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DIGITAL TWIN OPTIMIZATION APPROACH FOR FLEXIBLE MANUFACTURING SYSTEM SCHEDULING

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ABSTRACT

To remain competitive in an evolving market, enterprises must adopt modern approaches in their production lines. Flexible Manufacturing Systems (FMS) produce diverse, high-quality products with short processing times. New technologies have transformed manufacturing. Among them, Digital Twin (DT) technology improves decision-making through real-time simulations. Most studies on FMS focus on reducing makespan. This paper proposes a model optimizing the makespan and energy consumption and production costs. It also presents a DT framework with a physical and virtual part connected in real time. The framework includes production data, optimization, scheduling, and learning. Two experiments are conducted. The first uses Simulated Annealing (SA) to minimize makespan. Results show that SA is flexible, finding different schedules with the same makespan. The second applies Archived Multi-Objective Simulated Annealing (AMOSA) to optimize makespan, production cost, and energy consumption. Results show that AMOSA provides better trade-offs between objectives, making it effective for complex FMS.

1 INTRODUCTION

Industry 4.0 and smart manufacturing have transformed the way production is carried out. They are relied on advanced technologies such as simulation, cyber-physical systems, the Internet of Things (IoT), cloud computing, and artificial intelligence (AI). These systems are interconnected and communicate in real time, allowing them to analyze data and make decisions without human intervention. Smart manufacturing enhances productivity by integrating automation, robotics, and machine learning. The ultimate goal is to make production processes faster, smarter, and more efficient (Bin Touhid et al., 2023).

The Digital Twin (DT), introduced in 2002, is defined as *"a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level."* It connects the physical and digital worlds, using real-time data to predict system behavior, improve monitoring, and support decision-making. DT reduces risks and costs, enhances security and efficiency, and improves product quality. For example, according to Simio (2024), The digital twin system at Siemens' Amberg Electronics Plant has led to a 30% decrease in operational costs and a 50% reduction in time-to-market. By creating virtual models of factories and machines, it enables better planning and early problem detection (Mazumder et al. 2023; Grieves 2016; Segovia & Garcia-Alfaro 2022; Soori et al. 2023). Furthermore, Flexible Manufacturing Systems (FMS) are known as advanced production technologies. According to Ruiz et al. (2009), "*An FMS is a production system where a discrete number of raw parts are processed and assembled by controlled machines, computers and/or robots. It generally consists of a number of machine tools, robots, material handling, storage systems and computers*". FMS use automation and smart control systems to adapt quickly to production changes, reduce inventory, and improve efficiency. They also lead to lower space and equipment costs while enhancing product quality.

Combined with Digital Twin (DT), FMS can be monitored and optimized in real time (Zhang et al., 2023; Kaushal et al., 2016; Soleymanizadeh et al., 2023).

In recent years, many studies have examined DT applications in FMS and other systems like job shops and flexible job shops. Research on FMS scheduling has also grown, but it often focuses solely on minimizing makespan, with limited attention to production cost and energy consumption. Yet, optimizing all of them is crucial for complex systems like FMS. Several DT frameworks have been proposed (see Table 1), covering system modeling, virtual representation, scheduling, data acquisition, and product-process information. However, important aspects are frequently neglected, such as prognostics, which predict potential failures using real-time data; health management, which ensures continuous monitoring and timely intervention; user interface, which enables effective human interaction with the system; and learning modules, which help to improve system performance by learning from past data. This paper presents three main contributions. First, it introduces a multi-objective optimization approach that simultaneously minimizes makespan, production cost, and energy consumption. Second, it proposes a DT framework to enhance both optimization performance and maintenance scheduling. Third, it validates the proposed approach through two experimental studies: one focused on makespan reduction and the other on multi-objective optimization. The remainder of this paper is organized as follows. Section 2 provides a review of related work. Section 3 describes the case study and presents the mathematical model. Section 4 outlines the proposed Digital Twin framework. Section 5 presents the experimental setup and discusses the results. Finally, Section 6 concludes the paper and suggests directions for future research.

Table 1: Summary of existing frameworks (M: Machines, PI: Production Information, PD: Product data, AT: Acquisition technologies, SM: Simulation model, O: Optimization, PHM: Prognostic and Health Management, MD: Model data, KB: Knowledge base, LM: Learning module, UI: User Interface).

