Hybrid flow shop scheduling using Multi-Criteria Decision Making and Simulation

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Abstract

In manufacturing system, a developed form of Flow Shop known as a Hybrid Flow shop System (HFS) allows the simultaneous operation of many identical machines on each stage. Duplicators are used to scale up a factory, increase output, balance a production line, or reduce the impact of a bottleneck. Several industries, including automotive, accessories and electronics, make extensive use of HFS. This study addresses the scheduling among machines in the HFS by applying the Discrete event simulation (DES) modeling in conjunction with priority rules based on Multi-Criteria Decision Making (MCDMs) and Composite Dispatching Rules (CDRs). The model aims to reduce the Makespan, mean Flowtime, mean Tardiness, and maximum Tardiness considering multi criteria namely Cycle time, Set-up time, Due date, Order and Number of Operations. The suggested solution framework combines MCDM approaches, such as the technique for prioritize order by VIekriteri-jumsko KOmpromisno Rangiranje (VIKOR), separately to prioritize the jobs, and with Criteria Importance Through Inter-Criteria Correlation (CRITIC) for allocating weights to the criteria.

Keywords
Hybrid Flow-shop (HFS), Discrete Event Simulation (DES), Multi-Criteria Decision Making (MCDM), Composite Dispatching Rules (CDRs), Breakdown machine.

1. Introduction
In a flow-shop manufacturing process, jobs follow a fixed linear structure. Hybrid flow-shop (HFS) is one common type of flow-shop in which there are duplicating machines per stage. Duplicators are used to scale up a factory, increase output, balance a production line, or reduce the impact of a bottleneck. Several industries, including automotive, accessories and electronics, make extensive use of HFS. Scheduling problem becomes challenging when taking into account the complexity of production systems with multiple machines and the possibility of machine breakdowns, leading to increased makespan and tardiness, and decreased throughput. In order to improve the operation efficiency, research literature has suggested various approaches, from sophisticated scheduling algorithms, heuristic techniques, multi-criteria decision making (MCDM) models, to simulation. Exploration of different combinations of these methods promise unlimitted opportunities to maximize the shop performance.

1.1 Objectives
In this study, we will explore the combination of the Composite Dispatching Rules, MCDM method and simulation to prioritize jobs in an HFS in order to reduce Makespan, mean flow time, mean Tardiness, and maximum Tardiness.

While some studies have investigated the use of simulation and MCDM in scheduling for flow shop production with breakdown machines, there is still a need for more research in this area. For instance, the application of these methods in different industries, such as automotive or electronics, has not been explored extensively. Application of different CDRs and MCDM methods may have different results in different contexts. Our work follows the framework of

Thenarasu, M. *et al.* (2022), but in the context of HFS with a consideration of uncertainty factors. In addition, we will test the most promising CDRs and MCDM technique proposed in the literature for a case study adopted from Sels et al.(2012).

2. Literature Review

2.1.1. Overview of scheduling methods

Traditional scheduling methods include Gantt charts, critical path method (CPM), and program evaluation and review technique (PERT), which have been used for several decades in different industries. Gantt charts are visual tools that show the planned tasks and the duration of each task, while CPM and PERT use network diagrams to determine the critical path and the activities that can be delayed without affecting the project's completion time. Besides that, some common approaches is to use optimization techniques such as mixed-integer linear programming (MILP) or genetic algorithms (GA) to find an optimal or near-optimal solution. Other approaches include heuristic and meta-heuristic methods such as simulated annealing (SA), tabu search (TS), and ant colony optimization (ACO) (Bellabai et al. 2022).

The goal of (Reza 2022) was to reduce overall tardiness and carbon emissions while taking into account the permutation flow shop-scheduling challenge. A multi-objective flexible flow shop-scheduling issue with varying analyzing durations was examined by (Xiuli 2018). A hybrid nondominated sorting GA with variable local search was then suggested as a solution to the issue. The distributed permutation flow shop problem with constrained buffers was initially studied by (Lu 2022) with the aim of reducing the makespan and overall energy consumption. They outlined a collaborative multi-objective optimization method based on Pareto principles and created a speed-scaling technique in response to the issue. According to experimental findings, this problem could be solved using algorithms. (S.Ashin, 2016) questioned and researched in the manufacturing industry whether the potential of saving energy consumption by using various velocity of machining operations to produce different energy-consumption orders is reasonable or not. They compared the relation between the consumption of energy and the maximum completion time for the green flow part shop-scheduling mathematical problem. To address this issue, (Dunbing 2016) researched flexible saving energy consumption part shop scheduling in unexpected environments and created a better particle swarm optimization algorithm.

