simulation (DES) model with the state-of-the-art data gathering and analysis techniques, specifically cloud technology, to provide a real-time bottleneck detection tool. The authors employed simulation to model production processes and dispatching rules. Since real-time bottleneck analysis is highly sensitive to the amount of data available from the manufacturing system, a cloud-based service was established to provide real-time data. The data were fed to a simulation model to schedule production based on bottleneck machines using dynamic programming and fuzzy analysis.

In Lai et al. [3], the authors used a cloud-based “turning point” method to detect bottlenecks in an automotive smart manufacturing system. The cloud-based solution was developed to detect bottlenecks and visualize results. To this aim, the daily records of the manufacturing shop were stored in the cloud using an algorithm developed in Python, and the resulting predicted bottlenecks were sent to frontline experts using the internet. This program runs in the background continuously on the data stored in the cloud. When new data arrive, the feature extraction algorithm and bottleneck detection run results update in the cloud. The one-year pilot use of this method resulted in a 30 percent improvement in overall equipment effectiveness (OEE).

2.2. Visualization bottlenecks using cloud-based systems

Visualization is highlighted by several authors, including the studies by de Paula Ferreira et al. [13] and Ghobakhloo et al. [14], as one of the I4.0 design principles. Visualization assists manufacturing line managers in gaining deeper insights into real-world complexities. However, the amount of processing power required for visualizing the results of BA urges the use of cloud-based solutions.

Recently, Hofmann et al. [9] used augmented reality (AR) and real-time data to propose an augmented go-and-see approach. “GO & See” is one of the bottleneck detection techniques developed under lean manufacturing. Using this method, one can walk through the production line and draw applicable conclusions about the production flow. AR is one of the technologies rooted in Industry 4.0 that could significantly help this lean-based bottleneck detection approach. However, the lack of real-time data processing power while using added reality has imposed limitations on developing such methods. With higher processing power, such technologies are nowadays turning into reality. Hofmann et al. [9] proposed some key performance indicators to detect bottlenecks with AR. Based on the bring-your-own-device principle and image processing techniques, an application was developed to detect the cycle time and work in process (WIP) of the production line. This application was developed by Apple ARKit and employed radio-frequency identification (RFID) tags on entities to detect each machine's cycle time (part entering and leaving time) and buffer level (exiting parts of a station - entries to the next station). Using this data together with real-time KPI values for each station, the root causes of the bottlenecks could be easily determined. The results revealed that the use of the Augmented “GO & See” method by line managers led to significantly better performance than the traditional version. Augmented “GO & See” is classified as level 3 in the ACATECH Industry 4.0 maturity model [16].

2.3. Self-adaptive, cloud-based IoT

Managing and analyzing throughput bottlenecks can be challenging due to bottleneck shiftiness. Bottleneck shiftiness refers to the phenomenon where the bottleneck shifts from one resource to another due to planned events (such as maintenance or changes in production mix) and unplanned events (such as machine failure or variations in processing times) that occur on the production line [17]. Due to the shifting nature of bottlenecks, it is imperative to use a system capable of analyzing and generating solutions that can be manipulated in real-time. Without such a real-time and self-adaptive system, the solution's efficiency will be negatively affected by the delay between the decision-making process and its execution. It may be possible to resolve this issue using cloud-based IOT devices.

In a smart factory, IoT devices, which are classified into two categories: sensors and data transmission systems, enable the interconnection of machines and other resources. Using these interconnections, each smart factory resource can adapt to the the-real time changes on the shop floor to prevent bottlenecks [18]. Recently, IoT-based bottleneck prediction methods were studied by Fang et al. [10] and Huang et al. [19].

