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PRODUCTION SCHEDULING OPTIMIZATION FOR THE MANUFACTURING OF POWER PLUG ADAPTER USING A FLEXIBLE JOB SHOP APPROACH

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Abstract

The manufacturing of electrical connectors involves multiple sequential operations that frequently compete for shared machines and assembly workstations. Such resource conflicts often lead to idle times, bottlenecks, and extended production cycles. In this study, the production process for three types of electrical plugs is modeled and analyzed with the aim of minimizing the total manufacturing time. The process is formulated as a Flexible Job Shop Scheduling Problem (FJSSP), where each product is characterized by a fixed sequence of operations, several of which can be performed on alternative machines or assembly positions. Real processing-time data from the production system were used to construct the scheduling model. A baseline schedule was first generated using a Genetic Algorithm that assigns operations to the earliest available machine.

***Keywords**: Flexible Job Shop Scheduling, Production Optimization, Manufacturing, Production Time Minimization, Genetic Algorithm*

1 INTRODUCTION

The production of small-scale consumer electrotechnical products remains a dynamic and competitive segment of the manufacturing industry. Among such products, electrical connectors for residential or industrial use represent a significant category due to their frequent demand and recurring purchase cycles. In Serbia, the electronics and electronic component manufacturing industry encompasses more than a thousand registered companies, with a relevant sub-sector of component and board manufacturers. This industrial ecosystem includes firms producing a variety of electrotechnical components and assemblies, which underlines the potential scale and economic importance of connector manufacturing. The manufacturing process for electrical connectors typically involves multiple operation sequences and a diverse set of machines; in many cases, products are grouped by similarities, which allows grouping of both machines and operations. Therefore, process efficiency directly impacts productivity and competitiveness, which is a critical factor in a market characterized by high competition and demand for quality.

Small and medium-sized enterprises (SMEs) constitute the majority of firms operating in the electrotechnical manufacturing sector. Unlike large-scale production systems, where workflows are highly standardized and tightly controlled, SMEs often rely on more flexible and adaptive production structures. This flexibility allows them to switch rapidly between different products and respond effectively to fluctuating market demands, however, it also introduces significant organizational challenges [1]. In such environments, multiple products frequently share the same machines, tools, and assembly workstations. As a result, operations may compete for limited resources, leading to scheduling conflicts, process overlaps, and unbalanced workloads. These effects manifest as bottlenecks [2], extended waiting times between operations, and generally suboptimal utilization of available production capacities. Moreover, equipment failures or machine downtime do not affect only the product currently being processed. Because different product families rely on the same core set of machines and workstations, any interruption propagates through the entire system, delaying or halting the production of all affected products. This interconnectedness amplifies the impact of operational disturbances and further complicates the task of maintaining efficient flow in a multi-product manufacturing environment.

To reduce bottlenecks and production slowdown, especially common in small and medium-sized (SMEs) enterprises, effective production scheduling is essential. Its goal is to minimize makespan, eliminate idle times and overlaps, and improve the overall efficiency of manufacturing operations. Scheduling becomes particularly important in systems with many sequential tasks and shared machines, where even minor inefficiencies can propagate through the entire workflow. In this context, the Flexible Job Shop Scheduling Problem (FJSSP) offers an appropriate modeling framework, as it captures the complexity of multi-product environments while allowing operations to be performed on alternative machines or workstations [3].

Several studies have investigated scheduling problems involving parallel or multiple machines under various operational constraints. The work in [4] analyzes the scheduling of independent jobs with specified release dates and deadlines across several parallel machines. A genetic algorithm for parallel machine scheduling is introduced in [5], where the authors show that their approach outperforms other existing techniques. Similarly, [6] applies a simulated annealing strategy to parallel machine scheduling with setup considerations, using a restricted neighborhood search to limit computational effort. The study in [7] focuses on

minimizing total completion time in a two-machine parallel scheduling environment. Additionally, Ying et al. [8] investigate parallel machine scheduling under machine availability constraints and present a dynamic time-programming method along with a fully polynomial-time approximation scheme for the two-machine case. The work in [9] further examines parallel machine scheduling within manufacturing settings, emphasizing improvements in completion times to increase overall production efficiency.
In this study, the production of power plug adapters is modeled as a Flexible Job Shop Scheduling Problem using real processing-time data from an industrial manufacturing setting. The aim is to develop and evaluate scheduling strategies that reduce makespan and improve the utilization of shared machines and assembly workstations. By examining a practical multi-product environment characterized by sequential operations and resource overlap, the work provides insight into how scheduling optimization can significantly enhance efficiency in small and medium-scale manufacturing systems.