References	M	PI	PD	AT	SM	O	PHM	MD	KB	LM	UI
Coito et al. (2022)				X	X						
Magalhães et al. (2022)	X			X	X				X		X
Li and Chen (2023)	X	X	X	X	X	X		X			
Yan et al. (2021)	X				X				X		
Wang et al. (2023)	X	X	X	X	X	X			X		
Liu et al. (2022)	X	X			X	X	X		X		
Wang et al. (2022)	X				X		X		X		
Chen et al. (2023)	X			X	X	X		X			
Gao et al. (2024)	X	X		X	X			X	X		
Ouahabi et al. (2025)	X				X	X			X		
Fang et al. (2019)	X	X	X	X	X	X					
Li et al. (2023)	X	X	X		X	X	X	X	X		
Tarek et al. (2023)	X	X	X		X	X	X	X	X		X
Kim et al. (2025)	X				X	X			X		
Tarek et al. (2025)	X	X	X	X	X	X					X
This paper	X	X	X	X	X	X	X	X	X	X	X

2 RELATED WORKS

2.1 Digital twin optimization for Flexible Manufacturing System

Numerous studies have applied DTs to FMS. Fan et al. (2021) proposed the GHOST framework for simulating large-scale production. Coito et al. (2022) and Magalhães et al. (2022) focused on robotic systems, optimizing makespan and surface quality. Neto et al. (2023) validated DT flexibility in a real manufacturing plant. Li and Chen (2023) tackled makespan, production cost, and carbon emissions via metaheuristics. Other contributions addressed specific challenges such as bottlenecks and human-machine interaction (Florescu 2024), modular integration (Sobottka et al. 2024), KPI benchmarking (Ullah and Younas 2024), and real-time tracking with AI (Ullah et al. 2025). However, most of these approaches focus on single objectives, primarily makespan, and rely on offline or static optimization. Few integrate real-time decision-making or simultaneously address energy and cost. Additionally, scalability and robustness in dynamic DT environments remain underexplored.

2.2 Digital twin optimization for other manufacturing systems

While Flexible Manufacturing Systems (FMS), Flexible Job Shops (FJSP), and traditional Job Shops (JSP) share similarities in managing diverse production tasks, they differ significantly in flexibility and structure. FMS typically integrates machines and automated handling, FJSP allows routing flexibility through alternative machines, and JSP follows a fixed sequence of operations. The following subsections examine DT applications across these variants.

2.2.1 Digital Twin Optimization for Flexible Job shop

DT applications in Flexible Job Shops have largely focused on makespan optimization using various techniques. (Yan et al. 2021; Yan et al. 2022) used genetic algorithms (GA) and double-layer Q-learning. Liu et al. (2022) combined reinforcement learning with GA. Huo and Wang (2022) and Wang et al. (2023) addressed machine load and energy using Flexsim simulator bio-inspired and heuristic algorithms. Chen et al. (2023) extended the objectives to include production cost, emissions, and customer satisfaction. Some recent works (Gao et al. 2024; Ouahabi et al. 2025) applied evolutionary and deep learning approaches to enhance performance and reliability. These methods, though innovative, often require high computational resources and complex parameter tuning. Their real-time applicability is limited, and multi-objective trade-offs—particularly involving cost and energy—are rarely addressed simultaneously.

2.2.2 Digital Twin optimization for Job shop

DT optimization in Job Shops has explored various multi-objective and heuristic methods. Fang et al. (2019) used NSGA-II to optimize time, cost, and delivery under rescheduling. Li et al. (2023), Tarek et al. (2023), and Tarek et al. (2025) applied Grey Wolf Optimization and GA for makespan and deviation minimization. Ahmadi-Javid et al. (2023) used exact methods like constraint programming and MILP to reduce makespan. Other studies adopted custom heuristics (Zupan et al. 2024; Serrano-Ruiz et al. 2024), deep learning (Kim et al. 2025), or hybrid metaheuristics such as particle swarm optimization with variable neighborhood search (Javaid and Ullah 2025). While effective for static scenarios, many of these approaches are computationally intensive and difficult to scale. Exact methods lack flexibility for dynamic environments, and few studies evaluate performance under real-time constraints or system disruptions.

