Integrated Routing and Job-Shop Scheduling Model under Uncertainty

Mohammad Rajabpour [1], Masoomeh Zeinalnezhad [2*] Vahid Hajipour [2]

[1] Department of Industrial Engineering, Ki.C., Islamic Azad University, Kish, Iran
[2] Department of Industrial Engineering, WT.C., Islamic Azad University, Tehran, Iran

*** Corresponding author email address**: m.zeinalnezhad@gmail.com

Received: 2026-02-01 **Revised:** 2026-06-13 **Accepted:** 2026-06-20 **Initial Publish:** 2026-07-14 **Final Publish:** 2027-05-01

Abstract

The present study was conducted with the aim of developing an integrated mathematical model to address the routing and job-shop scheduling problem under uncertainty while considering system reliability and maintenance operations. In terms of purpose, this research is applied, and in terms of methodology, it follows a descriptive–analytical approach. The required data were collected through library-based and computational methods. In the first stage, the dimensions of the problem and its associated constraints were defined, and a multi-objective mathematical model was developed to simultaneously minimize costs, maximize reliability, and efficiently manage production resources. Subsequently, the proposed model was solved for small-scale instances using the GAMS software package in order to obtain exact solutions. Considering the combinatorial nature of the problem, its NP-hard complexity, and the exponential growth of the search space in large-scale instances, the multi-objective Non-dominated Sorting Genetic Algorithm II (NSGA-II) was employed to solve the model at realistic scales, and its implementation was carried out in the MATLAB environment. The results demonstrated that the NSGA-II algorithm, with a deviation of less than 3% from the exact solutions obtained by GAMS, was capable of generating high-quality solutions while maintaining an appropriate balance among conflicting objectives. A comparison of the performance of NSGA-II with the Multi-Objective Simulated Annealing (MOSA) algorithm under uncertain conditions also indicated its robustness and satisfactory accuracy in managing complex and dynamic scenarios. Furthermore, computational time analysis revealed that NSGA-II solved large-scale instances in less than one minute, exhibiting significantly faster and more efficient performance than the exact solution approach. In the largest test instance, the solution time of GAMS exceeded 7,200 seconds. The sensitivity analysis further confirmed the significant influence of key parameters, such as failure rate and maintenance duration, on solution outcomes and overall model performance. Overall, the findings indicate that the proposed integrated mathematical model, together with the NSGA-II algorithm, can serve as an effective decision-support tool for production planning, resource optimization, and the management of industrial systems under uncertainty. Moreover, it provides practical guidance for industrial managers seeking to reduce costs and enhance operational efficiency.

Keywords: *Routing and Job-Shop Scheduling, Uncertainty, NSGA-II Algorithm, Reliability, Maintenance Operations*

How to cite this article:

Rajabpour, M., Zeinalnezhad, M., & Hajipour, V. (2027). Integrated Routing and Job-Shop Scheduling Model under Uncertainty. Management Strategies and Engineering Sciences, 9(3), 1-10.

1. Introduction

In today's highly competitive manufacturing environment, organizations are continuously seeking ways to improve operational efficiency, reduce costs, enhance responsiveness to customer demands, and increase the reliability of production systems. The growing complexity of industrial operations, coupled with increasing market uncertainty and dynamic customer requirements, has made effective production planning and scheduling a strategic necessity. Among the most important challenges in manufacturing systems are production scheduling and material transportation planning, both of which directly affect resource utilization, production lead times, customer service levels, and organizational profitability [1, 2]. Traditionally, production scheduling and transportation planning have been addressed as separate decision-making problems; however, recent studies have demonstrated that independent optimization often leads to suboptimal system performance because of the strong interdependencies that exist between manufacturing and logistics activities [3, 4].

Job-shop scheduling represents one of the most challenging classes of production planning problems due to its combinatorial nature, multiple resource constraints, and highly dynamic operational conditions. In job-shop environments, different products follow distinct processing routes across multiple machines, creating complex sequencing and allocation decisions. As manufacturing systems become more flexible and customized, traditional scheduling approaches often fail to achieve satisfactory performance, especially when transportation resources, machine breakdowns, maintenance activities, and uncertainty factors are incorporated into decision-making processes [1, 5]. Consequently, researchers and practitioners have increasingly focused on developing integrated optimization frameworks capable of simultaneously coordinating production and logistics decisions.

The integration of scheduling and routing decisions has emerged as an important research direction in operations management and industrial engineering. Integrated production-routing models recognize that manufacturing and transportation activities are strongly interconnected and should therefore be optimized jointly rather than independently. Such integration can significantly reduce inventory levels, transportation costs, production delays, and overall operational expenses while improving service quality and system responsiveness [3, 6, 7]. Furthermore, coordinated production and routing decisions allow organizations to better synchronize manufacturing outputs with customer delivery requirements, thereby improving supply chain performance and competitiveness.

