International Journal of Industrial Engineering, 31(4), 907-922, 2024

RESILIENT OPERATOR-ROBOT COLLABORATION IN SMART FLEXIBLE MANUFACTURING SYSTEMS

Majed Masmali*

Industrial Engineering Department
College of Engineering
Northern Border University
Arar, Saudi Arabia
*Corresponding Author's email: majed.masmali@nbu.edu.sa

Manufacturing key metrics are a useful approach for evaluating shop floor operations. The collaboration between operators and robots is essential in maintaining a resilient performance within smart and flexible manufacturing systems. For effective collaboration, both operators and robots must possess varying degrees of resilience, including full resilience, partial resilience and the ability to handle total disruptions. In this paper, lead time is considered a significant key metric. When the system is fully resilient and dependable, it achieves the optimal lead time. Consequently, lead time serves as a benchmark for evaluating the system's performance. However, if the robot experiences significant performance issues, it can negatively impact the cycle time, resulting in longer lead times. The discrepancy between the optimal lead time and the lead time obtained during partial or complete disruption is subtracted from the optimal lead time. To ensure the validity of the findings, mathematical equations are utilized in combination with other relevant data. This approach contributes to the knowledge base in the field. Finally, the paper will provide suggestions for future research endeavors..

Keywords: Flexible Manufacturing System, Lead Time, Manufacturing Key Metrics, Manufacturing Resilience, Operator-Robot Collaboration, Smart Manufacturing.

(Received on August 5, 2023; Accepted on July 7, 2024)

1. INTRODUCTION

Manufacturing enterprises move forwards along with smart technological paradigms. However, there are certain issues that might hinder firms from achieving competitiveness. On the one hand, the unexpected events to the manufacturing processes cause loss in the production levels. On the other hand, the interactions between humans and advanced automated equipment in the shop floor need to be considered further. Operator-robot collaboration is a field of study that focuses on designing, developing, and utilizing robots that can work effectively and safely alongside operators (Panagou, 2023). These collaboration systems are designed to facilitate task-sharing and learning between operators and robots. Collaborative robots are specifically designed to physically cooperate with operators (Broum and Šimon, 2019). As noted by Lin and Lukodono (2021), the integration of operator and robot capabilities through collaboration is crucial to achieve optimal utilization of their respective strengths and weaknesses in manufacturing systems. This partnership allows for the supplementation of each other's abilities, resulting in a more productive and efficient production process. However, the performance of collaboration systems may be impacted by disruptive situations, such as those encountered in other manufacturing systems. Therefore, it is essential to maintain the sustainability and resilience of collaborative systems. Operator-robot collaboration systems have the ability to maintain a consistent cycle time when performing assigned tasks, even in the presence of disruptions or variations in inputs or resources. However, disruptions or variations can cause delays or interruptions in the cycle time, impacting the efficiency and consistency of task completion. As a result of these disruptions, the time required to complete tasks or deliver products/services can be extended, resulting in increased lead times. Therefore, it is imperative to effectively handle these challenges and utilizing key metrics presents a viable strategy to accomplish this goal. The evaluation of shop floor operations through metrics has garnered significant attention in both research and practical applications. Numerous studies have focused on the development and implementation of metrics to assess and improve operational performance in manufacturing environments. For instance, Meddeb *et al.* (2023) introduced a monitoring system tailored specifically for automated weighing and bagging machines, incorporating a user-friendly human-machine interface to enhance system performance. Qin *et al.* (2023) proposed a resilient flexible manufacturing system design method that involves route reconfiguration and increased storage capacity to absorb losses and promptly restore the system in the face of disruptions. Bhongade *et al.* (2023) investigated rescheduling methods in flow-shop manufacturing systems to mitigate disruptions, assessing the influence of

DOI: 10.23055/ijietap.2024.31.4.9545 **ISSN 1943-670X**

factors such as initial solutions, failure duration and rescheduling techniques on performance. Lead-time sensitivity and disruption risks were given priority in the study conducted by Taghavi *et al.* (2023). Industrial operations have undergone a significant transformation in the era of Industry 4.0, with a strong emphasis on integrating smart technologies and fostering collaboration between humans and robots.

However, the assessment of resilient collaborative system performance based on lead time had not been addressed fully yet in the earlier articles. Therefore, there is a need to propose an approach to evaluate the resilient collaborative system performance level in terms of lead time. The primary objective is to thoroughly evaluate the impact on lead time effectiveness, particularly in partially resilient or completely disrupted conditions. In this article, a methodology is proposed, and the following assumptions are made. It is assumed that in fully system-resilient conditions, the lead time is considered the benchmark and target value. Conversely, in cases of partial or total disruption within collaborative systems, fluctuations in the lead time are experienced. As a result, to evaluate performance, the deviation in lead time resulting from disruptions is calculated and subtracted from the yield value of lead time. However, it is important to acknowledge that the current approach does not account for post-disruption recovery. Nevertheless, the findings of this research would be highly valuable to operations managers, manufacturers, and scientific researchers in the field.

The structure of this paper is outlined as follows. At the beginning, the introduction section discusses the research aim, objectives, and research significance. The second section contains a literature review, which explores three domains related to the research topic, followed by the research contribution section. Subsequently, the research methodology is presented, followed by the findings and discussion. Lastly, the paper concludes with a conclusion section discussing the possibility of future research.

2. LITERATURE REVIEW

The literature review explored previous relevant studies across three domains: manufacturing key metrics employed in shop floor operations, the dynamics of human-robot collaboration in manufacturing systems, and the significance of resilience in operator-robot interactions.

Figure 1 visually represents the structure of the literature review within these domains.

