UNIVERSITY OF NIS FACULTY OF MECHANICAL ENGINEERING

THE TENTH INTERNATIONAL CONFERENCE
TRANSPORT AND LOGISTICS

til 2025

OPTIMIZATION OF FLEXIBLE JOB SHOP SCHEDULING WITH MACHINE TOOL BREAKDOWNS

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Abstract

The growing number of cyber-attacks on industrial systems increasingly affects manufacturing by causing unexpected machine tool failures and workflow interruptions. These security-driven disturbances demand scheduling models that can adapt rapidly. This research paper addresses the flexible job shop scheduling problem under temporary machine breakdowns triggered by cyber-attacks. After the attack is resolved, the affected machine tools must be efficiently reintegrated into the rescheduling process to maintain production stability. To generate effective rescheduling, this research applies the Genetic Algorithm, a biologically inspired metaheuristic especially suitable for solving complex NP-hard scheduling problems. The proposed method supports adaptive, real-time rescheduling while further addressing the optimization of two key performance criteria: balanced machine utilization and mean flow time. The approach is implemented in MATLAB® and validated through simulations on relevant benchmark problems. Experimental results confirm improved responsiveness, better resource balance, and enhanced efficiency under cyber-induced machine failures, contributing to a more flexible and resilient rescheduling.

Keywords: *genetic algorithm, rescheduling, optimization, manufacturing systems, machine tool breakdown, cyber-attack.*

1 INTRODUCTION

Production scheduling has become increasingly complex as manufacturing systems evolve toward higher levels of automation, connectivity, and digital integration. Among the various scheduling models, the Job Shop Scheduling Problem (JSSP) and its extended form, the Flexible Job Shop Scheduling Problem (FJSSP), have attracted significant research interest due to their relevance in real-world manufacturing environments. Unlike traditional JSSP, where each operation is assigned to a single predefined machine, FJSSP offers routing flexibility, allowing operations to be processed on multiple alternative machines. This additional flexibility expands the solution space but also increases computational complexity, placing the FJSSP among the most challenging NP-hard optimization problems [1]. While many studies on FJSSP focus on deterministic conditions – assuming stable processing times, uninterrupted machine availability, and predictable workflow – real manufacturing systems rarely operate under such ideal circumstances. Real manufacturing environments are exposed to a wide range of uncertainties, including variable processing times, the arrival of new or urgent jobs, and unexpected machine failures [2]. These disturbances can significantly degrade the performance of schedules generated under deterministic assumptions, making adaptability and robustness essential requirements for any practical rescheduling method. Robust approaches are designed to maintain stability of key scheduling criteria, such as makespan, flow time, and machine workload, while generating effective rescheduling plans in response to dynamic disturbances [3].

In recent years, a growing concern has emerged regarding cybersecurity risks in industrial systems. Cyber-attacks targeting machine tools, industrial controllers, or production databases can temporarily disable equipment, disrupt material flow, or cause unexpected shutdowns [4]. Such attacks introduce a new type of disturbance that is often difficult to predict, and capable of causing substantial scheduling instability. Once the consequences of the attack are resolved, the affected machines must be efficiently reintegrated into manufacturing system, making dynamic and responsive rescheduling critical maintaining overall system stability. As the adoption of smart manufacturing technologies expands, studies highlight that the exposure and frequency of cyber-induced disturbances continue to grow [5].

To address these challenges, researchers are increasingly adopting metaheuristic optimization techniques to manage large-scale, dynamic, and multi-objective scheduling problems. Genetic Algorithms (GA), inspired by biological evolution, have proven particularly effective for solving complex scheduling tasks due to their strong global search capabilities, robustness to dynamic changes, and flexibility in handling multiple objectives [6]. Moreover, their ability to continuously update the solution population allows GA to accommodate structural changes in the scheduling environment, making them well suited for adaptive rescheduling following the occurrence of the disturbance.

