Analysis of Priority Decision Rules Using MCDM Approach for A Dual-Resource Constrained Flexible Job Shop Scheduling by Simulation Method

Cao Hoang Bao Long, Pham Hoang Nam Quynh,
Pham Huynh Tram, and Ha Thi Xuan Chi
School of Industrial Engineering and Management
International University,
Ho Chi Minh City,
Vietnam
Vietnam National University, Ho Chi Minh City, Vietnam
IELSIU19040@student.hcmiu.edu.vn, IELSIU19066@student.hcmiu.edu.vn,
phtram@hcmiu.edu.vn, htxchi@hcmiu.edu.vn

Abstract

In the Dual-Resource Constrained Flexible Job Shop Problem (DRCFJSP), two different types of resources, such as workers and machines, are required to process each job's operations. The analysis and assessment of priority decision rules for scheduling production jobs in DRCFJSPs is the primary goal of this work. The evaluation criteria in this research consists of demand, due date, cycle time, number of operations, and setup time. Then, a set of priority rules for development is chosen after a review of the literature, including Composite Dispatching Rules (CDRs) and Multi-Criteria Decision Making (MCDM)-based priority rules like Preference Selection Index (PSI), and Proximity Index Value (PIV). The weights of criteria are obtained by fuzzy Stepwise Weight Assessment Ratio Analysis (Fuzzy SWARA). Discrete Event Simulation (DES) model is developed to assess the performance of the DRCFJSPs with different rules. Numerical examples and real-world problems (with 114 jobs, 28 machines, and 23 people) are used to determine the best-performing prioritization rule. For all cases, the CDR considering Processing Time, Least Work Remaining, Earliest Due Date were found to be the best. The PSI-based rule is in second rank for large-scale case. Overall, the suggested approach yields solid results and is easy to adapt to real-world scenarios.

Keywords
Dual-Resource Constrained Flexible Job Shop Scheduling (DRCFJSP), Discrete Event Simulation (DES), Priority Dispatching Rule (PDR), Multi-Criteria Decision Making (MCDM), and Composite Dispatching Rule (CDR)

1. Introduction
The Flexible Job Shop Scheduling Problem (FJSP) is one of the most important multimodal optimization issues, a well-known standard abstraction of the real production process. Routing and scheduling are the two subproblems that make up the FJSP (Soofi et al. 2021). The assigned processes must be sequenced across all machines in order to generate a workable schedule with a tolerable goal value. The routing sub-problem entails allocating each operation to one of a group of given machines. However, in practice, tasks cannot be completed if employees are not present or do not possess the necessary skills. The worker-resources constraint must be taken into consideration to get around this problem. Thus, the dual-resource limited flexible job shop scheduling problem—an expanded FJSP that considers the worker resources constraint—is suggested. Determining the operation order and allocating the resources, including employees and machinery, are necessary to solve the Dual-Resource Constrained Flexible Job Shop Scheduling (DRCFJSP).

In manufacturing, the presence of skilled operators is crucial for task completion. Processing times depend on operator efficiency and specialization, impacting the overall job shop schedule. Different operators using the same machine exhibit varied skills and speeds. Operator proficiency often corresponds to experience and specialization. This variation can lead to tasks being completed at different rates. In general, each job can only be handled by the appropriate equipment and operator for the assembly process to be successful. This implies that each job needs two distinct resources, a machine, and an operator, at the same moment from the standpoint of scheduling. Therefore, it is essential to properly allocate the operation to the workers and plan the tasks to control the machines in the jobs shop in order to reduce the batch makespan.

1.1 Objectives

This study encompasses three primary objectives. Firstly, the research aims to successfully formulate a set of hybrid dispatching rules employing Multi-Criteria Decision Making (MCDM) techniques. Secondly, it seeks to establish a Discrete Event Simulation (DES) model for the Dual-Resource Constrained Flexible Job Shop Scheduling Problem (DRCFJSP). Through this model, essential job shop performance evaluation metrics, namely Makespan, Mean Flow Time, Mean Tardiness, and Maximal Tardiness, will be extracted. Lastly, the objective involves acquiring job shop performance evaluation parameters founded upon the MCDM-based rules, followed by a comparative assessment against the outcomes of existing Composite Dispatching Rules (CDRs).

2. Literature Review

The intricacy of the problem has led to numerous techniques being suggested throughout the years. Because the DRCFJSP is NP-hard, finding the best solution may require some time and effort. As a result, many meta-heuristic solutions had been proposed: Simulated Annealing (SA), Genetic Algorithm (GA), and Vibration Damping Optimization (VDO) using a variety of neighborhood structures (Soofi et al. 2021 and Yazdani et al. 2015). These methods were perceived as capable of offering the best solutions for small- to medium-sized problems. Besides, Wu et al. (2018) investigate a flexible job shop scheduling problem with two resource restrictions, accounting for the employees' potential for learning to create a successful hybrid genetic algorithm to solve the issue. The outcomes show that the suggested approach can address the issue successfully and quickly. However, this study did not consider the Tardiness objective. Next, with a Makespan reduction objective, Zheng and Wang (2016) attempted to subsequently tackle a DRCFJSP. The research had suggested a new encoding technique and knowledge-guided fruit fly optimization. Two different kinds of permutation-based search operators were created for the proposed algorithm to carry out the smell-based search for operation sequence and resource assignment. However, this approach did not take into account reducing performance measures associated to tardiness.

To encourage the use of exact techniques and to make it simpler to evaluate the efficacy of heuristic approaches, two modeling frameworks—mixed-integer programming and constraint programming—were introduced (Kress and Müller 2019). Still, this study did not include assessing Tardiness metrics. Besides, a first investigation into a FJSP with multi-objective and operator adaptability is made in paper of Gong et al. (2018). The issue is illustrated using non-linear integer programming. Next, the proposed methodology is solved using a memetic algorithm (MA), whose goal is to minimize the Flow Time related measures, as well as workload related measures of all machines. The outcomes show that, for the proposed method, the MA performs better than alternative algorithms. However, this study also did not include considering assessing Tardiness metrics.

