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RESEARCH PAPER

A reactive hybrid product-driven system for rescheduling in a manufacturing planning

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ABSTRACT

Goal: This research aims to develop a novel scheduling model integrating the intelligent product paradigm of a product-driven system (PDS) with the shifting bottleneck heuristic (SBH) to enhance rescheduling efficiency and adaptability in dynamic job shop scheduling problems with disruptions (JSSP-D).

Design / Methodology / Approach: The model employs agent-based modeling, where products act as autonomous agents in rescheduling decisions. Simulations covered 151 scenarios across 14 benchmark instances of machine failures, with production time increases of 100%, 200%, and 300%. The model's performance was evaluated on its ability to minimize makespan deterioration and maintain efficiency under different disturbance levels.

Results: The PDS-SBH model effectively reduced production efficiency gaps, achieving an average makespan reduction of 7.81%, with peaks of 36.06%. Higher disturbance levels allowed for better rescheduling outcomes, albeit with increased variability. The model's adaptability provided solutions comparable or superior to stable scheduling benchmarks.

Limitations of the investigation: The study used 14 benchmark instances and focused solely on machine failures, limiting generalizability to other disruptions like resource shortages or order changes. Despite these constraints, the 151 scenarios and rigorous analysis strengthen result reliability.

Practical implications: The PDS-SBH model offers a robust approach for real-time schedule adjustments, maintaining operational continuity, and optimizing resource use. It provides practical insights for decision support systems and policy development in dynamic manufacturing.

Originality / Value: This study pioneers a hybrid approach combining intelligent product paradigms with SBH. It advances JSSP-D research by presenting a resilient, adaptive framework for dynamic scheduling, significantly contributing to manufacturing efficiency and robustness.

Keywords: Simulation; Scheduling; Flexible manufacturing; Planning; Agent based modelling and simulation.

1 INTRODUCTION

Job planning and scheduling in industrial settings encounter significant challenges due to the complex and dynamic operations nature. These challenges center around the efficient allocation of resources across various processes, prompting researchers and practitioners to devote considerable attention to studying these problems (Rasheed *et al.*, 2019). The Job Shop Scheduling Problem (JSSP) is a classic combinatorial optimization issue. Many studies have addressed it to improve job allocation efficiency, particularly under resource-limited conditions. However, the

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occurrence of perturbations, such as changes in resource availability, machinery failures, or workflow interruptions, adds an extra layer of complexity by challenging the efficacy of the initial planning (Meyer *et al.*, 2011). These perturbations necessitate a dynamic rescheduling of jobs due to the potential invalidity of the original schedule under new conditions. In some cases, minor adjustments may be sufficient to accommodate disruptions. However, in many situations, full-task rescheduling is required to minimize the impact and quickly recover a solution that approximates the original schedule (Zhang *et al.*, 2020).

The JSSP is a fundamental optimization challenge in operations research and computer science, focusing on the optimal assignment of jobs to resources at specific times. It involves a set of jobs, each consisting of a sequence of operations, which must be processed on a set of machines in a specified order. Each machine can handle only one operation at a time, and once an operation begins, it must continue until completion without interruption. The objective is typically to minimize the time required to complete all jobs (makespan). However, variations may aim to optimize other criteria, such as minimizing tardiness or maximizing resource utilization. The JSSP requires sophisticated scheduling algorithms due to its NP-hard nature, making it computationally challenging for even modest-sized problems.

The Shifting Bottleneck Heuristic (SBH) is a highly effective heuristic for addressing the JSSP, emphasizing the detection and step-by-step resolution of bottleneck operations in manufacturing. This heuristic operates by first breaking down the complex job shop environment into individual machine-centered subproblems. It then identifies the current bottleneck, the machine or operation with the most significant impact on the overall makespan, or another specified performance metric. Once identified, the heuristic optimally schedules jobs for that bottleneck resource, considering the current schedule of other machines. After resolving the bottleneck, the heuristic re-evaluates the production environment to identify the next bottleneck, shifting its focus and iteratively optimizing until all machines are addressed. This approach allows for a dynamic and focused improvement of the production schedule, tackling the most critical constraints one at a time to enhance operational efficiency.

The Job Shop Scheduling Problem with disturbances (JSSP-D) extends the classical JSSP to account for real-world operational uncertainties and disruptions that can affect the planned schedule. These perturbations can include machine breakdowns, unexpected maintenance, variations in operation times, the arrival of urgent jobs, or unavailability of resources, which necessitate dynamic adjustments to the existing schedule. The objective remains similar to the classic JSSP, such as minimizing the makespan or other performance metrics, but with the added complexity of incorporating flexibility and adaptability into the scheduling process. Solving the JSSP-P involves developing robust and resilient solutions that can quickly respond to changes and re-optimize the schedule in real-time or near-real-time, ensuring minimal impact on overall productivity and efficiency. This problem is inherently more complex than the static JSSP due to the need for continuous adjustment and evaluation of multiple potential future scenarios to maintain optimal or near-optimal performance under uncertainty.

Despite the critical role of rescheduling in Job Shop environments impacted by perturbations, existing research has addressed this issue in a somewhat limited capacity. To solve a JSSP, exact methods such as integer programming have been developed (Cui & Lu, 2017). However, the computational burden of these methods increases exponentially with the problem size, rendering the calculation time a significant constraint for the practical application of such algorithms in JSSP-D scenarios (Ku & Beck, 2016). Consequently, the industry often resorts to heuristic procedures like SBH that yield satisfactory outcomes within a reasonable timeframe (Bożek & Werner, 2018). Although such algorithms can be adapted to address JSSP-D, there's a pressing need for effective strategies to adapt to unexpected changes and reorganize jobs swiftly and accurately. This challenge could be tackled by implementing an intelligent system capable of making dynamic decisions as difficulties arise during machine operations. A promising approach to achieving this is adopting a Product-Driven System (PDS), which leverages products' inherent intelligence and communicative capabilities to facilitate adaptive and responsive scheduling processes.

