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Ranking of sequencing rules in a job shop scheduling problem with preference selection index approach

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Abstract

Scheduling different jobs in an appropriate sequence is very important in manufacturing industries due to the influence of conflicting criteria. It becomes difficult to sequence the jobs as the number of jobs increases due to the numerous computations involved. In this article, six jobs are considered to be treated on a machine one by one. Seven different priority sequencing rules provide seven different sequencing options for the jobs, which are assessed using a set of nine criteria. The Preference Selection Index (PSI) approach, a multi-criterion decision-making (MCDM) technique, is proposed to rank them from best to worst. The PSI approach, unlike other MCDM methods, does not require finding the relative significance of the criteria, which reduces the work of finding the criteria weights; hence, it is a very easy and effective tool for decision-making. A benchmark problem from previous literature is considered and solved using the PSI approach, and the obtained results are found to be correct.

Keywords: preference selection index, sequencing, scheduling, multi-criterion decision-making (MCDM).

1. Introduction

In production engineering, scheduling process determines when a particular manufacturing task can be feasibly accomplished. The boundary of the scheduling problem can be defined by specifying the resources, the time duration of the task, the initial time at which it may start and the time by which it is expected to finish. In fact, this is a decision-making procedure which optimizes one or more objectives (Pinedo, 2005). The purpose of the scheduling process is thus to decrease the end time of the task and to curtail the cost associated in completing that task. A scheduling problem provides decisions on allocating and sequencing of task. Mostly, scheduling is just allocation and in such cases to find an optimal decision, mathematical programming models are used. On the other hand, very often scheduling is purely sequencing. Sequencing thus is a specialized scheduling problem in which arrangement of the jobs totally defines a schedule. Simple sequencing is a single machine problem where the processing period of each work on the machine is deterministic. Sequencing is thus used to select a correct order for fixed number of dissimilar jobs to be carried out on a machine. This is helpful to find the best order of the jobs in such a way so that total time in completing the jobs is minimum.

Job shop have number of jobs waiting to be operated on a machine. As the quantity of jobs rises, problem becomes difficult to solve and it becomes non-deterministic polynomial-time hard (NP-hard). Therefore, some heuristic solution procedure is implemented that requires less calculation but does not assure optimality, rather they provide nearly ideal solutions that are satisfactorily acceptable for real-world purpose. Jobs in the job shops are therefore processed on a machine in a pre-determined sequence which is identified by simplified heuristics guidelines known as priority rules and use of these rules is a decision of the experienced human dispatcher. The jobs in job shop coming up for dispensation are scheduled using one of the many priority rules. Some of the frequently used priority rules for sequencing the jobs are shortest processing time (SPT) first, earliest due date (EDD) first and first come first served (FCFS). The choice of the objective function decides the selection of these priority rules and hence many times it makes sense to consider the alternative method. These priority rules are further discussed in section 2.

Preference selection index (PSI) is a technique to select the finest possible alternative among a certain set of alternatives without determining comparative significance among the attributes (Maniya and Bhatt, 2010). The approach was first developed for the material selection problem that met all the necessities of the design engineers. A research of the relevant literature yielded, the PSI has not been implemented on scheduling and sequencing problems in a job shop. In this article, the problem from Kumar et al. (2017) is considered and solved using the PSI. The result obtained from the PSI are compared with the previous researchers' results.

In this paper section 1.1 and 1.2 contains a literature analysis on scheduling problems and PSI approach respectively. Section 2 elaborates the scheduling and sequencing problem wherein input and output data is gathered. Here, seven various sequencing rules are taken as alternatives and nine different performance measures are considered as criteria. Section 3 illustrates the steps to be followed in the PSI methodology, whereas, at section 4 of this paper, a scheduling and sequencing problem is solved using PSI and the results are discussed at the end.

1.1 Scheduling problems

Scheduling principle first emerges in the mid-1950s and since then the problems related to this become nearer to industrial applications by considering layout of the shops, shops having number of identical machines, an operation requiring various resources at the same time or with multipurpose machines, etc. thus increasing in complexity (T'kindt and Billaut, 2005). The scheduling models can be categorized by identifying the resource configuration and the nature of the jobs (Baker and Trietsch, 2009). To be more specific, a model may contain single machine or multiple machines, it may be static (set of jobs does not change over time ready for scheduling) or dynamic (new jobs appear over time). From practical point of view, dynamic models are more important but still static models are extensively considered since they are useful to know the fundamentals. Analysis of static problems normally uncovers valuable understandings and then heuristic methods are used in dynamic situations. Lastly, the model may be deterministic (where certain assumptions are made with certainty) or stochastic (where uncertainty is recognized with explicit probability distributions).

