An Effective 4–Phased Framework for Scheduling Job-Shop Manufacturing Systems Using Weighted NSGA-II

Aidin Delgoshaei *, Mohd Khairol Anuar Bin Mohd Ariffin and Zulkiflle B. Leman

Abstract: Improving the performance of manufacturing systems is a vital issue in today’s rival market. For this purpose, during the last decade, scientists have considered more than one objective function while scheduling a production line. This paper develops a 4-phased fuzzy framework to identify effective factors, determine their weights on multi-objective functions, and, accordingly, schedule manufacturing systems in a fuzzy environment. The aim is to optimize product completion time and operational and product defect costs in a job-shop-based multi-objective fuzzy scheduling problem. In the first and second phases of the proposed framework, it was shown that the existing uncertainty of the internal factors for the studied cases causes the weights of factors to change up to 44.5%. Then, a fuzzy-weighted NSGA-II is proposed (FW-NSGA-II) to address the developed Non-linear Fuzzy Multi-objective Dual resource-constrained scheduling problem. Comparing the outcomes of the proposed method with other solving algorithms, such as the Sine Cosine Algorithm, Simulated Annealing, Tabu Search, and TLBO heuristic, using seven series of comprehensive computational experiments, indicates the superiority of the proposed framework in scheduling manufacturing systems. The outcomes indicated that using the proposed method for the studied cases saved up to 5% in the objective function for small-scale, 11.2% for medium-scale, and 3.8% for large-scale manufacturing systems. The outcomes of this study can help production planning managers to provide more realistic schedules by considering fuzzy factors in their manufacturing systems. Further investigating the proposed method for dynamic product conditions is another direction for future research.

Keywords: product scheduling; job-shop; weighted NSGA-II; product completion time

MSC: 90-10

1. Introduction

The job-shop facility location can be considered among the industry’s most frequently used facility location mode, applied in many industry sectors.

With the Industrial 4.0 revolution, the need to use heuristics and meta-heuristics to schedule manufacturing systems became increasingly obvious [1]. As a result, in recent years, many references used meta-heuristics as a core scheduling mechanism or part of it [2–4].

In a job-shop scheduling problem (JSSP), each in-process product passes through different shops, according to its operational requirements, where, in each shop, several parallel machines can serve an activity [5]. Traditionally, the main objective of job-shop scheduling problems was to find the best part routes of raw material throughout different shops until a product is completed [6]. However, today, various objective functions are taken into account in more complicated manufacturing environments [7]. Product completion time, quality, job tardiness, human resource scheduling, and operational cost can be considered the most frequently used objective functions during the last two decades.
Moreover, in the real industrial world, more than one objective should usually be considered while scheduling a manufacturing system [8]. This research then aims to answer the following questions: what are the most critical factors that should be considered while designing a job-shop-based manufacturing system? Are there any interactions between aims (objective functions) in a manufacturing system? If so, how strong are these interactions? How should a job-shop-based manufacturing system be scheduled using the factors above?

To answer the aforementioned questions, it is necessary to understand the factors that can influence the scheduling of a job-shop system. In this regard, the influential factors can be divided into two main groups, internal and external factors. Internal factors are those that exist inside a manufacturing system (including machinery, human resources, technology, capacity, etc.), while external factors include those where the source of the factor happens outside of a manufacturing system (such as market conditions, the political status of a country, market demand, etc.).

The purpose of the current research is to design a multi-stage framework for scheduling manufacturing systems by considering fuzzy internal factors, specifically focusing on job-shop-based manufacturing systems.

1.1. Novelties and Contributions

As seen at the end of Section 2 (Literature Review), the issues of optimizing product completion time, product defects, and human resource and operational costs in a fuzzy environment of multi-objective scheduling problems have not been addressed. Therefore, the novelties and contributions of the current research can be considered as follows:

- The first is to identify the influential internal factor influencing the scheduling of dual-resource-constrained job-shop-based manufacturing systems under uncertainty.
- To determine the effects of each uncertain factor on scheduling the multi-objective function of this research (time, defect, and HR cost).
- To propose a new method to schedule the dual-resource constrained manufacturing system using the found fuzzy weights.

1.2. Research Highlights

1. This research deals with fuzzy scheduling of job-shop scheduling which has previously been less developed.
2. In this study, a multi-objective non-linear mixed integer programming method is developed to minimize the makespan and completion cost and maximize the quality of products simultaneously.
3. A hybrid NSGA-II-SA, weighting, and Lp-metric method are proposed to solve the model. Note that the Lp-metric and hybrid NSGA-II-SA have not previously been used for job-shop scheduling problems.

1.3. Managerial Implications

The outcomes of this research will help managers of small and medium-scale manufacturing systems to schedule their job-shop-based systems more effectively by considering the fuzzy internal factors that can influence their systems. Moreover, the proposed method in phases 3 and 4 of this framework will help the managers find near-optimum solutions that can simultaneously improve completion time, product defect, and human resource and operational costs.

1.4. Importance and Necessity

In a real industrial environment, internal factors can influence the efficiency of the scheduling process, resulting in unrealistic schedules. However, such factors are usually ignored while scheduling a dual-constrained manufacturing system. In addition, the internal factors are uncertain, and such uncertainties for small elements may consequently cause increased uncertainty in a production schedule of a DRCSP [9]. As shown by Section 2
(literature review), there is no evidence of internal factors’ role in scheduling efficiency. Therefore, it is crucial to propose a new multi-step framework to identify influential factors, classify them, measure the levels of uncertainties, and schedule a DRCSP accordingly.

The rest of the paper is organized as follows: (i) In the first section, an in-depth review of the literature on scheduling manufacturing problems will be carried out. (ii) In the next section, a new 4-phased framework will be proposed; where, in the first phase, the influential factors in scheduling manufacturing systems will be identified, followed by determining the weights of each factor using data analytics methods (phase 2). In continuation, a new multi-objective mathematical model will be developed (phase 3). In the last phase, a new fuzzy-weighted NSGA-II will be proposed for scheduling manufacturing systems in the fuzzy environment (Phase 4). (iii) The proposed framework will then be applied to several case studies, (iv) followed by statistical measuring to determine the proposed framework’s performance.

2. Literature Review

During the last two decades, many scientists have focused on job-shop scheduling issues, where different objective functions were taken into account under various conditions. In the following, several opted references will be reviewed to determine the influential factors for the first phase of the proposed framework in the next section. Completion time is the main objective of job-shop scheduling, where the aim is to find the fastest production cycle by determining the best series of machines in different shops to complete parts.

Recently, a new concept in job-shop facility design emerged which focused on performing operations served by more than one machine. A vital issue for manufacturing systems is to respond to customers’ needs as quickly as possible. Therefore, scheduling processes are required to create more real-time schedules. In this regard, what makes job-shop scheduling important is the way of completing the required operations according to the operational process chart (OPC), where, for each operation, an appropriate machine should be selected among a set of parallel machines in a shop and then materials are transferred to visit a set of determined machines, accordingly. Delgoshaei, Ariffin, et al. focused on material movement problems in manufacturing systems by giving special attention to voids and idle machines [10]. Additionally, important factors play a vital role in scheduling job-shop-based manufacturing systems. In the following, the important factors will be reviewed; such factors will be used in the next section as the important factors for the proposed 4-phase framework.

2.1. Makespan

Product completion time is the first objective in classic job-shop scheduling problems. Liu et al. proposed a multi-objective-based Genetic algorithm framework (MPMOGA) for addressing multi-objective job-shop scheduling where product completion and total tardiness were considered [11]. In continuation, Kianpour et al. focused on due dates in job-shop scheduling while uncertain processing times were considered [12]. Later, Ying et al. proposed meta-heuristics for minimizing makespan in rapid job-shop-based manufacturing systems [13]. Then, Wang et al. proposed fuzzy job-shop scheduling where multi-objectives were considered [14]. Afsar et al. investigated the multi-objective scheduling of green job-shop scheduling by proposing hybrid Memetic and NSGA-II algorithms [15]. With multi-processing speed, Zheng et al. applied an NSGA-II to a bi-objective DRCJSP issue to reduce makespan and overall electricity consumption [16]. Their research discussed that a stochastic machine’s working process leads to non-deterministic job production time. This means that each activity’s processing time is determined by the machine deployed and the worker allocated to it.