In Huang et al. [19], the authors implemented IoT technologies, including sensors, RFID and WI-FI, as the first step of a bottleneck analysis method for a smart factory. The role of IoT was to provide real-time data from the shop floor. Using data provided by IoT, a deep neural network combined with time series was employed to predict the bottlenecks in real-time. This method was tested on a valve manufacturing company and successfully improved system throughput. Fang et al. [10] used the data provided by IoT systems of a large-scale job-shop for machining parts of an aero-engine in China. The real-time data was fed to a parallel gated recurrent units (P-GRUs) network in which the data of the present bottlenecks was analyzed to predict future bottlenecks.

3. Proposed framework for BA using CB-CPSs

In 2006, Hellen Gil proposed CPS to the National Science Foundation as one of the main technologies of I4.0 [20, p. 200]. In addition to connecting virtual spaces and physical reality, CPS is responsible for integrating computing, networking, and storage capabilities, resulting in an interactive industrial environment, which can be used to create Smart Factories. In general, CPSs integrate physical reality with communication networks and computing infrastructures [21]. CPSs differ from conventional embedded systems because they primarily focus on integrating networking devices to support I4.0 [22]. A CPS consists of a control unit interacting with the real world through sensors and actuators, obtaining data, and exchanging it with other systems and/or cloud services. To put it another way, CPSs are systems capable of sending and receiving data through a network; CPSs have the ability to obtain real-time information and services, independent of where the machines are located, via Internet access [23].

Cloud-based CPSs benefit from the enormous computational and processing power provided by cloud technology. The role of cloud technology is to provide CPSs with enough processing and storage capacity to handle data acquisition, data storage, and data processing power over big data generated from real systems [22]. Thus, it is of interest to both practitioners and researchers to develop and implement CB-CPSs in manufacturing.

3.1. The structure of the CB-CPSs

According to the results of performed literature review, real-time BA is a data-intensive and challenging task, to which CB-CPSs may contribute significantly. The application of CB-CPSs in BA starts with sensing the actual system through sensors, gathering and preparing the required data from different parts of the production environment, pre-processing the data, and making the data coming from different types of resources compatible for further analysis.

Moreover, CB-CPSs can contribute to BA by visualizing the state of the production line at present and in the near future. Visualization could add significant value, specifically for practitioners. Line managers could gain deeper insight into current and short-term congestion and use their knowledge and experience to elevate the proposed solutions resulted from BA.

Sensing the physical system, conducting BA, and presenting the outcomes of BA hold pragmatic significance in enhancing productivity. However, these actions alone may not suffice. An efficient BA solution must be able to manipulate the production line based promptly on BA results. This is due to the shifting nature of bottlenecks. The bottlenecks in real-world situations move from one part of the line to another. It is not uncommon for this shiftiness to occur within minutes. Thus, another aspect in which CB-CPSs can greatly contribute to BA is real-time manipulation of the physical system.

Potential steps in which BA might benefit from CB-CPSs capabilities are depicted in Fig 1. This figure highlights that the following functions could be included in a framework for BA using CB-CPSs, 1) sensing the physical layer of production, including machine status, material flow, failures, etc., 2) data storage and pre-processing, 3) extracting the required data for BA, 4) conducting BA, 5) visualization of the results, 6) interaction with decision makers to finalize a decision, 7) and taking action and manipulate the manufacturing system.

