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A Comparative Study of Genetic Algorithms for Integrated Predictive Maintenance and Job Shop Scheduling

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Abstract

Modern manufacturing environments seek adaptive solutions to integrate predictive maintenance into job shop scheduling. This paper conducts a comparative study of various Genetic Algorithm (GA) based approaches for Integrated Scheduling and Predictive Maintenance Planning (ISPMP). The study assesses the performance of four GAs across three job load conditions (i.e., Low, Medium, and High), considering both single and multiple machine breakdown scenarios. The results highlight the standard GA's potential for near-real-time scheduling solutions, emphasizing its adaptability and scalability. Bridging the theoretical innovations with practical applications, this research highlights an adaptive production planning paradigm, championing the role of GA-enabled simulation and decision support systems in the ever-evolving industrial landscape.

Keywords: Genetic Algorithms; Production Planning; Integrated Scheduling; Predictive Maintenance Planning, Job Shop Scheduling

1. Introduction

As we move towards increasingly complex production systems, the integration of production scheduling and maintenance planning (IPSMP) has become an essential task in operations management (Zhai et al., 2022). This task presents multiple challenges given the intertwined nature of scheduling production jobs and machinery maintenance, while accounting for unforeseen disruptions. In this context, the Job Shop Scheduling Problem (JSSP) with multiple machines emerges as a significant issue to address (Wocker et al., 2023). The complexity of the IPSMP problem is further amplified by the dynamic nature of modern production systems, where machine breakdowns and maintenance requirements are often unpredictable (Zandieh et al., 2017). This unpredictability necessitates the use of adaptive production scheduling technologies that uses proactive techniques to respond to changes in real-time, thereby enabling higher productivity and overall improved system resilience (Longo et al., 2022).

The advent of Big Data Analytics (BDA) has revolutionized industrial environments, with predictive analytics emerging as a significant technological spinoff from the abundance of industrial data (Mitchell, 1997). Predictive maintenance, a key pillar of this technological trend, not only allows for a more responsive approach to unforeseen anomalies but also enables planners to be proactive in their production scheduling. Here, simulation-based decision support systems (SDSS) play a pivotal role. By providing a virtual environment where different scenarios and strategies can be tested, SDSS serve as a bridge between predictive analytics and on-ground operations, ensuring that planners can anticipate, simulate, and decide on the most optimal course of action. This proactive approach, however, often implies handling the trade-off between prioritizing production over maintenance or vice versa (Gordon et al., 2020).

Genetic Algorithms (GA), a class of evolutionary algorithms inspired by the process of natural selection, have shown significant promise in solving complex optimization problems. Their ability to explore a vast solution space and adapt to dynamic environments makes them particularly suitable for adaptive production planning (Bierwirth & Mattfeld, 1999). However, the performance of GAs can vary significantly depending on the specific algorithm used, the parameters chosen, and the nature of the problem at hand, especially in the case of IPSMP (Assia et al., 2020). This necessitates a thorough benchmarking study to understand their strengths, weaknesses, and applicability within SDSS. To this end, the objective of this article is to conduct a benchmarking study on various GA algorithms for adaptive production planning, with a focus on their integration with SDSS. We aim to understand their performance and applicability within an adaptive production planning system, with the ultimate goal of achieving a prescriptive production planning system. This system would serve as an intelligent decision support tool for integrated predictive maintenance and production scheduling (Elbasheer et al., 2022).

The rest of the article is organized as follows: Section 2 provides a review of the relevant literature on GA-based algorithms for production planning and maintenance scheduling. Section 3 describes the methodology of our study, including the algorithms used and the experimental design. Section 4 presents and discusses the results of our experiments. Finally, Section 5 concludes the article and suggests areas for future research.

2. Literature review

The integration of Production Scheduling and Maintenance Planning (IPSMP) has been a focal point in operations management research due to the intricate and dynamic nature of modern production systems. Amidst this backdrop, the emergence of predictive maintenance—leveraging data analytics to preemptively address equipment failures and optimize Mean Time To Repair (MTTR)—has further accentuated the need for advanced optimization techniques. Genetic Algorithms (GAs) and their variants have been widely utilized in this context due to their ability to handle complex optimization problems and adapt to changing environments. However, the literature reveals a myriad of GA variants, each with its unique strengths and weaknesses, leading to a complex landscape for researchers and practitioners alike.

