Smart Optimized Scheduling Under Constraints in Industry 5.0 Through Intelligent Computational Methods

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Abstract: Production scheduling has become an integral component of next-generation industrial systems during the era of Industry 5.0, which emphasizes collaboration between humans and machines, sustainability, and hyper-personalization. To address complex scheduling challenges, this paper presents a smart scheduling framework based on metaheuristic optimization tailored for manufacturing environments incorporating 3D printing technologies. The proposed framework addresses several key objectives, including the optimization of energy consumption, efficient utilization of raw materials, and minimization of total production time. By incorporating metaheuristic algorithms such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization, the system demonstrates adaptability to multiple constraints and competing priorities. Experimental evaluations confirm the framework's effectiveness in enhancing operational efficiency, flexibility, and sustainability, in alignment with the core principles of Industry 5.0.

1 INTRODUCTION

With Industry 5.0, manufacturing has entered a new era, where humans-centric design, sustainability, and resilience are now equally important. Instead of focusing solely on smart automation, cyber-physical systems, and IoT integration, Industry 5.0 promotes a symbiotic collaboration between humans and machines. A flexible, adaptive, and intelligent production system is essential in this dynamic environment to meet demand for personalization, real-time responsiveness, environmental responsibility, and flexibility (Ghoujdam,2024).

An important enabling technology of Industry 5.0 is 3D printing, also known as additive manufacturing (AM) (Dehghan,2025). In addition to its ability to allow complex geometries, material efficiency, and minimal tooling, it also supports decentralized, on-demand, and sustainable manufacturing. Integration of 3D printing into broader industrial production workflows, however, presents complex scheduling challenges. There are numerous factors to consider, including variable job geometry, multiple material requirements, fluctuating energy availability, and the need to coordinate dynamically with other production units, including robotic arms, inspection systems, and finishing processes. The traditional deterministic scheduling algorithms are often inadequate in this context since they are poorly suited to cope with multi-objective, combinatorial, and dynamic production in Industry 5.0 (Chen,2024). Consequently, meta-heuristic optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are often considered effective alternatives. In NP-hard problems, these algorithms offer near-optimal solutions within a reasonable amount of time even if the data is incomplete or changing. We propose an intelligent production scheduling framework that uses metaheuristics and artificial intelligence algorithms to intelligently schedule 3D printer jobs in a cyber-physical production environment. It supports the following features:

- Optimization with multiple objectives, including energy efficiency, material use, and production delays.
- Interaction with operators, which allows them to intervene or guide scheduling decisions.

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2 RELATED WORKS

In manufacturing research, particularly in Industry 4.0, the issue of production scheduling has received considerable attention. For scheduling in static environments, linear programming, constraint-based optimization, and heuristic rules have long been used. The growing complexity of modern factories, especially those that use additive manufacturing (AM) often makes these methods unsuitable for real-time, multi-objective optimization. As a powerful tool for solving complex scheduling problems, metaheuristic algorithms have gained a lot of attention in recent years. In industrial scheduling problems, Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO) have been used because they are capable of escaping local optima. Accordingly, [Zhao et al., 2021] applied PSO for optimizing job-shop scheduling under energy constraints, whereas [Li and Wang, 2020] used GA in cloud-based smart factories for dynamic scheduling.

3 PROBLEM DEFINITION AND OBJECTIVES

3.1 Problem Definition

Since 3D printers are becoming increasingly integrated into production workflows, task scheduling has become increasingly difficult. Because 3D printing involves layer-by-layer geometry, extended production times, and high resource sensitivity - particularly filament availability - it presents unique challenges. In addition to static job allocation, scheduling must take into account fluctuating material stocks, tight delivery deadlines, and energy limitations, as well as the continuous influx of customer orders in real-time. The majority of existing research has focused on optimizing makespan and minimizing resource usage in controlled environments, often overlooking the dynamic nature of additive manufacturing. In most models, energy and material consumption are assumed to be constant, disregarding geometry complexity and machine state for their variability. It is also rare for conventional scheduling approaches to accommodate the need to reprioritize tasks in response to incoming orders or real-time disruptions. A novel scheduling framework for 3D printing environments is presented in this paper that takes into account raw material availability, energy constraints, delivery deadlines, and handling of orders in real-time. Using intelligent computational methods, we aim to ensure both operational efficiency and responsiveness in resilient, human-centric manufacturing systems.

