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Production planning optimization with fuzzy analytic hierarchy process and genetic algorithm

Fatih YIĞIT[1*], Ana LAZAREVSKA[2]

[1] Altinbas University, Faculty of Engineering and Architecture, Department of Industrial Engineering, Mahmutbey Campus, Istanbul
[2] Ss. Cyril and Methodius University in Skopje, Department of Mechanical Engineering, Üsküp, Makedonya

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Abstract

Proper production planning is essential for improving productivity and lowering resource (material, energy, employees) related costs in the highly competitive business world. Dealing with the challenges of asymmetric setup times—where the time required to switch between manufacturing different products varies —makes this task much more difficult. Conventional planning techniques frequently ignore these articulations and produce sub-optimal schedules. This paper proposes a novel approach to tackle the following challenge: optimizing production planning using the Fuzzy Analytic Hierarchy Process (FAHP) with asymmetric setup times and Genetic Algorithm (GA). The proposed methodology involves a step-by-step process. The first stage defines key objectives: makespan, total waste cost, and maximum weighted tardiness. Decision-makers compare the relative importance of each criterion within its hierarchy level using fuzzy numbers. The consistency of these comparisons is assessed using fuzzy consistency ratio computations. At the same time, the overall priority weights for each production planning alternative are determined by summing fuzzy judgments across the hierarchy. In the second stage, the production plan is optimized using GA, considering sequence and lot size variables and asymmetric setup times, by applying the computed weights. The comparisons are performed using the proposed approach with the optimum solution.

Keywords: *Fuzzy analytic hierarchy process (FAHP), multi-criteria decision-making, sequencing, metaheuristics, sequence-dependent setup times*

*Fatih YIĞIT, fatih.yigit@altinbas.edu.tr, http://orcid.org/0000-0002-7919-544X
Ana LAZAREVSKA, ana.lazarevska@mf.edu.mk, http://orcid.org/0000-0002-3493-8465

Bulanık analitik hiyerarşi prosesi ve genetik algoritma ile üretim planlama optimizasyonu

Öz

Rekabetin yoğun olduğu iş dünyasında, üretim planlamasının doğru bir şekilde yapılması, verimliliği artırmak ve kaynak (malzeme, enerji, çalışanlar) ile ilgili maliyetleri düşürmek için önemlidir. Farklı ürünler arasında geçiş sürelerinin değişiklik gösterdiği asimetrik kurulum süreleri ile başa çıkmak, bu görevi çok daha zorlaştırır. Geleneksel planlama teknikleri genellikle bu nüansları göz ardı eder ve optimal olmayan çizelgeler üretir. Bu makale, asimetrik kurulum süreleri ve Genetik Algoritma (GA) ile Bulanık Analitik Hiyerarşi Prosesi (B-AHP) kullanarak üretim planlamasını optimize etmeye yönelik yeni bir yaklaşım önermektedir.

BAHS, belirsizlik ve bulanıklığı kapsayan bulanık mantığın gücünü, Analitik Hiyerarşi Prosesi'nin (AHP) yapılandırılmış hiyerarşisiyle birleştirir. Önerilen metodoloji, adım adım bir süreç içerir. İlk aşama, temel hedefleri tanımlar: iş bitirme süresi, toplam atık maliyeti ve maksimum ağırlıklı gecikme. İlk aşamada karar vericiler, her kriterin kendi hiyerarşi seviyesindeki göreceli önemini bulanık sayılar kullanarak karşılaştırır. Bu karşılaştırmaların tutarlılığı, bulanık tutarlılık oranı hesaplamaları ile değerlendirilir. Aynı zamanda, her üretim planlama alternatifi için genel öncelik ağırlıkları, hiyerarşi boyunca bulanık yargıların toplamı alınarak belirlenir. İkinci aşamada, hesaplanan ağırlıklar kullanılarak, asimetrik kurulum süreleri ile sıralama ve lot büyüklüğü değişkenlerini dikkate alarak üretim planı GA ile optimize edilir. Optimum çözüm ile önerilen yaklaşım kullanılarak karşılaştırmalar gerçekleştirilir.