Having that in mind, this research focuses on the FJSSP under temporary machine tool failures caused by cyber-attacks. A GA-based rescheduling framework is developed to efficiently reintegrate machine tools into manufacturing system once they become operational again. The proposed method optimizes two key criteria: (i) balanced machine utilization [7] and (ii) mean flow time [8], to achieve stable, efficient, and resource-aware rescheduling. The methodology is implemented in MATLAB® and evaluated using benchmark problems to determine its responsiveness and effectiveness under real-world dynamic conditions.

The research paper is structured as follows: Section 2 presents the formulation of the dynamic FJSSP under machine tool breakdowns and defines the performance criteria used in this study. Section 3 describes the GA-based rescheduling methodology. Section 4 presents the experimental results, and Section 5 concludes the research paper with final remarks and directions for future research.

2 MACHINE TOOL BREAKDOWN

In Dynamic Flexible Job Shop Scheduling (DFJSS), machine tool breakdowns are among the most critical disturbances, directly affecting the continuity and reliability of the manufacturing process. When such breakdowns are intentionally induced or amplified by cyber-attacks, their impact becomes even more severe. These cyber-induced failures can temporarily disable multiple machine tools at different points in time, disrupt previously optimized schedules, and create complex rescheduling requirements. For this reason, it is essential to analyze machine tool breakdowns in detail and to develop rescheduling strategies that explicitly account for their timing, duration, and overall impact through the manufacturing system. The following subsections introduce the mathematical model and objective functions used to describe this disturbance type, as well as the rescheduling approach for generating optimal schedules after cyber-induced machine tool failures.

2.1. Objective functions

Based on the mathematical formulation defined in [9], three alternative manufacturing process plans are generated for each job, incorporating both operation processing times and transportation time between alternative machine tools. These alternative plans are generated based on the criterion of minimizing total production time. The resulting process plans provide key input parameters for the scheduling process, while the final assignment and sequencing of operations are established through the subsequent optimization process.
To determine the optimal scheduling and rescheduling plans, this research paper considers two objective functions originally formulated in [10]. The mathematical formulation of balanced machine utilization is defined as:

$$obj1 = \min\left(\max\{c_{ij}\} + \sum_{a=1}^{m}\left|\sum p_{ijm} - amt\right|\right) \quad (1)$$

$$amt = \frac{1}{m}\sum_{a=1}^{m}\sum p_{ij}, \quad (O_{ij} \in M_a) \quad (2)$$

where c_{ij} is the completion time of operation O_{ij}, $\sum p_{ijm}$ is the total processing time of a machine, amt is the average processing time of all machines, m is the total number of machines, O_{ij} is j-th operation of i-th job, and M_a is the alternative machine tool for operation O_{ij}.
The mathematical formulation of minimizing mean flow time is given with the following equation:

$$obj2 = \min\left(\frac{1}{N}\sum_{i=1}^{N} c_i\right) \quad (3)$$

where N is number of jobs, $i = 1, \dots, N$ and c_i is the completion time of the job i.

2.2. Description of the Machine Tool Breakdown

Before explaining the proposed rescheduling methodology in detail, it is necessary to clarify how disturbances affect the implementation of the initial schedule. Among the various disturbances that may occur in real manufacturing systems, a machine tool breakdown represents one of the most severe, as it directly interrupts the processing of ongoing operations and affects all subsequent operations assigned to the failed machine tool. To illustrate this disturbance and its impact on the scheduling process, a simplified example is introduced next. Selected alternative manufacturing process networks for processing three jobs are presented in Figure 1, where jobs 1 and 2 each involve three operations, while job 3 requires only two.

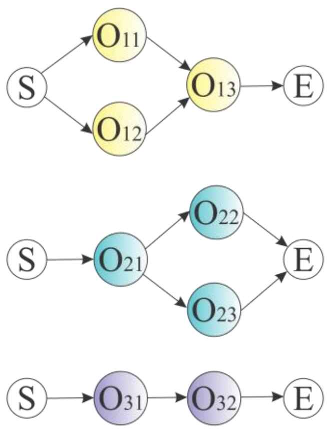

Figure 1. *Alternative process plans*

Figure 2 illustrates a simplified job shop scheduling problem in which three jobs are processed on three alternative machine tools. The Gantt chart represents the initial scheduling plan, as it would be carried out in an ideal manufacturing environment, providing a clear baseline representation of job sequences and machine tool allocations before the disturbance occurs.

