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A bi-objective Genetic Algorithm for flexible flow shop scheduling: A real-world application in the electrical industry

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A B S T R A C T

The electrical sector forces manufacturing companies of electrical solutions to continually innovate and implement new processes for greater efficiency. The growing demand for electrical energy, as well as the need to adapt to hybrid operations that combine multi-project operation models with continuous production models, requires efficient workflow management. Accordingly, this article proposes a Genetic Algorithm (GA) approach for solving the scheduling problem in a Flexible Hybrid Flow Shop (FHFS) environment considering a transfer batch approach to minimize makespan and total tardiness. The approach is inspired by a real-world application in the electrical industry and also accounts for unrelated parallel machines, precedence, release times, and due dates for jobs at each production center as key constraints. Three real-data scenarios were generated and evaluated. In the first scenario, a 7 % improvement in makespan was observed compared to real execution times. In Scenario 2, the makespan improved significantly by 33 %, and only 17.4 % of jobs were delayed, compared to 96 % in the real data. Likewise, GA showed a lightly better performance over Tabu Search (TS) in 3.01 % for makespan while the delayed jobs found by GA were 25 % below those obtained by TS. These results highlight the potential of the proposed method to improve overall production efficiency, not only in the electrical sector but also in similar industries.

A R T I C L E   I N F O

Keywords:
Production scheduling;
Flexible flow shop;
Genetic algorithm;
Makespan;
Tardiness;
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1. Introduction

In the rapidly evolving electrical sector, manufacturing companies face continuous challenges to innovate and implement new processes aimed at enhancing efficiency. The growing demand for electrical energy, driven by the increasing interconnectivity of devices through the Internet of Things (IoT) and emerging technologies, necessitates a shift toward hybrid operational models that blend multi-project frameworks with continuous production systems. This trend underscores the urgent need for effective workflow management and highlights the complexities of production processes. As the sector increasingly adopts electronic equipment and the infrastructure required for its operation, planning, scheduling, and production control have become critical to ensuring competitiveness and success. Companies are tasked with not only meeting rising production demands but also adapting to the customization requirements of their customers in an ever-changing market. This dynamic environment compels firms in the electrical sector to consistently align their operations with the rapid pace of technological advancements and evolving customer expectations.

Consequently, the production processes within these companies must navigate the dual challenge of enhancing efficiency while accommodating the growing demand for tailored solutions. This delightful balance is essential for maintaining relevance and achieving long-term sustainability in a sector characterized by constant change. Accordingly, the literature during the last decades has been describing a great amount of research focused on solving these kinds of problems from both real applications and theory points of view. Thus, this work made a review on this literature focus the search mainly on scheduling problems considering flexible production systems, one of the most used metaheuristics known as Genetic Algorithm and application on several industries, especially in electrical sector.

Initially, the flexible production systems, also known as Hybrid Systems (HS) or Flexible Hybrid Flow Shop Systems (FHFS), are defined as the scheduling of n jobs across m processing stages that consider a specific objective function, as determined by the production sequence of the job according to Xu *et al*. [1]. The scheduling problem in FHFS is known for its high combinatorial complexity. The allocation of resources to perform different operations in the production process results in a combinatorial complexity problem that must be optimized. In other words, the number of possible sequences and production route combinations can grow exponentially with the number of jobs and workstations; therefore, scheduling problems in an FHFS system are considered NP-Hard according to Gupta *et al*. [2]. Similarly, the objective functions considered are mainly the minimizing of total production time (makespan) [1, 4, 6-12, 14-17], followed by total tardiness [3, 5, 8, 12-13], productivity [1, 4-5, 7, 14, 16-17], among others.

The inherent flexibility of a flexible hybrid system implies the system must dynamically adapt to changes in demand, machine failures, or new work orders [1, 3, 5-7, 9-12, 16]. Optimization under these changing conditions requires algorithms that can handle uncertainty and variability, which is inherently complex and difficult to solve in polynomial time [1-17]. Most problems in an FHFS do not have a single objective [5, 8-9, 11-12, 15]. Generally, there are multiple objectives in conflict, such as minimizing production time, maximizing machine utilization, and minimizing costs, meaning that optimizing multiple objectives is even more complex. For example, Hasani *et al*. [15] proposed solving a bi-objective scheduling problem in a flexible Flow Shop with unrelated parallel machines, minimizing makespan and total production cost; authors introduced an approximate solution method based on a Non-dominated Sorting Genetic Algorithm (NSGA-II). Also, Jeen and Rajkumar [4] implemented a modified genetic algorithm in a Flow Shop production environment to minimize the makespan.

In addition, considering the approaches addressed to solve the FHFS scheduling problem, the Genetic Algorithm, which is nature-inspired, is one of the most used metaheuristics for this problem. For instance, Espitia and Mendoza [11] developed a scheduling methodology based on the use of a genetic algorithm as a solution method to minimize makespan and tardy jobs. Similarly, Salazar and Sarzuri [3] Considered a FSF environment with anticipatory sequence-dependent setup times, applying a genetic algorithm to minimize total tardiness by using dispatching rules for the initial population of EDD (Earliest Due Date). They also considered an IP neighbourhood search to enhance the performance of the proposed genetic algorithm. Likewise, Xu *et al*. [1] presents a case study where they develop a mathematical model aimed at minimizing the maximum completion time for a mixed flow shop scheduling problem, using a genetic algorithm to solve the problem. Najarro *et al*. [6] analysed the effect of including various constraints that negatively impact scheduling in a real Flow Shop environment, introducing an efficient genetic algorithm combined with a variable neighbourhood search, minimizing makespan. Han. and Lee [17] explored HFS pro-duction management based on an improved Genetic Algorithm (GA), proposing several assumptions for the multi-objective optimization problem of HFS production management. They introduced new constraints to the problem, such as multi-period control and job transport time, achieving efficiency in the experiments. As well, López *et al*. [16] selected a textile company as their case study and, through the coding of a simple genetic algorithm, developed a production scheduling methodology for Flexible Hybrid Flow Shop configurations, successfully reducing makespan.

Table 1 Classification of articles by production types

Method	Articles	Heuristic and Metaheuristic methods										Objective Function					Approach		Approach		
		AG	LS	TS	EA	ICA	NEH	NQ-L	NSGAII	SPEA 2	MOGA	Cmax	Tj	Energy	Tt	Cost	SP	ST	Stages	Hybrid	Lots
	[1] Xu, W. *et al.* (2022)	o										x					x			x	
	[3] Salazar, E. and Sarzuri R. (2015)	o											x							x	
	[4] Jeen, R and Rajkumar R. (2017)	o										x				x	x				
	[5] Kazemi, H. *et al.* (2017)					o							x				x		x	x	
	[6] Najarro, R. *et al.* (2017)	o	o									x								x	
	[7] Bedhief, A.O and Dridi. N. (2019)						o					x					x		x	x	
	[8] Tian, X. K. *et al.* (2019)	o										x	x								x
Flow Shop	[9] Shijin, W. *et al.* (2019)			o								x		x					x	x	
	[10] Waraporn, F. *et al.* (2020)			o								x								x	
	[11] Espitia, J.A. and Mendoza, G.L. (2021)	o									o	x			x					x	
	[12] Chen, D. and Zhao, X.R. (2021)	o										x	x			x		x		x	
	[13] Ištoković, D. *et al.* (2021)	o											x								x
	[14] Ren, J.F. *et al.* (2021)							o				x					x				x
	[15] Hasani, A. *et al.* (2022)	o			o				o	o		x				x			x		
	[16] López, J.C. *et al.* (2014)	o										x							x	x	
	[17] Han, J.H. and Lee, J.Y. (2023)	o										x					x	x	x		

AG: Genetic Algorithm; LS: Local Search; TS: Tabu Search; EA: Evolutionary Algorithm; ICA: Imperialist Competitive Algorithm; NEH: Nawaz, Enscore, Ham
NSGAII: Non-dominated Sorting Genetic Algorithm; NQ-L: Reinforcement Learning Method; SPEA2: Strength Pareto Evolutionary Algorithm
MOGA: Multi-Objective Genetic Algorithm SP: Scheduling Problem; ST: Setup Time; Cmax: Makespan; Tj: Total Tardiness; Tt: Tardy Jobs

In summary, Table 1 shows the consolidation of the main research reviewed, highlighting the different objectives, approaches, and research methodologies for solving production planning problems. Thus, one of the relevant findings is the predominant interest in makespan ($C_{\max}$) and tardiness $\left(T_j\right)$ minimization. Thus, this paper describes a Genetic Algorithm (GA) approach for solving the scheduling problem in a Flexible Hybrid Flow Shop (FHFS) environment, inspired by a real-world application in the electrical industry, the results show an important improvement on the current performance of production system resulting in a valuable tool in decision making for company.

The remaining content of this work is as follows. Section 1 provides a clear introduction to the problem being addressed, along with a literature review focused on the main topics, particularly in electrical industry applications and scheduling solution approaches. Section 2 presents the characterization of the production process for the real case. Sections 3 and 4 detail the problem definition and the proposed solution method, respectively. Section 5 explains the real instance of the production process in the case study as well as presents the results and analysis of the evaluated scenarios. Finally, Section 6 addresses the conclusions and potential ways for future research.

