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Optimizing Priority Sequencing Rules in Parallel Machine Scheduling: An Evaluation and Selection Approach using Hybrid MCDM Techniques

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ABSTRACT

Priority sequencing criteria are of utmost importance in the determination of the sequence in which jobs are processed at workstations in parallel machine scheduling. The utilization of diverse priority rules can result in varied sequencing arrangements, hence requiring more experimentation to ascertain the optimal rule. Hence, it is imperative to formulate a thorough approach for the selection of the most suitable priority sequencing rule from the standpoint of management decision-making. The objective of this research is to analyze and compare six different priority sequencing rules in the context of parallel machine scheduling. Additionally, a methodology is proposed for the assessment and selection of the most suitable rule. This methodology combines the full consistency method (FUCOM) with the measurement of alternatives and ranking according to compromise solution (MARCOS) method, which are both multi-criteria decision-making techniques. When reviewing and selecting the optimal priority sequencing rule, seven parameters are taken into consideration. The weights of these criteria are computed using the FUCOM method, while the relative proximity values of all priority sequencing rules are derived by the MARCOS method. The data indicate that the priority sequencing rules are prioritized according to their level of importance. The approach outlined in this study is essential for workstation management to make well-informed decisions regarding the choice of the most advantageous priority sequencing rule for parallel machine scheduling.

1. Introduction

Job sequencing entails determining the optimal order for processing jobs at one or multiple workstations. Workstations typically handle various tasks, and effective sequencing is crucial for

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minimizing costs associated with job waiting times and workstation idle times. Inadequate scheduling may result in job congestion and the formation of waiting queues, thereby increasing complexity and placing pressure on management to establish efficient scheduling procedures [1].

In this context, a range of priority sequencing rules or heuristics are utilized to ascertain the sequence in which jobs will be executed at workstations. The decision-making process regarding the allocation of workstations for further processing is guided by these principles. The incorporation of priority sequencing rules confers benefits due to their ability to incorporate current knowledge regarding operational conditions into developing schedules. The evaluation of the performance of a certain sequence generated by a priority sequencing rule is conducted using performance measurements such as average job completion time, average number of jobs in the system, mean job tardiness, and number of tardy jobs, among other metrics. The task of choosing the most appropriate priority sequencing rule for deciding the sequence of job processing at a workstation presents a complex and difficult problem. When considering workstation management, it is important to note that there is no definitive sequencing rule that can be universally regarded as the optimal choice [2, 3].

Therefore, an elaborate method for selecting the optimal priority sequencing rule is essential from a managerial decision-making perspective. The chosen methodology should effectively address the complexity of the problem by explicitly considering multiple criteria, leading to more informed and improved decision outcomes. Multi-criteria decision-making (MCDM) techniques fulfill these requirements by structuring complex problems and facilitating explicit consideration of multiple criteria [4,5].

The integration of MCDM techniques with sequencing rules in research studies has been relatively limited. Only a few studies have explored the potential benefits of combining MCDM approaches with priority sequencing rules. This research gap presents an opportunity to investigate the effectiveness of such hybrid methodologies in optimizing job sequencing in various contexts. By leveraging the strengths of MCDM techniques, which allow for explicit consideration of multiple criteria, and incorporating them into the selection of sequencing rules, researchers can potentially enhance the decision-making process and improve the overall performance of job sequencing systems. Therefore, further exploration and empirical validation of the combined MCDM and sequencing rules approach is warranted to advance the understanding and practical application of this integrated methodology. For instance, Kumar et al. [6] explored priority sequencing rules in job shop scheduling and proposed a comprehensive method for selecting the best rule using a hybrid multi-criteria decision-making technique. The methodology considered seven sequencing rules, evaluated them based on eight criteria and ranked them accordingly. The findings provided valuable guidance for workstation management in choosing the most beneficial sequencing rule. Thenarasu et al. [7] integrated discrete event simulation, composite dispatching rules (CDRs), and MCDM to solve the flexible job shop scheduling problem. The proposed approach minimized objective measures such as makespan, flow time, and tardiness. It was tested on benchmark problems and a real-world example. MCDM-based rules outperformed CDRs for large-scale problems, considering realistic criteria.