A PDS is an advanced manufacturing and production approach where the products carry information regarding processing, handling, and movement through the production line. For this reason, the products are known as intelligent products (IP). This approach leverages technologies such as RFID tags, smart sensors, and embedded systems to allow products to communicate with production equipment and management systems directly. The goal is to enhance manufacturing operations' efficiency, flexibility, and responsiveness by enabling products to guide their production processes, reducing manual intervention, and streamlining workflows.

In this study, a model is introduced that incorporates the IP paradigm within a PDS, utilizing the SBH as the core intelligence mechanism, thus creating a hybrid, adaptable, and robust model designed to tackle the challenges of the JSSP-P. In the proposed PDS, jobs and machines are represented as virtual entities endowed with the characteristics of intelligent products capable of making dynamic decisions in production scheduling (Sáez *et al.*, 2023). This approach successfully addresses the JSSP in a range of standard scenarios found in the literature of this field. Subsequently, a simulation of machine failures is conducted for each machine involved in the problem, leading to a deterioration of the solution and giving rise to a JSSP-P scenario. The PDS addresses the perturbed problem by seeking a new solution by applying SBH to post-perturbation jobs. The performance metric used to evaluate the proposal is the minimization of makespan. This approach aims to integrate the strengths of PDS and SBH, leveraging their capabilities to provide an efficient and flexible solution in the face of unforeseen situations affecting job scheduling in a dynamic Job Shop environment.

Unlike traditional heuristic or AI-based scheduling approaches, which typically rely on centralized decision-making, the proposed model introduces a decentralized, product-driven architecture. Each product operates as an autonomous agent capable of local decision-making and dynamic rescheduling, allowing the system to adapt flexibly and in real-time to disruptions. This structure aligns with the principles of Industry 4.0 and lays the foundation for more resilient and intelligent manufacturing systems.

The paper is structured as follows: Section 2 reviews the literature related to rescheduling in job shop environments. Section 3 details the problem description and the proposed model. Section 4 concentrates on the findings, whereas Sections 6 and 7 discuss these results and draw conclusions.

2 LITERATURE REVIEW

Task rescheduling is a crucial aspect of modern manufacturing, vital for enhancing operational efficiency in various settings such as Job Shops and Flow Shop Flexible Environment (Gao *et al.*, 2020; Kim & Kim, 2021; Li *et al.*, 2017). This area has been explored from multiple perspectives, focusing on diverse configurations, methodologies, and performance measures to address the dynamic challenges of production scheduling. Researchers have investigated various strategies, from mathematical models to heuristic approaches, to optimize production flow, reduce downtime, and improve overall productivity. The study of task rescheduling encompasses developing and applying innovative solutions to adapt to changes and maintain a competitive advantage in the manufacturing sector.

The classification of rescheduling problems provides a structured framework for understanding the multifaceted nature of scheduling challenges in manufacturing (Muhuri & Biswas, 2020). This classification encompasses divisions into specific environments, such as Job and Flow Shops, and extends to various manufacturing processes. It further categorizes rescheduling problems based on analysis policies, which dictate how and when rescheduling should occur, and resolution methods, which involve the specific strategies or algorithms employed to achieve optimal rescheduling. This comprehensive classification scheme aids in identifying the unique characteristics and requirements of different rescheduling scenarios, highlighting the complexity and variability inherent in optimizing production schedules in the face of dynamic and unforeseen changes.

Various rescheduling methods have been explored to optimize manufacturing processes, including integer programming, constraint-based rescheduling, genetic algorithms, and heuristic rescheduling (Bhongade *et al.*, 2023; Gao *et al.*, 2020). Each method offers distinct advantages: integer programming provides exact solutions but can be computationally intensive for large-size problems; constraint-based rescheduling allows for flexibility in handling complex constraints; genetic algorithms offer robust solutions across diverse scenarios with their ability to navigate vast search spaces; and heuristic rescheduling provides quick, practical solutions that, while may not always be optimal, are effective for real-time decision-making. Together, these methods form a comprehensive toolkit, enabling tailored approaches to meet the specific rescheduling needs of different manufacturing environments, balancing efficiency and adaptability.

Recent developments in AI-based rescheduling approaches have introduced powerful methods such as deep reinforcement learning (DRL) and hybrid metaheuristics to address complex and dynamic job shop environments (Pu & Rahimifard, 2024; Liu *et al.*, 2022). These approaches can analyze multiple variables in parallel and learn optimal or near-optimal rescheduling policies in real-time. Their application has shown promising results in high-dimensional and uncertain production settings, especially when conventional heuristics fall short.

Within the context of the JSSP-D, the research by M. Mahmoodjanloo *et al.* (Mahmoodjanloo *et al.*, 2022) and Miguel A. Salido (Salido *et al.*, 2017) significantly advances our understanding of dynamic scheduling. These studies explore innovative approaches to rescheduling, mainly focusing on how adjustments in machine speed can significantly impact the effectiveness of rescheduling efforts. Their work highlights these strategies within the JSSP-P framework, their work highlights the potential for adaptive scheduling solutions to mitigate disruptions and maintain production efficiency, demonstrating the importance of flexibility and quick responsiveness in modern manufacturing environments.