2. Description of production process

The electrical company specializes in the design and manufacturing of customized solutions under an Engineering to Order (ETO) production scheme. Its operation is divided into two key phases: the project-based model and the production-based model. The first phase encompasses all related from sales to the availability of materials, managing each project individually. This stage includes subprocesses such as sales, project management, engineering, procurement, logistics, and storage, where opportunities are identified, contractual aspects are managed, technical designs are developed, and necessary materials are ensured. The second phase, focused on productive execution through a Flexible Flow Shop approach, primarily concentrates on production processes, where raw materials are transformed, and the final product is assembled. This model allows manufacturing to be adapted to the specifications of each project, addressing several challenges in a structured manner. Mainly, the scheduling approach of this research is focusing only on the stages of the process that are directly related to product manufacturing. Thus, the set of production and project jobs merged from project-based model phase. Table 2 describes, for the project-based model, only the electrical and mechanical engineering stages, while the production-based model includes the production centres, and the stages required for the transformation of raw materials and assembly.

Table 2 Grouping of production and project tasks

Phase	Production center	Cod	Description
Project-based model	Electrical engineering	RITM	Information review
		ECU	Equalization meeting with the client – Tecnichal clarifications
		L090	List of electrical materials with delivery time greater than 90 days
		EPA	Development of basic engineering for client approval
		APRB	Approval of basic engineering by the client
		PED	Detailed electrical engineering by the client
		APRD	Approval of detailed engineering by the client
	Mechanical engineering	LME	List of mechanical materials for structures
		LMV	List of various mechanical materials and cooper vbars
Production-based model	Manufacturing	PCN	CNC programing
		FMC	Cutting and punching of steel metal
		FMD	Bending of sheet metal
		SOL	Welding
		TPI	Treatment and painting
		FBC	Manufacturing of cooper bars
	Assembly	EME	Mechanical assembly
		EEL	Electrical assembly
		EBC	Assembly of cooper busbars
		PRU	Testing

2.1 Production centre capacity

The capacity of the production centres is defined in terms of the amount of work each can perform within a specific time; it is measured in effective working hours for the context of this research. Each centre's capacity is determined by the number of personnel and/or the effective availability of the machines it comprises. The total capacity of the centre is obtained by adding up these individual capacities, expressed in terms of available working hours. Table 3 provides a detailed breakdown of the production centres (CP1, CP2, and CP3), which includes the production stages, the duration of each stage of 9 hours, the work shifts, and the required human resources, equipment, or machines. CP1 includes the electrical and mechanical engineering stages, each requiring six human resources. Meanwhile, CP2 focuses on manufacturing processes such as CNC programming, cutting, bending, welding, treatment, and copper bar fabrication, with personnel needs varying between one and four human resources, in addition to the use of machines. Finally, CP3 is dedicated to assembly, where the stages require between two and eight human resources. The distribution of work capacity among the various production centres illustrates the complexity and specialization of each stage in the production process. As manufacturing progresses, it is essential to consider both resource availability and process efficiency, as these factors will impact on the total production capacity and, ultimately, the timely delivery of the final products.

According to capacity determined in each production centre (CP1, CP2 and CP3), as well as the work centres into them, the production times were established and shown in Table 4; this table provides a comprehensive overview of the processing time required (in days) for various products across different production centres and stages of the process, organized into families and specific items. The columns "Family" and "Item" indicate the type of product being manufactured, where each "Family" represents a broader category, such as Medium Voltage (MT), which includes products designed for electrical solutions in installations ranging from 1 to 57.7 kV, and Low Voltage (BT), which encompasses solutions for electrical installations below 1 kV. Each "Item" specifies a product within that category, such as the Motor Control Centre (CCM) or the Auxiliary Services Panel (TSA). In addition, the table highlights the time required for each process—engineering, manufacturing, and assembly—across the production centres (CP1, CP2, and CP3). For example, the "Power Distribution Centre" (CDP) requires approximately 3.94 days for electrical engineering (CP1), 0.76 days for bending (CP2), and 4.68 days for testing (CP3). This detailed breakdown is essential for understanding production timelines and efficiently managing resource allocation.

Table 3 Production centre capacity

Production center	Stage	Description	Duration (hrs)	Work shifts	Human resources	Description
CP1	A	Electrical engineering	9	1	6	HR + CE
	B	Mechanical enginering	9	1	6	HR + CE
CP2	C	CNC programming	9	1	1	HR + CE
	D	Cutting and punching	9	1	2	HR + M
	E	Bending	9	1	2	HR + M
	F	Welding	9	1	4	HR + M
	G	Treatment and painting	9	1	2	HR + M
	H	Cooper busbar fabrication	9	1	2	HR + M
CP3	I	Mechanical assembly	9	1	4	HR + CE
	J	Electrical assembly	9	1	8	HR + CE
	K	Cooper busbar assembly	9	1	2	HR + CE
	L	Quality control and electrical testing	9	1	4	HR + CE

HR: Human resources; CE: Computer equipment; M: Machines

The result of data shown in Table 4, is the production system is settled as the diagram described in Fig. 1. At the top of the diagram, the general production centres are identified: CP1 (Engineering), CP2 (Manufacturing), and CP3 (Assembly). In the next level, the stages of the process are located, while the subsequent level details, the available resources, whether human or machine. The arrows represent the different routes the product can take through the various production centres and stages for its manufacturing. Thus, the production process is considered as a flexible flow shop model. Each box shows the number of machines and the consecutive id to identify it into the model. For example, the CP1 production centre has in total six (6) machines which are the first machines from the total list of resources which has in total 43 machines.

Table 4 Time required (days)

Description of products				Time required by process (days)											
				CP1 – Enginnering		CP2 – Manufacturing						CP3 – Assembly			
				1	2	3	4	5	6	7	8	9	10	11	12
Family	Item	Description	Type of solution	Electrical engineering	Mechanical engineering	PCN-CNC programing	FMC-Cutting and punching	FMD-Bending	SOL-Welding	TPI-Treatment and painting	FBC-Cu busbar fabrication	EME-Mechanical assembly	EEL-Electrical assembly	EBC-Cu busbar assembly	PRU-Testing
	1	Power distribution center	CDP	**3.94**	2.40	0.39	0.42	**0.76**	0.67	0.39	0.64	1.70	2.98	0.94	**4.68**
	2	Motor control center	CCM	4.92	3.20	0.39	0.31	0.66	0.40	0.57	0.81	1.93	4.25	1.02	5.78
	3	Auxiliary services panel	TSA	2.95	2.40	0.19	0.38	0.50	0.41	0.38	0.39	1.23	1.91	0.21	2.76
BT	4	Low voltage variable frecuency drives	VVB	3.94	2.54	0.19	0.44	0.86	0.97	0.42	0.56	1.75	4.46	0.79	4.82
	5	Low voltage soft starters	ASB	3.94	2.40	0.19	0.42	0.77	0.89	0.45	0.44	1.28	3.93	0.68	4.04
	6	Low voltage distribution panel	TDB	2.95	2.91	0.19	0.38	0.50	0.41	0.38	0.39	1.23	1.91	0.21	2.76
	7	Control and protection panel	TCP	6.89	2.40	0.19	0.38	0.58	0.42	0.30	0.11	0.89	6.38	0.19	6.80
	8	Medium voltage secondary switchgear 24 kV	CMS2	2.95	2.40	0.39	0.28	0.50	0.22	0.13	0.15	0.78	1.91	0.31	2.27
	9	Medium voltage secondary switchgear 36 kV	CMS3	3.94	3.20	0.39	0.28	0.79	0.29	0.13	0.16	1.35	2.34	0.34	2.59
	10	Medium voltage primary switchgear 17.5 kV	CMP1	4.92	3.20	0.39	0.51	0.88	0.67	0.39	0.64	2.07	5.38	0.94	4.68
MT	11	Medium voltage primary switchgear 36 kV	CMP3	4.92	3.20	0.39	0.58	0.92	0.78	0.56	0.68	2.14	5.38	1.20	4.68
	12	Primary medium voltage GIS switchgear	CMPG	4.92	4.00	0.39	0.58	0.93	1.29	0.86	0.34	2.53	5.54	0.71	4.68
	13	Medium voltage variable frecuency drives	VVMT	5.90	4.00	0.39	0.42	0.76	0.67	0.39	0.64	1.70	3.83	0.85	4.68
	14	Medium voltage soft starters	ASMT	5.90	4.00	0.39	0.36	0.65	0.57	0.33	0.55	1.45	3.32	0.72	4.68