3.2 Objectives

Scheduling tasks for 3D printing is aimed at optimizing efficiency, reliability, and quality in the production process. In order to minimize production times (makespan), print jobs must be ordered and allocated effectively across available printers. To accomplish this, machines, materials, and energy must be utilized most efficiently, while idle time and waste must be minimized. Moreover, meeting deadlines and prioritizing urgent tasks are essential to timely delivery. As well as reducing energy consumption and optimizing material usage, sustainability is also dependent on minimizing carbon emissions. A scheduling system must also guarantee a balanced workload among printers, adapt dynamically to unexpected changes such as machine failures or urgent jobs, and minimize setup and transition times. Furthermore, smart scheduling strategies contribute to a robust and efficient workflow for 3D printing by maintaining high product quality (Kantaros,2025).

3.3 Proposed Smart Scheduling Solution

3.3.1 Smart Scheduling Framework

Specifically, the Smart Scheduling Framework aims to optimize task allocation in Industry 5.0 environments through intelligent, modular systems. Dynamically generated task schedules are generated utilizing computational intelligence approaches such as Ant Colony Optimization, Artificial Bee Colony, or Discrete Particle Optimization.

Essentially, the framework consists of four components:

Input Layer: This layer collects information about printing jobs, materials, deadlines, machine availability, and filament types.

Optimisation Engine: Explores scheduling solution space using metaheuristic algorithms. In each algorithm, delays are minimized and filament changes are minimized.

Evaluation Module: This module provides a multi-criteria evaluation system for assessing the quality of the generated schedules (e.g., number of delays, total delay, filament changes, execution time). As a result, operational efficiency and real-time manufacturing goals are aligned.

Decision & Execution Interface: It provides a schedule for 3D printing, which can be re-evaluated or re-optimized in response to unexpected events.

3.3.2 3d Printing Task Scheduler Functional Diagram

The description of 3D Printing Task Scheduler Functional Diagram is provided in figure.1.

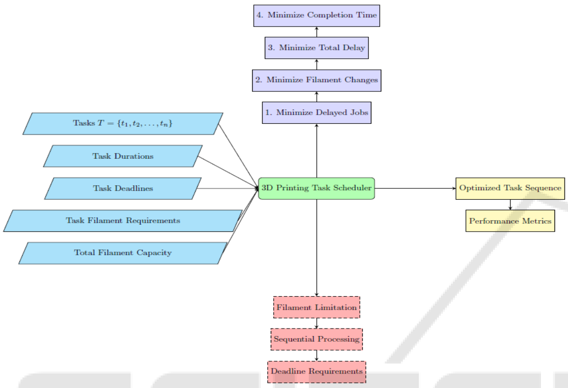

Figure 1: 3D Printing Task Scheduler Functional Diagram.

The diagram illustrates a multi-objective optimization system that balances competing priorities (speed, material efficiency, and deadline compliance) while staying within physical and resource constraints. In additive manufacturing, the arrows illustrate the flow of information from inputs through processing to final outputs.

Inputs:

Tasks T = {t_1, t_2, ..., t_n}: Set of printing tasks to be scheduled Task Durations: Estimated time required for each printing task.
Task Deadlines: Delivery deadlines for each task
Task Filament Requirements: Amount of filament material needed per task
Total Filament Capacity: Total available filament stock/capacity

Central Processing Unit: The 3D Printing Task Scheduler serves as the core optimization engine that processes all input data to generate an optimal printing schedule.

Optimization Objectives: The proposed system is designed to simultaneously optimize four key performance criteria that reflect both efficiency and sustainability in modern manufacturing. First, it seeks to minimize the overall completion time (makespan) in order to accelerate project delivery and improve throughput. Second, it aims to minimize the total delay, thereby reducing cumulative lateness across all scheduled tasks and ensuring smoother operations. Third, the system focuses on minimizing the number of filament changes, which not only shortens material changeover time but also decreases material waste and energy consumption. Finally, it strives to minimize the number of delayed jobs, ensuring that tasks are completed within their respective deadlines to enhance reliability and customer satisfaction.

System Constraints:

The scheduler operates under strict limitations:

Filament Limitations:

Material availability constraints
Sequential Processing: Tasks must be processed one at a time per printer
Deadline Requirements: Hard deadlines that must be respected

Outputs The system generates:

Optimized Task Sequence: The optimal order for executing printing tasks

Performance Metrics: Key performance indicators measuring schedule effectiveness
To ensure consistency and enable fair comparisons, all developed algorithms use a unified implementation framework. As a result of this standardization, all algorithms operate under the same conditions and can be evaluated equally (Figure 2).

Algorithm 1: Unified Job Processing Method.