Integrating artificial intelligence and innovative technologies into production systems is increasingly centered around IPs and PDS. This trend emphasizes the role of IPs and PDS in enhancing the adaptability and agility of rescheduling capabilities within manufacturing (Meyer *et al.*, 2011; Wu *et al.*, 2019). By embedding intelligence directly into products, these systems enable real-time, autonomous decision-making that can dynamically adjust to changes and disruptions in the production process. This approach improves the efficiency and flexibility of manufacturing operations and significantly reduces the need for manual intervention, paving the way for more resilient and responsive production environments.

Agent-Based Modeling (ABM) for PDS harnesses the power of simulation to create a responsive production environment. By representing various elements of the manufacturing process as agents with distinct levels of intelligence, ABM facilitates the emulation of complex, collective behaviors (Sáez *et al.*, 2023; Shukla *et al.*, 2019). These agents can dynamically interact, make decisions, and adapt to changing circumstances, significantly enhancing the flexibility and efficiency of production systems. This approach allows for granular analysis and optimization of production processes, improving operational resilience and responsiveness to unforeseen challenges.

In PDS, task rescheduling is pivotal for effectively managing operational disturbances. Studies by A. S. Bhongade *et al.*, (Bhongade *et al.*, 2023) and J. T. de Guimarães *et al.*, (Campos *et al.*, 2020) stand out, showcasing PDS's practical application and efficacy in overcoming rescheduling challenges. These investigations demonstrate how PDS, leveraging real-time data and autonomous decision-making capabilities of intelligent products, can dynamically adjust schedules in response to unexpected events. This approach minimizes downtime and optimizes production flow, illustrating PDS's substantial contribution to enhancing operational resilience and efficiency in manufacturing environments.

Complementarily, P. Mehrdad (Mehrdad *et al.*, 2021) introduced a novel multi-objective heuristic algorithm for multi-mode resource-constrained project scheduling (MRCPSP), addressing multiple goals such as makespan, quality, and net present value (NPV) under uncertainty. Their algorithm achieved fast and accurate solutions even in large-scale instances, suggesting that hybrid approaches can effectively balance competing objectives in complex scheduling problems. These studies reinforce the importance of intelligent, responsive, and scalable scheduling models—an area of our hybrid PDS-SBH model that directly contributes by combining decentralized intelligence with heuristic optimization.

SBH has been widely used to approach JSSP for several reasons. It targets the most critical constraints within the scheduling process, the bottlenecks, by dynamically identifying and addressing them one at a time. This approach allows for focused optimization efforts where they are most needed, significantly improving the overall efficiency of the production process. Additionally, by iteratively resolving bottlenecks and adapting to changes in the production environment, SBH offers a flexible and responsive solution, making it particularly suited for complex and dynamic industrial settings. Its methodical yet adaptable strategy ensures that it can provide practical, near-optimal solutions within a feasible computational time, making it a valuable tool for tackling the intricate challenges of job shop scheduling. The SBH has been explored in conjunction with various performance measures, such as total tardiness (Sahin *et al.*, 2013), maximum tardiness (Lin & Uzsoy, 2016), and the number of late jobs (Yadav & Jayswal, 2018). Additionally, SBH has been integrated with other heuristics, including genetic algorithms (Mönch *et al.*, 2007) and simulations (Fowler & Mönch, 2022), to enhance its effectiveness and adaptability in addressing scheduling challenges.

The convergence of PDS and SBH into a hybrid model represents a strategic evolution in addressing the complexity of rescheduling in industrial environments, particularly within JSSP-P with perturbations. This hybrid model leverages the dynamic adaptability of PDS, with its intelligent, autonomous products, and the focused efficiency of SBH in pinpointing and alleviating bottlenecks. Such integration offers a promising pathway to agile, practical strategies for dynamic adaptation to unforeseen changes, ensuring optimized scheduling and enhanced production flow despite the inevitable disruptions.

Despite the growing interest in rescheduling methods, there is still a notable gap in the literature concerning integrating PDS with scheduling heuristics such as the SBH. Furthermore, decentralized rescheduling strategies that enable autonomous agents to react to disturbances remain underexplored, particularly in complex job-shop environments. The proposed model addresses both gaps by combining PDS and SBH into a hybrid and adaptive framework.

3 MATERIALS AND METHODS

The proposed approach introduces a novel model that integrates the PDS's efficiency with the SBH's precision to obtain near-optimal solutions for the JSSP-P. This model distinguishes agents: products and machines, each with unique roles in the production process. Products act as intelligent agents capable of dynamically determining their production paths, while machines serve as resources with specific capabilities and availabilities. This differentiation allows for a more nuanced and responsive scheduling mechanism, leveraging the strengths of both PDS and SBH. By facilitating direct interaction between products and machines, the model enables real-time adjustments to scheduling, ensuring optimal production flow despite disruptions, thereby enhancing the resilience and adaptability of manufacturing systems.

In the proposed model, agents are categorized into product and machine agents, each possessing distinct states reflecting their status in the production process. Product agents transition through states such as "free," indicating availability for processing; "in process," denoting active engagement in production; "rescheduled," reflecting adjustments due to perturbations; and "completed," signifying the conclusion of their production cycle. Machine agents, on the other hand, have states like "available," "in process," and "disturbed," with "disturbed" highlighting periods of malfunction or downtime. These states facilitate the dynamic interaction between products and machines, enabling an adaptable and responsive scheduling system that efficiently manages planned tasks and unforeseen disruptions.

Figure 1 illustrates the proposed model's general schema, highlighting how product and machine agents virtually represent each physical component of the production system. The figure visually represents the integration of the physical components of the production system with their virtual counterparts, illustrating how product and machine agents within the virtual plane interact with and influence the operations on the physical plane. This dual-plane interaction is critical to the model's dynamic scheduling and rescheduling capabilities, enabling an adaptive response to real-world perturbations and changes in the production environment.