Recent studies have expanded the scope of integrated production-routing problems by incorporating additional operational considerations such as vehicle routing constraints, energy consumption, environmental sustainability, workforce allocation, and resource-sharing mechanisms. For example, coordinated algorithms have been proposed to jointly optimize production schedules and vehicle routing decisions, demonstrating substantial improvements in overall system performance compared with sequential approaches [3]. Similarly, integrated production scheduling and delivery route planning have shown significant benefits in real industrial environments involving multipurpose machines and heterogeneous delivery requirements [6]. Other studies have emphasized the importance of routing considerations in production systems by addressing multiple-trip vehicle routing, time windows, setup times, and transportation uncertainties [8-10].

The increasing complexity of manufacturing networks has also encouraged the development of integrated scheduling models in flexible and distributed production environments. Flexible job-shop scheduling has received substantial attention because of its capability to model modern manufacturing systems characterized by alternative machines, flexible process plans, and dynamic production requirements. Researchers have investigated various extensions of the flexible job-shop scheduling problem, including order cancellation, resource allocation, lot-sizing integration, machine flexibility, and parallel production resources [5, 11, 12]. The emergence of smart manufacturing and Industry 4.0 technologies has further accelerated interest in dynamic and intelligent scheduling approaches capable of responding to real-time production changes [13, 14].

A critical challenge facing manufacturing systems is uncertainty. Real-world production environments are affected by numerous uncertain factors, including machine failures, processing-time variability, fluctuating demand, transportation disruptions, and unexpected resource shortages. Traditional deterministic models often fail to capture these realities, resulting in schedules that perform poorly when unexpected events occur. Consequently, uncertainty management has become a central theme in production planning research. Various approaches have been proposed to address uncertainty, including stochastic optimization, robust optimization, dynamic scheduling, simulation-based optimization, and data-driven decision-making frameworks [15-18].

In routing-related research, uncertainty has been incorporated through stochastic travel times, variable customer demands, heterogeneous vehicle capacities, and uncertain transportation conditions. Studies have demonstrated that considering uncertainty during optimization significantly improves system resilience and operational robustness [8, 9, 15]. Similarly, in scheduling environments, uncertainty arising from machine breakdowns, dynamic job arrivals, and resource disruptions has motivated the development of adaptive and intelligent scheduling methods capable of maintaining high performance under changing operational conditions [17-19].

Another essential aspect of modern production systems is reliability. Manufacturing organizations increasingly recognize that machine reliability directly influences productivity, quality performance, delivery reliability, and operational costs. Equipment failures can cause significant production disruptions, resulting in schedule deviations, delayed deliveries, increased work-in-process inventory, and customer dissatisfaction. Consequently, maintenance planning has become an indispensable component of production management. Rather than treating maintenance as an independent support function, recent research emphasizes integrating maintenance decisions directly into production scheduling models to improve overall system performance [20-22].

Preventive maintenance has been extensively studied as a mechanism for reducing unexpected failures and improving system reliability. Researchers have demonstrated that integrating preventive maintenance activities into production schedules can significantly enhance equipment availability while reducing operational risks and maintenance costs [20, 23, 24]. Furthermore, maintenance planning has evolved beyond simple scheduling considerations to encompass workforce routing, maintenance support resource allocation, and coordinated maintenance-production decision-making frameworks [25-27].

Reliability-oriented production scheduling has emerged as an important research area because it directly links maintenance policies with production objectives. Integrated production-maintenance models seek to balance conflicting goals such as maximizing throughput, minimizing production delays, reducing maintenance costs, and improving system reliability. Such models have demonstrated substantial benefits in complex manufacturing environments characterized by multiple machines, resource-sharing constraints, and uncertain operating conditions [21, 22, 27]. Moreover, reliability considerations have become increasingly important in smart manufacturing systems where equipment performance data can be continuously monitored and incorporated into real-time decision-making processes.

The literature also reveals growing interest in integrated scheduling models that simultaneously consider multiple operational resources. Studies have examined human-machine resource interactions, workforce allocation decisions, additional resource requirements, and shift scheduling problems to better reflect the realities of industrial systems [12, 28-30]. These investigations highlight the importance of coordinated resource management in achieving operational efficiency and sustainable production performance. Similarly, multi-factory production networks, smart grids, and distributed manufacturing environments have introduced new challenges requiring integrated optimization approaches that coordinate production, transportation, and resource utilization across multiple facilities [31, 32].

