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Flexible and Sustainable Bread Production in SMEs: A Metaheuristic Scheduling Approach

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ABSTRACT:
Small and medium-sized bakery enterprises (SMEs) often face inefficiencies due to manual scheduling and limited automation. These challenges are most evident in coordinating multiple interdependent production stages such as fermentation, proofing, and baking. A common problem is suboptimal oven usage—long idle periods between batches lead to excessive energy consumption and environmental burden. This paper introduces an intelligent scheduling approach that combines agent-based modeling with metaheuristic optimization. Bakery production is modeled as a no-wait flexible flow process, and the system applies bio-inspired algorithms, specifically the Whale Optimization Algorithm (WOA) and Firefly Algorithm (FA), to generate optimized daily schedules. The approach adapts to real-world operational constraints, enabling dynamic scheduling across diverse bread types with differing production times, such as sourdough and brioche.
Simulation experiments based on realistic bakery production scenarios show that the proposed scheduling approach can shorten total production time and reduce oven idle periods. The system supports both productivity and environmental sustainability by enabling SMEs to better manage time in energy-intensive stages of production, such as baking. This research contributes to the UN Sustainable Development Goals, particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 12 (Responsible Consumption and Production), by proposing an accessible digital approach to support SME transformation toward smarter and greener food manufacturing.

Keywords: Metaheuristic Optimization, Agent-Based Scheduling, Bakery Production, Sustainable Manufacturing, SME Production Efficiency

1. Introduction

Small and medium-sized enterprises (SMEs) in the food production sector, particularly artisan bakeries, play a vital role in local economies and food security. These bakeries typically operate with limited automation and rely heavily on structured manual workflows. Although this lean operational model supports flexibility and low capital costs, it often introduces scheduling inefficiencies, particularly in coordinating multiple interdependent processing stages such as mixing, proofing, baking, and cooling. A prominent source of inefficiency lies in the utilization of shared resources, especially ovens, where long idle periods between batches result in extended makespan, underutilized capacity, and increased energy consumption.

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Manual scheduling strategies in such settings often follow simple heuristics. The First-In-First-Out (FIFO) approach, for instance, prioritizes job execution based on arrival sequence, while Shortest Processing Time (SPT) schedules jobs in increasing order of total processing duration. These techniques are intuitive and easy to implement, but they frequently overlook the complexity of multi-stage workflows and resource contention. As a result, manual scheduling often leads to suboptimal resource usage and inflated production time, particularly when longer jobs (e.g., sourdough) dominate early stages and delay shorter ones (e.g., burger buns).

To address these limitations, recent studies have explored the application of metaheuristic algorithms, computational strategies inspired by natural phenomena, for solving complex scheduling problems. Metaheuristics such as the Firefly Algorithm (FA) and Whale Optimization Algorithm (WOA) have demonstrated effectiveness in diverse domains including manufacturing, logistics, and energy systems. These algorithms are particularly attractive for bakery production scheduling due to their ability to explore large search spaces, escape local optima, and adapt to real-world constraints such as no-wait requirements and heterogeneous job durations.

Previous research has also demonstrated the potential of integrating metaheuristic optimization with multi-agent architectures to solve dynamic scheduling problems (Nugraheni & Abednego, 2013). Building on this foundation, the present study applies a similar agent-based perspective to the context of bakery production, where jobs and machines will later be modeled as intelligent agents interacting over shared resources.

In this study, we model the daily production workflow of a small-scale Indonesian bakery as a no-wait flexible flow shop, where multiple bread types (sourdough, brioche, toast bread, burger buns) must pass through shared resources with varying process durations. The study compares four scheduling strategies: two heuristics (FIFO, SPT) and two metaheuristics (FA, WOA), applied with both fixed and greedy resource assignments. The primary performance indicators include makespan (total production time) and oven idle time (as a proxy for energy inefficiency).