Other methods, such as Priority Dispatching Rules (PDRs) including both Composite Dispatching Rules (CDRs) and MCDM-based rules, and the combination of dispatching rules and DES, will be discussed more descriptively below.

2.1 Priority Dispatching Rule

In Job Shop Scheduling Problem (JSP), the next operation is chosen from the waiting queue using Priority Dispatching Rules (PDRs) (Sculli and Tsang 1990). These rules require several operations to be completed in the shop, which necessitates limitations on machine requirements, staff skills, flow patterns, and component assembly requirements. As work orders build up, facilities will be unable to satisfy all the urgent demands. As a result, the PDRs used, as well as the operational characteristics of the business, determine how long it takes to complete the operation and how frequently it is finished late. Unlike previous approaches, PDRs have been implemented by numerous researchers for determining job priority because of their easy accessibility, simplicity of execution, non-technological barriers, ability to come up with effective solutions in a shorter amount of time, as well as the potential to solve large-scale problems (Thenarasu et al. 2022).

Moreover, PDRs have never been used in the DRCFJS issue before, despite being used in Flexible Job Shop Scheduling (FJSP) (Thenarasu et al. 2022). Apart from that, the CDRs along with MCDM-based priority rules have not had much adoption in the scheduling problem, hence, these rules will be considered more.

2.1.1. Composite Dispatching Rule

Tay and Ho (2008) had used CDRs to tackle the multi-objective FJSP by reducing the Makespan, Mean Tardiness, And Mean Flow Time. It had been shown that for the benchmark case, CDRs surpassed SPRs. In addition, Sels et al. (2012) examined the Flow-Time and Tardiness-related measures of 30 distinct priority rules, including CDRs extracted from the literature. Furthermore, the analyses of the CDRs of Ashwin et al. (2022) and Thenarasu et al. (2022) showed that the CDRs from the previous two researches excelled in both small-scale and large-scale FJS issues. Therefore, this research would also retest these rules in the DRCFJSP.

2.1.2. Multi-Criteria Decision-Making Priority Rule

Research has found that MCDM implementation has had a tremendous effect on JSP (Thenarasu et al. 2020). To identify which dispatching rule offers the most effective solution, along with the application of CDRs, a hybrid Multi-Criteria Decision Making (MCDM) PDR-based strategy has been adopted in the FJSP (Thenarasu et al. 2022). In that study, five methods were applied. Despite having outstanding results, these rules had high processing techniques, an inconvenient weighting strategy, and the potential to reverse rank (Munier and Hontoria 2021). It is also possible to infer that even though there have been some MCDM-based priority rules proposed in the FJSP, not much MCDM application has been made to the DRCFJSP. Moreover, there are many more methods that should be considered.

Given its simplicity and ability to utilize easier pair-wise comparisons, fuzzy SWARA is among the most effective methods for obtaining the weights of criteria (Banihashemi et al. 2021 and Thakkar 2021). Besides that research, to prioritize the JSP sequencing rules from best to worst, the Preference Selection Index (PSI) technique was suggested (Bari and Karande 2022). This approach is much less complicated and more efficient than other MCDM methods because it does not consider determining the relative importance of the criteria, which minimizes the work required to calculate the weights of the criteria. Next, Mufazzal and Muzakkir (2018) recently designed an approach called PIV. In many areas, such as dispatching rules in job sequencing (Ahmad et al. 2021), this approach avoids the rank reversal that occurs with the traditional TOPSIS method (Thakkar 2021).

2.2 Combination of Dispatching Rule and Discrete Event Simulation

In the Job Shop Lot Streaming Problem (JSLSP), the simulation technique is employed with MCDM to decide the production scheduling strategy under various circumstances. The findings show that customer-oriented dispatching rules deliver better outcomes when important customers heavily outnumber other customer segments, while other traditional rules produce better results when customer segments have similar significance weights (Güçdemir and Selim 2018). Besides, Thenarasu et al. (2022) had proposed a DES model of an FJSP using Arena software to evaluate the best dispatching rule. It was determined that the suggested approach could be successfully applied to real-world circumstances. According to the literature, simulation-based models in job shop scheduling are useful for solving significant real-world issues and have become more popular because of advances in processing technology. The industrial issue can be represented in the DES model without sacrificing the limitations of reality. The effectiveness, economic sustainability, and competitiveness of industrial sectors on the world market can all be increased using modeling techniques. Unfortunately, the simulation-based approach still has not been adopted by the DRCFJSP.

In summary, there have been many research studies about solving the DRCFJSP using dispatching rules. However, there has not been a particular paper that addresses the application of simulation-based research under the dual-resource constrained situation. Hence, this study will suggest an innovative use of the CDRs and MCDM-based rules when combining with Arena simulation model that incorporates concurrent restrictions and parameters. Then, those dispatching rules are used to assess the efficiency metrics of real-world problems using the DES model.

3. Methods

According to Figure 1, this study will consist of three phases: (1) the development of hybrid MCDM-based priority rules; (2) the development of a discrete event simulation model; and (3) determining the best priority rule.

The initial phase involves several steps. Firstly, a set of criteria will be chosen, followed by the determination of their weights using Fuzzy SWARA. Subsequently, MCDM methods will be employed to formulate priority rules. In the next phase, input data alongside all rules will be fed into the simulation model. A priority rule will be selected, and resources—both machines and workers—will be assigned accordingly. The highest-priority jobs will then be allocated to workers on specific machines. Sequential testing of all rules will take place, concluding only after exhaustive examination. Consequently, performance metrics will be documented. In the final phase, this study will assess the performance of the priority decision rules across three benchmarks and a real-world case. Evaluation metrics, encompassing Makespan, Mean Flowtime, Mean Tardiness, and Maximum Tardiness, will be appraised. The most optimal solution, thus, will be determined by the rule yielding the best results.