2.3 Flexible Manufacturing System scheduling: recent works

In recent years, many studies have addressed FMS scheduling through various objectives and methods. Jerbi et al. (2022) optimized mean flow time, WIP, throughput, and transfer times using Arena simulator and multi-criteria methods. Xu and Chen (2022), Li et al. (2022), Bao et al. (2023) and Prasad and Rao (2022) applied GA, black widow, or time Petri nets with A* to improve makespan. Devi et al. (2022) and Nabavi et al. (2023) used hybrid metaheuristics such as flower pollination and simulated annealing to reduce idle time, penalty costs, and machining costs. Vlachos et al. (2022), Bozoklar and Yılmaz (2023), and Casella et al. (2024) focused on system performance and workload balancing through IoT evaluation, simulation, and the bat algorithm. Prayagi et al. (2023), Ashraf et al. (2023), and Ismayyir et al. (2024) used various dispatching rules, heuristics (NEH, SPT), or bio-inspired methods to enhance makespan and cycle time. Samsuria et al. (2023; 2024a; 2024b) applied GA, fuzzy approaches, and tabu search to minimize makespan respectively. Sagar et al. (2024) and Beigi et al. (2024) considered energy consumption, tardiness, and production-related costs. Waseem and Chang (2023), Masmali (2024), and He et al. (2024) addressed robustness against disruptions, learning-based recovery, and breakdown management. Pasha et al. (2024) improved lead time, capacity, and productivity using response surface methodology. Despite this diversity, many works focus on static scheduling and lack integration into DT frameworks. Trade-offs between objectives are often not explored, and comparisons between different techniques are seldom provided. Real-time adaptability and scalability remain key limitations.

Overall, most existing research in manufacturing optimization focuses on single objectives such as makespan, often overlooking energy consumption and production costs. This study addresses these limitations by introducing a simulation-based multi-objective optimization approach using AMOSA, integrated within a digital twin (DT). The proposed method allows for real-time adaptability while simultaneously optimizing makespan, energy usage, and cost, making it well-suited for complex and dynamic manufacturing environments.

3 PROBLEM DESCRIPTION

This study addresses a multi-objective job-shop scheduling problem within an FMS, aiming to optimize three performance criteria: makespan, production cost, and energy consumption. The system under study is based on the work of Bao et al. (2023) and consists of eight machines: two horizontal machining centers, one four-axis machining center, two three-axis machining centers, and three CNC lathes. A total of twelve parts (jobs) must be processed in this system. These parts include four boxes, three cylinders, three casings, and two liquid cool plates. Each part follows a fixed sequence of four operations, and each operation is assigned to only one eligible machine capable of processing it. The objective is to determine both the assignment and scheduling of these operations on the available machines in such a way that the makespan, total production cost, and energy consumption are minimized. All machines and jobs are assumed to be available at time zero. For this study, several assumptions are made. First, each operation is assumed to have a fixed and known processing time. Transport times between machines are neglected to reduce complexity. It is also assumed that each machine can process only one operation at a time. Finally, machine breakdowns and interruptions are not considered. The model involves the decision of assigning each operation to a specific machine and determining its start and completion times, while ensuring that technological precedence is respected and that no overlapping occurs on any machine. The makespan, denoted by C_{max} is defined as the maximum completion time among all operations across all jobs and machines. In other words, it represents the finishing time of the last operation completed in the entire system, which aligns with classical definitions in job-shop scheduling. The variables are highlighted in Table 2.

Table 2: Variable description.

Symbol	Definition
N	Number of jobs
J	Number of operations
M	Number of machines
i	Index of job/part $i = 1\ldots, N$
j	Index of operation $j = 1\ldots, J$
k	Index of machine $k = 1\ldots, M$
O_{ij}	The jth operation of job i
p_{ijk}	Processing time of operation Oij on machine k
S_{ijk}	Start time of operation Oij on machine k
C_{ijk}	Completion time of operation Oij on machine k
Pw_{ijk}	Processing power of operation Oij on machine k
K_{ijk}	Processing cost of operation Oij on machine k
Ip_k	Idle power of machine k
T_k	Idle time of machine k
C_{max}	Makespan
K	Production cost
E	Energy consumption
X_{ijk}	= 1, if operation O_{ij} is processed on machine k;