2.2. Setup Times

Loading and unloading parts to a device other time-consuming activities that are usually ignored during the scheduling. This challenge was addressed by Akbar et al. using
a GA in dual-resource constrained scheduling problems where the aim was minimizing the completion time [17]. In addition, workers vary in their loading and unloading times [18]. Such differences may happen as a result of skill, age, and experience. In many manufacturing systems, the setup of machines is based on product sequences (sequence-dependent) which influence the total completion time of a product accordingly [19].

2.3. Machine Amortization

Machine amortizations are the other important issue that may cause serious problems for effective scheduling [20]. Gupta et al. proposed an integrated method for scheduling job-shop-based manufacturing systems while machine failures played a vital role in scheduling [21]. Amelian et al. addressed the failure-prone job-shop scheduling using an NSGA-II algorithm [22]. Souza et al. focused on preventive and corrective maintenance in scheduling job-shop manufacturing systems where uncertain constraints existed [23].

2.4. Raw Material Quality

In their novel review, Mohan et al. considered raw materials the other important factor that can cause a job-shop manufacturing system’s failure [20]. For this purpose, many scientists considered the study of raw material requirements and specifications as the objective of their scientific activities. Zhang et al. focused on energy efficiency in the optimal control problem by developing a multi-objective model [24]. Ramya et al. integrated material requirements planning in job-shop scheduling using the Shuffled Frog Leaping Algorithm. For this purpose, they developed a new application with VB.NET and MySQL [25]. Abderrahim et al. proposed a heuristic for scheduling job-shop systems where processing resources and transportation were considered the main objectives [26]. Vaez developed a new method of scheduling industrial systems that considers job etiquette and fines for lateness [27]. H. Li et al. argued that most scheduling references focused on the time factor [28]. However, essential objectives should not be ignored while studying job-shop-based systems. For this purpose, they proposed a meta-heuristic considering energy-consciousness during job-shop system scheduling.

2.5. Material Transferring

Material transferring (handling) is another factor influencing completion time and system costs in job-shop systems. Saidi-Mehrabad et al. developed a mathematical model for scheduling process products in job-shop systems by considering movement times between and within shops [29]. Karthikeyan et al. proposed a meta-heuristic to solve the FJSP problem where machines can operate along many pathways [30]. Delgoshaei, Ali, et al. argued that improper scheduling in job-shop systems might cause machine imbalance in a shop, consequently decreasing system productivity while increasing machine emergency service costs. Moreover, they demonstrated that dynamic cost conditions influence material routing in the process and may cause machine load variance [31]. While re-entrant portions are allowed, Rabbani et al. employed NSGA-II for scheduling difficulties [32]. Later, Huang focused on the role of automated guided vehicles in scheduling job-shop systems [33]. Burdett et al. developed an operating coal export terminal as a flexible job-shop system where the aim was a material recall from terminals [34]. Sun et al. focused on deadlock and robot movements in scheduling automated job-shop-based manufacturing systems [35].

2.6. Workforce

In this research, human resources are considered the main workforce category, consisting of two parts: human resource skills and human resource costs. Although Industry 4.0 is built on quick allocation and sequencing decisions, it is asserted that the workers should still be considered a crucial component for coordination and management, necessitating exact schedules for each worker [36]. Worker flexibility is the main concept in the human resource scheduling of job-shop-based manufacturing systems [37]. Delgoshaei et al. addressed a meta-heuristic for solving worker assignment problems in manufacturing systems
while worker skills were considered [38]. Dhiflaoui et al. addressed worker flexibility in dual-constraint job-shop scheduling problems [39]. In the same year, Gong et al. proposed a GA and NSGA-II to solve the double flexible job-shop scheduling problem where workers and machines were considered [40]. Shahgholi Zadeh et al. used the Bee Colony optimization method to address double flexible job-shop scheduling problems while various activity processing times were possible [41]. On the other hand, Kress et al. argued that workers’ skills should not be ignored during a system’s job-shop scheduling [42].

2.7. Literature Review Gap and Problem Statement of the Research

An in-depth review of the opted references indicated that the issue of scheduling job-shop problems while optimizing completion time, product defect, and human resource and operational costs using a fuzzy environment to address the uncertainty of factors has not been developed before. Therefore, this paper will provide a base to generate an alternative schedule for optimizing the multi-objectives above using a fuzzy inference system. This research continues with Saidi-Mehrabad et al. who determined that scheduling is vital when product completion time, product defect, and human resource and operational costs in a fuzzy environment are considered in a fuzzy scheduling problem [29]. This research aligns with the core of Industry 5.0, where human resources are assigned to work better and faster using an advanced scheduling method [43].

3. A 4-Phased Framework

In this stage, a 4-phased framework will be developed. Figure 1 shows the flowchart of the proposed framework.

![Flow chart of the proposed 4-phased framework.](image-url)
This method starts with identifying the effective factors influencing the multi-objective fuzzy scheduling of job-shop-based manufacturing systems. For this purpose, a series of opted references were reviewed. Moreover, an interview with academic gurus and industrial owners will be performed. In continuation, statistical data analysis will be carried out to determine the weights of the factors. Then, in the next step (phase 2), a fuzzy inference system will be set up using Matlab® 2016 to determine the fuzzy weights of each influential factor. A new mathematical modeling program will be developed using fuzzy weights where multi-objective decisions are considered. The complexity of the developed model will be measured to propose the appropriate solving method. Then, in phase 4, a weighted NSGA-II will be presented to solve the model where small, medium, and large-scale case studies are considered. The performance of the proposed method will then be measured using some indexes.

That the main concept of the research is inspired by Saidi-Mehrabad et al., who addressed a new method for optimizing the transportation times between machines in a job-shop scheduling problem [29].

3.1. Assumption

Several assumptions are taken into account as follows to determine the optimum multi-objective function for the job-shop-based manufacturing systems under fuzzy conditions:

• The manufacturing system’s facility design is a job-shop, which means parallel machines exist in each shop that can perform a similar service.
• The number of machines in a shop is fixed and cannot be changed during manufacturing.
• Each product must receive services from parallel machines in the related shops.
• The internal factors are uncertain and might be varied due to various production circumstances.
• Each part can receive one service at a time.
• Each service can be completed by only one machine at a time.
• Part re-entrant is not considered in this model but can be regarded as an opportunity to expand the model for future studies.
• Each machine has a defect rate considered during services (service rate).
• Raw materials that have a defect rate may cause product failure.
• The period’s beginning inventory should be zero, and the period’s last inventory should also be zero.

3.2. Identify the Effective Factors (Phase 1)

This section will identify the influential internal factors that can influence the multi-objective function. For this purpose, several factors that are mostly taken into consideration by scientists are considered. Moreover, interviews with academic scientists and industry owners in Malaysia were conducted. Figure 2 shows a list of the internal factors that are identified by the literature review and interviews with the scientists and industry experts:
• The period’s beginning inventory should be zero, and the period’s last inventory should also be zero.

3.2. Identify the Effective Factors (Phase 1)

This section will identify the influential internal factors that can influence the multi-objective function. For this purpose, several factors that are mostly taken into consideration by scientists are considered. Moreover, interviews with academic scientists and industry owners in Malaysia were conducted. Figure 2 shows a list of the internal factors that are identified by the literature review and interviews with the scientists and industry experts:

Figure 2. Influential factors on the scheduling of multi-objective job-shop systems.