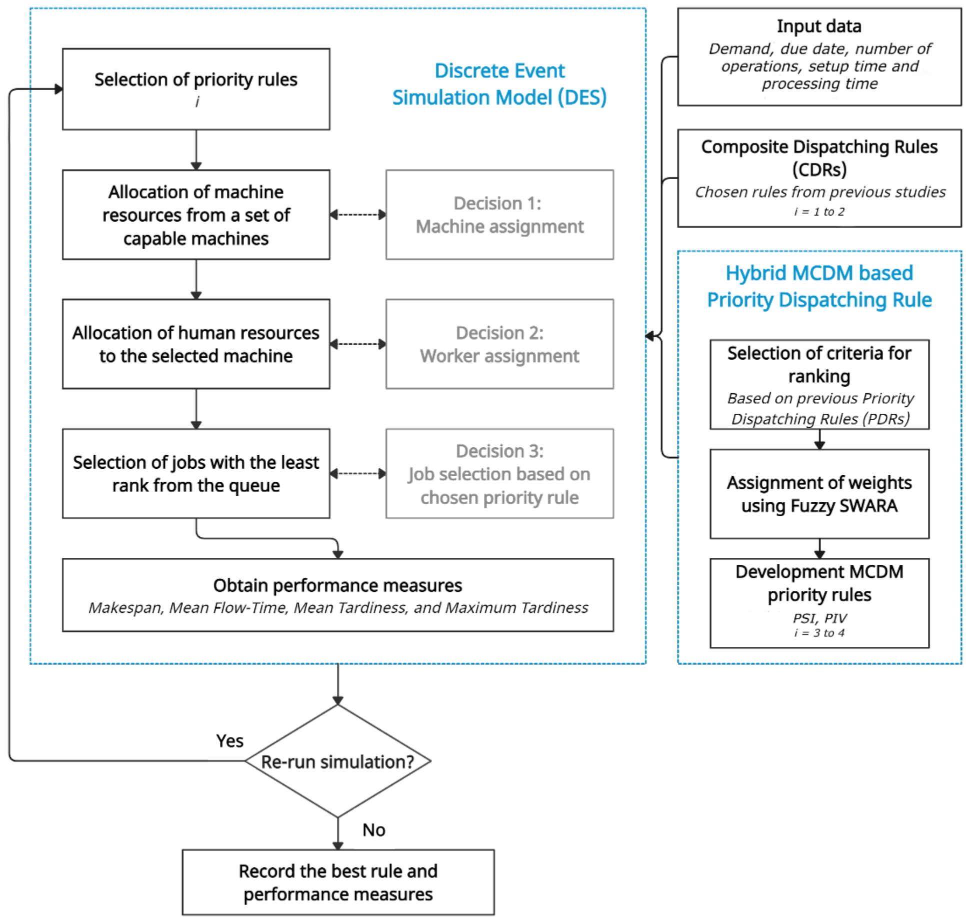

Figure 1. Methodology Framework

For the CDRs, we selected the composite rules proposed by Thenarasu et al. (2022) and Ozturk et al., (2019). The Hybrid MCDM based priority dispatching rule involves the usage of Fuzzy SWARA method to determine the criteria weights and the Preference Selection Index (PSI) and the Proximity Index Value (PIV) for ranking calculation.

- Rule 1 (R1): 2PT + LWKR + EDD (Thenarasu et al. (2022))
- Rule 2 (R2): AVPRO + PT + LWKR (Ozturk et al., (2019))
- Rule 3 (R3): Preference Selection Index (PSI)
- Rule 4 (R4): Proximity Index Value (PIV)

(PT- Process Time, LWKR- Least Work Remaining, EDD- Earliest Due Date, AVPRO- Average Processing time per Operation.)

3.1. The Development of Hybrid MCDM-Based Priority Rules

3.1.1. Determine The Set of Criteria

Cycle time refers to the duration needed to complete the entire production process of a single unit. When the objective is to minimize Flow Time and Tardiness related metrics in a scheduling problem, cycle time is ***non-beneficial***.

Number of operations refers to the quantity of individual tasks involved in a schedule. When the objective is to minimize Flow Time and Tardiness related metrics in a scheduling problem, number of operations is ***non-beneficial***.

Setup time criteria refers to the duration needed to prepare resources or equipment prior to commencing a task. When the objective is to minimize Flow Time and Tardiness related metrics, setup time is ***non-beneficial***.

Due date refers to the predetermined deadline for task completion. When the objective is to minimize Flow Time and Tardiness related metrics in a scheduling problem, incorporating the due date criteria as a decision factor is ***beneficial***.

Demand is the number of products that must be manufactured to meet the requirements of its customers or clients. When the objective is to minimize Flow Time and Tardiness related metrics, demand is ***non-beneficial***.

3.1.2. Weight Assignment for Criteria Using Fuzzy SWARA

In order to calculate the weights of each criterion, the Fuzzy SWARA method is applied.

Step 1: *Determine experts' scores.*
After determining a set of criteria, a survey of scoring those criteria will be conducted for three experts. The questionnaire includes asking about their experiences in the mechanical or manufacturing fields, as well as their scores for each criterion in scale from one to nine based on their opinion and knowledge.

Table 1. The experts' experience in the mechanical industry and their scores for each criterion

Expert	E1	E2	E3
Experience (years)	8	15	18
Cycle time	7	8	8
Due date	8	7	9
Number of operations	7	7	8
Setup time	6	6	7
Demand	9	8	9

Step 2: *List the criteria in descending order and make pairwise comparisons between criteria.*
Based on the calculated average score, list the criteria in the descending order and compute the comparative importance of average value s_j of the j^{th} criteria with respect to $(j^{th} - 1)$ criteria:

$$s_j = \frac{X_j - X_{j+1}}{X}$$

Where, X_j is the average score of j^{th} criteria.
X_{j+1} is the the average score of the next criteria.
X is the maximum value in the scale.

Step 3: *Transform the score to the fuzzy form.*
With the help of the linguistic scale of the fuzzy value, transform the crisp value of comparative importance of average value s_j to the fuzzy form $\widetilde{s_j}$.