Scheduling problem finds its application in almost all the sectors of activity. It can be problems related to production like flexible manufacturing system (FMS), non-traditional machining (NTM), automobile assembly lines or project scheduling problems, computer systems and so on. Scheduling can also find its application in timetable scheduling problems in educational institutes or universities to find the availability of teachers, students and classrooms.

Thörnblad et al. (2015) developed a time-indexed optimization system used in flexible job shop scheduling problem (FJSP) to schedule optimally the planned jobs on the resources which minimized the completion time and tardiness of the jobs. They also took into account the availability of fixtures and the prerequisite preventive maintenance activities. Hafez et al. (2018) evaluated the performance of dispatching rules when different number of jobs and machines are considered based on minimum total completion time. Kumar et al. (2017) considered seven different sequencing rules in a problem related to job shop scheduling. The authors applied a hybrid MCDM technique like analytical hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) to rank sequencing rules. Gharbi et al. (2015) explored a scheduling problem of single machine considering due dates, multiple planned unavailability time periods and job release date; and offered an algorithm to solve it. Ji et al. (2015) illuminated scheduling problem of a single-machine to reduce an aggregate cost that included the SLK due-window assignment, earliness, tardiness, and entire resource expenses. The authors showed that the optimal solution can be obtained considering dual resource consumption models which are functions of the job processing period. Keshavarz et al. (2019) studied a flow shop sequence-based cluster scheduling problem with the goal of reduction in overall weighted earliness and tardiness. The authors proposed a model based on mixed-integer linear programming (MILP) concept as well as established a timing procedure to find the best schedule for a certain and static sequence of jobs. They also developed a metaheuristic process built on particle swarm optimisation technique that found close optimal results for the study problem. Zou et al. (2021) proposed an algorithm for multimodal optimization of job shop scheduling problems which is a combination of k-means clustering algorithm and genetic algorithm (GA). k-means clustering algorithm is utilized to cluster built on some common features and then GA is applied to find the global optima within each cluster.

A problem based on scheduling of production and transportation where every job was transported towards an individual batching machine for additional processing was solved by Tang and Gong (2009). The aim was to optimize the entire completion period and the overall processing cost with polynomial time algorithm and pseudo-polynomial time algorithm. Cha et al. (2008) introduced a mathematical model along with dual algorithms for the combined replenishment with distribution scheduling of the warehouse. The authors developed a hybrid genetic algorithm and compared it with two recursive algorithms which showed the ability of hybrid genetic algorithm in dealing with resource limitations.

Ojstersek et al. (2020) discussed an existing research work from 2005 to 2019 in field of production scheduling. They have given representation, grouping of research work with some formulation. They explored survey built on multi objective optimization with evolutionary computation approaches for production scheduling issues that cuts the gap in this research area. Authors observed that, using hybrid techniques with simulating and building models researchers can still work in this area.

Scheduling problems were also studied in non-manufacturing areas. Yaghini et al. (2012) introduced a model for decomposition of a bigger railroad traveller scheduling problem into minor range problems, which is simple to resolve and deliver finer traveling schedule. They have applied this concept on different bulks of stations in the range of 5-20. Mixed integer optimization was done with General Algebraic Modeling System (GAMS) application on sets of stations and found simple to solve. Gholami and Sotskov (2014) discussed about railway scheduling problem for solo track to lessen the overall train unpunctuality. Authors stated the complete train delay was decreased approximately by twenty percent because of adjusting train speediness and the leaving times of the trains in three phases, first prescheduling by dispatch rule algorithm, later modifying leaving time of train and finally reconstruction of schedule. Czerniachowska (2019) studied and developed a novel approach for solving problem related to airtime advertising spots considering an objective of maximizing viewership. During that approach genetic algorithm was used to obtain the solution. It was motivated by the contemporary attention in advertising products in the breaks of TV series considering objective of maximising total viewership. Bodaghi et al. (2020) presented an emergency operation model which was an integration of geographical information systems (GIS) as well as Mixed Integer Programming (MIP) techniques. Objective of the paper was to expedite the scheduling and sequencing resources by means of several stochastic situations during disaster management. Ahsan and Dankowicz (2019) considered a scheduling and sequencing optimization problem applied for seeding process in farming. The objective was to find the locations where the seed transfer can be done from the mobile refiller vehicles to the seed containers on the planters so that the overall downtime is reduced. The authors applied the genetic algorithm to a model based on binary integer programming which signifies the judgement of whether or not to start refilling at a particular location along the path of the planter. Cheng et al. (2019) developed a model named, neural network long short term memory (NNLSTM) to find schedule completion in construction projects. Yang et al. (2020) tested scheduling paradigm on wafer probe card manufacturing and proposed that it will help in its production planning.