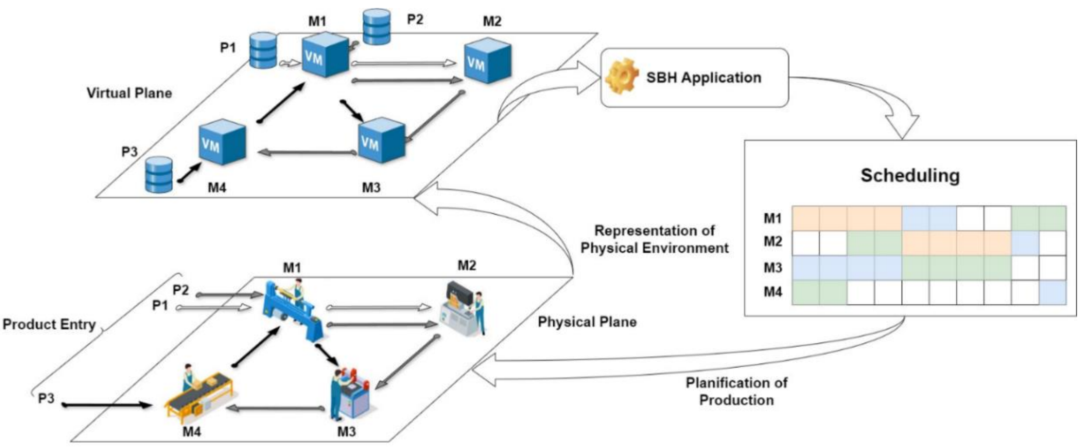

Figure 1. PDS-SBH application sequence diagram for JSSP programming

The proposed model's sequence generation and critical machine detection process begins with assigning product agents to their respective machines based on a predetermined sequence. This initial placement is crucial for establishing the workflow and prioritizing tasks. The model then identifies critical machines essential for the simultaneous completion of multiple products. This identification is crucial in optimizing the production schedule, as it allows for targeted adjustments to minimize bottlenecks and ensure efficient use of resources, enhancing the overall productivity and responsiveness of the manufacturing system.

In the proposed model, the handling of disturbances involves a dynamic reassessment and rescheduling process of product agents, following the principles of SBH. When disturbances occur, product agents evaluate their current position and dependencies within the production sequence and actively seek alternatives to mitigate the impact of the perturbation. Such an evaluation may involve selecting alternate machines, adjusting production sequences, or reprioritizing tasks. By leveraging the SBH, the system identifies and addresses the most critical bottlenecks resulting from the disturbance, ensuring a swift return to optimal production flow.

Figure 2 illustrates the flow of activities for product agents in the event of a disturbance, such as a machine breakdown, which increases its production time to double, triple, or quadruple its nominal value, simulating various severities of failures. In response to a disturbance, product agents reassess the sequencing of jobs following the disturbance to mitigate the impact of the failure. These decisions adhere to the SBH approach by setting initial conditions and resolving subproblems, effectively demonstrating the dynamic decision-making process of intelligent products post-disturbance.

The decision-making process for adjustment within the proposed model unfolds in three critical stages, guided by SBH principles. Initially, the model employs SBH for problem-solving, strategically identifying and addressing bottlenecks under normal conditions. Upon encountering a machine disturbance, the system activates a rescheduling protocol, where product and machine agents collaboratively reassess and adjust the production schedule to accommodate the disruption. Finally, this leads to a reprogramming phase, wherein agents apply SBH to the now-disturbed scenario, optimizing the schedule despite the disturbance and ensuring minimal impact on production efficiency.

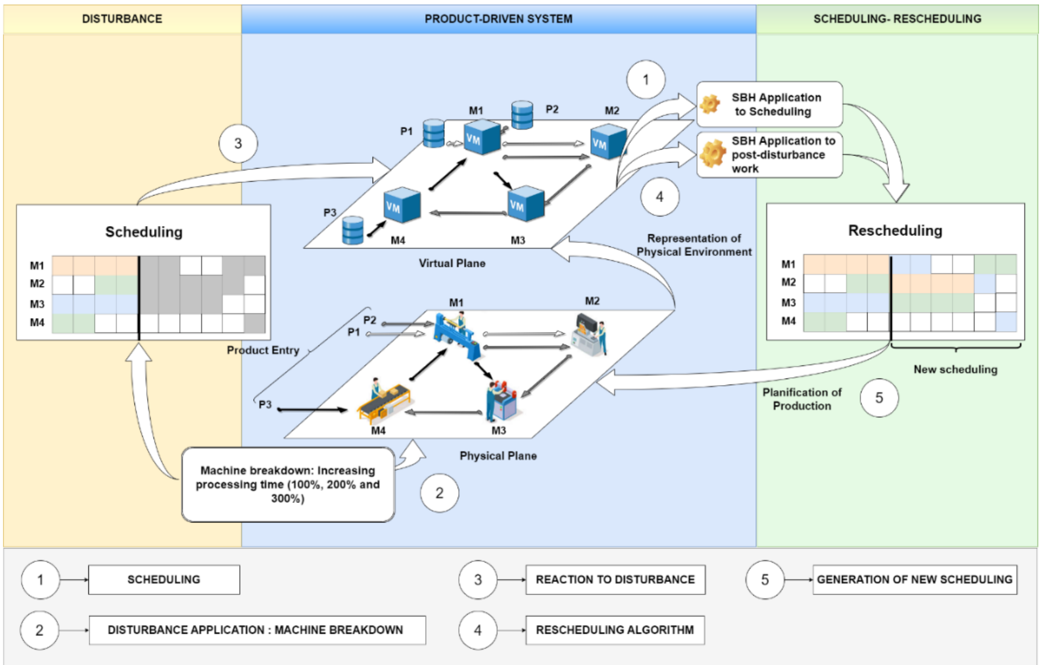

Figure 2 - Flowchart for the post-disturbance intelligent product decision-making process

4 EXPERIMENTAL DESIGN

Figure 3 presents a UML diagram that meticulously outlines the experimental design process, capturing the model's sequence of operations and interactions. It begins with loading the problem instance into the model and calculating the job sequence using SBH. This step involves determining the makespan by applying SBH to devise a sequence that minimizes it, thus setting up a baseline schedule without disturbances. Each product agent receives details on processing time and operation sequence, leveraging this information to craft a production schedule informed by SBH principles.