3.3. Questionnaire Designing and Data Gathering

After identifying the factors, a statistical survey is performed to determine the crisp weight of each factor. For this purpose, a questionnaire is designed. The Cronbach’s alpha values showed the reliability of the questions before gathering data from the real-world, which consisted of various automotive, house appliance, and metal forming industries that use job-shop facility locations. Table 1 shows Cronbach’s Alpha:

Table 1. Cronbach’s alpha values for the reliability of the designed questionnaire.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Scale Mean If Item Deleted</th>
<th>Scale Variance If Item Deleted</th>
<th>Corrected Item-Total Correlation</th>
<th>Squared Multiple Correlation</th>
<th>Cronbach’s Alpha If Item Deleted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1 In-shop Transportation</td>
<td>38.8636</td>
<td>33.284</td>
<td>0.471</td>
<td>0.775</td>
<td>0.916</td>
</tr>
<tr>
<td>Q2 Intra-shop Transportation</td>
<td>38.7159</td>
<td>31.073</td>
<td>0.689</td>
<td>0.777</td>
<td>0.905</td>
</tr>
<tr>
<td>Q3 Production Technology</td>
<td>39.2386</td>
<td>30.240</td>
<td>0.757</td>
<td>0.833</td>
<td>0.901</td>
</tr>
<tr>
<td>Q4 Part Rout</td>
<td>39.0795</td>
<td>29.662</td>
<td>0.755</td>
<td>0.823</td>
<td>0.901</td>
</tr>
<tr>
<td>Q5 Machine Amortization</td>
<td>39.1193</td>
<td>29.249</td>
<td>0.719</td>
<td>0.729</td>
<td>0.903</td>
</tr>
<tr>
<td>Q6 Number of Workers</td>
<td>39.0966</td>
<td>28.842</td>
<td>0.833</td>
<td>0.842</td>
<td>0.896</td>
</tr>
<tr>
<td>Q7 Workers’ Skills</td>
<td>38.7443</td>
<td>31.894</td>
<td>0.528</td>
<td>0.746</td>
<td>0.914</td>
</tr>
<tr>
<td>Q8 Teamwork</td>
<td>39.1591</td>
<td>29.140</td>
<td>0.805</td>
<td>0.926</td>
<td>0.898</td>
</tr>
<tr>
<td>Q9 Product Formula</td>
<td>38.9034</td>
<td>29.436</td>
<td>0.802</td>
<td>0.912</td>
<td>0.898</td>
</tr>
<tr>
<td>Q10 Raw Material Quality</td>
<td>39.0966</td>
<td>29.196</td>
<td>0.559</td>
<td>0.745</td>
<td>0.918</td>
</tr>
</tbody>
</table>
3.4. Pearson Correlation Test

The correlations between factors is then calculated using the Pearson Correlation Test. Table 2 indicates the Pearson Correlation Test results. The outcomes indicate that positive correlations exist between most of the factors. In the next step, those factors with strong correlations ($p \geq 0.6$) and whether the correlations are meaningful in the real world will be considered in the regression formula developed in the next section.

Table 2. Pearson’s Correlation results between the identified factors.

<table>
<thead>
<tr>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
<th>Q6</th>
<th>Q7</th>
<th>Q8</th>
<th>Q9</th>
<th>Q10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1 Pearson Correlation</td>
<td>1</td>
<td>0.435 **</td>
<td>0.653 **</td>
<td>0.289 **</td>
<td>0.502 **</td>
<td>0.482 **</td>
<td>0.140</td>
<td>0.607 **</td>
<td>0.316 **</td>
</tr>
<tr>
<td>Q2 Pearson Correlation</td>
<td>0.435 **</td>
<td>1</td>
<td>0.639 **</td>
<td>0.459 **</td>
<td>0.732 **</td>
<td>0.543 **</td>
<td>0.677 **</td>
<td>0.509 **</td>
<td>0.470 **</td>
</tr>
<tr>
<td>Q3 Pearson Correlation</td>
<td>0.653 **</td>
<td>0.639 **</td>
<td>1</td>
<td>0.582 **</td>
<td>0.596 **</td>
<td>0.560 **</td>
<td>0.528 **</td>
<td>0.656 **</td>
<td>0.526 **</td>
</tr>
<tr>
<td>Q4 Pearson Correlation</td>
<td>0.289 **</td>
<td>0.459 **</td>
<td>0.582 **</td>
<td>1</td>
<td>0.490 **</td>
<td>0.714 **</td>
<td>0.598 **</td>
<td>0.560 **</td>
<td>0.757 **</td>
</tr>
<tr>
<td>Q5 Pearson Correlation</td>
<td>0.502 **</td>
<td>0.732 **</td>
<td>0.596 **</td>
<td>0.490 **</td>
<td>1</td>
<td>0.668 **</td>
<td>0.382 **</td>
<td>0.607 **</td>
<td>0.494 **</td>
</tr>
<tr>
<td>Q6 Pearson Correlation</td>
<td>0.482 **</td>
<td>0.543 **</td>
<td>0.560 **</td>
<td>0.714 **</td>
<td>0.668 **</td>
<td>1</td>
<td>0.425 **</td>
<td>0.830 **</td>
<td>0.776 **</td>
</tr>
<tr>
<td>Q7 Pearson Correlation</td>
<td>0.140</td>
<td>0.677 **</td>
<td>0.528 **</td>
<td>0.598 **</td>
<td>0.382 **</td>
<td>0.425 **</td>
<td>1</td>
<td>0.306 **</td>
<td>0.426 **</td>
</tr>
<tr>
<td>Q8 Pearson Correlation</td>
<td>0.607 **</td>
<td>0.509 **</td>
<td>0.656 **</td>
<td>0.560 **</td>
<td>0.607 **</td>
<td>0.830 **</td>
<td>0.306 **</td>
<td>1</td>
<td>0.844 **</td>
</tr>
<tr>
<td>Q9 Pearson Correlation</td>
<td>0.316 **</td>
<td>0.470 **</td>
<td>0.526 **</td>
<td>0.757 **</td>
<td>0.494 **</td>
<td>0.776 **</td>
<td>0.426 **</td>
<td>0.844 **</td>
<td>1</td>
</tr>
<tr>
<td>Q10 Pearson Correlation</td>
<td>−0.007</td>
<td>0.301 **</td>
<td>0.442 **</td>
<td>0.597 **</td>
<td>0.469 **</td>
<td>0.560 **</td>
<td>0.247 **</td>
<td>0.505 **</td>
<td>0.673 **</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

3.5. Determining the Crisp Weights of the Variables

After determining the correlations between factors, the crisp weights for the variables (factors) are determined. For this purpose, a regression equation is developed by SPSS. The coefficients of variables are shown in Table 3:

Efficient Scheduling

\[
= 0.332 \times Q1 + 0.072 \times Q2 + 0.065 \times Q3 + 0.165 \times Q4 + 0.160 \times Q5 + 0.151 \times Q6 \\
+ 0.237 \times Q7 + 0.316 \times Q8 + 0.044 \times Q9 + 0.381 \times Q10
\]  

(1)

As shown by Equation (1), various variables impact efficient scheduling differently. In this regard, the part route, as question 6 found, is at the top of the list of influential factors that can influence scheduling efficiency. In addition, the statistical society believed that Workers’ Skills and Production Technology are the other most important factors that can significantly impact the scheduling of job-shop-based manufacturing systems. Meanwhile, they also believed that Machine Amortization and Raw Material Quality are vital factors that should not be ignored during the scheduling process. By contrast, it is found that Product Formula and Procedures have fewer impacts on the dependent variable.
Table 3. Determining the crisp weights of the factors using the regression coefficients.