2 CASE STUDY

This study was conducted in the company Elka Nova d.o.o., located in Niš, Serbia, which specializes in the manufacturing of electrotechnical consumer products. Within its production portfolio, several product families are grouped according to similarity in design and technological requirements. For the purpose of this analysis, three products belonging to the same family of power plug adapters were selected for scheduling optimization:

- J1 Three-phase power plug
- J2 “L-type” power plug
- J3 Flat power plug

a) b) c)

Figure 1 Product illustration

All three products follow a multi-stage production process consisting of sequential operations performed on a shared set of machines and assembly workstations. The available production resources used for their manufacturing are listed in Table 1.

Table 1 Production resources used in the case study

Label	Resource description
M1	Injection molding machine 1
M2	Injection molding machine 2
M3	Eccentric press
M4	Vertical drill
M5	Manual bending press
M6	Manual bending press 1
M7	Manual bending press 2
M8	Assembly workstation 1
M9	Assembly workstation 2
M10	Assembly workstation 3
M11	Assembly workstation 4

Each product consists of a fixed sequence of operations, many of which are similar across products and therefore executed on the same resource groups. Tables 2 list the operations for each product.

Table 2 Operations for products

J1 Three-phase power plug	J2 “L-type” power plug	J3 Flat power plug
O1.1 Plastic part molding	O2.1 Plastic part molding	O3.1 Plastic part molding
O1.2 Ground conductor fabrication	O2.2 Ground conductor fabrication	O3.2 Ground conductor fabrication
O1.3 Insertion of metal pins	O2.3 Placement of ground conductor into housing	O3.3 Crimping of ground conductor and cube terminal
O1.4 Tightening three screws	O2.4 Bending of grounding conductor	O3.4 Screw fastening of metal pins
O1.5 Thread cutting on ground contacts	O2.5 Thread cutting	O3.5 Fastening metal clamps
O1.6 Fastening metal clamps	O2.6 Screw fastening into ground contact	O3.6 Fastening a single screw onto the cube terminal
O1.7 Fastening the ground conductor	O2.7 Fastening metal clamps	O3.7 Placement of pins into housing
O1.8 Insertion of the grounding conductor	O2.8 Screw fastening of metal pins	O3.8 Final assembly and cap closing
O1.9 Bending of grounding conductor	O2.9 Placement of pins into housing	
O1.10 Final assembly and cap closing	O2.10 Final assembly and cap closing	

A distinctive characteristic of the analyzed production system is the presence of flexible machine assignments for several key operations. Specifically, the first operation for each product (O1.1, O2.1, O3.1) can be performed on either of the two injection molding machines (M1 or M2). In addition, all final assembly and several intermediate operations can be executed on any of the four available assembly workstations (M8–M11). This flexibility enables alternative route options for multiple operations across products, but it also increases the complexity of the scheduling problem, as the model must account not only for sequencing constraints but also for the optimal selection of machines among several feasible choices. The inclusion of these flexible machine groups effectively transforms the problem from a classical job shop configuration into a Flexible Job Shop Scheduling Problem (FJSSP), in which decisions about resource allocation play a critical role in minimizing the overall makespan and ensuring efficient utilization of shared production capacities.

The processing time for each operation on all feasible machines or workstations is provided in Figure 1. These times represent real measurement data obtained from the company's production environment. The table forms the basis for scheduling model development and subsequent simulation and optimization.

		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11
J1	O1.1	20	20									
	O1.2			2								
	O1.3						10					
	O1.4								10.2	10.2	10.2	10.2
	O1.5				11							
	O1.6								16	16	16	16
	O1.7								8.9	8.9	8.9	8.9
	O1.8								10.1	10.1	10.1	10.1
	O1.9					4						
	O1.10								12	12	12	12
J2	O2.1	20	20									
	O2.2			2								
	O2.3								4.9	4.9	4.9	4.9
	O2.4							4.8				
	O2.5								3	3	3	3
	O2.6								4.2	4.2	4.2	4.2
	O2.7								8.5	8.5	8.5	8.5
	O2.8								9.2	9.2	9.2	9.2
	O2.9								4	4	4	4
	O2.10								9	9	9	9
J3	O3.1	20	20									
	O3.2			2								
	O3.3							10.2				
	O3.4								9.2	9.2	9.2	9.2
	O3.5								8.5	8.5	8.5	8.5
	O3.6								2.1	2.1	2.1	2.1
	O3.7								9	9	9	9
	O3.8								11	11	11	11