The work of Sortrakul et al. (2005) and Liu et al. (2021) underscore the importance of considering the trade-offs between production and maintenance activities in IPSMP. Both studies utilized GA-based approaches to optimize production schedules while accounting for unpredictable machine failures and stochastic machine failures, respectively. These studies highlight the potential of GAs in addressing the challenges of IPSMP, but they also underscore the need for a comprehensive benchmarking study to understand the strengths and weaknesses of different GA variants.

The importance of real-time information for decision-making in IPSMP is emphasized by Ghaleb et al. (2021). They argue for the integration of Industry 4.0 concepts to gather real-time information, thereby enabling more effective joint optimization of production schedules and maintenance plans. This perspective aligns with the ultimate goal of our study aiming for the development of an intelligent decision support tool for integrated predictive maintenance and production scheduling.

Several studies in the literature have attempted to address the joint optimization of predictive maintenance planning and production scheduling. For instance, Liu et al. (2019) developed an integrated decision model that coordinates predictive maintenance decisions with single-machine scheduling decisions to minimize the total expected cost. This study demonstrates the effectiveness of GAs in IPSMP, but it also highlights the need for a systematic comparison of various GA-based algorithms, which is the focus of our study.

Chung et al. (2009) and Alemão et al. (2019) further illustrate the potential of GAs in addressing the challenges of IPSMP. Chung et al. (2009) proposed a modified GA approach to deal with distributed scheduling models with maintenance considerations, while Alemão et al. (2019) proposed a GA-based solution to solve the Job-Shop Scheduling Problem (JSSP) in Agile Manufacturing Systems (AMS). These studies underscore the versatility of GAs in addressing different aspects of IPSMP, but they also highlight the need for a comprehensive benchmarking study to understand the performance characteristics of different GA variants.

The literature reveals a complex landscape of GA-based solutions for IPSMP. While these solutions have shown promise in addressing the challenges of IPSMP, there is a clear need for a systematic benchmarking study to understand the strengths and weaknesses of different GA variants. This is the gap that our study aims to fill. By providing a comparative analysis of various GA-based algorithms, our study aims to clarify the landscape of GA-based IPSMP solutions and guide future research and integration with SDSS of industrial ecosystems.

3. Materials & Methods

The aim of this research is to investigate the performance of different GA based meta-heuristics in the task of IPSMP under the scenario of predictive maintenance. We seek to identify the most efficient GA-based meta-heuristic for integrated scheduling, determine the optimal parameters for the chosen meta-heuristic, and analyze the computational time required by each.

In our methodology, we employ the HeuristicLab software, a comprehensive environment for heuristic and evolutionary algorithms, to support our experiments (Wagner et al., 2014). HeuristicLab facilitates an advanced platform for the design and analysis of the meta-heuristic's performance, thereby providing a robust backbone to our research design. The experiments are designed to simulate varying levels of MTTR, numbers of machines, and job loads to thoroughly evaluate the GA-based meta-heuristics.

In this section, we detail the experimental design, GA-based algorithms under consideration, parameters setup, and how the data will be recorded and analyzed. The outcome of this rigorous experimental setup will offer valuable insights into the best performing GA-based meta-heuristic for integrated production and maintenance scheduling.

3.1. Candidate GA-based meta-heuristics

Meta-heuristic in general and specially GAs have proven their significant effectiveness to solve complex decision-intensive optimization problems due to their ability to explore a vast solution space and adapt to dynamic environments (Ansari et al., 2022).

In the context of Integrated Production Scheduling and Maintenance Planning (IPSMP) under the scenario of predictive maintenance, we have selected four Genetic Algorithm (GA) based meta-heuristics (Mirabelli & Solina, 2022). These algorithms were chosen based on their successful implementation on wide range application areas and their unique characteristics and potential advantages for ISPMP.

3.1.1. Genetic Algorithm

The notion of GA was inspired by the theory of evolution and the Darwinian principle of survival of the fittest (Holland , 1975). Therefore, the Genetic Algorithm is a search meta-heuristic that is rooted in the process of natural selection, using methods such as mutation, crossover, and selection to evolve a population of candidate solutions towards an optimal or near-optimal solution. The GA is a good fit for the IPSMP as it can efficiently explore a large search space to find patterns that match the user's intent. It is also robust to changes in the problem domain, making it a versatile choice for different types of pattern extraction tasks. GA's ability to balance exploration and exploitation can be particularly useful in finding optimal maintenance schedules that minimize downtime and maximize production efficiency. The GA's ability to handle a wide variety of optimization problems, coupled with its robustness and simplicity, makes it a popular choice in the field of IPSMP.