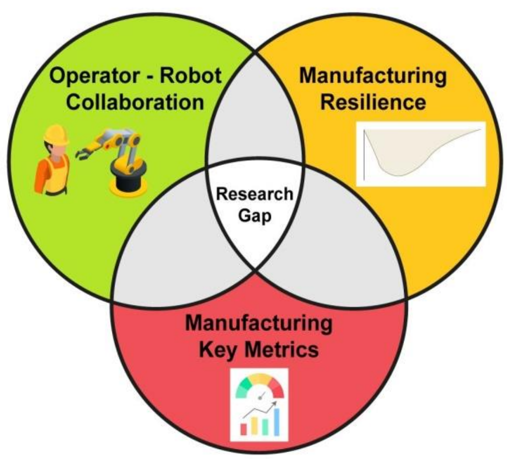

Figure 1. Research Gap

2.1 Manufacturing key metrics

Metrics play a fundamental role in quantifying and analyzing the performance of shop floor operations. Researchers and practitioners have recognized the importance of selecting appropriate metrics that align with the specific goals and objectives of manufacturing organizations. Metrics such as throughput, cycle time, utilization, quality metrics, and cost metrics have been widely adopted to measure and evaluate different aspects of shop floor operations. One notable study by Han and McGinnis (1989) introduced shop operating characteristics curves, which provide a visual representation of the relationship between various control rules and shop configurations. This work laid the foundation for evaluating and optimizing the performance of manufacturing systems through graphical analysis of metrics. Serkar *et al.*(1991) evaluated a double shuttle automated storage and retrieval system's performance, proposing a four-command cycle for increased throughput. Ulusoy and Bilge (1992) focused on minimizing makespan in the scheduling problem, specifically in the context of material handling and overall performance optimization. Perona and Portioli (1996) proposed an enhanced loading model that considers task allocation and resource utilization metrics to improve operational efficiency. Their work emphasized the importance of proper task allocation to achieve optimal performance on the shop floor. Parasuraman *et al.* (2000) developed a model for determining appropriate levels of automation in human-machine systems, taking into account metrics related to human performance consequences. This study highlighted the significance of finding the right balance between human and machine involvement based on performance metrics. Olsen and Goodrich (2003) introduced metrics for evaluating human-robot interactions, such as neglect tolerance, task effectiveness, and robot attention demand. These metrics aim to guide the design of effective human-robot interfaces that optimize task performance while considering the role of human attention and interaction effort. In Kim's (2006) study, market responsiveness and productivity were enhanced in flexible manufacturing systems through the application of neural networks and simulation, leading to superior performance in test scenarios. Chaudhry *et al.* (2011) employed a spreadsheet-based genetic algorithm to minimize completion time in the simultaneous scheduling of machines and automated guide vehicles within flexible manufacturing systems. Gröger *et al.* (2013) introduced the operational process dashboard for manufacturing to improve information availability and decision-making on the shop floor, enhancing agility in the manufacturing industry. Ho (2015) presented a system dynamics model for improving make-to-order production performance, considering factors like time delays, shortage handling, and resource optimization. Hwang *et al.* (2017) developed an IoT-based performance measurement system for smart factories, enabling real-time data capture and analysis to enhance manufacturing performance. Odedairo and Nwabuokei (2018) discussed the development of a decision support tool using discrete event simulation to measure past work-in-process, cycle time, and performance in small and medium-scale industries. Hellebrandt *et al.* (2019) proposed a human-centered approach to performance management on the shop floor, integrating worker perspectives and motivational gamification elements. The research conducted by Torres *et al.* (2020) investigates the consequences of incorporating smart technologies and digital features on the performance of shop floor management in the context of smart manufacturing. It provided a thorough analysis of the implications of these factors and underscored their substantial influence in enhancing overall operational performance.

Gutjahr *et al.* (2021) achieved exceptional performance in the cyclic flexible flow shop, significantly reducing AGV count and optimizing makespan with heuristic approaches. Zhou *et al.* (2021) investigated the impact of man-machine ratio on the performance of a one-person-multi-machine series production line in lean production systems. Ohlig *et al.*(2023) demonstrated that gamified information provisioning enhances operational performance and work motivation within a shop floor setting. Boschetti *et al.* (2023) investigated the effects of a geometric approach strategy for human-robot collaborative systems on system performance. Meddeb *et al.* (2023) introduced a monitoring system tailored for automated weighing and bagging machines, incorporating a user-friendly human-machine interface to improve system performance.

2.2 Operator -Robot Collaboration

Research on human-robot collaboration in manufacturing systems has garnered significant attention since its inception. Early studies by Paul and Nof (1979) compared the work methods of robots and human operators, favoring robot time and motion as a more suitable evaluation method. Ghosh and Helander (1986) addressed task allocation challenges between humans and robots, focusing on product design and specialized maintenance requirements. Abdel-Malek (1989) delved into optimizing robot base location to minimize cycle time in manufacturing cells. Rosenbrock (1990) advocated for responsible automation, emphasizing machines as tools to assist humans rather than control them. Advancements in the field continued as researchers explored various aspects of human-robot collaboration. Tan *et al.* (2009) provided insights into enhancing productivity and safety through human factors in cellular manufacturing systems. Tompkins *et al.* (2010) emphasized the flexibility and customization of manufacturing systems, combining machining, assembly, and material handling for diverse product output.

Further investigations focused on the dynamics of human-robot collaboration. Zanchettin *et al.* (2015) proposed a kinematic control strategy to ensure productivity and safety in collaborative manufacturing environments. Nilakantan and Ponnambalam (2016) optimized U-shaped assembly lines with robots and a particle swarm algorithm, aiming to minimize cycle time and improve production efficiency. Perona *et al.* (2016) proposed a method utilizing workload control and logistic operating curves to effectively reduce and stabilize manufacturing lead time. Botti *et al.* (2017) developed a model integrating ergonomics and lean principles, enhancing productivity by integrating manual workers and robots while optimizing assembly cycle time. Lee *et al.* (2018) proposed an augmented reality-based framework for human-robot collaboration, aiming to improve communication, reduce errors, and enhance production flexibility in a semi-automated process for electric motor manufacturing. Bauters *et al.* (2018) introduced a vision-based system for workstation analysis, facilitating anomaly detection and continuous improvement while reducing cycle time. Darvish *et al.* (2018) developed a flexible human-robot cooperation architecture to address interaction challenges in Industry 4.0. Lee *et al.* (2019) introduced hybrid assembly systems for flexible manufacturing, highlighting the significance of human-robot collaboration in improving productivity and adaptability in upcoming manufacturing settings. Nikolakisa *et al.* (2018) suggested a hybrid hierarchical model to allocate tasks in environments where humans and robots work together, with a focus on dynamic scheduling to improve the efficiency and adaptability of manufacturing processes. It introduces a manufacturing system that combines human workers and robots, enabling them to collaborate on flexible assembly tasks. The paper also presents a decision-making framework that considers multiple criteria for real-time scheduling and re-scheduling in response to unexpected events. Casalino *et al.* (2019) present an optimal scheduling method for collaborative assembly tasks using time Petri nets, minimizing idle time and accommodating variations in manufacturing processes. The approach is validated through experiments on a small assembly line with robots and a human operator. Zhang *et al.* (2019) addressed the optimization of energy-efficient U-shaped robotic assembly line balancing problems using a multi-objective approach and a modified bee colony algorithm. Malik *et al.* (2020) discussed the use of virtual reality and event-driven simulation to estimate human-robot cycle times for designing collaborative workspaces in manufacturing. Koltai *et al.* (2021) employed mathematical programming models to investigate how the assignment of tasks and cycle times are affected when robots are introduced to assembly lines operated by humans. Fast-Berglund and Thorvald (2021) conducted an examination of the variations in cycle time observed during collaborative interactions that involved both humans and robots performing knowledge-based tasks. Li *et al.* (2021) introduced an innovative method that employed a multi-objective migrating bird optimization algorithm to address the challenge of cost-oriented assembly line balancing with collaborative robots. Quenehen *et al.* (2021) explored the integration of lean techniques and collaborative robots, resulting in reduced cycle time and lead time, thus improving operational performance. Cardoso *et al.* (2021) assessed the impact of collaborative robotics on productivity, ergonomics, and worker well-being, leading to reduced production times and improved working conditions. Keshvarparast *et al.* (2023) proposed a bi-objective optimization model for collaborative assembly lines with cobots to minimize cycle time and physical workload while considering workforce diversity. Gusmao Brissi *et al.* (2022) reviewed the interactions between robotic systems and lean principles in offsite construction, highlighting benefits such as enhanced efficiency and reduced cycle time. Marinelli (2022) investigated synergies between lean production and human-robot collaboration in industrialized construction, focusing on waste reduction and improved cycle time. Liau and Ryu (2022) presented a framework to improve mold assembly using collaborative robots, prioritizing ergonomics and human ability. Chutima (2023) conducted a comprehensive review on assembly line balancing with cobots, highlighting their crucial role in enhancing resilience, disrupting traditional operations, and improving performance in manufacturing systems. Erol (2023) explored an energy-efficient assembly line balancing problem with human-robot collaboration. It investigates the integration of robots in assembly lines to enhance resilience, disrupt traditional operations, and improve performance in terms of flexibility, productivity, safety, and energy efficiency. Kim and Lee (2023) investigated the transformation occurring in mass customization research. It involved an examination of the scientific communities involved, tracking changes over time, and exploring the impact of emerging technologies, such as the collaboration between humans and robots. Further advancements have been made in optimizing collaboration and addressing specific challenges. Li *et al.* (2023) developed models and algorithms to optimize task assignment and worker-robot allocation in the U-shaped assembly line balancing problem with collaborative robots.