The researchers studied various scheduling techniques to account for machine failure to overcome these limitations. In running water shop production using faulty machines, simulation and MCDM have been proposed as a practical method to address the shortcomings of traditional planning techniques. To improve the efficiency of a production system, simulation requires building a virtual model of the system and testing multiple scenarios. To find the best planning solution, MCDM is used to evaluate many alternatives based on many factors, including cost, time, and quality. The planning of the flowing water store production system was optimized using simulation-based technology in "A Multi-Objective Decision Making Model for Scheduling of a Flow Shop Production System Using Simulation and Genetic Algorithm" (Istokovic et al. 2019). For flexible store systems, a simulation-based planning technique has been published in (Ortz Barrios et al. 2021). By using MCDM methods such as AHP and TOPSIS, the study prioritizes scheduling of tasks based on several goals, such as reducing completion times and delays. The results show that the proposed technology is effective in reducing the system completion time. A simulation-based optimization technique has been proposed for planning the studied flowing water outlet systems (Güçdemir&Selim 2018). The method prioritized the scheduling of activities based on various goals, like the degree of resource bottlenecking and customer importance by using MCDM techniques like AHP and WAM. The outcomes demonstrated that the suggested strategy was successful in close importance weights.

2.1.2. Priority dispatching rules for HFS

In manufacture planning and scheduling, priority dispatching rules (PDRs) are often applied to rank parts or jobs in a queue according to certain standards. There are many types of PDRs, and the choice of rule will depend on the unique characteristics of the generated diagram as well as the objectives of the sequence and the scheduling problem. Some common PDRs include First-Come-First-Serve (FCFS), Shortest-Processing-Time-First (SPT), Earliest-Due-Date (EDD), Critical-Ratio (CR), and many others.

To reduce production intervals, traffic times, and delays in traffic scheduling issues, CDR techniques are often used. CDR seeks to reduce machine idling time, alleviate the impact of bottlenecks, and improve overall system performance. Some examples of CDRs for flow shop production systems include the Longest Processing Time (LPT) rule, the Shortest Processing Time (SPT) rule, and the Moore rule, among others. According to Zini, H. & Elbernoussi, S. (2015), the goal function will be determined by a new heuristic that combines parallel priority dispatching rules to send jobs to machines at each stage because of its significance in the solution process.

2.1.3. Discrete event simulation

One method of modelling and analysis to track the behavior of complex systems that change over time is called discrete event simulation (DES). By modelling a manufacturing process as a sequence of discrete events, such as the delivery of parts, the start and end of operations, and machine failures, DES provides an accurate and complete description. about the behavior of the system. In order to improve resource usage in a hybrid flowshop system, Al Kattan, I., and Maragoud, R. (2008) used simulation to examine the performance of specific sequences. A simulation-based experimental investigation was also conducted by Kia, H. R., Davoudpour, and Zandieh (2010) for scheduling HFS taking sequence dependent setup durations into account.

2.1.4. Multi-criteria decision-making approaches

MCDM can be used to assess the results of the simulation and select the best scheduling strategy regarding multiple criteria, such as makespan, tardiness, cost, and resource utilization according to Thenarasu, M. *et al.* (2022).
Additionally, other MCDM techniques such as multi-objective optimization can be applied to the scheduling problem in hybrid flow shop production. This approach considers various objectives simultaneously, such as minimizing makespan and tardiness while maximizing resource utilization, to determine the optimal scheduling approaches. The proposed rule for the hybrid flow shop problem is a two-stage process. Begin with the first stage, the CRITIC method is applied to assign the weights to each criterion using the CRITIC method. In the last stage, parts are ranked by COPRAS, MOORA, and VIKOR in order and prioritized regarding the weights obtained in the previous stage. Previously, VIKOR has been refered in the paper of Uzun Araz, O., Eski, O., & Araz, C. (2019) to optimize Average Service Level, Mean Tardiness, Mean Flow Time in hybrid flowshop system. Besides, MOORA is chosen as its sentivity result it gives Qureshi, A.M. and Rachid, A. (2022).