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
</tr>
<tr>
<td>(Constant)</td>
<td>-0.767</td>
<td>0.126</td>
<td>-6.091</td>
<td>0.000</td>
</tr>
<tr>
<td>Q1</td>
<td>0.370</td>
<td>0.036</td>
<td>0.332</td>
<td>10.184</td>
</tr>
<tr>
<td>Q2</td>
<td>0.069</td>
<td>0.032</td>
<td>0.072</td>
<td>2.201</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.059</td>
<td>0.035</td>
<td>0.065</td>
<td>-1.706</td>
</tr>
<tr>
<td>Q4</td>
<td>-0.137</td>
<td>0.031</td>
<td>0.165</td>
<td>-4.469</td>
</tr>
<tr>
<td>Q5</td>
<td>0.121</td>
<td>0.023</td>
<td>0.160</td>
<td>5.384</td>
</tr>
<tr>
<td>Q6</td>
<td>0.122</td>
<td>0.032</td>
<td>0.151</td>
<td>3.871</td>
</tr>
<tr>
<td>Q7</td>
<td>0.212</td>
<td>0.028</td>
<td>0.237</td>
<td>7.695</td>
</tr>
<tr>
<td>Q8</td>
<td>0.259</td>
<td>0.047</td>
<td>0.316</td>
<td>5.548</td>
</tr>
<tr>
<td>Q9</td>
<td>-0.038</td>
<td>0.044</td>
<td>0.044</td>
<td>-0.847</td>
</tr>
<tr>
<td>Q10</td>
<td>0.236</td>
<td>0.019</td>
<td>0.381</td>
<td>12.448</td>
</tr>
</tbody>
</table>

* Dependent variable: efficient scheduling.

3.6. Fuzzy Inference System (Phase 2)

The weight factors calculated in the last section were crisp, meaning that the uncertainty has not been considered for them. However, in reality, the factors in a dynamic condition of the manufacturing system are not crisp and may be affected by uncertainty. For this purpose, in this section, a fuzzy inference system will be developed to involve the uncertainty level of the crisp factors, thus making them fuzzy weights. The fuzzy weights will be directly used in the mathematical model presented in the next section.

3.7. Fuzzy Inference System Model

In this research, the responders’ confidence level will involve uncertainty. For this purpose, the level of certainty was asked of responders after each question. This approach is inspired by Alazemi et al. [44]. For this purpose, the responders selected the level of confidence from a range of uncertainties for each factor. Then, the FIS model, where a multi-input single-output (MISO) design is used for each factor, is developed as follows (Figure 3):

- Define variables
- Score range
- Uncertainty rate
- Determine fuzzy domain functions
- Mamdani’s fuzzy function
- Set rules
- Transferring the results into a range
- Fuzzy weights for risk factors

Figure 3. The MISO-based FIS model.
Table 4 indicates the designed FIS model according to the structure explained in Figure 3.

Table 4. The FIS Model Description.

<table>
<thead>
<tr>
<th>Model Properties</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable Name</td>
<td>In-shop Transportation (Q1); Intra-shop Transportation (Q2); Production Technology (Q3); Part Rout (Q4); Machine Amortization (Q5); Number Of Workers (Q6); Workers’ Skills (Q7); Teamwork (Q8); Product Formula (Q9); and Raw Material Quality (Q10)</td>
</tr>
<tr>
<td>Score Range</td>
<td>Too Slow (1); Slow (2); Acceptable (3); Very Good (4); and Excellent (5)</td>
</tr>
<tr>
<td>Uncertainty Rate</td>
<td>Completely Unsure (0%); Unsure (25%); So-So (50%); Partially Sure (75%); and Confident (100%)</td>
</tr>
<tr>
<td>Fuzzy Domain Function</td>
<td>Trapezoidal Distribution Functions</td>
</tr>
<tr>
<td>Fuzzy Rule</td>
<td>9 Rules</td>
</tr>
<tr>
<td>Fuzzy Function</td>
<td>Mamdani rule: If (FP is i) and (FP’ is j) then (FO is k)</td>
</tr>
<tr>
<td></td>
<td>where FP can be considered as the first variable’s input and FP’ as the second variable’s input. FO will be a fuzzy output accordingly.</td>
</tr>
<tr>
<td>Fuzzy Model</td>
<td>Multi-Input Single-Output (MISO)</td>
</tr>
</tbody>
</table>

Figure 4 indicates an example of using Trapezoidal Distribution Functions while the lower bound is \(-3\) (\(a = -3\)) and the upper bound is \(+5\) (\(d = +5\)):

![Figure 4. Trapezoidal distribution functions for a specific data set.](image-url)

The trapezoidal distribution function is a commonly used function for expressing fuzzy ranges for a data series by considering breaking points to identify the range of data. It is selected in this article based on the scoring range in Section 3.3. Other distribution functions may be considered, such as the triangular distribution function.

The model design and fuzzy membership functions are shown in Figure 5. The model is then expanded and represented in Figure 6.
The trapezoidal distribution function is a commonly used function for expressing fuzzy ranges for a data series by considering breaking points to identify the range of data. It is selected in this article based on the scoring range in Section 3.3. Other distribution functions may be considered, such as the triangular distribution function. The model design and fuzzy membership functions are shown in Figure 5. The model is then expanded and represented in Figure 6.

Figure 5. Designed fuzzy model with fuzzy membership functions.

Figure 6. The expanded FIS model with ranges and fuzzy members.
Figure 7 presents the rules that are set for the developed FIS model.

Figure 7. Rules of the developed fuzzy inference system.

Then, the fuzzy weights for each of the risk factors can be calculated as follows (Figure 8):

Figure 8. Fuzzy weights output window.

The fuzzy weights can be calculated using Matlab’s fuzzy weights output window. Table 5 indicates the results of the fuzzy weights. The weights are then normalized to be applied to the mathematical model in the next section.
Table 5. Normalized fuzzy weights.

<table>
<thead>
<tr>
<th>Group Risk Factor</th>
<th>Time</th>
<th>Human Resource and Operations</th>
<th>Material</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
</tr>
<tr>
<td>Crisp Weight</td>
<td>0.332</td>
<td>0.072</td>
<td>0.065</td>
</tr>
<tr>
<td>Confidence Rate Avg.</td>
<td>56.5</td>
<td>82</td>
<td>79.3</td>
</tr>
<tr>
<td>Fuzzy Weight</td>
<td>0.165</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Normalized Fuzzy Weights</td>
<td>0.043</td>
<td>0.130</td>
<td>0.130</td>
</tr>
</tbody>
</table>

Figure 9 indicates the 3D graphical view of the FIS model, which shows the areas where uncertainty can affect the risk factors.
TH: Time horizon in a manufacturing period
\(\tau_{pk}\): The time required to perform an operation by the machine \(p\) in the shop \(k\)
\(\lambda_{qk}\): The time required to transporting one product using transportation type \(q\)
\(D_{pk}\): Demand of product type \(i\) in period \(t\)
\(OPC_{ik}\): Operation process chart of product (if product \(I\) needs service type \(k\))
\(C_{pk}\): Capacity of machine \(p\) in shop \(k\)
\(DP_{pk}\): Defect rate of machine \(p\) in shop \(k\th\)
\(Dr_{r}\): Defect rate of raw material type \(r\)
\(\alpha_{rk}\): The usage coefficient of raw material type \(r\) for producing one unit of product \(i\)
\(COC_{ipk}\): Operation cost of product \(ith\) using machine \(p\) in shop \(kth\)
\(TC_{ipk}\): Transfer cost of unit movement of product \(ith\) using transfer type \(q\)
\(Tr_{r}\): total available raw material type \(r\)
\(\omega_{1}\): Fuzzy weights for completion time
\(\omega_{2}\): Fuzzy weights for human resource and operations costs
\(\omega_{3}\): Fuzzy weights for defect rate

3.8.3. Decision Variables

The decision variables of the model will be explained as follow:

\[ X_{i,p,k,t} : \text{Number of operations type } k \text{ of product } i \text{ that are served by machine } p \text{ in time slot } t \text{ (integer)} \]  