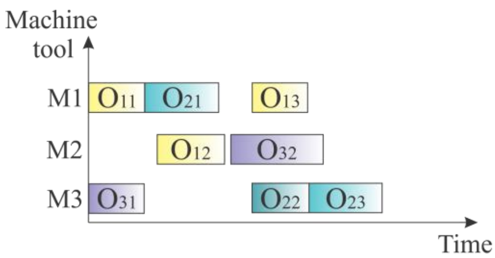

Figure 2. *Gantt chart of job shop scheduling*

A machine tool breakdown results in the rescheduling of all operations in progress on the failed machine that were unfinished at the moment of failure, as well as all operations scheduled to start after the breakdown, even if they were initially assigned to other machine tools that remain available. Modeling approaches for handling such disturbances typically assume that all incomplete operations are reassigned to alternative machine tools to continue processing the corresponding job, thereby maintaining efficiency and optimizing the rescheduling process. However, if no alternative machine tool is provided for processing the affected jobs, the affected operations must be performed on the original machine as soon as the breakdown is resolved (Figure 3).

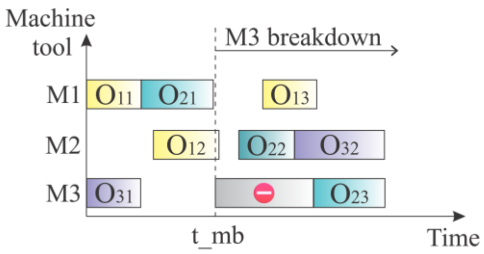

Figure 3. *Gantt chart of rescheduling due to the breakdown of machine tool M3*

The following assumptions are taken into account during the rescheduling processes illustrated in Figure 3:

- The time required for rescheduling is considered to have no substantial impact, and processing of all jobs on all machine tools resumes immediately after the rescheduling is completed.
- At any given moment, each machine tool can process only one operation of a single job.
- Jobs are available for processing starting from time $t_0 = 0$ in the initial scheduling plan, and from time $t = r_i$ after a disturbance occurs, where r_i represents the release time – the earliest moment when the next operation of job i can initiate.
- Different operations of the same job cannot be processed simultaneously.
- Once an operation on a machine tool is completed, the job is immediately transferred to the machine where the next operation is scheduled, considering also the transportation time between machines.
- The setup time of the machine tool, as well as other production resources for the subsequent operation, is not taken into account.

2.3. Mathematical formulation

The mathematical model of DFJSS problem under machine tool breakdown is based on relevant research in [11, 12].

List of symbols:

N – number of jobs $i = 1, \dots, N$;

M – number of machine tools, $m = 1, \dots, M$;

O_{ijk}^{m} – the k-th operation of the j-th alternative manufacturing process of job i executed on machine tool m;

r_i – release time for job i is the earliest time when the next operation of job i can start after the disturbance occurs;

r_m – release time for machine m is the earliest time when the next operation can start on machine tool m after the disturbance occurs;

t_{mb} – start time of the machine tool breakdown;

t_{dur} – duration of the machine tool breakdown;

s_{ijk}^{m} – start time of the operation O_{ijk}^{m};

c_{ijk}^{m} – completion time of the operation O_{ijk}^{m};

z_{ijk}^{m} – a binary variable that takes the value 1 if the machine tool assigned to perform O_{ijk}^{m} remains unchanged, and 0 otherwise.

In the case of a machine tool breakdown presented in Figure 3, the completed operations O_{11}, O_{21}, and O_{31}, are excluded from rescheduling, as well as operation O_{12} that was in progress on a machine unaffected by the failure. On the other hand, operations O_{22} and O_{23}, which were initially assigned to the failed machine tool after the disturbance occurred, must be included in the rescheduling process, along with all operations scheduled for later processing on other machines (such as O_{13} and O_{32}). The earliest possible start time of the next operation of job i after the occurrence of the disturbance can be calculated using equation (4) and equation (5):

$$r_i = c_{ijk}^{m} \times z_{ijk}^{m} + t_{mb} \times \left(1 - z_{ijk}^{m}\right), \;\; m \neq r, \qquad (4)$$

$$r_i = \left(c_{ijk}^{m} + t_{dur}\right) \times z_{ijk}^{m} + t_{mb} \times \left(1 - z_{ijk}^{m}\right), \\ m = r, \qquad (5)$$

where r represents the machine tool that has failed.