This paper introduces an integrated multi-criteria concept that combines the full consistency method (FUCOM) method for determining weighting coefficients of criteria and the measurement of alternatives and ranking according to compromise solution (MARCOS) method for job sequencing. The proposed multi-criteria framework represents a novel mathematical model, as it is the first of its kind in the literature to incorporate the integrated FUCOM-MARCOS methods for ranking jobs. The authors believe that the introduction of this new integrated multi-criteria concept for job sequencing will contribute to the advancement of methodologies within the subject area as addressed in the existing literature.

2. Parallel Machine Scheduling

In parallel machine scheduling environments, multiple jobs are performed across parallel workstations, each handling different types of tasks. It is crucial to carefully plan schedules to prevent congestion and the formation of waiting queues. The complexity of such situations necessitates the development of scheduling procedures to effectively manage the workload. One approach to creating schedules in a parallel machine environment is through the utilization of priority sequencing rules, allowing schedules to evolve. When a workstation is ready for further processing, the selection of the next job to be processed is made based on these priority sequencing rules [6, 8].

Priority sequencing rules are simple heuristics used to determine the order in which jobs are processed. Some commonly used rules include:

i. *Available time criticality score* (ATCS) – The rule is designed to prioritize jobs based on their available time and criticality.
ii. *First come, first served* (FCFS) – Jobs are processed according to their order, with the first-arrived job being prioritized.
iii. *Shortest processing time* (SPT) – Jobs are processed based on the least amount of processing time required, with the shortest job scheduled first.
iv. *Longest processing time* (LPT) – Jobs are processed based on the greatest amount of processing time required, with the longest job scheduled first.
v. *Earliest due date* (EDD) – Jobs are processed according to their delivery deadlines, with the earliest due job scheduled first.
vi. *Critical ratio* (CR) – Jobs are processed based on the increasing critical ratio, which represents the ratio of remaining work time to the time left to complete the job.

By employing these priority sequencing rules, job shop operations can streamline their scheduling process and enhance efficiency.

3. Calculation of Weight Coefficients using FUCOM

The FUCOM method is utilized to derive the weighting factors of criteria by employing the subsequent procedure [9-11]:

Step 1 – Initially, the process entails the ranking of the criteria from a predefined set of evaluation criteria $C = \{C_1, C_2, \dots, C_n\}$ is performed.

$$\boldsymbol{C}_{\boldsymbol{j}_{(\mathbf{1})}} > \boldsymbol{C}_{\boldsymbol{j}_{(\mathbf{2})}} > \cdots > \boldsymbol{C}_{\boldsymbol{j}_{(\boldsymbol{k})}}, \tag{1}$$

where *k* represents the rank of the criterion under consideration.

Step 2 – The criteria are ranked and compared to each other, and their comparative importance ($\varphi_{k/(k+1)}$) is determined as:

$$\boldsymbol{\Phi} = \left(\boldsymbol{\varphi}_{\mathbf{1/2}}, \boldsymbol{\varphi}_{\mathbf{2/3}}, \dots, \boldsymbol{\varphi}_{\boldsymbol{k/(k+1)}}\right), \tag{2}$$

Step 3 – Subsequently, the computation of the final values for the weighting coefficients of the evaluation criteria $(w_1, w_2, \dots, w_n)^T$ is performed. The final values must satisfy two conditions:

(1) It can be observed that the ratio of the weighting coefficients, denoted as $(\varphi_{k/(k+1)})$, is indicative of the relative significance assigned to the considered criterion. This observation is derived from **Step 2**, where the following condition is satisfied:

$$\frac{w_k}{w_{k+1}} = \varphi_{k/(k+1)}. \tag{3}$$

(2) The condition of mathematical transitivity, i.e. that $\varphi_{k/(k+1)} \otimes \varphi_{\frac{k+1}{k+2}} = \varphi_{\frac{k}{k+2}}$, should be met by the final values of the weighting coefficients. Since $\varphi_{k/(k+1)} = \frac{w_k}{w_{k+1}}$ and $\varphi_{(k+1)/(k+2)} = \frac{w_{k+1}}{w_{k+2}}$, then $\frac{w_k}{w_{k+1}} \otimes \frac{w_{k+1}}{w_{k+2}} = \frac{w_k}{w_{k+2}}$. So, the final values of the weighting coefficients of the evaluation criteria should fulfill the second condition, which is as follows:

$$\frac{w_k}{w_{k+2}} = \varphi_{\frac{k}{k+1}} \otimes \varphi_{\frac{k+1}{k+2}}. \tag{4}$$