3.8.4. Mathematical Model

In this section, the mathematical model will be developed as follow:

\[
\text{Min } Z_{1} : \omega_{1} \cdot \left( \sum_{i}^{T} \sum_{k}^{K} \sum_{p}^{P} \sum_{t}^{I} \tau_{pk} \cdot X_{i,p,k,t} + \sum_{i}^{T} \sum_{k}^{K} \sum_{p}^{P} \sum_{q}^{Q} \lambda_{qk} \cdot X_{i,p,k,t} \right) 
\]

\[
\text{Min } Z_{2} : \omega_{2} \cdot \sum_{i}^{T} \sum_{k}^{K} \sum_{p}^{P} COC_{ipk} \cdot X_{i,p,k,t} + TC_{ipk} \cdot X_{i,p,k,t} 
\]

\[
\text{Max } Z_{3} : \omega_{3} \cdot \left( \sum_{i}^{T} \sum_{k}^{K} \sum_{p}^{P} D_{p,r} \cdot X_{i,p,k,t} + \sum_{i}^{T} \sum_{k}^{K} \sum_{p}^{P} \sum_{r}^{R} Dr_{r} \cdot X_{i,p,k,t} \right) 
\]

s.t:

\[
\sum_{p}^{P} X_{i,p,k,t} / OPC_{ik} = D_{ii} \forall t & i 
\]

\[
\sum_{k}^{K} X_{i,p,k,t} \leq C_{pk} \forall t & k & p 
\]

\[
\sum_{i}^{I} X_{i,p,k,t} \cdot \tau_{pk} + \sum_{r}^{R} X_{i,p,k,t} \cdot \lambda_{qk} < TH \forall t & k & p 
\]

\[
\sum_{i}^{I} \sum_{k}^{K} \sum_{p}^{P} \alpha_{rk} \cdot X_{i,p,k,t} \cdot (1 + Dr_{r}) \leq Tr_{r} \forall t & r 
\]

\[
\sum_{i=1}^{3} \omega_{i} = 1 
\]

\[ X_{i,p,k,t} : \text{integer} \]

The first objective function is to minimize completion time (Equation (26)). This objective includes two main parts: in the first part, the operational time is minimized, and in the second part, transportation time is minimized. The second objective targets operational and transportation costs within and between shops to complete all essential services (Equation (27)). The third objective tries to minimize the defect rate of the products.
by considering the raw material defect rate and machine defect rate (Equation (28)). The first constraint guarantees that in each production period, the market demands must be fulfilled (Equation (29)). For this purpose, the number of total operations are divided into the total number of required operations for each product. For example, if the number of total operations for product 1 is determined as 300 (\(\sum_{k}^{P} \left(\sum_{p}^{P} X_{i,p,k,t}\right)\)) in a manufacturing period, and for completing each unit of product type one, five operations are suggested in the OPC matrix \(\sum_{k}^{K} \left(\sum_{p}^{P} OPC_{ik}\right)\), then the total number of product type 1 in the period will be 60 (\(\sum_{k}^{K} \left(\sum_{p}^{P} X_{i,p,k,t}/OPC_{ik}\right)\)). The second constraint is ensuring that the number of operations for all products in a production period will not exceed the machine’s capacity (Equation (30)). The third constraint supports the time horizon in each manufacturing period by ensuring that the total times for production and transferring of all product types will not exceed the available time horizon in that period (Equation (31)). The fourth constraint shows that the total amount of each raw material type used for manufacturing the products will not exceed the total available raw material in that period (Equation (32)). The fuzzy weights (\(\omega_{i}\)) extracted in the previous part are used here as the weights of the objective functions (Equation (33)).

Table 6 compares the contribution and novelty of this study to those of other similar studies in the literature.
### Table 6. Contribution and novelties of this research.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Mathematical Model</th>
<th>Objective Function</th>
<th>Objectives</th>
<th>Fuzzy Weights</th>
<th>Solving Algorithm</th>
<th>Case Studies</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Adams, 2019) [45]</td>
<td>NL-MIP</td>
<td>Single</td>
<td>Minimize makespan</td>
<td>-</td>
<td>Two Algorithmic Procedures</td>
<td>5</td>
<td>Focused on sequence-dependent setup times and training option</td>
</tr>
<tr>
<td>(Akbar et al., 2018b) [46]</td>
<td>NL-MIP</td>
<td>Multi-objective</td>
<td>Minimize makespan</td>
<td>Operator Workload Balance</td>
<td>-</td>
<td>NSGA-II</td>
<td>Minimized makespan and operator workload balance</td>
</tr>
<tr>
<td>(Jaber et al., 2010) [47]</td>
<td>MIP</td>
<td>Multi-objective</td>
<td>Minimizing reducing idle</td>
<td>Maximizing average workload</td>
<td>-</td>
<td>Excel Solver with VBA</td>
<td>18</td>
</tr>
<tr>
<td>(Mlekusch et al., 2022) [48]</td>
<td>MIP</td>
<td>Single</td>
<td>Minimize makespan</td>
<td>-</td>
<td>A Hybrid Genetic Algorithm</td>
<td>5</td>
<td>Re-Entrant flexible flow shop</td>
</tr>
<tr>
<td>(Tao et al., 2019) [49]</td>
<td>IP</td>
<td>Single</td>
<td>Minimize makespan</td>
<td>-</td>
<td>A Hybrid Genetic Algorithm and Simulated Annealing Algorithm</td>
<td>2</td>
<td>Two resources without storage buffers were considered, along with the differences between disturbance types</td>
</tr>
<tr>
<td>(X. Wu et al., 2021) [50]</td>
<td>NL-MIP</td>
<td>Multi-objective</td>
<td>Minimize makespan</td>
<td>Setup time of the fixtures</td>
<td>-</td>
<td>NSGA-II</td>
<td>10</td>
</tr>
<tr>
<td>(Ying et al., 2022) [51]</td>
<td>MIP</td>
<td>Single</td>
<td>Minimize total completion time</td>
<td>-</td>
<td>Backtracking Multi-Start Simulated Annealing</td>
<td>40</td>
<td>Tried to escape local optimum points by using Simulated Annealing</td>
</tr>
<tr>
<td>(F. Zheng et al., 2019) [16]</td>
<td>NL-MIP</td>
<td>Multi-objective</td>
<td>Minimize makespan</td>
<td>Total electricity consumption</td>
<td>-</td>
<td>NSGA-II</td>
<td>1</td>
</tr>
<tr>
<td>(X.L. Zheng et al., 2016) [52]</td>
<td>BP</td>
<td>Single</td>
<td>Minimize makespan</td>
<td>-</td>
<td>A knowledge-guided fruit fly optimization algorithm</td>
<td>22</td>
<td>Used the alignment of operation sequence and resources assignment for scheduling</td>
</tr>
<tr>
<td>(Yazdani et al., 2015) [53]</td>
<td>MIP</td>
<td>Multi-objective</td>
<td>Minimize makespan</td>
<td>-</td>
<td>Simulated Annealing and Vibration Damping Optimization</td>
<td>16</td>
<td>Focuses on the different meta-heuristics in DRCSPs.</td>
</tr>
<tr>
<td>Reference</td>
<td>Mathematical Model</td>
<td>Objective Function</td>
<td>Objectives</td>
<td>Fuzzy Weights</td>
<td>Solving Algorithm</td>
<td>Case Studies</td>
<td>Contribution</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>--------------------</td>
<td>--------------------</td>
<td>--------------------------------</td>
<td>---------------</td>
<td>-------------------</td>
<td>--------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>(Vital-Soto et al., 2022)</td>
<td>NL-MIP</td>
<td>Multi-objective</td>
<td>Minimize makespan</td>
<td>Maximal worker workload</td>
<td>Weighted Tardiness</td>
<td>NSGA-II</td>
<td>2</td>
</tr>
<tr>
<td>Saidi-Mehrabad et al. [29]</td>
<td>NL-MIP</td>
<td>Single</td>
<td>Minimize makespan</td>
<td>-</td>
<td>-</td>
<td>ACO</td>
<td>13</td>
</tr>
<tr>
<td>J.-Q. Li et al. [54]</td>
<td>-</td>
<td>Multi-objective</td>
<td>Completion time</td>
<td>Total workload</td>
<td>Workload of the critical machine</td>
<td>ABC</td>
<td>15</td>
</tr>
<tr>
<td>Hasan et al. [55]</td>
<td>-</td>
<td>Single</td>
<td>Minimize makespan</td>
<td>-</td>
<td>-</td>
<td>GA</td>
<td>1</td>
</tr>
<tr>
<td>This Research</td>
<td>NL-IP</td>
<td>Multi-objective</td>
<td>Completion time</td>
<td>HR and operations cost</td>
<td>Quality ratio</td>
<td>Fuzzy Weighted NSGA-II</td>
<td>7</td>
</tr>
</tbody>
</table>