If $m \neq r$, two possible cases arise. The first case occurs when operation O_{ijk}^{m} was performing at the moment of the failure of another machine tool, in which case $z_{ijk}^{m} = 1$, i.e., the operation continues to be performed on machine m, and the equation (4) reduces to the equation (6):

$$r_i = c_{ijk}^{m} = \left\{ s_{ijk}^{m} + t_{ijk}^{m} \,\middle|\, s_{ijk}^{m} < t_{mb} < c_{ijk}^{m} \right\}, \\ i \in N. \qquad (6)$$

The second case applies when operation O_{ijk}^{m} was completed before the failure of the other machine tool, in which case $z_{ijk}^{m} = 0$, since it is unknown whether the next operation of job i will be performed on the same machine m as the previous one, as presented in equation (7):

$$r_i = t_{mb} = \max\left(\left\{ c_{ijk}^{m} \,\middle|\, c_{ijk}^{m} < t_{mb} \right\}, t_{mb} \right), \;\; i \in N. \qquad (7)$$

If $m = r$ and $s_{ijk}^{m} < t_{mb} < c_{ijk}^{m}$, this indicates that the machine tool on which the operation O_{ijk}^{m} was in progress has failed. For the further processing of the interrupted operation, two cases are possible. The first case assumes transferring the operation O_{ijk}^{m} to another alternative machine tool m, in which case $z_{ijk}^{m} = 0$, and equation (5) is replaced by equation (8):

$$r_i = t_{mb}. \qquad (8)$$

The second case occurs when the operation must resume on the same machine tool that is currently failed. In this situation, $z_{ijk}^{m} = 1$, and the repair time t_{dur} of machine m must be included, as expressed in equation (9):

$$r_i = c_{ijk}^{m} + t_{dur}. \tag{9}$$

It should be noted that in equation (9), c_{ijk}^{m}, the completion time of the operation O_{ijk}^{m}, takes the value t_{mb}, because the operation is interrupted at the moment the disturbance occurs. Therefore, that moment is considered the current end time of processing for operation O_{ijk}^{m}.

Following the previous evaluation of the time when processing of job i can be resumed – r_i, the time at which the machine tool m can resume processing the job – r_m, is calculated according to expression (10) and equation (11):

$$r_m = c_{ijk}^{m} \times z_{ijk}^{m} + t_{mb} \times \left(1 - z_{ijk}^{m}\right), \;\; m \neq r, \tag{10}$$

$$\begin{aligned} r_m = &\left(c_{ijk}^{m} + t_{dur}\right) \times z_{ijk}^{m} + \\ &+ (t_{mb} + t_{dur}) \times \left(1 - z_{ijk}^{m}\right), \;\; m = r. \end{aligned} \tag{11}$$

3 GA METHODOLOGY

A Genetic Algorithm (GA), as a biologically inspired optimization approach, is employed to generate an optimal scheduling plan based on the formulated mathematical model. Accordingly, the GA encodes each scheduling solution as a chromosome composed of two structured substrings: the primary substring encodes the operation sequence that defines the scheduling plan, while the secondary substring represents the selected alternative manufacturing process plans (Figure 4). The initial population is generated according to the number of jobs and the maximum number of operations, while the objective functions are evaluated using the mathematical models for optimization defined in equations (1), (2), and (3).