Environmental sustainability and energy efficiency have also become important considerations in production scheduling and routing research. Studies have investigated green scheduling strategies, energy-efficient production planning, carbon-emission reduction, and environmentally sustainable transportation decisions. The results consistently indicate that integrated approaches can achieve both economic and environmental objectives simultaneously [33-36]. These developments demonstrate the evolving nature of production systems and the increasing need for comprehensive optimization frameworks capable of addressing multiple, often conflicting objectives.

Despite the significant progress achieved in the literature, several research gaps remain. First, many existing studies focus exclusively on scheduling or routing decisions without fully integrating both components into a unified optimization framework [4, 37]. Second, while maintenance planning and reliability considerations have received growing attention, relatively few studies simultaneously incorporate production scheduling, routing decisions, reliability measures, and maintenance activities within a single mathematical model [20, 21]. Third, many existing models assume deterministic operating conditions, limiting their applicability in highly uncertain industrial environments where machine failures, transportation disruptions, and dynamic operational changes frequently occur [16, 19].

Furthermore, although recent advances in dynamic scheduling, Industry 4.0 technologies, reinforcement learning, and intelligent optimization have improved decision-making capabilities, practical implementation still requires robust mathematical frameworks capable of generating high-quality solutions within acceptable computational times [14, 17, 18]. The NP-hard nature of integrated scheduling and routing problems makes exact optimization methods computationally challenging for large-scale industrial applications. Therefore, advanced metaheuristic approaches remain essential for obtaining efficient and near-optimal solutions in realistic settings [5, 37, 38].

Recent research has increasingly emphasized transportation-resource integration within flexible job-shop systems, highlighting the necessity of considering material movement alongside production activities. Studies investigating transportation resources, open-shop scheduling integration, and energy-efficient production-routing systems have demonstrated considerable performance improvements when both domains are jointly optimized [36-38]. Nevertheless, a comprehensive framework that simultaneously addresses job-shop scheduling, routing decisions, maintenance activities, reliability requirements, and uncertainty management remains insufficiently explored.

Therefore, the objective of this study is to develop an integrated mathematical model for the joint optimization of job-shop scheduling and routing decisions under uncertainty while explicitly incorporating system reliability and maintenance activities, and to solve the proposed model using the multi-objective NSGA-II algorithm in order to enhance resource utilization, reduce operational costs, and improve decision-making effectiveness in industrial production systems.

2. Methodology

The present study is applied in terms of its objective, as it aims to develop a mathematical model for solving a real-world routing and job-shop scheduling problem while considering reliability and maintenance activities under uncertain conditions. The findings of this research can be utilized in production planning and the management of industrial systems.

In terms of its nature and methodology, this study follows a descriptive–analytical approach. First, the dimensions and characteristics of the problem are described, and the corresponding mathematical model is formulated. Subsequently, the problem is analyzed using the multi-objective optimization algorithm NSGA-II, and optimal solutions are derived. Furthermore, if the model is implemented in a specific workshop or manufacturing facility, the research can also be classified as a case study.

In this study, data collection was conducted through both library-based and computational methods. The information and data required for developing the mathematical model were initially gathered through a review of reputable scientific sources, specialized journal articles, relevant books, and scientific databases. In the subsequent stage, hypothetical or real-world data related to job-shop scheduling, reliability, and maintenance operations under uncertainty were employed for problem analysis and model solution.

Additionally, for model validation and evaluation of the NSGA-II algorithm, computationally generated datasets were processed using specialized software packages such as MATLAB and GAMS.

The data analysis procedure was conducted in multiple stages in accordance with the research objectives. Initially, the proposed mathematical model was solved using GAMS software to obtain exact solutions. Subsequently, for solving large-scale and real-world instances requiring metaheuristic approaches, the NSGA-II algorithm was implemented and executed in MATLAB. The outputs generated by the algorithm consisted of a set of Pareto-optimal solutions, enabling decision-makers to select the most appropriate solution according to their preferences.

To evaluate the algorithm's performance and compare it with the mathematical model results, standard evaluation metrics—including average distance from the optimal solution, solution diversity, and Pareto-front coverage—were employed. Finally, sensitivity analysis was performed to examine the effects of changes in key model parameters on the obtained results and to assess the validity and reliability of the solutions. The final results were presented through analytical tables and figures, serving as the basis for the study's conclusions and recommendations.

3. Findings and Results

Main Research Question: How can an integrated mathematical model be developed for job-shop scheduling and raw material routing while considering existing constraints and capacities?

Table 1. Dimensions of the Test Problems Used to Demonstrate Computational Complexity

Example No.	P (Number of Activities)	C (Number of Sets)	m (Number of Machines)
1	2	4	3
5	4	10	5
10	6	18	7

The routing and scheduling problem belongs to the class of NP-hard problems due to its combinatorial nature. As the problem dimensions increase (as shown in Table 1), the search space grows exponentially, resulting in a substantial increase in solution time within GAMS. For large-scale instances, obtaining exact solutions becomes computationally infeasible, thereby justifying the need for metaheuristic algorithms such as NSGA-II.