1.2 Preference Selection Index Approach

PSI technique was presented by Maniya and Bhatt (2010) to solve the problems related to material selection. The results found by using PSI method were matched with that of graph theory and matrix approach as well as TOPSIS technique. Later, PSI approach in facility layout design selection problem was also implemented by Maniya and Bhatt (2011). Sawant et al. (2011) presented a technique to pick automated guided vehicle in industrial atmosphere for certain application. This process was built using PSI and TOPSIS by considering entropy method for weights calculation. Joseph and Sridharan (2011) considered a scheduling problem of FMS for investigation. They used PSI approach to order the scheduling rules like launching, routing and sequencing of part by considering the criteria like average flow time, average tardiness, fraction of tardy parts, average consumption of machines and average work in process. Madić et al. (2017) applied the PSI technique for distinct optimization for cutting of stainless steel by CO2 laser considering optimizing measures such as irregularity of the cut surface, heat affected zone, kerf width and material removal rate. Borujeni and Gitinavard (2017) presented a case study related to mining industry to select a mining contractor considering hesitant fuzzy-preference selection index technique. The authors took into account hesitant fuzzy sets theory to demonstrate the real-life circumstances under hesitant situations with uncertain data so that the decision makers (DMs) judgemental error can be avoided. Kumar and Kumar (2019) used PSI method to order the composite materials by considering its properties such as density, wear resistance, flexural strength, tensile strength, impact strength, etc.

Apart from the implementation of PSI method for solving problems in the above manufacturing or industrial area, PSI has also been implemented in the following non-technical areas like, interval valued fuzzy-preference selection index technique proposed by Vahdani et al. (2014) as an appropriate decision aid for assessment in addition to a suitable tool to handle the selection issues in uncertain condition for human resource management. This technique uses linguistic variables which are simple to understand and state the subjectivity or/and qualitative imprecision in the assessments by the DMs. Siahaan and Mesran (2017) used PSI method for selection of scholarship recipients for students. Puspitasari et al. (2020) provided a ranking method for activities of the education system based on the evaluation of accreditation forms considered in the program by means of PSI. The study helped in ranking the activities and reducing their number by combining the worst ranked activities with some other ones.

2. Scheduling and Sequencing of Jobs

Early growths in the area of scheduling were inspired by problems arising in manufacturing arena and hence the terminology of manufacturing is often used even though it is used in many non-manufacturing areas now-a-days. Scheduling problems commonly deal with two types of feasibility constraints. First constraint is the restrictions on the capacity of machines and the second one restrictions on the order in which the different jobs can be accomplished. In other words, scheduling problem provides two types of decision-making, one is allocation and other is sequencing. Hence, sequencing problem may be considered to be a specific scheduling problem where ranking of the jobs completely decides a schedule.

Following assumptions are generally used in the priority sequencing rules:

- There are n single operation jobs concurrently available for processing on the machine.
- More than one job cannot be carried out at a time on the machine.
- Processing times include setup time of jobs.
- Processing time remains deterministic and is known.
- Disruptions such as machine breakdowns, accidents etc. is not considered while processing.
- Machine is not kept idle at any given time.
- Once an operation starts, it continues without break, with no new jobs arriving and no jobs are cancelled.

Now, while considering a single machine model, the below mentioned details which is known beforehand assists as input to the scheduling method:

- Processing time (p_j) - The overall period needed for handling job j.
- Release date (r_j) - The period at which a job j occurs for handling.
- Due date (d_j) - The period at which a job j is to be accomplished.