Require: Job j_i with filament demand f_i and processing time p_i;
    Printer state S_p with `current_time`, `remaining_filament`
Ensure: Updated printer state and job timing information

```
filament_change ← false
if f_i > S_p.remaining_filament then                      ▷ Insufficient filament
    S_p.current_time ← S_p.current_time + T_change         ▷ Reload filament
    S_p.remaining_filament ← S_p.remaining_filament + F_new
    filament_change ← true
end if
start_time ← S_p.current_time
S_p.remaining_filament ← S_p.remaining_filament − f_i
S_p.current_time ← S_p.current_time + p_i
finish_time ← S_p.current_time
return (start_time, finish_time, filament_change)
```

Figure 2: Algorithm to process a job on a printer, updating its timing and filament state.

4 METAHEURISTIC ALGORITHMS USED

4.1 Ant Colony Optimization (ACO)

An Ant Colony Optimization (ACO) algorithm is a powerful metaheuristic algorithm that can be used to assign print jobs to available printers with the best or near-optimal sequence while satisfying a variety of constraints such as time, material availability, and energy consumption in the context of 3D printing task scheduling. The ACO model is based on the foraging behaviour of ants, where each node represents a specific task or decision point (e.g., assigning a job to a printer at a certain time). Pheromone trails (which encode past schedule quality) and heuristic information (such as estimate printing time) are used to allow artificial "ants" to explore different scheduling combinations. Pheromone levels are updated after solutions are constructed to reinforce the paths that lead to better performance - like reduced total production time, balanced printer loads, or lower energy consumption - while allowing less effective paths to fade over time (Sarder,2023).

4.2 Particle Swarm Optimizer (PSO)

For solving optimization problems, PSO uses a nature-inspired, population-based metaheuristic algorithm. Using this method, animal groups such as bird flocks or fish schools can be simulated (Gad,2022). In PSO, each possible solution is modeled as a moving "particle" guided by both its own best position and the best known position found by the swarm. Through these interactions, particles are able to converge towards optimal or near-optimal solutions over time. Each particle's position and velocity are determined by equations that take into account inertia, cognitive properties, and social factors.

4.3 Greedy Algorithm

In Greedy Algorithm, we select the locally optimal choice at each decision point as we build a solution step by step (Zhao, 2021). 3D printing task scheduling algorithms that prioritize immediate gains, such as minimizing machine idle time or start time, utilize greedy algorithms to assign tasks to the earliest available slot and printer. Despite being computationally efficient and able to produce acceptable schedules in very short periods of time, this method ignores the global structure of the problem, resulting in suboptimal long-term results. It may, for example, result in many delays or excessive filament changes due to short-sighted decisions.

4.4 Migratory Bird Optimisation (MBO)

Using the Migratory Bird Optimization algorithm, we can simulate the migration behavior of migratory birds in V-formations using a population-based metaheuristic. This algorithm represents each solution as a "bird" in a formation, with the best performing solution taking the lead. To avoid stagnation, birds periodically change positions based on local and global neighborhood evaluations (Wei,2023). Using MBO, scheduling problems can be balanced between exploration and exploitation, with the aim of finding globally efficient task sequences. Although it avoids extremes, MBO rarely achieves optimal performance in any single metric: in practice, it tends to yield average results across all metrics.

4.5 Discrete Particle Optimisation (DPO)

Particle Swarm Optimization (PSO) is adapted for discrete and combinatorial problems, such as task scheduling, by Discrete Particle Optimization (DPO) (Franzoi,2022). Each particle represents a possible sequence or configuration of scheduled tasks, with the particle's movement determined by discrete operators (e.g., swap, insertion) instead of continuous velocity updates. Using both personal (personal best) and collective (global best) experiences, DPO guides the search for optimal outcomes. While DPO has an intelligent search mechanism, it may suffer from premature convergence or reduced diversity in discrete spaces, reducing its effectiveness when scheduling scenarios are highly constrained. We found that DPO generated a relatively high number of delayed tasks and a high total delay in our experiments, showing that it had difficulty optimizing task sequences under practical constraints.

5 RESULTS AND DISCUSSION

As part of this study, we utilized the Raise3D Pro2 (figure 3), a high-performance Fused Deposition Modeling (FDM) 3D printer that was well-suited for industrial-grade applications. Dual extrusions allow the printer to print multi-materials or colors, which introduces an additional level of complexity in scheduling tasks. A 305 mm x 305 mm x 300 mm build volume allows for the printing of medium to large-sized parts that often require lengthy print times. In addition to standard 0.4 mm nozzles, a range of diameters can be selected based on the throughput required. A wide range of filament types can be used with Raise3D Pro2, including PLA, ABS, PETG, TPU, and Nylon, each of which has its own thermal and handling parameters. It also features a filament run-out detection system and power loss recovery, which enhance the reliability and resilience of the production workflow. A heated bed and enclosed build chamber ensure better print stability, but they also add energy consumption constraints. The printer's integrated touchscreen interface, remote monitoring capabilities, and network and cloud connectivity enable it to communicate with centrally managed or artificially intelligent scheduling systems.