Sub-Question: How can cost reduction and resource optimization be achieved?

Table 2. Performance of NSGA-II in Achieving Minimum Cost (Small-Scale Instances)

Example No.	GAMS Solution (Cost)	NSGA-II Solution	Deviation (%)
1	32.2	32.3	0.31%
3	76.1	77.6	1.97%
5	123.4	127.0	2.92%

To achieve cost reduction, the algorithm's performance was compared with exact solutions obtained through GAMS for small-scale instances. The low deviation percentages (maximum 2.92%) indicate that the proposed model and algorithm are capable of identifying cost-optimal solutions and allocating resources with a very high degree of accuracy.

Sub-Question: What is the role of uncertainty management in production and logistics processes?

Table 3. Comparison of NSGA-II and MOSA under Large-Scale and Uncertain Conditions

Example No.	Cost Deviation (%)	Time Deviation (%)	C	P	M
1	0.45%	0.76%	20	5	2
3	1.61%	2.08%	30	7	3
5	2.48%	2.95%	40	10	4

Under uncertainty conditions, such as fluctuations in reliability levels, the NSGA-II algorithm was compared with the Multi-Objective Simulated Annealing (MOSA) algorithm. The results presented in Table 3 indicate that even as problem dimensions and scenario complexity increase, the deviation between the two methods remains below 3%. This stability demonstrates the effectiveness of the proposed model in managing stochastic variables and uncertain production scenarios.

Sub-Question: How can production productivity be increased and production cycle time be reduced?

Table 4. Comparison of Computational Time (Seconds) for Reducing Problem-Solving Cycle Time

Number of Sets (C)	GAMS (Exact Solution)	NSGA-II	MOSA
8	8	10	15
12	321	22	45
18	7,201	58	142

In this study, productivity is defined as the speed of obtaining optimal solutions. As shown in Table 4, when the problem size increases to 18 sets, the solution time in GAMS exceeds two hours (7,201 seconds), whereas NSGA-II reaches a solution in less than one minute (58 seconds). This computational efficiency reduces waiting times in production planning and enhances overall operational productivity.

Sub-Question: What constraints are associated with machinery maintenance operations?

Table 5. Parameter-Tuning Results (Based on the Taguchi Method)

Key Parameter	Optimal Value (Pareto Level)
Mutation Rate	0.05
Initial Population Size	100

Maintenance constraints are incorporated into the model through the mutation rate and initial population size parameters within the optimization algorithm. A mutation rate of 0.05 allows the model to simulate random variations caused by machine failures without violating feasibility constraints. These parameter settings, obtained through the Taguchi experimental design approach, provide the best balance between exploration (searching for new solution paths) and exploitation (improving existing schedules).

4. Discussion and Conclusion

The primary objective of this study was to develop an integrated mathematical model for the simultaneous optimization of job-shop scheduling and routing decisions under uncertainty while explicitly incorporating reliability and maintenance considerations. The results demonstrated that the proposed model successfully addressed the complexities associated with integrated production and logistics planning and provided high-quality solutions through the application of the NSGA-II algorithm. The findings confirmed that the integrated approach can effectively coordinate production resources, transportation activities, and maintenance operations while maintaining acceptable computational performance in large-scale problem instances.

The first major finding of the study was related to the successful formulation of an integrated mathematical model capable of simultaneously considering job-shop scheduling, material routing, reliability, and maintenance constraints. The complexity analysis revealed that the problem belongs to the NP-hard class and that computational requirements increase exponentially as problem dimensions grow. This result is consistent with previous studies that have identified production scheduling and integrated scheduling-routing problems as computationally challenging combinatorial optimization problems requiring advanced solution approaches [1, 4, 38]. The observed increase in solution complexity as the number of activities, machines, and routing alternatives expanded further supports the conclusions of researchers who emphasized that integrated scheduling environments exhibit significantly higher computational complexity than traditional scheduling problems [30, 32]. Therefore, the findings reinforce the argument that exact optimization approaches become increasingly impractical as manufacturing systems become more complex and interconnected.

Another important finding concerns the effectiveness of the proposed model in achieving cost minimization and resource optimization. The comparison between the exact solutions generated by GAMS and the solutions obtained through NSGA-II demonstrated that the proposed algorithm produced near-optimal results with deviations below 3%. Such a small deviation indicates that the integrated model accurately captures the interactions among scheduling, routing, maintenance, and reliability decisions while allowing efficient allocation of resources. This finding aligns with previous research demonstrating that integrated optimization approaches outperform isolated planning methods by reducing operational costs and improving resource utilization [6, 7, 36]. Similarly, studies focusing on coordinated production and routing decisions have reported significant reductions in overall system costs through synchronized decision-making processes [3, 37]. The current results extend these findings by showing that the inclusion of reliability and maintenance considerations does not diminish optimization effectiveness and may further enhance resource allocation efficiency.