Anahtar kelimeler: *Bulanık mantık, üretim planlama, analitik hiyerarşi prosesi, metasezgisel, genetik algoritma, çok kriterli karar verme*

1. Introduction

Optimizing production planning is vital in the manufacturing landscape, where efficiency and adaptability are significant concerns. Minimizing costs associated with lowering resources (material, energy, employees) is essential in the highly competitive business world. Traditional methods often struggle to account for the inherent uncertainties and dependencies within production processes, particularly in environments characterized by sequence-dependent setup times (SDST). SDST refers to the varying durations required to prepare equipment or processes for production, depending on the order in which tasks or products are arranged. These setup times are influenced by factors such as tooling changes, cleaning, or recalibration, which differ based on the sequence of the operations. Accounting for sequence-dependent setup times is critical in production scheduling to minimize downtime and optimize efficiency. This study suggests a novel approach that combines SDST challenges with the fuzzy analytical hierarchy process (FAHP) in a flow shop system to solve these challenges. The fuzzy logic principles of FAHP, which are widely used for their capability to handle uncertainty, provide an organized framework for decision-making. SDST accounts for the variations in setup durations between the processing of each job. By synergizing FAHP with SDST, this research aims to develop a robust decision support system tailored for efficient resource allocation and scheduling in manufacturing based on the importance of objectives. The proposed model is the fuzzy-analytic-based, sequence-dependent setup model (FASD).

Flowshops are commonly seen in manufacturing settings, where the processing sequence is unidirectional and rigid due to technical constraints. Such a manufacturing environment encompasses several production contexts, including steel manufacturing, chemical production, and nonferrous metallurgy. Therefore, applying an integrated optimization problem to solve such problems is essential. The objective of any general scheduling problem is vital for an accurate modelling problem. The typical objectives are minimization of makespan, maximum weighted tardiness, and lateness, as well as newly introduced sustainability objectives such as minimum cost, waste, and use of resources.

Constraints are also crucial in scheduling problems, such as no waiting, blocking, preemptions, and permutation. Sequence-dependent setups are also seen in the manufacturing environment. A typical example is the fabric dyeing process. The time needed to switch between the white dye process and the black dye is much shorter than vice versa. The white is unlikely to contaminate black fabric, whereas just a drop of black dye may contaminate white fabric. As a result, the cleaning and washing of the machines between setups are asymmetrical. The flow shop scheduling problem is a (Non-Deterministic Polynomial) NP-complete problem; when the problem's size increases, the solution may become hard or even impossible to solve in acceptable times. Metaheuristics are widely used to solve such problems. Particle swarm optimization, ant colony optimization, and GA are some examples of metaheuristics.

Via empirical validation and case studies, the proposed study attempts to demonstrate the proposed methodology's effectiveness and practical applicability, thereby contributing to the advancement of production planning methodologies and enhancing the competitiveness of manufacturing operations in dynamic business environments. Section 2 gives a brief literature review of the proposed model's subsections. The respective methodology is presented in Section 3. In Section 4, applications are presented, while conclusions, limitations, and future work are given in Section 5.

2. Literature review

Manufacturing is a vital part of a business because, among other contributions, it creates assets converted into products. The production process is subject to a variety of decisions and multiple objectives. Some examples are investment decisions, production planning, inventory management, and human resources [1]. As a result, the methods aim to achieve the objectives either simultaneously or in a collaborative way. Multi-objective optimization problems (MOOPs) offering optimal solutions in the space of objective functions are denoted as the Pareto front. MOOPs are widely used in production problems [2- 4]. These solutions are called the Pareto front. The proposed study aims to use multi-criteria decision-making (MCDM) in the decision-making process.

2.1. Fuzzy analytic hierarchy process

MCDM methods are used for modelling decision-making processes [5- 6]. To name a few of the recent models, AHP, Elimination of choice Translation Reality (ELECTRE), Level-Based Assessment Method (LBWA), Decision making trial and evaluation laboratory (DEMATEL), The Full Consistency Method (FUCOM), Best-Worst Method (BWM) are among them [7]. Recent research shows that AHP is the most widely used decision-making approach [8]. Based on this finding, the proposed approach uses an extension of AHP, FAHP. FAHP is also one of the most widely used approaches along with AHP for MCDM [8].

