

Swarm Intelligence-Driven Dispatching Rules for Large-Scale Semiconductor Production: Integrating Simulation and Optimization to Enhance Operational Efficiency

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Abstract. The escalating complexity of semiconductor production, characterized by high-volume, low-mix and low-volume, high-mix environments, demands advanced dispatching strategies that transcend traditional rule-based systems. This paper introduces a novel set of dispatching rules derived from Swarm Intelligence techniques, specifically designed to tackle the intricate dynamics of large-scale semiconductor manufacturing. The research integrates simulation and optimization methodologies to investigate and enhance operational efficiency, addressing both the scalability of solutions and their practical implementation. We employ a customizable simulation framework to model a semiconductor manufacturing environment, wherein various dispatching rules, including FIFO, CR, RANDOM, and our proposed SI-driven method, are assessed. The core of our approach lies in its ability to adaptively reconfigure scheduling priorities based on real-time production dynamics, thus significantly improving the responsiveness and throughput of manufacturing processes. The effectiveness of these dispatching rules is quantitatively evaluated through a series of simulations that measure key performance indicators such as Work in Progress (WIP) levels, throughput, and operational variability across different production scenarios. This study not only elucidates the potential of swarm intelligence in refining production dispatching but also provides a framework that incorporates scalable simulation tool that can assist in the further development of intelligent dispatching systems.

Keywords: Swarm intelligence · Ant colony optimization · Greedy search · Semiconductor production · Scheduling · Dispatching · Simulation

1 Introduction

Dispatching and scheduling are critical in semiconductor manufacturing because they directly impact the throughput and utilization of resources. Dispatching refers to the

process of assigning work to specific machines in real-time, while scheduling involves pre-planning the sequence and timing of operations to optimize certain objectives, such as minimizing the total completion time or balancing the load across different machines [4].

For smaller volumes at workcenters in the semiconductor fab, which can be modeled as flexible job shops, optimal solutions can be achieved using mathematical optimization [12]. However, in larger and more dynamic environments, the complexity and computational time constraints limit the feasibility of applying mathematical optimization. Consequently, optimization is typically implemented on a local scale, isolated to individual workcenters. In complex scenarios, this localized approach to production scheduling may lead to solutions that are globally sub-optimal.

Dispatching involves determining which job should be performed at which time, by which resource. This decision is based on the availability of resources and the urgency of job orders [2]. However, as production scenarios become more complex, particularly in high-tech industries such as semiconductor manufacturing, the static nature of traditional dispatching rules often proves insufficient. These rules typically do not account for the rapid changes in production conditions or the intricate dependencies between different production processes. Traditional dispatching solutions often fall short in such an environment, as they cannot adequately adapt to the dynamic and complex nature of semiconductor production. This inadequacy can lead to sub-optimal decisions that compromise operational efficiency [3].

The complexity of scheduling in large-scale semiconductor production, a cornerstone of operational management, is significantly influenced by the unpredictable nature of processing times and machine availabilities. Variability in processing times can arise from differences in equipment performance, material handling durations, or the unique characteristics of each set of wafers, while frequent machine breakdowns can cause substantial disruptions, underscoring the need for strong and adaptable scheduling strategies [13]. Scheduling involves meticulously planning and organizing production activities to ensure optimal resource utilization and synchronized product flows across various manufacturing stages, which is crucial not only for maintaining high throughput but also for minimizing makespan [4]. The task is particularly daunting in semiconductor manufacturing due to the high variability in production processes, the sensitive nature of the materials, and stringent quality requirements [5]. Each semiconductor product may pass through hundreds of processing steps, requiring precise timing and coordination. The complexity is further compounded by the need to accommodate a high mix of product types, each with distinct processing needs and priorities, and to integrate new product introductions seamlessly into the production schedule without disrupting ongoing operations [6].

In this paper, we explore the complexities of scheduling within large-scale Semiconductor Manufacturing Scheduling Problems (SMSP), commonly referred to as fabs. Fabs are intricate production settings distinguished by their specialized job flows and advanced machinery. Modern semiconductor fabs manage the processing of tens of thousands of operations daily across over 1000 different machines [1]. These machines are grouped by functionality—such as diffusion, etching, or metrology—and each step in the manufacturing process can be assigned to any machine that offers the neces-

sary capabilities. The scheduling challenge in semiconductor production thus involves assigning specific operations to appropriate machines and determining the optimal sequence of these operations on each machine. Additionally, schedules must be flexible and capable of rapid adjustments in response to machine failures or deviations in the process.

In our previous work [7], we proposed a Greedy Search based Ant Colony Optimization (GSACO) algorithm for (re-)scheduling semiconductor production operations. Our algorithm harnesses Ant Colony Optimization (ACO) [8] for exploration, while Greedy Search (GS) [9] enables responses in short time. In this way, GSACO overcomes limitations of a state-of-the-art Constraint Programming approach [10] on large-scale SMSP instances. Our approach synergistically combines probabilistic operation sequencing with a greedy machine assignment strategy, targeting up to five operations per lot with the primary objective of minimizing makespan. Building on this foundational work, this paper extends these initial concepts by proposing an enhanced approach, GSACO-O, specifically designed to optimize operational throughput in addition to minimizing makespan. This development marks a significant advancement in our methodology, aiming to refine the dispatching rules further through simulation.

The paper is organized as follows. Section 2 provides literature review. In Section 3, we formulate SMSP in terms of the well-known flexible job shop scheduling problem (FJSSP). Our GSACO-O algorithm is presented in Section 4. In Section 5 we present the customized simulation adopted from [11]. Section 6 provides and discusses experimental results. Finally, Section 7 concludes the paper.

2 Literature Review

We briefly survey the relevant literature on the challenges inherent in SMSP, a sector marked by its complex operational dynamics and the critical need for highly efficient dispatching systems. Semiconductor production processes are characterized by their high variability, sophisticated product mixes, and stringent quality demands, which collectively necessitate innovative approaches to production scheduling and dispatching. Later, we survey the relevant literature on methods for FJSSP, which we use as general scheduling model to represent semiconductor production processes and SMSP. Then we explore the traditional dispatching methods detailing their advantages and limitations within the context of semiconductor fabrication facilities. These conventional methods form the baseline against which the efficacy of advanced dispatching techniques, particularly those driven by Swarm Intelligence (SI), are evaluated. Furthermore, the review will cover essential performance metrics traditionally used to assess the effectiveness of dispatching rules.

2.1 Semiconductor Manufacturing Scheduling Problem (SMSP)

Semiconductor manufacturing is characterized by its complex multi-step fabrication process, each involving highly precise and controlled conditions. The fabrication of semiconductor devices often requires hundreds of steps during the photolithography,

etching, and chemical deposition phases, among others. This complexity is compounded by the requirement for extremely clean environments to avoid contamination of the microscopically small circuits, making operational excellence a challenging goal [5].

Unlike other manufacturing industries that produce a limited range of products, semiconductor manufacturers typically deal with a high mix of products on the same production line. This high mix coupled with the rapid product evolution typical of the tech industry results in significant fluctuations in production volumes. Manufacturers must, therefore, be highly responsive to changes in demand and technology without compromising on the speed or quality of production .

The SMSP is a complex and critical challenge to optimize scheduling tasks during the manufacturing process of a semiconductor. Different methods have been adopted for a long time for varied types of machines [15]. The core aspects include job scheduling, batch processing, priority constraints, setup times of the machine, machine availability, and reentrant flow. The key challenges stay with complexity, dynamic job arrivals, and reducing downtime while maximizing throughput [18]. Many researchers and developers have been working on the topic and suggested their methods to solve the problem.