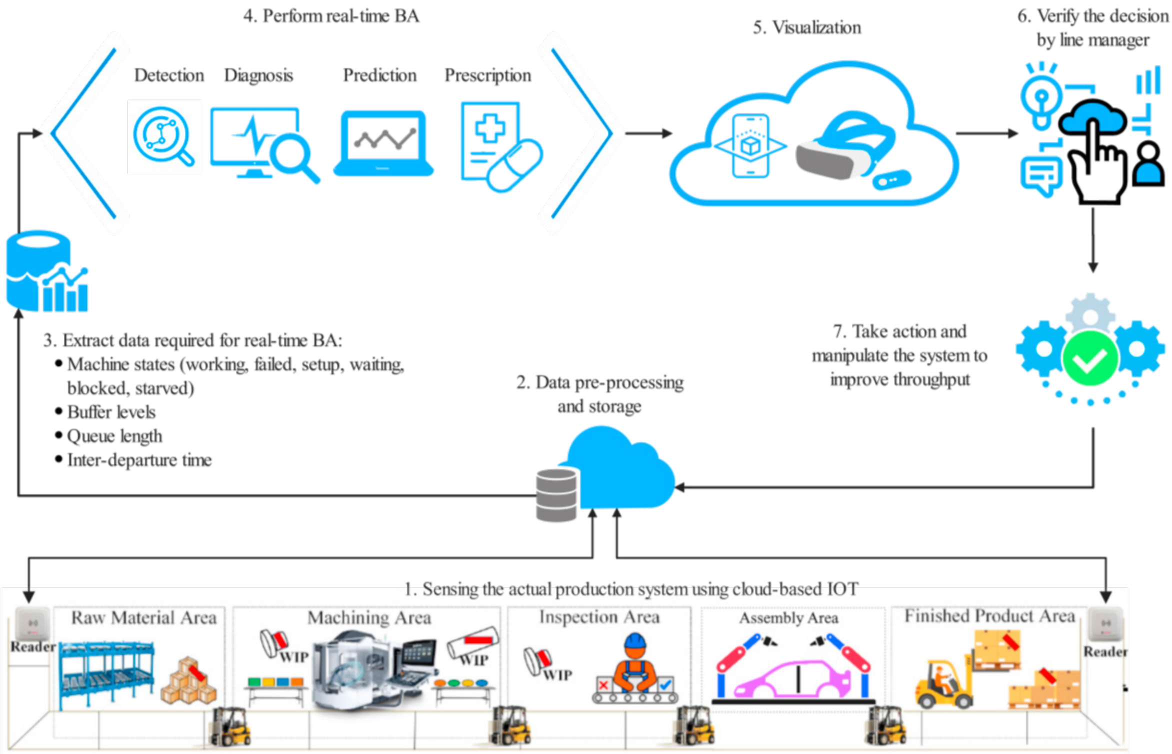

Fig 1. A framework for using cloud-based CPSs in data-driven BA

4. Implications in a real-world case

The implementation of the proposed framework in practical production settings necessitates a degree of self-adaptation and heightened flexibility in the machinery. Such a level of self-adaption may not have been realized yet. However, an area where the application of this framework has been observed to be feasible is in the domain of automated material handling units, such as Automated Mobile Robots (AMRs). AMRs are present in numerous industrial production facilities. This study examines the application of the proposed framework on a real-world marine engine production line in Sweden.

The production of marine engines typically involves a series of distinct steps, including manufacturing and fabrication (such as casting and forging, machining, heat treatment, and surface treatment), pre-coat assembly, leakage testing (cold testing), coating, post-coat assembly, quality control and inspection (hot testing), customization, and packaging. Each of these production processes requires varying degrees of automation, decoupling the production line into multiple segments to accommodate differences in production rates.

In the studied case, AMRs transport materials between these decoupled sections. The AMRs operate on a call-based system; a call to the AMRs is made when a station releases an engine at a decoupling point and the engine must be transported to another station. To evaluate the effect of the proposed framework on the throughput of the production line, DES, a powerful tool for mimicking the behavior of complex real-world systems such as manufacturing [24], transportation, and logistics [25], is employed. Subsequently, a simulation model is constructed and validated using real-world data. Then the throughput of the production line is compared between the assignment of AMRs using FIFO and, the bottleneck-based assignment of AMRs.

4.1. Simulation model

The simulation model emulates the operations of the real system and is constructed using Arena simulation software. At present, the allocation of AMRs to workstations is based on FIFO logic. The above statement denotes that the calls originating from stations to AMRs are systematically archived in a time-ordered sequence. Nonetheless, such an approach could potentially lead to increased waiting times for workstations, which are already a bottleneck, thereby negatively impacting the overall throughput of the production line. To mitigate this issue, an enhanced AMRs allocation methodology, which is exclusively viable through the suggested CB-CPSs, is modeled and contrasted with the present situation.