3. Methods

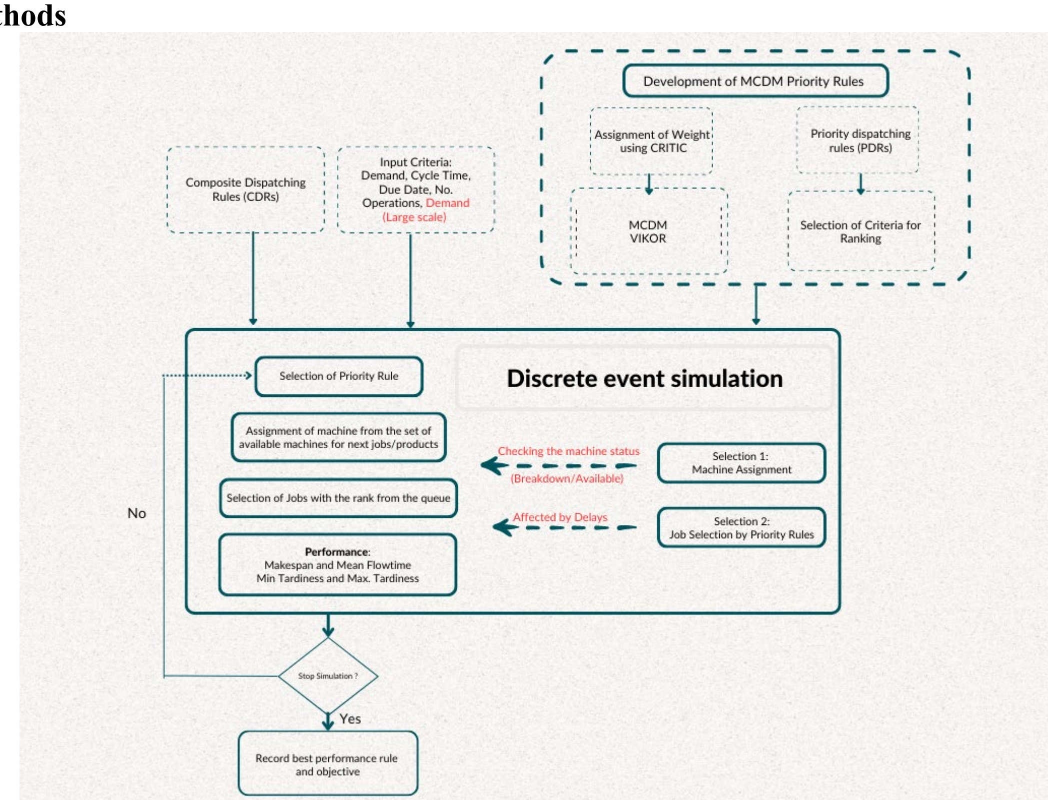

Figure 1. Framework for Development of MCDM and Simulation

The set of rules that were selected and developed by MCDM and Priority Dispatching Rules in the first stage will be combined with the DES model in the second stage to recur the case through replication. Thereafter, performance index was recorded to observe specifically to the Makespans, Mean Flowtime, Minimum Tardiness and Maximum Tardiness.

3.1. The Development of Hybrid MCDM-Based Priority Rules

There are three steps in the MCDM method: criteria determination, criteria weight calculation and alternative ranking. In our study, common criteria in scheduling are selected from the literature. CRITIC (CRiteria Importance Through Intercriteria Correlation) is chosen as the preferred weight calculation approach due to its objective statistical process and independence from decision-maker input. For ranking, VIKOR (VlseKriterijumska Optimizcija I Kaompromisno Resenje in Serbia) was picked for its popularity.

3.1.1. Determine The Set of Criteria

Due Date enables work prioritization and scheduling in accordance with their due dates, resulting in better timeliness, shorter flow times, fewer tardies, and shorter project durations. Therefore, it is assigned as a **Beneficial criteria**.

Cycle time helps determine the system's capacity and throughput, it is essential for the efficient planning and optimization of production efficiency. Therefore, it is assigned as a **Beneficial criteria**.

Number of operations refers to the wise scheduling decisions which utilized to evaluate complexity, resource needs, and overall effectiveness but these performance metrics are directly impacted by the number of operations criteria alone. Therefore, it is assigned as a **Non-beneficial criteria**.

Set-up time is an important criteria since organizations can gain quicker changeovers, more throughput, less downtime, and better resource usage by cutting it. Therefore, it is assigned as a **Non-beneficial criteria.**

Order with the rising demand means that the company has the high chance of gaining the revenue. Therefore, it is assigned as a **Beneficial criteria**.

3.1.2. Weight Assignment for Criteria

The CRITIC method is applied to calculate the weights of each criterion
The decision matrix was first normalized using:

$$\rho_{ij} = \frac{y_{ij} - y_j^{min}}{y_j^{max} - y_j^{min}} \quad ,i = 1..m; j = 1..n$$

For Beneficial criteria

$$\rho_{ij} = \frac{y_j^{max} - y_{ij}}{y_j^{max} - y_j^{min}} \quad ,i = 1..m; j = 1..n$$

For Non-beneficial criteria
Where y_{ij} is the value of alternative i in criteria j
y_j^{min} is minimum value in criteria j
y_j^{max} is maximum value in criteria j
Then, to estimate the criteria's weight, we must compute a linear correlation coefficient between the values of the criteria in the matrix by:

$$v_{ij} = \frac{\sum_{i=1}^{m}(\rho_{ij} - \overline{\rho_j})(\rho_{ik} - \overline{\rho_k})}{\sqrt{\sum_{i=1}^{m}(\rho_{ij} - \overline{\rho_j})^2 \sum_{i=1}^{m}(\rho_{ik} - \overline{\rho_k})^2}} \quad ,j,k = 1..n$$