2.2 Flexible Job Shop Scheduling

Considering the manufacturing industry, FJSSP is a common problem, especially for small batch and custom productions. The mathematical models allow us to solve the optimality issue for small-scale instances. As [19] explains, it is important to assign the FJSSP on a machine in a particular sequence. As the optimization criteria need the start time of all the operations, it is important to optimize the completion time also. The most suitable approach to solve this time problem depends on the function and the mathematical properties associated with it. Researchers also explained that many studies are optimizing non-regular criteria that require equal efforts for timing decisions to get the best sequencing decisions in solution approaches.

The study [20] explained that the existing methods to solve NP-hard combinatorial optimization problems are either exact or approximate. The exact methods are challenging to solve FJSSP when problems need large-size scheduling. Considering their NP-hardness, it is difficult to allocate reasonable time. [20] have also explained that FJSSP instances intractability is in constant need of more approximate methods. So many solutions like machine learning techniques, heuristics, meta-heuristics methods, and more are continuously being developed to tackle real-world problems more effectively.

2.3 Ant Colony Optimization

ACO is a meta-heuristic algorithm that mimics the foraging behavior of ants [23]. It was originally devised to solve the traveling salesperson problem [24], and meanwhile ACO has been adopted to various optimization problems, including routing [25], scheduling [26], task allocation [27], project planning [28], and network optimization [29].

ACO is a well-suited metaheuristics algorithm to solve SMSP as it is highly appropriate to handle the dynamic and complex nature of semiconductor scheduling with its

multi-objective nature [21]. ACO has a history of application to be applied to SMSP for wafer scheduling to balance the load and minimize the makespan. The dynamic nature of the ACO algorithm continuously updates the “pheromone” based on the completed jobs, and guides others to follow the optimal scheduling decisions, ultimately making the system reduce their decision-making time [22].

The common idea is that artificial ants construct paths through a graph, making probabilistic decisions based on problem-specific heuristic information as well as temporary pheromone trails that indicate promising search directions. Particular strengths of ACO lie in the high potential for parallelization, given that ants can be simulated in parallel, and a certain robustness against getting stuck in local optima, as the probabilistic decision rules of ants promote exploration. However, a specific difficulty in the ACO algorithm design concerns the tuning of hyperparameters, such as the number of ants to consider, the trade-off between heuristic information and pheromone trails, and the pheromone evaporation rate.

Among meta-heuristic FJSSP solving techniques, ACO has been shown to be a particularly promising approach [30]. The practical difficulty remains to escape local optima and reliably converge to high-quality solutions within a short computing time limit. This challenge has brought about a variety of extended ACO algorithms as well as hybrid approaches that combine ACO with local search methods [31–36]. While these methods have been designed and evaluated on small to medium-scale FJSSP benchmarks [35], our work addresses the large-scale SMSP instances encountered in the domain of semiconductor production scheduling [1]. Beyond FJSSP and SMSP investigated here, we note that hybrid optimization algorithms integrating meta-heuristics and local search have also been adopted in a variety of other application settings [37–41].

2.4 Dispatching

In semiconductor manufacturing, the efficient management of production flow is crucial for maintaining high throughput and minimizing delays. This section explores dispatching methods that have been traditionally employed to orchestrate the flow of work-in-process (WIP) through the various stages of production.

FIFO is one of the simplest and most widely used dispatching rules in various manufacturing sectors, including semiconductors. It prioritizes jobs in the order they arrive, regardless of their complexity or processing time. While FIFO is straightforward to implement and ensures a fair processing order, it may not be optimal in environments where job priorities vary significantly, leading to potential inefficiencies in the handling of urgent or time-sensitive processes [42].

The Critical Ratio is a more sophisticated dispatching method that prioritizes jobs based on the ratio of the remaining processing time to the time remaining until the job’s due date. This method aims to minimize tardiness and is particularly useful in semiconductor manufacturing, where delivery schedules are tight, and delays can be costly. However, its effectiveness is highly dependent on accurate estimates of processing times and can become complex to manage in high-mix production environments [43].

Random dispatching assigns priorities to jobs at random, irrespective of their characteristics or deadlines. This method is often used as a benchmark in simulation studies to demonstrate the effectiveness of more sophisticated rules. While it does not optimize

Table 1: Basic notations (adapted from [7])

Symbol	Description
J	Total number of <i>jobs</i>
T	Total number of <i>tool groups</i>
M	Total number of <i>machines</i>
N	Total number of <i>operations</i>
t_m	Tool group t of machine m
$O_{i,j,t}$	Operation i of job j on tool group t
$d_{i,j,t}$	Duration of operation $O_{i,j,t}$ on tool group t
$O_{i,j,t,m}$	Operation i of job j on machine m of tool group t
$s_{i,j,t,m}$	Start time of operation $O_{i,j,t}$ on machine m of tool group t

any specific performance metric, random dispatching can sometimes yield surprisingly good average performance due to its stochastic nature, though it generally lacks consistency and predictability [44].

These conventional methods provide a baseline for managing operations but often fall short in environments characterized by high variability and complex product mixes, such as in semiconductor manufacturing. Given the limitations of these conventional methods, there is a significant opportunity for advanced dispatching approaches that can adapt to the dynamic conditions of semiconductor production lines. The integration of real-time data analytics and more sophisticated algorithms, such as those derived from Swarm Intelligence, could address these gaps by providing more flexible and responsive dispatching solutions.

3 Problem Formulation

We formulate SMSP in terms of the general FJSSP model, using the basic notations listed in Table 1 (see [7]). In detail, our setting for scheduling the production of a semiconductor fab is characterized as follows:

- The fab consists of M machines, which are partitioned into T tool groups, where $t_m \in \{1, \dots, T\}$ denotes the tool group to which a machine $m \in \{1, \dots, M\}$ belongs.
- There are J jobs, where each $j \in \{1, \dots, J\}$ represents a sequence of operations $O_{1,j,t_1}, \dots, O_{n_j,j,t_n}$, to be performed on a production lot. Note that $t_i \in \{1, \dots, T\}$ specifies the tool group responsible for processing an operation O_{i,j,t_i} , but not a specific machine of t_i , which reflects flexibility in assigning operations to machines. The total number of operations is denoted by $N = \sum_{j \in \{1, \dots, J\}} n_j$.
- For each operation $O_{i,j,t}$, the duration $d_{i,j,t}$ is required for processing $O_{i,j,t}$ on some machine of the tool group t .

Our SMSP model incorporates key features drawn from the semiconductor production scenarios outlined in the SMT2020 dataset [1]. In these scenarios, each job corresponds to a specific product, with operation sequences—referred to as production routes—remaining consistent across the same product type. Given that these production

routes can span several months and encompass hundreds of operations within a physical fab, it's common for different lots of the same product to be at various stages of their production routes during (re-)scheduling. Therefore, our model does not differentiate production routes by product; instead, we focus on the operation sequences of a specific length n_j related to each job j . This approach facilitates the management of operations for lots at different stages within the same production route.

Moreover, the machines belonging to a tool group are assumed to be uniform, i.e., an operation requiring the tool group can be processed by any of its machines. This simplifying assumption ignores specific machine setups, which may be needed for some operations and take additional equipping time, as well as unavailabilities due to maintenance procedures or breakdowns. However, the greedy machine assignment performed by our GSACO-O algorithm in Section 4 can take such conditions into account for allocating an operation to the earliest available machine. In addition, some transportation time is required to move a lot from one machine to another between operations, which is not explicitly given but taken as part of the operation duration in the SMT2020 scenarios.