Table 2. Fuzzy and linguistic scale

Linguistic scale	Response scale		
Absolutely less significant	1	1	1
Dominantly less significant	1/2	2/3	1
Much less significant	2/5	1/2	2/3
Really less significant	1/3	2/5	1/2
Less significant	2/7	1/3	2/5
Moderately less significant	1/4	2/7	1/3
Weakly less significant	2/9	1/4	2/7
Equally significant	0	0	0

Step 4: *Calculate the coefficient values and weight values of criteria.*
During this step, the weight values of the criteria are reevaluated, and the final relative importance scores of the selection criteria are calculated. The coefficient value $\widetilde{k_j}$ is determined using the following formula:

$$\widetilde{k_j} = \begin{cases} \tilde{1}, & j = 1 \\ \widetilde{s_j} + \tilde{1}, & j > 1 \end{cases}$$

Then, calculate the weights values of the criteria $\widetilde{q_j}$:

$$\widetilde{q_j} = \begin{cases} \tilde{1}, & j = 1 \\ \dfrac{\tilde{q}_{j-1}}{\widetilde{k_j}}, & j > 1 \end{cases}$$

Step 5: *Calculate the fuzzy weight coefficients values of criteria then defuzzying them.*
The formula to compute the fuzzy weight coefficients values of criteria:

$$\widetilde{w_j} = \frac{\widetilde{q_j}}{\sum_{j=1}^{n} \widetilde{q_j}}$$

After that, defuzzying the weights of criteria by using the formula:

$$w_{crisp\ value} = \frac{w^{(l)} + 4w^{(m)} + w^{(u)}}{6}$$

Table 3. Weights of criteria

Criteria	Demand	Due date	Cycle time	Number of operations	Setup time
Crisp value	0.322	0.241	0.187	0.146	0.104

3.1.3. The MCDM Methods

Preference Selection Index (PSI)	Proximity Index Value (PIV)
Step 1: *Create a decision matrix of criteria and alternatives.* $D_{m\times n} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \cdots & \cdots & \cdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$ In the above representation, each element a_{ij} in the decision matrix $D_{m\times n}$ corresponds to the actual value of the i^{th} alternative in term of j^{th} criterion.	
Step 2: *Normalize the decision matrix.* If j^{th} criterion is beneficial, $r_{ij} = \frac{X_{ij}}{X_j^{max}}\ for\ i = 1,2,\dots,m;\ j = 1,2,\dots,n$ If j^{th} criterion is non-beneficial, $r_{ij} = \frac{X_j^{min}}{X_{ij}}\ for\ i = 1,2,\dots,m;\ j = 1,2,\dots,n$ Where, r_{ij} is the normalized value of the decision matrix. X_{ij} is the original score of decision matrix. X_j^{max} and X_j^{min} are the maximum and minimum scores of decision matrix for each j^{th} criterion.	***Step 2:*** *Normalize the decision matrix.* $r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}}\ for\ i = 1,2,\dots,m;\ j = 1,2,\dots,n$ Where, r_{ij} is the normalized value of the decision matrix. X_{ij} is the original score of decision matrix.
Step 3: *Calculate the preference variation value* (PV_j) Calculate the average normalized value for j^{th} criterion: $\overline{r_j} = \frac{\sum_{i=1}^{m} r_{ij}}{m}\ for\ j = 1,\dots,n$ Then, calculate the preference variation value (PV_j): $PV_j = \sum_{i=1}^{n} \left[r_{ij} - \overline{r_j}\right]^2$	***Step 3:*** *Calculate the weighted normalized decision matrix.* $v_{ij} = w_j \times r_{ij}$ Where, v_{ij} is an element in the weighted normalized matrix. w_j is the corresponding element in the weight vector.
Step 4: *Calculate the overall preference value* (ψ_j)*:* Firstly, calculate the deviance in PV_j: $\phi_j = 1 - PV_j$ Then, calculate the preference variation value (PV_j):	***Step 4:*** *Calculate the weighted proximity index.* If j^{th} criterion is beneficial, $u_{ij} = v_j^{max} - v_{ij}$ If j^{th} criterion is non-beneficial, $u_{ij} = v_{ij} - v_j^{min}$ Where, u_{ij} is the weighted proximity value. v_j^{max} is the maximum weighted normalized value for j^{th} criterion.

$$\psi_j = \phi_j / \sum_{j=1}^{n} \phi_j$$	v_j^{min} is the minimum weighted normalized value for j^{th} criterion
Step 5: *Calculate the PSI score.* $$I_i = \sum_{j=1}^{n} r_{ij} \times \psi_j \ for\ i = 1, \ldots, m$$	***Step 5:*** *Calculate the overall proximity value.* $$d_i = \sum_{j=1}^{n} u_{ij}$$
Step 6: *Rank the alternatives*	

The job rankings obtained from the two MCDM based priority rules PSI and PIV are shown in Table 4.

Table 4. Job rankings using eight MCDM-based priority rules in real-world problem.

Job / Rule	1	2	3	…	113	114
PSI	91	34	53	…	76	56
PIV	40	62	10	…	78	109

3.2. The Development of Discrete Event Simulation Model
3.2.1. Numerical example

The study evaluates suggested rules using three numerical data set from Brandimarte (1993). These examples vary in the number of jobs, machines, operations, and workers. The model assumes a range of values for these parameters across different scenarios. Machine processing times are determined using uniform distribution within specified limits. The model considers situations where one machine and one worker can perform various operations. Multiple machines can perform similar operations with different times. Machines rely on workers for operation. The study also assumes that machines require setup before each operation, even for consecutive similar operations.

Table 5. Descriptions of the numerical instances and real-world case.

Instances	(n × m × k × w) *	NOP	Flexibility Factor **	Job per 1 batch	Processing time (T.U)	Due Date (T.U)	Setup time (T.U)
MK1	10 × 6 × 54 × 4	5 to 7	3	50	1 to 7	35-55	0.35–1.14
MK2	15 × 8 × 82 × 6	3 to 10	3	50	1 to 10	65-135	3.42–10.55
MK3	20 × 10 × 141 × 8	5 to 10	2	50	5 to 20	145-215	6.45-16.43
Real-World	114 × 28 × 245 × 23	1 to 14	4	5000	2 to 32	120–360	0.12–0.48

Note: * n – No. of Jobs, m- No. of Machines, k- Total operations and w- No. of Workers, NOP- Number of operations per Job. T.U- Time Units. Time units for MK1, 2, 3 are in minutes, for real case are in hours. ** Flexibility Factor: maximum number of equal machines per operation.