AHP, initially proposed by Saaty [9], uses an easy-to-understand comparison of criteria relevant to the decision. This approach allows for the assessment of the weight of each criterion. Since its introduction, many new extensions have been proposed. Voting AHP (VAHP) is the priority of the requirements and alternatives by substituting in place of the pair-wise comparison matrices [10]. Stepwise Weight Assessment Ratio Analysis (SWARA)-AHP combines the flexibility of VAHP to determine the local priorities of the criteria [11]. FAHP is an extension of AHP employing fuzzy logic in the AHP. A detailed study has been conducted on recent developments in FAHP [12]. AHP and FAHP are widely used in different areas, including selection of learning systems, supplier evaluation, and assessment of e-service quality in the airline sector [13 - 15]. Based on the wide availability of different application areas and the most used method for applying AHP and FAHP, the study involved FAHP for the first stage of the model.

2.2. Genetic Algorithm

It is essential to optimize complex models with different parameters. Different objective functions are used to model for various purposes. Some examples of optimization are location selection, layout planning, inventory management, and production planning. Due to the time limitations that any manufacturing process faces, finding the global optimum of an objective function is not feasible. As a result, real-life cases prefer sub-optimum solutions that can be reached within an acceptable time. Such methods are called metaheuristics and can be applied to various areas.

Various metaheuristics exist, such as particle swarm optimization, simulated annealing, ant colony optimization, and GA. GA is widely used in different areas, e.g., when combined with artificial neural networks to optimize perishable inventory management [16]. A hybrid clustering approach is used for the Internet of Things (IoT), which is network optimization [17]. Similar hybrid approaches are also referred to for different objectives [18]. As given in such studies, GA is flexible enough for other methods. Consequently, optimizing the flow shop model uses GA with the objective of multi-criteria optimization.

2.3. Multi-Criteria Application of Flowshop Scheduling Optimization

In a production environment, where products are moved between processing lines, machines are vital assets that convert inputs to outputs. This model is commonly observed in real-world situations. Hence, it has been investigated in various novel studies since its introduction [19]. A recent literature review gives information about studies related to flow-shop scheduling [20]. Metaheuristics are widely used optimization techniques that sacrifice certain performance for optimum solutions but offer satisfactory results in a predefined time. As a result, since finding the optimum solution is complex, metaheuristics are widely used in flow shop scheduling [21 - 22]. Genetic Algorithm (GA) is a metaheuristic used for optimization. It has been used in many different areas [23 - 25].

The proposed model is new in the literature, as it employs a multi-criteria approach using asymmetric setup times and asymmetric optimization for flow-shop scheduling. The comparison with other studies is given in Table 1. Also, as presented in the recent survey related to a job shop and flow shop, it is underlined that objectives employ cost- and revenue-based objectives. The proposed study integrates such an objective into the model [20].

In Table 1, classifications of research are given such as Step-wise Weight Assessment Ratio Analysis (SWARA), Multi-Attributive Border Approximation Area Comparison (MABAC), and Simulated Annealing (SA). The manuscript contributes significantly to production planning by introducing a hybrid optimization framework that combines the Fuzzy Analytic Hierarchy Process (FAHP) and Genetic Algorithm (GA) to address the challenges of sequence-dependent setup times in flow shop scheduling. By integrating FAHP for multi-criteria decision-making and leveraging GA for optimizing complex scheduling scenarios, the study tackles critical objectives such as minimizing makespan, total waste cost, and maximum weighted tardiness. The proposed method demonstrates a novel approach to handling asymmetric setup times, enhancing decision-making robustness, and achieving near-optimal solutions efficiently. This work provides a practical and adaptable methodology for improving resource allocation and operational efficiency in dynamic manufacturing environments. [26], [27], [28], [29], [30], [31], [32]

3. Method

The details of the method are given in the following sub-sections.

Stage-1: Fuzzy analytic hierarchy process

FAHP uses expert opinions as inputs by employing cross-comparisons. After applying the following workflow, the outputs are generated as weights [33].