A schedule allocates each operation $O_{i,j,t}$ to some machine $m \in \{1, \dots, M\}$ such that $t_m = t$, and we denote the machine assignment by $O_{i,j,t,m}$. Each machine performs its assigned operations in sequence without preemption, i.e., $s_{i,j,t,m} + d_{i,j,t} \leq s_{i',j',t,m}$ or $s_{i',j',t,m} + d_{i',j',t} \leq s_{i,j,t,m}$ must hold for the start times $s_{i,j,t,m}$ and $s_{i',j',t,m}$ of operations $O_{i,j,t,m} \neq O_{i',j',t,m}$ allocated to the same machine m . The precedence between operations of a job $j \in \{1, \dots, J\}$ needs to be respected as well, necessitating that $s_{i,j,t,m} + d_{i,j,t} \leq s_{i+1,j,t',m'}$ when $i < n_j$. Assuming that $0 \leq s_{1,j,t,m}$ for each job $j \in \{1, \dots, J\}$, the makespan to complete all jobs is given by $\max\{s_{n_j,j,t,m} + d_{n_j,j,t} \mid j \in \{1, \dots, J\}\}$. We take makespan minimization as an optimization objective for scheduling, as it reflects efficient machine utilization and maximization of fab throughput. Additionally, we aim to optimize the number of operations completed within a specified planning horizon, enhancing overall productivity and operational efficiency. This approach ensures not only the effective use of available machinery but also strives to maximize the output within time constraints, thereby optimizing operational flow and throughput within the manufacturing process.

An example schedule generated by GSACO-O for instance in Table 3 whose operations and their average processing times are given in Table 3a is displayed in Figure 3 and Figure 4.

4 GSACO Algorithm

The framework of GSACO-O algorithm is illustrated in Figure 1 and the input and internal parameters, is summarized in Table 2. The four main submodules, highlighted in bold, are discussed in detail in the following subsections.

For a configurable cycle number or time limit l , each of the k ants applies greedy search using the GS procedure with respect to the objective. That is, the first GS phase constructs an operation sequence, which is then taken as basis for greedily assigning the operations to machines in the second phase. Note that the ants run independently, so that their GS trials can be performed in parallel. As a result, k schedules along with

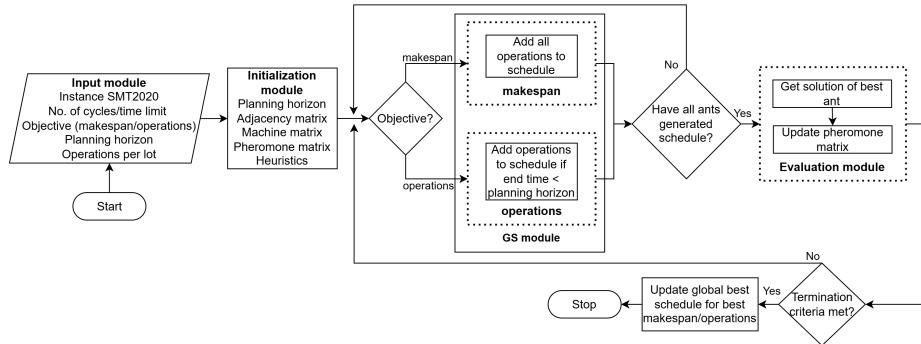


Fig. 1: GSACO-O framework

Table 2: GSACO-O parameters

Parameter	Description
o	Objective
l	Cycles/time limit
n	Operations per lot
h	Planning horizon
k	Number of ants
τ_y	Initial pheromone level
τ_z	Minimum pheromone level
τ_e	Pheromone level on edge e
ρ	Evaporation rate
c	Contribution of best schedules

edges between operations (described in Subsection 4.2) that have been selected for their construction are obtained. If some of these schedules improves the makespan over the best schedule found in previous iterations (if any), the best schedule gets updated. As common for ACO algorithms, pheromones τ_e on edges e are subject to evaporation, according to the formula $\rho \cdot \tau_e$, while edges selected to construct the best schedule obtained so far also receive a pheromone contribution, calculated as $\tau_e + c$. Such pheromone deposition increases the chance for edges contributing to the current best schedule to get re-selected in forthcoming iterations.

Algorithm 1 provides a pseudo-code representation of GSACO-O for minimizing makespan and optimizing operations within the planning horizon.

4.1 Input Module

This module reads in an SMSP instance obtained from SMT2020 dataset [1]. Additionally, it also configures the instance from the simulator develop by [11] for the average processing times of the operations. The instance includes tool groups with their respective machines, jobs currently in progress, and production routes. In terms of dynamic state, the processing times for these routes are stochastic. Conversely, the simulator pro-

```

Input: dataset, instance,  $l$ 
Output: best schedule found by ants
Parameters:  $o, n, h, k, \tau_y, \tau_z, \rho, c$ 
Initialize adjacency, pheromone, and machine matrix;
if  $o == \text{Makespan}$  then
    |  $makespan \leftarrow \infty;$ 
else
    |  $operations \leftarrow 0;$ 
end
while cycle or time limit  $l$  is not reached do
    | foreach ant from 1 to  $k$  do
        | | Run GS procedure to find a schedule;
    | end
    | if  $o == \text{Makespan}$  then
        | |  $new \leftarrow$  shortest makespan of ants' schedules;
        | | if  $new < makespan$  then
        | | |  $makespan \leftarrow new;$ 
        | | |  $best \leftarrow$  an ant's schedule of minimum  $makespan$ ;
        | | end
    | else
        | |  $new \leftarrow$  maximum operations of ants';
        | | if  $new > operations$  then
        | | |  $operations \leftarrow new;$ 
        | | |  $best \leftarrow$  an ant's schedule of maximum  $operations$ ;
        | | end
    | end
    | foreach edge  $e$  in pheromone matrix do
        | |  $\tau_e \leftarrow \max\{\rho \cdot \tau_e, \tau_z\};$  // evaporation
    | end
    | foreach edge  $e$  selected by best ant do
        | |  $\tau_e \leftarrow \tau_e + c;$  // deposit pheromones
    | end
end
return  $best;$ 

```

Algorithm 1: Greedy Search based ACO (GSACO-O) for Scheduling

vides observed averages for processing times and job releases. Additionally, the module takes several inputs for the GSACO-O optimization process such as the objective o , planning period h , operation per lot n and a limit l on either the number of cycles or the time allocated for optimization.

4.2 Initialization Module

In view of long production routes with hundreds of operations in the SMT2020 dataset, we introduce a configurable operations per lot n as upper bound on the length n_j of the operation sequence for a job j . The operations per lot thus constitutes a scaling factor for the size and the resulting complexity of SMSP instances. In practice, unpre-

dictable stochastic events make long-term schedules obsolete and necessitate frequent re-scheduling, where limiting n upfront provides a means to control the search and enable short response times.

To express SMSP as a search problem on graphs, we identify an instance with the disjunctive graph

whose vertices V contain the operations $O_{i,j,t}$ plus a dummy start node 0, conjunctive edges

$$\begin{aligned} E_c = & \{(0, O_{1,j,t_1}) \mid O_{1,j,t_1} \in V\} \\ & \cup \{(O_{i-1,j,t_{i-1}}, O_{i,j,t_i}) \mid O_{i,j,t_i} \in V, i > 1\} \end{aligned} \quad (1)$$

connect the dummy start node 0 to the first operation and each operation on to its successor (if any) in the sequence for a job, and disjunctive edges

$$E_d = \{(O_{i,j,t}, O_{i',j',t}) \mid O_{i,j,t} \in V, O_{i',j',t} \in V, j \neq j'\} \quad (2)$$

link operations (of distinct jobs) sharing a common tool group, as such operations may be allocated to the same machine.