3.2.2. Real-World Problem

A real-world case is a press plant had 28 machines with varying capacities, and it needed to complete 114 tasks involving 245 procedures for producing vehicle parts. Each task required one to fourteen operations, and tasks had specific orders to be executed on available machines. The production was based on a monthly demand. The work schedule was from 7 am to 11 am and 1 pm to 5 pm, with ten workers available for overtime from 7 pm to 10 pm.

Table 6. Data of Press-shop industry contain detailed elements of jobs.

Job	Operation	Processing time (Hrs.)	Eligible worker (Worker number)	Monthly Demand	Due Date (Days)	Cycle Time (Hrs.)	Setup Time Distribution (Hrs.)
Job 1 (Part 1)	Blanking	M1 (8), M11 (7), M23 (15), M24 (24)	1, 2, 3, 4, 6, 8, 12, 14, 15, 20, 21, 22	20,000	9	256	UNIF (0.12,0.48)

	Trimming	M1 (2), M7 (32), M13 (30), M15 (23)	1, 2, 3, 4, 6, 8, 14, 16, 20, 21				
Job 114 (Part 114)	Piercing	M5 (24), M16 (3), M22 (3), M25 (23)	1, 2, 7, 9, 10, 15, 16, 17, 20, 22	15,000	5	192	UNIF (0.12,0.48)
	Slitting	M14 (6), M15 (14), M27 (6), M28 (8)	4, 5, 12, 17, 18, 23				

3.2.3. The Arena model

After setting up a conceptual model and collecting required data, the Arena model is built. The development of simulation models considers the static nature of task arrivals for processing. Jobs in small-scale instances are processed in a predictable amount of time. In contrast, in the real-world case, the setup time is determined using the relevant probability distributions. By doing statistical analysis on historical data, the probability distribution is determined.

The simulation model begins with the part arrival module which defines job arrival information such the quantity of jobs arriving at the shop floor and the inter-arrival time. For each incoming work, the total/maximum number of operations that the job must go through is defined. The model receives a definition of the number of batches and the batch size as inputs. Then, the machine loading rule is used to specify and map the number of machines that may execute each operation for each task. According to the user-selected priority rule, jobs that are awaiting processing are given precedence at each workstation. Following the conclusion of each operation in the model, the job ranks are updated. Arena offers simple queuing priority options such as first in first out, last in first out or by attribute values. For more complicated decision rules such as the CDRs and MCDM in this work, we need to employ VBA in Arena or Excel. The simulation model is then divided into three main phases, namely (a) Step 1: assigning work to machines, (b) Step 2: prioritizing jobs, and (c) Step 3: gathering performance metrics.

- **Step 1: Assign operations to machines (Figure 2)**

Step 1 involves the creation of jobs and the assignment of characteristics. Processing speed, machine adaptability, deadline, the quantity of processes, etc. are some of the attributes. Entities are directed to the appropriate machines depending on their sequences of operation once the characteristics have been assigned. We assumed that the entities created would be the jobs and one entity will be the batch of 5000 products. Only one entity would be created per arrival as well as there are 114 arrivals in real-world problem. After that, the job type, entity sequence, entity picture are the attributes which are assigned to the entity. The sequence will follow the data file and the entity picture will be based on the attribute job type. The module Route will transfer the job to the station in its sequence. When they have done the process, they will be moved to the record station (step 3).

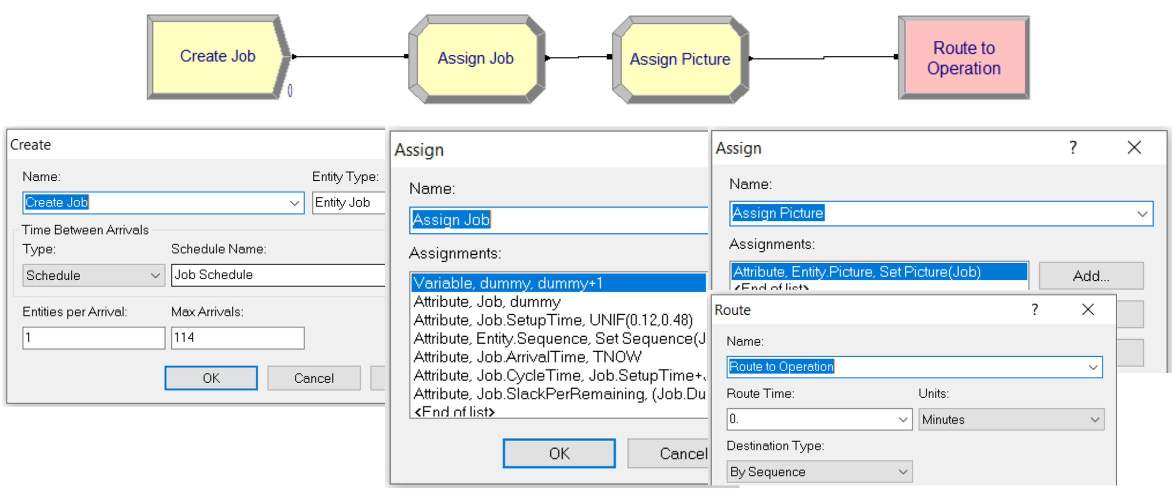

Figure 2. Arena Modules of step 1

- **Step 2: Determine the order job based on priority rules. (Figure 3-5)**

After jobs are assigned to the machine that is not busy, the job priorities in queue are determined by the hybrid MCDM rules and CDR.

Figure 3. Determine the job priority based on priority rules.