2. Literature Study

Research on production scheduling in small and medium-sized bakery enterprises has gained increasing attention in recent years, particularly due to the sector's role in local food supply chains and its susceptibility to inefficiencies in resource usage. Several studies highlight the challenges of coordinating multi-stage production in bakeries, especially under no-wait constraints and variable job durations (Nouri et al., 2021; Yildiz & Yildiz, 2020). These constraints are commonly addressed through flexible flow shop scheduling models, which have been shown to reflect the operational characteristics of SME bakeries more accurately than classical job shop models (Wang et al., 2019).

Heuristic methods such as FIFO and SPT have traditionally been employed in practice due to their simplicity and low computational cost. However, their effectiveness is limited when dealing with complex multi-stage production processes involving shared resources. As noted by Nasution et al. (2020), such heuristics can result in bottlenecks and long idle times, especially when longer jobs occupy critical resources early in the schedule.

To overcome these limitations, metaheuristic algorithms have emerged as powerful tools for production scheduling. The Firefly Algorithm (FA), introduced by Yang (2009), has been applied in manufacturing systems for its simplicity and strong convergence properties. Recent studies by Alkahtani et al. (2021) and Sahu et al. (2022) demonstrate the effectiveness of FA in minimizing makespan and balancing resource utilization in flow shop environments. Similarly, the Whale Optimization Algorithm (WOA), proposed by Mirjalili and Lewis (2016), has been successfully implemented for scheduling problems involving complex constraints. Its applications in industrial settings include hybrid flow shops, robotic cell scheduling, and batch processing systems (Gomes da Silva et al., 2023; Pradana et al., 2021). In a related study, Nugraheni et al. (2025) applied WOA for production scheduling in Indonesian bakery SMEs, demonstrating its suitability in capturing real-world constraints. Further developments explored WOA-based solvers for no-wait FFS problems (Jonathan et al., 2024).

Additionally, agent-based modeling has been increasingly adopted for simulating production systems and developing decentralized scheduling frameworks. According to Garro and Vetrano (2019), agent-based systems provide flexibility, scalability, and adaptability in dynamic environments. In the context of SME bakeries, such models can facilitate autonomous decision-making by representing each job or machine as an intelligent agent capable of negotiating for resource access and managing time-sensitive tasks. Similar agent-based scheduling frameworks have also been explored in the context of single-machine production systems. Nugraheni and Abednego (2013) proposed a multi-agent architecture that integrates hyper-heuristics with agent coordination to address dynamic scheduling challenges. Their results demonstrated the scalability and flexibility of agent-based control when coupled with heuristic-based decision-making in real production environments.

These existing works form the foundation for the present study, which integrates a no-wait flexible flow shop model with metaheuristic scheduling and explores the potential for agent-based implementation. By combining these approaches, the research aims to produce actionable insights and tools that support the digital transformation of small-scale food producers.

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3. Methods

3.1 Illustrative Example of the Scheduling Problem

To clarify the scheduling logic used in this study, we present a simplified example involving four jobs processed sequentially through four stages: mixing, proofing, baking, and cooling. Each stage is operated by a single machine, and a no-wait constraint is enforced between the first three stages. This example illustrates how task timing and resource contention emerge under realistic production constraints. Table 1 lists the processing times for each job, measured in minutes.

Assuming a First-In-First-Out (FIFO) scheduling rule, the resulting schedule is visualized in Figure 1 using a Gantt chart. The diagram highlights how the no-wait constraint between mixing, proofing, and baking shapes the job sequence and causes resource blocking across stages. This illustrative case provides a conceptual foundation for understanding the more complex real-world scenarios analyzed in subsequent sections.

Table 1: Processing Times for Illustrative Example (in minutes).