3.1.2. SASEGASA (Self-Adaptive Segregative Genetic Algorithm.)

SASEGASA is a generic evolutionary algorithm that aims to prevent premature convergence by dynamically adjusting the selection pressure and using parallel subpopulations (Affenzeller & Wagner, 2004). It combines two methods: a self-adaptive selection scheme that maintains the genetic diversity within the population and detects when the search is stagnating, and a segregative genetic algorithm that splits the population into smaller groups that evolve independently and exchange information periodically (Affenzeller et al., 2012). In the context of IPSMP, SASEGASA's ability to maintain genetic diversity and adapt to stagnation makes it a promising choice for solving complex scheduling problems under predictive maintenance scenarios. Its segregative nature allows for the exploration of diverse solution spaces, potentially leading to more robust and efficient maintenance schedules (Affenzeller & Wagner, 2003).

3.1.3. Island-GA

Island genetic algorithms are a type of parallel genetic algorithms that use multiple subpopulations (islands) to explore different regions of the search space. Each island evolves independently with its own genetic operators and parameters, and occasionally exchanges some individuals (migrants) with other islands (Nakajima & Takata, 2021). This way, island genetic algorithms can maintain diversity, avoid premature convergence, and exploit the benefits of parallelism. Island genetic algorithms can be implemented on distributed systems, such as clusters or grids, using various communication topologies and migration policies (Gong & Fukunaga, 2011). Island genetic algorithms have been applied to many optimization problems, such as packing, scheduling, and multi-objective optimization (Miranda et al., 2021). To this end, Island-GA can enhance the exploration and exploitation capabilities of the GA, making it a good fit for the IPSMP, where a diverse set of solutions may be needed to accurately schedule production and maintenance tasks.

3.1.4. ALPS (Age-Layered Population Structure Genetic Algorithm)

ALPS (Age-Layered Population Structure Genetic Algorithm) is a metaheuristic that aims to reduce the problem of premature convergence in evolutionary algorithms (Hornby, 2006). ALPS works by dividing the population into different layers based on the age of the individuals, which is a measure of how long their genetic material has been evolving in the population. ALPS also introduces new, randomly generated individuals in the bottom layer at regular intervals, to maintain diversity and explore new regions of the search space (Opoku-Amankwaah & Ombuki-Berman, 2017). In the context of IPSMP, ALPS's age-layered structure can help maintain diversity in the solution space and prevent premature convergence, potentially leading to more effective maintenance schedules that balance production efficiency and equipment longevity.

Despite the unique characteristics of each of these GA-based meta-heuristics, they share several common parameters that influence their performance. These include population size, number of generations, crossover probability, and mutation probability. In this study, we focus on these common parameters to provide a fair and systematic comparison of the algorithms. Table 1 provides a brief description of each of these common parameters.

Table 1. Common GA-based meta-heuristics parameters.

Parameter	Description
Population size	The number of individuals in the population.
Number of generations	The number of iterations the algorithm performs.
Crossover probability	The probability that two individuals will exchange genetic material.
Mutation probability	The probability that an individual's genetic material will be randomly changed.

By focusing on these common parameters, we aim to provide insights that are broadly applicable across different GA-based meta-heuristics and can guide the selection and tuning of these algorithms for IPSMP under predictive maintenance scenarios.

3.2. Basic Premises for ISPM & JSSP

Our study is grounded on several assumptions that guide our simulation-based experimentation. These assumptions pertaining to the job shop scenarios we consider are as follows:

- **Assumption 1**: We assume a job shop scenario where there are multiple machines available for scheduling jobs. The scheduler has full discretion in assigning jobs to machines based on their routing.
- **Assumption 2**: The Remaining Useful Life (RUL) is considered as the time required by the scheduler to plan for maintenance and production tasks. This aligns with the context of predictive maintenance where an alarm or alert notifies the scheduler of upcoming machine breakdowns, thereby triggering a scheduling and re-scheduling process.
- **Assumption 3**: In scenarios where multiple maintenance orders arise simultaneously (i.e., the predictive maintenance system detects impending breakdowns in more than one machine), the scheduling time window is determined by the smallest RUL among all machines. This assumption highlights the urgency of integrating maintenance and production scheduling under multiple machine breakdown scenarios.
- **Assumption 4**: We operate under the assumption that the Mean Time to Repair (MTTR) is always less than the Remaining Useful Life (RUL). This assumption ensures that there is always enough time to perform maintenance before the predicted machine breakdown occurs.