The results also highlighted the significance of integrating routing decisions with production scheduling activities. Traditional production planning models frequently treat transportation operations as secondary decisions made after production schedules are established. However, the present findings indicate that simultaneous optimization creates additional opportunities for cost reduction and operational coordination. This observation supports the conclusions reported by several studies that emphasized the benefits of integrated scheduling-routing frameworks in improving production performance and logistics efficiency [8-10]. Furthermore, the results corroborate recent reviews suggesting that production and outbound logistics should be viewed as interconnected components of a unified decision-making system rather than independent operational functions [4].

A particularly important contribution of the study concerns uncertainty management. The comparison between NSGA-II and MOSA under uncertain conditions revealed that solution deviations remained below 3% even as problem dimensions and uncertainty levels increased. This result suggests that the proposed framework exhibits a high degree of robustness and stability when confronted with stochastic operational conditions. Such findings are consistent with previous studies investigating uncertainty in production scheduling and transportation systems. Researchers have demonstrated that uncertainty associated with travel times, demand fluctuations, machine failures, and resource availability can substantially affect operational performance if not properly incorporated into optimization models [9, 15, 16]. The robustness observed in the current study indicates that integrating uncertainty directly into the optimization process can significantly improve decision quality and reduce vulnerability to operational disruptions.

The effectiveness of the proposed model in handling uncertainty can also be explained through its ability to simultaneously account for multiple interacting variables. Modern manufacturing environments are characterized by dynamic changes, including unexpected machine failures, order modifications, transportation delays, and fluctuating resource availability. Studies focusing on dynamic flexible job-shop scheduling have emphasized the necessity of adaptive optimization mechanisms capable of responding to such changes in real time [13, 14, 17]. The stability of the proposed solutions under uncertain conditions suggests that the integration of reliability and maintenance considerations contributes significantly to overall system resilience. This conclusion is further supported by recent developments in intelligent and dynamic scheduling frameworks that emphasize proactive rather than reactive decision-making approaches [5, 18].

The findings related to computational efficiency represent another significant contribution of the study. The results showed that while exact optimization methods required more than two hours to solve large-scale instances, the NSGA-II algorithm produced high-quality solutions in less than one minute. This substantial reduction in computational time demonstrates the practical applicability of the proposed approach in real industrial environments where decisions must often be made rapidly. Similar observations have been reported in studies employing metaheuristic algorithms for integrated scheduling and routing problems, where exact methods become computationally prohibitive as problem size increases [37, 38]. The present results therefore confirm that metaheuristic approaches remain indispensable tools for solving large-scale integrated optimization problems. Furthermore, the ability of NSGA-II to generate a diverse set of Pareto-optimal solutions provides decision-makers with greater flexibility in balancing conflicting objectives, an advantage frequently emphasized in multi-objective optimization literature [5, 33].

The incorporation of reliability and maintenance activities into the integrated model also produced important insights. The sensitivity analysis revealed that parameters associated with machine failures and maintenance durations significantly influenced overall system performance. These findings are highly consistent with prior research demonstrating the strong relationship between equipment reliability and production efficiency [21, 22]. Researchers have repeatedly shown that maintenance decisions should not be treated independently from production planning because maintenance schedules directly affect machine availability, production capacity, and operational continuity [20, 27]. The current findings further support this perspective by demonstrating that maintenance-related parameters substantially alter optimization outcomes and therefore must be incorporated into strategic production planning models.

The parameter tuning results obtained through the Taguchi approach further support the effectiveness of the proposed optimization framework. The identified mutation rate and population size provided an effective balance between exploration and exploitation, enabling the algorithm to search broadly while maintaining convergence toward high-quality solutions. This observation is consistent with the broader metaheuristic optimization literature, which emphasizes the importance of parameter calibration in achieving superior search performance [5, 36]. Moreover, the ability of the algorithm to effectively simulate disruptions associated with machine failures reflects the importance of integrating maintenance-related uncertainty into evolutionary optimization procedures.

Another noteworthy implication of the findings concerns the growing relevance of Industry 4.0 technologies and smart manufacturing systems. The proposed framework is particularly compatible with digital manufacturing environments where real-time information regarding machine conditions, transportation status, and production progress can be continuously collected and analyzed. Recent studies have highlighted the transformative role of data-driven scheduling and intelligent manufacturing systems in improving operational responsiveness and decision quality [13, 14]. The integration of reliability, maintenance, routing, and scheduling decisions within a single optimization framework may therefore provide an effective foundation for future smart manufacturing applications.