The simulation model incorporates a centralized queue where requests for AMRs are accumulated from various decoupled workstations on the shop floor. Each request comprises an attribute called *Station_BA_Rank*, denoting the bottleneck ranking of the station that initiated the request. The Station_BA_Rank attribute undergoes periodic updates, occurring at a frequency of one update per second, facilitated by a control entity. The utilization method, as proposed by Hopp and Spearman [2], is employed to identify bottlenecks. This approach has been deemed effective and appropriate for bottleneck analysis based on simulation and data, as evaluated by Thürer et al. [17]. The utilization method, as described by Hopp and Spearman [2], identifies bottlenecks by measuring the utilization (u_s). The bottleneck is determined as the station with the highest utilization, which can be expressed as $max\ (u_1, u_1, \ldots, u_m)$, with m being the number of machines.

The average utilization of workstations is monitored regularly using the utilization method. After that, the "Rankings element" changes the order of the engines in the request queue according to average utilization of workstations. Fig. 2 depicts an aggregated simulation model from the stations located before the paint shop. In Fig. 2, the engines (yellow and blue balls) in the queue of Request 2 represent the engines that have completed their processing at their respective stations and are awaiting transportation. The yellow balls represent engines that have successfully passed the cold test without any failures, while the blue balls represent engines that have undergone repairs due to leakage. As shown in Fig. 2, the engines coming from the Repair area, found after cold testing, are sorted with a higher priority to be transferred by AMRs (the blue-colored balls remaining in the queue of Request 2). The current prioritization of requests directed toward (AMRs) by the repair station is attributed to the presence of three engines that have been deemed defective and require immediate repair. However, this manufacturer's ability to perform repairs is limited to only two simultaneous engines. These circumstances resulted in the repair process being transformed into an excessively utilized station, and subsequently, the requests coming from this station were given priority. The allocation of requests may vary depending on the circumstances and events on the shop floor. Fig. 3 depicts a moment in the simulation run where only one engine has been rejected, as indicated by the blue ball in the Request queue. Consequently, priority for transportation is allocated to other requests.

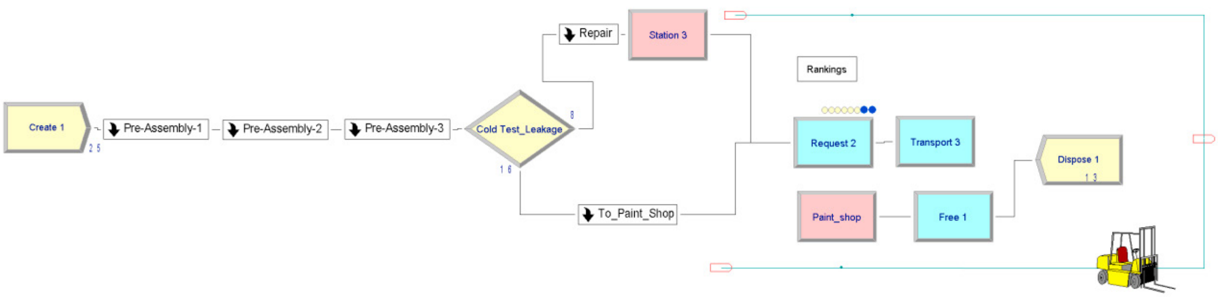

Fig 2. An aggregated version of the simulation model under BA-based request prioritizing through CB-CPSs