3.3. Experimentation Design

Our experimentation design seeks to rigorously evaluate and compare the performance of the chosen GA meta-heuristics (i.e., GA, SASEGASA, Island-GA, and ALPS) under different IPSMP-based predictive maintenance scheduling scenarios. The experimental design aims to comprehensively assess the general performance of the meta-heuristics. To this end, we manage to analyze the performance and solution quality of the different algorithms with different Job shop configurations. The simulation-based experimentation enables to test the different GAs with various job shop scenarios based on varying number of disrupted machines, varying MTTR, and varying Job loads.

3.3.1. Performance Analysis

In this stage of the study, we aim to identify the best performing meta-heuristic algorithm under the previously discussed (table 1) commonly used parameter setups. This analysis will provide insights into the base performance of each meta-heuristic without any fine-tuning. It Is important to note that these setups may not necessarily represent the best or optimized configurations for these algorithms. They, however, present a valid comparative ground to understand the algorithms performance. Table 2 shows the selected parameters set up for the four meta-heuristics considered in this study.

Table 2. Initial parametrical setup for selected GA-based meta-heuristics

Parameter	Initial setting
Population size	- *Population size = 100*
Number of generations	- *Generations = 1000*
Crossover probability	- Crossover probability = 5%
Mutation probability	- Mutation probability = 5%

Each meta-heuristic will be tested against 18 different experimental scenarios, covering various MTTR scenarios and machine numbers. The metrics of Makespan and execution time will be evaluated for each scenario. The different scenarios of this study vary in terms of the MTTR, number of machines requiring maintenance, and total number of jobs to be scheduled. The scenarios were designed as follows, considering that the available planning window corresponds to the shortest Remaining Useful Life (RUL) of available machines:

1. **Varying MTTR**: We assess the time required for maintenance in relation to the available scheduling window, which is reflected in three scenarios:

- ***Low MTTR***: MTTR ≤ 25% of RUL (Planning horizon).
- ***Medium MTTR***: 25% < MTTR ≤ 50% of RUL.
- ***High***: MTTR > 50% of RUL.

2. **Varying number of machines**: We account for different levels of machine maintenance intervention within the planning horizon. This variable is expressed in two scenarios:

- ***Single machines***: Only one machine requires intervention within the planning horizon.
- ***Multiple machines***: More than one machine requires intervention.

3. **Varying number of Jobs:** We consider the total number of jobs to be scheduled in our scenarios, classified into three levels:

- ***Low Job Load***: Less than 10 jobs
- ***Medium Job Load***: 10 to 20 jobs
- ***High Job Load***: More than 20 jobs

These scenarios lead to a total of 18 experimental setups (3 MTTR scenarios x 2 machine number scenarios x 3 job number scenarios), for each of which every meta-heuristic will be tested. Table 3 depicts each one of these scenarios explaining the Individual characteristics of each experimental setup.

Scenario ID	Number of Jobs to be scheduled			Number of machines to be disrupted		MTTR		
	Low	*Medium*	*High*	*Single Machine*	*Multiple machines*	*Low*	*Medium*	*High*
#001	✓	×	×	✓	×	✓	×	×
#002	✓	×	×	✓	×	×	✓	×
#003	✓	×	×	✓	×	×	×	✓
#004	✓	×	×	×	✓	✓	×	×
#005	✓	×	×	×	✓	×	✓	×
#006	✓	×	×	×	✓	×	×	✓
#007	×	✓	×	✓	×	✓	×	×
#008	×	✓	×	✓	×	×	✓	×
#009	×	✓	×	✓	×	×	×	✓
#010	×	✓	×	×	✓	✓	×	×
#011	×	✓	×	×	✓	×	✓	×
#012	×	✓	×	×	✓	×	×	✓
#013	×	×	✓	✓	×	✓	×	×
#014	×	×	✓	✓	×	×	✓	×
#015	×	×	✓	✓	×	×	×	✓
#016	×	×	✓	×	✓	✓	×	×
#017	×	×	✓	×	✓	×	✓	×
#018	×	×	✓	×	✓	×	×	✓

4. Results & Discussion

Based on the scenarios description of table 3, the simulation-based experimentation results are organized into three main job load categories: low, medium, and high. Within each category, the performance of the four GA-based meta-heuristics (i.e., GA, SASEGASA, Island-GA, and ALPS) was analyzed and compared based on two primary metrics: makespan (in hours) and execution time (in minutes). Figure 1 outlines the different results of algorithms performance for these important metrics.