Based on the above discussion, a final model can be developed to ascertain the definitive values of the weighting coefficients for the evaluation criteria.

$$\begin{aligned}
&\min \chi \\
&s.t. \\
&\left| \frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)} \right| = \chi, \ \forall j \\
&\left| \frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \right| = \chi, \ \forall j \\
&\sum_{j=1}^{n} w_j = 1, \\
&w_j \geq 0, \ \forall j
\end{aligned} \tag{5}$$

4. Ranking the Alternatives using the MARCOS Method

The MARCOS technique was founded on the analysis of the interrelationships between alternatives and reference values, namely ideal and anti-ideal alternatives [12-15]. The decision-making process in this method primarily relies on the concept of utility function. The utility function can be conceptualized as an alternative perspective linked to optimal and suboptimal solutions [16,17]. Hence, the optimal selection is the option that exhibits the greatest proximity to the ideal point, thereby resulting in the greatest distance from the anti-ideal point. The steps of the method are explained below [18-20].

Step 1 – The initial decision matrix is formatted.

Step 2 – The second step in the process involves the formation of an extended initial matrix. This step encompasses the determination of the ideal and anti-ideal solutions. The ideal solution represents the alternative that performs optimally across certain criteria, while the anti-ideal solution represents the alternative that performs the worst across those criteria. These solutions are determined using the following equations, which allow for the identification of the most desirable and least desirable:

$$\boldsymbol{AAI = \min_j x_{ij} \;\; \text{if} \;\; j \in B \; \text{and} \;\; AAI = \max_j x_{ij} \;\; \text{if} \;\; j \in C}, \tag{6}$$

$$\boldsymbol{AI = \max_j x_{ij} \;\; \text{if} \;\; j \in B \; \text{and} \;\; AAI = \min_j x_{ij} \;\; \text{if} \;\; j \in C}. \tag{7}$$

In this context, B represents the criteria that are to be maximized, whereas C represents the criteria that are to be minimized.

Step 3 – It is the process of normalizing the extended starting matrix. Normalization is conducted through the utilization of the subsequent formulae:

$$\boldsymbol{n_{ij} = \frac{x_{ai}}{x_{ij}} \; \text{if} \; j \in C}, \tag{8}$$

$$\boldsymbol{n_{ij} = \frac{x_{ij}}{x_{ai}} \; \text{if} \; j \in B}. \tag{9}$$

where x_{ij} represents the elements from the initial decision matrix.

Step 4 – It is the process of establishing a weighted matrix. This process involves the multiplication of normalized matrix values by their respective weights.

Step 5 – The calculation of the utility degree of the alternatives K_i. The utility degree is determined by applying the following equations:

$$\boldsymbol{K_i^- = \frac{S_i}{S_{aai}}}, \tag{10}$$

$$\boldsymbol{K_i^+ = \frac{S_i}{S_{ai}}}. \tag{11}$$

where S_i (i=1, 2, .., m) represents the sum of the elements of a difficult matrix:

$$\boldsymbol{S_i = \sum_{i=1}^{n} v_{ij}}. \tag{12}$$

Step 6 – The formation of the utility function of the alternatives $f(K_i)$. The utility function is calculated by using the following equation:

$$\boldsymbol{f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}}}, \tag{13}$$

where $f(K_i^-)$ is the utility function versus the anti-ideal solution, while $f(K_i^+)$ is the utility function versus the ideal solution. The utility functions are calculated by using the following equations:

$$\boldsymbol{f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}}, \tag{14}$$

$$\boldsymbol{f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-}}. \tag{15}$$

Step 6 – The final step involves ranking the alternatives based on their utility function values. The alternatives are assigned a rank based on the final value of their utility function. Ideally, the alternative with the highest value of the utility function is considered the most desirable. This ranking enables a clear comparison and identification of the alternative that offers the greatest utility or benefit according to the evaluation criteria.