Any feasible schedule induces an acyclic subgraph (V, E) of the disjunctive graph G such that $E_c \subseteq E$, and $(O_{i,j,t}, O_{i',j',t}) \in E_d \cap E$ iff $s_{i,j,t,m} + d_{i,j,t} < s_{i',j',t,m}$ for distinct jobs $j \neq j'$, i.e., the operation $O_{i,j,t}$ is processed before $O_{i',j',t}$ by the same machine m of tool group $t_m = t$. Conversely, the search for a high-quality solution can be accomplished by determining an acyclic subgraph (V, E) of G that represents a schedule of short makespan.

For example, Table 3 shows a small instance that follows the explanation of the proposed GSACO-O algorithm. In Table 3a, the operations belonging to two jobs can be obtained with the parameter $n = 5$. The average duration of the operations for given tool group is given in seconds to avoid float calculation. Later the duration is converted to the minutes for visualization purpose. The lots that belong to the products are shown in Table 3b. The lots are at different stages of the production identified by the step number.

Table 3: Example instance

(a) Operations				(b) Lots		
No.	Operation	Tool group name	Avg duration (sec)	Lot	Product	Step
1	$O_{1,1,2}$	TF_Met_FE_45	588	1	1	1
2	$O_{2,1,3}$	WE_FE_108	59	2	2	2
3	$O_{3,1,4}$	WE_FE_83	62	3	1	1
4	$O_{4,1,5}$	WE_FE_84	54	4	2	3
5	$O_{5,1,1}$	LithoTrack_FE_115	130	5	1	1
6	$O_{1,2,2}$	TF_Met_FE_45	588	6	2	2
7	$O_{2,2,3}$	WE_FE_108	59	7	1	1
8	$O_{3,2,4}$	WE_FE_83	62	8	2	3
9	$O_{4,2,5}$	WE_FE_84	54	9	1	1
10	$O_{5,2,0}$	Litho_FE_111	130	10	2	2

Conjunctive edges connect the dummy start node 0 to the operations which come first in their jobs and all operations to their successors. In addition, mutual disjunctive edges link operations to be processed on the same tool group. Since the products are at different stages and the remaining operations to schedule are obtained from the step given in Table 3b up to the maximum step in Table 3a for corresponding lot and product. The resulting $(N+1) \times (N+1)$ adjacency matrix, where $N = 43$ is the total number of operations, 0 entries indicate the absence, and 1 entries the existence of edges, is given in Figure 2a.

$$\begin{array}{c}
 \begin{matrix} & 0 & 1 & 2 & \dots & 41 & 42 & 43 \\
 0 & \left[\begin{matrix} 0 & 1 & 0 & \dots & 0 & 0 & 1 \end{matrix} \right] \\
 1 & \left[\begin{matrix} 0 & 0 & 1 & \dots & 0 & 0 & 0 \end{matrix} \right] \\
 2 & \left[\begin{matrix} 0 & 0 & 0 & \dots & 1 & 0 & 0 \end{matrix} \right] \\
 \vdots & \left[\begin{matrix} \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \end{matrix} \right] \\
 41 & \left[\begin{matrix} 0 & 0 & 0 & \dots & 0 & 1 & 0 \end{matrix} \right] \\
 42 & \left[\begin{matrix} 0 & 0 & 0 & \dots & 0 & 0 & 1 \end{matrix} \right] \\
 43 & \left[\begin{matrix} 0 & 0 & 1 & \dots & 0 & 0 & 0 \end{matrix} \right] \end{matrix} \\
 \text{(a) Adjacency matrix} \\
 \\
 \begin{matrix} & 1 & 2 & 3 & \dots & 10 & 11 & 12 \\
 0 & \left[\begin{matrix} 0 & 1 & 0 & \dots & 0 & 0 & 0 \end{matrix} \right] \\
 1 & \left[\begin{matrix} 0 & 0 & 1 & \dots & 0 & 0 & 0 \end{matrix} \right] \\
 2 & \left[\begin{matrix} 0 & 0 & 0 & \dots & 1 & 0 & 0 \end{matrix} \right] \\
 \vdots & \left[\begin{matrix} \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \end{matrix} \right] \\
 41 & \left[\begin{matrix} 0 & 0 & 0 & \dots & 0 & 1 & 0 \end{matrix} \right] \\
 42 & \left[\begin{matrix} 0 & 0 & 0 & \dots & 0 & 0 & 1 \end{matrix} \right] \\
 43 & \left[\begin{matrix} 0 & 0 & 1 & \dots & 0 & 0 & 0 \end{matrix} \right] \end{matrix} \\
 \text{(b) Machine matrix} \end{array}$$

Fig. 2: Matrices for instance in Table 3

As initial pheromone level on edges $e \in E_c \cup E_d$, we take $\tau_y = 1$ by default. In general, representing pheromone levels by an $(N+1) \times (N+1)$ matrix similar to the adjacency matrix, the entries τ_e are initialized according to the following condition:

$$\tau_e = \begin{cases} \tau_y & \text{if } e \in E_c \cup E_d \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

With $\tau_y = 1$, this reproduces the adjacency matrix in Figure 2a as initial pheromone matrix for our example.

We additionally represent the possible machine assignments by an $(N+1) \times M$ machine matrix, where M is the total number of machines. For example, with two machines per tool group and the mapping $t_m = \lceil \frac{m}{2} \rceil$ from machine identifiers $m \in \{1, \dots, 12\}$ to the tool groups $t \in \{1, \dots, 6\}$, responsible for processing the remaining operations in Table 3, we obtain the machine matrix shown in Figure 2b.

4.3 GS Module

The general goal of greedy search methods consists of using heuristic decisions to find high-quality, but not necessarily optimal solutions in short time. Within GSACO-O, each ant applies greedy search to efficiently construct some feasible schedule for a given SMSP instance. The GS procedure based on the given objective o , outlined by the pseudo-code in Algorithm 2, includes two phases: operation sequencing and machine assignment.

```

Input: horizon  $h$ 
Output: schedule, selected edges of an ant, and operations finished in horizon  $h$ 
sequence  $\leftarrow []$ ;
selected  $\leftarrow \emptyset$ ;
next  $\leftarrow \{(0, O_{1,j,t}) \mid j \in \{1, \dots, J\}\}$ ;
while next  $\neq \emptyset$  do
    foreach  $e \in \text{next}$  do  $p_e \leftarrow \frac{\tau_e}{\sum_{e' \in \text{next}} \tau_{e'}}$ ;
        Randomly select an edge  $e$  based on  $p_e$ ;
        for selected edge  $e = (O', O_{i,j,t})$  do
            sequence.enqueue( $O_{i,j,t}$ );
            selected  $\leftarrow \text{selected} \cup \{e\}$ ;
            next  $\leftarrow \{(O_1, O_2) \in \text{next} \mid O_2 \neq O_{i,j,t}\}$ ;
             $E \leftarrow \{(O_{i,j,t}, O_{i+1,j,t'}) \mid i < n_j\}$ 
                 $\cup \{(O_{i,j,t}, O_{i',j',t}) \mid (O_1, O_{i',j',t}) \in \text{next}\}$ ;
            next  $\leftarrow \text{next} \cup E$ ;
        end
    end
    foreach  $m \in \{1, \dots, M\}$  do  $a_m \leftarrow 0$ ;
    finished  $\leftarrow 0$ ;
    while sequence  $\neq []$  do
         $O_{i,j,t} \leftarrow \text{sequence.dequeue}()$ ;
         $a \leftarrow \infty$ ;
        foreach  $m$  from 1 to to  $M$  do
            if  $t_m = t$  and  $a_m < a$  then
                 $a \leftarrow a_m$ ;
                 $b \leftarrow m$ ;
            end
        end
         $s_{i,j,t,b} \leftarrow \max(\{a\}$ 
             $\cup \{s_{i-1,j,t',m} + d_{i-1,j,t'} \mid i > 1\})$ ;
         $a_b \leftarrow s_{i,j,t,b} + d_{i,j,t}$ ;
        if  $a_b \leq h$  then finished  $\leftarrow \text{finished} + 1$ ;
    end
return  $\langle \{s_{i,j,t,m} \mid (O', O_{i,j,t}) \in \text{selected}\}, \text{selected}, \text{finished} \rangle$ ;
Algorithm 2: Greedy Search (GS)