Low Job Load

Scenario ID	Genetic Algorithm (GA)		SASEGASA		Island-GA		ALPS Genetic Algorithm		
	Makespan [h]	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	
#001	55	00:27.9	55	03:39.4	55	01:53.4	55	02:45.3	Single Disruption
#002	55	00:17.6	55	03:00.8	55	01:20.3	55	02:01.5	
#003	63.5	00:21.0	63..55	03:22.6	63.5	01:28.6	63.5	02:09.5	
#004	55	00:20.5	55	03:27.6	55	01:31.4	55	02:17.5	Mutliple Disruptions
#005	58.5	00:20.8	58.5	04:01.7	58.5	01:33.6	58.5	02:16.6	
#006	77.5	00:22.3	77.5	03:56.1	77.5	01:34.3	77.5	02:25.8	

Medium Job Loads

Scenario ID	Genetic Algorithm (GA)		SASEGASA		Island-GA		ALPS Genetic Algorithm		
	Makespan [h]	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	
#007	685.75	00:27.2	685.75	05:43.9	685.75	02:12.2	685.75	03:22.9	Single Disruption
#008	757.15	00:35.4	757.15	05:17.4	757.15	02:20.6	757.15	03:07.8	
#009	983.25	00:29.8	983.25	04:49.5	983.25	02:11.6	983.25	02:56.3	
#010	685.75	00:29.5	685.75	05:07.6	685.75	02:08.2	685.75	02:54.9	Mutliple Disruptions
#011	757.15	00:29.4	757.15	05:08.3	757.15	02:15.4	757.15	03:01.9	
#012	897.25	00:55.6	897.25	05:11.7	897.25	02:29.8	897.25	03:15.0	

High Job Loads

Scenario ID	Genetic Algorithm (GA)		SASEGASA		Island-GA		ALPS Genetic Algorithm		
	Makespan [h]	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	*Makespan [h]*	*Execution Time [min]*	
#013	1409.5	01:33.3	1409.5	14:27.0	1409.5	06:39.3	1409.5	08:22.6	Single Disruption
#014	1557.1	01:25.7	1557.1	13:43.9	1557.1	06:37.9	1557.1	08:17.8	
#015	2024.5	01:30.4	2024.5	13:59.2	2024.5	06:49.4	2024.5	08:39.3	
#016	1409.5	01:36.2	1409.5	16:26.2	1409.5	07:31.5	1409.5	09:25.6	Mutliple Disruptions
#017	1557.1	01:53.5	1557.1	17:24.5	1557.1	08:07.8	1557.1	10:04.8	
#018	2024.5	01:37.9	2024.5	16:22.2	2024.5	07:30.3	2024.5	09:35.7	

Figure 1 Experimental result for the different GAs mapped to different job loads.

4.1. GA-based ISPMP Solution

The adoption of a Genetic Algorithm (GA) approach to the Integrated Scheduling of Production and Maintenance Planning (ISPMP) problem provides a viable solution for balancing production efficiency and predictive maintenance requirements. This is particularly critical when early alarm systems embedded within production systems trigger maintenance needs.

A GA-based ISPMP solution's strength lies in its flexibility to adapt to different job load scenarios, ranging from low to high. This adaptability is critical in production environments, where job loads can vary significantly. Each scenario presents unique challenges to the production scheduler, especially when a predictive maintenance requirement is introduced into the mix.

In a low job load scenario, the GA-based ISPMP approach can seamlessly integrate maintenance tasks into the production schedule due to the availability of slack time. However, as the job load increases, the complexity of the scheduling problem escalates. Under medium job load conditions, the GA-based ISPMP solution can find a balance between production tasks and maintenance requirements, ensuring that neither is compromised. This capability becomes even more critical in high job load scenarios, where the GA-based ISPMP solution must find the optimal time slot to inject maintenance activities without disrupting the tightly packed production plan. The Gantt charts in figure 2 provide a visual representation of the GA-based ISPMP solution for low, medium, and high job load scenarios. The upper part of each chart represents the planned timespan for different tasks, while the lower part illustrates the results of the integrated scheduling process for some sample scenarios extracted from table 3 (i.e., #003, #009, and #015).