5. Case Study

The selection of qualitative criteria for parallel machine scheduling in this study was based on a comprehensive review of relevant literature. To ensure the credibility and validity of the criteria, experts in the field were invited to participate in the evaluation process, providing their expert opinions on the significance of each criterion. The identified criteria utilized in this study are presented in Table 1, serving as a framework for the subsequent analysis and evaluation of parallel machine scheduling performance. Priority sequencing rules aim to minimize completion time, the number of jobs in the system, and job lateness, while maximizing facility utilization. The evaluation of a particular sequencing sequence's effectiveness is determined by considering various performance measures. Table 1 provides a comprehensive list of criteria, which are used as performance measures to assess and evaluate job sequencing rules.

Table 1
List of criteria used

Criteria	Description
C_1	Makespan/total processing time
C_2	Maximum job tardiness
C_3	No. of late jobs
C_4	Total flow time
C_5	Total tardiness
C_6	Total weighted flow time
C_7	Total weighted tardiness

The process of assessing the weights of the criteria was carried out through the implementation of the following steps:

Step 1 – The decision-makers ranked the criteria in the following order: $C_1>C_5>C_3>C_6>C_7>C_2>C_4$.

Step 2 – The decision maker performed pairwise comparisons between the ranked criteria produced in **Step 1** and C_1. The analysis was performed with a standardised scale ranging from 1 to 9. The resulting priority of all criteria ranked in Step 1 are presented in Table 2.

Table 2
Priorities of the criteria

Criteria	C_1	C_5	C_3	C_6	C_7	C_2	C_4
$\varpi_{C_{j(k)}}$	1	2.5	3	4	4.5	6	7.5

The weight coefficients and DFC, characterized by a value of χ=0.00, were determined through the solution of the model. The relative importance of the criteria was assessed through the initial ratings assigned, as illustrated in Figure 1. The Microsoft Excel solver was employed to obtain the solution for the model. Analysis of the results indicates that C_1 emerged as the most significant criterion, while C_5 was identified as the second most significant criterion. These findings provide valuable insights into the prioritization and assessment of criteria within the decision-making process. Additionally, the utilization of mathematical modeling and optimization techniques, such as the Microsoft Excel solver, contributes to the rigor and accuracy of the analysis and decision-making process.

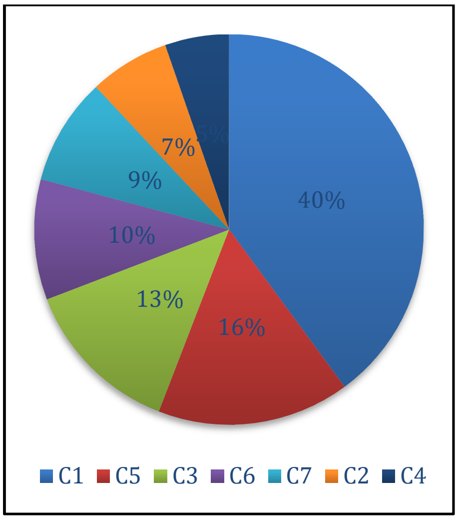

Fig. 1. The value of decision criteria

Table 3 displays the collected data about the processing time, including setup times, and due dates for the six jobs awaiting processing at the workstations.

Table 3
Data collected for the case study

Job	Processing time	Due date	Weight
A	3	7	1
B	2	16	2
C	5	9	3
D	10	17	1
E	7	18	2
F	4	8	2
J	6	13	1

The performance measures, representing the criteria, were computed and organized into Table 4 for each of the priority sequencing rules, which served as the alternatives. Consequently, Table 4 functions as the initial comparison decision matrix, presenting the assessment of alternatives to each criterion.

To facilitate further analysis, the normalized decision matrix is constructed and presented in Table 5. The objective was to minimize makespan.