	= 0, otherwise

The following mathematical model aims to minimize the makespan, energy consumption, and production cost. This model was inspired from the works of (Li and Chen 2023; Wang et al. 2023).

$$f = \min(C_{max}, K, E) \quad (1)$$

Subject to

$$C_{max} = \max_{i,j,k}(C_{ijk}) \quad (2)$$

$$K = \sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{k=1}^{M} K_{ijk} * p_{ijk} * X_{ijk} \quad (3)$$

$$E = \sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{k=1}^{M} Pw_{ijk} * p_{ijk} * X_{ijk} + \sum_{k=1}^{M} Ip_k * T_k \quad (4)$$

$$C_{ijk} = S_{ijk} + p_{ijk} * X_{ijk} \quad (5)$$

$$T_k = C_{max} - \sum_{i=1}^{N}\sum_{j=1}^{J} p_{ijk} * X_{ijk} \quad (6)$$

$$C_{ijk} - C_{i(j-1)k} \geq p_{ijk} \quad (7)$$

$$C_{ijk} \leq S_{i(j+1)k} \quad (8)$$

$$\sum_{k=1}^{M} X_{ijk} = 1 \quad (9)$$

$$X_{ijk} \in \{0,1\} \quad (10)$$

Equation (1) is multi-objective function. Equations (2), (3), and (4) represent the makespan, production cost, and energy consumption respectively. Constraint (5) calculates the completion time of each operation j of job i in machine k. Constraint (6) determines the idle time of each machine k. Constraints (7) and (8) determine the precedence constraint between each operation of job i. Constraint (9) requires that each operation must be processed by one machine only. Constraint (10) represents the range of the variable X_{ijk}.

4 DIGITAL TWIN FRAMEWORK FOR FLEXIBLE MANUFACTURING SYSTEM

This Section presents the Digital Twin (DT) approach developed for the studied Flexible Manufacturing System (FMS). As noted in the introduction and illustrated in Table 1, certain DT modules—such as Prognostics and Health Management, User Interface, and Learning—remain underexplored. Moreover, an analysis of existing frameworks (Table 1) highlights a gap in the integration of execution-related aspects of the physical system, particularly in the context of FMS. In our previous work (Sid-Lakhdar et al., 2024), we introduced a DT framework for FMS (DT-FMS), focusing on essential aspects of smart manufacturing, including interconnectivity, machine learning, and simulation-based optimization. While that work outlined the structural design of the DT-FMS, it did not fully address the feedback loop between the physical and virtual components. Additionally, rescheduling capabilities in response to disruptions such as machine failures were only partially considered. In this study, we propose a more comprehensive and responsive DT framework that addresses these limitations. The updated framework emphasizes bidirectional data flow between the digital and physical environments, incorporating detailed feedback on processing times, machine availability, product specifications, optimization outcomes, and scheduling schemes. It builds upon previous contributions by Fang et al. (2019), Tarek et al. (2023), and Sid-Lakhdar et al. (2024). The enhanced DT framework is illustrated in Figure 1.

As shown in Figure 1, the framework establishes a real-time connection between the physical and virtual layers, enabling continuous monitoring, dynamic optimization, and informed decision-making. The primary objective is to enhance three key performance indicators: makespan, production cost, and energy consumption. The physical part represents the actual manufacturing system, specifically the flexible automated production line described in Sid-Lakhdar et al. (2024). It includes various components such as machining centers, CNC lathes, storage units, material handling systems, and control devices. This layer collects a wide range of process data—such as scheduling information, setup times, workloads, transport activities, and maintenance events—as well as product-related data including types, costs, assembly steps, and component lists. A crucial component of the system is the Acquisition Technologies module, which uses Industrial Internet of Things (IIoT) devices and smart sensors to capture and transmit real-time data. This data is sent immediately to the virtual part, where it is processed for analysis and optimization (Sid-Lakhdar et al. 2024). A key enhancement in this framework is the inclusion of the Scheduling Execution module within the process data layer. This module receives the optimal scheduling plan generated by the simulation-based optimization engine. The schedule defines the best configuration for minimizing makespan, production cost, and energy consumption (Fang et al. 2019), and is transferred to the Resources module for execution. Upon execution, real-time updates from the physical system are sent back to the virtual model to maintain synchronization and enable adaptive decision-making. The execution of the optimal schedule in the physical environment is ensured through real-time communication protocols, such as OPC UA and MQTT, which allow seamless and instant data exchange. These protocols enable the physical system to report execution outcomes and status updates in real time, while the virtual system delivers instructions and adjustments without delay.