Three types of system disturbances are defined. Each disturbance consists of increasing the processing time of each machine. $Dist_{100}$ means a 100% increase in processing time, while $Dist_{200}$ implies a 200% increase in the value of processing time, and analogously, $Dist_{300}$ involves a 300% increase in processing time. The procedure is the following:

• Initially, a solution for the JSSP is determined using the SBH. The makespan of each instance is calculated, generating a gap related to the problem instance's lower bound.

• A JSSP-D is constructed by introducing one of the three types of disturbances when the execution time of the production plan generated for JSSP reaches 50% of the instance LB.

• To solve the JSSP-D, the PDS-SBH reschedules the remaining operations and evaluates the resulting makespan.

Upon disturbance, product agents receive updated information about the affected machine's occurrence and extended operation time. Armed with this data, agents for sequenced but unprocessed products assess the solution's degradation and reapply the SBH to adjust post-disturbance jobs. The rescheduling aims to improve upon the compromised solution, a new, optimized makespan if successful. Otherwise, the system retains the prior, deteriorated arrangement.

The experimental setting utilizes problem instances described in Table 1, characterized by the number of jobs, machines, and their respective operations. For instance, the abz5 instances comprise ten jobs and ten machines, amounting to 100 operations with varying processing times. This specification provides a structured framework for assessing the model's efficiency across different scenarios, allowing for a comprehensive evaluation of its performance under varied operational complexities.

The model was implemented on version 6.3 of the Netlogo platform using an AMD Ryzen 5 3550H, a 2.1 GHz processor (8 cores), and 12 GB RAM.

Table 1 - Problem instances used in experimentation

Instance	Jobs	Machine	Operation	Instance	Jobs	Machines	Operations
Ft06	6	6	36	La21	15	10	150
La01	10	5	50	La29	20	10	200
La06	15	5	75	La38	15	15	225
Abz05	10	10	100	Abz07	20	15	300
Abz06	10	10	100	Abz08	20	15	300
La16	10	10	100	Abz09	20	15	300
La11	20	5	100	Yn04	20	20	400

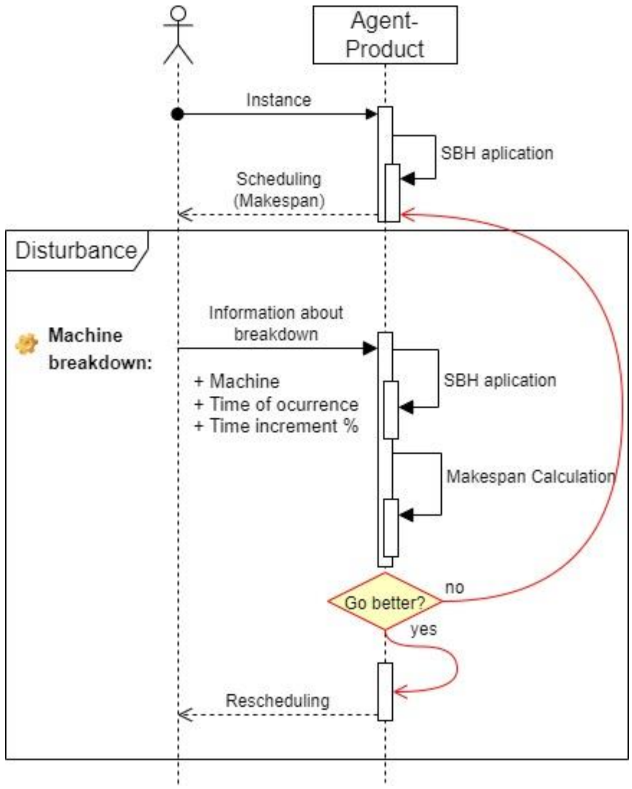

Figure 3 - UML sequence diagram in the model PDS-SBH

5 RESULT

This section discusses the results from simulations executed across various scenarios, comprising 151 simulations—one for each machine involved in the problem instances. It compares the performance of undisturbed problems against those with individual machine failures simulated with $Dist_{100}$, $Dist_{200}$, and $Dist_{300}$.

The solution obtained for the JSSP shows that the SBH consistently produces results higher than the lower bounds, indicating potential suboptimality. Table 2 presents the results of problem instances analyzed without disturbances, including the lower bound from the literature, the makespan obtained using the SBH, and the percentage gap between the SBH result and the lower bound. The percentage gaps vary significantly across instances, from 4.17% (La01) to 48.69% (La38). Several instances exhibit relatively large gaps, suggesting the SBH method may struggle to find near-optimal solutions, while others have smaller gaps, implying better performance. The results suggest the SBH method's effectiveness depends on instance characteristics, and further improvements may be necessary to achieve better solutions, especially for instances with more significant gaps. In summary, the gap values show that SBH is a feasible alternative to produce a rescheduling when a disturbance appears.