Generally, all the jobs can be considered to be available at any given time for machining and hence the release date for such jobs will be zero.

$$r_j = 0 \tag{1}$$

Now, the scheduling decisions are generated from scheduling functions which can be considered as output and are as given below:

- Completion time (C_j) - The period when the processing of job j is ended.
- Flow time (F_j) - The entire period, job j expends on the machine.

$$F_j = C_j - r_j \tag{2}$$

- Lateness (L_j) - The difference between the period at which job is ended and the period at which job is to be accomplished.

$$L_j = C_j - d_j,\ L_j > 0 \text{ or } L_j \leq 0 \tag{3}$$

If $L_j < 0$ that means prior service to the customer than demanded, if $L_j > 0$ late service to the customer than demanded while zero represents service on time as requested. Many a times, distinct fines are imposed with positive lateness, but no profits are gained with negative lateness. It is therefore, better to work with positive lateness only; which can be represented as followed by:

- Tardiness (T_j) – It is a job's lateness if job does not get completed by its due date, or else nil.

$$T_j = max\{0, L_j\} \tag{4}$$

- Total tardiness: The tardiness of all jobs with $L_j > 0$.

$$T = \sum_{j=1}^{n} T_j \tag{5}$$

Total quantities that include information of all the jobs help to assess the scheduling problem. Assuming that n jobs are to be scheduled for processing,

$$\text{Average job completion time} = \frac{F}{n} \tag{6}$$

where F is Total flow time,

$$F = \sum_{j=1}^{n} F_j \tag{7}$$

$$\text{Average jobs in the system} = \frac{F}{max\,\{F_j\}} \tag{8}$$

$$\text{Total utilization of the system} = \frac{Maximum\ flow\ time}{F} \tag{9}$$

where Maximum flow time is $\max_{1 \leq j \leq n} \{F_j\}$.

$$\text{Maximum tardiness} = \max_{1 \leq j \leq n} \{T_j\} \tag{10}$$

$$\text{Number of tardy jobs} = \sum_{j=1}^{n} \delta(T_j) \tag{11}$$

where $\begin{cases} \delta(x) = 1 \ if\ x > 0 \\ \quad\quad\ = 0\ otherwise \end{cases}$

Average Tardiness = $\frac{T}{n}$ (12)

Average lateness $= \frac{1}{n}\sum_{j=1}^{n} L_j$ (13)

where, Lateness is the summation of earliness as well as tardiness.

Considering above terms, the following performance measures are considered as the decision criteria (DC) for evaluating the job sequencing rules (Bari and Karande, 2021),

- DC_1 - Total flow time,
- DC_2 - Average job accomplishment time,
- DC_3 - Average jobs in the model,
- DC_4 - Total % utilization of the model,
- DC_5 - Total tardiness,
- DC_6 - Maximum job tardiness,
- DC_7 - Mean tardiness,
- DC_8 - Mean lateness,
- DC_9 - Number of tardy jobs.

Below mentioned various sequencing rules as listed in Table 1 are taken as alternatives that allow the schedule for a workplace to develop over a time period. Priority rules of sequencing are simplest heuristics methods considered for choosing the sequence of jobs where they are to be operated on a machine.

Table 1. Sequencing Rules

Sequencing Rules	Abbreviation	Definition
First come, first served	FCFS	Job is operated in series as and when it reaches to the machine.
Last come, first served	LCFS	Job is operated in series from latest to earliest as and when it reaches to the machine.
Shortest processing time first	SPT	Jobs are operated according to their processing time. The job needing minimum processing time on the machine is arranged at the earliest.
Longest processing time first	LPT	Jobs are operated according to their processing time. The job needing the lengthiest processing time on the machine is arranged at the earliest.
Earliest due date first	EDD	Jobs are operated in series in which they are in line for supply to the consumer.
Critical ratio	CR	Jobs are operated in sequence of ascending critical ratio.
SLACK	SLACK	Jobs are operated in series of ascending slack time (difference between period till due date and left over period to operate).

Above mentioned rules of sequencing are taken as alternatives for the given problem.

- A_1 – FCFS,
- A_2 – LCFS,
- A_3 – SPT,
- A_4 – LPT,
- A_5 – EDD,
- A_6 – CR,
- A_7 – SLACK.