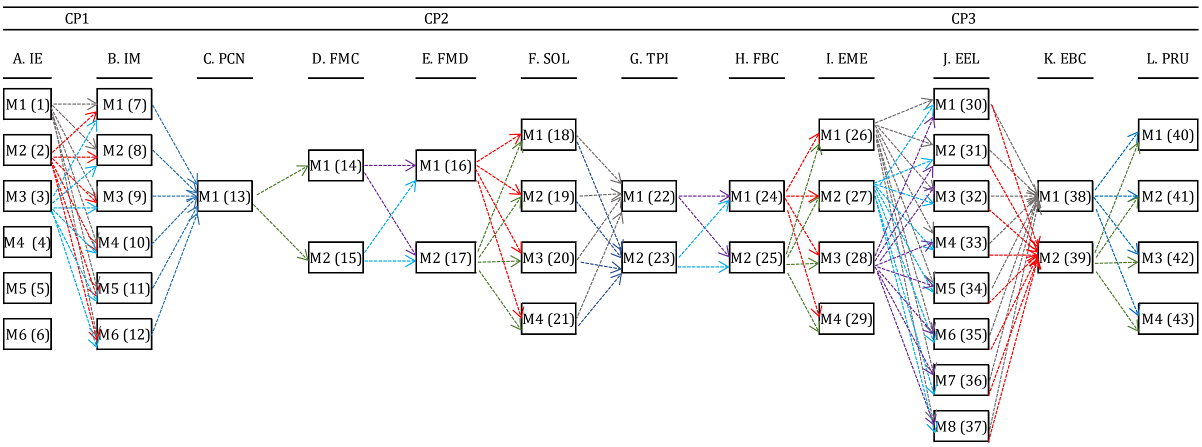

Fig. 1 Flow diagram of the production process

3. Construction of the HFS scheduling model

This study addresses the scheduling and permutation of tasks in a project planning environment within a Flexible Hybrid Flow Shop (HFS) production system. This system includes three production centres with unrelated parallel machines, dedicated to the fabrication, transformation, and testing of semi-finished and finished products for industrial electrical equipment projects. Key variables such as processing times, release times, and due dates are directly influenced by the production centre assigned. The objective functions considered are makespan and total tardiness, as main constraints are related to transfers lots, unrelated parallel machines, setup times. Accordingly, to Graham *et al*. [21], notation, the problem addressed is:

$$HFFS_m \ / \ R_m, r_j, S_{jk}, batch(b) \ / \ C_{max}, \sum T_j$$

The Hybrid Flow Shop (HFS) manufacturing environment presents complex scheduling challenges, involving the coordination of multiple jobs across various processing stages [1]. This problem is classified as strongly NP-Hard, meaning exact methods become infeasible for large instances, as confirmed by prior studies like those of Gupta *et al*. [2]. To address this complexity, metaheuristic algorithms, specifically Genetic Algorithms (GA), from mathematical model, is performed to provide approximate solutions.

In this study, a GA algorithm is adapted to optimize the scheduling process by minimizing makespan, total tardiness, and the number of delayed jobs in the HFS system; it means it is necessary to determine the optimal assignment of jobs j to machines k, within a sequence of production centres l, in such makespan (C_{max}) and total tardiness ($\sum T_j$) are minimized.

In addition, the developed algorithm does not consider dynamic inputs, which means that production orders arriving continuously or in real-time during the execution of the plan are not included; so, all production orders are predefined, and their characteristics are known at the beginning of the process due to this information is given by Planning and Production control Department of the company. Thus, the proposed Hybrid Flow Shop (HFS) production model is developed considering the following assumptions:

- Each machine can process only one job at a time.
- Each job is processed by only one machine at any given time.
- Jobs follow a fixed sequence of production centres (e.g. CP1, CP2, and CP3).
- Once started, a job is processed to completion without interruptions.
- The number of jobs and their processing times are deterministic.
- Setup times are considered negligible to simplify the model.
- Jobs can only be processed if the corresponding production centre is available.
- Transportation times between machines depend on the predefined sequence.
- Jobs can be assigned to any available machine within their respective set.
- Maintenance schedules are predefined and occur outside production times.
- Materials and inputs required are guaranteed to be continuously available throughout the scheduling process.

To establish a mathematical model for the HFS scheduling problem for electrical companies, the following notation is defined:

j	Set of jobs to be processed on the machines $\{1,2,\ldots,n\}$ where n is the total number of jobs, ($j \in J$, for every job)
l	Set of production centres $\{1, 2, \ldots, L\}$ where L is the total number of production centres, ($l \in L$, for every production centre)
N_i	Set of operations per job $\{1,2,\ldots,n_i\}$, where n_i is number of operations for job j, ($j \in N_i$, for every operation)
K	Set of machines $\{1,2,\ldots,k\}$, where k is the total number of machines, ($k \in K$, for every machine)
TP_{ikl}	Processing time of job j assigned to machine k in production center l
CP_l	Time capacity in production centres
d_j	Due date of job j

P_{jkl}	Duration of job j on machine k in production center l
ω_j	Weighting factor
r_j	Release time of job j
X_{jkl}	Binary variable equal to 1 if job j is processed by machine k in production center l, and 0 otherwise X_{jkl} for X_{jkl} = 0, 1 j = 1, 2…, n, k = 1, 2…, n, l = 1, 2…, n
C_{jkl}	Completion time of job j on machine k in production center l
T_{jkl}	Star time of job j on machine k in production center l
T_j	Job j tardiness
T_{kl}	Start time of machine k in production center l
β_k	Total number of jobs assigned to machine k
T_{nj}	Start time of operation n of job j
$C_{\max}$	Makespan, the maximum completion time of all processes in the last production centre

The bi-objective function, denoted as Z, seeks to minimize both the weighted total production time $Z_{makespan}$ and the weighted total tardiness $Z_{tardiness}$. Thus, a unique objective function is defined using a weight ω_j which works as ponderator obtaining as a result the following equations.

$$Min\, Z = \omega_j \cdot Makespan + (1 - \omega_j) \cdot Tardiness \qquad 0 \leq w \leq 1 \tag{1}$$

where:

$$Z_{makespan} = max_j(max_l(C_{jkl}) \tag{2}$$

$$Z_{tardiness} = \sum_{j=1}^{n} T_j \tag{3}$$

In this way, the objective function is obtained as follows:

$$Z = (\omega_1 \cdot z_{makespan}) + (\omega_2 \cdot z_{tardiness}) \tag{4}$$

Subject to:

$$\sum_{j,k}^{N} X_{jkl} \cdot TP_{jkl} \leq CP_l \quad \forall\, l\, \in \mathrm{L} \tag{5}$$

$$\sum_{k}^{k} X_{jkl} = 1,\ \forall\, j, l \tag{6}$$

$$\sum_{j=1}^{n} X_{jkl} \leq 1,\ \forall\, k, l \tag{7}$$

$$\sum_{j}^{n} X_{jkl} = \beta_k \quad \forall\, k, l \tag{8}$$

$$C_{jkl} = T_{jkl} + P_{jkl} \tag{9}$$

$$T_j = \max(0, C_{jkl} - d_j) \tag{10}$$

$$T_{nj} \geq T_{kl} + P_{jkl} \cdot (1 - X_{jkl}) \quad \forall\, j, k, l \tag{11}$$

$$C_{jl} \leq d_j \quad \forall\, j,\, l \tag{12}$$

$$P_{jkl} \geq 0, \quad \forall\, j, k, l \tag{13}$$

$$\beta_k \geq 0, \ \forall\, k \tag{14}$$

$$T_{jkl} > 0, \quad \forall\, j \tag{15}$$

$$C_{jl} \geq 0, \quad \forall\, j, l \tag{16}$$

The set of constraints (Eqs. 1 to 16) describes mathematical model. Eqs. 1 to 4 refer to objective function. Likewise, constraint Eq. 5 corresponds to the capacity constraint associated with the processing times of the jobs; constraint Eq. 6 ensures that each job (j) is assigned to exactly one machine (k) in the production centre (l); constraint Eq. 7 limits the number of jobs assigned to a specific machine (k) and production centre, ensuring that no more than one job is assigned in each case. Meanwhile, constraint Eq. 8 ensures that the total number of jobs (j) assigned and not assigned to each machine and production centre is balanced; constraint Eq. 9 calculates the completion time of the jobs; constraint Eq. 10 guarantees that jobs are completed within their deadlines and penalizes any delays; constraint Eq. 11 ensures that an operation cannot begin until the machine to which it has been assigned is available and until its predecessor has been completed. Constraint Eq. 12 guarantees that job (j) is not completed after its due date. Finally, constraints Eqs. 13 to 16 correspond to non-negativity constraints, ensuring that the initial and final times are greater than 0.

It is worth to mention that, not only this approach could be focusing on electrical sector manufacturing production process, but also it could be easily applicable to production environments with similar structures, particularly those that operate with production centres and stages, processing products in a defined sequence using parallel machines. It is especially suitable for systems where production times at each stage are known in advance, enabling planning and process optimization. This latter is possible because of the algorithm is constructed modularly and sequentially in stages, allowing for modifications to the network structure of the proposed production model. Thanks to this design, machines can be added or removed at each stage, and the processing times of products can be dynamically adjusted at every stage.

4. Genetic algorithm for scheduling in a flexible hybrid flow shop (FHFS)

Based on the mechanisms of artificial selection, the Genetic Algorithm (GA) combines the concept of fittest survival among solutions with a structured random exchange of information, and the creation of offspring [18]. The Genetic Algorithm repeats the processes of evaluation, selection, crossover, and mutation after initialization until the stopping condition is reached. The GA is inherently parallel and exhibits implicit parallelism [19], which means that it does not evaluate and improve a single solution but rather analyses and modifies a set of solutions simultaneously. Fig. 2 describes the flowchart of the GA addressed in this study.