Where $\overline{\rho_j}$ and $\overline{\rho_k}$ are the sample means average(ρ_{ij}) and average(ρ_{ik})
Finally, weight of each criteria is determined by:

$$w_j = \frac{\beta_j}{\sum_{k=1}^{n}\beta_k}$$

Where $\beta_j = \sigma_j \sum_{k=1}^{n}(1 - v_{ij})\ ; j = 1..n$

3.1.3. Formulas of MCDM Methods-VIKOR

Step 1: Establish the decision matrix:

$$[f_{ij}]_{mxn} = \begin{bmatrix} a_{11} & a_{21} & a_{31} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{32} & \dots & a_{2n} \\ a_{31} & a_{23} & a_{33} & \dots & a_{3n} \\ \dots & \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}$$

Step 2: Determine the best f_i^* and the worst f_i^- values of all criteria.

If the ith criterion represents a benefit (the greater the better) then $f_i^* = max_j f_{ij}$ and $f_i^- = min_j f_{ij}$ if the ith criterion represents a cost (the lower the better) then $f_i^* = min_j f_{ij}$ and $f_i^- = max_j f_{ij}$

Step 3: Computer the values S_j and R_j by the relationships:

$$S_j = \sum_{i=1}^{n} w_i(f_i^* - f_{ij})/(f_i^* - f_i^-)$$

$$R_j = max_i\,[\frac{w_i(f_i^* - f_{ij})}{f_i^* - f_i^-}]$$

Where w_i is the weight of the ith criterion, S_j and R_j stand for the utility measurement and regret measurement, respectively.

Step 3: Calculate the VIKOR index- Q_j:

$$Q_j = \frac{v(S_j - S^*)}{(S^- - S^*)} + (1 - v)\frac{(R_j - R^*)}{(R^- - R^*)}$$

Where $S^* = min_j S_j$, $S^- = max_j S_j$, $R^* = min_j R_j$, $R^- = max_j R_j$, S_j and R_j are estimated in Step 2 and v is specified as the weight of the strategy "majority criteria" (or "maximum group utility"); in this case, V = 0,5.
Step 4: Use the value Q to rank your preferences.
The best value is found to be the alternate with the lowest VIKOR value. Based on what is deemed to be the best by the measure Q, suggest a solution that is close to the optimum point (Minimum).

3.2. Selection of Composite Priority Rules

We select a CDR from Ozturk et al., (2019) as a current best-executed preference rules for comparison with the proposed Hybrid MCDM-Based Priority Rule. This CDR is a composite of Earliest Due Date (EDD), Least Remaining number of operations (LRnOps), Least Total work content (LTWRK), Least Remaining work content (LRWRK), and Least number of operations (LnOps). Priority will be given to the job that has minimum value of [EDD + [(LRnOps + LTWRK)/(LRWRK-LTWRK)] * LnOps] * LRnOps

3.3. The Development of Discrete Event Simulation Model

3.3.1. DRCFJSP small scale instances

There are three small scale instances (MK1, MK2, MK3). The number of jobs, number of operations and number of machines at each stage are listed in Table 1. Processing time, due date and set up time are uncertain factors and assumed to follow uniform distribution.

Table 1. Data of each instance

Instances	(n x m x k*)	NOP	Processing time (min)	DueDate	Setup time
MK1	6 x 4 x 2	1 to 2	30-50	50-150	15-30
MK2	6 x 8 x 4	2 to 4	30-70	200-300	15-30
MK3	6 x 18 x 9	4 to 7	30-250	650-850	15-30
Large-scale	60 x 58 x 9	5 to 7	1400-15000	30000-46000	15-30

*Note: n – No. of Jobs, m- No. of Machines, k- Total operations and NOP- Number of operations per Part.

3.3.2. Real-World Problem

The case study is a tire factory that manufactures vehicle parts and has 58 machines with different capacities. A total of 60 orders were required to be fulfilled. Each job requires between four and nine operations. Each order has a certain operation route (Table 2) that needs to be completed on available machines. Processing time, due date and set up time are generated in ARENA following uniform distribution (Table 1).

Table 2. Route data

ID	Sequence								Cycle Time	Due Date
PartType	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Hour	Hour
1	Banbury Mixer	Final Banbury	Calendering	Cutting	Cushion	Tire Building	Tire Curing	Out	496.15	620.217
2	Banbury Mixer	Final Banbury	Extrusion	Tire Building	Tire Curing	Out	Null	Null	487.0666667	617.333
3	Banbury Mixer	Final Banbury	Bead forming	Tire Building	Tire Curing	Out	Null	Null	497.1666667	609.533
4	Banbury Mixer	Final Banbury	Calendering	Cushion	Cutting	Tire Building	Tire Curing	Out	645.3333333	764.017
5	Banbury Mixer	Final Banbury	Extrusion	Tire Building	Tire Curing	Out	Null	Null	330.3333333	450.633
6	Banbury Mixer	Final Banbury	Tire Building	Tire Curing	Out	Null	Null	Null	331.2666667	432.467
59	Banbury Mixer	Final Banbury	Extrusion	Tire Building	Tire Curing	Out	Null	Null	486.6333333	588.183
60	Banbury Mixer	Final Banbury	Tire Building	Tire Curing	Out	Null	Null	Null	373.6833333	482.133