3. Preference Selection Index Methodology

PSI technique was offered by Maniya and Bhatt (2010) to solve the problems related to material selection. The PSI technique uses data from the decision matrix to find criteria weights. The PSI approach, do not require finding of the relative significance of the attributes as used in the majority of other MCDM approaches. In PSI approach, it is not required to allocate comparative significance among attributes, however the overall preference value of attributes is found with idea of statistics. Now with the overall preference value, PSI for every alternative is found. Then the alternative having the maximum PSI number is chosen as the finest one.

PSI procedure is explained step by step in following stages:

Stage 1: Structuring the decision problem and identifying the goal.

It comprises input data to PSI, for example to estimate every probable priority sequencing rule, choice criteria and measures related to it for the assumed problem, etc. The goal is identified using all these things. The conclusive goal is to be at the topmost, assessing criteria at intermediate level while alternatives are placed at the bottom of order. As a result, the hierarchal arrangement related to considered problem is shown in Figure 1.

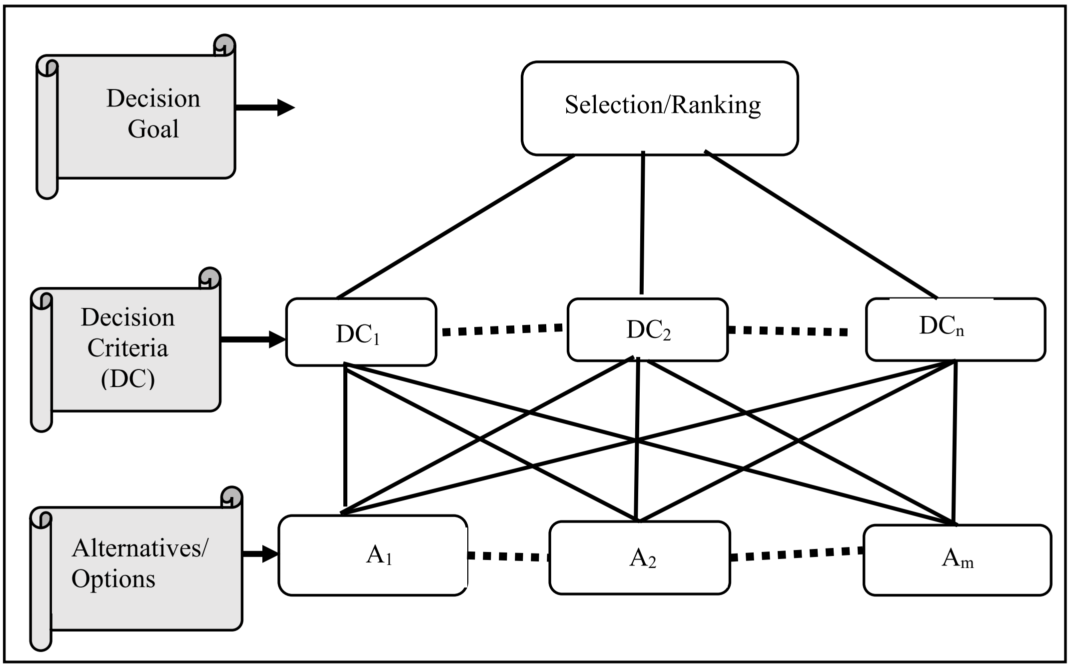

Figure 1. Hierarchal structure for decision- making

Stage 2: Construction of decision matrix.

Resolving every multi attribute decision making (MADM) problem initiates by creating decision matrix. Considering *m* alternatives (priority sequencing rules) to be assessed in reference to *n* selection criteria. Matrix D_m which is a decision matrix with element x_{ij}, presented by equation (14) denotes the utility ratings of alternative in regard to selection criteria.

$$D_m = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{14}$$

Stage 3: Normalizing the decision matrix.

Normalization is a process of converting attribute's performance scores in the scale of 0-1. This is necessary in MADM approaches for converting performance ratings having diverse data measurement units in a decision matrix into an attuned unit. For normalizing the decision matrix equations (15) and (16) are used. The normalization of attribute performance measures is different for beneficial and non-beneficial criteria. For criteria which is beneficial in nature (higher the better), then attribute performance measures are normalized as given below:

$$R_{ij} = \frac{x_{ij}}{x_{jmax}} \quad (15)$$

For the criteria which is non-beneficial in nature (lower the better), then attribute performance measures are normalized as given below:

$$R_{ij} = \frac{x_{jmin}}{x_{ij}} \quad (16)$$

where x_{ij} is the attribute measures (where *i* is 1 to *n and j* is 1 to *m*)

Stage 4: Computation of preference variation value (PV_j).