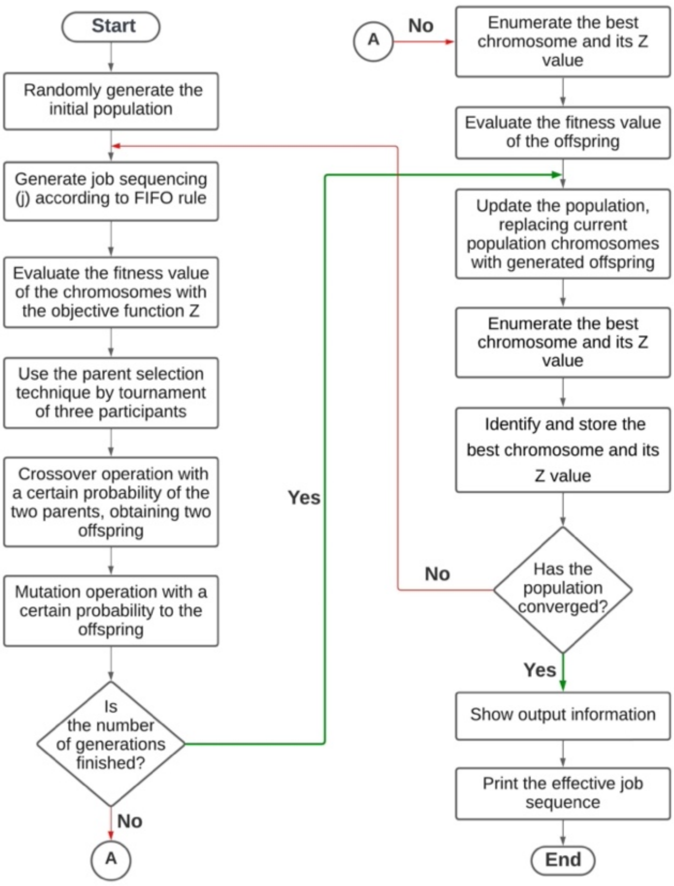

Fig. 2 GA approach flowchart (Adapted from Jeen and Rajkumar [4])

4.1 Parameters

The encoding of each solution alternative for the Flexible Sequential Hybrid Flow (FSHF) problem is represented by a vector of size n, where each position k of the vector indicates the job that will be performed in the k^{th} place [6]. The population (set of solutions) is created from a specific number of chromosomes, which each one represents the sequence that jobs will be scheduled. To ensure the validity of the chromosome, no job should be repeated, ensuring that all of them are completed and the total completion time and total tardiness of all jobs can be calculated. Fig. 3 shows the composition of the vector for a chromosome for 8 jobs.

7	1	5	6	2	3	8	4

Fig. 3 Vector – representation of job order

Regarding the initial population, according to the study by López *et al.* [16], a binary matrix of size $i \; x \; k$ was used to represent jobs and machines, where each row is a chromosome. In the study by Najarro *et al.* [6], the initial population is generated randomly, and its size varies depending on the number of jobs (n) and machines (m), where $Pob_{ini} = n * m$. The initial population is created by repeating the chromosome generation process as many times as the population size is set. The genetic algorithm in this study involves several key steps to optimize task scheduling by minimizing makespan and weighted tardiness, as is shown in Fig. 4. The fitness function evaluates everyone in the population, assigning a value that reflects the quality of the task sequence in meeting the scheduling objectives [3]. A lower fitness value indicates a superior solution. About selection is performed using the tournament selection method, which balances exploration and exploitation [19]. In this study, individuals compete in tournaments, with the best-performing ones proceeding to genetic operations. A tournament size of three is used, allowing for quicker algorithm convergence compared to methods like roulette wheel selection.

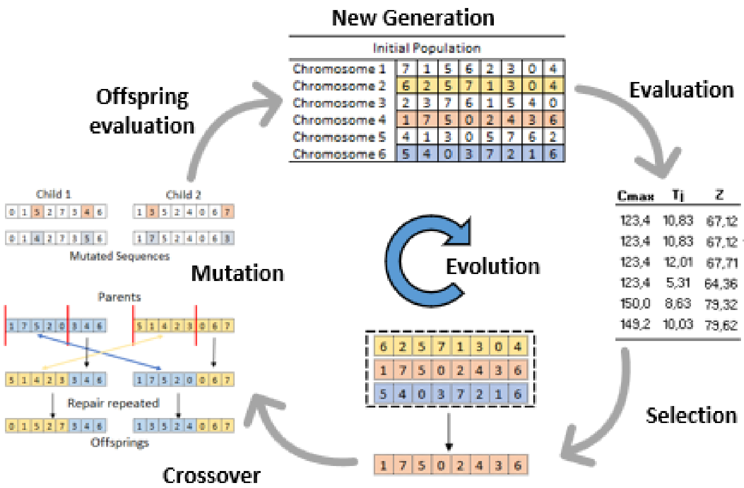

Fig. 4 Process cycle in genetic algorithm

Likewise, the Double Point Crossover (DPX) operator is applied to combine genetic material from two parent solutions, with repair mechanisms preventing duplicate jobs in the offspring [20]. After crossover, the offspring's fitness is evaluated, and the best individuals are selected for the next generation. Regarding, mutation is performed using a two-point mutation technique, where two positions in the offspring's sequence are randomly selected, and the segment between them is re-versed. This probabilistic process generates new solutions, which are evaluated for fitness, with the best-performing solutions advancing to the next generation [20]. In addition, the replacement process ensures the evolution of the population by selecting individuals from the current generation to create the next, based on their fitness. Finally, the algorithm employs stopping criteria that prevent infinite runs, including a maximum number of generations and stopping after several generations without improvement.

5. Results and discussion

This section explains how the instances were created with real data from electrical sector. In addition, three scenarios were created and performed, and the obtained results of each are discussed. Likewise, the GA algorithm is compared to TS (Tabu Search) method to evaluate its performance and results obtained are also argued. Finally, Computational time behaviour of all tests was analysed to evaluate the functioning of the model.

5.1 Real instance of the production process

Previously, in the planning process at the company, a dedicated department handles production planning and control, conducted daily with the support of an expert professional using Excel. The planning process varies depending on project complexity, often leading to delays in both planning and production. The production area receives a schedule, which includes project details, task numbers, product references, and start and delivery dates. Based on this information, production management is expected to allocate resources effectively to meet delivery deadlines, heavily relying on staff experience. Fig. 5 shows the behaviour of deliveries in the evaluated period. The red line illustrates the planned deliveries, and the black line identifies the actual behaviour of the same.

An analysis of a six-month period for 27 tasks revealed a 96 % non-compliance rate, with 25 tasks delivered late. The planned makespan was 370 days, but the actual execution took 538 days, a 31 % increase, resulting in a weighted tardiness of 102.96 days.

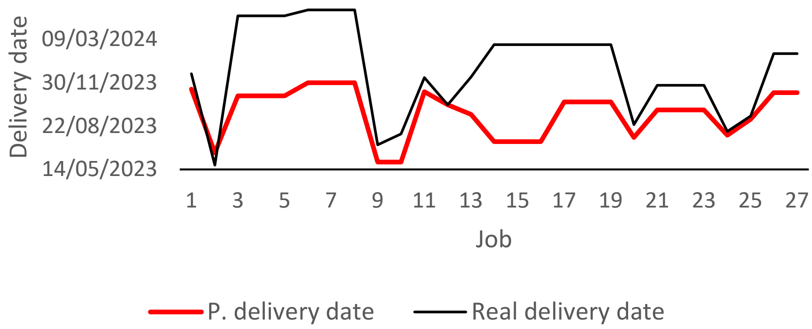

Fig. 5 Actual delivery performance – 6-month period

5.2 Test instances

Based on the results obtained during the data analysis, changes are proposed to focus on the number of jobs to be processed. This involves adjusting quantities to create more efficient transfer batches that provide effective solutions in the transformation and execution processes within each production centre based on the research made by Kazemi *et al*. [5].

A set of three simulations was managed considering the number of jobs to be performed and the number of available machines, referred to as scenarios 1, 2, and 3. Additionally, the Genetic Algorithm (GA) parameters were adjusted for each scenario to achieve more efficient results closer to the optimal. The scenarios included three production centres with a total of 43 machines; the only difference between them lies in the number of jobs: scenarios 1, 2, and 3 have 27, 46, and 87 jobs, respectively. These jobs are divided into transfer batches, which are scheduled independently. To illustrate the distribution of these transfer batches, Table 5 shows how the distribution of jobs is planned.

The Gantt charts show the job distribution, and the convergence graphs confirm that the algorithm reached solutions close to the optimum. To ensure job precedence in each scenario, the difference between due dates and completion times is compared for each task. The results of the best sequencing in Production Centre 1 (CP1) determine the start times for each job in Production Centre 2 (CP2), and in turn, the results from CP2 establish the release times for Production Centre 3 (CP3). Once the simulation for CP3 is complete, the results are used to evaluate the performance of each scenario and transfer batch.

Table 5 Transfer batch – Scenarios 1, 2 and 3

Job	Project	Product	T. batch size
1	Proj. # 1	CMP1	27

Job	Project	Product	T. batch size
1	Proj. # 1	CMP1	5
2		CMP1	5
3		CMP1	5
4		CMP1	6
5		CMP1	6

Job	Project	Product	T. batch size
1	Proj. # 1	CMP1	3
2		CMP1	3
3		CMP1	3
4		CMP1	3
5		CMP1	3
6		CMP1	3
7		CMP1	3
8		CMP1	3
9		CMP1	3

5.3 Results of Scenario 1

Fig. 6 presents the results obtained for this scenario. Gantt charts are divided into three production centres, each showing the behaviour of jobs in terms of sequencing, indicating the completion time of each task and the makespan for each centre, highlighting the best sequencing solutions. The analysis reveals that in Production Centre 1 (CP1), Task 27 is the last to finish, with a makespan of 243.1 days. In Production Centre 2 (CP2), Task 26 is the last to finish, with a makespan of 262.9 days. Finally, in Production Centre 3 (CP3), Task 1 is the last to complete the process on the last machine, with a total time of 502 days.