```

The first phase constructs an ordered list of operations within an SMSP instance, planned to schedule. This is achieved through a probabilistic decision-making rule derived from the pheromone matrix, which selects edges $(O', O_{i,j,t})$ and sequentially adds their target operations $O_{i,j,t}$ to the list. To ensure the feasibility of the resulting schedule, the prerequisite operation $O_{i-1,j,t'}$ for the same job j must already belong to the sequence in case $i > 1$. This requirement is met by maintaining a set next of selectable conjunctive and disjunctive edges $(O', O_{i,j,t})$ such that O' is the dummy start node 0 or already in sequence, while $O_{i,j,t}$ is the first yet unsequenced operation of its job j .

For example, starting with an empty sequence of operations, as outlined in Table 3, the search begins at a start node 0 which symbolizes the initial state where no operations

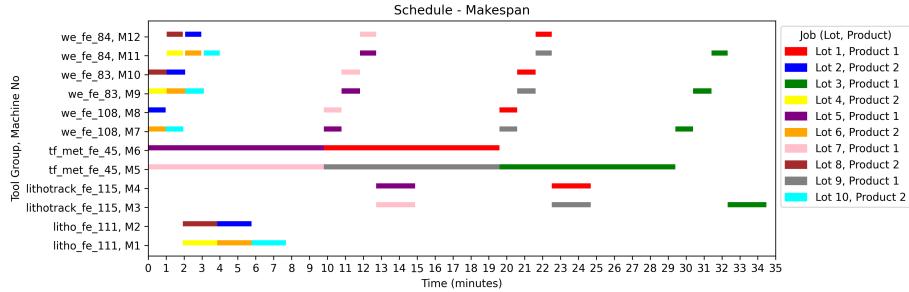


Fig. 3: Feasible schedule for the instance in Table 3

have been processed yet. The first step involves identifying all initially selectable edges, which correspond to the first operation in each lot.

To minimize the makespan, the algorithm selects a random edge and the selection process continues iteratively, with each step involving the evaluation of available operations that can be added to the existing sequence. As operations get selected, their corresponding edges are directed, indicating a fixed order. This directionality prevents the reselection of these operations. The procedure is completed once all operations are integrated into the sequence. It is important to note that the chosen disjunctive edges connect operations based on their tool groups, meaning they do not dictate the machine assignments, which are determined in the subsequent phase. With a complete sequence of operations available, the second phase involves the allocation of each operation to the earliest available machine. This machine assignment step follows the order established in the first phase to create a feasible schedule that assigns machines and start and end times to all operations. The schedule is shown in Figure 3.

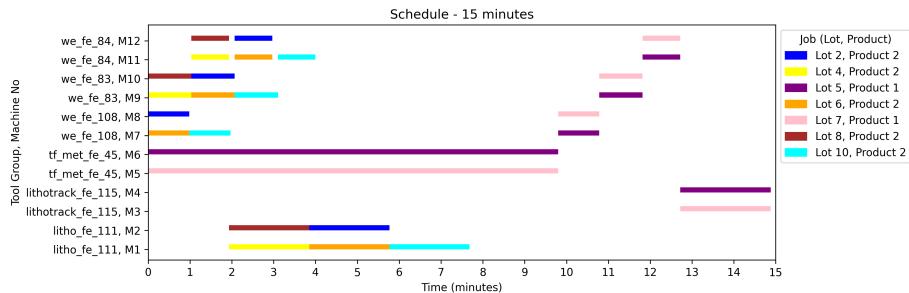


Fig. 4: Feasible schedule for the instance in Table 3

To optimize operations within the planning horizon h , the algorithm initiates by selecting a random edge from the list of candidate operations. The start time for the first operations is set to zero. Based on the duration of each operation and taking into

account the earliest available machine, the algorithm calculates the operation's end time. If this end time falls within the planning horizon h , indicating that the operation can be accommodated within the schedule, it is then added to the sequence. The algorithm continues this process iteratively, adding one operation at a time. In each iteration, it reassesses the remaining operations to determine which can fit into the updated schedule without exceeding the planning horizon. This iterative process persists until no more operations can be added within the designated periods, thereby optimizing the use of available time and resources within the planning horizon. The schedule for 15 minutes is shown in Figure 4.

4.4 Evaluation Module

While each ant independently constructs a feasible schedule by means of the GS procedure, the evaluation module collects the results obtained by the ants in a GSACO-O iteration. Among them, a schedule of shortest makespan or schedule of maximum operations is determined as outcome of the iteration and stored as new best solution in case it improves over the schedules found in previous iterations (if any). After evaporating pheromones τ_e by $\rho \cdot \tau_e$, where τ_z remains as minimum pheromone level if the obtained value would be smaller, the edges e that have been selected by the GS procedure for constructing the current best schedule receive a pheromone contribution and are updated to $\tau_e + c$.

Note that our contribution parameter c is a constant, while approaches in the literature often take the inverse of an objective value [30], i.e., of the makespan in our case. The latter requires careful scaling to obtain non-marginal pheromone contributions, in particular, when makespans get as large as for SMSP instances. We instead opt for pheromone contributions such that the edges selected to construct best schedules are certain to have an increased chance of getting re-selected in forthcoming iterations.

5 Simulation

To simulate a semiconductor fab, we adapted the simulator PySCFabSim developed by [11] designed for optimizing the scheduling of semiconductor fabrication plants. The simulator is intended for both academic research and practical application, facilitating the development, testing, and deployment of new scheduling algorithms. It supports various approaches including reinforcement learning, priority-based rules, and evolutionary algorithms.

Commercial simulators used for optimizing semiconductor fabs often face deployment challenges in research settings due to licensing and proprietary limitations. These constraints hinder reproducibility and adaptation to new research needs. To address these issues, the authors have developed a customizable, open-source simulation tool that supports extensive experimentation and algorithm development.

It operates using a dispatcher that dynamically allocates lots to machines at each decision point, which could involve choosing a batch of lots waiting for machine availability. This functionality is crucial in simulating real-world manufacturing scenarios where dispatch decisions significantly impact operational efficiency.