PV_j for every criteria is calculated using idea of sample variance correlation with following equation:

$$PV_j = \sum_{i=1}^{n} \left[R_{ij} - \bar{R}_j\right]^2 \quad (17)$$

$\bar{R}_j$ is the average normalized data for attribute *j*, and

$$\bar{R}_j = \frac{1}{n} \sum_{i=1}^{n} R_{ij} \quad (18)$$

Stage 5: Computation of overall preference value (Ψ_j).

Ψ_j is calculated for every criteria. For finding the value of Ψ_j, it is necessary to calculate deviance (Φ_j) in PV_j. It is found using the equation given below:

$$\emptyset_j = 1 - PV_j \quad (19)$$

Ψ_j is estimated using the equation given below. For uniformity, the summation of overall preference value of all the criteria must be one ($\Sigma\ \Psi_j = 1$)

$$\Psi_j = \emptyset_j / \sum_{j=1}^{m} \emptyset_j \quad (20)$$

Stage 6: Calculation of PSI score (I_i).

The I_i score for each alternative is calculated using equation shown below:

$$I_i = \sum_{i=1}^{m} R_{ij} * \Psi_j \quad (21)$$

Stage 7: Computed values of I_i, are utilised to order the alternatives as per its decreasing series i.e. largest to smallest. With the help of I_i value alternatives are ordered from highest to lowest and thereafter creating related explanations or suggestions.

4. Numerical Illustration

In this section, data for scheduling and sequencing problem from a previous literature of Kumar et al. (2017) is considered. The authors in their work demonstrated the method of calculating and choosing the finest sequencing rule by using hybrid MCDM technique i.e. AHP and TOPSIS. The approach proposed by Kumar et al. (2017) is tedious since it requires numerous calculations. However, PSI approach does not require determining the criteria weights separately since they are found from the figures provided within the decision matrix itself. The integrated weight approach is helpful if there is clash while deciding criteria weights by the decision makers. Furthermore, two more performance measures (criteria) are added i.e. average lateness and number of tardy jobs. Average lateness gives an idea that on an average by what time the jobs will be late to the customer while the number of tardy jobs provide the information about how many jobs are completed after their due dates. These two criteria help customer to understand the delay in job well in advance. The total processing time is not considered, for a single machine problem this time is same for all the jobs.

A flowchart given in Figure 2 presents the combined procedure of scheduling sequencing problem with application of PSI method to it.

Processing time (p_j) and due dates (d_j) of six jobs coming up for operation on the machine are arranged in Table 2. Table 3 presents the computed values for the performance of all the sequencing rules (alternatives) in reference to each decision criteria. Accordingly, Table 3 is reflected as the pair-wise assessment decision matrix of alternatives concerning all criteria.

Table 2. Processing time and due dates of jobs

Job	Processing Time	Due Dates
1	2	7
2	8	16
3	4	4
4	10	17
5	5	15
6	12	18

Stage 1: Structuring the decision problem and identifying the goal: Seven commonly used sequencing rules and nine performance measures as mentioned in section 2 are considered as the alternatives and criteria respectively. The goal is to list the ranking of these alternatives and find out the best priority sequencing rule considering these nine criteria.

Stage 2: Constructing a decision matrix: The scheduling decisions which are considered as the output for the scheduling process are computed with the help of formulae given in the section 2. DC_1 and DC_2 are computed by using equation (7) and equation (6). DC_3 and DC_4 are computed using equation (8) and equation (9). DC_5 is computed by equation (5). Equation (10), equation (12) and equation (13) are used to calculate DC_6, DC_7 and DC_8 respectively. Finally, DC_9 is computed using equation (11) and the following decision matrix is developed, presented in Table 3.