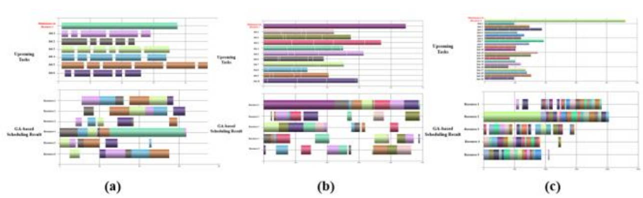

Figure 2 Sample for the GA-based scheduling results, (a) sample results from the low job load scenarios load (#003), (b) sample results from the medium job load scenarios load (#009), and (c) sample results from the high job load scenarios load (#015).

4.2. Performance Evaluation

The performance analysis provides a deep understanding of how the selected genetic algorithms, namely the standard Genetic Algorithm (GA), SASEGASA, Island-GA, and ALPS Genetic Algorithm, respond to different job loads and machine breakdown scenarios. The analysis is synthesized across Makespan and execution time, offering critical insights into the algorithms' efficiency and applicability.

4.2.1. Estimated Makespan

The Makespan, representing the total time required to complete all jobs, is a critical metric for assessing scheduling efficiency. Analyzing the Makespan across algorithms reveals an intriguing uniformity. The Makespan values for all algorithms are almost identical for both predicted single and multiple machine breakdown scenarios across various job loads.

As illustrated in figure 3, the uniformity in the average Makespan suggests that all tested algorithms can provide consistent scheduling solutions. However, a closer look reveals a proportional increase in Makespan with job load levels, reflecting the inherent complexity of scheduling more jobs. The similarity in Makespan across single and multiple machine breakdown scenarios further reveals the resilience of these algorithms to varying degrees of scheduling challenges. Even though Makespan remains largely similar across different conditions, this uniformity emphasizes the robustness and flexibility of the genetic algorithms in handling complex scheduling tasks.

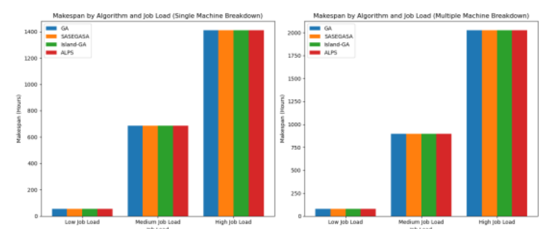

Figure 3 Average Makespan by the different metaheuristics.

4.2.2. Execution Time

While the average values of Makespan provides a consistent picture across algorithms, execution time reveals significant distinctions. As shown in figure 4, the standard GA emerges as the most computationally efficient solution, with the fastest average execution times across all job load levels and scenarios.

SASEGASA, despite matching the Makespan uniformity, requires substantially more computation time, reflecting its complexity. Island-GA and ALPS position themselves between GA and SASEGASA, revealing a balance between efficiency and exploration depth.

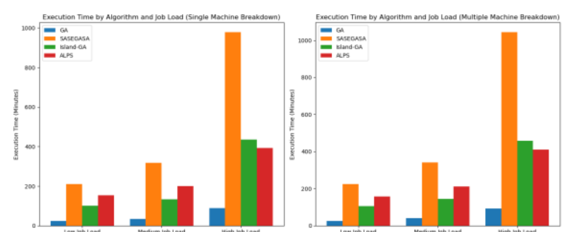

Figure 4 Average execution time by algorithm and job loads.

The contrasting execution times underscore the trade-offs between computational efficiency and exploration capabilities. The provided figures visually represent these distinctions, with varying bar heights indicating the differences in execution time across conditions.

The analysis of execution time emphasizes the importance of considering computational resources in selecting an algorithm, making the standard GA an attractive choice for further parameter tuning and optimization.