2.3 Manufacturing Resilience

Zieba *et al.* (2010) conducted a study on resilient human-machine cooperation and proposed the use of adjustable autonomy and human-machine cooperation as methods to achieve system resilience. They emphasized the importance of considering affordances and introduced three indicators to assess different aspects of resilience. The study aimed to optimize human-robot interaction and develop dynamic systems capable of anticipating, reacting, and recovering from errors and disturbances. Germs (2012) investigated order acceptance and order release strategies to optimize the order pool in make-to-order production systems, aiming to achieve shorter and more reliable delivery times. The effects of operational disruptions on production lead times are investigated by Finke *et al.* (2012), with a focus on deviations in task processing time. Emphasis is placed on the impact of lead time variability on overall system performance, accompanied by a discussion on the utilization of quantitative analysis and mitigation strategies. Ouedraogo *et al.* (2013) proposed a functional architecture to learn from the resilience of human-machine systems. It defines resilience, presents indicators for assessing it, and discusses learning from resilience through a feedback-feedforward architecture. Charalambous *et al.* (2015) investigated organizational human factors for the effective implementation of human-robot collaboration, including enhancing resilience in manufacturing. The role of cooperation in supporting resilience in human-agent systems was examined by Chiou and Lee (2016). It was found that the cooperativeness of automated agents had a direct influence on human agents, highlighting the importance of considering this factor in the design and evaluation of teams involving autonomous agents. Wang *et al.* (2019) proposed a robust scheduling optimization model for flexible manufacturing systems that accounts for uncertain machine failures. A mixed-integer linear program is applied to utilize threshold scenarios to ensure production due dates are achieved within a certain bound. Romero and Stahre (2021) introduced the "Resilient Operator 5.0" concept and Operator 4.0 typology, aiming to create smart and resilient manufacturing systems from a human-centric perspective. Cortés-Leal *et al.* (2022) proposed the maintenance 5.0 framework, integrating emerging technologies and human workers to enhance the resilience of physical assets in smart manufacturing. Alexopoulos *et al.* (2022) developed a method to quantify resilience in manufacturing systems, demonstrating its application during the COVID-19 pandemic. Yang *et al.* (2022) discussed the critical role of human-machine interaction in Industry 5.0, analyzing potential challenges and opportunities. Pupa *et al.* (2022) proposed a resilient task scheduling framework for effective human-robot collaboration in the industry, considering uncertainties and deviations and promoting parallel work.

The challenge of achieving smooth and resilient human-machine teamwork for Industry 5.0 was discussed, with a proposal made to utilize the joint cognitive systems approach, actor-network theory, and ethically aware design (Kaasinen *et al.*, 2022). Lead-time sensitivity and disruption risks are given priority in the study conducted by Taghavi *et al.* (2023). Qin *et al*. (2023) proposed a method for resilient FMS design involving route reconfiguration and increased storage capacity to absorb losses and restore the system promptly in the face of disruptions. Ojstersek *et al.* (2023) utilized simulation modeling tools to evaluate the importance of sustainable manufacturing within the context of human-robot collaboration. Pizoń and Gola (2023) emphasized the need for developing a roadmap for the human-machine relationship in Industry 5.0.

3. RESEARCH CONTRIBUTION

Based on the existing literature review, this study makes a significant research contribution by identifying key metrics for evaluating resilience in the shop floor, with a specific focus on smart, flexible manufacturing systems. The evaluation of resilient performance in human-robot collaboration becomes crucial when unexpected events disrupt the ability of one or both elements to perform their tasks. This study highlights the importance of these key metrics and discusses their role in maintaining system resilience.

In the context of smart, flexible manufacturing systems, the collaborative system's effectiveness is often measured by its ability to meet delivery time requirements. Therefore, the lead time emerges as a critical key metric in assessing and enhancing resilience. This research opportunity aims to evaluate the impact of lead time on resilient robot-operator collaboration within a smart, flexible manufacturing system.

4. RESEARCH METHODOLOGY

The research aims to evaluate the resilient collaboration system between a robot and an operator. Figure 2. illustrates these two components work together in tandem, but it is important to acknowledge the possibility of disruptions affecting either or both elements within the system.

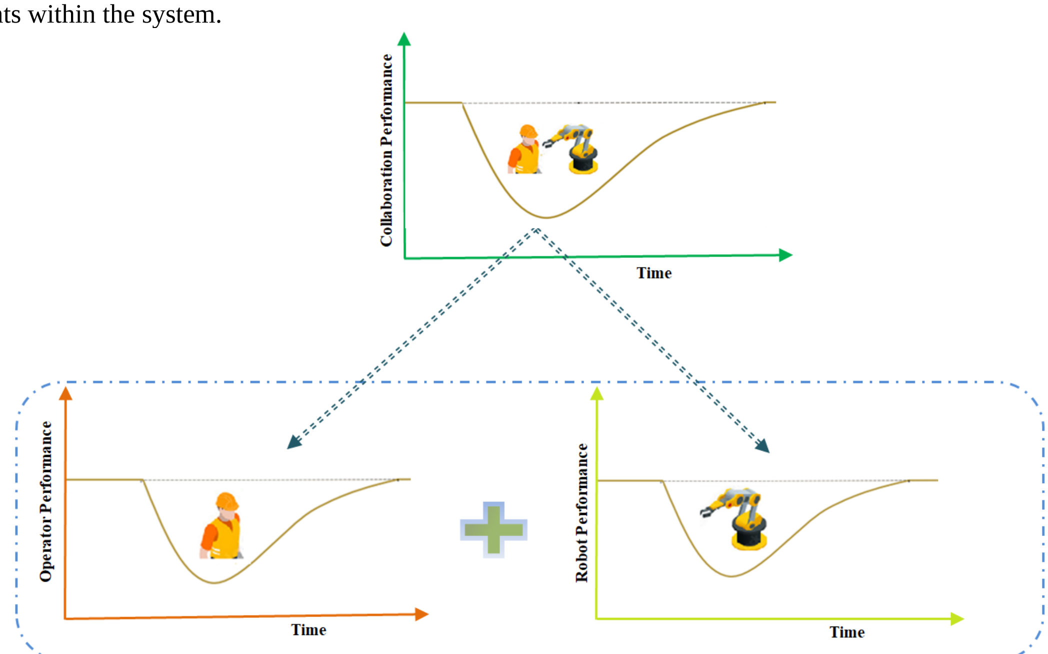

Figure 2. Proposed Approach

It is crucial to note that any interruption or disruption of a task can have a significant impact on the cycle time, leading to an increase in lead time. As lead time serves as a key metric for measuring the resilience of a collaboration system. In the research design study, mathematical equations are integrated as a fundamental component to assess the resilience of the collaboration system between a robot and an operator. These equations serve as quantifiable measures to evaluate the system's performance in terms of resilience.

Equation (1) represents the cycle time for operators in the collaborative manufacturing system. The parameter CT_{OP} specifically quantifies the time required for operators to complete their tasks.

$$CT_{OP} = CT \tag{1}$$

while the cycle time of the robot CT_{RO} can be calculated in Equation (2):

$$CT_{RO} = \xi\ CT \tag{2}$$

The parameter ξ is a non-negative value that is strictly less than 1, representing the proportion of workload assigned to the robot. To account for disruptions and resilience, Equation (3) calculates the overall cycle time, considering both operators and robots.

$$CT_{OP\text{-}RO} = [\ \psi\ (CT_{OP} + CT_{RO})]\ x\ \delta \tag{3}$$

The parameter ψ represents the status of the collaborative system, indicating whether it is resilient or disruptive. It can take the following values:

$$\psi = \begin{cases} 1, \text{if the collaborative system is resilient} \\ 0, \text{otherwise} \end{cases} \tag{4}$$

while δ a factor used to balance the cycle time, where $0 < \delta < 0.5$.