Table 3. Decision Matrix

Alternatives /Decision Criteria	DC_1	DC_2	DC_3	DC_4	DC_5	DC_6	DC_7	DC_8	DC_9
A_1	120	20.00	2.92	34.16	54	23	9.00	7.16	4
A_2	167	27.83	4.07	24.55	96	34	16.00	15.00	5
A_3	108	18.00	2.63	37.96	40	23	6.66	5.16	4
A_4	179	29.83	4.36	22.90	108	35	18.00	17.00	5
A_5	110	18.33	2.68	37.27	38	23	6.33	5.50	3
A_6	133	22.16	3.24	30.82	58	24	9.66	9.33	4
A_7	133	22.16	3.24	30.82	57	26	9.50	9.33	3

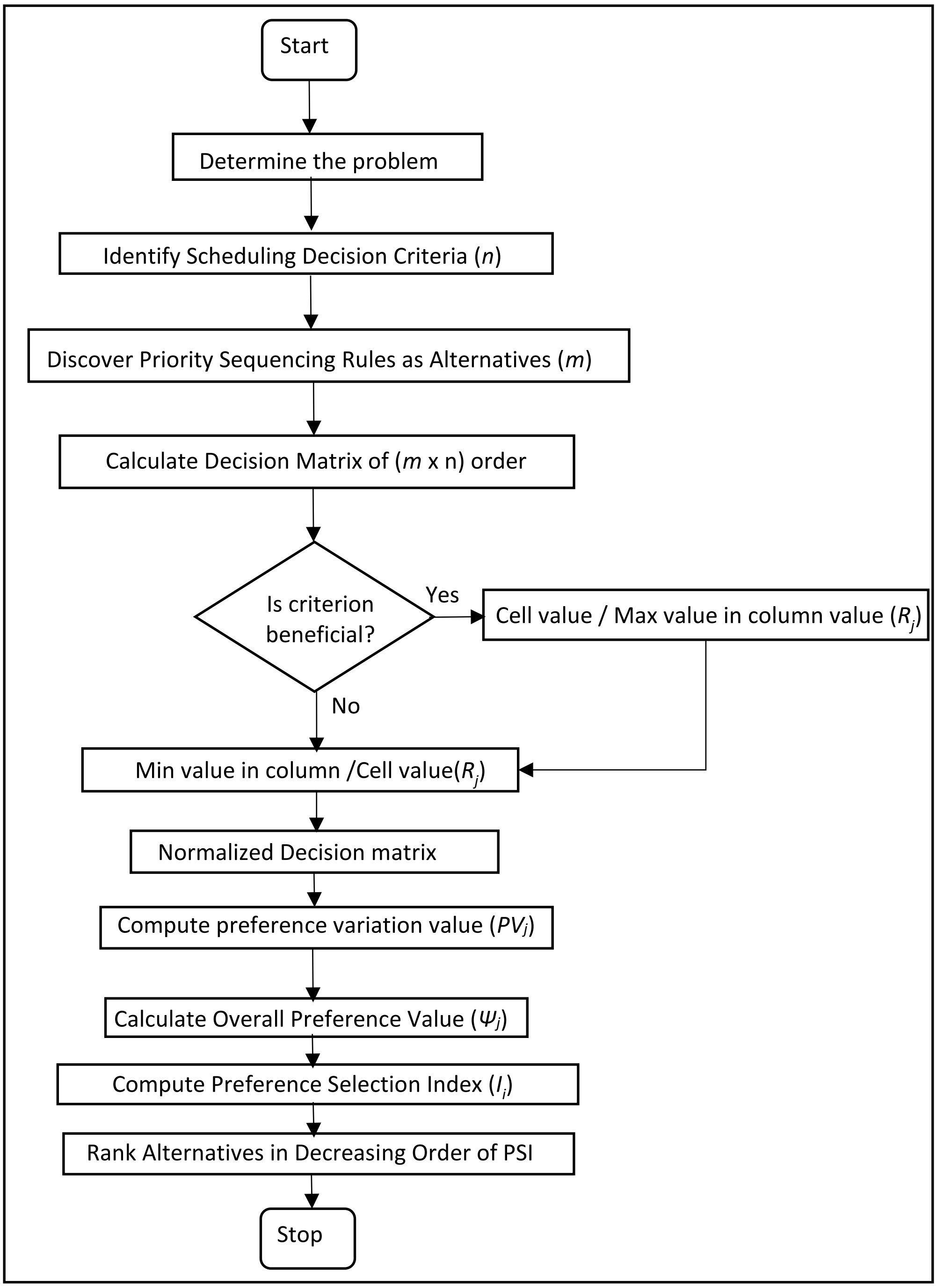

Figure 2. Flowchart for Scheduling and Sequencing problem using PSI method

Stage 3: Normalizing the decision matrix: Data given in the decision matrix is to be converted in the range of 0-1 which is shown in the normalized decision matrix Table 4. It is created with the help of equation (15) and equation (16). Except utilization all other criteria are beneficial in nature.