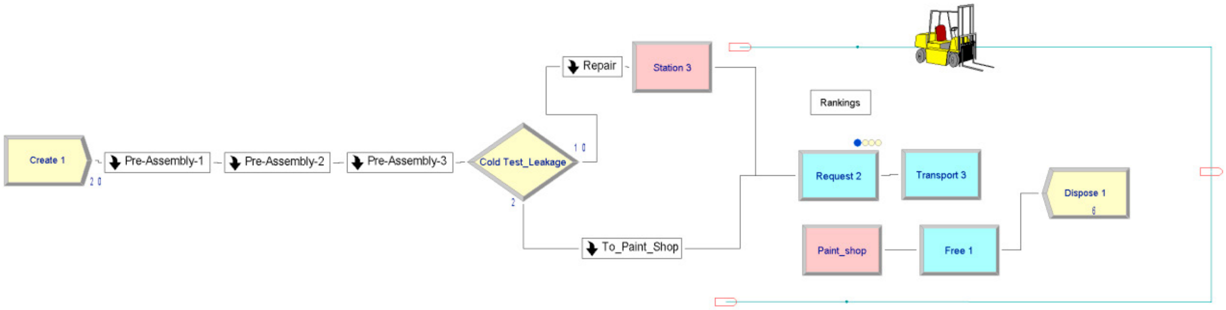

Fig 3. An aggregated version of the simulation model under BA-based request prioritizing through CB-CPSs

4.2. Comparing bottleneck-based and FIFO in assigning AMRs

A complete and detailed simulation model of the system was developed and validated to compare the production line's throughput and evaluate the CB-CPS effect in BA. The throughput of the production line, extracted from the real-world data, the simulation model under the current scenario, and the simulation model under the BA-Based assignment of AMRs are depicted for a 90-day production period in Fig 4. The real data dates to a 6-month period from year 2021. In Fig. 4, the comparison between boxplots of Real-world Throughput and Simulation Throughput-FIFO reveals that the simulation model is capable of accurately capturing the system's throughput. The higher variability observed in the simulation model, as compared to the real-world system, can be attributed to the absence of necessary data for determining the probability distribution of the Repair process.

Additionally, the boxplot of Simulation Throughout-Bottleneck Based, shows a higher value of mean throughput, indicating that bottleneck-based approach can lead to significant throughput improvement. The main reason for throughput improvement under BA-Based assignment of AMRs is that the requests that have blocked the production line are prioritized over others. Thus, the flow of material gets smoother and the throughput of the production line, increases.

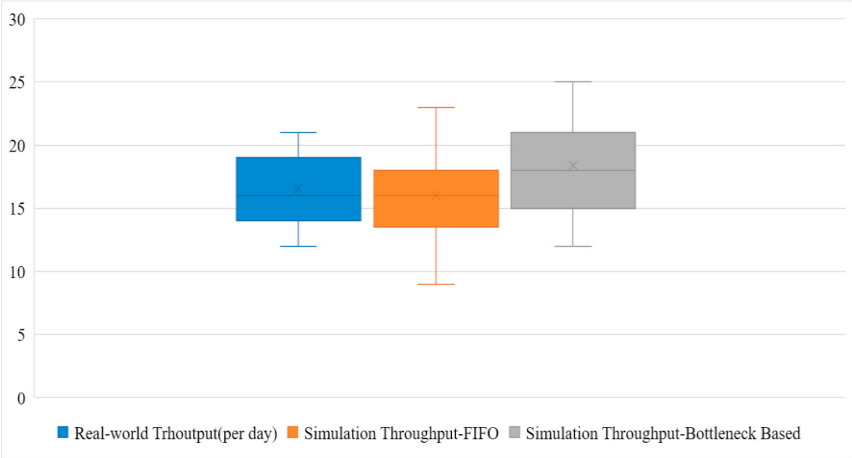

Fig 4. The comparison between the production line's throughput calculated based on real-world data, simulation model under the current situation, and bottleneck-based assignment of AMRs

5. Conclusion and future research

The first objective of this study was to investigate the various applications of CB-CPSs within the domain of BA and to propose a framework grounded in the existing literature. The secondary objective was to show an area of application of the proposed framework in the AMRs control system of a marine engine manufacturer. This study reviewed the literature on BA to achieve the first objective. The performed literature review indicated that, despite the limited research available on the subject, the utilization of cloud technology, or CPSs, in the context of BA within manufacturing industries has the potential to yield significant improvements in production processes. Based on the evidence gathered from the literature, the utilization of CB-CPSs in the context of BA can enhance various aspects of data collection, analysis, and visualization.