Equations (5) and (6) further explore the cycle time difference between operators and robots.

$$CT_{OP} = \psi\ CT\ (1 - \lambda) \tag{5}$$

$$CT_{RO} = \psi\ \xi\ CT\ (\lambda) \tag{6}$$

The variable λ, defined using a piecewise function, determines whether the system is operated manually or automatically.

$$\lambda\ = \begin{cases} 1, if\ the\ system\ is\ operated\ manually \\ 0, if\ the\ system\ is\ operated\ automated \end{cases} \tag{7}$$

Equation (5) calculates the cycle time for operators based on ψ CT and (1 - λ), while Equation (6) calculates the cycle time for the robot using ψ ξ CT and λ. According to Womak *et al.* (1990), the computation of lead time can be achieved through the implementation of equation (8):

$$L_{AC} = CT\ x\ WIP \tag{8}$$

This equation establishes a direct correlation between the lead time (L_{AC}), the cycle time (CT), and the work in progress (WIP) residing between workstations within the shop floor. By multiplying the cycle time by the work in progress, equation (6) enables precise quantification of the lead time within a collaborative manufacturing system.

Equations (9) and (10) focus on monitoring and evaluating lead time in the context of collaboration between robots and humans. Equation (9) calculates the yield lead time (L_{TR}) by subtracting the deviation in lead time (ΔL) from the baseline lead time.

$$L_{TR} = L_{TR}\text{-}\ \Delta L \tag{9}$$

The yield lead time represents the optimum lead time achievable when the collaboration system is fully resilient. Equation (10) computes the deviation in lead time (ΔL) by subtracting the actual lead time (L_{AC}) from the target lead time achieved when the system is fully resilient.

$$\Delta L = L_{AC} - L_{TR} \tag{10}$$

Collecting and analyzing lead time data, along with factors such as start and end times, delays, and disruptions, helps identify areas for improvement and evaluate the effectiveness of process improvements. The target lead time achieved when collaboration is fully resilient serves as a benchmark for evaluating the system's performance and identifying optimization opportunities.

The generation of a performance resilience curve visually demonstrates the interconnectedness of resilience and performance in the collaborative manufacturing system. This curve aids in identifying vulnerable points and guiding decision-making to enhance system resilience and performance, ultimately improving efficiency, productivity, and overall system performance. Table 1 represents the description of nomenclature and symbols for mathematical equation.

Table 1. List of Nomenclature and Symbols

Symbol	Description
CT	Cycle Time
CT_{OP}	Operator Cycle Time
CT_{RO}	Robot Cycle Time
CT_{OP-RO}	Collaborative System Cycle Time
L_{AC}	Actual Lead time
L_{TR}	Target Lead Time
ΔL	Deviation in Lead Time
WIP	Work in Progress
δ	a Factor used to Balance the Cycle Time
λ	a piecewise function
ξ	workload proportion assigned to the robot
ψ	status of the collaborative system

It illustrates the key components and their relationships, including the calculation of cycle time for operators and the collaborative robot, the consideration of disruptions and resilience, the assessment of lead time, and the evaluation of performance using a resilience curve. This visual representation aids in understanding the methodology and serves as a guide for analyzing and optimizing collaborative manufacturing systems.

5. FINDINGS AND DISCUSSION

The ensuing section discusses the results of the proposed model and provides valuable insights into the resilience and performance of flexible manufacturing systems. It includes a thorough analysis of the probabilities of systems' resilience performance, as well as the effects of cycle time and lead time, with implications for future research and practical applications.

5.1 Disruption and Resilience Probability

The possibilities of achievement the smart flexible manufacturing systems resilience performance based on human-robot interactions can be described in. The likelihood of collaborative systems achieving resilience performance under different scenarios of human-robot interactions is shown in Table 2.

To estimate the likelihood and impact of disruptions, Table 3 presents a discrete probability distribution function. This function represents the probabilities associated with different numbers of disruptions. The variable (*X*) represents the number of disruptions, while *f(x)* represents the probability of observing (*X*) disruptions.

Table 2. The Probability of System

Probabilities	 Robot	 Operator	 Collaborative System
1st Scenario	Resilient	Resilient	Fully Resilient
2nd Scenario	Resilient	Disruptive	Partially Resilient
3rd Scenario	Disruptive	Resilient	Partially Resilient
4th Scenario	Disruptive	Disruptive	Fully Disruptive

This distribution can be used to assess the likelihood and potential impact of disruptions on system performance. For example, according to the table, there is a 25% chance of experiencing no disruptions (X = 0), a 50% chance of encountering one disruption (X = 1), and a 25% chance of facing two disruptions (X = 2).

Table 3. Discrete Probability Distribution.

X	0	1	2
$f(x)$	0.25	0.5	0.25

Table 4 provides probability metrics specifically for the disruptive scenarios. These metrics offer insights into the characteristics of the disruptive system, including the mean, variance, and standard deviation.

Table 4. Disruption Probability Metrics

Probability Metrics	Value
Mean	1
Variance	0.5
Standard Deviation	0.7

These metrics assist in quantifying the mean number of disruptions, the degree of variability in disruption values and the extent to which values deviate from the mean.

The responsibility of decision-makers in prioritizing the resilience and long-term sustainability of the system cannot be overstated. It is imperative for them to fully comprehend the implications of disruptions on system performance, particularly the resulting increase in cycle time. In this case, the mean represents an average of 1 disruption, while the variance reflects the spread or variability of disruptions, measured at 0.5. Additionally, a standard deviation of 0.7 provides insight into the dispersion of disruptions around the mean.

To minimize disruptions and optimize cycle time, decision-makers need to undertake a comprehensive analysis of the probability distribution and its associated metrics. This rigorous examination equips them with the necessary information to make well-informed choices regarding system design and operation. By leveraging this understanding, decision-makers can navigate the delicate balance between reducing disruptions, fostering resilience, and ensuring consistently optimal performance.

Decision-makers bear a critical responsibility in prioritizing the impact of disruptions on system performance, encompassing the subsequent increase in cycle time for both the robot and the operator. By meticulously scrutinizing the probability distribution and related metrics, decision-makers can make informed choices that not only mitigate disruptions but also cultivate resilience and safeguard the system's long-term sustainability.

Through their discerning decision-making and strategic actions, decision-makers guide the system toward attaining and sustaining optimal performance. Their ability to navigate these complexities with acumen and prudence is instrumental in shaping the system's triumph and endurance.

5.2 Cycle Time Analysis

The evaluation of cycle time in a smart flexible manufacturing systems based on the disruption and resilience probability. Figure 3 presents the estimated values of cycle time, which vary significantly and have been significantly affected by disruptive situations and fully or partially resilient systems.