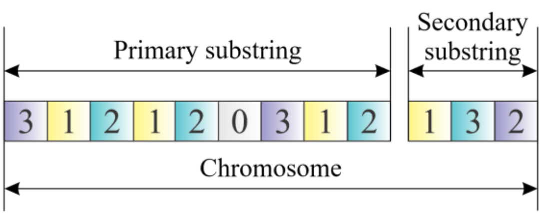

Figure 4. *Scheduling plan and alternative manufacturing processes*

To obtain optimal scheduling plans, the GA implements an iterative evolutionary process. At the beginning, the following parameters are initialized: the population size, the total number of generations, the crossover probability p_c, the mutation probability p_m, and the number of elite chromosomes. Elite chromosomes represent the best individuals of the current generation and they are passed directly into the next generation. Each generation is improved by applying the GA operators of selection, crossover, and mutation. This process allows the algorithm to explore a vast solution space, maintain diversity, and converge toward optimal or near-optimal schedules. Selection involves selecting two parent chromosomes from the current population using roulette-wheel selection, where the probability of choosing a particular chromosome is proportional to its objective function value.

During the crossover step, the operator is first applied to the secondary substring, in which randomly selected genes from Parent1 and Parent2 define the secondary substring of Offspring1 (Figure 5). Offspring1 inherits the second gene from Parent1 in its secondary substring which represents the gene for the second job; therefore, the corresponding genes from the primary substring of Parent1 are copied into the same positions of Offspring1 (including the zero element). The remaining positions are then sequentially filled with the remaining genes from Parent2. Similarly, Offspring2 is created by reversing the parental roles: the same exchange is applied to the secondary substring, the corresponding genes from the primary substring of Parent2 are copied into their positions, and the empty positions are filled with the remaining genes from Parent1.

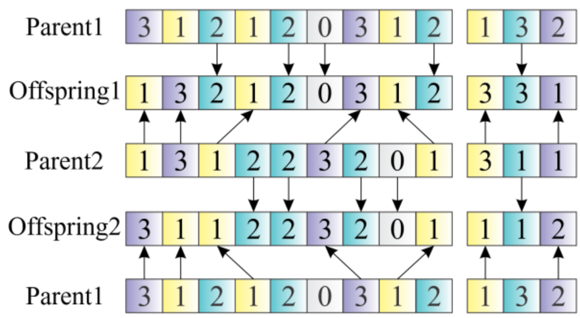

Figure 5. *Crossover*

The first mutation operator is a two-position swapping mutation, performed in three steps. First, one Parent chromosome is selected. Second, two genes within the primary substring (the scheduling plan) are randomly chosen. Finally, a new Offspring chromosome is generated by exchanging the positions of the randomly selected genes (Figure 6).

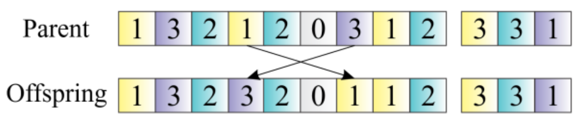

Figure 6. *First mutation operator*

The second mutation operator is used to generate new Offspring by modifying one alternative manufacturing process plan of a selected job. This operator changes a single gene in the secondary substring, in this way introducing a different alternative process plan for the third job and increasing the diversity of potential scheduling solutions (Figure 7).

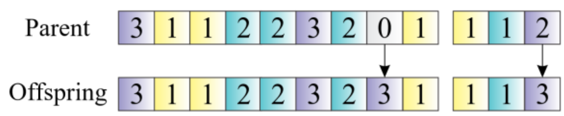

Figure 7. *Second mutation operator*

When a disturbance occurs, the GA generates an optimal rescheduling plan by repeating the same evolutionary steps of selection (via roulette wheel), crossover, and mutation, considering machine tool breakdowns. In this process, the initial population is generated to reflect the current state of the manufacturing system.

4 RESULTS AND DISCUSSIONS

To verify the mathematical models developed for the DFJSS problem under machine tool breakdowns, two comprehensive experiments were carried out using Problem 24 from the relevant literature. This problem includes 18 benchmark jobs with AND/OR networks of alternative manufacturing processes, all adopted from the reference [10]. For each job, three alternative process plans were generated and used during the scheduling optimization.

A genetic algorithm was applied for both the initial scheduling and the rescheduling process following a machine breakdown disturbance. The first experiment used balanced machine utilization as the objective function for the optimization, while the second experiment focused on minimizing mean flow time. For the initial scheduling phase, the GA parameters were set to a population size of 100, a maximum of 80 generations, a crossover probability of 0.8, a mutation probability of 0.2 and 2 elite chromosomes. In the rescheduling phase, the population size was increased to 120 and the number of generations to 100 to enhance solution diversity after the disturbances. The crossover and mutation probabilities, as well as the number of elite chromosomes, were kept identical to those used in the initial phase. The proposed method and the corresponding experiments are implemented and tested in MATLAB® environment.