Table 4. Normalized Decision Matrix

Alternatives /Decision	DC_1	DC_2	DC_3	DC_4	DC_5	DC_6	DC_7	DC_8	DC_9
A_1	0.9000	0.9000	0.9006	0.8998	0.7037	1.0000	0.7033	0.7206	0.7500
A_2	0.6467	0.6467	0.6461	0.6467	0.3958	0.6764	0.3956	0.344	0.6000
A_3	1.0000	1.0000	1.0000	1.0000	0.9500	1.0000	0.9504	1.0000	0.7500
A_4	0.6033	0.6034	0.6032	0.6032	0.3518	0.6571	0.3516	0.3035	0.6000
A_5	0.9818	0.9819	0.9813	0.9818	1.0000	1.0000	1.0000	0.9381	1.0000
A_6	0.8120	0.8122	0.8117	0.8119	0.6551	0.9583	0.6552	0.5530	0.7500
A_7	0.8120	0.8122	0.8117	0.8119	0.6666	0.8846	0.6663	0.5530	1.0000

Stage 4: Computation of preference variation value: PV_j for the attributes is calculated using equation (17) and equation (18) and are arranged within Table 5 below.

Table 5. Preference Variation Value

Decision Criteria	DC_1	DC_2	DC_3	DC_4	DC_5	DC_6	DC_7	DC_8	DC_9
PV_j	0.1420	0.1420	0.1422	0.1420	0.3648	0.1404	0.3653	0.4403	0.1642

Stage 5: Determine overall preference value (Ψ_j): Deviance in preference value is computed with equation (19) and arranged in Table 6. These deviation values are used to calculate the overall preference value with equation (20) and arranged in Table 7.

Table 6. Deviation in preference value

Decision Criteria	DC_1	DC_2	DC_3	DC_4	DC_5	DC_6	DC_7	DC_8	DC_9
Deviation in Preference value	0.8579	0.8579	0.8577	0.8579	0.6351	0.8595	0.6346	0.5596	0.8357

Table 7. Overall Preference value

Decision Criteria	DC_1	DC_2	DC_3	DC_4	DC_5	DC_6	DC_7	DC_8	DC_9
Overall Preference value	0.1233	0.1233	0.1233	0.1233	0.0912	0.1235	0.0912	0.0804	0.1201

Stage 6 and Stage 7: Computation of preference selection index score (I_i): I_i scores for every sequencing rule is determined with equation (21) and tabulated in Table 8 in descending values of I_i.

Table 8**.** Preference Selection Index Scores

Methods	Preference Selection Index
EDD	0.9860
SPT	0.9608
FCFS	0.8441
SLACK	0.7961
CR	0.7731
LCFS	0.5745
LPT	0.5395

It is observed that EDD is found to be the most appropriate priority sequencing rule followed by SPT. In fact, SPT is far closer to EDD in terms of preference selection index score. Result shows that SPT sequencing is mostly used to minimize the flow time or job completion time and EDD sequencing is mostly used to reduce the tardiness of the jobs. FCFS, Slack and CR are ranked third, fourth and fifth respectively while LCFS and LPT are the worst choices among all. This model determines the optimal sequence of alternatives, without calculating the weight of criteria, however, the reference study finds weight for criteria and then these weights are used to rank the alternatives.

5. Conclusions

In this article, the PSI method is successfully implemented for solving a scheduling and sequencing problem. The problem was taken from previous literature wherein AHP was used to develop the criteria weights created using pairwise comparison, while TOPSIS was used for assessing and choosing the best sequencing rule. Instead of using two different methods, PSI method alone is useful for solving scheduling and sequencing problems. It does not require to find relative significance of the attributes, as well as apply some complex, tiring and time consuming MCDM method. The final results obtained using PSI approach are compared with that of derived in the previous literature and found to be exactly corroborating.

The scheduling problem solved in this article is performed by considering certain assumptions. The problem can be extended to uncertainty, with multiple machines and dynamic in nature as a future scope.

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