Step 1. Setup Hierarchy Architecture

Step 2. Setup Fuzzy Pair-wise Comparison Matrix Using Opinions from each decision-maker

$$\overline{D} = \begin{bmatrix} (1,1,1) & a_{12} & \cdots & a_{1n} \\ a_{21} & (1,1,1) & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & \ldots & \ldots & (1,1,1) \end{bmatrix}$$

where a_{ij} x $a_{ji} = 1$ and $a_{ij} = w_i / w_j$ i, j = 1, 2, 3, 4,…n

Step 3. The fuzzy geometric value is calculated to combine multiple opinions as given in Eq. (1)

$$\check{r}_i = (a_{i1} * \ a_{i2} * \ldots * \ a_{in})^{1/n} \tag{1}$$

Step 4. The fuzzy weight $\breve{w}_i$ for each criterion, i is calculated as given in Eq. (2)

$$\breve{w}_i = (\check{r}_i \ x \ (\check{r}_1 + \ \check{r}_2 + \cdots + \check{r}_n)^{-1}) \tag{2}$$

where $\check{r}_k = (l_k, m_k, u_k)$ are lower, medium, and upper limits for fuzzy sets.

Step 5. The fuzzy weights are defuzzied by using any available methods. The details of the application can be found in the study proposed by Liou and Wang for further information [34].

Table 1 Literature Review Summary

Year	Author	Delphi & Fuzzy Delphi	AHP & FAHP	TOPSIS & Fuzzy TOPSIS	SWARA	MABAC	MCDM	MODM	Asymmetric	Symmetric	GA	SA	Other	Application Area	Application Type	Positive Aspects	Drawbacks	Identified Challenges	Uncovered Research Topics	Applicative Flexibility	Future Studies
Proposed Model			x				x		x		x			**Flow shop scheduling problem with asymmetric parameters**	**Experimental Study**						
2018	Veskovic et al. [26]	x			x	x	x							Evaluation of the Railway Model	Case Study	The study uses multiple methods for a hybrid approach.	The disadvantages of the Delphi Method pose a risk.	Selection of the right expert may be hard to measure the accuracy of the selection.	The applied method is conducted on a specific case. The hybrid approach may be used in a different area.	Sensitivity analysis is performed regarding the outputs. The results indicate the flexibility in the model.	In future research, the Rough SWARA Method will be used to determine the significance of the criteria.
2023	Zhao and Wang [27]									X			X	No-Wait Flow Shop	Case Study	The study optimizes using a hybrid approach	Complexity of the models	The models can be hard to implement due to complexity	Actual problems may need to be used for the application	The actual cases may cause some shortcoming of the proposed model	More effective algorithms may be implemented.
2020	Li et al. [28}								X			X		Asymmetric Flow Shop problem	Experimental Study	The proposed model performs better compared to altenative models	The encoding and decoding approach limits the solution space of the IABC and is unable to produce the best solution for every case.	The parameters may affect the results dramatically.	Actual problems may need to be used for the application	The constraints may limit to reach an optimal solution.	In order to adapt to the diversified production scenario, future research will take into account heterogeneous factories with various production processes.
2011	Chen et al. [29]								X				X	Travelling Salesman Problem	Experimental Study	Asymmetric travelling salesman problem is solved	Based on the study, extremal dynamics and cooperative optimization strategy are crucial to achieve good optimization performances	The results show the imprtonace of external dynamics' importance	The study uses asymmetric approach but not for a production environment.	The metaheuristic can be applied to different problems.	-
2023	Xin et al. [30]							X	X				X	Asymmetric Flow Shop problem	Experimental Study	The problem in question centres on two optimisation goals, namely the makespan and TEC.	-	Manufacturers should give attention to the use of energy-saving strategies and balance the makespan and Total enrgy condumption	Another possible line of inquiry is the use of different algorithms, like the shuffling frog-leaping algorithm or beam search algorithm, to produce high-quality solutions.	The model can be applied with different objectives. As a result proposed model may be applied to a different dataset.	Future research is how to create efficient precise and meta-heuristic algorithms to provide the best Pareto front for various problem sizes.
2023	Wu and Liu [31]							X	X				X	Asymmetric Green Hybrid Model	Experimental Study	The study used bi-objective for optimization	This study only takes into account one-way travel times.	-	The model only takes into consideration one-way transportation times. This aspect may not fully cover the actual models.	The model can be applied to similar models with different objectives and constraints.	Construct scheduling rules based on the characteristics of the problem, taking into account the number of transportation vehicles and transportation capacity.
2023	Zhao et al. [32]							X		X			X	Energy-Efficient Distributed Blocking Flow Shop Scheduling Problem	Existing dataset with m	HHQL algorithm has better performance than the well-established algorithms.	Given that decision-makers must create LLHs that address the issue. Furthermore, the suggested algorithm needs some specialised knowledge and is not entirely independent.	Proposed algorithm is not completely autonomous and requires some special experience	Historical data and problem-specific knowledge that are concealed in the algorithm are retrieved to direct the algorithm's search for a promising area.		Distributed production scheduling in an uncertain environment, and distributed production scheduling in a heterogeneous environment. when thinking about upcoming projects.