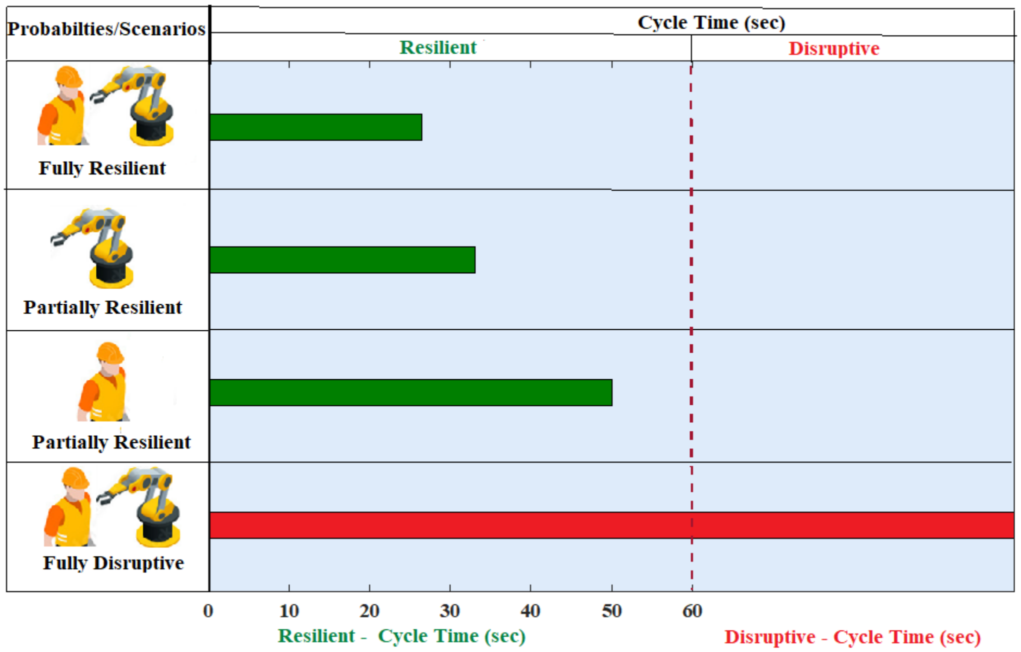

Figure 3. Cycle Time

In the case of a fully disrupted system, all workload stations stop, whereas in partially or fully resilient systems, the workload can be restored. Achieving the optimum cycle time is possible in a resilient system where operator performance can improve the skill and cognitive abilities of the operator.

It can be noted that the cycle time is less for the robot when it operates without human engagement. However, the cycle time reaches a minimum when the human works alongside the robot. The resilience of the system plays a significant role in reducing cycle time. The findings of the study highlight the importance of considering the impact of disruptive situations and system resilience on cycle time in a smart flexible manufacturing system.

Improving the skills and cognitive abilities of the operator and enhancing the system's resilience can lead to a reduction in cycle time and greater efficiency in a smart flexible manufacturing system. Based on the output, There is an opportunity to explore the integration of cutting-edge technologies, such as artificial intelligence and machine learning, to elevate the performance and reliability of flexible manufacturing systems.

The integration holds the potential to achieve further reductions in cycle time and enhance overall system efficiency. Additionally, it can investigate the integration of human-robot collaboration to achieve optimal cycle time in a smart flexible manufacturing system operations.

5.3 Lead Time Performance

The performance of a flexible manufacturing system that entails collaboration between humans and robots, with a focus on lead time. The study introduced the concept of yield lead time, which signifies that the optimal lead time can be achievable.

Figure 4 illustrates the actual lead time based on robot performance tasks and the difference between it and the yield lead time when human workers are disrupted. The results indicate partial resilience of the system, along with measures taken to address unexpected events affecting human workers.

The findings emphasize the significance of considering the system's resilience to disruptions such as labor strikes or power outages to ensure sustainable performance and minimize disruption effects on lead time.

The resilience curve presented in Figure 5 depicts the system's response when the robot is disrupted, and the human worker takes over the task to continue the system's work. The graph highlights a significant gap between the yield lead time and actual lead time, indicating the impact of disruptions on the system's performance. The emphasis lies in recognizing the value of the resilience curve as a tool to understand how the system responds to disruptions and identify factors that contribute to resilience.

It can be highlighted the potential benefits of human-robot collaboration in flexible manufacturing systems. The use of advanced technologies, such as artificial intelligence and machine learning, can further improve the resilience of the production process and reduce the impact of disruptive events on lead time. The results underscore the importance of giving equal attention to both lead time performance and resilience aspects in flexible manufacturing systems.

The resilience curve and the use of advanced technologies can enhance the system's resilience and minimize the impact of disruptive events on lead time, ultimately leading to greater efficiency and productivity in manufacturing processes. It can be provided guidance to decision-makers in the manufacturing industry to optimize the performance of their systems and improve their resilience to disruptions.

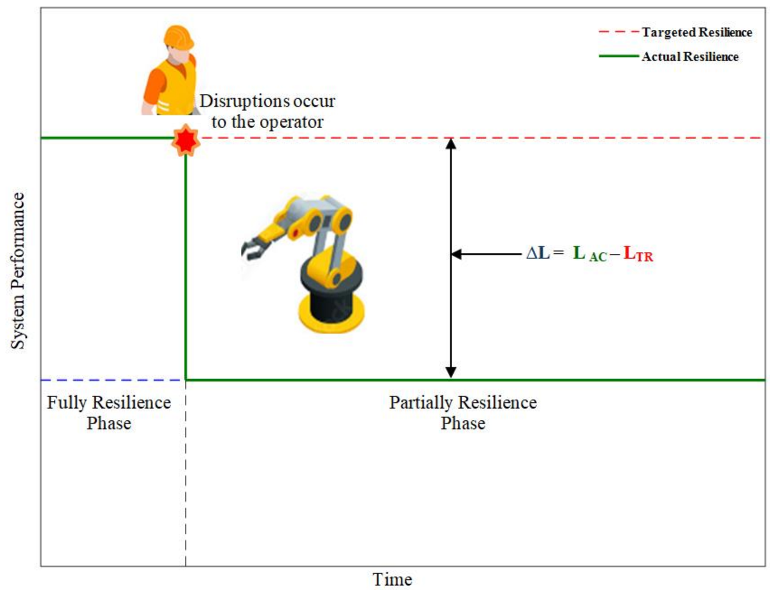

Figure 4. System Performance (Partially Resilient; Robot Resilient, and Operator Disruptive)

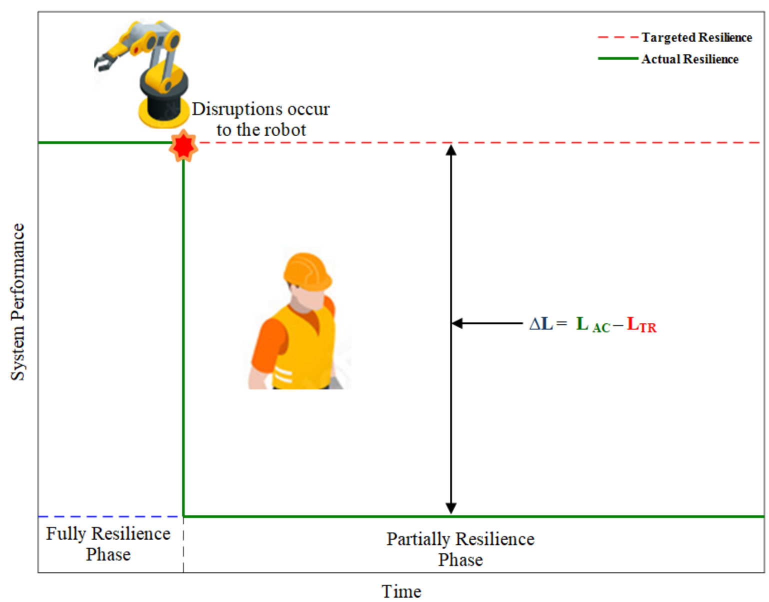

Figure 5. System Performance (Partially Resilient; Operator Resilient and Robot Disruptive)

5.4 Remarks and Outlook

The outcomes of this research align with the findings of previous studies, demonstrating consistency in the observed results. Moreover, the present study suggests that the approach outlined in the work of Quenehen *et al.* (2021) can be extended to incorporate additional lead time. Promising future prospects involve expanding the scope of this research to encompass the integration of recovery processes.