3.9. Weighted NSGA-II (Phase 4)

The developed model in phase 3 is multi-objective. Usually, multi-objective models are complex, and there is no exact optimum point that can optimize all objectives simultaneously. For this purpose, in most cases, scientists used heuristics and metaheuristics to solve multi-objective models [8,56–58]. However, the classic NSGA-II does not consider the uncertainty variables (factors) in its calculation. As a result, to address this issue, a new fuzzy-weighted NSGA-II will be proposed in this research to solve the developed model. NSGA-II was firstly proposed by Srinivas et al. [59] and has been widely used to solve multi-objective models many times [60–62]. Verma et al. provided a novel review on using NSGA-II for combinational optimization problems [63]. Recently, fuzzy NSGA-II has attracted the attention of scientists due to its high capability to consider uncertainty in multi-objective optimization problems [64,65]. This research proposes a new fuzzy weight NSGA-II to solve the multi-objective job-hop-based scheduling problem in a fuzzy environment. The flowchart of the proposed fuzzy-weighted NSGA-II is shown in Figure 10. Then, the pseudo-code for the FW-NSGA-II is shown in Algorithm 1.

The algorithm starts by entering algorithm parameters (including population size, generations, and mutation rate) along with the case study parameters (including the number of products, machines, raw material type, shops, and demand). According to OPC, the algorithm then recognizes the possible list of solutions for the machines that can serve the required operations consecutively. At this stage, using the crossover operator, the part routes for the possible solutions will be determined (Equation (41)). Then, a list of possible solutions, called a part route list, will be further processed by calculating fuzzy weighted objective functions. In continuation, those solutions that achieved greater multi-function objective function will be stored in the tournament list for the next generations. In the next generations, new solutions will be generated by changing the possible part routes using parallel machines in the same shop. The process will be repeated until the maximum number of generations is achieved (stop criterion).

3.9.1. Cross-Over Operator

The cross-over operator for the proposed method will be explained as follow:

For $i \in I$

For $p \in OPC_i$

List the required machines for the operation $i$

Find potential machines in the related shop

If $C'_{pk} < C_{pk}$:

Remove $p$ from the machine list;

Select a machine from the machine list

Generate the new part route list

* $C'_{pk}$ is the remained capacity of a machine

3.9.2. Setting NSGA-II Parameters

Before using the proposed NSGA-II for the solving algorithms, the algorithm parameters such as the number of generations, population size, cross-over rate, mutation rate, and neighborhood ratio should be set. The aim is to tune up the NSGA-II to achieve maximum efficiency. For this purpose, a Taguchi model is designed using Minitab® 18.0. The outcomes of the best values that were estimated for each of the solving algorithm parameters are shown in Table 7:
Algorithm 1 Pseudo code of the proposed FW-NSGA-II algorithm

Insert Dataset
- Input data sets (TH, S, \( t_{pk}, D_{it}, OPC_{ik}, C_{pk}, Q_{PK}, CO_{ipk}, M_{k} \))
- Input parameters (population size, mutation rate, generations)
- Input Fuzzy Weights (\( \omega_{1}, \omega_{2}, \omega_{3} \))

For Generation 1:1:N:

for Population 1:1: pop.size:
- If \( t \) is 1:
  - Find appropriate machines that can serve the first operations
- Else
  - Choose a member from the candidate list
  - List the required consecutive operations to complete a product (OPC_{ix})
  - Find tournament list
  - Activate Cross-over Operator
  - Choose the best part route
  - Call Mutation Operator
  - Rand a number (Y: \( \text{Rand}(1) \)):
    - If \( Y \leq \text{Ma} \):
      - Find another list of suitable machines by choosing other possible candidates
      - If \( p \& p' \in \text{Tournament list}_i \):
        - \( w_{ipk}\text{ft}=1 \) and \( w_{ip'k}\text{ft}=0 \); DO
        - \( w_{ipk}\text{ft}=0 \) and \( w_{ip'k}\text{ft}=1 \)

- Calculate Remained \( D_{it} \)
  - If Remained \( D_{it} > 0 \):
    - Go line 10
  - Calculate Multi-Fitness Function:
    - Min \( Z_1: \omega_1\sum_{T \times K \times P \times I} T \sum_{k} p_{k} X_{ipk,t} + \sum_{T \times P \times Q} q \sum_{k} p_{k} X_{ipk,t} + \sum_{T \times K \times P \times I} T \sum_{k} p_{k} X_{ipk,t} \)
    - Min \( Z_2: \omega_2\sum_{T \times K \times P \times I} T \sum_{k} p_{k} X_{ipk,t} + \sum_{T \times K \times P \times I} T \sum_{k} p_{k} X_{ipk,t} \)
    - Max \( Z_3: \omega_3\sum_{T \times K \times P \times I} T \sum_{k} p_{k} X_{ipk,t} + \sum_{T \times K \times P \times I} T \sum_{k} p_{k} X_{ipk,t} \) (35)

- Calculate Multi Weighting Objective Function: \( \text{MOFV} = \omega_1Z_1 + \omega_2Z_2 + \omega_3Z_3 \) (36)
- If \( \text{MOFV} < \text{mean(MOFV)} \):
  - List Solution in the Best Solution String (STR)
    - \( \text{OFV}_{\text{best}} = \text{OFV}_i \) (37)
    - \( \text{STR}_{\text{best}} = \text{STR}_{\text{itr}} \) (38)
    - \( \text{Tournament list}_i = \text{STR}_i \) (39)

Else
  - Call Simulated Annealing Local Escape Operator:
    - Rand a Number (R)
    - If \( R < \text{L.E.R} \):
      - List Solution String in the Best Solution
        - \( \text{Tournament list}_i = \text{STR}_i \)
    - Calculate \( \text{OFV}_i \)
      - If \( \text{OFV}_i \leq \text{min}_{\text{itr}}(\text{OFV}) \):
        - \( \text{Tournament list}_i = \text{STR}_i \)
        - \( \text{OFV}_{\text{best}} = \text{OFV}_i \) & \( \text{STR}_{\text{best}} = \text{STR}_{\text{itr}} \) (40)

Check Stopping Criteria
Exit
Figure 10. Flowchart of the proposed fuzzy weight NSGA-II.
Table 7. The estimated setting values for the proposed NSGA-II method.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Small Scale</th>
<th>Medium Scale</th>
<th>Large Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Generations</td>
<td>10</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>Population Size</td>
<td>20</td>
<td>50</td>
<td>80</td>
</tr>
<tr>
<td>Cross-Over Rate</td>
<td>0.95</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>0.05</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Neighborhood Ratio</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>L.E.R</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1</td>
</tr>
</tbody>
</table>

3.9.3. Evaluating the Performance of the Model Using Lp-Metric and Weighting Methods (Lingo 12.0)

The Lp-metric method is a well-known and robust technique for solving multi-objective algorithms. The Lp-metric algorithm starts by solving models and their routes ($p = 2, 3, \text{etc.}$). This strategy enables the algorithm to find solutions with higher quality. The algorithm stops whenever the solutions of two consecutive routes are the same (for example, the results of solving the second and third routes of the model became equal).

In continuation, similar to the previous algorithm, the algorithm is applied for a small-size case study. The results showed that the solver (Branch and Bound Algorithm) stopped in iteration 22 by falling into a local optimum point. Table 8 shows that the Lp-metric algorithm found the same (and best) solutions in the third route ($p = 3$).