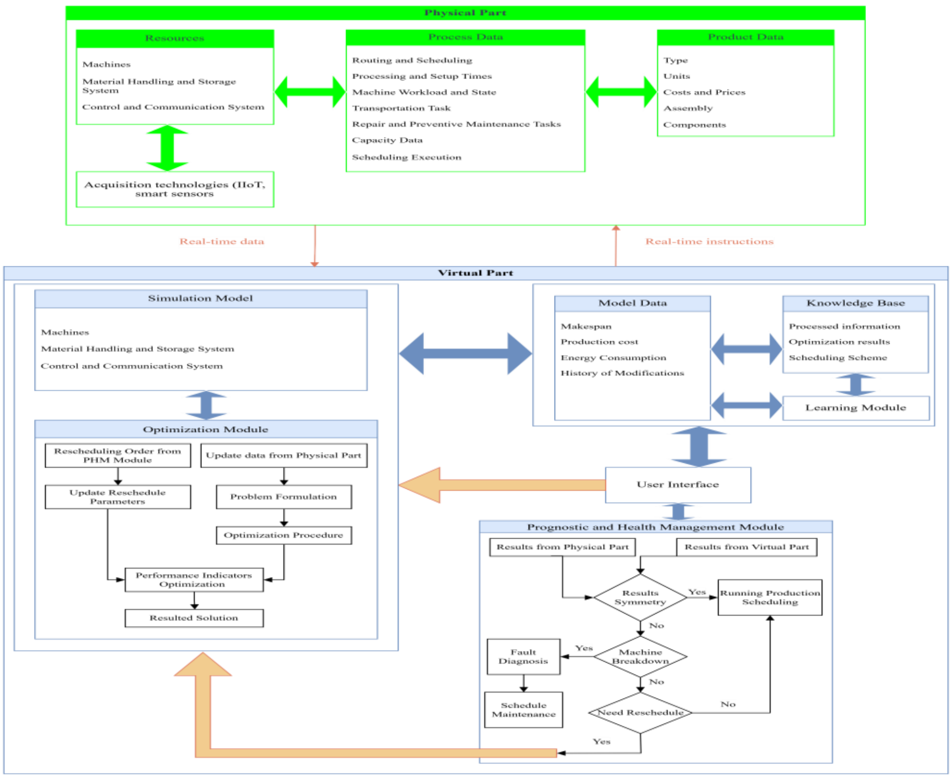

Figure 1: The Flexible Manufacturing System – Digital Twin framework.

The Virtual Part acts as a digital replica of the physical system, enabling real-time analysis, prediction, and decision-making. It includes a simulation model that mirrors real-world operations using simulation software, as described in Sid-Lakhdar et al. (2024). The Model Data module continuously monitors key performance indicators such as makespan, production cost, energy consumption, and tracks historical changes. The Knowledge Base supports decision-making by storing optimization results, scheduling schemes, and system insights. The Learning module leverages historical data to enhance system performance over time and strengthen operational resilience (Sid-Lakhdar et al., 2024). At the core of this virtual environment is the Optimization module, which dynamically adjusts scheduling parameters to improve the system's efficiency and responsiveness. This process follows four main steps adapted from Tarek et al. (2023): Step 1: Define the optimization objectives, assumptions, and constraints, as outlined in the previous Section. Step 2: Collect and structure relevant data, including job and operation details, machine eligibility, processing times, and power consumption parameters. Step 3: Apply an optimization algorithm to minimize the multi-objective fitness function, which includes makespan, production cost, and energy consumption, and generate the optimal schedule. Step 4: If necessary, update input parameters and refine the schedule accordingly. To further enhance system reliability, the framework integrates a Prognostics and Health Management (PHM) module, based on Tarek et al. (2023). This module compares real-time performance data from both the physical and virtual parts. If the measured and simulated results match, the system proceeds without intervention. In case of discrepancy, the system first checks for potential equipment failures. If a failure is detected, a fault diagnosis is triggered, the user is notified, maintenance is scheduled, and the faulty machine is removed from the production schedule. If no failure is found, the system determines whether rescheduling is needed based on updated performance conditions. Thanks to real-time communication protocols, all adjustments—whether due to optimization or maintenance—are applied instantly. Once the optimization module generates a new scheduling solution, a forward simulation is performed to assess its dynamic feasibility with respect to the current state of the physical system. This step ensures that the schedule remains executable, especially in the presence of real-time changes such as machine failures or unexpected delays. If the simulation confirms feasibility, the schedule is transmitted to the Physical Part for execution. Execution feedback is then returned to the Virtual Part for monitoring and continuous improvement. All updated results, including the optimization outcomes and revised scheduling schemes, are stored in the Knowledge Base. Finally, all modules are accessible via the User Interface, which allows operators to monitor system status, visualize key performance indicators, trigger optimization routines, and plan maintenance activities as needed (Sid-Lakhdar et al. 2024).