Stage 3.2: Genetic algorithm approach for flow shop scheduling

This study addresses the flow shop scheduling problem with sequence-dependent setup times (FSSDST) by proposing a comprehensive methodology. First, the method formulates the mathematical model for FSSDST by defining the objective function to minimize the makespan, total waste loss, and maximum weighted tardiness. GA is applied to solve the problem using the mentioned metaheuristics. Metaheuristics effectively solve complex optimization problems, including FSSDST. In GAs, a population of potential solutions, represented as chromosomes or individuals, evolves over generations through selection, crossover, and mutation.

Initially, a diverse population is generated, and individuals are evaluated based on a fitness function that measures their suitability for the given problem. Individuals with higher fitness values are more likely to be chosen for reproduction through selection mechanisms such as tournament or roulette wheel selection. During crossover, pairs of selected individuals exchange genetic information, simulating genetic recombination in nature to create offspring with characteristics inherited from both parents. Mutation introduces random variations into the offspring, promoting the exploration of new regions in the solution space. This iterative process continues until termination criteria are met, such as reaching a maximum number of generations or achieving a satisfactory solution quality. A detailed overview of GA is proposed in a recent study, whereby workflows and recent developments are provided [35].

GAs offer several advantages, including handling complex, nonlinear, and multimodal optimization landscapes and their parallelizable nature and flexibility in problem representation. However, their ultimate performance is influenced by population size, crossover, and mutation rates, which require careful tuning for optimal results. In general, GAs provide a powerful and versatile approach for solving optimization problems such as FSSDST, offering a balance between exploration and exploitation to efficiently search for high-quality solutions in large solution spaces.

4. Numerical study

The study has 2 stages. In the first stage, FAHP is used to assess the importance of criteria for flow-shop scheduling, including the model's modelling, while the second phase optimizes the model using GA.

Stage 1: Assessment of Weights using Fuzzy Analytic Hierarchy Process

FAHP converts expert opinions into weights of the corresponding identified objectives. There are widely used objectives in flow-shop scheduling. A list of used objectives is given in the study [20]. As alternatives in the present study, minimization of makespan (C_{max}), maximum weighted tardiness (WT_{max}), and total waste cost (TWC) are the objectives chosen for the model as given in Table 2. Makespan is essential for the decision maker as it calculates the total time required to produce a given input of jobs. Tardiness is vital as it directly affects customer service when there are late deliveries. Finally, sustainability concerns are essential for any business as decisions may affect the environment's and society's well-being. The minimization of total waste cost between different products in each machine is also calculated as an objective function. After receiving a bi-comparison table from a single expert, two other defuzzification and weight calculation methods are performed to compare results [34], [36]. The expert works in

production planning and has over 10 years of experience. Bicomparisons are received using Microsoft Excel. The information sharing and relevant feedback are received on 08.06.2024.
Table 2 and Fig. 1 show that the Chang method tends to reduce the least preferred method to “0” weight [37]. As a result, the Liou-Wang method is used with more balanced weights. The details of both methods are given in their respective studies [34], [36]. Since no objective received the most minor importance among other alternatives, Liou-Wang’s method is considered more suitable for the study.