Fig. 7 shows the convergence behaviour of the algorithm in each phase of the production process. Thus, in the first 10 generations, the convergence is slow; after that, the best fitness value decreases until it reaches optimal convergence around 40 generations. Likewise, Fig. 8 describes the difference between the delivery dates of the real execution and those obtained with the GA algorithm. On average, it is seen that the GA finds earlier delivery dates for jobs, which results in better tardiness performance. These results suggest a slight improvement in reducing delayed tasks across the different production centres, which may be related to the large number of jobs assigned to each project. However, there are still high delay values that require further analysis to optimize task planning and sequencing. Fig. 6 also details the behaviour of the genetic algorithm in this first scenario. Upon analysing the results, a 26.3 % increase is observed compared to the planned makespan of 370 days, while there is a 6.7 % reduction when compared to the actual makespan of 538 days.

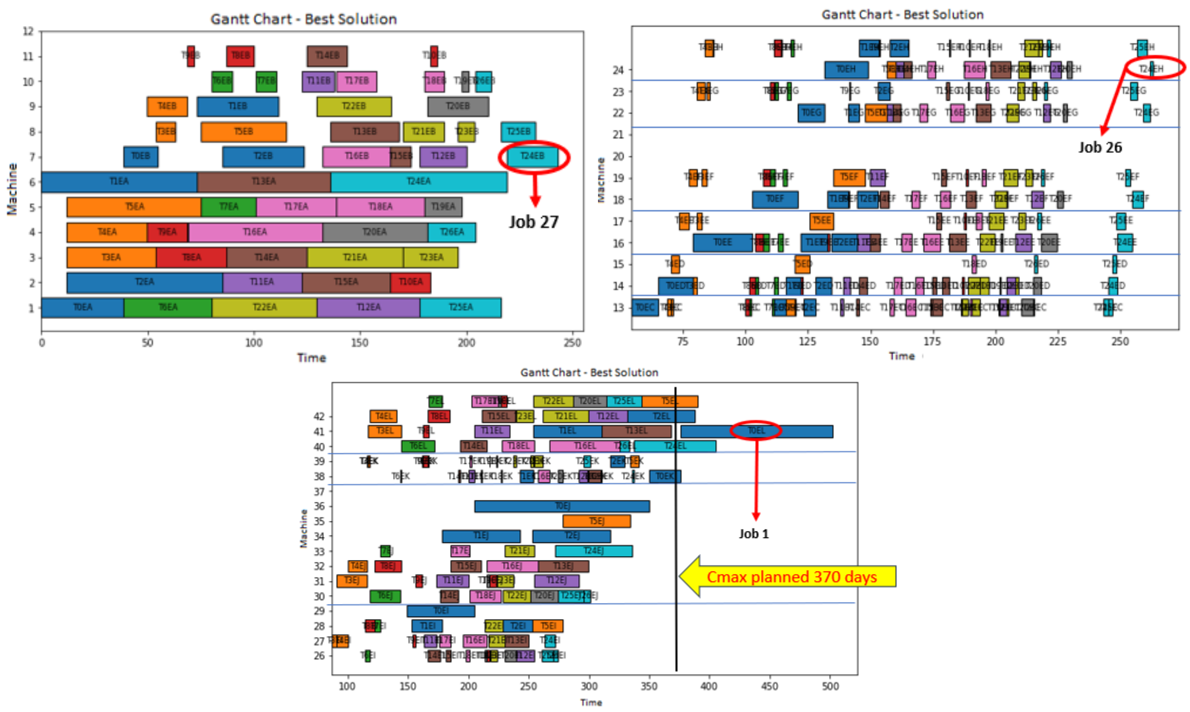

Fig. 6 Gantt chart – Transfer batch 1 – PC 1, PC 2, PC 3 – 27 jobs

In conclusion, although the genetic algorithm has proven to be more effective than the real instance, it has not yet reached the efficiency needed to surpass the company's planned objectives. These findings emphasize the importance of continuing to investigate and adjust the algorithm's parameters to improve its performance in future production scenarios. Here is where transfer batch approach gets importance into the model.

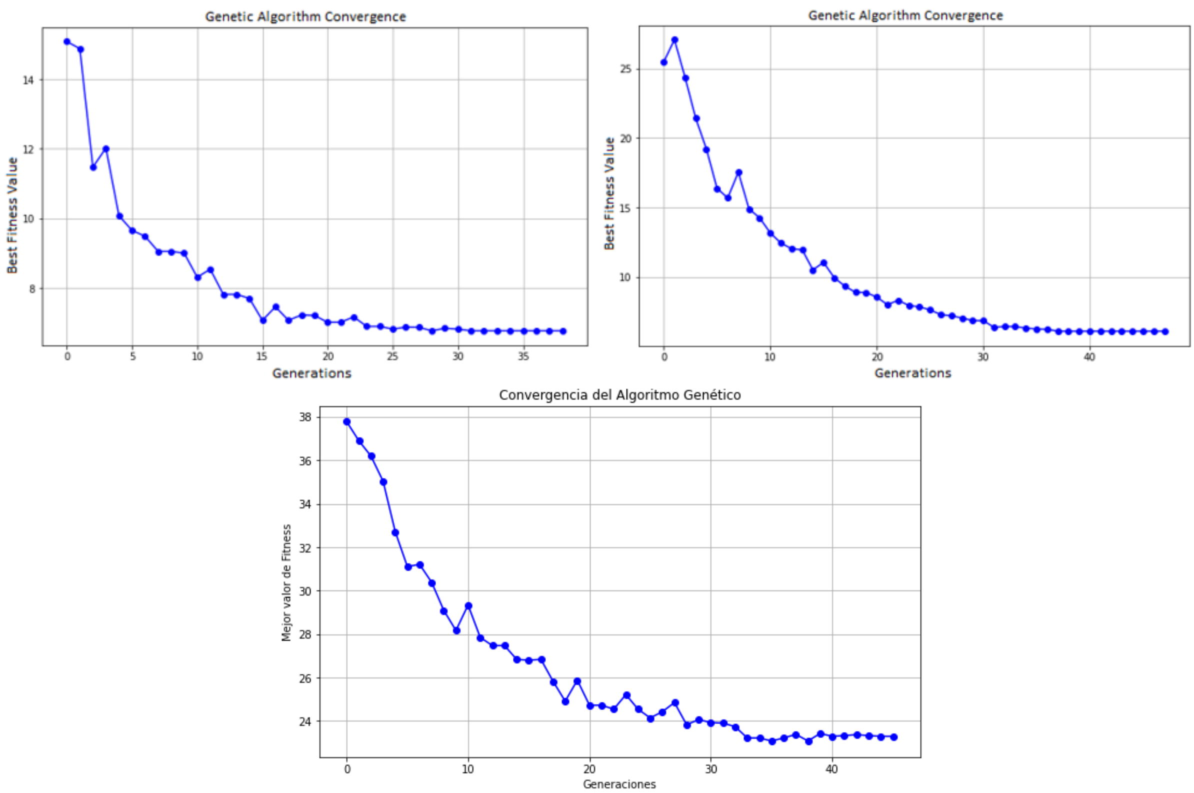

Fig. 7 Convergence graph – Transfer batch 1 – PC 1, PC 2, PC 3 – 27 jobs

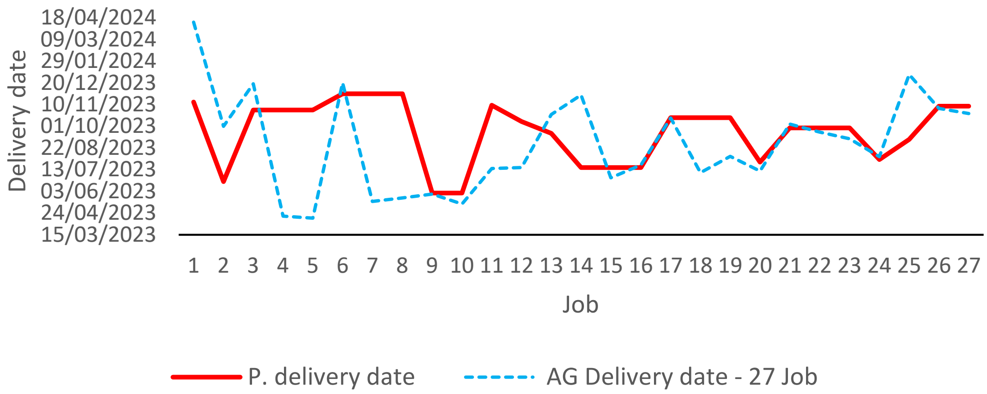

Fig. 8 Real delivery performance vs GA – 27 jobs

5.4 Results of Scenario 2

In this scenario, 46 jobs were evaluated with the aim of improving production through batch transfers. Project 26, initially composed of 27 jobs, was divided into smaller batches. As a result, makespan was reduced by 2.4 % compared to the previous scenario. At the same time, delayed jobs decreased, and only 17.4 % of the jobs missed their deadlines. Among the results obtained, it was observed that in CP1 and CP2, job 32 had the greatest delay, with 99.1 and 104.2 days, respectively. In CP3, the job with the greatest delay was job 23, with 91.5 days, processed on machine 40 and at stage L.

Figs. 9, 10 and 11 show the sequencing behavior found by the G.A in this scenario. The results show that the use of transfer batches and genetic operators in this scenario achieved significant improvements in delivery times. The makespan was reduced to 361.29 days, compared to the actual makespan of 538 days, and the number of delayed jobs decreased from 46 to 8. Additionally, the weighted tardiness was reduced to 6.27 days. These results highlight the effectiveness of the genetic algorithm in achieving the planned completion time of 370 days, improving the efficiency of the production system in this second scenario.