Figure 2 Processing times

3 METHODOLOGY

The scheduling optimization in this study was carried out using a Genetic Algorithm (GA), a metaheuristic widely recognized for its effectiveness in solving complex combinatorial problems such as the Flexible Job Shop Scheduling Problem. Originally developed by Holland in the 1970s, the GA mimics biological evolutionary principles, most notably selection, crossover, and mutation, to iteratively improve candidate solutions within a population. In the context of the present work, each candidate solution represents a feasible production schedule, encoded as a chromosome that contains information on job sequencing, machine assignments, and operation ordering. The algorithm begins by generating an initial population of such chromosomes, after which successive generations are produced by applying genetic operators. Selection favors solutions with better fitness, in this case, schedules with shorter makespan, while crossover and mutation introduce controlled variability, preventing premature convergence and enabling the exploration of a broader search space. This evolutionary process allows the GA to effectively navigate the high-dimensional and nonlinear nature of FJSSP scheduling, where both sequencing and resource assignment decisions must be optimized simultaneously. The overall structure of the genetic algorithm used in this study is summarized in Figure 2, and Table 3 represent input parameters used for GA.

Define the objective function $f(x)$, where $x = (x_1, x_2, ..., x_n)T$ represents a solution vector
  for resource allocation and scheduling
Encode each solution x into a chromosome (e.g., binary or integer string representing
  job sequences, machine assignments, start times, etc.)
Define the fitness function F such that $F \propto f(x)$ for maximization (e.g., minimizing makespan,
  maximizing resource utilization, or minimizing total delay)
Generate an initial population of chromosomes (solutions)
Initialize crossover probability pc and mutation probability pm
While ($t < Max$ number of generations or stopping criteria not met)
  For each pair of selected parent chromosomes:
    If $rand < pc$, perform crossover to generate offspring
    If $rand < pm$, apply mutation to introduce variability
  Evaluate the fitness of new offspring
  If the fitness of an offspring is better than the parent(s), accept the offspring
  Apply selection strategy (e.g., tournament or roulette-wheel) to choose individuals
    for the next generation based on fitness
  Update the current best solution found so far
  Increment generation counter t
end while
Decode the final solution(s) from chromosomes into real resource plans and schedules
Visualize or interpret results for decision-making (e.g., Gantt chart or schedule table)

Figure 3 Pseudo code of GA

Table 3 Input parameters used for the optimization processes of the GA

GA parameters			
MaxIterations	nPop	Mij	Cross
500	250	0.02	0.4

4 RESULTS AND DISCUSION

The objective of this study was to evaluate the impact of scheduling optimization on the production of three types of power plug adapters within a real industrial environment. Using the processing-time data collected from the manufacturing system, a baseline schedule was first generated through a simple heuristic that assigns each operation to the earliest available feasible machine or workstation. This initial schedule reflects the natural, non-optimized flow of operations and serves as a reference for performance comparison. Subsequently, a Genetic Algorithm–based optimization procedure was applied to minimize makespan while considering sequencing constraints and machine flexibility inherent to the Flexible Job Shop Scheduling Problem. The results presented in this section compare the baseline and optimized schedules and demonstrate the extent to which the proposed approach can improve overall production efficiency.

Figure 3. represents optimized production schedule generated by the GA, showing the allocation of all operations for Jobs 1–3 across resources M1–M11.

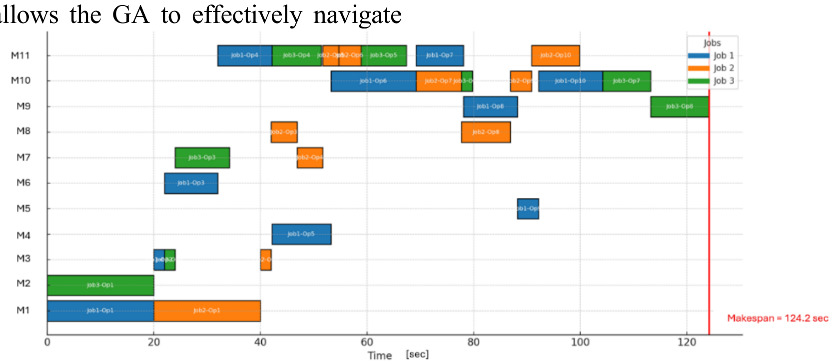

Figure 4 Optimized production schedule generated by the Genetic Algorithm

The optimized schedule in Figure 3 presents the distribution of all operations across the eleven resources and workstations included in the manufacturing system. Each colored block corresponds to a specific operation from one of the three jobs, allowing a clear visualization of how the GA allocated tasks over time. The resulting makespan of 124.2 seconds represents the total processing time required for all operations to be completed under the optimized configuration.