Table 3. Time based data

ID	Cycle Time		Due Date		Setup time		NoOpe	Number in Order	Average PT
PartType	Min	Hour	Min	Hour	Min	Hour			
1	29769	496.15	37213	620.217	18	0.300	7	47	4250.14
2	29224	487.067	37040	617.333	21	0.350	5	53	5840.60
…	…	…	…	…	…	…	…	…	…
59	29198	486.633	35291	588.183	22	0.367	5	56	5835.20
60	22421	373.683	28928	482.133	25	0.417	4	44	5599.00

The table below shows detailed data on processing time for each machine. In the model, there are 9 stages corresponding to 9 operations that the Parts will go through. Each stage will have 4 machines consisting of 2 types: fast machine and slow machine. The fast machine will have shorter processing time for all parts.

Table 4. Processing time

Station	Type of machine (according to speed)	No. machine	Processing time of each type of product (mins)						
			1	2	3	4	5	6	60
Banbury Mixer	*Quick*	2	1410	2385	1710	3186	1520	1365	1540
	Slow	2	1551	2491	1881	3540	1786	1638	1848
Final Banbury	*Quick*	2	2350	3445	2850	3245	2090	2067	2332
	Slow	2	2585	3816	3135	3481	2470	2262	2552

Calendering	*Quick*	2	1410	1325	1710	1770	1140	1755	1980
	Slow	2	1692	1855	2052	2478	1444	2106	2376
Extrusion	*Quick*	2	1880	1749	2280	2006	760	1248	1408
	Slow	2	2021	1961	2451	2183	1178	1677	1892
Bead forming	*Quick*	2	2162	2173	2622	2360	1596	1365	1540
	Slow	2	2303	2385	2793	2537	2014	1677	1892
Cutting	*Quick*	2	2444	2597	2964	2714	2432	2340	2640
	Slow	2	2585	2809	3135	2891	2850	2886	3256
Tire Building	*Quick*	7	3008	3445	3648	3422	4104	2847	3212
	Slow	3	3149	3657	3819	3599	4522	3120	3520
Cushion	*Quick*	2	5734	6466	6954	7198	4636	4758	5368
	Slow	2	5875	6625	7125	7375	4750	4875	5500
Tire Curing	*Quick*	10	11280	12561	13338	13747	8740	10023	11308
	Slow	10	12314	14310	14877	15340	9614	11076	12496

3.3.3. Arena Logic
There are three main stages in the Arena logic.

Stage 1: Generating jobs (parts) and assigning routing sequences

In the first stage, parts are generated and assigned attributes such as processing time, due date, and quantity of orders. These parts are then directed to their corresponding machines based on their sequence (F igure 2, 3, 4)

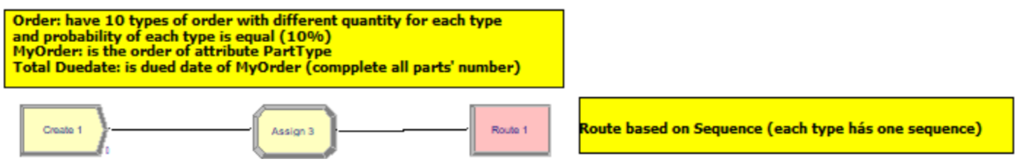

Figure 2. Simulation for first stage

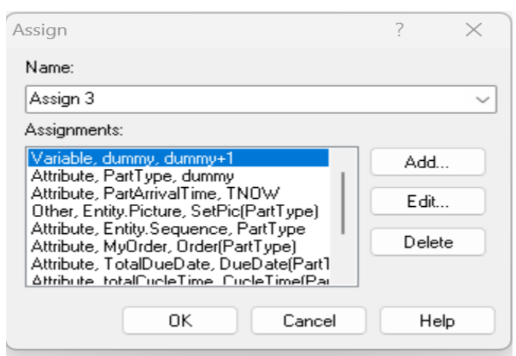

Figure 3. Set up Assign module

Route - Advanced Transfer

	Name	Route Time	Units	Destination Type
1	Route 1	0.	Minutes	By Sequence
2	Route 3	0.	Minutes	By Sequence
3	Route 4	0.	Minutes	By Sequence
4	Route 5	0.	Minutes	By Sequence
5	Route 6	0.	Minutes	By Sequence
6	Route 7	0.	Minutes	By Sequence
7	Route 8	0.	Minutes	By Sequence
8	Route 9	0.	Minutes	By Sequence
9	Route 10	0.	Minutes	By Sequence
10	Route 2	0.	Minutes	By Sequence

Figure 4. Set up Route modules

Stage 2: Assigning machines and prioritizing jobs by CDR or MCDM rules

Parts are firstly assigned to the fasted available machines (Figure 5,6). Next, the parts waiting on queue to be processed by the machine get priority based on the CDR or MCDM rules. After the process completion, the parts are released and moved to the next operation as defining in the Route module. All the machines work for 10 hours per day. Besides, failure can occur at some stations that have many parts go through (Figure 7)

In the second stage (Figure 3), work is prioritized by the selected CDR or MCDM rules.