The scheduling of the selected manufacturing processes for the initial set of jobs (1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18 – Problem 24) proceeded without disturbance until the breakdown of machine tool M2 at 30 s, machine tool M7 at 20 s, machine tool M10 at 40 s, and machine tool M13 at 35 s, with each machine requiring a different amount of time to be to be fixed and become operational again. In the initial phase, before any breakdowns occurred, the GA generated an initial scheduling plan that selected alternative manufacturing processes for all eighteen jobs. Within the proposed rescheduling strategy, the schedule is not updated at the exact moment an individual breakdown occurs. Instead, all breakdown events are first identified based on their start times and durations, after which the affected operations are detected and removed from the original schedule. A new partial schedule is then generated that contains only the operations completed prior to the occurrence of any machine tool breakdown.

Once all machine tools are restored and available again, a single global rescheduling process is performed. The GA is then applied to reschedule only the remaining operations, ensuring that all machine tool failures (regardless of their order or timing) are handled simultaneously through a single rescheduling process.

A new primary substring is generated to encode all unfinished operations, including those in progress at the time of the breakdowns or scheduled to start during downtime on the failed machine tools. A new secondary substring is also generated, reflecting the updated selection of alternative manufacturing processes available for each job. During this step, if an alternative process plan that avoids machine tools affected by breakdowns is available, the algorithm selects this alternative to achieve a more efficient rescheduling. If an alternative process of this type is not available for a particular operation, the operation remains assigned to its original machine tool, but its earliest possible start time is shifted to the moment when the machine is fully functional again. In such cases, the start time is computed as the breakdown end time plus the required transportation time from the previous machine, if applicable. In the second phase, the GA performs rescheduling using the updated set of operations and manufacturing routes, ensuring that all remaining operations comply with the constraints imposed by machine tool downtime and the subsequent machine recovery process.

Figure 8 shows the Gantt chart representing the initial, optimal scheduling plan prior to the machine tool breakdowns, obtained by applying balanced machine utilization (*obj1*) as the objective function.

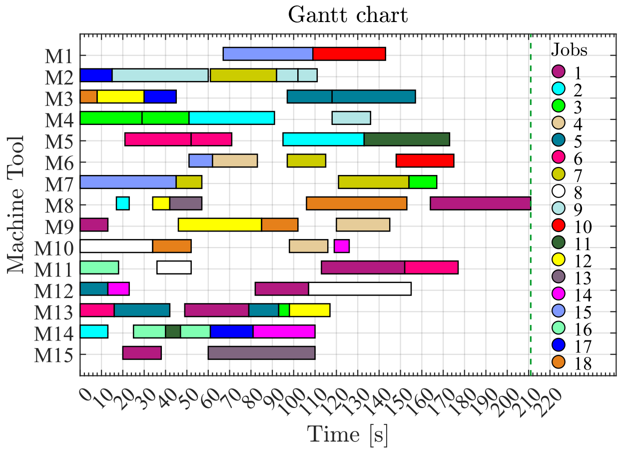

Figure 8. *Gantt chart of the initial scheduling plan (balanced machine utilization - obj1)*

After the four machine tool breakdowns and the following optimization, a new rescheduling plan is formed and shown in Figure 9.