6. CONCLUSION

To sum up, the study highlights the significance of manufacturing key metrics in evaluating resilient shop floor operations. The findings indicate that lead time is a capable metric for assessing the resilient of operator-robot collaboration in a smart flexible manufacturing system. The output of this study encourages to conduct further research in this field. Although the limitation in this research should be acknowledged. It is important to point out the need for further research to address the recovery from unexpected events and to develop reliable models through experimental and numerical analysis.

In addition, the study suggests that future investigations should consider integrating safety and ergonomics considerations into the evaluation of resilient manufacturing systems. The collaboration between robots and humans offers significant potential for risk assessment and monitoring. Robots equipped with sensors and data collection capabilities can gather real-time data on environmental factors, structural conditions, and potential hazards. This data empowers humans to make well-informed decisions in risk management and resilience-building. Further research can focus on optimizing the collaboration between robots and humans, exploring ways to enhance the effectiveness of data collection, analysis, and risk modeling in this partnership.

ACKNOWLEDGEMENT

The author extend his appreciation to the Deanship of Scientific Research at Northern Border University, Arar, Saudi Arabia, for funding this research work through the project number NBU-FFR-2024-2976-01.

REFERENCES

Abdel-Malek, L. L., and Li, Z. (1989). Robot Location for Minimum Cycle Time. *Engineering Costs and Production Economics*, *17*(1-4), 29-34. DOI: https://doi.org/10.1016/0167-188x(89)90052-9

Alexopoulos, K., Anagiannis, I., Nikolakis, N. and Chryssolouris, G. (2022). A Quantitative Approach to Resilience in Manufacturing Systems. *International Journal of Production Research*, *60*(24), 7178-7193. DOI: https://doi.org/10.1080/00207543.2021.2018519

Bauters, K., Cottyn, J., Claeys, D., Slembrouck, M., Veelaert, P., and Van Landeghem, H. (2018). Automated Work Cycle Classification and Performance Measurement for Manual Work Stations. *Robotics and Computer-Integrated Manufacturing*, *51*, 139-157. DOI: https://doi.org/10.1016/j.rcim.2017.12.001

Bhongade, A. S., Khodke, P. M., Rehman, A. U., Nikam, M. D., Patil, P. D., and Suryavanshi, P. (2023). Managing Disruptions in A Flow-Shop Manufacturing System. *Mathematics*, *11*(7), 1731. DOI: https://doi.org/10.3390/math11071731

Boschetti, G., Faccio, M., Granata, I., and Minto, R. (2023). 3D Collision Avoidance Strategy and Performance Evaluation for Human–Robot Collaborative Systems. *Computers & Industrial Engineering*, *179*, 109225. DOI: https://doi.org/10.1016/j.cie.2023.109225

Botti, L., Mora, C., and Regattieri, A. (2017). Integrating Ergonomics and Lean Manufacturing Principles in A Hybrid Assembly Line. *Computers & Industrial Engineering*, *111*, 481-491. DOI: https://doi.org/10.1016/j.cie.2017.05.011

Broum, T. and Šimon, M. (2019). Preparation of Collaborative Robot Implementation in The Czech Republic. in *Proceedings of The International Conference on Industrial Engineering and Operations Management*, 453-460. DOI: https://doi.org/10.17973/mmsj.2020_03_2019136

Bruno, G., and Antonelli, D. (2018). Dynamic Task Classification and Assignment for The Management of Human-Robot Collaborative Teams in Workcells. *The International Journal of Advanced Manufacturing Technology*, *98*, 2415–2427. DOI: https://doi.org/10.1007/s00170-018-2400-4

Casalino, A., Zanchettin, A. M., Piroddi, L., and Rocco, P. (2019). Optimal Scheduling of Human–Robot Collaborative Assembly Operations with Time Petri Nets. *IEEE Transactions on Automation Science and Engineering*, *18*(1), 70-84. DOI: https://doi.org/10.1109/tase.2019.2932150

Cardoso, A., Colim, A., Bicho, E., Braga, A. C., Menozzi, M., and Arezes, P. (2021). Ergonomics and Human Factors As A Requirement to Implement Safer Collaborative Robotic Workstations: A Literature Review. *Safety*, *7*(4), 71. DOI: https://doi.org/10.3390/safety7040071

Charalambous, G., Fletcher, S., and Webb, P. (2015). Identifying The Key Organisational Human Factors for Introducing Human-Robot Collaboration in Industry: An Exploratory Study. *The International Journal of Advanced Manufacturing Technology*, *81*, 2143-2155. DOI: https://doi.org/10.1007/s00170-015-7335-4

Chaudhry, I. A., Mahmood, S., and Shami, M. (2011). Simultaneous Scheduling of Machines and Automated Guided Vehicles in Flexible Manufacturing Systems Using Genetic Algorithms. *Journal of Central South University*, *18*, 1473-1486. DOI: https://doi.org/10.1007/s11771-011-0863-7

Chiou, E. K., and Lee, J. D. (2016). Cooperation in Human-Agent Systems to Support Resilience: A Microworld Experiment. *Human Factors*, *58*(6), 846-863. DOI: https://doi.org/10.1177/0018720816649094

Chutima, P. (2023). Assembly Line Balancing with Cobots: An Extensive Review and Critiques. *International Journal of Industrial Engineering Computations*, 14(4), 785-804. DOI: https://doi.org/10.5267/j.ijiec.2023.7.001

Cortés-Leal, A., Cárdenas, C., and Del-Valle-Soto, C. (2022). Maintenance 5.0: Towards A Worker-In-The-Loop Framework for Resilient Smart Manufacturing. *Applied Sciences*, *12*(22), 11330. DOI: https://doi.org/10.3390/app122211330

Darvish, K., Wanderlingh, F., Bruno, B., Simetti, E., Mastrogiovanni, F., and Casalino, G. (2018). Flexible Human–Robot Cooperation Models for Assisted Shop-Floor Tasks. *Mechatronics*, *51*, 97-114. DOI: https://doi.org/10.1016/j.mechatronics.2018.03.006

Erol, G. (2023). *An Energy Efficient Assembly Line Balancing Problem with Human-Robot Collaboration*. Master's Thesis, Middle East Technical University, Ankara, Turkey. DOI: https://hdl.handle.net/11511/105171

Fast-Berglund, Å., and Thorvald, P. (2021). Variations in Cycle-Time When Using Knowledge-Based Tasks for Humans and Robots. *IFAC-Papersonline*, *54*(1), 152-157. DOI: https://doi.org/10.1016/j.ifacol.2021.08.017

Finke, G. R., Singh, M., and Schönsleben, P. (2012). Production Lead Time Variability Simulation-Insights from A Case Study. *International Journal of Industrial Engineering: Theory, Applications and Practice*, *19*(5). DOI: https://doi.org/10.23055/ijietap.2012.19.5.702

Germs, R. (2012). *Controlling The Order Pool in Make-To-Order Production Systems*. University of Groningen.