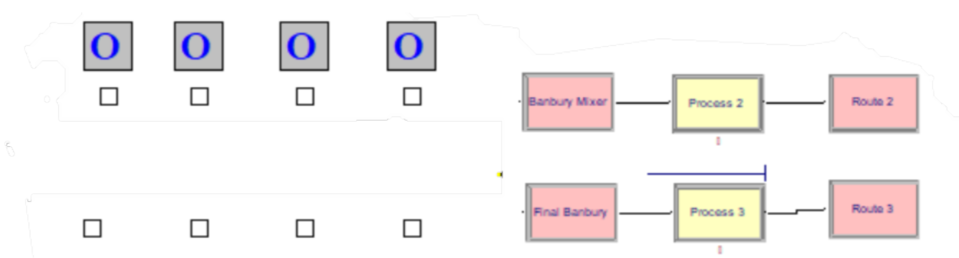

Figure 5. Simulation for second stage

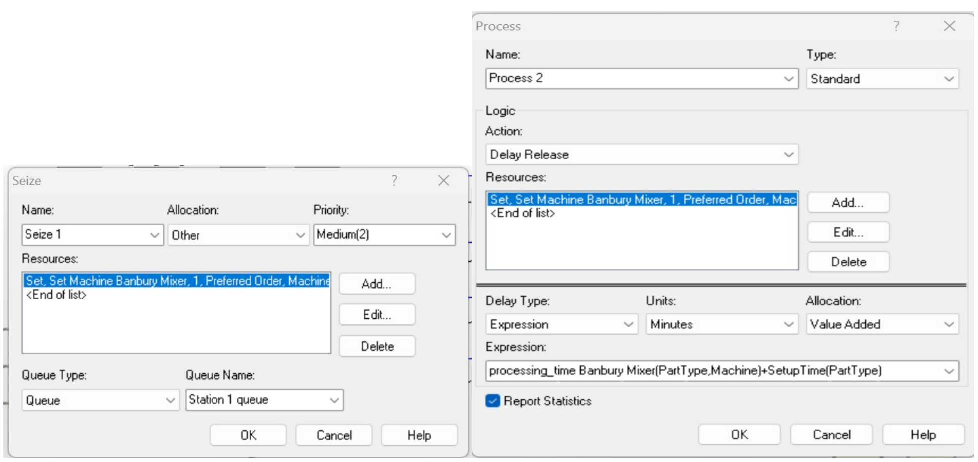

Figure 6. Set up Process modules

.It is noted that Arena allows simple queueing priority such as First In First Out, Last In First Out, or by atribute values. For complicated queuing rules such as the CDR and MCDM in this study, the Visual Basic Application (VBA) which is available in ARENA and EXCEL is employed.

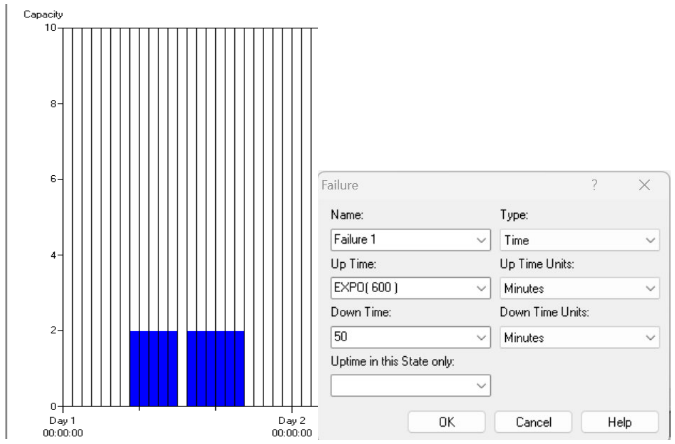

Figure 7. Set up Schedule for machine and possibility of failure

Stage 3: Recording the performance measures.
After all operations are completed, performance measurements are recorded, including Total Process Time, Due Date, and Tardiness (Figure 8). The model can account for changes in part arrivals, processing time, machine breakdown, capacity, and other factors.