Overall, the findings demonstrate that integrated decision-making significantly outperforms fragmented planning approaches. By simultaneously considering production scheduling, routing operations, reliability requirements, maintenance activities, and uncertainty factors, the proposed model achieves superior operational performance while maintaining computational efficiency. The results extend previous research on integrated scheduling and routing by incorporating additional dimensions of reliability and maintenance under uncertain conditions, thereby providing a more realistic representation of modern industrial systems [4, 21, 36]. Consequently, the study contributes both theoretically and practically to the literature on production planning, logistics optimization, and industrial systems management.

One limitation of the present study is that the proposed model was evaluated primarily using computationally generated test instances rather than extensive real-world industrial datasets. Although synthetic datasets are widely used for validating optimization models, actual manufacturing environments may exhibit additional complexities that are difficult to capture fully within a mathematical framework. Furthermore, the uncertainty parameters were represented through predefined assumptions, which may not encompass all possible operational disruptions encountered in practice. Another limitation relates to the computational experiments, which focused on a specific set of problem dimensions and parameter configurations. Consequently, caution should be exercised when generalizing the findings to highly specialized industrial contexts with substantially different operational characteristics.

Future studies may extend the proposed framework by incorporating additional sources of uncertainty, such as fluctuating customer demand, supply-chain disruptions, workforce absenteeism, and energy price volatility. Researchers may also investigate the integration of real-time data acquisition technologies, digital twins, and machine learning methods to support adaptive scheduling and routing decisions. Comparative analyses involving other advanced metaheuristic and hybrid optimization algorithms could provide further insights into algorithmic performance. In addition, future research may evaluate the proposed model using real industrial case studies from various manufacturing sectors to enhance practical validation and generalizability. Multi-echelon supply-chain integration and sustainability-oriented objectives may also represent promising directions for future investigation.

Industrial managers should consider adopting integrated planning approaches that simultaneously coordinate production scheduling, material transportation, maintenance activities, and reliability requirements. Such integration can improve resource utilization, reduce operational costs, and enhance system responsiveness under uncertain conditions. Organizations implementing advanced manufacturing systems may benefit from incorporating metaheuristic optimization tools into their decision-support infrastructure to facilitate rapid and informed decision-making. Maintenance planning should be strategically integrated with production scheduling rather than managed independently, as equipment reliability significantly influences overall operational performance. Furthermore, managers are encouraged to utilize sensitivity analyses when implementing optimization models to better understand the effects of critical operational parameters and to develop more resilient production strategies.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] H. Abedinnia, C. H. Glock, E. H. Grosse, and M. Schneider, "Machine Scheduling Problems in Production: A Tertiary Study," *Computers & Industrial Engineering,* vol. 111, pp. 403-416, 2017, doi: 10.1016/j.cie.2017.06.026.

[2] T. Vidal, G. Laporte, and P. Matl, "A Concise Guide to Existing and Emerging Vehicle Routing Problem Variants," *European Journal of Operational Research,* vol. 286, no. 2, pp. 401-416, 2020, doi: 10.1016/j.ejor.2019.10.010.

[3] X. Zou, L. Liu, K. Li, and W. Li, "A Coordinated Algorithm for Integrated Production Scheduling and Vehicle Routing Problem," *International Journal of Production Research,* vol. 56, no. 15, pp. 5005-5024, 2018, doi: 10.1080/00207543.2017.1378955.

[4] L. Berghman, Y. Kergosien, and J. Billaut, "A Review on Integrated Scheduling and Outbound Vehicle Routing Problems," *European Journal of Operational Research,* vol. 311, no. 1, pp. 1-23, 2023, doi: 10.1016/j.ejor.2022.12.036.

[5] N. Zhu, G. Gong, D. Lu, D. Huang, N. Peng, and H. Qi, "An Effective Reformative Memetic Algorithm for Distributed Flexible Job-Shop Scheduling Problem with Order Cancellation," *Expert Systems with Applications,* vol. 237, p. 121205, 2024.

[6] S. Mohammadi, S. M. Al-e-Hashem, and Y. Rekik, "An Integrated Production Scheduling and Delivery Route Planning with Multi-Purpose Machines: A Case Study from a Furniture Manufacturing Company," *International Journal of Production Economics,* vol. 219, pp. 347-359, 2019, doi: 10.1016/j.ijpe.2019.05.017.

[7] H. Chevroton, Y. Kergosien, L. Berghman, and J. Billaut, "Solving an Integrated Scheduling and Routing Problem with Inventory, Routing and Penalty Costs," *European Journal of*

Operational Research, vol. 294, no. 2, pp. 571-589, 2021, doi: 10.1016/j.ejor.2021.02.012.