Moreover, the literature review revealed that most of the research conducted in the field of BA acknowledges and highlights the characteristic of bottleneck shiftiness; however, they often fail to propose viable solutions to address this challenge. This gap can be attributed, in part, to the assumption made in existing research that manufacturers must wait until self-correcting and highly flexible robots become economically justifiable for production purposes. Such self-correcting systems can employ the results of BA and manipulate themselves to keep the throughput of the production line. However, this research focusses on certain functions within manufacturing that already are flexible enough to be manipulated, on real-time. One such area is AMRs, which possess the capability to adapt their behavior based on different planning scenarios.

Although CB-CPSs have potential benefits, there are still challenges that must be overcome. One of the primary difficulties faced by BA through CB-CPSs is the challenge of gathering a significant volume of data from various sources involved in the manufacturing process. The next challenge pertains to the considerable time required to perform data-driven bottleneck analysis to implement CPSs. These two challenges present two future research directions for academic research, which could yield advantages for academic researchers and industry practitioners. The first suggestion for future research is to focus on data gathering, analysis, and dimension reduction techniques for BA, as well as providing standards that can facilitate the implantation of the CB-CPSs for BA. The second direction can investigate the development of data-driven BA analysis approaches compatible with future generations of manufacturing systems.

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Declaration of Generative AI and AI-assisted technologies

During the preparation of this work, the author(s) used QuillBot in order to proofread and improve the originally written text. After using QuillBot, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

[1] Jalal Possik, Anne Zouggar-Amrani, Bruno Vallespir, and Gregory Zacharewicz, (2021) "Lean techniques impact evaluation methodology based on a co-simulation framework for manufacturing systems" *International Journal of Computer Integrated Manufacturing* **35** (**1**) 91–111.
[2] J. Wallace Hopp and L. Mark Spearman, (1996) *Factory Physics: Foundations of Manufacturing Management*. Waveland Press, Inc.
[3] Xingjian Lai, Huanyi Shui, Daoxia Ding, and Jun Ni, (2021) "Data-driven dynamic bottleneck detection in complex manufacturing systems" *Journal of Manufacturing Systems* **60** 662–675.
[4] Pooya Alavian, Yongsoon Eun, Semyon M. Meerkov, and Liang Zhang, (2019) "Smart production systems: automating decision-making in manufacturing environment" *International Journal of Production Research* **58** (**3**) 828–845.
[5] Eliyahu M Goldratt and Jeff Cox, (1986) *The Goal: A Process of Ongoing Improvement*. Routledge.
[6] Roger W. Schmenner, (2012) *Getting and staying productive : applying swift, even flow to practice*. Cambridge University Press.
[7] Yongyang Zhang, Lianghua Zeng, Engao Peng, Zhenkun Luo, and Da-wei Zhou, "An Intelligent Prediction Model for Bottleneck in Production System Based on Cloud Manufacturing," in *Mechanisms and Machine Science*, **105**, Springer, Cham, 2021, 237–245.
[8] Nikolai West, Marius Syberg, and Jochen Deuse, (2022) "A Holistic Methodology for Successive Bottleneck Analysis in Dynamic Value Streams of Manufacturing Companies" *Lecture Notes in Mechanical Engineering* 612–619.
[9] Constantin Hofmann, Tom Staehr, Samuel Cohen, Nicole Stricker, Benjamin Haefner, and Gisela Lanza, (2019) "Augmented Go & See: An approach for improved bottleneck identification in production lines" *Procedia Manufacturing* **31** 148–154.
[10] Weiguang Fang, Yu Guo, Wenhe Liao, Shaohua Huang, Nengjun Yang, and Jinshan Liu, (2020) "A Parallel Gated Recurrent Units (P-GRUs) network for the shifting lateness bottleneck prediction in make-to-order production system" *Computers & Industrial Engineering* **140** 106246.
[11] Mukund Subramaniyan, Anders Skoogh, Azam Sheikh Muhammad, Jon Bokrantz, and Ebru Turanoğlu Bekar, (2019) "A prognostic algorithm to prescribe improvement measures on throughput bottlenecks" *Journal of Manufacturing Systems* **53** 271–281.
[12] Ehsan Mahmoodi, Masood Fathi, and Morteza Ghobakhloo, (2022) "The impact of Industry 4.0 on bottleneck analysis in production and manufacturing: Current trends and future perspectives" *Computers & Industrial Engineering* **174** 108801.
[13] A. F. Brochado, E. M. Rocha, D. Almeida, A. de Sousa, and A. Moura, (2022) "A data-driven model with minimal information for bottleneck detection - application at Bosch thermotechnology" *International Journal of Management Science and Engineering Management* 1–14.
[14] William de Paula Ferreira, Fabiano Armellini, and Luis Antonio De Santa-Eulalia, (2020) "Simulation in industry 4.0: A state-of-the-art review" *Computers & Industrial Engineering* **149** 106868.
[15] Morteza Ghobakhloo, Masood Fathi, Mohammad Iranmanesh, Parisa Maroufkhani, and Manuel E. Morales, (2021) "Industry 4.0 ten years on: A bibliometric and systematic review of concepts, sustainability value drivers, and success determinants" *Journal of Cleaner Production* **302** 127052.
[16] Violett Zeller, Christian Hocken, and Volker Stich, (2018) "acatech Industrie 4.0 Maturity Index – A Multidimensional Maturity Model" *IFIP Advances in Information and Communication Technology* **536** 105–