Job	Mixing	Proofing	Baking	Cooling
J1	20	10	30	15
J2	25	12	35	15
J3	15	11	40	10
J4	22	10	32	18

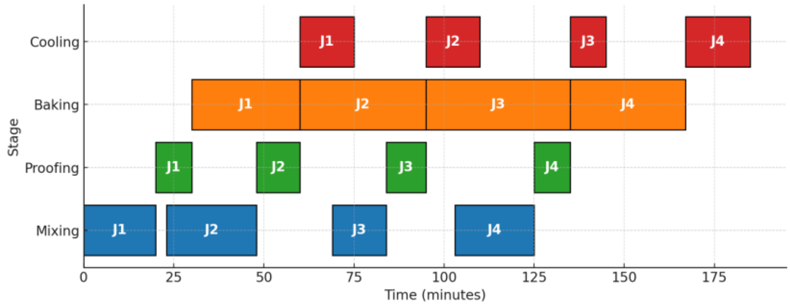

Figure 1. Gantt Chart for Illustrative FIFO Schedule With No-Wait Constraint.

3.2 Case Study Description

The real-world case study for this research involves the daily production operations of a small-scale bakery in Indonesia that specializes in a wide variety of bread products commonly produced by small Indonesian bakeries. The bakery produces **20 types of bread**, including *roti sobek*, *roti keju manis*, *roti isi pisang*, *croissant*, *danish coklat*, *roti isi sosis*, *roti gulung coklat*, and others. Each type of bread requires a specific combination of processing times for mixing, proofing, baking, and cooling stages.

In total, 20 jobs are scheduled each day, each corresponding to one batch of a different bread type. Each bread type follows a sequential process involving multiple stages: mixing, fermentation and proofing, baking, and cooling. The duration and complexity of each stage vary by product, as summarized in Table 2. Each job represents a single batch, with batch sizes varying from 18 to 25 pieces depending on the bread type. For example, burger buns are produced in batches of 18 pieces, while sourdough and toast bread reach up to 25 pieces per batch. These jobs are processed through four main stages: mixing, proofing, baking, and cooling. The bakery utilizes shared resources in each stage: 2 mixers, 2 proofers, 2 ovens, and 2 cooling racks. All machines of the same type are treated as identical (homogeneous), following a first-available assignment policy.

A no-wait constraint is enforced between the mixing and proofing stages to reflect actual operational behavior, where the dough must proceed immediately from mixing to proofing without delay. This constraint applies only to the first two stages, while waiting is allowed between proofing, baking, and cooling depending on equipment availability. While this no-wait condition reflects the actual workflow of the case study bakery, it is acknowledged that in other SME contexts, occasional delays between stages may occur due to human or operational variability.

The case study captures the typical production environment of Indonesian micro, small, and medium-sized enterprises (MSMEs) in the bakery sector, which often rely on semi-automated equipment and practical scheduling habits. This model allows us to evaluate intelligent scheduling algorithms under realistic and heterogeneous conditions, including variability in bread processing requirements and equipment usage.

Table 2: Processing durations per bread type (in minutes).

Job	Mixing	Proofing	Baking	Cooling
J1	25	150	35	45
J2	20	120	30	35
J3	22	130	35	40
J4	20	90	30	35
J5	22	120	35	40
J6	20	120	35	40
J7	22	90	25	30
J8	18	100	30	30
J9	18	90	25	30
J10	20	60	25	30
J11	22	180	40	50
J12	22	150	35	40
J13	20	120	30	35
J14	20	90	30	35
J15	18	120	35	40
J16	24	180	40	40
J17	20	120	35	40
J18	20	100	30	35
J19	18	90	25	30
J20	20	100	30	35

3.3 Scheduling Problem Formulation

The production process is modeled as a no-wait flexible flow shop scheduling problem (NWFSP), in which multiple jobs must pass through four stages (mixing, proofing, baking, cooling), each equipped with two parallel machines of the corresponding type. Due to the no-wait constraint between mixing and proofing stages, these two are grouped into a single processing block (Block A) to ensure uninterrupted flow and realistic modeling of early-stage operations. Each job consists of three processing blocks: Block A (Mixing and Proofing), Block B (Baking), and Block C (Cooling). The main objectives are to minimize the overall makespan and reduce total oven idle time, reflecting both productivity and energy efficiency.