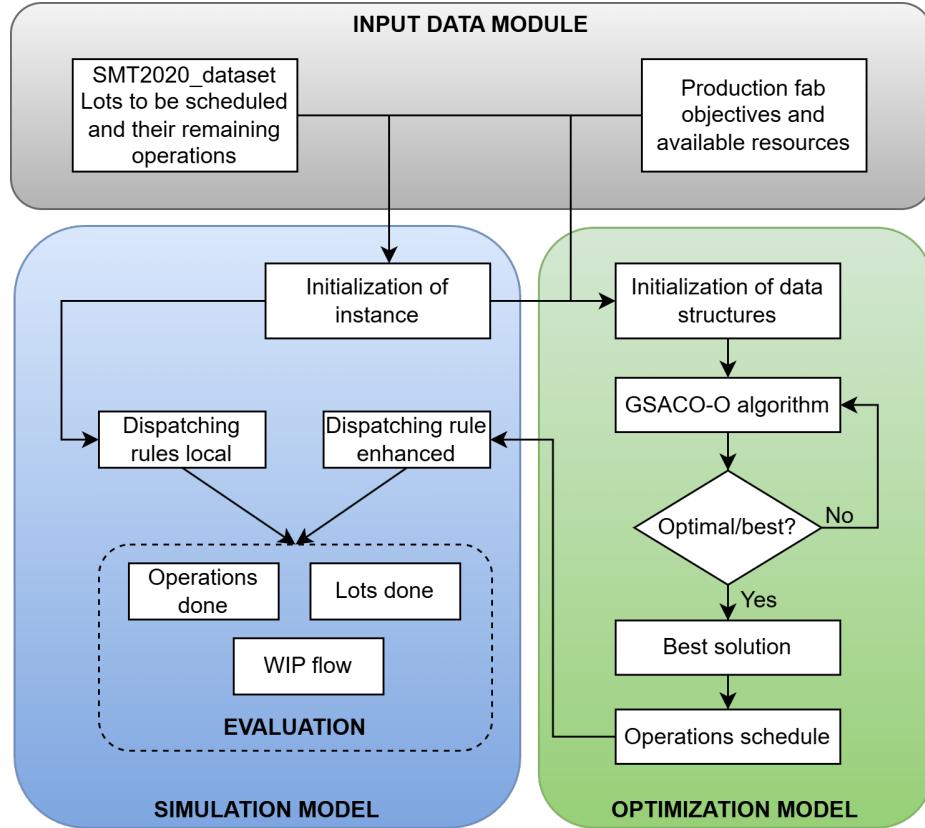


Fig. 5: Simulator-Scheduler framework

An interface is provided within the simulator to facilitate the connection between the dispatching logic and the simulator's operational flow. This interface allows the simulator to integrate various dispatching methods, including those based on traditional rules or any enhanced rules.

The paper discusses the incorporation of priority-based dispatching rules, which are commonly used in industrial contexts. These rules prioritize lot dispatch based on various criteria such as:

1. FIFO: Lots are processed in the order they arrive or based on their waiting time.
2. Critical Ratio: This method involves calculating a ratio of the remaining time to the due date divided by the expected processing time, prioritizing lots based on how critical their timing is relative to scheduled deadlines.
3. Random: Lots are processed in a random draw.

Additionally, we have integrated enhanced dispatching algorithms derived from the GSACO-O algorithm, which leverage more sophisticated decision-making processes

to optimize scheduling tasks further. These enhancements not only improve the precision of the simulation but also significantly extend its applicability and effectiveness in complex manufacturing scenarios.

The framework depicted in Figure 5 outlines a sophisticated approach for scheduling operations within a production setting, incorporating both simulation and optimization models to enhance efficiency. At the core, the Input Data Module manages crucial scheduling data, including the SMT2020 dataset that lists lots to be scheduled with their remaining operations, alongside data concerning production objectives and available resources. This information feeds into the initialization processes for both the simulation and optimization modules.

The Simulation Model kicks off with an initialization of instances based on the dataset, where it sets up the environment for running simulations with different dispatching rules—both local and enhanced. Moreover, it generates the average processing time of operations for the scheduling purpose. The dispatch rules are tested under different processing times to observe their effectiveness in managing operations and lot completions, as well as the flow of work-in-process.

On the optimization side, the GSACO-O algorithm takes the stage to refine scheduling further. This component iteratively searches for the best solutions, assessing each iteration against a criterion to determine if a preferable solution has been achieved. Upon finding the best solution, it finalizes the operations schedule, which details the best sequence and allocation of operations, given is given to the simulator for evaluation over different processing times.

6 EXPERIMENTAL EVALUATION

We implemented GSACO-O algorithm in Python using PyTorch, as it handles tensor operations efficiently and provides a multiprocessing library for parallelization, thus significantly speeding up the ants' execution of the GS procedure in each GSACO-O iteration.³ The first challenge consists of determining suitable values for the input parameters listed in Table 2, i.e., all parameters but the internally calculated pheromone level τ_e on edges e . We adhere to the parameters specified in Table 4, setting a time constraint l of 10 minutes for objective makespan and 5 minutes for objective operations. Setting different time limits for these two aspects allows the algorithm to tailor its computational efforts to the specific demands of each task. While makespan optimization seeks the best possible sequence over all operations (requiring extensive computation), optimizing operational efficiency focuses on making quicker adjustments that enhance day-to-day operations without the need for extensive computation. For the SMSP instances derived from the SMT2020 dataset, we consider up to 5 operations per job for minimizing makespan and up to 15 operations per job for optimizing operational throughput. These parameters are practical, given the stochastic nature of the problem which often necessitates frequent rescheduling. Additionally, we define a short planning horizon h to accommodate near-term scheduling requirements. For the initial pheromone level τ_y , we start from value 1, and take 0.00001 as the minimum τ_z to avoid

³ The source code is publicly available in our GitHub repository: <https://github.com/prosysscience/GSACO>

Table 4: GSACO input parameter values

Parameter	Value
o	<i>makespan/operations</i>
l	10/5
n	1–5/15
h	1–6
k	10
τ_y	1
τ_z	0.00001
ρ	0.7
c	0.5

Table 5: Number of jobs, machines, and operations for SMSP instances

Scenario	J	M	O
LV/HM	2156	1313	up to 10747
HV/LM	2256	1443	up to 11218

going down to 0, considering that the GS procedure can only select edges with non-zero entries in the pheromone matrix. The values for the number k of ants, the evaporation rate ρ , and the pheromone contribution c are more sophisticated to pick. That is, we tuned these parameters in a trial-and-error process that, starting from a baseline, inspects deviations of the final makespan and convergence speed obtained with iterative modifications. Certainly, an automated approach would be desirable to perform this task efficiently for new instance sets.

To evaluate large-scale SMSP instances, we consider two semiconductor production scenarios of the SMT2020 dataset: Low-Volume/High-Mix (LV/HM) and High-Volume/Low-Mix (HV/LM). As indicated in Table 5, both scenarios include more than 2000 jobs and more than 1300 machines, modeling the production processes of modern semiconductor fabs. The main difference is given by the number of products and associated production routes for jobs, where LV/HM considers 10 production routes varying between 200–600 steps in total, while HV/LM comprises 2 production routes with about 300 or 600 steps, respectively. Originally, the LV/HM and HV/LM scenarios have been designed to represent fab load at the start of simulation runs, so that the jobs are at different steps of their production routes. We focus on scheduling for operations n from 1 up to 5, to be performed per job. Hence, the operations O to schedule gradually increase from the number J of jobs, in case of the operations $n = 1$, to more than 10000 operations for the longest horizon $n = 5$.