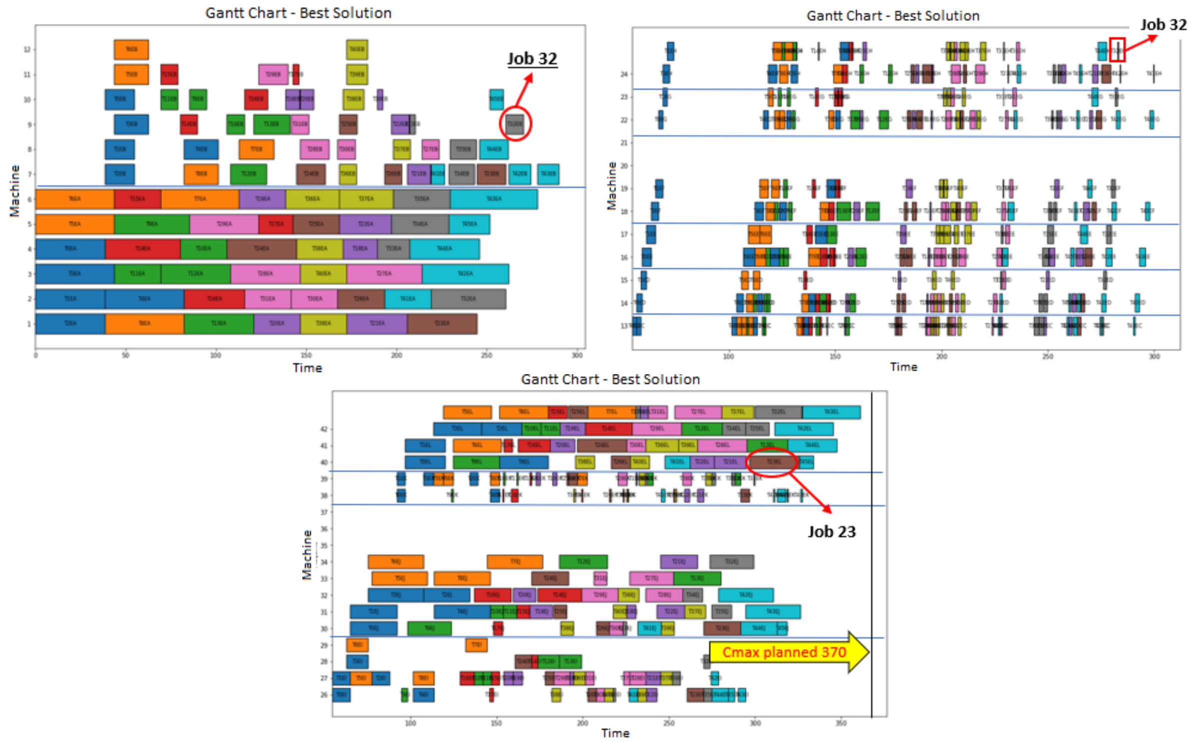

Fig. 9 Gantt chart – Transfer batch 2 – PC 1, PC 2, PC 3 – 46 jobs

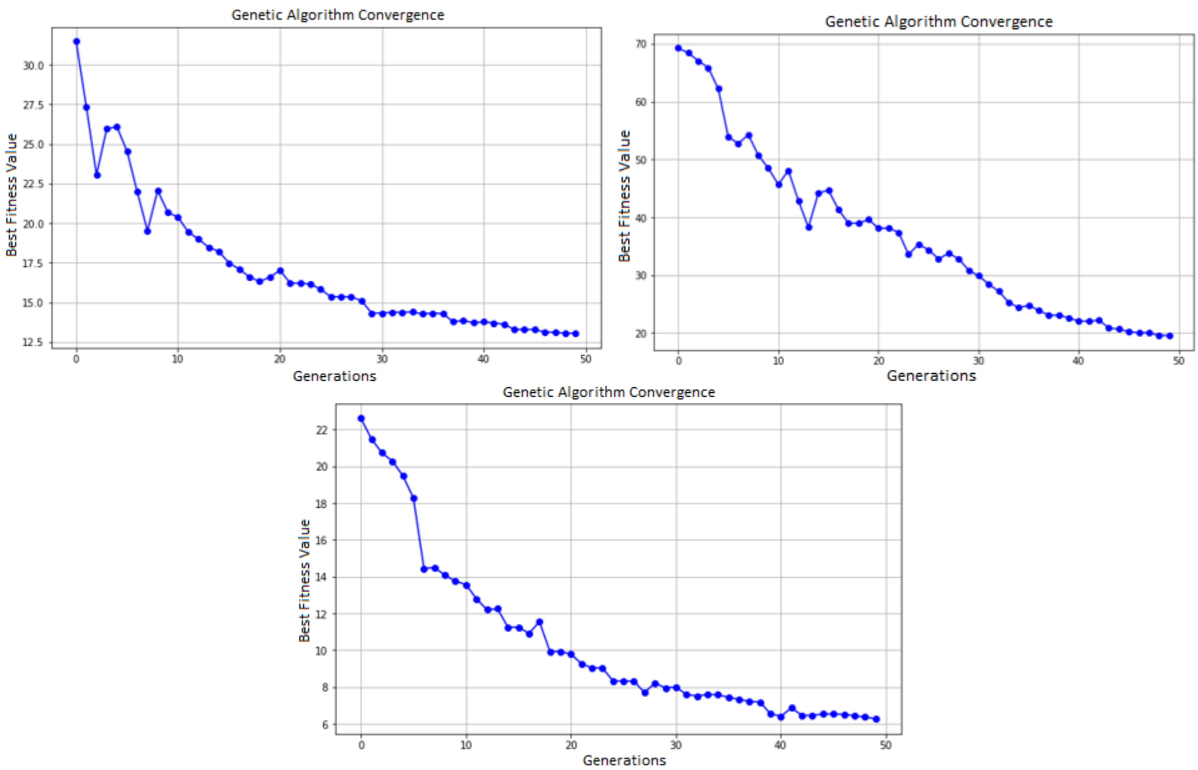

Fig. 10 Convergence graph – Transfer batch 2 – PC 1, PC 2, PC 3 – 46 jobs

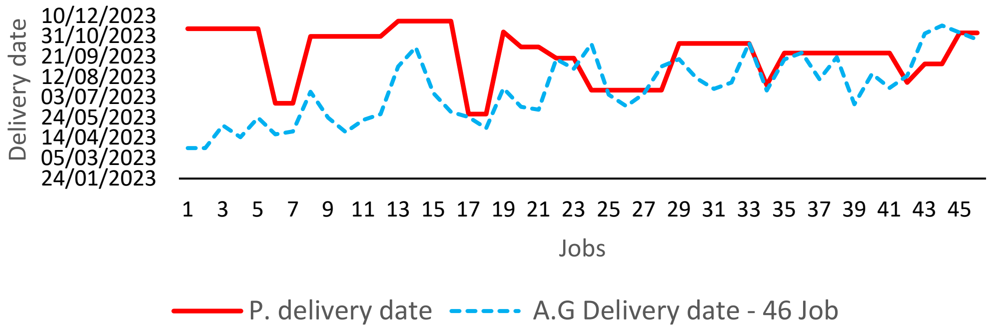

Fig. 11 Real delivery performance vs GA – 46 jobs

5.5 Results of Scenario 3

This scenario involved 87 jobs and revealed a compact distribution of tasks due to uniform processing times, which led to efficient sequencing. However, the larger number of machines required more computational resources, and the high number of delays (peaks) indicated that this approach was less effective for higher work volumes.

Figs. 12, 13, and 14 present the distribution and sequencing of the solution found by the genetic algorithm. They illustrate how the use of the largest number of available machines has been optimized at each stage of the process, and they also allow the convergence process to be identified. The results indicate that this scenario presents significantly high delay values. Although the number of delayed jobs was reduced by 52 % compared to the initial 87 jobs, this percentage is not substantial enough to be considered effective for implementation in the production plant. When compared to other scenarios, the obtained makespan of 443 days represents a 19.7 % increase over the planned makespan of 370 days. However, compared to the actual makespan of 538 days, there is a 17.7 % reduction, and relative to scenario 1 (502 days), there is an 11.8 % decrease. Finally, when analysing the difference with scenario 2 (361.29 days), there is an 18.4 % increase.