Each job is treated as an independent unit that must pass through the blocks in sequence without delay between stages in Block A. The assignment of jobs to available ovens and racks is handled using either fixed (pre-assigned) or greedy (first-available) strategies. The scheduling algorithm generates ordered job sequences. These sequences are then evaluated through simulation procedures that determine resource allocation and compute performance metrics.

3.4 Heuristic Scheduling Approaches

Two classical heuristics are implemented for baseline comparison:

- First-In-First-Out (FIFO): Jobs are scheduled strictly in the order of their arrival. This method reflects the typical manual scheduling approach observed in many SMEs.
- Shortest Processing Time (SPT): Jobs are sorted by their total expected processing time (sum of mixing, proofing, baking, and cooling durations), with shorter jobs processed earlier.

Both heuristics are evaluated using a greedy resource assignment policy, where each job is allocated to the first available machine at each stage. The resulting schedules are assessed based on makespan and oven idle time.

3.5 Metaheuristic Optimization

This study employed two population-based metaheuristic algorithms: Firefly Algorithm (FA) and Whale Optimization Algorithm (WOA), selected for their complementary strengths in local exploitation and global search. Both algorithms were adapted to handle job sequencing in the no-wait production environment using position-based solution encoding.

To ensure comparability, both algorithms used the same parameter settings: population size of 50 and maximum iteration of 100. Further details on algorithm-specific behavior can be found in the cited references. Their objective functions were evaluated under three scenarios: (1) makespan minimization, (2) total oven idle time minimization, and (3) Pareto-based multi-objective optimization.

3.6 Evaluation Procedure

The quality of each schedule was assessed using two metrics: total makespan and total oven idle time. For the metaheuristic methods, each experiment was repeated ten times to account for stochastic variation. To compare the heuristic baselines (FIFO and SPT) with metaheuristic outcomes, a paired-sample t-test will be conducted for each optimization scenario. The statistical tests were performed at a 95% confidence level. Detailed results and interpretation are presented in Section 4.4.

3.7 Integration Plan with Agent-Based Architecture

The optimized job sequences produced by the metaheuristic algorithms in this study are designed to be operationalized within an agent-based scheduling architecture, as shown in Figure 2. This approach is adapted from earlier work on multi-agent hyper-heuristic systems for single-machine scheduling (Nugraheni & Abednego, 2013), which demonstrated the benefits of decentralized control, agent coordination, and dynamic adjustment. In the envisioned implementation, each job and machine will be represented by intelligent agents, with a SchedulerAgent managing the application of heuristic-derived sequences and resolving conflicts in real time. This direction aligns with the goal of enabling responsive and robust decision-making in small-scale, resource-constrained bakery environments.

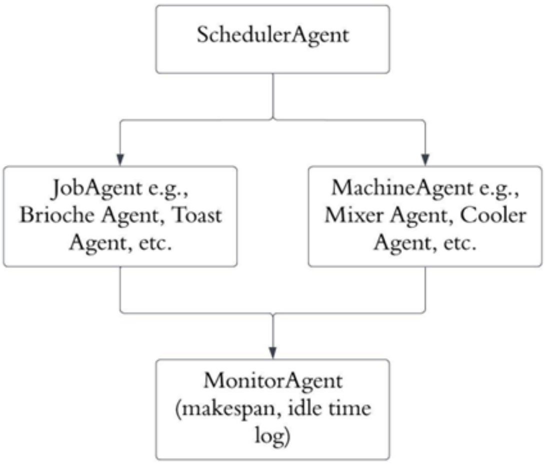

Figure 2. Conceptual architecture of the agent-based bakery scheduling system.

In this architecture, each JobAgent represents a batch of bread to be processed, negotiating access to shared resources with MachineAgents, which control the status and availability of mixers, proofers, ovens, and cooling racks. A central SchedulerAgent oversees the execution of the optimized job sequence and manages reordering when disruptions occur. Optionally, a MonitorAgent may be employed to track key performance metrics—such as makespan and idle time—and to provide feedback for runtime adaptation. This agent-based configuration enables distributed control while preserving the global optimization objectives defined by the metaheuristic layer.