Ghosh, B. K., and Helander, M. G. (1986). A Systems Approach to Task Allocation of Human-Robot Interaction in Manufacturing. *Journal of Manufacturing Systems*, *5*(1), 41-49. DOI: https://doi.org/10.1016/0278-6125(86)90066-x

Gröger, C., Hillmann, M., Hahn, F., Mitschang, B., and Westkämper, E. (2013). The Operational Process Dashboard for Manufacturing. *Procedia Cirp*, *7,* 205-210. DOI: https://doi.org/10.1016/j.procir.2013.05.035

Gusmao Brissi, S., Wong Chong, O., Debs, L., and Zhang, J. (2022). A Review on The Interactions of Robotic Systems and Lean Principles in Offsite Construction. *Engineering, Construction and Architectural Management*, *29*(1), 383-406. DOI: https://doi.org/10.1108/ecam-10-2020-0809

Gutjahr, M., Kellerer, H., and Parragh, S. N. (2021). Heuristic Approaches for Scheduling Jobs and Vehicles in A Cyclic Flexible Manufacturing System. *Procedia Computer Science*, *180*, 825-832. DOI: https://doi.org/10.1016/j.procs.2021.01.332

Han, M. H., and Mcginnis, L. F. (1989). Shop Operating Characteristics Curves for Shop Control. *The International Journal of Production Research 27*(11), 1843-1853. DOI: https://doi.org/10.1080/00207548908942658

Hwang, G., Lee, J., Park, J., and Chang, T. W. (2017). Developing Performance Measurement System for Internet of Things and Smart Factory Environment. *International Journal of Production Research*, *55*(9), 2590-2602. DOI: https://doi.org/10.1080/00207543.2016.1245883

Hellebrandt, T., Ruessmann, M., Heine, I., and Schmitt, R. H. (2019). Conceptual Approach to Integrated Human-Centered Performance Management on The Shop Floor. *Proceedings of The AHFE 2018 International Conference on Human Factors, Business Management and Society, July 21-25, 2018, Loews Sapphire Falls Resort At Universal Studios, Orlando, Florida, USA 9* (Pp. 309-321). Springer International Publishing. DOI: https://doi.org/10.1007/978-3-319-94709-9_30

Ho, Y.-L. E. (2015). Application of A System Dynamics Model to Improve The Performance of Make-To-Order Production. *The South African Journal of Industrial Engineering*, *26*(2), 115–127. DOI: https://doi.org/10.7166/26-2-787

Kaasinen, E., Anttila, A.-H., Heikkilä, P., Laarni, J., Koskinen, H., and Väätänen, A. (2022). Smooth and Resilient Human–Machine Teamwork As An Industry 5.0 Design Challenge. *Sustainability*, *14*(5), 2773. DOI: https://doi.org/10.3390/su14052773

Keshvarparast, A., Battini, D., Battaia, O. and Pirayesh, A. (2023). Collaborative Robots in Manufacturing and Assembly Systems: Literature Review and Future Research Agenda. *Journal of Intelligent Manufacturing, 1-54.* DOI: https://doi.org/10.1007/s10845-023-02137-w

Kim, D. (2006). *Intelligent Scheduling and Control of Automated Guided Vehicle Considering Machine Loading in A Flexible Manufacturing System: Using Hopfield Networks and Simulation*. Ph.D. Thesis, University of New South Wales, Sydney, Australia. DOI: http://hdl.handle.net/1959.4/29542

Kim, S., and Lee, K. (2023). The Paradigm Shift of Mass Customisation Research. *International Journal of Production Research*, *61*(10), 3350-3376. DOI: https://doi.org/10.1080/00207543.2022.2081629

Koltai, T., Dimény, I., Gallina, V., Gaal, A., and Sepe, C. (2021). An Analysis of Task Assignment and Cycle Times When Robots Are Added to Human-operated Assembly Lines, Using Mathematical Programming Models. *International Journal of Production Economics*, *242*, 108292. DOI: https://doi.org/10.1016/j.ijpe.2021.108292

Lee, E., Barthelmey, A., Reckelkamm, T., Kang, H., and Son, J. (2019). A Study on Human-Robot Collaboration Based Hybrid Assembly System for Flexible Manufacturing. in *IECON 2019-45th Annual Conference of The IEEE Industrial Electronics Society* (Vol. 1, Pp. 4197-4202). IEEE. DOI: https://doi.org/10.1109/iecon.2019.8927154

Lee, H., Liau, Y., Kim, S., Ryu, K. (2018). A Framework for Process Model Based Human-Robot Collaboration System Using Augmented Reality. In: Moon, I., Lee, G., Park, J., Kiritsis, D., Von Cieminski, G. (Eds) Advances in Production Management Systems. Smart Manufacturing for Industry 4.0. APMS 2018. IFIP Advances in Information and Communication Technology, Vol 536. Springer, Cham. DOI: https://doi.org/10.1007/978-3-319-99707-0_60

Li, Z., Janardhanan, M. N., and Tang, Q. (2021). Multi-Objective Migrating Bird Optimization Algorithm for Cost-Oriented Assembly Line Balancing Problem with Collaborative Robots. *Neural Computing and Applications*, *33*(14), 8575-8596. DOI: https://doi.org/10.1007/s00521-020-05610-2

Li, Z., Janardhanan, M., Tang, Q. and Zhang, Z. (2023). Models and Algorithms for U-Shaped Assembly Line Balancing Problem with Collaborative Robots. *Soft Computing*, *27*(14), 9639–9659. DOI: https://doi.org/10.1007/s00500-023-08130-y

Liau, Y. Y., and Ryu, K. (2022). Application Framework of Collaborative Robot to Mold Assembly Processes. *Industrial Engineering & Management Systems*, *21*(4), 658-669. DOI: https://doi.org/ 10.7232/iems.2022.21.4.658

Lin, C. J. and Lukodono, R. P. (2021). Sustainable Human–Robot Collaboration Based on Human Intention Classification. *Sustainability*, *13*(11), 5990. DOI: https://doi.org/10.3390/su13115990

Malik, A. A., Masood, T., and Bilberg, A. (2020). Virtual Reality in Manufacturing: Immersive and Collaborative Artificial-Reality in Design of Human-Robot Workspace. *International Journal of Computer Integrated Manufacturing*, *33*(1), 22-37. DOI: https://doi.org/10.1080/0951192x.2019.1690685

Marinelli, M. (2022). Human–Robot Collaboration and Lean Waste Elimination: Conceptual Analogies and Practical Synergies in Industrialized Construction. *Buildings*, *12*(12), 2057. DOI: https://doi.org/10.3390/buildings12122057

Meddeb, H., Abdellaoui, Z. and Ezzine, O. (2023). Human Machine Interface Design of Industrial Automated Machine Using SIMATIC SCADA System. *International Journal of Industrial Engineering: Theory, Applications and Practice*, *30* (2). 435-450. DOI: https://doi.org/10.23055/ijietap.2023.30.2.8561

Mukund Nilakantan, J., and Ponnambalam, S. G. (2016). Robotic U-Shaped Assembly Line Balancing Using Particle Swarm Optimization. *Engineering Optimization*, *48*(2), 231-252. DOI: https://doi.org/10.1080/0305215x.2014.998664

Nikolakis, N., Kousi, N., Michalos, G., and Makris, S. (2018). Dynamic Scheduling of Shared Human-Robot Manufacturing Operations. *Procedia CIRP*, *72*, 9-14. DOI: https://doi.org/10.1016/j.procir.2018.04.007

Odedairo, B. O., and Nwabuokei, N. (2018). Framework for Operational Performance Measurements in Small and Medium Scale Industries Using Discrete Event Simulation Approach. *Engineering, Technology & Applied Science Research, 8*(4), 3103–3107. DOI: https://doi.org/10.48084/etasr.2106

Ohlig, J., Hellebrandt, T., Pötters, P., Heine, I., Schmitt, R. H., and Leyendecker, B. (2023). Human-Centered Performance Management in Manual Assembly – The Impact of Gamified KPI Provision on Performance and Motivation. International Journal of Computer Integrated Manufacturing, 36(1), 51–69. DOI: https://doi.org/10.1080/0951192x.2022.2078512

Ojstersek. R, Buchmeister B. and Javernik. A. (2023). Human-Robot Collaboration, Sustainable Manufacturing Perspective. *Proceedings of FAIM 2023 32nd International Conference on Flexible Automation and Intelligent Manufacturing, June 18–22, Porto, Portugal, Volume 1: Modern Manufacturing*, 71–78. DOI: https://doi.org/ 10.1007/978-3-031-38241-3_9

Olsen, D. R., and Goodrich, M. A. (2003). Metrics for Evaluating Human-Robot Interactions. in *Proceedings of PERMIS* (Vol. 2003, P. 4).