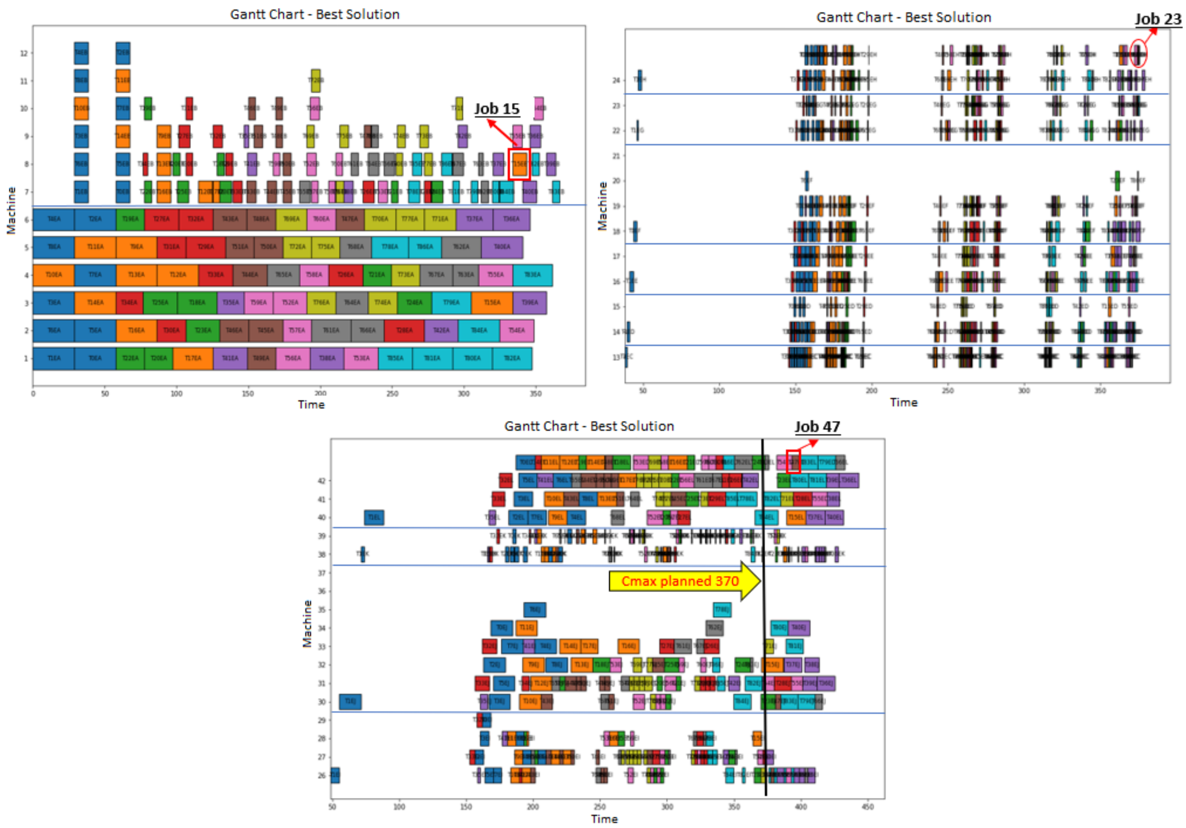

Fig. 12 Gantt chart – Transfer batch 3 – PC 1, PC 2, PC 3 – 87 jobs

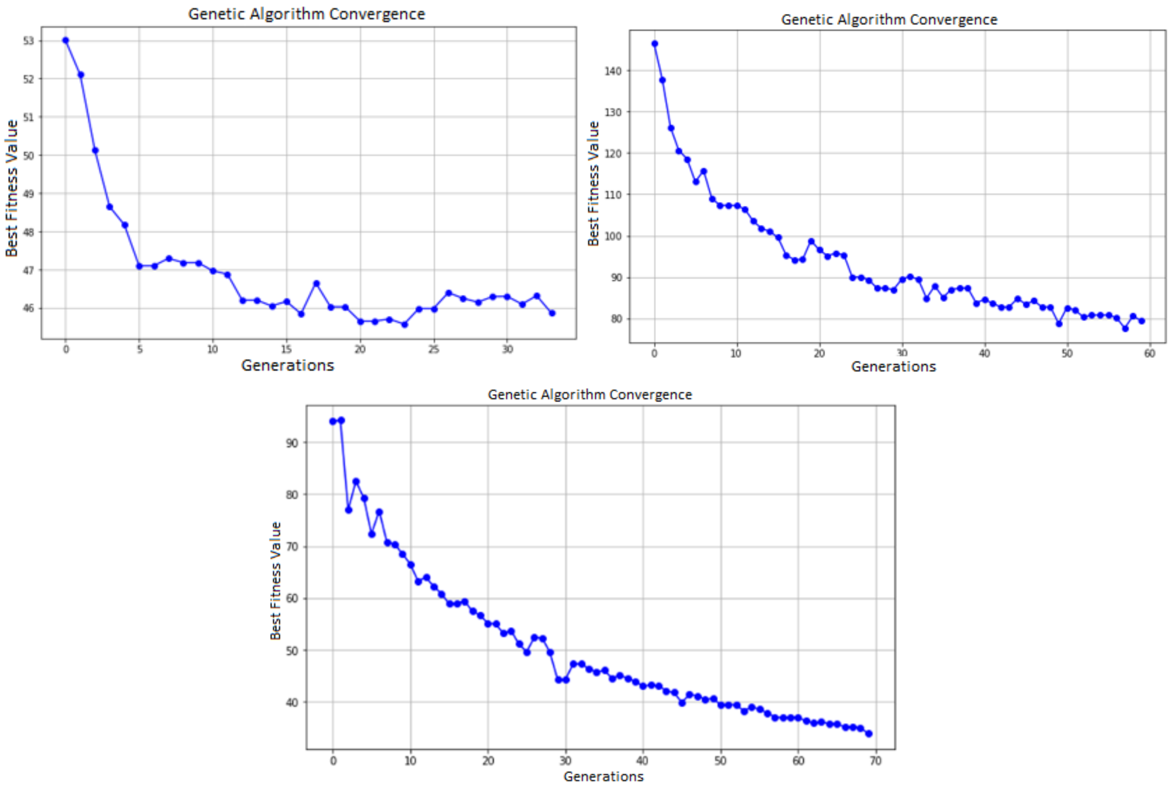

Fig. 13 Convergence graph – Transfer batch 3 – PC 1, PC 2, PC 3 – 87 jobs

This third scenario demonstrates that, although the transfer batch approach has potential, its effectiveness significantly decreases with a substantial increase in the number of jobs. The high delay values suggest that further adjustments in planning and the configuration of the genetic algorithm are necessary to efficiently handle larger workloads.

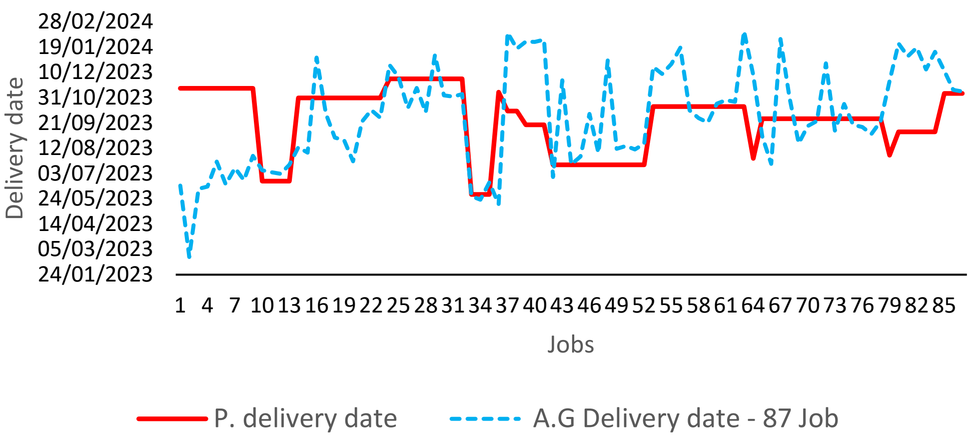

Fig. 14 Real delivery performance vs GA – 87 jobs

5.6 Genetic Algorithm vs. Tabu Search for HFS

The Genetic Algorithm approach was compared with another well-studied method known as Tabu Search (TS). TS is a metaheuristic based on local search, whose primary objective is to escape local optima and efficiently explore the solution space through adaptive memory, known as the tabu list [10].

By applying Tabu Search to the case study and comparing it with GA, Scenario 2, previously described, was evaluated. This scenario had previously demonstrated the best performance using the Genetic Algorithm in terms of execution time (makespan) and total tardiness. Fig. 15

shows the sequencing of jobs in the production centers in a Gantt chart. After analysing the data obtained through TS, slight differences were identified at each stage of Scenario 2. For example, in Production Centre 1 (CP1), the execution time (makespan) was reduced by 8.57 %, while total tardiness and the number of delayed jobs increased by 20.71 % and 9.09 %, respectively, compared to GA.

Likewise, a reduction was observed compared to GA in the completion time (makespan), total tardiness, and the number of delayed jobs by 6.4 %, 47 %, and 44.44 %, respectively. For Production Centre 3 (CP3), the data is particularly significant, as it evaluates how closely the planned in Production Centre 2 (CP2), completion time of 370 days is achieved. In this centre, an increase of 3.01 % in the makespan was observed when employing the TS method. Additionally, 12 delayed jobs were recorded compared to the 8 delayed jobs obtained using GA.
Table 6 provides a summary of the results obtained through both methods, highlighting the differences in their performance and showcasing the behaviour of TS as an effective alternative for solving the problem under study.