5 EXPERIMENTATION AND RESULTS

To validate our approach, we implemented the proposed mathematical model in Python, based on the case study presented in Section 3, which includes eight machines and twelve jobs, each composed of four operations. We conducted two experiments using metaheuristic algorithms: SA for mono-objective optimization and AMOSA for multi-objective optimization. Both algorithms depend on three key hyperparameters—maximum number of iterations (Max_It), initial temperature (T), and cooling rate (α)—which were carefully tuned to balance exploration and exploitation and enhance solution quality. Specifically, Max_It controls the duration of the search, T influences the acceptance of suboptimal solutions early in the process, and α determines how rapidly the search converges. We also assumed that if the processing time p_{ijk} of an operation is zero, the corresponding operation O_{ij} cannot be assigned to machine k. Two experiments were carried out: the first aimed at minimizing the makespan, while the second targeted a simultaneous reduction of makespan, production cost, and energy consumption. The experimental data used for both experiments are presented in Table 3. Parameters that follow a uniform distribution (UD) are also noted accordingly.

Table 3: Parameters used for both experiments.

Parameter	Distribution	unit	Reference
Processing time	See Bao et al. (2023)	hours	Bao et al. (2023)
Processing power	UD [1.6, 4.6]	kW	Wang et al. (2023)
Idle power	UD [0.7, 2.1]	kW	Wang et al. (2023)
Processing cost	From part 1 to part 4: UD [80, 120] From part 5 to part 7: UD [50, 100] From part 8 to part 10: UD [100, 150] From part 11 to part 12: UD [160, 420]	euro /hour	Zintilon (2023) Kingsun (2024) LongSheng (2025)

5.1 Experiment one: Reducing Makespan

In this first experiment, we perform a mono-objective optimization focused solely on minimizing the makespan of the studied FMS. The optimization is implemented in Python using the SA. Several configurations of SA were tested by varying the hyperparameters Max_It, T, and α. We obtained three distinct scheduling solutions, all achieving the same makespan of 52 hours. The corresponding Gantt charts are presented in Figures 2, 3, and 4. Each solution satisfies all model constraints and is considered feasible and efficient. The first solution was found using parameters (Max_It = 100,000; T = 1,000; α = 0.99), with a CPU time of 12 seconds. The second and third solutions were obtained using (Max_It = 500,000; T =

50,000; α = 0.995), requiring a CPU time of 45 seconds. Although the job sequences differ across these solutions, the final makespan remains unchanged. Machine utilization is high, and idle times are minimal, demonstrating effective resource allocation. These results illustrate the robustness and flexibility of Simulated Annealing, as it is able to identify multiple high-quality schedules with equivalent performance in terms of makespan.

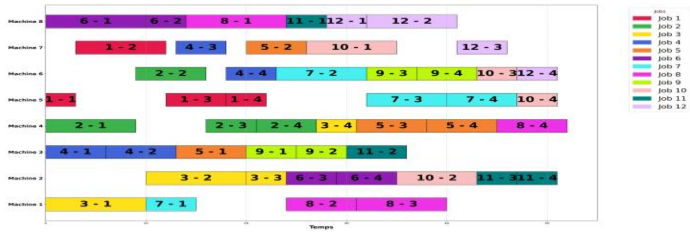

Figure 2: Gantt chart for Solution 1.