Table 4
The initial decision matrix

Criteria weight	**0.399**	**0.067**	**0.133**	**0.053**	**0.160**	**0.100**	**0.089**
Rules	C_1	C_2	C_3	C_4	C_5	C_6	C_7
ATCS	23	6	1	73	6	108	6
FCFS	20	9	2	76	16	123	25
SPT	22	5	1	68	5	107	5
LPT	19	11	4	99	29	172	53
EDD	20	3	1	72	3	119	3
CR	19	4	5	88	11	147	18
MAX	23	11	5	99	29	172	53

During this phase, the collected data was subjected to a normalization process to ensure homogeneity. The MARCOS model employs a simple linear normalization method for this purpose. In order to minimize the criteria, the minimum value for each criterion was determined. The resulting normalization matrix can be observed in Table 5.

Table 5
The normalized decision matrix

Rules	C_1	C_2	C_3	C_4	C_5	C_6	C_7
ATCS	0.826	0.50	1.0	0.932	0.50	0.991	0.50
FCFS	0.950	0.333	0.50	0.895	0.188	0.870	0.120
SPT	0.864	0.60	1.0	1.0	0.600	1.0	0.60
LPT	1.000	0.273	0.250	0.687	0.103	0.622	0.057
EDD	0.950	1.0	1.0	0.944	1.0	0.899	1.0
CR	1.0	0.750	0.20	0.773	0.273	0.728	0.167

Following the normalization of the initial matrix considering the weights assigned to each criterion, the weighted matrix was computed. Subsequently, the utility scores were calculated. To facilitate this process, the ideal and anti-ideal solutions, representing the maximum and minimum values for each criterion, were determined. The decision-weighted matrix, along with the ideal and anti-ideal solutions, are presented in Table 6.

Table 6
The weighted normalized decision matrix and the negative-ideal solution

Rules	C_1	C_2	C_3	C_4	C_5	C_6	C_7
ATCS	0.330	0.034	0.133	0.049	0.080	0.099	0.045
FCFS	0.379	0.022	0.067	0.047	0.030	0.087	0.011
SPT	0.345	0.040	0.133	0.053	0.096	0.10	0.053
LPT	0.399	0.018	0.033	0.036	0.017	0.062	0.005
EDD	0.379	0.067	0.133	0.050	0.160	0.090	0.089
CR	0.399	0.050	0.027	0.041	0.044	0.073	0.015
Ideal	0.399	0.067	0.133	0.053	0.160	0.10	0.089
Anti-Ideal	0.330	0.018	0.027	0.036	0.017	0.062	0.005

Using the MARCOS method, **Step 6** entails the computation of the utility function utilizing Eq. (13). This significant step was carried out to establish the utility function for each alternative under consideration. Specifically, the utility functions for both the ideal and anti-ideal solutions were initially calculated. Subsequently, based on these utility functions, the ranking of the alternatives was determined. The resulting rankings are presented in Table 7, providing valuable insights into the relative performance and desirability of the different alternatives. This step plays a crucial role in the decision-making process by facilitating the comparison and selection of the most favorable alternative among the available options.

Table 7
The weighted normalized decision matrix and the negative-ideal solution

Rules	K_i^-	K_i^+	$F(k_i)$	Rank
ATCS	1.555	0.768	0.660	3
FCFS	1.300	0.642	0.552	5
SPT	1.658	0.819	0.704	2
LPT	1.154	0.570	0.490	6
EDD	1.957	0.967	0.831	1
CR	1.310	0.647	0.556	4

6. Conclusion

The primary aim of this study was to present a methodology for evaluating and selecting the most suitable priority sequencing rule for job processing at a workstation, utilizing a hybrid MCDM. The FUCOM was employed to determine criteria weights through pairwise comparisons, while the MARCOS method was utilized to evaluate and select the optimal priority sequencing rule. A numerical illustration, involving seven primary criteria and six alternatives, was considered as a case study to demonstrate the application of the methodology.

The outcomes of the study provided valuable guidance to workstation management in selecting the priority sequencing rule that could offer maximum benefits. Future research directions may involve incorporating grey numbers to address uncertainties in various factors and exploring the adoption of hybrid MCDM techniques within a grey number environment.

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Conflicts of Interest
The authors declare no conflicts of interest.

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