While running with a time limit l of 10 minutes, Table 6 reports the makespans of current best schedules found by the CP solver OR-Tools and our GSACO implementation at 1, 3, 5, 7, and 9 minutes of computing time. Considering that the SMSP instances are large, OR-Tools now takes 3 minutes to come up with the first solution(s) for the shortest planning horizon $n = 1$ on the LV/HM scenario. Within the same fraction of computing time, GSACO-O already converges to a makespan of 3725 and then proceeds with iterations that do not yield further improvements. That the best schedule found by

Table 6: SMSP results obtained with CP and GSACO [7]

n	Scenario	1 min		3 min		5 min		7 min		9 min	
		CP	GSACO								
1	LV/HM	-	3735	18572	3725	3746	3725	3723	3725	3723	3725
	HV/LM	-	1405	-	1405	2242	1405	1609	1405	1600	1405
2	LV/HM	-	3773	-	3751	-	3750	-	3739	4398	3739
	HV/LM	-	1653	-	1644	-	1611	-	1611	-	1611
3	LV/HM	-	3880	-	3867	-	3836	-	3834	-	3834
	HV/LM	-	1902	-	1889	-	1889	-	1876	-	1876
4	LV/HM	-	4578	-	4540	-	4540	-	4540	-	4540
	HV/LM	-	2207	-	2113	-	2113	-	2093	-	2093
5	LV/HM	-	4680	-	4680	-	4553	-	4553	-	4553
	HV/LM	-	2667	-	2566	-	2566	-	2518	-	2518

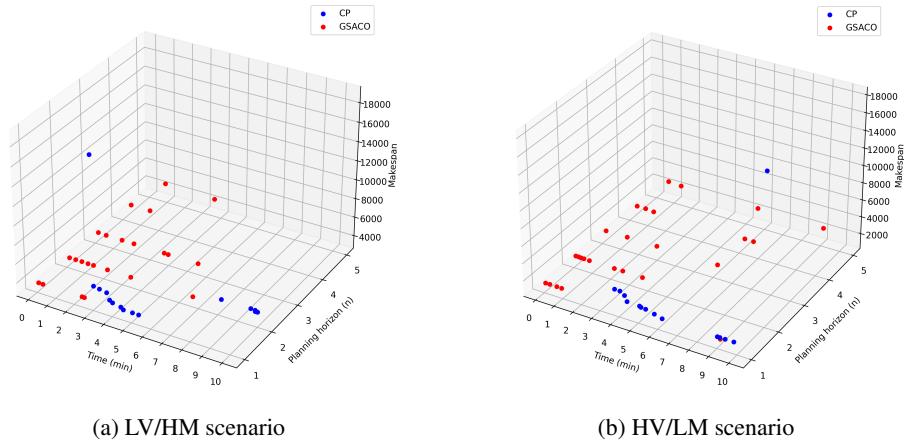


Fig. 6: Makespan improvements of schedules for SMSP instances obtained with CP and GSACO [7]

GSACO is not optimal is witnessed by a marginally better solution obtained by OR-Tools after 7 minutes. However, for the other SMSP instances, OR-Tools is unable to improve over GSACO within 9 minutes, and it cannot even provide feasible schedules for planning horizons from $n = 2$ on the HV/LM scenario or $n = 3$ on LV/HM. We performed our experiments on a TUXEDO Pulse 14 Gen1 machine equipped with an 8-core AMD Ryzen 7 4800H processor at 2.9GHz and onboard Radeon graphics card.

The quick convergence of our GSACO implementation is also outlined by the makespan improvements plotted in Figure 6. On the LV/HM scenario displayed in Figure 6a, GSACO obtains its best schedules within 7 minutes for all planning horizons. Only for the longest planning horizon $n = 5$ on the HV/LM scenario in Figure 6b, an improvement occurs after more than the 9 minutes of computing time listed in the right-most column of Table 6. Comparing the SMSP instances for which OR-Tools manages to provide feasible schedules, the convergence to makespans in roughly the range of

Table 7: Percentage Change in Dispatcher Performance Over Planning Hours LV/HM

Planning horizon	Dispatcher								Scheduler	
	FIFO		CR		RANDOM		GSACO-O		GSACO-O	
	Ops/Lots	Change	Ops/Lots	Change	Ops/Lots	Change	Ops/Lots	Change	Ops/Lots	Change
1	1419/0	-	1416/0	-0.21%	1403/0	-1.12%	1442//0	1.62%	1422	0.21%
2	2249/0	-	2328/0	3.51%	2275/0	1.15%	2409/0	7.11%	2368	5.29%
3	2384/0	-	3372/0	2.67%	3314/0	0.91%	3427/0	4.35%	3234	-1.52%
4	4018/1	-	4083/1	1.61%	4039/1	0.52%	4272/1	6.32%	4015	-0.07%
5	4901/1	-	5023/1	2.48%	4972/1	1.44%	5174/2	5.57%	4722	-3.65%
6	5665/4	-	5799/3	2.36%	5767/1	1.80%	6014/2	6.16%	5306	-6.33%

Table 8: Percentage Change in Dispatcher Performance Over Planning Hours HV/LM

Planning horizon	Dispatcher								Scheduler	
	FIFO		CR		RANDOM		GSACO-O		GSACO-O	
	Ops/Lots	Change	Ops/Lots	Change	Ops/Lots	Change	Ops/Lots	Change	Ops/Lots	Change
1	1821/0	-	1798/0	-1.26%	1810/0	-0.60%	1831/0	0.54%	1848/0	1.48%
2	2831/0	-	2811/0	-0.71%	2852/0	0.74%	2957/0	4.45%	2960/0	4.55%
3	4020/1	-	4021/1	0.02%	4065/1	1.12%	4162/1	3.53%	4093/1	1.81%
4	4914/4	-	4934/3	0.40%	4975/3	1.24%	5118/3	4.15%	4970/3	1.07%
5	5960/6	-	6003/5	0.72%	6026/5	1.10%	6263/5	5.08%	5975/5	0.25%
6	6841/8	-	6946/8	1.53%	6973/9	1.92%	7162/7	4.69%	6716/7	-1.82%

GSACO’s results takes significantly more computing time. Hence, the time limit that would be necessary to break even with GSACO, as accomplished within 7 minutes for the shortest planning horizon $n = 1$ on the LV/HM scenario, cannot be predicted for the SMSP instances with longer planning horizons. Moreover, we observe that the initial schedules obtained in the first GSACO iteration by some of the ants running in parallel are of relatively high quality, while OR-Tools sometimes finds outliers as its first solutions. This phenomenon occurs for the planning horizons $n = 1$ and $n = 2$ on the LV/HM or HV/LM scenario, respectively, where the latter schedule of makespan 17664 is found after more than 9 minutes and thus not listed in Table 6.

explain here

The plots in Figure 7 presents the performance of various dispatching rules—FIFO, CR, RANDOM, and GSACO—across different planning horizons ranging from 1 to 6 hours. Each plot illustrates the total number of operations dispatched by each rule within these time frames, offering a clear comparison of their efficiency and effectiveness in handling operational tasks within a semiconductor manufacturing.