Ouedraogo, K. A., Enjalbert, S., and Vanderhaegen, F. (2013). How to Learn from The Resilience of Human-Machine Systems? *Engineering Applications of Artificial Intelligence*, *26*(1), 24-34. DOI: https://doi.org/10.1016/j.engappai.2012.03.007

Panagou, S. (2023). Human Centric Collaborative Workplace: The Human Robot Interaction System Perspective. Ph.D. Thesis, School of Engineering of University of Basilicata, Potenza, Italy. DOI: https://hdl.handle.net/11563/165834

Parasuraman, R., Sheridan, T. B., and Wickens, C. D. (2000). A Model for Types and Levels of Human Interaction with Automation. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *30*(3), 286-297. DOI: https://doi.org/10.1109/3468.844354

Paul, R. L., and Nof, S. Y. (1979). Human and Robot Task Performance. *Computer* Vision and Sensor-Based Robots. Springer, Boston, MA. DOI: https://doi.org/10.1007/978-1-4613-3027-1_2

Perona, M., and Portioli, A. (1996). An Enhanced Loading Model for The Probabilistic Workload Control Under Workload Imbalance. *Production Planning & Control*, 7(1), 68–78. DOI: https://doi.org/10.1080/09537289608930326

Perona, M., Saccani, N., Bonetti, S., and Bacchetti, A. (2016). Manufacturing Lead Time Shortening and Stabilisation by Means of Workload Control: An Action Research and A New Method. *Production Planning & Control*, *27*(7–8), 660–670. DOI: https://doi.org/10.1080/09537287.2016.1166283

Pizoń, J. and Gola, A. (2023). Human–Machine Relationship—Perspective and Future Roadmap for Industry 5.0 Solutions. *Machines*, *11*(2), 1–29. DOI: https://doi.org/10.3390/machines11020203

Pupa, A., Van Dijk, W., Brekelmans, C., and Secchi, C. (2022). A Resilient and Effective Task Scheduling Approach for Industrial Human-Robot Collaboration. *Sensors*, *22*(13), 4901. DOI: https://doi.org/10.3390/s22134901

Qin, T., Du, R., and Zhong, Y. (2023). on The Design of Resilient Flexible Manufacturing Systems. *Computers & Industrial Engineering*, *183*, 109483. DOI: https://doi.org/10.1016/j.cie.2023.109483

Quenehen, A., Pocachard, J., Klement, N., Roucoules, L., and Gibaru, O. (2021). Lean Techniques Application Towards Efficient Collaborative Robot Integration: An Experimental Study. *Production*, *31*, E20190160. DOI: https://doi.org/10.1590/0103-6513.20190160

Romero, D. and Stahre, J. (2021). Towards The Resilient Operator 5.0: The Future of Work in Smart Resilient Manufacturing Systems. *54th CIRP Conference on Manufacturing Systems, 104,* 1089–1094. DOI: https://doi.org/10.1016/j.procir.2021.11.183

Rosenbrock, H. H. (1990). Machines with A Purpose. New York: Oxford University Press.

Sarker, B. R., Sabapathy, A., Lal, A. M., and Han, M. H. (1991). Performance Evaluation of A Double Shuttle Automated Storage and Retrieval System. *Production Planning & Control*, *2*(3), 207-213. DOI: https://doi.org/10.1080/09537289108919348

Taghavi, S. M., Ghezavati, V., Mohammadi Bidhandi, H., and Mirzapour Al-E-Hashem, S. M. J. (2023). Supply Portfolio Selection for Lead-Time Sensitive Manufacturers Under Operational and Disruption Risks. *Kybernetes*. DOI: https://doi.org/10.1108/k-10-2022-1493

Tan, J. T. C., Duan, F., Zhang, Y., Watanabe, K., Kato, R. and Arai, T. (2009). Human-Robot Collaboration in Cellular Manufacturing: Design and Development. *in 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems* (Pp. 29-34). IEEE. DOI: https://doi.org/10.1109/iros.2009.5354155

Tompkins, J. A., White, J. A., Bozer, Y. A., and Tanchoco, J. M. A. (2010). *Facilities Planning.* John Wiley and Sons.

Torres, D., Pimentel, C. and Duarte, S. (2020). Shop Floor Management System in The Context of Smart Manufacturing: A Case Study, *International Journal of Lean Six Sigma*, Vol. 11 No. 5, Pp. 823-848. DOI: https://doi.org/10.1108/ijlss-12-2017-0151

Tsarouchi, P., Matthaiakis, A. S., Makris, S., and Chryssolouris, G. (2017). on A Human-Robot Collaboration in An Assembly Cell. *International Journal of Computer Integrated Manufacturing*, 30(6), 580–589. DOI: https://doi.org/10.1080/0951192x.2016.1187297

Ulusoy, G., and Bilge, Ü. (1992). Simultaneous Scheduling of Machines and Material Handling System in An FMS. *IFAC Proceedings Volumes*, *25*(8), 15-25. DOI: https://doi.org/10.1016/s1474-6670(17)54042-2

Wang, Z., Pang, C. K., and Ng, T. S. (2019). Robust Scheduling Optimization for Flexible Manufacturing Systems with Replenishment Under Uncertain Machine Failure Disruptions. *Control Engineering Practice*, *92*, 104094. DOI: https://doi.org/10.1016/j.conengprac.2019.07.012

Womak, J., Jones, D. T. and Roos, D. (1990). The Machine That Changed The World. *New York: Rawson Associates*.

Yang, J., Liu, T., Liu, Y. and Morgan, P. (2022). Review of Human-Machine Interaction Towards Industry 5.0: Human-Centric Smart Manufacturing. *Proceedings of ASME 2022 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *August 14–17*, 1–10. DOI: https://doi.org/10.1115/detc2022-89711

Zanchettin, A. M., Ceriani, N. M., Rocco, P., Ding, H. and Matthias, B. (2015). Safety in Human-Robot Collaborative Manufacturing Environments: Metrics and Control. *IEEE Transactions on Automation Science and Engineering*, *13*(2), 882-

893. DOI: https://doi.org/10.1109/tase.2015.2412256

Zieba, S., Polet, P., Vanderhaegen, F., and Debernard, S. (2010). Principles of Adjustable Autonomy: A Framework for Resilient Human–Machine Cooperation. *Cognition, Technology & Work*, *12*(3), 193-203. DOI: https://doi.org/10.1007/s10111-009-0134-7

Zhang, Z., Tang, Q., Li, Z., and Zhang, L. (2019). Modelling and Optimisation of Energy-Efficient U-Shaped Robotic Assembly Line Balancing Problems. *International Journal of Production Research*, *57*(17), 5520–5537. DOI: https://doi.org/10.1080/00207543.2018.1530479

Zhou, Y., Kong, F. and Chen, T. (2021). Influence of Man-Machine Ratio on System Performance of One-Person-Multi-Machine Series Production Line. *International Journal of Industrial Engineering: Theory, Applications and Practice*, *28*(4), 412–424. DOI: https:// doi.org/10.23055/ijietap.2021.28.4.6531