[8] V. Baradaran, A. Shafaei, and A. H. Hosseinian, "Stochastic Vehicle Routing Problem with Heterogeneous Vehicles and Multiple Prioritized Time Windows: Mathematical Modeling and Solution Approach," *Computers & Industrial Engineering,* vol. 131, pp. 187-199, 2019, doi: 10.1016/j.cie.2019.03.047.

[9] J. Wang, S. Yao, J. Sheng, and H. Yang, "Minimizing Total Carbon Emissions in an Integrated Machine Scheduling and Vehicle Routing Problem," *Journal of Cleaner Production,* vol. 229, pp. 1004-1017, 2019, doi: 10.1016/j.jclepro.2019.04.344.

[10] G. Wu, C. Cheng, P. Pourhejazy, and B. Fang, "Variable Neighborhood-Based Cuckoo Search for Production Routing with Time Window and Setup Times," *Applied Soft Computing,* vol. 125, p. 109191, 2022, doi: 10.1016/j.asoc.2022.109191.

[11] Mahimini and Q. Bidgoli, "Simultaneous Scheduling and Lot-Sizing in a Flexible Flow-Shop Environment Considering Buffer Constraints between Workstations and a General Buffer," *Modern Research in Decision Making,* vol. 8, no. 1, pp. 114-144, 2023.

[12] H. Babaei and Behnamian, "Modeling and Solving a Bi-Objective Flexible Job-Shop Scheduling Problem Considering Parallel Machines and Dual Human-Machine Resources," *Industrial Management Perspective,* vol. 12, no. 3, pp. 203-237, 2022.

[13] S. Ji and J. Yan, "Scheduling Optimization of Flexible Workshop Dynamics Based on Big Data," in *2023 28th International Conference on Automation and Computing (ICAC)*, 2023.

[14] A. Tariq, S. A. Khan, W. H. But, and T. Shehryar, "An IoT-Enabled Real-Time Dynamic Scheduler for Flexible Job Shop Scheduling (FJSS) in an Industry 4.0-Based Manufacturing Execution System (MES 4.0)," *Ieee Access,* vol. 12, pp. 49653-49666, 2024, doi: 10.1109/access.2024.3384252.

[15] R. Eshtehadi, M. Fathian, and E. Demir, "Robust Solutions to the Pollution-Routing Problem with Demand and Travel Time Uncertainty," *Transportation Research Part D: Transport and Environment,* vol. 51, pp. 351-363, 2017, doi: 10.1016/j.trd.2017.01.003.

[16] S. Shahbazi and Vahidi, "Simulation-Based Optimization of the Number of Machines in the Job-Shop Production Scheduling Problem under Uncertainty and Budget and Space Constraints," *Research in Production and Operations Management,* vol. 15, no. 1, pp. 113-136, 2024.

[17] S. Lassoued, "Policy-Based Reinforcement Learning With Action Masking for Dynamic Job Shop Scheduling Under Uncertainty: Handling Random Arrivals and Machine Failures," 2026, doi: 10.48550/arxiv.2601.09293.

[18] M. Xu, J. Liu, H. Yu, and Y.-S. Ong, "TransGP: Task-Conditioned Transformer-Guided Genetic Programming for Multitask Dynamic Flexible Job Shop Scheduling," 2026, doi: 10.48550/arxiv.2604.03705.

[19] P. Soufi, Yazdani, Amiri, Maqsoud, Adibi, and M. Amin, "Modeling and Solving the Flexible Job-Shop Scheduling Problem under Dual Human and Machine Resource Constraints Considering Machine Breakdowns," *Decision Making and Operations Research,* vol. 8, no. 1, pp. 153-175, 2023.

[20] A. Kolus, A. El-Khalifa, U. M. Al-Turki, and S. O. Duffuaa, "An Integrated Mathematical Model for Production Scheduling and Preventive Maintenance Planning," *International Journal of Quality & Reliability Management,* vol. 37, no. 6/7, pp. 925-937, 2020.

[21] C. Gu, Y. He, Z. Chen, X. Han, D. Zhou, and A. Zhang, "Mission Reliability-Oriented Integrated Scheduling Optimization Model by Combining Production Planning and Maintenance Activities," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture,* vol. 235, no. 5, pp. 839-849, 2021.

[22] J. Bhatti, N. Bhardwaj, and S. Kumar, "Mathematical Modelling to Industrial Repair and Maintenance Policy System for Its Reliability," *Mathematical Modeling and Computing,* vol. 8, pp. 465-473, 2021.