4. Results

4.1 Summary of Optimization Results

Table 3 and Figure 3 summarize the performance of all four scheduling methods across three optimization scenarios: makespan minimization (M), idle time minimization (I), and Pareto-based multi-objective optimization (P). The metaheuristics (FA and WOA) consistently outperformed heuristics (FIFO and SPT) across all cases, either in minimizing total production time, reducing oven idle time, or balancing both.

Table 3: Best and Average Performance of Heuristic and Metaheuristic Methods across Three Optimization Scenarios.

		Makespan (M)		Idle Time (I)		Makespan (P)		Idle Time (P)	
Method	Type	Best	Average	Best	Average	Best	Average	Best	Average
FIFO	Heuristic	1280	-	1465		1280		1465	
SPT	Heuristic	1298	-	1036		1298		**1036**	
FA	Metaheuristic	1235	1242.0	1780	1785.4	**1233**	**1238.9**	1776	**1781.6**
WOA	Metaheuristic	**1233**	**1234.8**	**615**	**779.1**	1235	1241.8	1778	1784.3

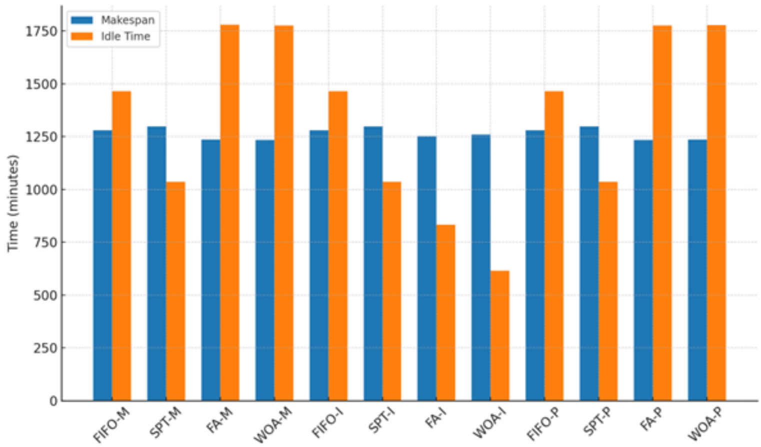

Figure 3: *Best makespan and oven idle time values achieved by each scheduling method under three optimization objectives: makespan minimization (M), idle time minimization (I), and Pareto-based multi-objective optimization (P).*

In the makespan minimization scenario, WOA achieved the lowest completion time (1233 minutes), slightly outperforming FA (1235 minutes) and clearly outperforming the heuristics. Conversely, in the idle time minimization scenario, WOA produced the most efficient oven usage (615 minutes idle), followed by FA (833 minutes). These results indicate WOA's strength in focused single-objective search.

For the Pareto-based scenario, FA obtained the best overall trade-off solution with 1233 minutes of makespan and 1776 minutes of idle time. The results highlight that WOA tends to perform best under single-objective goals, while FA excels in balancing multiple objectives.

These findings are visually reinforced in Figure 3, where the makespan and idle time metrics are plotted for each method and optimization strategy. This comprehensive comparison confirms the practical benefit of adopting metaheuristic strategies in small-scale, no-wait production settings.

4.2 Summary of Optimization Results

To validate the observed performance improvements, paired-sample t-tests were conducted to compare heuristic results against metaheuristic outcomes across all three optimization scenarios. Each test evaluated whether the reductions in makespan and oven idle time achieved by FA and WOA were statistically significant at a 95% confidence level.

The results confirm that the improvements were statistically significant for both performance metrics. In makespan minimization, both FA and WOA yielded significantly lower completion times than FIFO and SPT. In the idle time minimization experiment, metaheuristics again outperformed heuristics with strong statistical support. The Pareto-based results further reinforced the overall advantage of metaheuristic approaches in producing high-quality, balanced solutions.

These statistical findings support the rejection of the null hypothesis and affirm the effectiveness of metaheuristic methods in optimizing scheduling performance under realistic production constraints.