113.

[17] Matthias Thürer, Lin Ma, Mark Stevenson, and Christoph Roser, (2021) "Bottleneck detection in high-variety make-to-Order shops with complex routings: an assessment by simulation" *Production Planning & Control*

[18] Lihui Wang and Xi Vincent Wang, *Cloud-Based Cyber-Physical Systems in Manufacturing*. Cham: Springer International Publishing, 2018.

[19] Binbin Huang, Wenbo Wang, Shan Ren, Ray Y. Zhong, and Jingchao Jiang, (2019) "A proactive task dispatching method based on future bottleneck prediction for the smart factory" *International Journal of Computer Integrated Manufacturing* **32** (**3**) 278–293.

[20] Lee Edward, "Cyber-physical systems-are computing foundations adequate," *Position paper for NSF workshop on cyber-physical systems: research motivation, techniques and roadmap*, 2006.

[21] Lihui Wang, Martin Törngren, and Mauro Onori, (2015) "Current status and advancement of cyber-physical systems in manufacturing" *Journal of Manufacturing Systems* **37** 517–527.

[22] Alberto Villalonga, Gerardo Beruvides, Fernando Castano, and Rodolfo E. Haber, (2020) "Cloud-Based Industrial Cyber-Physical System for Data-Driven Reasoning: A Review and Use Case on an Industry 4.0 Pilot Line" *IEEE Transactions on Industrial Informatics* **16** (**9**) 5975–5984.

[23] Xifan Yao, Jiajun Zhou, Yingzi Lin, Yun Li, Hongnian Yu, and Ying Liu, (2019) "Smart manufacturing based on cyber-physical systems and beyond" *Journal of Intelligent Manufacturing* **30** (**8**) 2805–2817.

[24] Carlos Alberto Barrera Diaz, Masood Fathi, Tehseen Aslam, and Amos H. C. Ng, (2021) "Optimizing reconfigurable manufacturing systems: A Simulation-based Multi-objective Optimization approach" *Procedia CIRP* **104** 1837–1842.

[25] Hamidreza Eskandari and Ehsan Mahmoodi, (2016) "A simulation-based multi-objective optimization study of the fleet sizing problem in the offshore industry" *Maritime Economics & Logistics* **18** (**4**) 436–457.