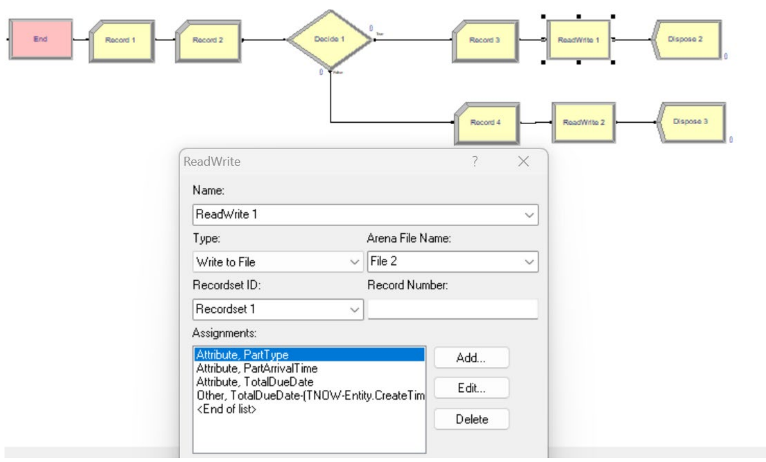

Figure 8. Record modules and Write result to file.

4. Results and Discussion

The following calculation is used to evaluate the performance of each rule based on the percentage deviation from the best performing rule:

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

where Z^B is the average objective function value of the best scheduling rule and Z^x is the value of average objective function of the evaluated rule.

4.1. The Best Performing Rule in the DRCFJSP small scale instances

The benchmark results show that for practically every performance indicator, the CDRs outperform the MCDM-based priority rules. The VIKOR is the best performing rule overall with the exception of minimizing Makespan. Considering the average performance measure of all objectives, the CDR performs the best overall.

Table 5. %Dev of each rule in every performance metric of the small scale instances

Priority rule	Makespan	Mean Flowtime	Mean Tardiness	Max Tardiness
R1: [EDD+[(LrnOps/LTWRK)/(LRWRK-LTWRK) * LrnOps] * LrnOpS	0.39	0.00	0.00	0.00
R2: VIKOR	0.00	0.005	0.03	0.28

4.2. The Best Performing Rule in Real-World Case

The real case results show that for practically every performance indicator, the CDRs outperform the MCDM-based priority rules. For the objective of minimizing makespan, the CDR and VIKOR are equivalent. The CDR also performs best considering the average performance measure of all objectives.

Table 6. %Dev of each rule in every metrics of real case

Priority rule	Makespan	Mean Flowtime	Mean Tardiness	Max Tardiness
R1: [EDD+[(LrnOps/LTWRK)/(LRWRK-LTWRK) * LrnOps] * LrnOpS	0.00	0.00	0.00	0.00
R2: VIKOR	0.00	0.007	0.415	0.944

That the CDR surpasses the MCDM rule can be explained by looking into the way these rules are integrated into the simulation. The CDR is coded with VBA embeded in ARENA, which enables its criteria of due date, remaining number of operations, total work content, remaining work content and number of operations updated each time a part visiting a machine. On the other hand, the ranking by MCDM with criteria of due date, cycle time, number of operations, set-up time and demand, is performed only at the very begining of the operation and is not updated at the subsequent stages. In our future work, this discrepancy will be addressed.

5. Conclusion

This work aims to solve the HFS scheduling problem by comparing a selected best CDR and a hybrid MCDM priority rule via DES modeling. The selected CDR considers a combination of Earliest Due Date, Least Remaining number of operations, Least Total work content, Least Remaining work content, and Least number of operations. The MCDM employs the CRITIC method to weigh cirteria of due date, cycle time, number of operations, set-up time and demand, and VIKOR method to give priority rank to a job.Three small scale instances and a large scale realworld case are tested. For the makespan performance, the MCDM is found consistently performing well. On the other hand, the CDR surpasses the MCDM in the performance of mean flowtime, min and max tardiness. In our future work, we will consider updating the ranking by the MCDM rule at each new operation, making it suitable for real time application.

References

Bellabai, J. R., Leela, B. N. M., & Kennedy, S. M. R., Testing the Performance of Bat-Algorithm for Permutation Flow Shop Scheduling Problems with Makespan Minimization. *Brazilian Archives of Biology and Technology*, *65*, e20210840, 2022. https://doi.org/10.1590/1678-4324-2022210840

Dunbing, T., *Energy-efficient dynamic scheduling for a flexible flow shop using an improved particle swarm optimization—ScienceDirect, 2016*. https://www.sciencedirect.com/science/article/abs/pii/S0166361515300476?via%3Dihub

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

Istokovic, D., Perinic, M., Dobovicek, S., & Bazina, T., Simulation framework for determining the order and size of the product batches in the flow shop: A case study. *Advances in Production Engineering & Management*, *14*(2), 166–176, 2019. https://doi.org/10.14743/apem2019.2.319