Table 8. Results of solving the case studies with Lp-Metric method ($p = 1, 2, 3$).

<table>
<thead>
<tr>
<th>Problem (i/j/k/m/p/TH)</th>
<th>W1</th>
<th>W2</th>
<th>W3</th>
<th>Iteration</th>
<th>Type</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/4/4/3/3</td>
<td>0.42</td>
<td>0.238</td>
<td>0.238</td>
<td>22</td>
<td>NL-IP</td>
<td>Local Optimum</td>
</tr>
</tbody>
</table>

A weighting method coded with Lingo 12.0$^\circledR$ is used to solve the multi-objective job-shop-based scheduling model that enables us to compare the results with the fuzzy-weighted NSGA-II. The algorithm is then applied to a small case study. Lingo 12.0 can easily recognize the model as mixed integer programming (MIP) and find the global optimum solution in 31 iterations. Lingo used the branch and bound method to solve the model using the multi-objective weighting technique.

The algorithm is then applied to seven data sets generated considering different data sets. The outcomes in Table 9 show that the method could find global optimum solutions for small-scale problems. However, it could only find the local optimum for large-scale problems. In addition, the elapsed time for solving the case studies increased dramatically by increasing the size of the variables.

Table 9. Results of solving the case studies with the multi-objective weighting method.

<table>
<thead>
<tr>
<th>Problem (i/j/k/m/p/TH)</th>
<th>W1</th>
<th>W2</th>
<th>W3</th>
<th>Iteration</th>
<th>Type</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/4/4/3/3</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
<td>31</td>
<td>MIP</td>
<td>Global Optimum</td>
</tr>
</tbody>
</table>

4. Results and Discussion

In order to check the performance of the proposed method, a number of case studies on a small, medium, and large scale will be solved. The outcomes’ performance will then be examined using some metrics (Table 10). Note that all case studies were solved by a personal laptop supported by Intel(R) Core(TM) i7, CPU @ 2.40 GHz, and 8 GB RAM.
The findings showed that the proposed FW-NSGA-II could solve all the case studies in a reasonable time.

Table 10. Results of solving the case studies using NSGA-II.

<table>
<thead>
<tr>
<th>No.</th>
<th>Size</th>
<th>Case Study (i/k/s/t)</th>
<th>Gen</th>
<th>Pop</th>
<th>Mu</th>
<th>LER</th>
<th>Objective Functions</th>
<th>Elapsed Time (seconds)</th>
<th>Multi-Objective Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Small</td>
<td>3/4/1/2</td>
<td>10</td>
<td>20</td>
<td>0.05</td>
<td>0.1</td>
<td>1.96</td>
<td>1.973</td>
<td>1.973</td>
</tr>
<tr>
<td>2</td>
<td>Small</td>
<td>5/6/1/2</td>
<td>10</td>
<td>20</td>
<td>0.05</td>
<td>0.1</td>
<td>4.85</td>
<td>1.329</td>
<td>34.4</td>
</tr>
<tr>
<td>3</td>
<td>Medium</td>
<td>10/6/1/3</td>
<td>20</td>
<td>80</td>
<td>0.05</td>
<td>0.2</td>
<td>24.6</td>
<td>1.605</td>
<td>127.3</td>
</tr>
<tr>
<td>4</td>
<td>Medium</td>
<td>20/4/1/3</td>
<td>20</td>
<td>80</td>
<td>0.05</td>
<td>0.2</td>
<td>21.82</td>
<td>2.974</td>
<td>61.00</td>
</tr>
<tr>
<td>5</td>
<td>Large</td>
<td>40/5/1/3</td>
<td>50</td>
<td>80</td>
<td>0.1</td>
<td>0.2</td>
<td>45.03</td>
<td>2.256</td>
<td>171</td>
</tr>
<tr>
<td>6</td>
<td>Large</td>
<td>50/5/1/3</td>
<td>50</td>
<td>80</td>
<td>0.1</td>
<td>0.2</td>
<td>67.73</td>
<td>2.828</td>
<td>227.5</td>
</tr>
<tr>
<td>7</td>
<td>Large</td>
<td>100/5/1/3</td>
<td>50</td>
<td>80</td>
<td>0.1</td>
<td>0.2</td>
<td>89.24</td>
<td>2.345</td>
<td>231</td>
</tr>
</tbody>
</table>

Then, the model is solved by other methods, namely the Sine Cosine Algorithm, Simulated Annealing, Tabu Search, and TLBO heuristic. The results showed that, in many cases, the proposed method could provide better solutions (Table 11).

Table 11. Results of comparing the proposed method with other methods.

<table>
<thead>
<tr>
<th>No.</th>
<th>Case Study (i/k/s/t)</th>
<th>Fuzzy NSGA-II-SA</th>
<th>Sine Cosine Algorithm</th>
<th>Simulated Annealing</th>
<th>Tabu Search</th>
<th>TLBO Heuristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3/4/1/2</td>
<td>1.973</td>
<td>1.973</td>
<td>1.973</td>
<td>1.973</td>
<td>1.973</td>
</tr>
<tr>
<td>2</td>
<td>5/6/1/2</td>
<td>1.329</td>
<td>2.1703</td>
<td>1.375</td>
<td>2.1703</td>
<td>2.5649</td>
</tr>
<tr>
<td>3</td>
<td>10/6/1/3</td>
<td>1.605</td>
<td>2.3676</td>
<td>1.605</td>
<td>2.5649</td>
<td>2.1703</td>
</tr>
<tr>
<td>4</td>
<td>20/4/1/3</td>
<td>2.974</td>
<td>3.1703</td>
<td>3.5649</td>
<td>3.5649</td>
<td>3.3676</td>
</tr>
<tr>
<td>5</td>
<td>40/5/1/3</td>
<td>2.256</td>
<td>2.3676</td>
<td>2.4703</td>
<td>2.5649</td>
<td>2.3676</td>
</tr>
<tr>
<td>6</td>
<td>50/5/1/3</td>
<td>2.828</td>
<td>2.9676</td>
<td>2.8676</td>
<td>2.9703</td>
<td>2.9703</td>
</tr>
<tr>
<td>7</td>
<td>100/5/1/3</td>
<td>2.345</td>
<td>2.3676</td>
<td>2.5649</td>
<td>2.9676</td>
<td>2.9703</td>
</tr>
</tbody>
</table>

4.1. Verification of the Model by Application to a Real Manufacturing Firm

In the next step, the proposed FW-NSGA-II was applied to a medium-scale metal-forming company located in Malaysia. The manufacturing plant has four workshops to produce various products. The firm contains cutting, bending, welding, and painting shops. Figure 11 shows the workshop view:
Table 11. Results of comparing the proposed method with other methods.

<table>
<thead>
<tr>
<th>No.</th>
<th>Case Study</th>
<th>Fuzzy NSGA-II-SA</th>
<th>Sine Cosine Algorithm</th>
<th>Simulated Annealing</th>
<th>Tabu Search</th>
<th>TLBO</th>
<th>Heuristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3/4/1/2</td>
<td>1.973</td>
<td>1.973</td>
<td>1.973</td>
<td>1.973</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>5/6/1/2</td>
<td>1.329</td>
<td>2.1703</td>
<td>1.375</td>
<td>2.1703</td>
<td>2.5649</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>10/6/1/3</td>
<td>1.605</td>
<td>2.3676</td>
<td>1.605</td>
<td>2.5649</td>
<td>2.1703</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>20/4/1/3</td>
<td>2.974</td>
<td>3.1703</td>
<td>3.5649</td>
<td>3.5649</td>
<td>3.3676</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>40/5/1/3</td>
<td>2.256</td>
<td>2.3676</td>
<td>2.4703</td>
<td>2.5649</td>
<td>2.3676</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>50/5/1/3</td>
<td>2.828</td>
<td>2.9676</td>
<td>2.8676</td>
<td>2.9703</td>
<td>2.9703</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>100/5/1/3</td>
<td>2.345</td>
<td>2.3676</td>
<td>2.5649</td>
<td>2.9676</td>
<td>2.9703</td>
<td></td>
</tr>
</tbody>
</table>

In the next step, the proposed FW-NSGA-II was applied to a medium-scale metal-forming company located in Malaysia. The manufacturing plant has four workshops to produce various products. The firm contains cutting, bending, welding, and painting shops. Figure 11 shows the workshop view:

![Graphical view of the case study.](image)

*The numbers in the parenthesis show the quality ratio of outcomes by using a machine.