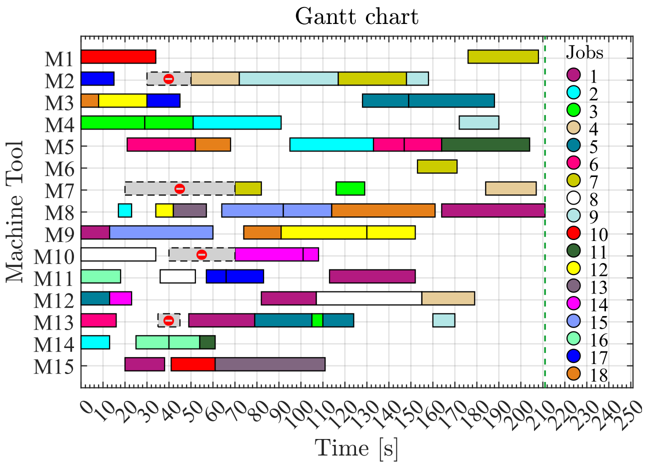

Figure 9. *Gantt chart of the rescheduling plan (balanced machine utilization - obj1)*

Figure 10 illustrates the initial optimal scheduling plan before the machine tool breakdowns, generated using mean flow time (*obj2*) as the objective function.

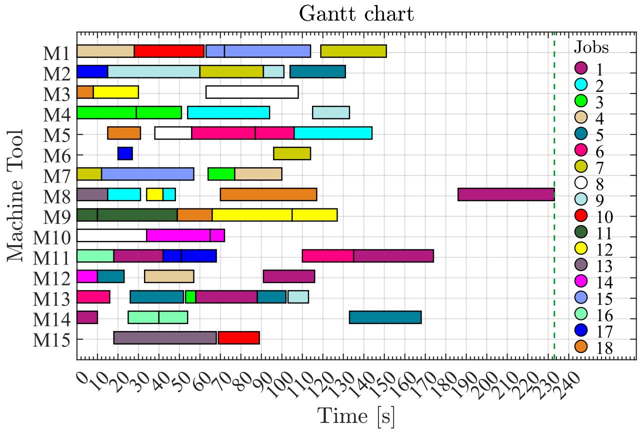

Figure 10. *Gantt chart of the initial scheduling plan (mean flow time - obj2)*

As in the previous experiment, following the four machine tool breakdowns and the subsequent rescheduling process, a new optimized plan is generated and shown in Figure 11.

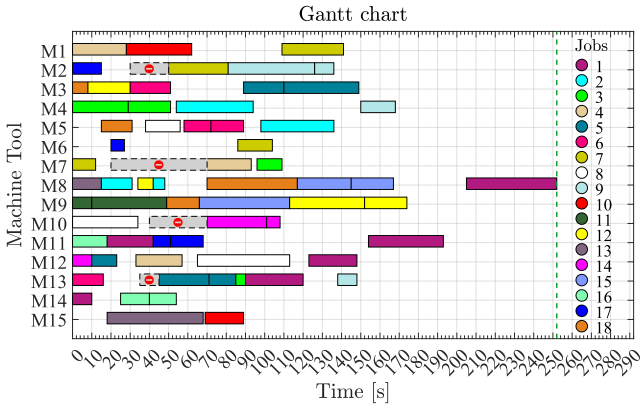

Figure 11. *Gantt chart of the rescheduling plan (mean flow time - obj2)*

The resulting Gantt charts confirm that the proposed method successfully generates a new rescheduling plan under multiple machine tool breakdowns. In both experiments, the algorithm effectively reschedules the remaining operations to the available machine tools, while respecting process constraints, operation sequences, and downtime intervals. The balanced machine utilization criterion leads to a more uniform workload distribution across machines, whereas the mean flow time criterion results in faster completion of individual jobs. Overall, the visualized schedules demonstrate that the method maintains system stability and achieves the intended optimization objectives despite significant disturbances.

5 CONCLUSION

This research analyzed the flexible job shop rescheduling process under machine tool breakdowns occurring on multiple machines at different time instances, reflecting real cyber-induced disturbances in modern manufacturing environments. By employing a GA and evaluating the performance of the manufacturing system through balanced machine utilization and mean flow time, the proposed approach demonstrated the ability to efficiently reschedule operations during periods of machine unavailability while maintaining overall stability.
Two separate experiments were carried out, one focusing on balanced machine utilization and the other on minimizing mean flow time, to evaluate the overall performance of the manufacturing system under different optimization objectives. The results indicate that, even when disturbances interrupt the workflow, the system can dynamically reschedule the remaining operations across the available machine tools without creating excessive bottlenecks or overloading specific resources. Once the consequences of the cyber-attacks and the corresponding machine tool failures are resolved, the approach effectively reintegrates the recovered machine tools into the rescheduling plan, resulting in successful optimization of the defined criteria. Therefore, this adaptability contributes to a more uniform workload distribution and reduced flow times, ensuring a robust and resilient scheduling process under security-driven disturbances. Future research may focus on incorporating predictive mechanisms for early disturbance detection, as well as on exploring advanced or hybrid metaheuristic methods to further improve responsiveness and enhance the resilience of scheduling systems operating in cybersecurity-aware manufacturing environments.