Table 6 Results of scenario 2, AG and TS

Scenario 2						
Metrics	CP1		CP2		CP3	
	AG	TS	AG	TS	AG	TS
Makespan	**290,09**	**267,2**	**300**	**282,9**	**361,29**	**372,5**
Weighted Tardiness	13,04	15,74	19,56	9,19	6,27	5,13
Number of Delays	24	0	27	12	8	12

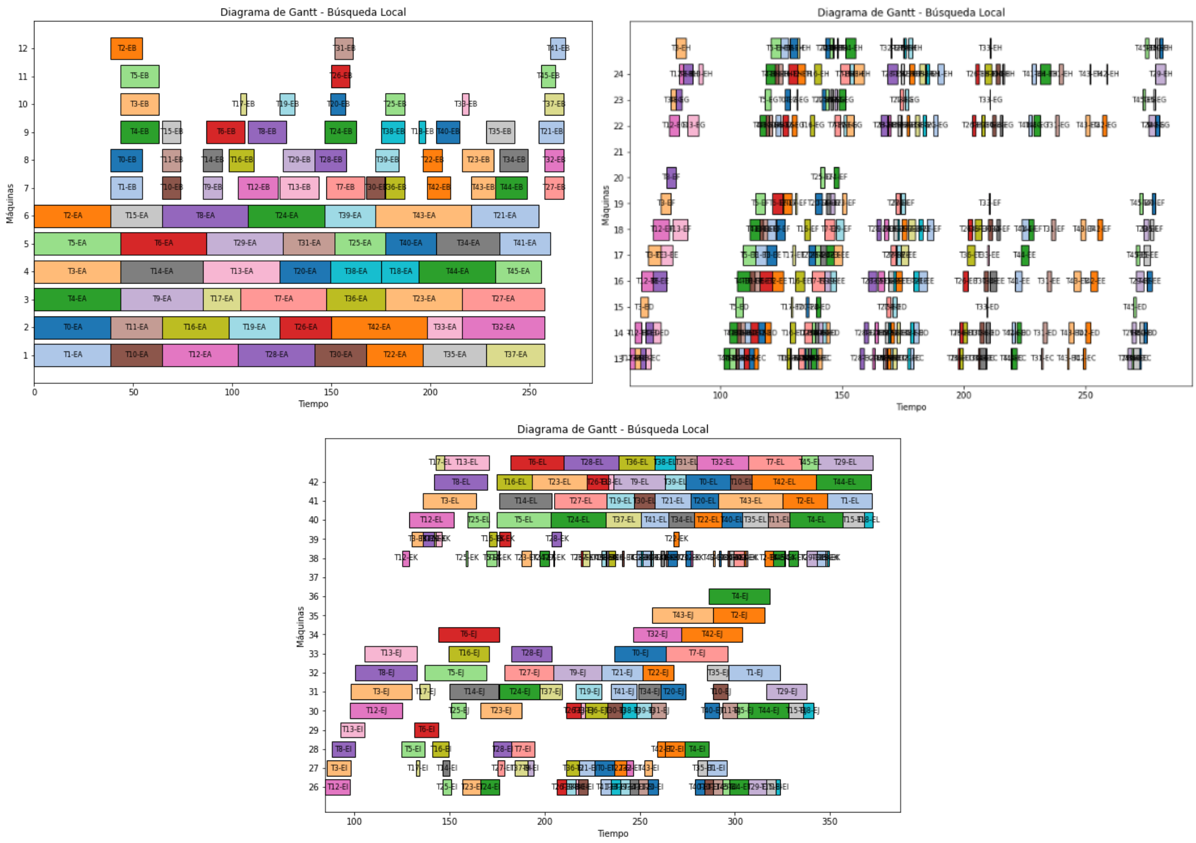

Fig. 15 Gantt chart – Transfer batch 2 – PC 1, PC 2, PC 3 – 46 jobs – TS

A comparative analysis of the two methods reveals very similar behaviour. As shown in Fig. 16, jobs tend to meet the planned delivery dates. However, in both methods, there are jobs that exceed the planned times. It is determined that the GA meets the planned makespan constraint of 370 days and results with a lower number of delays. Nevertheless, the results obtained with Tabu Search (TS) demonstrate it can be considered like an alternative approach for achieving positive outcomes in FHFS production environments.

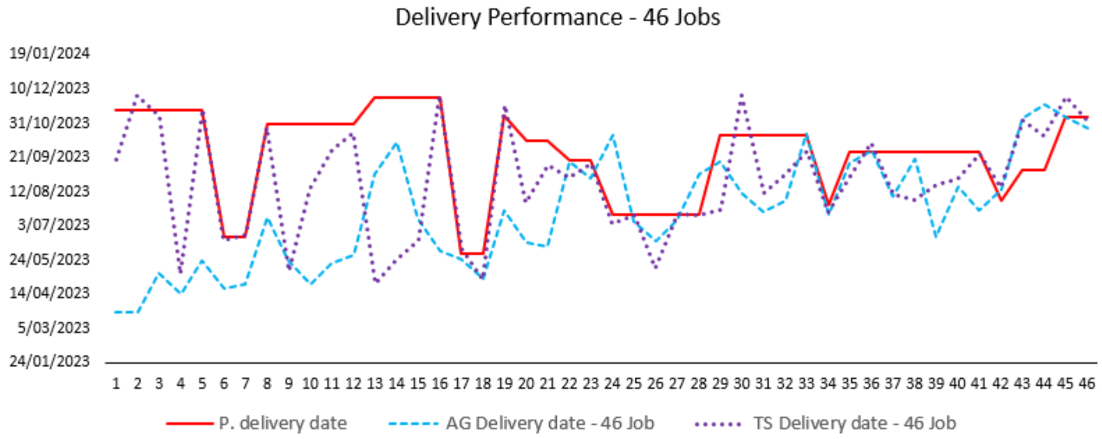

Fig. 16 TS vs GA performance – 46 jobs

5.7 Evaluation of robustness under disruptive production environments

In the context of production planning in real-world environments, it is common to face significant disruptions that hinder the achievement of objectives within the planned time horizon. These disruptions include machine failures or shutdowns and the introduction of new orders with tight delivery schedules.

To evaluate the performance and robustness of the Genetic Algorithm (GA) under these conditions, modifications to the algorithm were introduced, and two test instances were generated using the transfer batch from Scenario 2. In the first instance (AG-1), machines were randomly selected across different production centres, simulating their inactivity. In the second instance (AG-2), eight new jobs with various products, delivery times, and release times were added. The corresponding simulations were conducted, consolidating the results in Table 7, which allowed for analysing the impact of these disruptions on the algorithm's performance.

The results obtained show that disturbances in the evaluated scenarios have a significant impact on makespan and total tardiness, especially in more complex environments such as Production Centre 3 (CP3). It is observed that, in general, both indicators tend to increase in the disturbed scenarios (AG-1 and AG-2) compared to the baseline scenario (AG).

Table 7 Results of scenario 2, different environments

	CP 1			CP 2			CP 3		
	AG	AG - 1	AG - 2	AG	AG - 1	AG - 2	AG	AG - 1	AG - 2
Makespan	**290.1**	**339.9**	**325.0**	**300.0**	**350.8**	**345.2**	**361.3**	**421.0**	**436.5**
Total Tardiness	13.04	32.98	16.34	19.56	40.62	33.92	6.27	25.46	44.75
Number Delays	24	27	24	27	33	26	8	18	20

5.8 Computational time

Based on the data in Table 8, a growing trend in CPU time is observed as the number of jobs increases. In Scenario 1, with 27 jobs, CPU time ranges between 22 and 72 minutes, being the lowest compared to the other scenarios. In Scenario 2, with 46 jobs, CPU time progressively increases from 62 to 142 units as the stages advance. Finally, in Scenario 3, with 87 jobs, the highest CPU times are recorded, rising from 76 to 304 minutes.

Likewise, there is a correlation between CPU time and makespan; as the makespan increases, CPU time also tends to grow. This is clear in Scenario 3, Stage 3, where the makespan reaches 443.0, and CPU time registers its highest value (304 minutes). In conclusion, the number of jobs and the computational load required in later stages significantly increase CPU time. This suggests that the Genetic Algorithm (GA) solution demands greater computational time as the size and complexity of the problem increase.

Table 8 Performance metrics and CPU time in FHFS

Solution	Flexible Flow Shop Scheduling							
	Scenario	Stage	Makespan	F.O (Z)	T. Tardiness	Jobs	N° Delays	CPU Time
Actual (empirical)	*	*	**538**	*	**1.933**	27	25	**5040**
AG	1	1	243	124.93	6.8	27	13	22
		2	263	134.5	6.1	27	12	43
		3	**502**	262.5	23.1	27	10	**72**
	2	1	290	151.6	13.0	46	24	62
		2	300	159.8	19.6	46	27	97
		3	**361**	183.8	6.3	46	8	**142**
	3	1	366	206	45.6	87	50	76
		2	379	228.2	88.8	87	78	186
		3	**443**	254.8	34.1	87	45	**304**

6. Conclusion

The results of this research demonstrate that the proposed model for production scheduling, sequencing, and control achieves significant reductions in both makespan and tardiness. In Scenario 2, a makespan of 361.29 days was achieved, representing a 32.85 % improvement compared to the 538 days of the current model. Similarly, tardiness was reduced from 96 % to 17.4 %, significantly enhancing customer satisfaction and operational efficiency.

In addition, the comparative analysis between the GA and TS (Tabu Search) methods reveals similar behaviours in job scheduling. Regarding the planned completion time of 370 days, the GA achieved a 2.41 % reduction, while the TS showed a 0.54 % increase. Furthermore, 8 delays were observed with the GA compared to 12 with the TS. Based on these results, the GA method is identified as the most suitable tool for addressing scenarios like the one presented in the case study.

Also, it was observed that CPU time is directly influenced by the number of jobs, the size of the makespan, and the number of machines at each stage. This suggests that, as the size and complexity of the problem increase, the solution based on the Genetic Algorithm requires more computational time.

A key advantage of the model is the substantial reduction in scheduling time when using the Genetic Algorithm (GA) compared to manual methods using transfer batches. Results showed this approach improves resource allocation, ensures more efficient deliveries, and has proven to be robust, adapting to various production scenarios. Additionally, it offers flexibility to meet the specific needs of other production systems, allowing customization based on the characteristics of the environment, such as product types, machine capacities, and operational constraints. This makes it applicable to various production models, including hybrid flow shops, assembly lines, cellular manufacturing systems, and batch production configurations.

Finally, as an opportunity for future research, the development of algorithms that allow dynamic inputs for real-time decision-making is proposed. The incorporation of variables such as maintenance, inventory, and logistics could significantly expand the applicability of the model to different industrial sectors.

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