Table 2 - Lower bound, makespan, and gap concerning the optimal result

Instance	LB	SBH	Gap [%]
Ft06	55	61	9.83
La01	666	695	4.17
La06	926	1060	12.64
Abz05	1234	1592	22.49
Abz06	943	1120	15.80
La16	717	1240	42.18
La11	1222	1433	14.72
La21	935	1398	33.12
La29	1105	1635	32.42
La38	943	1838	48.69
Abz07	656	870	24.60
Abz08	648	960	32.50
Abz09	678	1005	32.54
Yn04	929	1323	29.78

For the JSSP-D, the average makespan reduction increases with higher levels of disturbance, from 7.23% for Dist100 to 8.62% for $Dist_{300}$. Table 3 shows the results for JSSP-D by applying disturbances $Dist_{100}$, $Dist_{200}$, and $Dist_{300}$ to each machine in all problem instances. The table presents the statistical results derived from applying disturbances to all problem instances, specifically to each machine on each problem instance, and the increase and subsequent reduction in the makespan after applying the PDS-SBH. We denote the makespan value after disturbance as MD, the makespan value after disturbance and using SBH as MD-SBH, the relative percentage of MD related to LB as MD%, and the relative percentage of MD-SBH related to MD as MD-SBH%. Thus MD-SBH% is the improvement achieved due to PDS-SBH, which is measured as a percentage reduction in the deterioration produced by disturbances. The average, standard deviation, and maximum and minimum values are presented. In general, out of the 151 simulations performed for each disturbance, it is observed that the effects of the disturbance were mitigated by the PDS-SBH solution on average by 7.23%, 7.59%, and 8.62%, respectively, achieving maximum reductions of up to 36.06%. These results are significant since the PDS-SBH model generated substantial reductions in completion times, reaching decrease percentages of 58.94%, 62.91%, and 60.26%.

Table 3 - Makespan reduction by implementing disturbances

	$Dist_{100}$	$Dist_{200}$	$Dist_{300}$
Performance	$M_{D\text{-}SBH\%}$ [%]	$M_{D\text{-}SBH\%}$ [%]	$M_{D\text{-}SBH\%}$ [%]
Average	7.23	7.59	8.62
Standard deviation	4.90	5.47	6.47
Maximum value	18.97	26.27	36.06
Minimum value	0.08	0.11	0.21

Table 4 provides a detailed breakdown of the results obtained for each instance. The first column presents the instance name, followed by the percentage increase in the completion time after applying the disturbance. The third column reflects the increase in completion time after rescheduling using PDS-SBH (δ). Finally, it highlights the discrepancy between the deteriorated result and the one achieved through PDS-SBH. This analysis is performed for disturbances $Dist_{100}$, $Dist_{200}$, and $Dist_{300}$. For example, the problem instance Ft06 has a 14.21% increase in makespan after the disturbance with $Dist_{100}$ without achieving a reduction after rescheduling. In contrast, for the same problem instance with $Dist_{300}$, a 1.09% reduction is achieved compared to the deteriorated solution.

Table 4 - Detailed results of deterioration reduction by instance

	Dist$_{100}$			Dist$_{200}$			Dist$_{300}$		
Instance	$M_{D\%}$ [%]	$M_{D\text{-}SBH\%}$ [%]	δ [%]	$M_{D\%}$ [%]	$M_{D\text{-}SBH\%}$ [%]	δ [%]	$M_{D\%}$ [%]	$M_{D\text{-}SBH\%}$ [%]	δ [%]
Ft06	14.21	14.21	0.00	32.51	31.69	0.82	50.82	49.73	**1,09**
La01	17.04	14.39	2.65	44.00	40.78	3.22	70.96	67.74	3,22
La06	16.85	9.96	6.89	37.98	33.75	4.23	61.49	57.13	4,36
Abz05	10.86	0.59	10.27	21.38	12.17	9.21	36.17	25.16	**11,01**
Abz06	12.38	12.38	0.00	31.07	29.78	1.29	52.04	49.88	**2,16**
La16	7.58	3.19	4.39	19.76	13.21	6.55	33.60	29.39	4,21
La11	14.89	8.32	6.57	39.11	34.07	5.04	66.64	61.20	5,44
La21	14.92	12.40	2.52	36.25	30.70	5.55	59.11	52.37	**6,74**
La29	10.09	6.15	3.94	29.58	26.06	3.52	51.39	47.78	3,61
La38	5.51	**-5.96**	11.47	15.46	6.53	8.93	28.05	20.49	7,56
Abz07	15.09	12.93	2.16	37.01	34.48	2.53	61.17	57.19	**3,98**
Abz08	8.98	7.82	1.16	28.75	25.94	2.81	48.68	44.42	**4,26**
Abz09	8.60%	1.33	7.27	23.81	14.50	9.31	40.43	32.50	7,93
Yn04	5.14%	4.11	1.03	17.27	15.34	1.93	32.55	30.08	**2,47**