Table 2. Weights of Objectives

		Chang [36]	Liou- Wang [34]
C1	WT_{max}	0.00	0.16
C2	TWC	0.17	0.31
C3	C_{max}	0.83	0.53

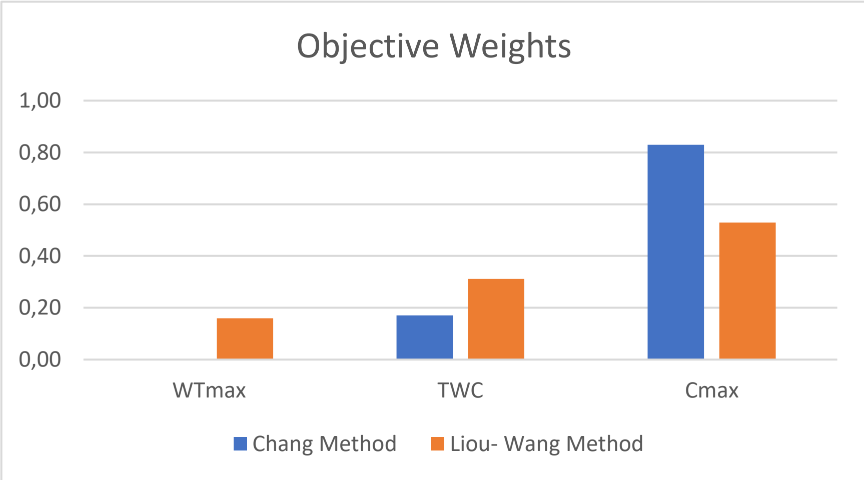

Figure 1. Objective Weights Based on Chang and Liou-Wang Methods

Stage 2: Genetic Algorithm Optimization for Flowshop Scheduling

Flowshop scheduling optimization is performed in this stage. To the best of our research, no dataset can be used for the optimization. We applied the proposed model using a randomly generated case. The model used for flow-shop scheduling can be classified as given below.
$Fm/S_{jk}\,,prec/C_{max}\,,WT_{max},TWC$
$Fm/S_{jk}\,,prec/C_{max}\,,WT_{max},TWC$, represent flexible flow shop, Sequence-dependent setup times, precedent constraints, makespan, maximum weighted tardiness, and total weighted completion time consecutively.
The algorithm in this paper is written in Matlab®, and the environment is a computer with an operating system using Windows 10, Intel Core i7-10510U CPU @2.30GHz, and 16G RAM. The herein study aims to be a starting point for comprehensive research. As a result, the proposed model is applied to a small dataset for optimization. Due dates, processing times, sequence-dependent setup times, waste per product setup, and relevant costs are generated. A summary of the application parameters is given in Table 3.
The GA, or generally metaheuristic models, do not guarantee that the best solution among all alternatives is found. A comparison is made between the best solutions and

metaheuristics results to assess our model's performance. Table 4 represents the difference between the best solution and genetic algorithm.

5. Sensitivity analysis

A sensitivity analysis is performed to assess the performance of the proposed model under different parameters. The proposed model is expected to give similar results based on parameter changes. In the sensitivity analysis, the makespan weight is increased by 20%. Similarly, the other objective functions are reduced, which makes the total weight equal to 1. As expected, the total objective function is reduced as the makespan's value is lower than the waste cost. The scenario-1 performed as expected for the amendment. In the second scenario of the sensitivity analysis, the waste range is increased from a range of (1-10) to a range of (20-50). As a result, the objective function is dramatically in the objective function as expected. As a part of sensitivity analysis, the second scenario is also successful. Finally, in the third scenario, SDST is increased from (1-5) to (10-20). Like other scenarios, the objective function is increased by 84.70%, as expected. Based on these analyses, the sensitivity analysis showed that parameter changes affect the model as expected. A more comprehensive range of parameters increases the objective function, and weight changes also affect the results associated with an increase or decrease in the objective function. Table 6 summarizes the outcomes.

Table 3. Parameters of the Objective Function

	Input	Lower Limit	Upper Limit
Number of Jobs	9		
Number of Machines	5		
Number of generations	2000		
Population Size	10000		
Due Time		20	30
Processing Times		1	10
SDST		1	5
Waste		1	10
Waste Cost per Unit		1	10

The results after 1000 epochs are given in Table 4 and Fig. 1.