ACKNOWLEDGMENT

This research was supported by the Science Fund of the Republic of Serbia, Grant No. 17801, Cybersecurity of Motion Control Systems in Industry 4.0 - MCSecurity, as well as by the Ministry of Science, Technological Development, and Innovations of the Serbian Government under Contract No. 451-03-137/2025-03/200105.

REFERENCES

1. E. Ahmadi, M. Zandieh, M. Farrokh, and S. M. Emami, *A multi-objective optimization approach for flexible job shop scheduling problem under random machine breakdown by evolutionary algorithms*, Computers and Operations Research, vol. 73, pp. 56–66, 2016.
2. M. Nouiri, A. Bekrar, A. Jemai, D. Trentesaux, A. C. Ammari, and S. Niar, *Two-stage particle swarm optimization to solve the flexible job shop predictive scheduling problem considering possible machine breakdowns*, Computers and Industrial Engineering, vol. 112, pp. 595–606, 2017.
3. N. Al-Hinai and T. Y. ElMekkawy, *Robust and stable flexible job shop scheduling with random machine breakdowns using a hybrid genetic algorithm*, International Journal of Production Economics, vol. 132, no. 2, pp. 279-291, 2011.
4. L. J. Wells, J. A. Camelio, C. B. Williams, and J. White, *Cyber-physical security challenges in*

manufacturing systems, Manufacturing Letters, vol. 2, no. 2, pp. 74–77, 2014.
5. R. Masum, *Cyber Security in Smart Manufacturing (Threats, Landscapes & Challenges)*, Department of Computer Science, Tennessee Tech University, Cookeville, TN, USA, preprint arXiv:2304.10180, Apr. 2023.
6. Z. Liang, P. Zhong, C. Zhang, W. Yang, W. Xiong, S. Yang, and J. Meng, *A genetic algorithm-based approach for flexible job shop rescheduling problem with machine failure interference*, Eksploatacja i Niezawodność – Maintenance and Reliability, vol. 25, no. 4, pp. 642–654, 2023.
7. Boudjemline, I. A. Chaudhry, A. F. Rafique, I. A.-Q. Elbadawi, M. Aichouni, and M. Boujelbene, *Multi-Objective Flexible Job Shop Scheduling Using Genetic Algorithms*, Tehnički vjesnik – Technical Gazette, vol. 29, no. 5, pp. 1706–1713, 2022.
8. O. Gholami, Y. N. Sotskov, and F. Werner, *A genetic algorithm for hybrid job-shop scheduling problems with minimizing the makespan or mean flow time*, Journal of Advanced Manufacturing Systems, vol. 17, no. 4, pp. 563–578, 2018.
9. M. Petrović, N. Vuković, M. Mitić, and Z. Miljković, *Integration of process planning and scheduling using chaotic particle swarm optimization algorithm*, Expert Systems with Applications, vol. 64, pp. 569–588, 2016.
10. M. M. Petrović, *Design of intelligent manufacturing systems by using artificial intelligence*, Ph.D. dissertation, University of Belgrade – Faculty of Mechanical Engineering, Belgrade, Serbia, 2016.
11. S. Lv and L. Qiao, *Process planning and scheduling integration with optimal rescheduling strategies*, International Journal of Computer Integrated Manufacturing, vol. 27, no. 7, pp. 638–655, 2014.
12. H. Xia, X. Li, and L. Gao, *A hybrid genetic algorithm with variable neighborhood search for dynamic integrated process planning and scheduling*, Computers & Industrial Engineering, vol. 102, pp. 99–112, 2016.

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