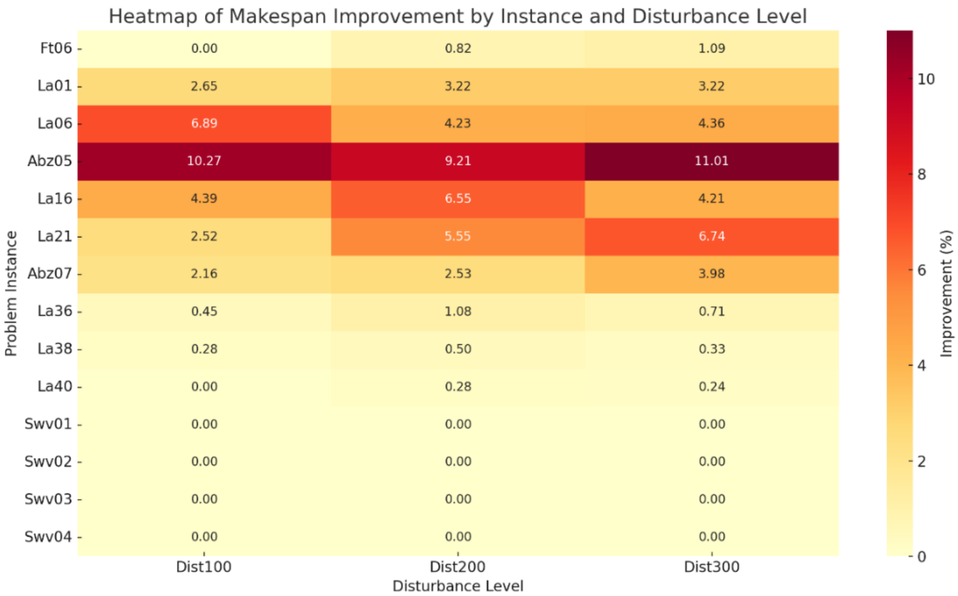

Figure 4 - Heatmap of makespan improvement (%) across benchmark instances under three disturbance levels (Dist100, Dist200, Dist300).

In the figure 4, the darker shades represent greater improvements achieved by the PDS-SBH model compared to the baseline, emphasizing the model's ability to mitigate scheduling disruptions more effectively in certain scenarios.

Notably, for the Dist$_{100}$ disturbance, no makespan reduction is achieved with PDS-SBH rescheduling for the instances FT06 and ABZ06, which seems to be due to the structure of both instances having a highly constrained critical path of tasks. On the other hand, a makespan reduction is achieved after the Dist$_{300}$ disturbance for seven out of the fourteen instances. This fact seems to be due to longer processing times, which allow for more flexible reconfiguration of other jobs. However, although these are the best results, they are not significantly better than those observed for the same instances with Dist100, with only a 1.76% difference between them, suggesting that the proposed methodology mitigates the increase in makespan against disturbances, regardless of the magnitude of the disturbance.

The best result for Dist$_{100}$ disturbances appears in instance L38, achieving a dampening of 11.47%. The subsequent increase in value after the disturbance was negative, indicating that not only was the deterioration mitigated, but the product agents also generated a job sequence that improved upon the initial job sequence produced by SBH under normal conditions. This new perspective integrates the possibility of making the process more flexible, responding to potential disturbances on the production plan without human intervention, and taking advantage of instances of change to generate better production plans.

The results reveal that increasing disturbance time from Dist$_{100}$ to Dist$_{300}$ enhances the possibility of generating better rescheduling solutions. Figure 5 illustrates the distribution of dampening results for all the problems studied. Although the mean of the three disturbance levels is similar, the data dispersion increases as the disturbance time grows.

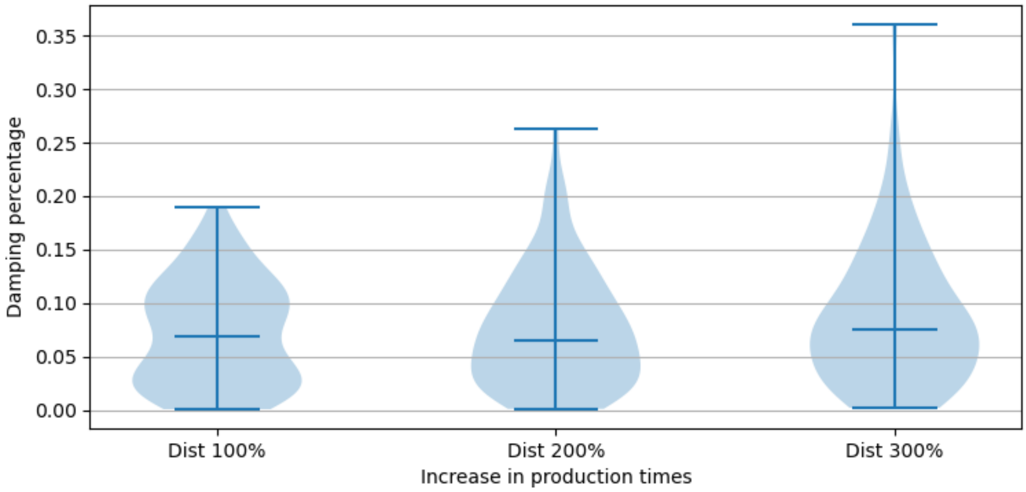

Figure 5 - Distribution of improvement results

6 DISCUSSION

The study introduced a model integrating the intelligent product paradigm of a PSD with the SBH to address job shop scheduling problems with disturbances that we call JSSP-D. Across 151 simulations on 14 instances with disturbances increasing production times by 100-300%, the PDS-SBH model reduced deterioration in the production gap by 7.81% on average, with maximum reductions up to 36.06%. Higher disturbance levels tended to allow better rescheduling solutions but with more variability. In 7 JSSP-D instances, notable adaptation occurred after 300% production time increases, though not significantly better than lower disturbances. Overall, the model demonstrated adaptability across disturbance levels, providing solutions comparable or superior to those for stable conditions in literature.

The findings demonstrate the effectiveness of the proposed PDS-SBH model in mitigating the impacts of disturbances on job shop scheduling problems. By integrating intelligent product agents with SBH, the model could dynamically adapt schedules in response to disruptions like machine failures. The ability to reduce deterioration in production gaps by up to 36% confirms the model's capacity to reschedule jobs effectively under uncertainty, aligning with the core objectives of job shop rescheduling approaches. The trend of higher disturbance levels enabling better rescheduling, albeit with more variability, suggests the model leverages increased flexibility from prolonged processing times to explore improved solutions. The model's performance, comparable or superior to stable scheduling benchmarks, highlights its strength in maintaining operational efficiency despite disruptions - a key challenge addressed by integrating PDS and operations research techniques observed in prior studies.