Figure 3: Gantt chart for Solution 2.

Figure 4: Gantt chart for Solution 3.

5.2 Experiment two: Reducing Makespan, Production cost, and Energy consumption

In this second experiment, we perform a multi-objective optimization of the studied use case, simultaneously minimizing makespan, production cost, and energy consumption. To this end, we implement AMOSA in Python to solve the proposed mathematical model. Approximately ten independent replications of the algorithm were conducted while varying the same hyperparameters (Max_It, T, and α). Among the generated solutions, we identified three non-dominated schedules, each respecting all model constraints and offering distinct trade-offs among the three objectives. These solutions are summarized in Table 4, and the corresponding Gantt charts are presented in Figures 5 to 7. As illustrated in Table 4 and Figures 5 to 7, these solutions lie on the Pareto front, reflecting optimal compromises between the conflicting objectives. For instance, a schedule with a shorter makespan may incur higher energy consumption or production cost, and vice versa. The final parameter configuration that led to these results is: Max_It = 500,000, T = 50,000, and α = 0.98, with a CPU time of 7 seconds. This experimental setup allowed the algorithm to maintain a good balance between exploration and exploitation. The outcomes clearly demonstrate the effectiveness and flexibility of AMOSA in addressing complex multi-objective scheduling problems, while producing a set of diverse, feasible, and high-quality solutions. It is worth noting that this second experiment builds upon the insights gained in the first one. While the mono-objective scenario helped establish a performance baseline, the multi-objective approach provides a more realistic and comprehensive decision-making framework. It highlights the inherent trade-offs between conflicting objectives, which are crucial for effective production planning in real-world manufacturing environments.

Table 4: Solutions found using AMOSA.

Solution	Solution 1	Solution 2	Solution 3
Makespan (h)	82	69	76
Production cost (€)	37841	42372	35903
Energy consumption (kWh)	1117.2	1113.4	1120.4

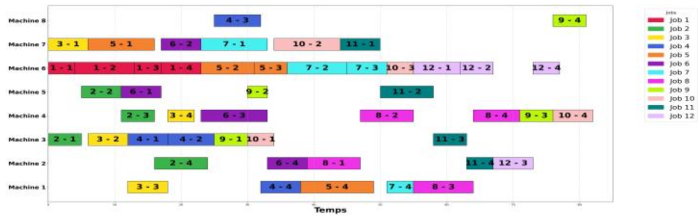

Figure 5: Gantt chart for Solution 1.

Figure 6: Gantt chart for Solution 2.

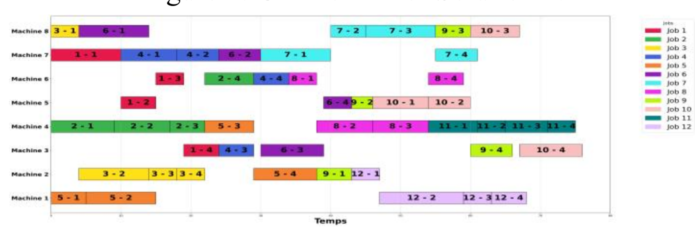

Figure 7: Gantt chart for Solution 3.

6 CONCLUSION

This paper proposes a mathematical model and a DT framework for optimizing an FMS with respect to makespan, production cost, and energy consumption. The DT integrates real-time data flow between the physical and virtual systems to support decision-making and rescheduling. The model was validated via two experiments: a mono-objective optimization using SA, and a multi-objective optimization using AMOSA. The results show that the model produces efficient and feasible schedules, with AMOSA offering well-balanced trade-offs. Future work includes implementing the DT framework on a real FMS, incorporating real-time data from machines, robots, and handling systems. We will also enhance the simulation module to reflect dynamic behaviors (e.g., machine failures, urgent orders) and extend the model to include more stochastic and uncertain events. Although we used metaheuristics like SA and AMOSA for practicality and adaptability, future studies will compare various optimization methods to identify the most suitable ones in dynamic environments. The mono-objective case will serve as a reference baseline in such comparisons.

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