4.3. Real-world Applicability: Towards a swift and accurate ISPMP system

Navigating the complex landscape of integrated scheduling and predictive maintenance planning in modern manufacturing environments is still in its infancy. The benchmarking of Genetic Algorithm (GA) based approaches in this study offers a glimpse into the heart of a prospective technological innovation in ISPMP applications. The insights derived pave the way for future innovations and present the following implications:

Insight 1: ***GAs as Enablers Integrating Predictive Maintenance in Scheduling***

The ability of GA-based ISPMP to accommodate both single and multiple machine breakdown scenarios is indicative of a seamless integration of predictive maintenance into scheduling. Single machine breakdowns can be viewed as localized challenges, whereas multiple machine breakdowns represent complex, system-wide disruptions. GA's ability to adapt to both scenarios symbolizes its role as a unifier between predictive maintenance and scheduling, fostering a proactive approach and resonating with modern industrial trends.

Insight 2: ***Real-time and Scalable Solutions***

The relatively quick execution time of standard GA, compared to other algorithms, highlights its potential for real-time scheduling solutions. Even in dynamic environments such as IoT and edge devices within the industrial system. Its robustness across high, medium, and low job load conditions further reinforces its scalability. Whether in decentralized manufacturing setups or large-scale industrial applications, GA's speed, and adaptability position it as a versatile choice for diverse real-time applications.

Insight 3: ***GA's Adaptability in Varied Manufacturing Contexts***

In a manufacturing setting, the adaptability of scheduling solutions to different production scales and machine configurations is paramount. The GA-based approaches tested in this study displayed consistent makespan across different job load conditions. This uniformity can be attributed to GA's inherent flexibility, allowing for the exploration of diverse solution spaces and the tailoring of scheduling solutions to specific needs. The adaptability ensures that GA-based solutions can be customized to fit a wide range of manufacturing scenarios, from small-scale workshops to large, complex industrial operations.

Insight 4: ***GA as a Catalyst for Prescriptive Planning Systems***

The standard GA's capabilities extend beyond mere optimization; they pave the way for advanced, integrated production planning systems. The speed and efficiency of GA, especially when dealing with both single and multiple machine breakdowns, demonstrates its potential to serve as a core component in a prescriptive production planning system. By integrating predictive maintenance seamlessly into scheduling, GA-based ISPMP moves beyond traditional reactive approaches. It enables a more cohesive coordination between maintenance and production, facilitating real-time adjustments and scalability. This synergy represents a significant step towards achieving a sophisticated prescriptive production planning system that aligns with the evolving complexity of modern manufacturing environments.

Insight 5: ***Adaptive Decision Support through swift optimized Plans***

The insights from the GA-based scheduling study can be harnessed to build decision support systems that facilitate strategic planning. By combining production scheduling, machine breakdowns, and maintenance planning, GA-based ISPMP offers a comprehensive view of production dynamics. It fulfills the objective of creating a decision support tool that aids in making well-informed decisions, supporting the overarching goal of an integrated predictive maintenance and production scheduling system.

5. Conclusion

The study of GA-based ISPMP systems offers an insightful perspective on the challenges and opportunities in integrating predictive maintenance into job shop scheduling. This research has embarked on a benchmarking study, evaluating various GA algorithms' performance in adaptive production planning. While it represents a step towards understanding the intersection between predictive maintenance and production scheduling, the findings must be interpreted within the context of its limitations. The study remains predominantly conceptual, with the modeled simulation scenarios serving as approximations to various JSSP. These scenarios, although insightful, are not fully reflective of real industrial situations, and the assumptions underlying them may not hold in more complex environments. Additionally, the relative simplicity of the handled scenarios and the algorithms' quick convergence to a global optimum mean that a more extensive sensitivity analysis of the algorithm parameters was not conducted. Such analysis might have provided a nuanced understanding of the algorithms' behavior.

Despite these constraints, the research provides valuable insights into the potential application of GA-based ISPMP systems in different manufacturing settings. It highlights the role of standard GA in real-time scheduling solutions, underlining its robustness to different job load conditions, and pointing towards its versatility in diverse industrial applications. Importantly, this study lays the groundwork for future development of simulation-based decision support systems, harnessing the power of prescriptive analytics to bridge the gap between theoretical models and real-world production challenges. Future research should prioritize the validation of these results within real industrial scenarios. The integration of GA-based optimization with a simulation-empowered decision support system may further contribute to achieving prescriptive planning. This would allow for a more holistic approach to maintenance and production coordination, aligning with the industry's shift towards intelligent manufacturing systems.

In conclusion, this research adds to the growing body of knowledge on integrated scheduling and predictive maintenance planning in manufacturing. While it opens avenues for exploration and innovation, it also underscores the need for rigorous validation, practical applicability, and careful consideration of the complexities inherent in real-world manufacturing environments.

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