This study's findings are significant for advancing job shop scheduling research and practice. The successful integration of PDS and SBH introduces a novel hybrid approach that synergizes intelligent autonomous products with efficient bottleneck resolution. This combinatorial technique contributes new insights into leveraging product intelligence and multi-agent interactions for dynamic rescheduling under uncertainties like machine failures. By demonstrating the model's ability to minimize makespan deterioration across varying disturbance levels, the study highlights PDS-SBH's potential as a responsive solution for the broader family of job shop scheduling problems with disruptions. The adaptive rescheduling capabilities observed expand the theoretical foundations of JSSP-D, providing a framework for future research into resilient scheduling methods that harmonize product autonomy with focused optimization heuristics. The model offers a viable decision support system for real-time schedule reconfiguration for manufacturing practice, enhancing operational agility. Insights from this work could also inform policymaking for innovative manufacturing initiatives, underscoring the value of intelligent product paradigms and bolstering the adoption of resilient scheduling technologies. However, for real-world implementation, some practical considerations must be addressed, such as system integration with existing ERP/MES platforms, data acquisition from shop-floor equipment, and operator training. These challenges are typical in deploying decentralized agent-based systems, but current advancements in Industry 4.0

technologies make them increasingly feasible.

While the study provides valuable insights, certain limitations should be acknowledged. The experiments were confined to a limited set of 14 benchmark problem instances, which may not fully capture the diversity and complexity of real-world production environments. Additionally, the investigation focused solely on machine failures as the source of disturbances, neglecting other potential disruptions like resource unavailability or order changes. These methodological constraints limit the generalizability of the findings to a broader range of scheduling scenarios. However, the study's strengths lie in its rigorous experimental design, simulating 151 distinct disturbance cases across varying severity levels. This comprehensive approach enhances the reliability and validity of the observed results. Furthermore, the study's comparison against established lower bounds and stable scheduling benchmarks provides a robust baseline for evaluating the PDS-SBH model's performance.

Despite the promising results demonstrated by the PDS-SBH model, several avenues for further exploration emerge. Future studies could investigate the model's performance under various disturbances beyond machine failures, such as resource shortages, order changes, or supply chain disruptions. Incorporating these diverse uncertainties would provide a more comprehensive understanding of the model's adaptability and robustness in dynamic manufacturing environments. Additionally, expanding the experimental scope to include a larger set of benchmark instances and real-world case studies would enhance the generalizability of the findings. Moreover, future studies should assess the scalability of the proposed PDS-SBH model in more extensive and complex job shop environments. Evaluating performance under higher job and machine counts and real-time decision contexts will help determine its feasibility for industrial-scale deployment. Another direction could involve integrating the PDS-SBH approach with other optimization techniques, such as meta-heuristics or machine learning algorithms, potentially yielding more efficient scheduling solutions. Furthermore, examining alternative performance metrics beyond makespan, such as tardiness or system nervousness, could offer insights into balancing responsiveness with schedule stability. Finally, exploring decentralized multi-agent architectures that leverage edge computing capabilities could facilitate real-time decision-making and enhance the model's scalability for large-scale industrial applications.

While the current model leverages the Shifting Bottleneck Heuristic within a decentralized, product-driven framework, it provides a robust foundation for future extensions incorporating learning-based components. Integrating DRL agents into the decision-making layer of intelligent products or hybridizing the SBH logic with swarm-based or evolutionary metaheuristics could significantly enhance adaptability and global search capabilities in real-time scheduling scenarios.

7 CONCLUSION

This study presents a novel approach to dynamic job shop scheduling by integrating the intelligent product paradigm of PDS with the SBH. The proposed PDS-SBH model demonstrated remarkable adaptability and resilience in mitigating the impacts of disturbances across a diverse set of problem instances. The model could rapidly reschedule tasks by leveraging autonomous product agents and targeted bottleneck resolution, reducing makespan deterioration by up to 36% under varying disturbance severities.

This paper introduced a novel approach to rescheduling dynamic manufacturing environments by integrating a PDS with the SBH. Through comprehensive analysis involving 151 simulated scenarios, each depicting individual machine failures, the efficacy of the PDS-SBH in mitigating disturbance impacts was explored. Comparing undisturbed scenarios with those experiencing significant production time increases provided insight into the methodology's effectiveness.

The results highlighted the PDS-SBH model's robustness, particularly in handling disruptions that traditionally challenge production schedules. Through the detailed analysis of increased production times due to machine failures, the model not only minimized the adverse effects of such disturbances but also demonstrated a capacity for significant improvement in operational resilience. The study's simulations, encompassing 151 scenarios, underscored the PDS-SBH model's effectiveness in mitigating disturbances, evidenced by a systematic improvement in makespan reductions across various levels of machine failures. Specifically, the model achieved an average makespan reduction of 7.23% for Dist100, escalating to 8.62% for Dist300, with individual instance improvements peaking at a 36.06% reduction. Such results demonstrate the model's capacity to significantly enhance production efficiency and resilience, even under severe disruptions.

Exploring the PDS-SBH model opens new avenues for future research, particularly incorporating more complex disturbances, varied performance metrics, and enhanced agent communication strategies. These areas promise to refine and expand the model's applicability and effectiveness in dynamic manufacturing settings. By continuing to evolve the integration of product-driven systems with sophisticated scheduling heuristics, the potential to revolutionize production processes becomes increasingly tangible, offering a pathway to achieving unparalleled operational efficiency and resilience in the face of unpredictable challenges. The PDS-SBH model's hybrid nature (combining intelligent, autonomous decision-making with targeted heuristic optimization) positions it as a valuable contribution to the development of smart manufacturing systems. This integration aligns with the vision of Industry 5.0, where adaptability, resilience, and human-machine collaboration are paramount.

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