[23] P. Khaksari and Q. Bidgoli, "Mathematical Modeling and Solving of the No-Wait Flow-Shop Scheduling Problem Considering Release Time and Preventive Maintenance Activities," *Industrial Engineering Research in Production Systems,* vol. 11, no. 23, pp. 39-55, 2024.

[24] Nikouei, Amiri, Maqsoud, K. Firouzabadi, S. Mohammadali, and Yazdani, "Flexible Job-Shop Scheduling with Job Rejection Policy and Preventive Maintenance," *Industrial Management Perspective,* 2024.

[25] C. Guan, H. Lu, and Y. Liu, "Integrated Scheduling Methods of Maintenance Support Resource," in *Journal of Physics: Conference Series*, 2019.

[26] L. Dahite, A. Kadrani, R. Benmansour, R. N. Guibadj, and C. Fonlupt, "Multi-Objective Model and Variable Neighborhood Search Algorithms for the Joint Maintenance Scheduling and Workforce Routing Problem," *Mathematics,* vol. 10, no. 11, p. 1807, 2022.

[27] N. Ettahiry, Z. Chekoubi, W. Trabelsi, S. Dellagi, I. Majdouline, and S. Bouslikhane, "Optimal Management of Production and Maintenance Actions According to an Integrated Scheduling Strategy with Operational Considerations," in *2022 IEEE Information Technologies & Smart Industrial Systems (ITSIS)*, 2022.

[28] F. Santos, R. Fukasawa, and L. Ricardez-Sandoval, "An Integrated Personnel Allocation and Machine Scheduling Problem for Industrial Size Multipurpose Plants," *IFAC-PapersOnLine,* vol. 51, no. 18, pp. 156-161, 2017, doi: 10.1016/j.ifacol.2018.09.292.

[29] M. Schulze and J. Zimmermann, "Staff and Machine Shift Scheduling in a German Potash Mine," *Journal of Scheduling,* vol. 20, pp. 635-656, 2017, doi: 10.1007/s10951-017-0527-z.

[30] L. Fanjul-Peyro, F. Perea, and R. Ruiz, "Models and Matheuristics for the Unrelated Parallel Machine Scheduling Problem with Additional Resources," *European Journal of Operational Research,* vol. 260, no. 2, pp. 482-493, 2017, doi: 10.1016/j.ejor.2017.01.002.

[31] N. Bagheri-Rad and Behnamian, "Solving the Multi-Factory Smart Grid Scheduling Problem in a Job-Shop Production Environment Using an Improved Lagrangian Relaxation Algorithm," *Industrial Engineering Research in Production Systems,* vol. 11, no. 22, pp. 31-43, 2023.

[32] B. Havad and K. Sara, "Unrelated Parallel Machine Scheduling with Sequence-Dependent Setup Times in a Multi-Factory Production Network: Modeling and Solution Algorithm," ed, 2023.

[33] C. Lu, L. Gao, X. Li, Q. Pan, and Q. Wang, "Energy-Efficient Permutation Flow Shop Scheduling Problem Using a Hybrid Multi-Objective Backtracking Search Algorithm," *Journal of Cleaner Production,* vol. 144, pp. 228-238, 2017, doi: 10.1016/j.jclepro.2017.01.011.

[34] D. Wang, J. Zhu, X. Wei, T. Cheng, Y. Yin, and Y. Wang, "Integrated Production and Multiple Trips Vehicle Routing with Time Windows and Uncertain Travel Times," *Computers & Operations Research,* vol. 103, pp. 1-12, 2019, doi: 10.1016/j.cor.2018.10.011.

[35] M. Rostami and S. Pour, "Optimization of the Green Hybrid Flow-Shop Scheduling Problem with a Batch Delivery System," *Modern Research in Decision Making,* vol. 7, no. 4, pp. 126-155, 2022.

[36] E. Yağmur and S. E. Kesen, "Integrated Production Scheduling and Vehicle Routing Problem with Energy Efficient Strategies: Mathematical Formulation and Metaheuristic Algorithms," *Expert Systems with Applications,* vol. 237, p. 121586, 2024, doi: 10.1016/j.eswa.2023.121586.

[37] J. Su, Y. Fu, K. Gao, H. Dong, and J. Mou, "Integrated Scheduling Problems of Open Shop and Vehicle Routing Using an Ensemble of Group Teaching Optimization and Simulated Annealing," *Swarm and Evolutionary Computation,* vol. 83, p. 101373, 2023, doi: 10.1016/j.swevo.2023.101373.

[38] L. Berterottière, S. Dauzère-Pérès, and C. Yugma, "Flexible Job-Shop Scheduling with Transportation Resources," *European Journal of Operational Research,* vol. 312, no. 3, pp. 890-909, 2024, doi: 10.1016/j.ejor.2023.07.036.