Seize module and queue element are used to assign the priorities. A combo box was created in the simulation to allow users to choose the preferred rule. VBA coding (Figure 6) is required to calculate the ranking. After the job is completed in the process module, it is released to next operation by Route module.

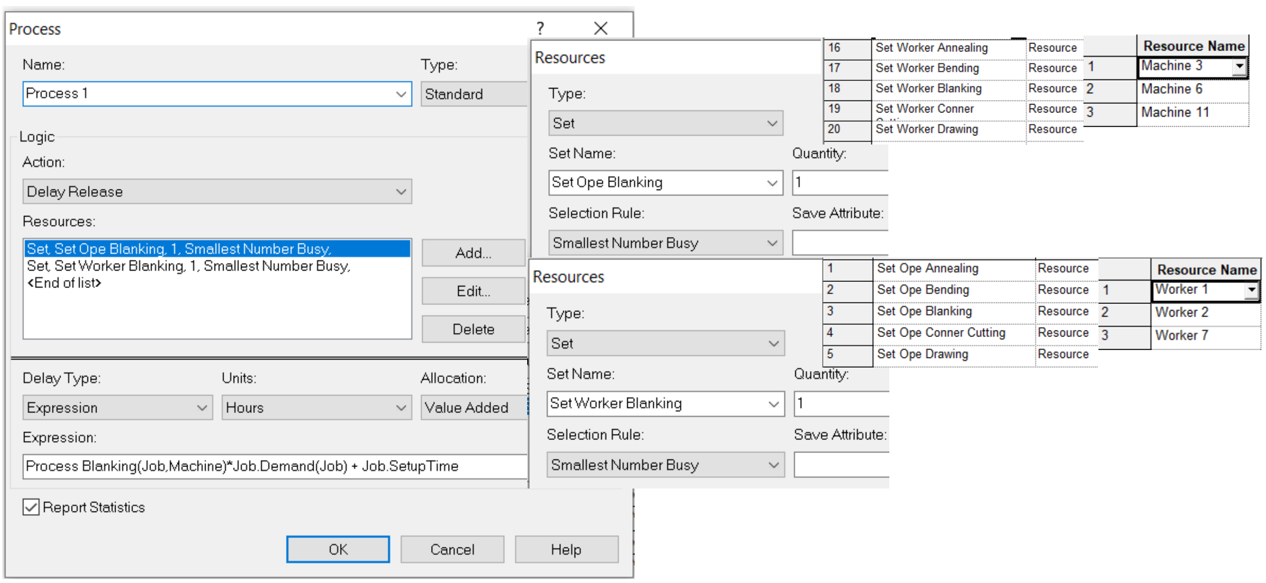

Figure 4. Logic of decide modules to choose machine worked

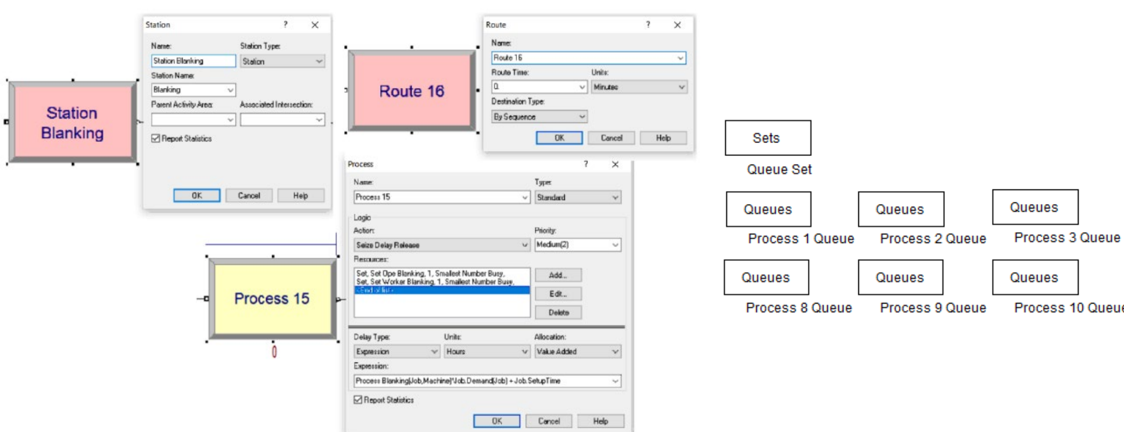

Figure 5. Arena Modules of step 2

```
RULE 1

  If ComboBox1.value = ("1. 2PT + LWKR + EDD") Then

  For k = 0 To tP 'Loop for 14 process
      I = MyModel.Modules.Find(smFindTag, qName(k))
      If I > 0 Then
      Set mObj = MyModel.Modules.Item(I)
      Else
      ' If the module was not found, display a message and exit
      MsgBox "Did not find module with tag Process " & k + 1
      Exit Sub
      End If

      With mObj
      .Data("Ranking") = "LVF"
      .Data("RankExp") = "2*" & procName(k) & "(Job,Machine) + ((Job.NoOpe(Job) +1-Entity.JobStep)*Job.AvgProcessTime(Job)/Job.NoOpe(Job)) + Job.DueDate(Job)"
      End With

  Next k
  End If
```

Figure 6. Example of VBA coding in Arena for Rule 1: 2PT + LWKR + EDD)

- **Step 3: Recording the performance measures (Figure 7)**

Prior to leaving the system, the record modules are used to record the Job Type, Total Process Time, Due Date, Tardiness of each job. Following that, the lateness and earliness are also measured and wrote to the output file.