Table 4. Results of the FASD Model

	Average Value	St. Deviation
Objective Function	167.45	26.18
WT_{max}	66.83	9.24
TWC	768.89	165.74
C_{max}	121.19	26.18

Fig. 1 Total Performance of the Model

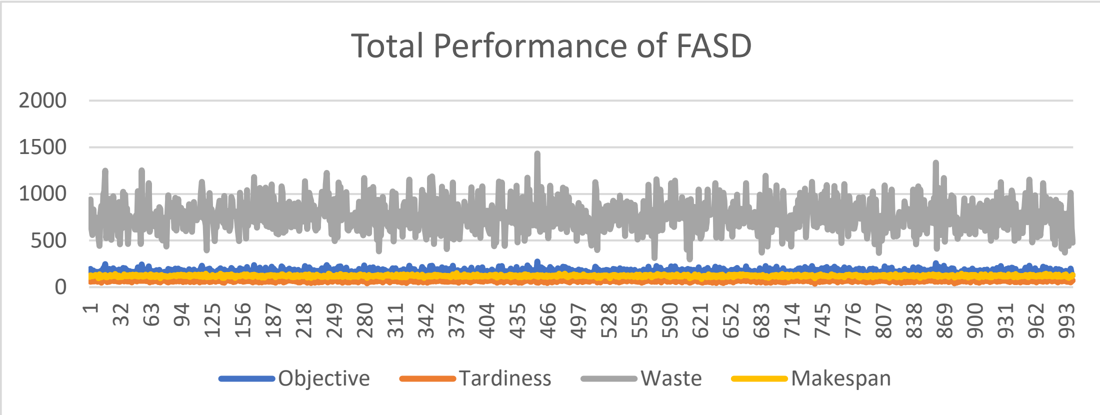

Table 5. Comparison with the Optimum Solution for 1000 Epochs

	Average Value of Objective Function	Time	Optimum Solution Success Rate
FASD	167.45	1.23	65.60%
Optimum Solution	166.97	4.02	
Difference	0.28%	-69.53%	

Table 6. Sensitivity Analysis Results

Model	Amendment	Results	Difference
Original Model	Last Epoch	126.53	
Scenario-1	Makespan Weight +%20	115.50	-8.72%
Scenario-2	Waste and Waste Cost per Unit Range = [10 20]	1371.40	983.83%
Scenario-3	SDST = [10 20]	176.04	39.13%

6. Conclusion

The production environment is a crucial component of any company. Decision-making is inherent in such an environment, and accurate decision-making contributes to the success of any business. In production environments, flow shops consisting of multiple machines are used in flow shop layouts. The proposed study integrates accurate decision-making, incorporating multiple objectives using novel MCDM approaches. AHP combined with fuzzy logic is used for the first stage of the proposed research. AHP is the most widely used approach for MCDM. Vague information is inherent in human thinking; as a result, fuzzy hybrid approaches are used to integrate fuzzy logic with AHP. In return, FAHP is used for the first stage. In the second stage, the GA is used for optimization, a well-known metaheuristic.

A simulation using experts' input is performed to evaluate the proposed model and assess the objectives' weights. The utilized objectives are makespan, maximum weighted tardiness, and total waste. Makespan is the objective with the highest importance; maximum weighted tardiness is the least important, and total waste is the objective between these two. The weights are 0.53, 0.31, and 0.16, respectively. GA coded in Matlab® is used to optimize schedules. As shown in Section 4, the application exhibited close to optimum results.

The study applied the proposed model to a case of 9 jobs and 5 machines. The proposed model reached the optimum solution in 65.60% of all cases, and the general deviation from the optimum solution is 0.28%. In comparison, the processing time is 69.53% shorter than the time needed to find the minimum solution by applying all combinations. The study has limitations because it is part of a more comprehensive study that aims to use a novel MCDM model with more experts employing a real-life case. As a result, the extension of the pool of experts is an area that will be focused on to overcome this limitation. Similarly, a real-life case will help the model overcome another limitation. Such an application will aim to add additional constraints to the problem to simulate the actual case better.

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