The following table shows the OPC products (Table 12).

Table 12. Operational process chart of the case study.

<table>
<thead>
<tr>
<th>Product/Machine</th>
<th>Cutting Workshop</th>
<th>Bending Workshop</th>
<th>Welding Workshop</th>
<th>Painting Workshop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product 1</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Product 2</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Product 3</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>

In Table 12, the operation sequence of the products is displayed. Intersections in the table with a zero number indicate that the product is not needed.

The demand for products for the three planning periods is as follows (Table 13):

Table 13. Market demands of the case study (product units).

<table>
<thead>
<tr>
<th>Product</th>
<th>T:1</th>
<th>T:2</th>
<th>T:3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product 1</td>
<td>500</td>
<td>300</td>
<td>600</td>
</tr>
<tr>
<td>Product 2</td>
<td>400</td>
<td>350</td>
<td>300</td>
</tr>
<tr>
<td>Product 3</td>
<td>300</td>
<td>300</td>
<td>400</td>
</tr>
</tbody>
</table>

In addition, the amount of time required (minutes) for each operation is listed in Table 14.

Table 14. Process time of each of the services for the case study (seconds).

<table>
<thead>
<tr>
<th>Machine Product</th>
<th>C</th>
<th>P</th>
<th>W</th>
<th>Pn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>c₁</td>
<td>c₂</td>
<td>p₁</td>
<td>p₂</td>
</tr>
<tr>
<td>Product 1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Product 2</td>
<td>2</td>
<td>2.5</td>
<td>2.5</td>
<td>2</td>
</tr>
<tr>
<td>Product 3</td>
<td>3</td>
<td>4</td>
<td>2.1</td>
<td>2</td>
</tr>
<tr>
<td>Time capacity</td>
<td>1200</td>
<td>600</td>
<td>900</td>
<td>800</td>
</tr>
</tbody>
</table>
Then, the best combination of production and sequence of operations for such a combination is found. The quality coefficient of each machine in the given layout is specified in blue and is given in Table 15.

### Table 15. Quality coefficient of the machines of the case study.

<table>
<thead>
<tr>
<th>Quality/Machine</th>
<th>C</th>
<th>P</th>
<th>W</th>
<th>Pn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>c1</td>
<td>c2</td>
<td>p1</td>
<td>p2</td>
</tr>
<tr>
<td>Quality Ratio</td>
<td>90%</td>
<td>95%</td>
<td>87%</td>
<td>86%</td>
</tr>
</tbody>
</table>

The capacity of each manufactured machine is shown below:

- C = (C1, C2) = (1200, 600)
- W = (W1, W2, W3) = (1200, 800, 700)
- P = (P1, P2, P3) = (900, 800, 850)
- Pn = (Pn1, Pn2, Pn3) = (600, 900, 1200)

The model is solved and validated in this section with a precision method. For this purpose, issues are solved using LINGO® 12.0 software installed on a laptop with a processor speed of 7.2 GH.

The results of the exact solution of the model are shown in Tables 16–18. The best solution was found by NSGA-II.

### Table 16. The results of solving the model by NSGA-II.

<table>
<thead>
<tr>
<th>Method</th>
<th>Completion Time</th>
<th>Operational Cost</th>
<th>Defect Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSGA-II</td>
<td>11,005.00</td>
<td>19,771.20</td>
<td>969,560</td>
</tr>
</tbody>
</table>

### Table 17. The exact solution of the model obtained by the weighting method.

<table>
<thead>
<tr>
<th>Method</th>
<th>Objective Function Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighting Method</td>
<td>9266.663</td>
</tr>
</tbody>
</table>

### Table 18. The exact solution of the model obtained by the Lp-Metric method.

<table>
<thead>
<tr>
<th>Method</th>
<th>Objective Function Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LP-metric</td>
<td>0.42 0.238 0.238 9337.38</td>
</tr>
</tbody>
</table>

### 4.2. Managerial and Practical Implications

It was found that strong correlations exist between the total completion time, product defect costs, human resources, and operational costs that should not be ignored during the scheduling of a dual-resource-constrained manufacturing system.

In addition, it was shown that the uncertain environment has a strong effect on the crisp weights of the studied factors, changing the completion time, human resource and operations, and material risk factors from 0.413, 0.366, and 0.221 to 0.582, 0.203, and 0.215, respectively.

Moreover, minimizing the total objective function consisting of completion time, cost, and product defect to 11.2% using the proposed method can be considered another implication of using the proposed method.

### 4.3. Technological Opportunities

The proposed framework can be used as the core of scheduling software to improve scheduling efficiency by considering factors’ real values in a DRC manufacturing system. For this purpose, a cloud-based system can be designed to obtain real-time data from the manufacturing system and forward it to a scheduling software where the proposed solving method can be used to schedule the system.
5. Conclusions

This paper presents a 4-phased fuzzy framework for the multi-objective scheduling of job-shop-based manufacturing companies where product completion time, operational cost, and product defect cost were considered as the objective functions. For this purpose, an NL-IP mathematical model is developed, which is then solved by a proposed fuzzy-weighted NSGA-II method for seven case studies.

In the first phase of the framework, the influential factors in scheduling manufacturing systems in the fuzzy environment were identified. Then, using a fuzzy inference system, the fuzzy weight of the factors was determined. A multi-objective mathematical model was developed in the next phase to optimize the product completion time, operational cost, and product defect costs using the determined fuzzy weights. In the last phase, a fuzzy-weighted NSGA-II was proposed to solve the fuzzy multi-objective scheduling of job-shop-based manufacturing companies.

The outcomes of the research are threefold. First, it was demonstrated that the unpredictability of the environment had a significant impact on the crisp weights of the factors under study, causing the completion time, operational, and material risk factors weights to change from 0.413, 0.366, and 0.221 to 0.582, 0.203, and 0.215, respectively. Then, it was found that while using the proposed framework, the total objective function is boosted up to 5% for small-scale, 11.2% for medium-scale, and 3.8% for large-scale studied cases. Second, it was found that there are interactions between the studied objective functions, wherein minimizing the total completion time and the product defect costs have a strong adverse correlation (up to 7.5% for the studied cases). Additionally, there was a negative interaction between product completion time and human resource and operational costs (up to 14.3% for the studied cases). Finally, the correlations between product defect and human resource and operational costs had super strong correlations of 23.2%.

Third, although the proposed weighted NSGA-II method was slower in terms of solving time, at the same time, it showed superiority when applied to the fuzzy multi-objective scheduling of job-shop-based manufacturing companies.

Further expansion of the proposed framework can be carried out by considering the external factors influencing a manufacturing system. Moreover, the integration of the proposed model with real-time data application is suggested for future research.

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References

2. Tran, L.V.; Huynh, B.H.; Akhtar, H. Ant colony optimization algorithm for maintenance, repair and overhaul scheduling optimization in the context of industry 4.0. *Appl. Sci.* **2019**, *9*, 4815. [CrossRef]


43. Skobelev, P.; Borovik, S.Y. On the way from Industry 4.0 to Industry 5.0: From digital manufacturing to digital society. *Ind. 4.0* 2017, 2, 307–311.

63. Verma, S.; Pant, M.; Snasel, V. A comprehensive review on NSGA-II for multi-objective combinatorial optimization problems. *IEEE Access* 2021, 9, 57757–57791. [CrossRef]