5. Discussion

The experimental findings offer strong evidence of the advantages provided by metaheuristic scheduling methods over traditional heuristics in small-scale, resource-constrained production environments. Across all three optimization scenarios: makespan minimization, idle time minimization, and Pareto-based multi-objective optimization, both Firefly Algorithm (FA) and Whale Optimization Algorithm (WOA) consistently produced superior schedules.

In single-objective optimization, WOA achieved the lowest makespan (1233 minutes) and the lowest idle time (615 minutes) when each objective was targeted independently. These results indicate WOA's strength in intensification and its ability to converge on high-quality solutions within a focused search. FA also performed competitively, particularly in makespan optimization, delivering improvements over both FIFO and SPT baselines.

In the multi-objective scenario, where makespan and idle time were jointly optimized, FA delivered the best overall trade-off, achieving 1233 minutes of makespan and 1776 minutes of idle time in its best run. This highlights FA's capability in maintaining diversity and exploring the solution space effectively under conflicting objectives.

To further understand the consistency and robustness of each method, Figure 4 presents the distribution of scheduling performance metrics across 10 independent runs of FA and WOA. The boxplots show both the variability and the central tendency of makespan and oven idle time.

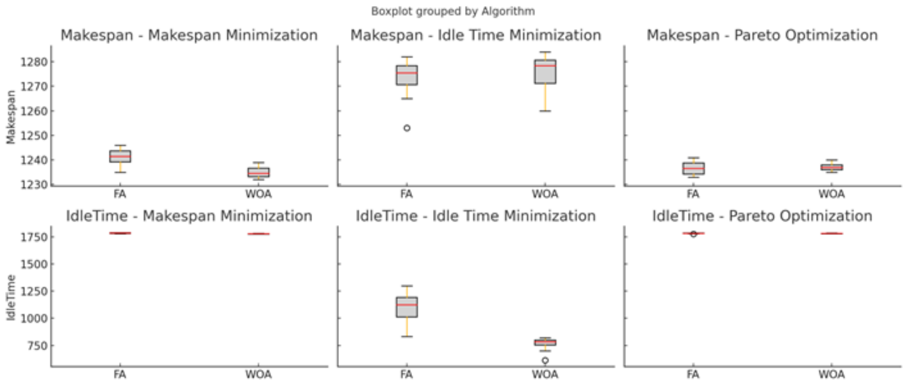

Figure 4: *Distribution of FA and WOA performance across 10 runs.*

In the makespan minimization scenario, WOA exhibits lower variance and a slightly better median makespan than FA, confirming its effectiveness and consistency for this objective. For idle time minimization, WOA also demonstrates superior performance with significantly lower idle time values and a more compact distribution, indicating strong suitability for oven efficiency optimization.

In the Pareto-based multi-objective scenario, FA achieves better trade-offs, with lower median values for both makespan and idle time. This supports earlier observations that FA is more capable of maintaining balanced solutions under competing objectives.

These results reinforce the earlier findings that WOA is well-suited for focused, single-objective optimization, while FA provides more balanced solutions in multi-objective contexts. Statistical hypothesis testing confirmed the significance of these improvements. Paired-sample t-tests showed that the differences between heuristic and metaheuristic methods were statistically significant at the 95% confidence level across all scenarios. These findings support the conclusion that metaheuristic algorithms are not only more effective in practice but also offer statistically reliable enhancements in both completion speed and resource utilization.

Overall, the results demonstrate that FA and WOA are practical, adaptable, and high-performing alternatives to rule-based heuristics, with the flexibility to suit different production goals. For small-scale enterprises aiming to improve efficiency without major system overhauls, metaheuristic scheduling provides a compelling and scalable solution.

While the empirical results offer clear support for the proposed metaheuristic approach, it is also important to reflect on the methodological assumptions and contextual boundaries that may influence its broader application. The following considerations highlight areas for refinement and extension.