Figure 3: Raise3D Pro2 printer.

5.1 Evaluation of Metaheuristics for 3D Printing Task Scheduling

As part of the evaluation of metaheuristic algorithms for 3D printing task scheduling, a number of key performance metrics were considered to assess both the quality and applicability of the solutions. The key metrics for our framework are filament changes, total delay, and execution time. Delays indicate the system's ability to respect timing constraints, an essential factor in high-speed production. Furthermore, the total delay provides a deeper understanding of the extent of disruptions, even when the number of delays remains low. Material efficiency and machine downtime are also affected by the number of filament changes, which lead to higher operational costs and reduced printer availability. As a final consideration, the algorithm's execution time determines its suitability for real-time or near-real-time scheduling, particularly in Industry 5.0 environments. We gain a comprehensive view of each algorithm’s performance by analyzing these metrics together: some methods reduce total delay but produce excessive filament changes or compute too slowly, while others balance speed, precision, and resource efficiency better. Through table 1 and table 2, we ensure that both technical constraints and industrial objectives are aligned with the scheduling strategy chosen.

Table 1: Evaluation of metaheuristics for 3d printing task scheduling.

Algorithm	No. of Delays	Number of Filament Changes	Total Delay (s)	Execution Time (s)
Greedy	142	38	184,579.709	13,846.793
Artificial Bee Colony	60	37	307,032.071	13,816.793
Migratory Bird Optimisation	67	38	434,737.523	13,846.793
Ant Colony Algorithm	49	38	249,998.075	13,846.793
Discrete Particle Optimisation	89	37	467,556.575	13,816.793

Table 2: Summary Analysis.

Algorithm	Summary Analysis
Greedy	Lowest total delay, but too many individual delays
Artificial Bee Colony	Good trade-off: fast, few delays
Migratory Bird Optimisation	Average performance, not optimal in any specific criterion
Ant Colony Algorithm	Best overall compromise
Discrete Particle Optimisation	Globally inefficient despite good execution time

5.2 Discussion

Based on the comparability of the five algorithms, distinct performance characteristics can be identified in terms of scheduling efficiency, resource optimization, and execution time. It is clear from the Greedy algorithm's results (184,579.709) that it successfully prioritizes task allocation in the short run. Despite this, it exhibits a very high number of individual delays (142), indicating poor robustness in situations with tight deadlines. Compared to other algorithms, the Artificial Bee Colony (ABC) has relatively few delays (60) and the shortest execution time (13,816.793), making it an ideal choice for real-time or near-real-time scheduling in Industry 5.0. The slightly higher total delay (307,032.071) can be attributed to the algorithm's efficiency. There is no clear advantage in any of the metrics in the Migratory Bird Optimization (MBO) algorithm. There is a possibility that its lack of specialization could limit its applicability in situations where specific performance objectives are important (e.g., minimizing delays or changing resource allocations). In terms of global efficiency, the Ant Colony Algorithm (ACO) stands out as the most balanced approach. Providing the best overall balance between delay minimization and stability, it has the least number of delays (49) and a moderate total delay (249,998.075).

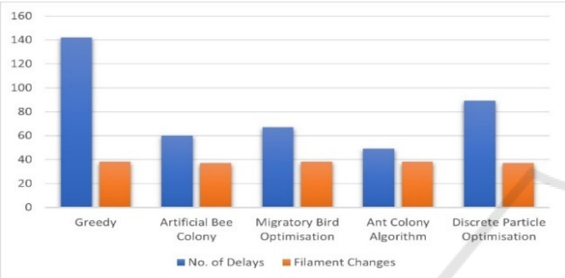

Figure 4: Results of metaheuristic Algorithms.

Thus, it is a good candidate for scheduling systems that are adaptive and dynamic in smart manufacturing. As a result, Discrete Particle Optimization (DPSO), though slightly faster in execution, exhibits a relatively high number of delays (89) and a higher total delay (467,556.575). Despite its speed, it cannot optimize task sequencing effectively, making it less practical for industrial applications requiring quality and timeliness. As a result, the Ant Colony Algorithm is the most robust and consistent approach, followed by the Artificial Bee Colony algorithm, which offers good speed-to-effectiveness tradeoffs. In general, the Greedy and DPSO methods are unreliable. Figure 4 shows these results.