Lu, C., *A Pareto-based collaborative multi-objective optimization algorithm for energy-efficient scheduling of distributed permutation flow-shop with limited buffers—ScienceDirect, 2022*. https://www.sciencedirect.com/science/article/abs/pii/S0736584521001575?via%3Dihub

Ortíz-Barrios, M., Petrillo, A., De Felice, F., Jaramillo-Rueda, N., Jiménez-Delgado, G., & Borrero-López, L. (2021). A Dispatching-Fuzzy AHP-TOPSIS Model for Scheduling Flexible Part-Shop Systems in Industry 4.0 Context. *Applied Sciences*, *11*(11), 5107, 2021. https://doi.org/10.3390/app11115107

Reza, G. S. (2022). *Minimizing the total tardiness and the total carbon emissions in the permutation flow shop scheduling problem—ScienceDirect*. https://www.sciencedirect.com/science/article/abs/pii/S0305054821003245 S.Ashin, M., *Green scheduling of a two-machine flowshop: Trade-off between makespan and energy consumption—ScienceDirect, 2016*. https://www.sciencedirect.com/science/article/pii/S0377221715008206?via%3Dihub

Sels, V., Gheysen, N., & Vanhoucke, M., A comparison of priority rules for the part shop scheduling problem under different flow time- and tardiness-related objective functions. *International Journal of Production Research*, *50*(15), 4255–4270, 2012. https://doi.org/10.1080/00207543.2011.611539

Uzun Araz, O., Eski, O., & Araz, C. , A Reactive Scheduling Approach Based on Fuzzy Inference for Hybrid Flowshop Systems. *International Journal of Simulation Modelling*, *18*(1), 5–18, 2019. https://doi.org/10.2507/IJSIMM18(1)448

Wang, B., Wang, X., Lan, F., & Pan, Q., A hybrid local-search algorithm for robust part-shop scheduling under scenarios. *Applied Soft Computing*, *62*, 259–271, 2018. https://doi.org/10.1016/j.asoc.2017.10.020

Xiuli, W. (2018). *Sustainability | Free Full-Text | Multi-Objective Flexible Flow Shop Scheduling Problem Considering Variable Processing Time due to Renewable Energy*. https://www.mdpi.com/2071-1050/10/3/841

Zhengcai, C., *An Adaptive Scheduling Algorithm for Dynamic Parts for Dealing with the Flexible Part Shop Scheduling Problem | SpringerLink, 2019*. https://link.springer.com/article/10.1007/s12599-019-00590-7?error=cookies_not_supported&code=8f71fe06-2e62-4bba-8e81-a8108dc34b65

Thenarasu, M. *et al.* (2022) 'Development and analysis of Priority Decision Rules using MCDM approach for a flexible job shop scheduling: A simulation study', *Simulation Modelling Practice and Theory*, 114, p. 102416. doi:10.1016/j.simpat.2021.102416.

Istokovic, D. *et al.*, 'Minimizing total production cost in a hybrid flow shop: A Simulation-Optimization Approach', *International Journal of Simulation Modelling*, 19(4), pp. 559–570, 2020. doi:10.2507/ijsimm19-4-525.

Uzun Araz, O., Eski, O. and Araz, C. , 'A reactive scheduling approach based on fuzzy inference for hybrid Flowshop Systems', *International Journal of Simulation Modelling*, 18(1), pp. 5–18, 2019. doi:10.2507/ijsimm18(1)448.

Malekpour, H., Hafezalkotob, A. and Khalili-Damghani, K., 'Product processing prioritization in hybrid flow shop systems supported on Nash bargaining model and simulation-optimization', *Expert Systems with Applications*, 180, p. 115066, 2021. doi:10.1016/j.eswa.2021.115066.

Wedley, W.C., 'Combining qualitative and quantitative factors—an analytic hierarchy approach', *Socio-Economic Planning Sciences*, 24(1), pp. 57–64, 1990. doi:10.1016/0038-0121(90)90028-6.

Qureshi, A.M. and Rachid, A. (2022) 'Comparative analysis of multi-criteria decision-making techniques for outdoor heat stress mitigation', *Applied Sciences*, 12(23), p. 12308. doi:10.3390/app122312308.

Zini, H., & Elbernoussi, S. , A discrete particle swarm optimization with combined priority dispatching rules for hybrid flow shop scheduling problem. Applied Mathematical Sciences, 9(24), 1175-1187, 2015.

Al Kattan, I., & Maragoud, R., Performance analysis of flowshop scheduling using genetic algorithm enhanced with simulation. *International Journal of Industrial Engineering: Theory, Applications and Practice*), 62-7, 2008.

Kia, H. R., Davoudpour, H., & Zandieh, M., Scheduling a dynamic flexible flow line with sequence-dependent setup times: a simulation analysis. International Journal of Production Research, 48(14), 4019-4042, 2010.

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