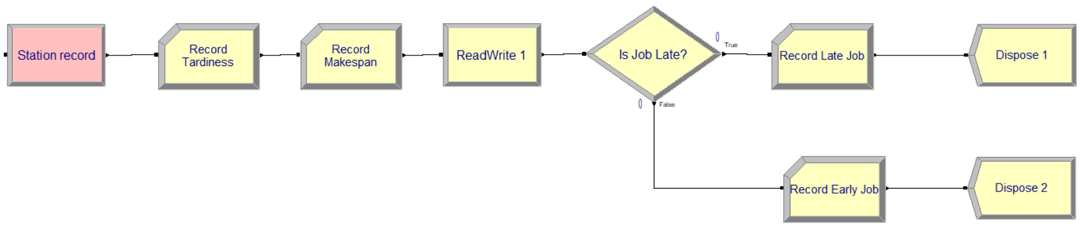

Figure 7. Recording the performance measures

4. Results and Discussion

The following equation is used to calculate each rule's performance in terms of percentage of departure from the best-performing rule:

$$\%\ \boldsymbol{Dev} = \frac{\boldsymbol{Z^X} - \boldsymbol{Z^B}}{\boldsymbol{Z^B}}$$

where $\boldsymbol{Z^X}$ is the average objective function value over the same instances produced by the priority rule that is being evaluated over all cases, and $\boldsymbol{Z^B}$ is the average objective function value over the same instances acquired by the best priority.

4.1. Selection of The Best Performing Rule in small-scale instances

The outcomes of the benchmarks reveal that the CDRs mostly outperform the MCDM-based priority rules for almost every performance metric (Table 7). Except in terms of minimizing Makespan, R4: PIV is the best performing rule. Overall, the CDR R1: 2PT + LWKR + EDD rule is the one that performs best, according to the average performance measure of all objectives. Between the two MCDM-based rules, R4: PIV has shown to be the better rule.

Table 7. Top priority rules on objective functions (1 - %Dev) of 3 small-scale instances. Number 1 indicates the best performance

Priority rule	Makespan	Mean Flowtime	Mean Tardiness	Max Tardiness	Average
R1: 2PT + LWKR + EDD	0.982	0.985	0.943	**1**	**0.977**
R2: AVPRO + PT + LWKR	0.932	**1**	**1**	0.869	0.950
R4: PIV	**1**	0.921	0.704	0.927	0.888
R3: PSI	0.938	0.966	0.873	0.695	0.868

4.2. Selection of The Best Performing Rule in large-scale case

The outcomes of the real-world problem reveal that most CDRs in Table 8 outperform the MCDM-based priority rules for every performance metric. Overall, the CDR R1: 2PT + LWKR + EDD rule is the one that performs the best, according to the average performance measure of all objectives. And between two MCDM-based rules, R3: PSI has shown to be a better rule.

Table 8. Top priority rules on objective functions (1 - %Dev) of large-scale case study. Number 1 indicates the best performance

Priority rule	**Makespan**	**Mean Flowtime**	**Mean Tardiness**	**Max Tardiness**	**Average**
R1: 2PT + LWKR + EDD	**1**	**1**	**1**	0.985	**0.996**
R3: PSI	0.9997	0.982	0.789	0.937	0.927
R2: AVPRO + PT + LWKR	0.9997	0.990	0.895	0.816	0.925
R4: PIV	**1**	0.934	0.263	**1**	0.799

Overall, it is evident that in both small-scale and real-world situations, the effectiveness of CDRs, especially R1: 2PT + LWKR + EDD, surpassed that of MCDMs. This discrepancy in performance, as indicated by the average measure across all objectives, could be attributed to the inherent feature of preprogrammed job prioritization within CDRs, a characteristic absent in MCDMs. The CDR approach dynamically recalculates job priority whenever modifications occur in the criteria data during simulation, in contrast to the MCDM-based rules which establish job ranking solely during the initial phase without subsequent updates.

5. Conclusion

In this research, hybrid MCDM-based priority rules were created as an innovative solution to the DRCFJSP. The MCDM approaches are used with a Fuzzy SWARA method to calculate criteria's weights. Job prioritizing was accomplished using two MCDM techniques, i.e., PSI, and PIV. A DES model is also built to assess the DRCFJSPs' efficiency metrics.

To evaluate the effectiveness of the CDRs and MCDM-based priority rules, we used numerical instances of small scale and a case study of large scale. For all cases, the CDR considering processing time, Least Work Remaining, Earliest Due Date (R1) were found mostly outperforming the MCDM-based priority rules for almost every performance metric. The PSI-based rule is in second rank after the R1 for large-scale case. However, the MCDM-based rules offer the flexibility to change the ranking criteria and the optimal weights depending on the expert's knowledge. The performance of the shop floor may be enhanced by using MCDM-based priority rules for complex issues involving numerous factors, such as demand, due date, setup time, cycle time, and the number of operations. The suggested technique is straightforward and user-friendly in practical settings. The research's drawback, however, is that for the MCDM method, it fails to automatically update the new criteria information once each operation is completed, which prevents the simulation from automatically updating the new job rating. This can be solved by integrating VBA coding in Arena, which will be addressed in our future work.

References

Ahmad, S., Akber, A., Khan, Z. A., and Ali, M., Selection of Best Dispatching Rule for Job Sequencing Using Combined Best–Worst and Proximity Index Value Methods, *Lecture notes in mechanical engineering*, pp. 783–792, 2021, https://doi.org/10.1007/978-981-15-8542-5_68.

Ashwin, S., Shankaranarayanan, V., lamy, D., Anbuudayasankar, S. P., and Thenarasu, M., Development and Analysis of Efficient Dispatching Rules for Minimizing Flow Time and Tardiness-Based Performance Measures in a Job Shop Scheduling, *Intelligent Manufacturing and Energy Sustainability*, vol. 265, pp. 337–345, 2022, https://doi.org/10.1007/978-981-16-6482-3_34.

Banihashemi, S., Khalilzadeh, M., Antucheviciene, J., and Šaparauskas, J., Trading off Time–Cost–Quality in Construction Project Scheduling Problems with Fuzzy SWARA–TOPSIS Approach, Trading off Time–Cost–Quality in Construction Project Scheduling Problems with Fuzzy SWARA–TOPSIS Approach, *Buildings*, vol. 11, no. 9, pp. 387, 2021, https://doi.org/10.3390/buildings11090387.

Bari, P., and Karande, P., Ranking of sequencing rules in a job shop scheduling problem with preference selection index approach, *Journal of Decision Analytics and Intelligent Computing*, vol. 2, no. 1, pp. 12–25, 2022, https://doi.org/10.31181/jdaic10028042022b.