5.3 Results

An overview of the 3D printing job schedule is provided by a Gantt chart, which makes it easy to see which jobs are running, waiting, or finished, and how resources are allocated. The use of this type of visualization helps production managers optimize printer utilization, minimize idle time, and meet deadlines by adjusting job sequences accordingly. A gantt chart in 3D printing scheduling offers several key features that enhance management and planning. Their timelines provide a clear picture of when each job begins and ends. Additionally, they help to understand task relationships and potential conflicts by displaying work dependencies and overlaps. In addition to highlighting current progress and resource usage, Gantt charts facilitate effective monitoring of ongoing jobs. Using this visualization, planners can identify bottlenecks or scheduling conflicts quickly and make interactive adjustments, making it easier to improve efficiency and meet deadlines. Each green bar represents a print job in a horizontal Gantt chart labeled "Print Job Schedule." Each bar corresponds to the job's start and end times on the timeline below, visually identifying when each job begins and ends (Figure 5 and figure 6). Using the chart, you can see how jobs overlap or are sequenced, providing a clear view of the schedule. Users can also track progress in real time by using a "Current Time" marker.

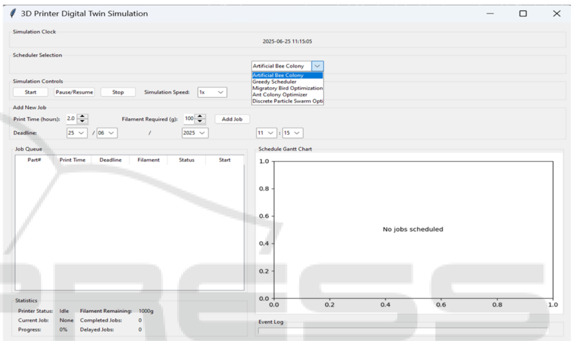

Figure 5: Scheduling interface for 3D printing tasks.

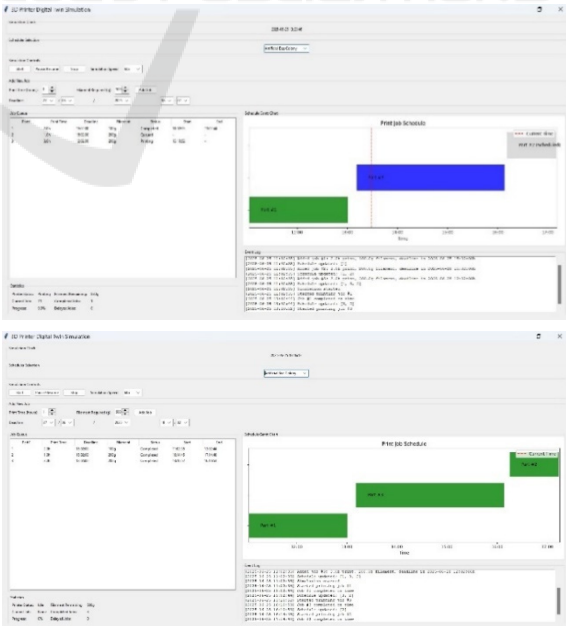

Figure 6: Gantt chart-based scheduling interface for 3D printing tasks.

6 CONCLUSIONS

This study evaluated and compared several metaheuristic algorithms (greedy, artificial bee colony, migratory bird optimization, ant colony algorithm, and discrete particle optimization) for the complex task of scheduling 3D printing operations. Our evaluation relied on four critical performance metrics: number of delays, filament changes, total delay, and execution time. The results demonstrate that no single algorithm excels in all aspects, highlighting the trade-offs between speed, accuracy, and operational efficiency.

Overall, these findings emphasize the importance of multi-criteria evaluation when selecting a scheduling strategy for industry 5.0 systems, where real-time responsiveness, material efficiency, and reliability are key. Future work may explore hybrid metaheuristics, reinforcement learning, or adaptive scheduling frameworks that can dynamically respond to changing constraints and workload priorities in cyber-physical environments. As a perspective for this work, Artificial Intelligence (AI) will play a strong role in enhancing our system. AI techniques can be integrated to model and optimize energy consumption (Nakkach, 2023), (Nakkach, 2024) enabling more sustainable and efficient production planning. Moreover, predictive maintenance based on computer vision and deep learning (Nakkach, 2022) can be employed to detect early signs of wear, anomalies, or defects in machines and 3D-printed parts. Such capabilities will help anticipate failures, minimize downtime, and improve overall system reliability. Together, these AI-driven approaches will reinforce the adaptability, efficiency, and sustainability of cyber-physical production environments in line with the vision of Industry 5.0.

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