Before introducing scheduling optimization, the average production time per unit, measured over a full 8-hour shift, was 182 seconds. During this period, the order of operations was determined manually by the production supervisor, often relying on experience and moment-to-moment decisions, which introduced unnecessary idle periods and inconsistencies in workflow organization. The GA produced an optimized schedule with a predicted processing time of 124.2 seconds, representing a theoretical reduction of 31.8% compared to the baseline. When the optimized schedule was implemented in the real production environment, the measured average processing time per unit decreased to 141 seconds, corresponding to an actual improvement of 22.5% relative to the pre-optimization state. The discrepancy between the GA-predicted time and the real post-optimization performance (a difference of 16.8 seconds, or 13.5%) is primarily attributed to factors not explicitly modeled in the scheduling algorithm. These include handling and positioning time between workstations, micro-delays associated with manual operations, variations in operator speed, momentary fatigue, setup adjustments, and other forms of stochastic human or environment induced variability. Despite these deviations, the implementation of the GA-generated schedule still resulted in a substantial and measurable improvement of production efficiency in the real system (see Figure 3).

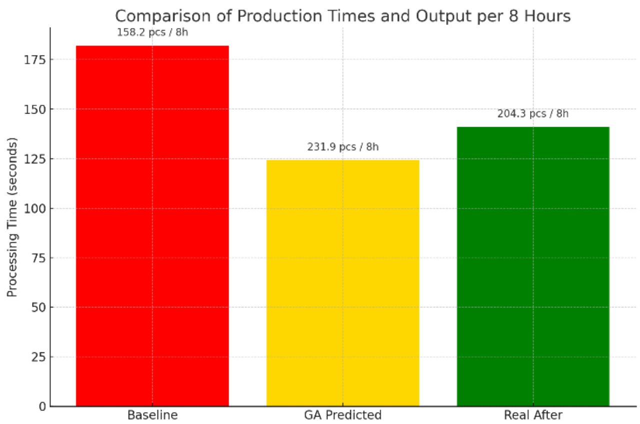

Figure 5 Comparison of production times before and after GA optimization

5 CONCLUSION

This study addressed the problem of optimizing the production of power plug adapters in a real manufacturing environment using a Flexible Job Shop Scheduling formulation and a Genetic Algorithm–based optimization framework. Three products with similar technological structures were analyzed, each requiring sequential operations performed on shared machines and flexible assembly workstations. The availability of alternative machines for several key operations introduced significant scheduling complexity, making the system an appropriate candidate for heuristic optimization. The Genetic Algorithm successfully generated optimized schedules that substantially reduced makespan compared to the non-optimized baseline. The algorithm predicted a processing time of 124.2 seconds, representing a theoretical improvement of 31.8% relative to the initial average of 182 seconds. When the optimized schedule was implemented in the real production system, the measured average processing time per unit decreased to 141 seconds, corresponding to an actual improvement of 22.5%. Although the real-world results did not fully match the idealized prediction, the difference can be attributed to practical factors not included in the scheduling model, such as manual handling time, material repositioning, minor operator delays, fatigue effects, and other stochastic elements of human-centered manufacturing processes. Despite these inherent variabilities, the applied optimization approach demonstrated clear benefits by improving resource utilization, reducing idle time at shared workstations, and providing a systematic procedure for determining operation order and machine assignment—replacing the previously intuitive and experience-based decision-making process. The findings confirm that the use of heuristic optimization techniques such as Genetic Algorithms can significantly enhance productivity in small and medium-sized manufacturing enterprises, especially in environments characterized by multi-product flow and flexible resource assignments.

Future work may include extending the model to incorporate stochastic elements, transportation and handling times, operator-specific performance characteristics, or multi-objective optimization criteria, such as energy consumption or workload balancing. Integrating such factors would enable a more comprehensive representation of real production conditions and could further improve the accuracy and robustness of the optimized schedules.

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