First, the present study focuses on the application of individual metaheuristic algorithms. However, recent advancements in hybrid and adaptive scheduling approaches suggest promising avenues for further performance improvements. Hybrid algorithms that combine metaheuristics with local search techniques, adaptive parameter tuning, or hyper-heuristic strategies have shown strong potential in various production environments. Future research may explore whether combining the exploration strength of WOA or the multi-objective capability of FA with adaptive or hybrid components could yield superior results in complex bakery scheduling contexts.

Second, one important modeling assumption in this study is the strict no-wait constraint between mixing and proofing stages. This constraint was adopted to accurately mirror the workflow observed in the studied bakery, where continuous dough processing is necessary to preserve fermentation quality. However, in broader SME bakery settings—especially those with manual or semi-automated processes—minor delays between stages may naturally occur. Relaxing the no-wait constraint could enhance model generalizability and allow for greater adaptability under real-world uncertainties such as labor availability or equipment sharing. Future work may explore the effect of partial-wait conditions on the performance of metaheuristic algorithms and their ability to accommodate less rigid workflows.

Finally, it is important to acknowledge that the case study used in this research is based on a single small-scale bakery in Indonesia. While the modeled scenario captures common operational patterns in SME bakery production—such as semi-manual workflows and shared equipment—the diversity of bakery operations across different regions may limit the direct generalizability of these findings. Factors such as batch sizes, layout constraints, labor practices, or cultural variations in product mix could influence scheduling dynamics. Future research should therefore consider cross-validation using data from multiple bakeries with varying capacities and operational characteristics to evaluate the scalability and adaptability of the proposed approach.

6. Conclusion

This study investigated the application of metaheuristic algorithms to a no-wait flexible flow shop scheduling problem, using a real-world case of an artisan bakery with shared equipment and semi-manual operations. Two heuristic baselines (FIFO and SPT) were compared with two bio-inspired metaheuristics: Firefly Algorithm (FA) and Whale Optimization Algorithm (WOA), across three optimization scenarios: makespan minimization, idle time minimization, and multi-objective trade-off.

The results demonstrate that metaheuristics consistently outperformed heuristics in all scenarios. WOA delivered the best performance in single-objective runs, achieving the lowest makespan (1233 minutes) and the lowest idle time (615 minutes). In multi-objective optimization, FA produced the most balanced solution, achieving a strong trade-off between the two criteria. Statistical testing confirmed that the improvements achieved by metaheuristics were significant at the 95% confidence level.

These findings validate the potential of metaheuristic scheduling as a practical and scalable alternative for small-scale production environments. Their flexibility in targeting specific objectives or balancing trade-offs makes them especially suitable for resource-constrained SMEs seeking to improve production efficiency without major capital investments.

Importantly, the optimized scheduling solutions produced in this study will be implemented as the decision-making logic of an autonomous agent within an agent-based production scheduling system currently under development. This integration enables real-time, adaptive scheduling capabilities for SME bakeries, further enhancing system responsiveness and operational efficiency.

Future research may incorporate additional real-world factors such as operator availability, stochastic job arrivals, or energy constraints, and may explore hybrid or adaptive algorithmic strategies to further boost performance. Beyond its technical contributions, this study supports broader sustainability goals by enabling better utilization of energy-intensive equipment through intelligent scheduling. The approach aligns with SDG 9 (Industry, Innovation and Infrastructure) and SDG 12 (Responsible Consumption and Production), contributing to more responsible and efficient production systems in the SME sector.

Future research may incorporate real-time operational factors such as fluctuating energy prices, worker availability, or machine reliability to further enhance the practical applicability of the proposed scheduling system. These variables reflect real-world uncertainties often faced by SME bakeries and could be modeled through dynamic simulation or adaptive control strategies. Additionally, the integration of hybrid metaheuristics or learning-based approaches, such as reinforcement learning or hyper-heuristics, offers a promising direction for improving performance under complex and evolving conditions. Interdisciplinary collaboration with energy analysts, behavioral scientists, and systems engineers will be essential in extending the scope and realism of the proposed framework.

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