The performance of dispatching rules based on specific operational times and goals are analyzed. While simpler rules like FIFO and CR are predictable and may perform adequately in stable environments, their performance can lag in more dynamic or complex scenarios where adaptive strategies like GSACO provide significant advantages. Random dispatching, surprisingly effective in some cases, suggests that stochastic elements might occasionally align with operational demands, although this method’s reliability is less consistent. GSACO’s consistently superior performance advocates for its

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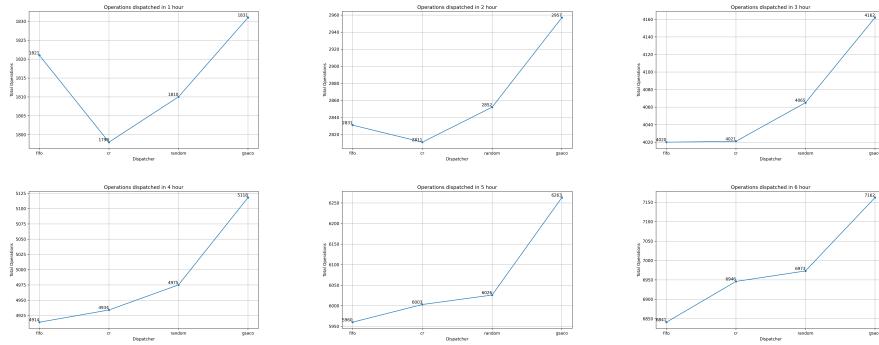


Fig. 7: Completed operations for HV/LM

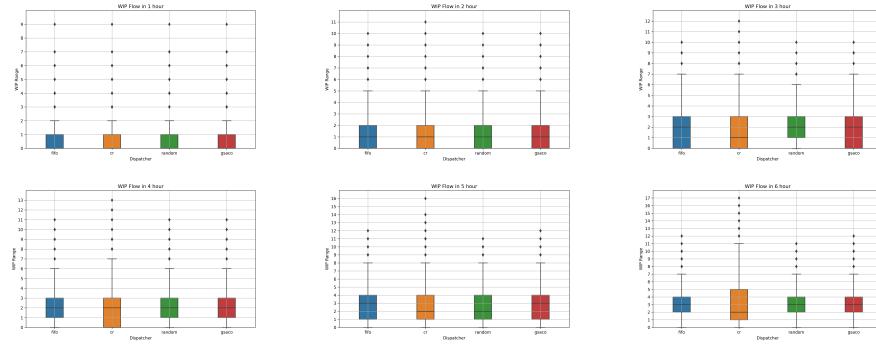


Fig. 8: WIP flow for HV/LM

use in environments where maximizing operational throughput is critical. This analysis not only aids in strategic decision-making but also highlights the potential for further refining these algorithms to enhance their applicability and effectiveness across various manufacturing contexts.

The plots in Figure 8 illustrate the Work in Progress (WIP) flow across various dispatching rules—FIFO, CR, RANDOM, and GSACO—over different planning horizons ranging from 1 to 6 hours. Each bar demonstrates the minimum and maximum WIP levels reached during the simulation period under each dispatching rule, with the height of the bar indicating the variability or stability of the WIP flow.

FIFO shows the lowest range of WIP variability, suggesting consistent and predictable processing under this rule within the first hour. CR and Random display slightly higher variability, indicating a less stable WIP flow. GSACO exhibits the highest range, potentially due to more aggressive reordering and optimization strategies that initially increase variability before stabilizing.

As the planning horizon extends to 2, 3, 4, 5, and 6 hours, all methods show an increase in the maximum WIP range. FIFO consistently maintains a relatively lower

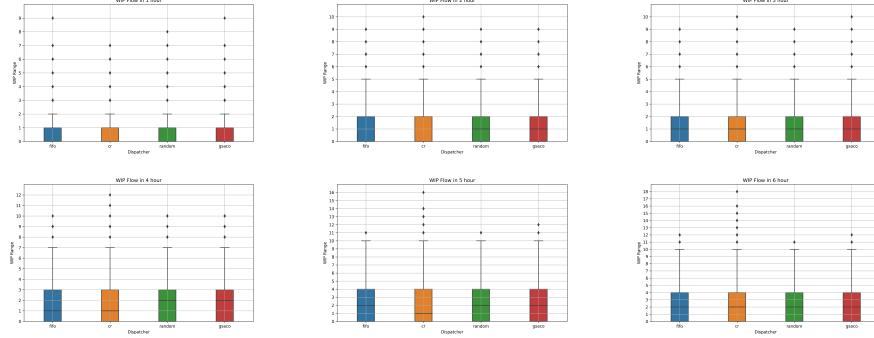


Fig. 9: WIP flow for LV/HM

range of WIP compared to other methods, indicating its less dynamic but stable approach. CR's performance exhibits moderate variability, reflecting its strategy of prioritizing jobs based on their deadlines, which might not always align with minimizing WIP. Random shows a moderate to high variability, which aligns with its inherent unpredictability. GSACO consistently demonstrates the highest variability. This could be attributed to its optimization processes, which might involve significant shifts in job prioritization and scheduling to achieve long-term efficiency, leading to larger fluctuations in WIP.

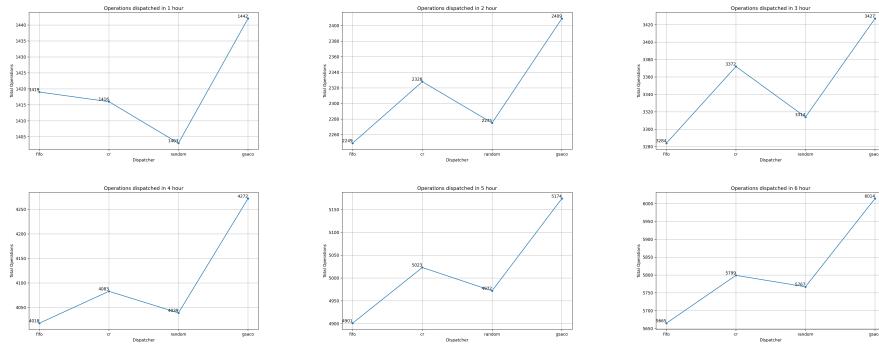


Fig. 10: Total operations completed LV/HM

7 Conclusion

Modern semiconductor fabs are highly complex and dynamic production environments, whose efficient operation by means of automated scheduling and control systems constitutes a pressing research challenge. In this work, we model the production processes

of large-scale semiconductor fabs in terms of the well-known FJSSP. In contrast to classical FJSSP benchmarks, this leads to large-scale scheduling problems, even if short planning horizons cover only a fraction of the long production routes with hundreds of operations. The resulting size and complexity of large-scale SMS instances exceed the capabilities of common FJSSP solving methods. We thus propose the GSACO algorithm combining probabilistic operation sequencing with greedy machine assignment. Its efficient implementation utilizing tensor operations and parallel ant simulations enables GSACO’s convergence to high-quality solutions in short time. In this way, GSACO overcomes the scalability limits of exact optimization by means of a state-of-the-art CP approach and achieves the performance required for frequent re-scheduling in reaction to process deviations.

While simplified FJSSP models of semiconductor manufacturing processes provide insights regarding the scalability of scheduling methods, in future work, we aim at extending GSACO to incorporate the specific conditions and functionalities of tools performing the production operations. Such features include, e.g., machine setups to be equipped before performing operations, preventive maintenance procedures for which a machine needs to stay idle, and batch processing capacities to handle several production lots in one pass. In practice, these specifics matter for machine assignment strategies and should also be reflected in the respective greedy phase of GSACO.

Our second target of future work concerns the utilization of schedules found by GSACO for decision making and control within simulation models of semiconductor fabs. This goes along with the extension of optimization objectives to practically relevant performance indicators, such as deadlines for the completion of jobs and minimizing the tardiness. In view of the dynamic nature of real-world production operations and unpredictable stochastic events, quantifying the improvements by optimized scheduling methods requires their integration and evaluation in simulation.

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