Brandimarte, P., Routing and scheduling in a flexible job shop by tabu search, *Annals of Operations Research*, vol. 41, no. 3, pp. 157–183, 1993, https://doi.org/10.1007/BF02023073.

Ghasemi, P., Mehdiabadi, A., Spulbar, C., and Birau, R., Ranking of Sustainable Medical Tourism Destinations in Iran: An Integrated Approach Using Fuzzy SWARA-PROMETHEE, *Sustainability*, vol. 13, no. 2, pp. 683, 2018, https://doi.org/10.3390/su13020683.

Gong, X., Deng, Q., Gong, G., Liu, W., and Ren, Q., A memetic algorithm for multi-objective flexible job-shop problem with worker flexibility, *International Journal of Production Research*, vol. 56, no. 7, pp. 2506–2522, 2018, https://doi.org/10.1080/00207543.2017.1388933.

Güçdemir, H., and Selim, H., Integrating simulation modelling and multi criteria decision making for customer focused scheduling in job shops, *Simulation Modelling Practice and Theory*, vol. 88, pp. 17–31, 2018. https://doi.org/10.1016/j.simpat.2018.08.001.

Kress, D., and Müller, D., Mathematical Models for a Flexible Job Shop Scheduling Problem with Machine Operator Constraints, *IFAC-PapersOnLine,* vol, 52, no. 13, pp. 94–99, 2019 https://doi.org/10.1016/j.ifacol.2019.11.144.

Mufazzal, S., and Muzakkir, S. M., A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals, *Computers & Industrial Engineering*, vol. 119, pp. 427–438, 2018, https://doi.org/10.1016/j.cie.2018.03.045.

Ozturk, G., Bahadir, O., and Teymourifar, A., Extracting priority rules for dynamic multi-objective flexible job shop scheduling problems using gene expression programming, *International Journal of Production Research*, vol. 57, no. 10, pp. 3121–3137, 2019, https://doi.org/10.1080/00207543.2018.1543964.

Sculli, D., and Tsang, K. K., Priority dispatching rules in a fabrication/assembly shop, *Mathematical and Computer Modelling*, vol. 13, no. 3, pp. 73–79, 1990, https://doi.org/10.1016/0895-7177(90)90372-T.

Sels, V., Gheysen, N., and Vanhoucke, M., A comparison of priority rules for the job shop scheduling problem under different flow time- and tardiness-related objective functions, *International Journal of Production Research*, vol. 50, no. 15, pp. 4255–4270, 2012, https://doi.org/10.1080/00207543.2011.611539.

Soofi, P., Yazdani, M., Amiri, M., and Adibi, M. A., Robust Fuzzy-Stochastic Programming Model and Meta-Heuristic Algorithms for Dual-Resource Constrained Flexible Job-Shop Scheduling Problem Under Machine Breakdown, *IEEE Access*, vol. 9, pp. 155740–155762, 2021, https://doi.org/10.1109/ACCESS.2021.3126820.

Tay, J. C., and Ho, N. B., Evolving dispatching rules using genetic programming for solving multi-objective flexible job-shop problems, *Computers & Industrial Engineering*, vol. 54, no. 3, pp. 453–473, 2008, https://doi.org/10.1016/j.cie.2007.08.008.

Thakkar, J. J., *Multi-Criteria Decision Making,* vol. 336, Springer Singapore, 2021.

Thenarasu, M., Rameshkumar, K., Anbuudayasankar, S. P., Arjunbarath, G., and Ashok, P., Development and selection of hybrid dispatching rule for dynamic job shop scheduling using multi-criteria decision-making analysis (MCDMA), *International Journal for Quality Research*, vol. 14, no. 2, pp. 487–504, 2020, https://doi.org/10.24874/IJQR14.02-10.

Thenarasu, M., Rameshkumar, K., Rousseau, J., and Anbuudayasankar, S. P., Development and analysis of priority decision rules using MCDM approach for a flexible job shop scheduling: A simulation study, *Simulation Modelling Practice and Theory*, vol. 114, pp. 102416, 2022, https://doi.org/10.1016/j.simpat.2021.102416.

Wu, R., Li, Y., Guo, S., and Xu, W., Solving the dual-resource constrained flexible job shop scheduling problem with learning effect by a hybrid genetic algorithm, *Advances in Mechanical Engineering*, vol. 10, no. 10, pp. 168781401880409, 2018, https://doi.org/10.1177/1687814018804096.

Yazdani, M., Zandieh, M., Tavakkoli-Moghaddam, R., and Jolai, F., Two meta-heuristic algorithms for the dual-resource constrained exible job-shop scheduling problem, *Scientia Iranica*, 2015.

Zheng, X., and Wang, L., A knowledge-guided fruit fly optimization algorithm for dual resource constrained flexible job-shop scheduling problem, *International Journal of Production Research*, vol. 54, no. 18, pp. 5554–5566, 2016, https://doi.org/10.1080/00207543.2016.1170226.

Biographies

Mr. Cao Hoang Bao Long is a senior university student at International University in Ho Chi Minh City. His major is in Logistics and Supply Chain Management. And his research interests include logistics, simulation, among others.

Ms. Pham Hoang Nam Quynh is a senior university student at International University in Ho Chi Minh City. Her major is in Logistics and Supply Chain Management. And her research interests include logistics, MCDM, among others.

Dr. Pham Huynh Tram got her Doctorate in Innovation in Manufacturing and Technology from Nanyang Technological University - Singapore. She has been lecturing in Department of Industrial and Systems Engineering of International University- Vietnam National university HCMC since 2012. Her research interest is in operations research, simulation and lean manufacturing

Dr. Ha Thi Xuan Chi is the Vice Dean of School of Industrial Engineering and Management and Head of Department of Industrial Systems Engineering. She got her Doctorate in Industrial Management from National Taiwan University of Science and Technology, 2014. Her research interest is in Fuzzy Multi-criteria Decision Making, Vehicle routing problem, Network flows and Integer programming